Collective Moral Hazard as a Source of Systemic Risk in Financial Markets – An analysis of the financial crisis 2007–2009

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‘Systemic risk is a term that is widely used, but is difficult to define and quantify. Indeed, it is often viewed as a phenomenon that is there ‘when we see it’, reflecting a sense of a broad-based breakdown in the functioning of the financial system, which is normally realized, ex post, by a large number of failures of financial institutions (usually banks).’

International Monetary Fund (2009a), p. 113

Acknowledgements

Seeing the financial crisis 2007–09 unfold in its early stages was one of the key motivations of this dissertation project. How could such substantial systemic risks in the financial system, that seemed so obvious in retrospect, have accumulated within the largest financial institutions worldwide, almost unnoticed? There were daunting questions to be addressed: were the main actors blindfolded and focusing on the wrong risks? Or was there even a deliberate acceptance of these risks for the own benefit, a moral hazard that collectively applied to the main agents in global financial markets?

As the crisis evolved in the subsequent years, so did this research project, and one main theme was the systemic aspect of risk. Being able to conduct vast parts of my research at different places around the world, I became aware of the many narratives on the crisis, which were told as individual stories, and yet, were strongly interconnected. These experiences contributed to shaping the goal of this dissertation: exploring the 'systemic' aspect of systemic risk and the origination, identification and governance of this phenomenon in global financial markets. The results presented on the subsequent pages are for an audience interested in a perspective change on risk in financial markets, not focusing on purely quantitative approaches but, instead, interdependencies and feedback effects that drive the dynamics of the financial system.

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Abstract

This dissertation focuses on the financial crisis 2007–09 which started with the US subprime mortgage crisis and which, over several phases, developed into one of the most fundamental crises of the modern financial system. The ensuing discussion on consequences for the governance of systemic risk in financial markets has brought out many contributions, different narratives on the evolution of systemic risk and strategies for improving the resilience of the financial system. An important limitation of these contributions is their often myopic view on isolated features of systemic risk, failing to recognize that the fundamental aspect of systemic risk is the systemic aspect, itself.

The main contribution of this dissertation is to elaborate on the change in perspective needed to understand systemic risk as a truly systemic phenomenon. Hypothesizing that the crisis cannot be explained by individual factors, but rather by grasping their interdependencies, we develop a comprehensive systemic framework which adds a new dimension to the debate. This systemic analysis of the crisis evolution shows a joint failure of relevant stakeholder groups to impose limits on financial market dynamics, and mitigate the evolving vulnerability. Our model also defines 'risks of condition', see Haller (1986), that are outside the scope of ordinary risk models.

Our focus then is on the relevance of the collective behavior of financial institutions as a source of systemic risk, and particular explanations of collective forms of moral hazard. We present two in-depth research modules covering both theoretical and empirical point of view. The theoretical study of collective moral hazard identifies a major issue, that is financial market participants are not internalizing the risk impact of their joint actions at the systemic level. Empirically, we provide statistical evidence—for a 'systemic core' of US financial institutions—that systemic risk increased prior to the 2007–09 financial crisis. Yet, discussing the statistical limitations of our and other studies, we conclude that the measurement of systemic risk, as the basis for macroprudential regulation, still contains notable risks.

Discussing our analyses, we are able to specify some key challenges for research on systemic risk, arguing that systemic risk cannot be fully understood without acknowledging its systemic dimension. An essential aspect to take into account is the interplay of dynamics at the individual, institutional and systemic levels. Here our analysis pinpoints the risks of proposed regulatory reforms—macroprudential as well as private sector measures—calling for a more integrated understanding of governance. Our main point for the ongoing debate is: we need to address with greater clarity the ratio of risk to return at the macro level of financial markets, in order to shape an overall equilibrium of governance, and to determine the desired contributions of the public and private sectors.

Zusammenfassung

Dieses Dissertationsprojekt untersucht die Finanzkrise 2007–09, die sich ausgehend vom US-Hypothekenmarkt in mehreren Phasen zu einer der schwerwiegendsten Krisen unseres heutigen Finanzsystems entwickelte. In der bereits zu Beginn der Krise aufkommenden Debatte über Reformen der Finanzmarktregulierung gibt es vielfältige Sichtweisen, verschiedene Narrative zur Entstehung systemischer Risiken, aus denen Strategien zur Stärkung der Stabilität des Finanzsystems abgeleitet werden. Eine zentrale Schwäche der Forschung zu systemischem Risiko im Finanzsektor ist jedoch, dass zumeist einzelne, isolierte Aspekte untersucht werden. Der Kernaspekt systemischen Risikos, nämlich der systemische Aspekt, wird hingegen vernachlässigt.

Hauptbeitrag der Dissertation ist die Untersuchung des Perspektivenwechsels, der notwendig ist, um systemisches Risiko als wirklich systemisches Phänomen zu begreifen. Unsere Hypothese ist, dass die Krise nicht durch Einzelfaktoren erklärbar ist, sondern nur durch die Analyse von deren Zusammenhängen und Abhängigkeiten. Das entwickelte Systemmodell bringt eine gänzlich neue Perspektive in die Debatte ein. Es verdeutlicht die gemeinschaftliche Verantwortung verschiedener Finanzmarktakteure, welche kritische Marktdynamiken bzw. die entstehende systemische Verwundbarkeit hätten beeinflussen können. Ferner werden verschiedene Bedingungsrisiken, siehe Haller (1986), identifiziert, die nicht in üblichen Risikomodellen abbildbar sind.

Wir untersuchen dann die Relevanz von kollektivem Verhalten von Finanzmarktakteuren als Quelle systemischer Risiken, insbesondere kollektive Formen von Moral Hazard, aus theoretischer und empirischer Perspektive. In der theoretischen Analyse entsteht kollektiver Moral Hazard, da die Akteure die Folgen ihres gemeinsamen Handelns, auf Systemebene, nicht internalisieren. Empirisch belegen wir für einen 'systemischen Kern' von US-Finanzinstitutionen die Hypothese, dass ein Anstieg systemischer Risiken vor der Krise erkennbar war. Aufgrund gravierender statistischer Limitationen, denen auch andere Studien unterliegen, ist die Messung systemischer Risiken, als Grundlage makroprudenzieller Regulierung, jedoch kritisch zu hinterfragen.

Schliesslich benennen wir einige zentrale Herausforderungen der Forschung bzgl. systemischer Risiken, insbesondere dass ein Verständnis ohne Einbezug der systemischen Dimension nicht möglich ist. Dafür muss auch das Zusammenspiel von Dynamiken auf individueller, institutioneller und systemischer Ebene untersucht werden. Für eine nachhaltige Reform der Finanzmarktregulierung müssen auch Governancestrukturen einbezogen werden. Von besonderer Bedeutung ist ein Diskurs, auf Makroebene, zum Verhältnis von Risiko und Rendite, um darauf aufbauend das Verhältnis der Beiträge privater und öffentlicher Anspruchsgruppen zu Governance im Finanzmarkt entsprechend definieren zu können.

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Chapter 1

Introduction

The financial crisis 2007–09 marks a profound event in the history of financial crises. Despite sophisticated risk management systems within financial institutions[1] and the regulatory framework of the financial sector, systemic risk evolved almost unnoticed. Early warnings, as summarized by the International Monetary Fund (2009b), did not foresee the acuteness of the effects of the forces in play. Even the early stages of the crisis are distinguished by a constant under-estimation of the looming debacle. Financial market observers were able to identify the critical aspects of systemic risk only ex post. The magnitude of the breakdown, puts into question the general dealing with risk in financial markets, as well as the limits of the public sector to act as a lender-of-last-resort (LOLR) and to provide emergency support to financial institutions on the brink of collapse.

A striking feature of the crisis is that its culmination can be viewed in different phases; see Bank for International Settlements (2009) and Liedtke (2010). The commonly held starting point, its first phase, is the subprime mortgage-related market turmoil. This segment had been struggling since early 2007; then major events in May and June 2007 produced a full-blown collapse. These events include the closure of UBS' Dillon Reed Capital Management, a first round of downgrades of subprime mortgage-backed securities by Moody's, and an emergency capital injection into two troubled hedge funds of Bear Stearns. Each phase was triggered by a new form of systemic risk: several rounds of writedowns caused heavy losses in financial institutions; liquidity interruptions in interbank-markets due to information effects and eroding confidence led to funding

[1] As defined in the Oxford dictionary (online), we apply the term financial 'institution' as 'a large company or other organization involved in financial trading'. In the context of this thesis it describes legal entities and organizations of the financial system, or corresponding groups; e.g. insurance institutions as a subset of financial institutions as they are only active in the insurance sector. We refer to financial intermediaries in a more specific way, describing those institutions offering financial intermediation services. Our use of the term 'institution' does not relate to sociological or normative aspects as under the umbrella of institutional theory.

pressures on financial institutions due to their high maturity mismatch; and a temporary reprieve brought about by progressive policy interventions.

The crisis entered its second phase after the emergency acquisition of Bear Stearns by JP Morgan Chase in March 2008, backed by the US Federal Reserve (Fed). After a short period of market easing, worries about the solvency of major international financial institutions resurfaced. This led to a desperate situation at the three major federal mortgage associations. After IndyMac collapsed in June 2008, in September the US government announced it would seize control over Fannie Mae and Freddie Mac, which held mortgage portfolios worth more than USD 5 trillion. Shortly afterwards, the bankruptcy of Lehman Brothers marked a turning point, and the next phase. A global loss of confidence sparked a deadlock in major parts of the financial system and threatened to bring down even the largest global financial institutions.

Only unprecedented, internationally-orchestrated policy intervention limited the fallout. However, markets today remain suppressed as recessionary effects developed in the real economy, due to the market turmoil. Although further interventions have helped to re-stabilize developments, and financial markets have celebrated a temporary recovery from mid-2009, the sheer volume of governmental interventions in both the financial markets and the real economy has become a subject of concern. In early 2010 the European sovereign debt crisis began. The Greek government made its first request for support from the European Union, the European Central Bank and the International Monetary Fund. Greece was followed by Ireland, in late 2010, and Portugal, in early 2011. Throughout 2012 there was a series of struggles in the Spanish banking system (e.g. Bankia) that ended in another bailout by the European Union, injecting funds into four Spanish banks.

Today the problem remains unresolved, with financial markets and the real economy on fragile paths of recovery, and still vulnerable to a renewed deepening of the crisis. The very recent escalation in the Cypriot banking system in March 2013 highlights this fragility. A critical aspect in this bailout was the consideration to impose a levy on private bank deposits, as part of a possible bailout. This sent fears of contagion throughout southern Europe and the Euro in general, and caused allegations that the Cypriot government was trying to save the domestic financial system, positioned mainly as an offshore marketplace, at the cost of international financial stability.

In the first phases discussion ensued on the consequences of regulation, or the governance of systemic risk. Research concentrated on two predominant issues: first, how can the ex ante identification of systemic risk be improved; and second, what mechanisms can be developed within the regulatory framework or financial institutions to put the financial system on a more sustainable path, by strengthening the resilience of financial institutions and markets and by fostering an early adaptation once critical dynamics have been identified. Mandated by the G20, major international bodies have reported on shortcomings and proposed reform measures to the regulatory framework of international financial markets. The debate is ongoing, as the repercussions of the crisis continue to be felt throughout the financial system and the ongoing sovereign debt crisis in Europe threatens to spark another blow.

Today there is a wide spectrum of contributions from many different stakeholders. These include reports issued by the Financial Stability Forum (FSF), Basel Committee for Banking Supervision (BCBS), International Monetary Fund (IMF), Senior Supervisors Group (2008), etc.[2] Publications by private think tanks and other special committees include the Group of Thirty (2009, 2010, 2011), Lord Turner (2009) in the UK, De Larosière et al. (2009) in the European Union, Brunnermeier et al. (2009), and the Institute of International Finance (2008). Representatives from academia have also extensively contributed to the debate; see e.g. Acharya and Richardson (2009) and Acharya et al. (2010a) amongst many others[3]. The major slant of these contributions is the design of macroprudential regulation to tame (endogenous) systemic risks within financial markets and safeguard the stability of the global financial system.

However, one has to acknowledge the limitations of these analyses, as they often apply a myopic focus on individual aspects and fail to account for their interdependencies with other factors. For example, researchers talk about causes separately—the relevance of macroeconomic dynamics between the US and China, regulatory loopholes and market biases created through governmental policies, complexity and flawed risk assessments, speculative euphoria, as well as critical incentives and moral hazard—without acknowledging that it is the combination of these factors that determine the disastrous extent of the crisis.

The origins of the pre-crisis boom were created by benign macroeconomic conditions, favorable monetary policy, and a continuously strong development of US real estate markets. In financial markets, there was a fundamental change in the risk perception of market participants, driven by purely quantitative approaches to risks and the wider application of fair value accounting. Progressing disintermediation created new potential for growth; see Liedtke (2010). Risk appetite gradually increased as the cycle evolved, through shadow-financial institutions that could, due to the weaker regulatory restrictions, create portfolios with higher risk profiles. As a result, and in a continuing low-interest-rate environment, regulated financial institutions increasingly searched for yields. At this stage, microstructural changes in terms of leverage and maturity mismatch would have already been noticeable, but they were not yet significant. Due to regulatory capture,

[2] All these reports can be accessed online.

[3] Lo (2012) provides an extensive survey of major academic and journalist contributions on the crisis.

authorities imposed no limits on these developments, and they further instigated an emphasis on short-term incentives and moral hazard. Overall, these aspects created the systemic exposure, primarily through their combination. By singling out likely individual assessments, researchers commonly neglect a fundamental aspect of systemic risk, that is, the *systemic* aspect.

This dissertation contributes to the debate on the governance of systemic risk in financial markets, by elaborating on the perspective change that is needed to understand systemic risk as a truly systemic phenomenon. By specifically acknowledging the systemic dimension in our conceptual approach, we hypothesize that the crisis cannot be explained by analyses of individual factors, but rather by grasping their interdependencies. Thus, we offer a method that integrates important issues within a comprehensive systemic framework. This adds a new dimension to the debate. Conceptually, the research rationale implies two important distinctions from other analyses: we address financial market dynamics from a systemic context to account for interdependencies of otherwise distinct arguments; and we take a comprehensive view of governance in financial markets, involving major stakeholders rather than concentrating only on specific areas of the regulatory framework. For this, we introduce the concept of the 'governance triangle' in the fundamentals chapter.

The focus of our analyses then is on the relevance of collective behavior as a source of systemic risk, and particularly the explanations of collective forms of moral hazard. For this we present (1) the systemic analysis of the crisis evolution, and (2) two in-depth research elements, focusing on the collective behavior of financial institutions from both theoretical and empirical perspectives. This allows us to specify some key challenges for research on systemic risk—which we conclude in support of our hypothesis—arguing that systemic risk cannot be fully understood without acknowledging its systemic dimension. An essential aspect to take into account is the interplay of dynamics at the individual, institutional and systemic levels. Here our analysis pinpoints the risks of proposed regulatory reforms—macroprudential as well as private sector measures—calling for a more integrated understanding of governance. Our main point for the ongoing debate is: we need to address with greater clarity the ratio of risk to return at the macro level of financial markets, in order to determine the desired contributions of the public and private sectors, and to shape an overall equilibrium of governance.

After chapter 2 introduces the fundamental concepts we advance our line of argument in several steps. Initially, we focus on the origins of the 2007–09 financial crisis from a systemic perspective (chapter 3). We point out several narratives[4] that focus on specific

[4] As the Oxford dictionary (online) defines, the term 'narrative' refers to 'a spoken or written account of connected events', and specifically 'a representation of a particular situation or process in such a way as to reflect or conform to an overarching set of aims or values'.

aspects being relevant in the evolution of the crisis. Yet, these suffer from their limited perspectives and are often biased by personal background and political or economic interests. The evolution of a system model of financial markets, following on the approach of Vester (2002), allows us to assess the individual narratives in relation to one another. Vester offers a heuristic to analyze dynamics of complex systems in a holistic manner. Our model allows us to explain the phased development of the crisis by illustrating how a general endogenous dynamic is affected by a new form of systemic risk materializing in each step.

Our conclusion from the systemic analysis (1) is that there was a joint failure of all relevant stakeholder groups—the public sector, investors and financial institutions—to impose limits on the unfolding of systemic risk prior to the crisis. We emphasize shifts in financial market regulations that limited the governance of behavioral dynamics. While higher market efficiency and interconnectedness—representing economies of scale in an expanding financial system—reduced the probability of market disruptions, they, at the same time, increased the potential impact from such events. Haller (1986) defines this phenomenon as 'diseconomies of risk' (section 2.1.1). With these fundamental changes and the resulting collective vulnerability not being identified, severe risks evolved in underlying conditions of market interactions: through the focus on purely quantitative risk assessments and the assumptions engrained in models to assess transactions (e.g. assuming liquid markets in valuation models), these models, instead of supporting an identification of risks, became risky themselves. Therefore, to assess corresponding risks ex ante, an essential change of perspective in current research is needed. Our model attempts such a change, as we identify not only factors that contributed to failures in governance and enforced the evolution of diseconomies of risk, but also reactive variables, which indicate certain forms of systemic risk further enforce the endogenous crisis dynamics. These variables point towards potential areas for reform.

The systemic approach defines the context for our subsequent analysis (chapter 4) focusing on the collective behavior of financial institutions (2). The concept under analysis is collective moral hazard and its relevance for systemic risk. Under collective moral hazard, financial institutions intentionally induce systemic risk because they have incentives for collective behavior. Levin and Coburn (2011) have brought forward allegations that moral hazard led to excessive risk-taking which resembles a particularly strong market failure. In our theoretical analysis, we establish a microfoundation for collective moral hazard that builds on strategic complementarities, and negative externalities especially. While the issue can be somehow reduced through regulation, it poses the challenge that various other incentive structures can lead to collective behavior, as well: e.g. those internal in financial institutions, or those which result from aggregate coordination failures in financial markets. Discussing our results in the wider context of the literature, we conclude that the crux of a microfoundation of collective behavior lies in the fact that financial market participants do not internalize the risk impact of their joint actions at the systemic level.

From an empirical perspective on collective behavior of financial institutions we study prospects for an ex ante identification of systemic risk. Using two samples covering both international and US contexts, we analyze the hypothesis that there was empirical evidence of an increase of systemic risk prior to the financial crisis 2007–09. Our results, building on a simple measurement of interdependencies, support this hypothesis, but only when focusing on a 'systemic core' of US financial institutions. An interesting aspect is that these results are compatible with more sophisticated approaches, such as Acharya et al. (2010b), and underscore that their added value, as compared to simple indicators, still remains to be clarified; see Drehmann and Tarashev (2011a,b). Furthermore, statistical challenges that apply to our study, similar to other methods, show that the measurement of systemic risk, as an important basis for macroprudential regulation, still contains notable risks and limitations.

Combining the findings of both the theoretical and empirical analyses of collective behavior of financial institutions (2), we conclude that it is difficult to address the dynamics which evolve from an interplay of individual, institutional and systemic levels in the financial system. In addition, the dynamics of financial markets and their resulting influence on incentives pose a special challenge for regulation, as it can give rise to collective moral hazard. Lastly, the design of a safety net and related LOLR policies need to be addressed. Discussing our results in the context of the ongoing debate on reforms to the regulatory framework in financial markets (chapter 5), we conclude that current proposals seek to tackle many of the drivers included in our system model individually. Importantly though, they fail to address interconnections and the feedback loops that can be identified only from the systemic perspective. Elaborating on this change in perspective—regarding systemic risk as a truly systemic phenomenon—is the main contribution of this dissertation. This allows us to pinpoint the risk in proposed macroprudential initiatives, as well as reforms in private sector governance.

In our synthesis, we argue that an important aspect which has not yet been addressed in the debate, with the clarity that it deserves, is the ratio of risk to return at the macro level of financial markets that is considered acceptable from a societal perspective. If there is consensus that society does not want to take the risks of a crisis similar to the one of 2007–09, it has to be made clear that a reduction of risk will require, amongst other things, a substantial deleveraging in the financial system, which will come with adverse effects on economic prospects. A debate on this issue will help to determine the extent of financial intermediation to be regarded as a public good, and then focus on the adequacy and effectiveness of regulatory structures. However, the consideration cannot be based on a solely technical approach to risk, but has to achieve a higher level of objectivity, see Haller (1999), integrating psychological and sociological aspects. Reflecting on our overall results (chapter 6), we argue in support of a continued attempt to build on the specific characteristics of systemic risk as a systemic phenomenon, and integrate this perspective into the debate. Due to the limitations of the often myopic focus of existing analyses and the aspiration needs to be to develop more comprehensive and interdisciplinary approaches to systemic risk.

Chapter 2

Fundamental concepts

At the center of this thesis is the study of systemic risk in financial markets, as well as its regulation. This section gives a conceptual introduction, presenting fundamentals for our subsequent analysis. A vast body of scientific literature supposes that the term *risk* is based on a clear-cut, and universally applicable definition. As this is not the case, applied concepts of risk need to be specified according to their distinct context. Common ground for a discussion can only be achieved by integrating all stakeholder perspectives, as well as their individual perspectives on risk.

Here we begin with a brief survey on selected approaches to (systemic) risk and its regulation, as well as important differentiations for our later analysis. It highlights criticisms with reference to technical risk analyses ordinarily applied in the financial sector. The fundamentals are laid out in three sections: general considerations on risk and uncertainty (section 2.1); concepts of systemic risks commonly used in scientific studies of financial intermediaries, markets, or the financial system (section 2.2); and, aspects of regulation addressing systemic risk in financial markets (section 2.3).

2.1 Initial considerations on risk

2.1.1 Defining risk

A well-established definition of risk, generally applied in financial literature, is proposed by Knight (1921), part III, ch. 8, who distinguishes risk and uncertainty:

> The practical difference between the two categories, risk and uncertainty, is that in the former the distribution of the outcome in a group of instances

is known (either through calculation a priori or from statistics of past experience), while in the case of uncertainty this is not true, the reason being in general that it is impossible to form a group of instances, because the situation dealt with is in a high degree unique.

This abstract definition can be better grasped by taking the example of an entrepreneur assessing whether to pursue an economic project or not. As the outcome of the project is uncertain, the entrepreneur will try to break it down into specific aspects—e.g. market size, pricing, cost of goods sold, competition—for which he will build individual expectations that help him to transform the overall uncertainty of the project into an assessment of risks and opportunities. He then can be assumed to pursue the project only if the overall assessment, based on his individual preferences, is positive[5]. For this example, we can identify two important limitations of applying the prior definition of risk: (1) statistical properties give the entrepreneur only a fragmented picture of risks in his projects; (2) there must be a further distinction in the type of risks relevant in specific projects.

Addressing these limitations, Haller (1986) gives a more general definition of risk to be regarded as the sum of possibilities that certain expectations in the projects are not fulfilled, due to specific interferences in the process of their realization. Expectations relate not only to purely economic aspects but also include technical or social aspects. Furthermore, it is important to note that expectations not only refer to individuals but can also relate to a specific group[6]: a corporation, society, etc. In terms of interferences, Haller differentiates between two major types: (1) direct interferences tied to specifically defined expectations regarding outcomes of actions (e.g. producing a product with the expectation to sell it at a specific price but then deviating from this expectation, or experiencing problems in the production process); and (2) indirect interferences that apply to the underlying conditions of those expectations and are rather implicit (e.g. the market that the product is produced for is eliminated, following a scandal that leads to a tighter regulatory framework).

Building on these two types of interferences, Haller (1986) distinguishes *risks of actions* ('Aktionsrisiken', direct interferences) from *risks of conditions* ('Bedingungsrisiken', indirect interferences). As the denotation suggests, risks of actions are related to specific actions. More general, one could also relate these risks to processes (e.g. supply, production, sales) for which certain outcome goals have been defined. The risk is to deviate from

[5]From a purely economic perspective it would be common to calculate the expected value of such a project, which is the sum of all possible outcomes each multiplied by their probability. When comparing this expected value to the initial investment, a rational and risk-neutral agent will pursue the project only if the expected value at least equals his investment. If the expected value is lower than the initial investment, he expects to loose money and does not pursue the project.

[6]The application of probabilistic measurements only emphasizes that a decision-maker aligns his actions to rationally expected outcomes, as a commonly known concept (see our comments on the interpretation of risk, section 2.1.3)

the these goals and one can suppose that this type of risks is closely monitored through a corporation's management.

Risks of conditions are more of a subliminal type and relate to changes in basic conditions that can fundamentally affect processes and actions. An important feature of risks of conditions is that they are often implicit and, ex ante, it will be hard to formulate any expectations about them. Thus, without having the right experiences or information, these risks will be hardly monitored in corporations or accounted for in risk management models, although their impact can be much more fundamental[7]. Lately, Bernet (2012) has promoted the concept of risks of conditions in relation to the management of financial institutions. He argues that systemic risk is a fundamentally different type of risk as can be assessed through an aggregation of individual risk measures. Therefore, the challenge is to better understand the implications of changes in underlying conditions in general, and their causal linkage to market events.

Also related to the concept of risks of conditions is the notion of a 'black swan', which has recently become an often applied term in the economic literature referring to rare chance occurrences that often falsify common assumptions[8]. As no defined expectations are involved, and since the impact is not related to a specific action, a black swan necessarily assumes the form of risks of conditions. Thus, it represents a one-time event with highly disruptive consequences, and that occurs rather randomly. When classifying an event as random, there is an important distinction by Sieferle, quoted in Haller (2004): while the causes of an event might be truly indeterminate and random, alternatively, we might refer to an event as random, simply since its causes are too complex to be understood.

With regard to complexity and risk, and their potential consequences in aggregate systems, e.g. societies, Haller (1999) offers a dynamic perspective in his concept of *'dis-economies of risk'*, which bases on two types of developments in a system: (1) individual (sub-)systems—say specific market segments—striving for economies of scale to achieve growth and higher levels of efficiency[9]; and (2), at an aggregate system level, an increasing integration of the individual subsystems. At first sight, growth and the increased efficiency

[7]This is similar to Luhmann (2003)'s distinction of *risk* ('Risiko') and *danger* ('Gefahr'), Luhman's definition only applies at a highly aggregated level. In his view, risk necessarily involves a decision tied to the probability of damage or loss. Danger, however, is considered an external factor that is determined by the surrounding environment and affects someone even without actively taking a decision. In comparison, Haller's concept appears more general, as risks of conditions can still be (implicitly) connected to a decision, but are not directly relevant for it. They are determined by the environment and the decision-maker is not actively aware of these risks.

[8]The term 'black swan' goes back to the expedition of Nicolas Baudin to Australia in the early 19th century. The rich collection brought back from the expedition contained a black swan, which falsified the common belief of swans to be of white color only. Recently, the term has been reused by Taleb (2007) to build up a conjecture on 'low-probability, high-impact events'. These can be characterized by three aspects: (1) an extreme outlier if assessed against ex ante expectations; (2) an extreme impact; and (3) the development of retrospective explanations for the occurrence of a black swan in order to allow rationalization in society, which, in fact, fosters ignorance towards black swans, but derives from the wish to structure the world into orderly processes and interactions.

[9]This also refers to a goal of achieving further growth and accumulating higher levels of wealth in society.

are positive and supposed to contribute to the quality of risk management and to the system's resilience. Yet, Haller argues that, although the number of risk events decreases, the impact potential of an adverse event magnifies at the same time, and disproportionally to the growth that has been achieved.

This observation describes a vulnerability arising from increasing complexity and an incapability of dealing with sudden adverse changes in fundamental conditions that apply for the system as a whole, as compared to the confined consequences of specific actions. In an aggregate system, the vulnerability also arises due to the increased interconnectedness and it is important to note that the continued integration further broadens the scope of vulnerabilities: for example as cultural or social factors, e.g. perceptions of certainty and risk, and seamless communication among different (groups of) actors become critical prerequisites for the system's functioning. Beck (2003) speaks of the concomitance of wealth and its endangerment due to functional differentiation. Diseconomies of risk are strongly related to risks of conditions rather than risks of actions, especially as many ruptures are acknowledged only after materializing. This underscores the challenge to systematically identify risks connected to such categories from an ex ante perspective.

2.1.2 Identifying and measuring risk

Following the initial definition—uncertainty being transformed into a risk by applying statistical properties—we can extend our considerations with regard to the identification and measurement of risk[10]. Here, the basic argument is that one does not only need to assess the measured level of risk but, similarly, scrutinize the adequacy of the construction process. A risk assessment in probabilistic terms determines risk as the sum of negative deviations from the expected outcome each multiplied by their probability. Two important elements need to be scrutinized in the construction process: how probability can be approached (e.g. in terms of a probability distribution); and whether certain probabilities shall be excluded from the assessment.

For probability assumptions, as a crucial ingredient for quantitative measurements of risk, conditions to make adequate assumptions are that; see Haller (2004): the outcome of an action cannot be influenced (randomness); there is a large number of similar observations (homogeneity); and observations establish a stable data set, in terms of a statistical distribution. Although the probabilistic concept appeals in theory some important limitations apply in real terms: it is problematic that the risk measure focuses

[10]Taleb (2007) argues strongly against (quantitative) risk assessments: striving to explain the world as an orderly and understandable system, analyses would intentionally ignore black swans, specifically due to three cognitive fallacies: a 'narrative fallacy' describes our endeavor to explain random occurrences ex post; a 'ludic fallacy' implies that when thinking of randomness in life, we compare it to structural randomness in games (such as our lottery example); and lastly a 'statistical regress fallacy' points towards the flawed assumption that we can infer a statistical distribution from a limited number of measurements.

on average probabilities, while a risk event is a one-time realization; a limited set of observations will not allow to determine the effective distribution, especially in the tails, which have the highest impact[11]; and, it is challenging to account for interdependencies; one event triggering another one (clustering).

For financial risk assessment, a widely-used measure of risk is Value-at-Risk (VaR), which we take as an example to highlight some general limitations of quantitative risk measures; see Zimmermann (1999, 2001, 2008). According to the definition by Jorion (2006), p. 22, VaR 'summarizes the worst loss [e.g. in a portfolio of financial assets[12]] over a target horizon that will not be exceeded with a given level of confidence'. However, conventional confidence levels already exclude the most extreme outcomes—low-probability, high-impact events—to which past observations and the inferred distribution attribute only minimal probability. Due to this criticism, other measures have been proposed to better account for the tails of distributions, e.g. expected shortfall (ES, also conditional VaR); see Arztner et al. (1999)[13].

VaR requires that statistical properties be inferred from past observations, i.e. market information, and have to be stable enough to allow a calculation over a specified time frame. Since the efficiency of market information can decrease in a crisis—due to information effects or other behavioral dynamics that create noise or liquidity interruptions in specific market segments—VaR measures may lose their informational power exactly in a situation where they would be most important. Furthermore, Borio et al. (1999), and many others, point to the pro-cyclicality of VaR, which is similar for other risk measures. Such concepts hardly offer an ex ante indicator of risk: in a stable market environment with low volatility, VaR will decrease gradually. An increase of VaR only occurs once volatility has already risen, and a crisis has already erupted[14]. Information processed to calculate VaR is subject to different biases, e.g. a survivorship-bias as failed institutions drop out of the included time-series and only surviving ones remain; compare Zimmermann (2000)[15].

Abstracting from VaR, (quantitative) risk models generally transform uncertainty into a risk by processing information from past events through a pre-defined method:

[11] Technically, because of its heavier tails, a t-distribution attributes higher probabilities to tail events than a standard Gaussian distribution. Yet, this does not imply that the increased probability is sufficient.

[12] If applied in a financial portfolio, the risks of individual assets have to be separable with correlations between individual assets being known, in order to account for diversification effects in contrast to systematic risk.

[13] Arztner et al. (1999)'s expected shortfall specifically measures those losses beyond the threshold of a typical VaR model. In addition to the risk threshold, criticism of VaR extends to the measure being incoherent: VaR of a portfolio can be higher than the sum of VaRs for the same portfolio, split into two sub-portfolios. Longin (2000) proposes an extension for the VaR methodology building on extreme values.

[14] The issue of pro-cyclicality is aggravated by endogenous amplification of shocks through interdependent choices. If financial intermediaries jointly liquidate investment positions upon an increase of VaR, they further accelerate the downturn; see Morris and Shin (1999), or Danielsson et al. (2010).

[15] For technical discussion on the limitations of VaR measures and possible ways to overcome these, see Jorion (2006), p. 488 sqq.

risks are being constructed. Common types of risks to be considered in the financial market context are liquidity, credit and market risks. Despite their differentiation in theory, there are numerous interrelations among these categories in reality[16]. We will later show that some financial innovations even seek to create such interdependencies. Furthermore, other categories of risk, such as operational, legal, or reputational risks, influence the behavior of market participants[17], but, due to their qualitative nature, are especially hard to incorporate into risk models.

The fact that global financial markets are in fact a highly complex system of human agents who do not necessarily behave according to standard economic assumptions aggravates these limitations; see Zimmermann (2001)[18]. Technically, the sociological dimension of interactions, and connections between different subsystems, translates into time-lags, and feedback loops (circularities), as well as non-linear, or path-dependent dynamics. The characterization of financial markets as a system implies that many risks considered as exogenous events are in fact endogenous, but only from a higher-order perspective[19].

The division between endogenous and exogenous events also points out a basic problem of financial risk management: as risks are constructed by processing information, the results complement the information set and trigger a learning process, which will, in turn, cause an adaptation of behavior. Therefore, the measurement creates feedback on the risk[20]. From a system theory perspective, a 'second-order observation' is necessary to understand the endogenous effects of the representation of a risk; see von Foerster (1993). By observing the system from a second-order perspective, it is also possible to acknowledge that many risks classified as an (exogenous) danger—due to the system's boundaries—are in fact endogenous and should be approached differently because they cannot be separated from the system.

These issues shed important light on standard approaches of risk assessment (in financial markets). Risks are inevitable to the construction, not only as model risks, such

[16]As one example, Minsky (1977) points out that at the peak of a business cycle, the constant increases of market prices begin to stall (market risk). Available funding for projects drops due to worsening expectations (liquidity risk). These dynamics increase the riskiness of projects that rely on constant refinancing (credit risk) and force them to sell assets, what again aggravates market risks and causes fire sales, which, in turn, aggravate liquidity risks. Such a vicious circle can also be started by a different event related to another risk category.

[17]A brief description of the risk categories mentioned here can be found e.g. in Jorion (2006), p. 15 ff.

[18]Deviations from rationality, such as variations of a standard utility function have been a core subject of behavioral finance, a research strain started by the seminal contribution of Kahneman and Tversky (1979), who show that low-probability (high-impact) events are being overrated compared to higher probability events. Biases in rating such events are also the subject of the salience theory by Shleifer et al. (2010).

[19]Luhmann (2003) demonstrates that different definitions of a system—in terms of its boundaries—affect the classification as risk or danger: events that are triggered outside the system's boundaries are exogenous (danger). Yet by extending the boundaries to include the underlying drivers of such events, a danger can become endogenous and can thus be classified as a risk.

[20]Approaching this topic from sociological perspective, Luhmann (2003) states that perceptions of risk are dynamic over time and will change rapidly post eventum. Consequently, the mere anticipation of a risk already creates additional uncertainty (and risk) in the present, although the odds of an event itself remain steady. Soros (2008) refers to 'reflexivity' in financial markets, which implies that agents acting upon specific positive/negative expectations will also contribute to market development.

as using wrong parameters, but also integral to the construction process itself. Complex aspects cannot, or only imperfectly, be incorporated into quantitative risk models. The wide-spread assumption of risks being driven by exogenous events has to be scrutinized from a systemic perspective as, from a second-order observation, risks are endogenous and the representation of risk will influence the risk itself. Zimmermann (2008) concludes that knowledge about risks in financial markets seems to be overstated: the sophistication of statistical models convey a critical sense of certainty as long as risks do not materialize. Stress tests do not mitigate this observation, as they mostly change parameters rather than seek to falsify the overall model of risk.

As the efficiency of managing risks in the financial sector increases, one can establish a parallel to the concept of 'diseconomies of risk'. Although we increase our knowledge of certain risks, models of interaction become more vulnerable with regard to other types of risks, those being not adequately represented. Zimmermann (2001) argues that instead of seeking to further enhance the accuracy of risk measurements, one should focus on applying knowledge of risks in the right manner and be aware of its limitations. 'Risk histories' might help to understand the causal relationships among different types of risk and their interactions in a crisis. A further aspect for research is how sociological factors, and specifically a second-order observation, can be integrated in risk analyses: the emergence of risk might be described as a sociological pattern within the financial system, involving 'stars' or 'sociotops'; see Zimmermann (2001). One critical problem that impedes progress along these lines is that approaches and methodologies to assess risks are often segregated from a wider public discourse and confined to technical experts.

2.1.3 Interpreting risk

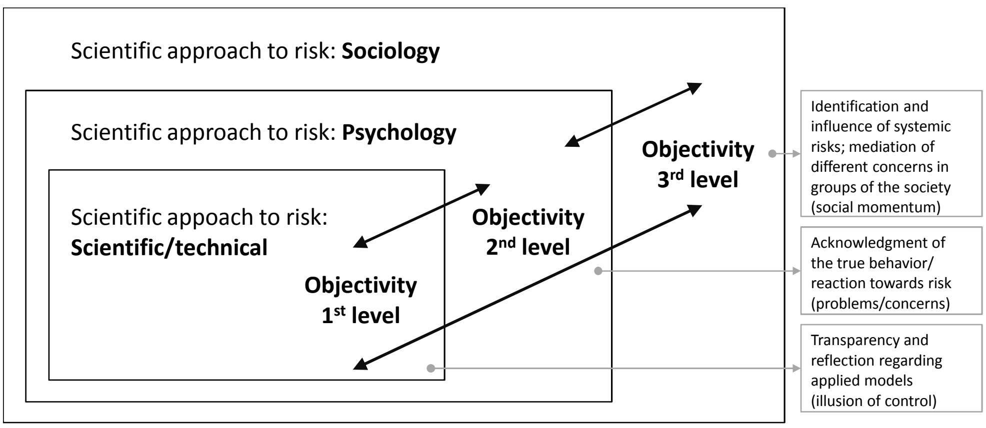

Figure 1: Haller (1999)'s model of three scientific approaches (objectivities) to risk

Expanding upon the construction of risks and focusing on their interpretation, Beck (2003) points out that most approaches to risk are focused on technical applicability, e.g.

in the context of managing a corporation. Haller (1999) reinforces this when he argues that an objective risk assessment cannot be technical only, but must be context-specific. He then differentiates three separate levels of objectivity, as treated in three essential scientific approaches towards risk (figure 1), which have to be integrated in order to achieve a true ‘objectivity’ on specific risks:

At the *first level* of Haller (1999)’s model are *scientific/technical approaches to risk*, which often base on probablistic assessments similar to Knight (1921)’s definition. In line with our earlier example, statistical or other technical properties are applied to transform uncertainty into a risk and derive a specific risk measurement, e.g. Value-at-Risk (VaR). This technical description of risk offers objectivity in terms of an abstracted risk measurement. However, it suffers from two important drawbacks: first, the power of the result itself is limited and uncertainties remain; and, second, it is only useful for decision-making if the set of actors being affected by a decision is assumed to be homogeneous, e.g. as rational and utility-maximizing agents with strictly identical utility functions.

Acknowledging the limitations of technical objectivity, the *second level* incorporates *psychological approaches to risk* and focuses on describing patterns in the individual and group-specific behavior towards/under risk. Goal is to identify factors which influence an individuals and (individual) groups perception of risk and specifically determine risk aversion. It is important to note that this second level does not generally contradict results from the first level. Instead, it comprehends the first-level assessment by adding in psychological factors, the relevance of which has been proven in many scientific analyses. In their seminal contribution, Kahneman and Tversky (1979) show that low-probability events with extreme results will be overrated in comparison to more frequent events. Objectivity at the second level can deviate from first-level objectivity.

Haller and Allenspach (1995), citing Sauer (1991), list additional psychological factors, including voluntariness[21], manageability, singularity, innovative character, reversibility, temporal affectedness, complexity, and sensual perception, all of which have an influence on individual risk aversion. In general, there is more aversion towards a danger than towards a risk[22]. So, the second level emphasizes patterns in individual and group-specific, subjective attitudes towards risk and the resulting behavior.

The *third level* amends the discussion by introducing *sociological approaches to risk* by taking an aggregate perspective on society. This is more comprehensive than at the

[21] Luhmann (2003) notes that the question whether a risk/danger is borne by an individual voluntarily or not has strong impact on its perception.

[22] We have cited Kahneman and Tversky (1979) showing that people tend to overrate low-probability events. From a psychological view, this view can be extended: if a risk is not entered voluntarily or the individual cannot influence the outcome, these increase risk aversion. This is similar, if the risks take into account innovations and are possibly hard to understand or perceive. Furthermore, risk aversion increases if damages are irreversible, if they occur immediately rather than in the future, or events seem to be impossible to control or mitigate.

prior levels, as it draws attention to differences in the perception and behavior of parts of the social system and highlights the problem of aggregating a risk assessment for a wider society. Thus, it links strongly to Luhmann (2003)'s argument that society is not driven by individual actions, but by the dynamics of interaction within a complex social system. An important element is the differences in values among various parts of society, as well as their modalities of communication/interaction. In that sense, probabilistic risk assessments, at the first level, commonly used to reach consensus for decision-making in private sector businesses are probable to fail in a wider social context, and with heterogenous agents.

Referring to the earlier distinction regarding risks of conditions and risks of actions, or the notion of voluntariness, it is evident that an action will always involve both aspects in a society: whereas some parts of society actively take a decision (risk of actions), others, and probably a larger part, are only (implicitly) exposed to potential consequences and 'social detriment'[23] (risk of conditions), Haller (1999). This transformation of the presence of risk within a society, seeking to achieve steady growth, is also a central thesis of Beck (2003)'s 'risk society' ('Risikogesellschaft'). Research at this level focuses on cumulative effects and consequences on the aggregate system. Thus, this perspective only observes events of a certain magnitude that develop repercussions for the overall system.

An important problem at this stage is the diseconomies of risk and the disproportionally increasing risk exposure of the society that can be created by an individual subsystem. Therefore, the assessment of risk again accounts not only for the direct consequences of a specific risk, but also includes indirect ones (second-round effects) and their distribution throughout the society. The question to be asked is how the materialization of a risk affects the functional capability of society—as the aggregate system—and its impact on specific values and a society's identity. Such a comprehensive view of risk has to be contrasted to the technical perception of risk (at the first level) of a corporate decision-maker. Again, there are different objectivities towards risk in different parts (subsystems) of society that need to be integrated. These predetermine tensions and emphasize the need for a wider, value-based consensus[24]. Such a consensus will not be reached within an economic marketplace or through probabilistic risk assessments; see Luhmann (2003).

[23] In the context of nuclear risks this is intensively discussed by Haller and Allenspach (1995), p. 214.

[24] Haller (1992) argues for the necessity of a risk-dialogue, which integrates the perspectives on risk of the different levels. As an iterative process, scientific expert knowledge, as well as its integration into a wider system approach which allows the change of perspective highlighted before, would complement each other and foster the understanding of individual logic or approach to risk. Furthermore, such a dialogue should focus specifically on the part of risk that affects the wider society and specifically those who do not control the underlying risk—being exposed involuntarily. Following the earlier distinction, the core focus of the dialogue then shifts towards risks of conditions in the wider society. In other words, instead of risk one would speak of threat or fear. Conducted in a neutral and open manner, such a risk-dialogue changes the perception of risks for the participating groups. Bearing in mind that the risks being discussed are often yet without substance—they have not been experienced—it will lead to a new approach to interpret, or further develop, technical risk measures. In addition, an honest application will foster trust between the participating parties.

Overall, these initial considerations make the point that the notion of 'risk' is not as clear-cut as often supposed. One must not only scrutinize the risk measure itself, but also the process by which it has been constructed. Especially relevant is the distinction between exogenous and endogenous risks. This distinction highlights the relevance of a second-order perspective, a commonly neglected aspect, similar to the importance of sociological factors, of high relevance for the realization of risk. Lastly, even in financial markets, where the focus is mostly on technical/probabilistic risk assessment, other levels of objectivity must not be neglected, as the consequences of a financial crisis can cause social detriment in the wider society.

2.2 Systemic risk and crises in financial markets

2.2.1 Definition and basic typologies of financial crises

Though the financial crisis 2007–09 is often considered an unprecedented series of events, it has to be viewed against history. In his extensive survey Kindleberger (1989) traces financial crises back to the Dutch Tulip Mania in the 17th century and highlights various parallels, but also the differences in these crises. He points out that the definition of a financial crisis is generally fuzzy. Instead of proposing his own definition, he refers to Raymond Goldsmith, who stated that a financial crisis consists of 'a sharp, brief, ultracyclical deterioration of all or most of a group of financial indicators: short-term interest rates, asset prices (stock, real estate, land), commercial insolvencies, and failures of financial institutions', p. 6.

Traditionally, financial crises have been distinguished as (national) *banking crises*, often accompanied by stock market crashes, and *currency crises*, which regard sudden changes to the flow of funds in the international financial system. A combined occurrence of both types of crises is defined as a *twin crisis*; see Allen and Gale (2008)[25]. Bordo and Murshid (2000) observe that the intensity of financial crises in the international financial system can be divided into several periods, with a recent renaissance of financial crises occurring after the end of the Bretton Woods system.

Recent studies, such as Laeven and Valencia (2008) or Reinhart and Rogoff (2009), propose quantitative thresholds regarding severity, duration and depth to determine whether a certain event marks a crisis. Such an approach delineates inflation crises, currency crashes or debasement, and bursting asset price bubbles[26]. From a different

[25] Reinhart and Rogoff (2009), ch. 16, argue for a crises pattern by which parallel banking and currency crises and the central banks' intervention to both can cyclically aggravate in an overall twin crisis.

[26] Asset price bubbles can refer to a broad variety of assets. Kindleberger (1989), ch. 3, compiles a list of 'objects' that were relevant in financial crises.

perspective, crises can also be marked by specific events: bank runs, public seizure of financial institutions or large-scale government assistance as lender-of-last-resort (LOLR); a sovereign default on outstanding debt and other extraordinary measures such as forced conversions, etc.

Another distinction is between financial crises and systemic financial crises. Yet, the distinction is not straightforward: first, one might argue that it is already incorporated in quantitative thresholds, as systemic crises—in terms of their impact—will most probably exceed more confined financial crises. Second, the definition is naturally complicated because it requires a definition of the 'system' in which the crisis unfolds: e.g. crises can be confined to the national system, but also unfold in the global financial system. Thus, it will depend on the observer's perspective whether a crisis is regarded as systemic or not.

In line with our later analysis, Laeven and Valencia (2008), p. 5, offer the following definition for a banking crisis with systemic extent[27]:

> [...] in a systemic banking crisis, a country's corporate and financial sectors experience a large number of defaults and financial institutions and corporations face great difficulties repaying contracts on time. As a result, non-performing loans increase sharply and all or most of the aggregate banking system capital is exhausted. This situation may be accompanied by depressed asset prices (such as equity and real estate prices) on the heels of run-ups before the crisis, sharp increases in real interest rates, and a slowdown or reversal in capital flows. In some cases, the crisis is triggered by depositor runs on banks, though in most cases it is a general realization that systemically important financial institutions are in distress.

Although this definition focuses on the national banking system, it can be easily adapted to an international context to include a group of countries, such as industrialized economies, where financial institutions are affected by a crisis and the effects can be measured. However, the length of the definition itself underlines the challenge to generalize from observed types of financial crises.

2.2.2 Common patterns in the history of financial crises

Allen and Gale (2008) point out that there are two contrasting approaches to explain financial crises, both with a long evolution. The first theory states that a crisis will erupt

[27] Reinhart and Rogoff (2009) give a working definition of a 'global financial crisis'. As this definition strongly focuses on macroeconomic implications and their geographical distribution, we decided to follow Laeven and Valencia (2008) as he emphasizes implications on the banking system.

spontaneously, as a *sunspot event*. These analyses mostly focus on multiple equilibria, where at least one equilibrium triggers a crisis[28]. The traditional example of multiple equilibria models are bank runs as they have been observed in earlier crises, such as the Great Depression, but also in the financial crisis 2007–09 with the run on Northern Rock Bank in the UK[29]. Microfoundations for bank runs have been developed in seminal contributions of Bryant (1980) and Diamond and Dybvig (1983)[30].

The second theory links financial crises to the *business cycle*. Gorton (1988) offers an extensive historical overview. He proposes empirical evidence for the US, showing that liabilities of failed businesses can be an effective lead indicator of banking crises. The main rationale of this approach is that as an economy dives into recession returns on bank assets will decrease. The problem for banks is that liabilities are fixed, e.g. in terms of deposits with specific interest rates, and consequently there can be a shortfall of income, causing the bank to fail. The interdependence of crises and business cycles is also a theme of Reinhart and Rogoff (2009)'s quantitative survey. They argue that there are many common macroeconomic patterns in the evolution of financial crises, such as leverage increases, soaring asset prices and institutional profits, as well as imbalanced capital flows. However, specific dynamics and especially innovation induce a notion of 'this time is different', implying that traditional risks have been effectively mitigated through innovations.

Overall, one can state that any turmoil in the financial sector relates to specific vulnerabilities, referred to as systemic risk, which is further reviewed in the subsequent subsection. Thus, financial crises need to be assessed in the wider context of events triggering a crisis, as well as the corresponding actions to resolve it. From his extensive comparison of financial crises, Kindleberger (1989), ch. 2, outlines an 'anatomy of a typical crisis' in financial markets[31], which strongly relates to the 'financial instability hypothesis' of Minsky (1977).

The starting point is a 'displacement' as a result of a positive exogenous shock. Kindleberger refers to such a shock as political events, such as the end of a war, economic innovations, etc. The result from this shock is a significant (positive) change in economic expectations and the prospects of important sectors in an economy. Entrepreneurs start launching new projects for which they seek financing. Naturally, those projects financed at the beginning of an economic boom are relatively safe and, as banks expand credit supplies, they start fueling the upswing.

[28] For a comprehensive survey and discussion of theory and evidences see Calomiris and Gorton (1991).

[29] See our overview of events in the financial crisis 2007–09 (section 3.1).

[30] A more extensive survey on these models will be given in our theoretical analysis (section 4.1).

[31] A similar description is given by Summers (2000). Llewellyn (2002) summarizes common issues that can be identified in banking crises, of which many are related to concepts of moral hazard.

As this upswing continues, it can eventually become a 'speculative mania', due to positive feedback that reinforces dynamics as the expansion of money transmits into stronger demand for goods and financial assets. Price increases, in turn, open new speculation opportunities and a wider range of projects can receive financing. Minsky (1977) indicates three types of projects according to their inherent risks: initial safe projects ('hedge finance'); riskier projects in a boom ('speculative finance') which still have a positive net present value, but are sensitive to economic factors such as changes in the interest rate; and the riskiest projects ('Ponzi finance'), which receive financing at the stage of market exuberance.

Owners of 'Ponzi finance' projects seek to realize profits by selling off at increased prices, while the required interest service can even exceed cash flows. Kindleberger (1989) notes that an often observed feature in later stages of a boom are sociological dynamics that motivate even less sophisticated agents to participate. Behavior, in terms of expectations, often exhibits features such as deviations from rationality. Whereas projects were initially fueled by increases in reserves and 'high-powered money', this reverses in later stages of the boom.

Due to the increasing risk of new projects, economic dynamics become vulnerable to shocks; the realization of a shock being a 'Minsky moment'. One source can be a gradual turn in boom dynamics as first investors leave the market and realize profits. Price increases start to slow and once the boom levels off, expectations change. After surpassing a certain threshold, this leads to a 'flight to liquidity', with disastrous consequences for the economy. In contrast, a sunspot event implies a sudden shift to another equilibrium inducing a cyclical downturn[32]. Since the downturn is cyclical it can only be stopped by a circuit breaker[33].

This generalized anatomy of financial crises can be applied to many historic events that have occurred. It is similar to the findings of Reinhart and Rogoff (2009). At the core of the model are *instabilities of expectations* due to a mixture of endogenous and exogenous factors[34] that lead to abrupt market (re-)actions. A further consequence is herding behavior, which develops contagion that goes beyond the parts of the system being initially infected.

[32] The downturn is often observed to be overshooting in a negative direction. This is partially due to sequential servicing constraints in a bank run or financial markets in general, where prices can change due to executed transactions before subsequent transactions can be executed.

[33] Kindleberger (1989) argues that, similar to the peak of the boom, prices can fall to such low levels that investors will decide to buy assets again and thus stop selling. Otherwise, external interventions are needed, e.g. exchanges can be shut down temporarily in order to stop a selling spiral. Alternatively, price limits can be instituted to stop the downfall, or a 'lender of last resort' intervention occurs, providing markets with liquidity.

[34] Following the model described here, expectations can change either gradually, due to speculation and positive feedback in a boom (in his 'reflexivity' theory, Soros (2008) describes a mechanism in which expectations strongly influence the outcomes) or suddenly shift to another equilibrium, due to an exogenous sunspot event, which can also cause an premature break in the boom.

2.2.3 Systemic risk in financial markets

The issue of systemic risk in financial markets received great attention from researchers, especially in the aftermath of financial crises. Ultimately, an early identification of systemic risk would help to prevent such crises and their disastrous economic consequences. Despite its significance, similar to banking crises, there is no clear-cut definition of the term 'systemic risk'[35]. Our prior comments on risk spell out that, as systemic risk is the result of a complex social interplay of agents within a network, an adequate representation of systemic risk poses a challenge. It will be particularly problematic to define the corresponding 'system' ex ante. Thus, many studies, such as International Monetary Fund (2009a), p. 113, refer to systemic risk as a phenomenon that is there 'when we see it'. The Group of Ten (2001), p. 126, formulates a commonly applied working definition of systemic risk[36]:

> Systemic financial risk is the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainly about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy. Systemic risk events can be sudden and unexpected, or the likelihood of their occurrence can build up through time in the absence of appropriate policy responses.

Following this definition, research on systemic risk can be understood along a time-dimension, including the evolution of systemic risk[37], the triggering phase of systemic crises, as well as (ex post) propagation, often referred to as contagion; see Borio and Drehmann (2009). De Bandt and Hartmann (2000) distinguish a horizontal dimension of contagion within financial markets and a vertical dimension within the real economy.

From a methodological perspective, research includes three major categories: empirical analyses of specific aspects of systemic crises; theoretical microfoundations of behavioral dynamics; and descriptive studies or qualitative accounts of systemic crises. While our subsequent analysis will make extensive references to studies of systemic risk in all regards, we confine ourselves at this stage to illustrating major types of systemic risk and contagion, as well as its sources. Since our work focuses on the financial system, vertical dimensions of contagion are excluded[38].

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[35] The absence of a clear-cut definition is pointed out by many contributions to the literature; see the comprehensive reviews by Bartholomew (1998) De Bandt and Hartmann (2000), Dow (2000), Kaufman (1996, 2000), Group of Ten (2001), Summer (2002), Hendricks et al. (2006), etc.

[36] Further definitions of systemic risk are discussed in Summer (2002).

[37] Note that the definition specifically acknowledges that systemic events can erupt suddenly. This is similar to the above-mentioned distinctions between risk and danger or risks of actions and risks of conditions, and refers to the vulnerability of the financial system to an exogenous shock.

[38] For a discussion of vertical contagion see Bank for International Settlements (2001, 2002).

The Group of Ten (2001) proposes three distinct sources of financial instability. These are general channels of contagion and, thus, immanent sources of systemic risk[39]. They relate to (1) the inherent structure of banks, (2) interconnections of financial institutions, and (3) information intensity of financial contracts and credibility problems. The *inherent structure of banks* and other types of financial institutions is vulnerable to a sudden withdrawal of funds (deposits), in the form of a bank run due to their intrinsic maturity mismatch[40]. As mentioned before, explanations of bank runs depend on multiple-equilibria, where the reasons for a change in equilibrium can be many; see Calomiris and Gorton (1991). Yet, information effects are an important feature (see below). In consequence of a run the bank is forced to raise additional funds (liquidity) through a premature liquidation of its assets. As this will cause losses solvency issues can arise.

With regard to *interconnections of financial institutions*, a differentiation between direct and indirect interdependencies can be applied. Direct interdependencies, often referred to as network externalities, imply that the failure of one institution causes second-round effects in other institutions, requiring them to write down claims on the failing institution: a 'domino effect'. Related contributions have focused on systemic risk arising from interbank loans as well as payment systems; see e.g. Rochet and Tirole (1996), Staub (1998) and Furfine (2003). Allen and Gale (2008), ch. 10, focusing on credit exposures between institutions/regions, introduce a distinction of spillover effects (low severity) and contagion (severe effects, causing further bank failures). In response to the 2007–09 financial crisis, recent research, such as Brunnermeier (2009) and the International Monetary Fund (2009a), ch. 2, analyzes areas of direct exposure under the umbrella of financial institutions being 'too-interconnected-to-fail', and in relation to the effects of market liquidity interruptions.

In contrast, indirect or aggregate interdependencies of financial institutions describe correlated exposures that increase systematic risk. As a shock now simultaneously affects multiple institutions, it is likely to reach a systemic dimension, thus posing a source of systemic risk. This concept is extensively explored by Dow (2000) and Summer (2002). Borio (2003) argues that the relevance of indirect exposures (especially on the asset side) has increased tremendously and aggravates the cyclicality of crises. Some researchers link this to the evolution of industry structures; see Group of Ten (2001), De Nicoló and Kwast (2002), Boyd and De Nicoló (2005), and Bekaert et al. (2008). Hellwig (1995, 1998) shows how common (macroeconomic) risk factors can be a source of systemic risk in financial markets. Besides correlated exposure to specific assets, systemic risk can also

[39]Kaufman (2000) proposes a similar taxonomy.

[40]Note that the risk of a bank run is not confined to banks and deposits. Brunnermeier (2009) argues that runs can also occur in other markets which provide financing to financial institutions and incorporate a maturity mismatch, such as commercial papers.

be the consequence of hidden aggregate exposures[41]. Staub (1998) argues that off-balance sheet transactions such as OTC derivatives are particularly relevant sources of hidden aggregate exposures. Schnabel and Shin (2004), Rajan (2005), and Brunnermeier (2009) discuss related risks in the context of liquidity runs. This sort of risk shares features with vulnerabilities inherent in the structure of financial institutions. A common argument is that the perception of too little aggregate liquidity in the system triggers additional demands for liquidity and, consequently, leads to an endogenous market dry-up.

Information-based contagion, the third category, refers to systemic risk as a result of the information sensitivity of financial transactions. This form of contagion generally encompasses effects on market movements and behavior, which are triggered by information signals or sudden changes in expectations. The contagion can pose an independent source of systemic risk, which it turn complements other channels of contagion. In a strict sense, a bank run can be regarded as a form of information contagion, since the shift in equilibrium is often because of an information shock. The majority of concepts describing information contagion are related to forms of herding in financial markets; see our theoretical analysis (section 4.1).

An important conclusion from this overview on systemic risk is that a systemic crisis not necessarily involves the whole system initially. After erupting in a confined area of the system, the crisis spreads to larger systems through contagion. The financial system is naturally prone to contagion, and it can be aggravated by correlated exposures or other biases in the aggregate risk allocation; see Summer (2002). Furthermore, we have already pointed to the relevance of often-neglected psychological or sociological factors, especially regarding a sudden reaction to shocks. The anatomy of systemic risk shares parallels with Haller (1999)'s concept of 'diseconomies of risk', reviewed in the previous section. This is, as, despite positive growths dynamics and improvements to the efficiency of managing individual risks, the impact potential of major interruptions, with repercussions throughout the whole system, can increase disproportionally at the same time. Mostly, such interruptions relate to sudden changes in basic market conditions, which are not actively accounted for and thus rather pose risks of conditions. Similarly, instabilities of a subsystem can infect other (healthier) parts of the wider financial system (horizontal contagion), and as well the real economy (vertical contagion). Therefore, an increase in risk appetite in a small area of the system can have disastrous effects for the whole.

Systemic risk also relates to Samuelson (1998)'s distinction of micro and macro efficiency in financial markets. He argues that even in markets with strong information efficiency available information can be adequate to predict the development of individual

[41] Due to multiple layers and interconnections of financial contracts, every agent adds to an aggregate exposure (e.g. maturity transformation), which is particularly hard to identify, but which can bear systemic consequences.

stocks (*microefficiency*), but there is no evidence of a powerful prediction of aggregate dynamics and related cycles (*macroefficiency*). In addition, Mishkin (1995) argues that the (macro-)efficiency of allocation mechanisms can be impaired due to hidden aggregate exposures or other vulnerabilities such as flawed incentives and coordination problems similar to the ones mentioned before.

Financial markets are necessarily about the allocation of risk, and the challenge is to determine a critical threshold at which a deviation from the efficient allocation of risk poses a bias so strong that it can lead to a systemic crisis. From the research perspective, common patterns in financial crises can be identified, but many challenges remain, e.g. understanding why a crisis erupts at a particular point in time, and what are the factors and main channels of contagion that set it off. Zimmermann (2008) cited the example of von Foerster, who compares the vulnerability of a system with a knitted vest: such a vest can be deconstructed from virtually any point and although we can describe this deconstruction, it is almost impossible to exactly identify its starting point and further development ex ante. De Bandt and Hartmann (2000) state that the source of shocks has received less attention than the functioning of different possible propagation mechanisms. Clearly it is still a matter of debate, and an important subject of this thesis: whether and to what extent systemic risk and its underlying sources can be effectively identified ex ante.

2.3 Regulation and governance in financial markets

2.3.1 Framework of governance in financial markets

The strong-form efficient market hypothesis (EMH) of Fama (1970) suggests that in a market of economically rational and utility-maximizing agents, where private information is instantly reflected in prices, no agent can consistently realize excess returns. Instead, combined actions of individual agents allow an efficient allocation of resources. In reality, due to existing information asymmetries, financial markets can only assume a semi-strong form of efficiency. Samuelson (1998) argues that the hypothesis should be applied at the level of individual stocks rather than at the market level, as financial markets are micro-, but not macroefficient. Biases in the actions of agents have been proposed from the behavioral perspective as agents deviate from full rationality; see Sewell (2008). In addition, agency problems can reduce overall welfare due to biased incentives; see Windram (2005).

These biases cause inefficiencies and constitute the ultimate reason for regulation[42]: to establish boundaries in the free interaction of stakeholders, ensuring a fair

[42] Comprehensive summaries on regulation in financial markets are Goodhart et al. (1998), Llewellyn (1999), Llewellyn

(competitive) conduct among market participants, and minimizing inefficiencies in their transactions and the subsequent consequences for the overall economy. By definition, the term ‘regulation’ comprises the set of rules being defined, implemented and overseen by public institutions to place constraints upon the interaction of private sector stakeholders within an open market environment; see Organization for Economic Co-Operation and Development (1993).

To account for the fact that the private sector complements the regulatory framework by subordinating to certain standards or codes of conduct without being specifically obliged by regulation, we apply a broad definition of ‘governance’ which includes all kinds of policy decisions, rules, principles, etc., set by public as well as private actors[43]. Llewellyn (2000, 2003) states that these do not only comprise ‘explicit’ provisions, but also sociological conventions that are determined as part of a corporate culture[44]. He frames governance structures in financial markets within the concept of a ‘*regulatory regime*’. An effective regulatory regime is built upon an optimal combination of key components such as: (1) rules set by regulatory agencies; (2) monitoring and supervision by official agencies; (3) incentive structures faced by the different stakeholders; (4) extent of market discipline and monitoring; (5) intervention in the event of bank failure; (6) internal corporate governance and control systems; and (7) disciplining by and accountability of regulatory agencies.

Table 1: Stakeholder perspectives in the governance triangle

Stakeholder group	**Description**
Public sector	Public institutions (national/international), which monitor or (in-)directly regulate financial markets and institutions, or enact policies influencing market development; regulatory and supervisory bodies, central banks, etc.
Financial markets (e.g. investors/creditors)	Institutions that act as investors or creditors in financial markets, that supply liquidity or create demand for financial instruments. Institutions such as analysts, rating-agencies, etc. that serve investors’ interests, e.g. by conducting external risk-assessments.
Financial intermediaries	Financial institutions offering intermediation services in financial markets, e.g. throughout the securitization value-chain, and thus being in a potentially asymmetric information-relation to other market participants.

Lindgren et al. (1996) identify three major dimensions of governance in financial markets: structures of governance internal to the firm (corporate governance), market forces (often also termed market discipline), and regulation and supervision by the public sector. Accordingly, we differentiate among three stakeholder groups (table 1). We

(2000), Summers (2000), Hellwig (2005), Rajan (2005), and Laeven and Levine (2009). Issues regarding regulation and governance structures concerning systemic risk in financial markets are addressed by Kaufman (1996, 2000), Crockett and Cohen (2001), Summer (2002), Allen and Gale (2006) and Brunnermeier et al. (2009).

[43] van Aaken (2007) points out the inconsistency of the various terms being used in regulatory definitions: guidelines; principles; standards; best practices etc.

[44] From that perspective Llewellyn (2000) argues that an extensive set of explicit rules can lead to a decrease of implicit conventions, or their role in guiding the actions of agents. Instead, the focus shifts to mere compliance with the explicit set of rules.

integrate these stakeholder perspectives and the variety of instruments in our *governance triangle* for financial markets (figure 2). This framework underlines our holistic perspective in the later analyses. In line with the aforementioned contributions, it resembles a broad interpretation of governance and argues that the principles of an effective regulatory regime need to incorporate a wider range of issues than only those rules imposed by the public sector. Each group implements a variety of instruments and policies that contribute to governance in financial markets.

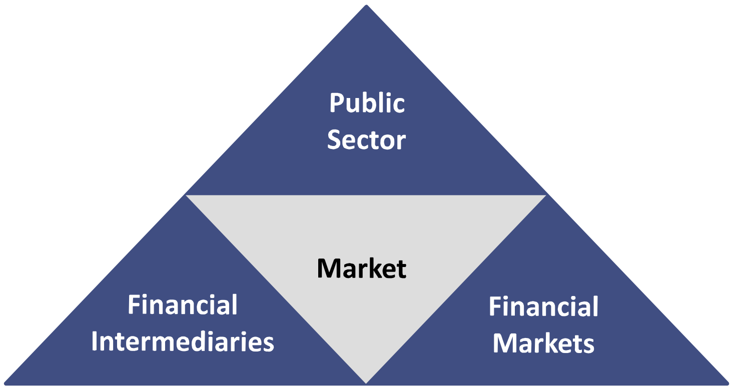

Figure 2: Framework for financial market governance: the governance triangle

Every stakeholder group has different interests which are mediated within financial markets ('market' in figure 2). The triangular shape of the governance triangle allows us to account for potentially arising conflicts of interest. The financial system provides the marketplace for intermediation between financing and saving needs of individual counterparties. In this crucial function the system has always been an important driver of economic development; see Bank for International Settlements (2002). The stability of financial markets, as it contributes to stable and positive economic development, of critical interest to the public sector.

It is the basic objective of governance to ensure that the mediation among individual stakeholders is efficient. In order to achieve that regulation, or other governance mechanisms, seeks to counterbalance identified biases in the distribution of risks among the stakeholder groups and an equilibrium of governance evolves. Summer (2002) argues that lack of coordination within different components of the framework can impair the overall efficiency of governance mechanisms and induce aggregate welfare losses. Crockett and Cohen (2001) point out that the equilibrium will change over time, due to innovation or other structural evolution in financial markets. Along this line, Bordo and Murshid (2000) highlight that an overall trend of market liberalization during recent decades shifted priorities of public sector regulation from active interventions towards fostering market transparency and discipline. As such dynamics can also be accounted for in the triangle, our framework develops Llewellyn (2000)'s approach into a dynamic perspective.

With regard to stakeholder contributions to governance, Hellwig (2008) states that optimal *public sector regulation* targets possible market inefficiencies, and in particular the risk consequences of strategic choices taken by banks that might come with adverse effects for their creditors or the financial system as a whole. From this we can see two important rationales of regulation[45].

First, imperfect information and agency problems are a wide-spread source of market inefficiencies and biases of competition. Information asymmetries, combined with little disclosure and high complexity, give rise to moral hazard and adverse selection problems. Major conflicts of interest arise between financial intermediaries (supplying financial services) and financial markets (demanding financial services; investors, creditors, or depositors), as the latter have only imperfect information about the risk profile of the intermediary. Furthermore, the limited liability of financial intermediaries[46] induces incentives for excessive risk-taking; see e.g. Borio et al. (1999) or Dow (2000). Resulting agency cost and other inefficiencies reduce aggregate welfare. Consequently, there is a demand for a centralized regulator to ensure the quality and fairness of financial transactions, and to impose disclosure requirements to enhance transparency, and eliminate these adverse effects; see Brunnermeier et al. (2009).

Second, externalities from systemic failures, in consequence of exogenous or endogenous shocks to the financial system, can impair its overall functioning. With the increased interconnection of global economies the propagation of such shocks through the system has increased sharply, similar to the cost of financial instability; see Borio (2003) and our prior discussion on fundamental aspects of systemic risk (section 2.2.3). Hence, regulation seeks to achieve an ex ante reduction of (systemic) risk. Beyond that, it embodies instruments to facilitate the orderly resolution of financial crises, or moderate their impact through governmental interventions; see also below.

Against this background, it is important to note the character of regulation as a transfer mechanism—of risk or other transaction cost—among individual stakeholder groups. By, say, imposing risk limits on certain activities, regulation reduces the potential returns of financial institutions while at the same time limiting risks for its funding stakeholders. Naturally, this redistribution implies trade-offs, especially as benefits or costs can often not be clearly identified. Also, regulatory decisions involve political aspects, since they are determined by officials with particular political interests; see Llewellyn (2000). Although Llewellyn (1999), p. 47, notes that 'regulation vs. competition is a false dichotomy' and optimal regulation will lead to a maximization of aggregate welfare, one

[45] For a detailed discussion of economic rationales for regulation see Llewellyn (1999).

[46] Windram (2005) points out that it is difficult to imagine that, without limited liability, managers would participate in the losses of an institution. Due to their limited wealth, such participation would be highly limited and managers would exhibit very low risk-taking behavior.

can also account for the flip side—that costs of imperfect regulation can neutralize or even outweigh potential benefits through adverse effects.

In contrast to public regulation, *private sector governance* comprises different sorts of principles, standards and implicit rules set by private sector institutions. Two perspectives—internally, within financial institutions, and externally, in capital markets—have to be considered. Internally corporate governance and compliance establish a system of checks and balances within the organization, in terms of incentives, disclosure principles, and accountability; see Mikdashi (2003). While compliance focuses on the company's conduct in accordance with the legal framework, corporate governance is concerned with the internal agency problems of the organization. Both functions interact strongly, sometimes integrated in a risk management context.

From an external perspective, Hellwig (2005), p. 4, defines 'market discipline [...] as a device to affect the behavior of a corporate manager or a banker so as to reduce the agency costs associated with external financing of this person's operations'. A variety of private sector institutions seeks to reduce informational asymmetries and respective agency issues between financial intermediaries and external stakeholders by adding to the quality of information; see Mikdashi (2003): by contributing to a 'true and fair' view on financial institutions, such as accounting standards boards, audit companies, or offering external assessments of risks, like rating agencies. Other institutions strive to enhance the consistency of (national) regulatory frameworks, as a fragmentation creates additional complexity and is potentially inefficient[47].

Hellwig (2005) argues that a critical rationale for private sector governance is that, by enhancing transparency in financial markets, a system of mutual checks and balances will be created which ensures market discipline and thus aligns risk-taking incentives[48]. However, multiple failures in recent history call for scrutiny regarding the effectiveness of such a system. Rajan (2005) points out that fundamental assumptions regarding incentives of individual stakeholders seem idealistic, as they can, in fact, foster risk-taking and add to financial instability. For comprehensive surveys of this debate see Hellwig (2005) and Llewellyn (2002). The Senior Supervisors Group (2008) concludes that often too much attention is attributed to compliance with regulatory requirements, while the real issues of risk and its governance remain unaddressed.

Table 2: Macro- vs. microprudential regulation

	Macroprudential	**Microprudential**
Proximate objective	Limit financial system-wide distress	Limit distress of individual institutions
Ultimate objective	Avoid macroeconomic cost (GDP) linked to financial instability	Consumer (investor/depositor) protection
Characterization of risk	'Endogenous' risk (dependent on collective behavior)	'Exogenous' risk (independent of individual agent's behavior)
Institutional correlations and common exposures	Important	Not important
Calibration of prudential controls	Top-down; in terms of system-wide risk	Bottom-up; in terms of risks of individual institutions

2.3.2 Macro- and microprudential regulation

There are two basic regulatory approaches to safeguarding financial stability—micro- and macroprudential. Borio (2003) highlights some stylized divisions of both approaches (table 2)[49]. Historically, many financial crises were triggered by the failure of an individual institution, and that led to contagion of others. Therefore, the traditional view of regulation was primarily microprudential: regulation aimed at strengthening the robustness of individual financial institutions (at the micro-level), as this would also mitigate the systemic dimension of risk in financial markets.

In contrast, Clement (2010) argues that the definition of macroprudential regulation remained fuzzy until the 2007–09 financial crisis, although the term 'macroprudential' had already evolved in the 1970s. Galati and Moessner (2011) assert that the crisis induced a shift of the regulatory perspective on financial stability to a macroprudential view on regulation; this is also a subject of this contribution. Instead of a systemic crisis being sparked by an individual failure, the crisis—and we will support this argument in our later analysis—leaves no doubt that financial institutions can also be systemic in a herd; see Brunnermeier et al. (2009). Caruana, cited in Galati and Moessner (2011), defines the ultimate goal of macroprudential regulation as 'to reduce systemic risk by explicitly addressing the interlinkages between, and common exposures of, all financial institutions, and the pro-cyclicality of the financial system'.

Yet, there are many obstacles to an effective implementation of macroprudential regulation; see Borio (2010). Our concluding discussion (section 5.1), based on our sub-

[47]Financial intermediaries have founded international organizations, e.g. the Institute of International Finance (IIF), primarily to represent their interests. Besides, these institutions also foster global coordination and best practice sharing by issuing reports such as Institute of International Finance (2008).

[48]For an extensive survey of risk-taking incentives in financial markets see Windram (2005).

[49]For comprehensive overviews on the evolution of these terms, relevant issues and tools, see Bank for International Settlements (2001), Borio (2003), Brunnermeier et al. (2009), Bank of England (2009), Borio (2010), Group of Thirty (2010), Galati and Moessner (2011) as well as the extensive references therein.

sequent analyses, makes a contribution to the debate on the power of macroprudential regulation to effectively reduce systemic risk. At this stage, we briefly point out two important instruments that public sector regulation builds on: (1) capital adequacy regulation, and (2) governmental interventions as lender of last resort (LOLR).

Under the realm of the Basel Capital Accord, *capital adequacy regulation* is one of the major cornerstones of the international regulatory framework. Capital buffers aim to prevent excessive risk-taking of financial institutions and limit their vulnerability against shocks pertaining to the major risk categories: credit and market risk; see Goodhart et al. (1998). Yet, commentators have voiced fundamental criticism of the concept of a buffer. Hellwig (2008) makes the argument that once minimum standards are imposed, a buffer becomes obsolete and no longer fulfills its function, since it must not fall below the minimum standard[50]. On a different note, capital buffers offer a solution, though many standardizations have to be defined, to accomplish a relatively simple and effective set of capital ratios and avoid an overly complex regulatory framework. Nevertheless, Greenspan (1998) acknowledges that there has been frequent criticism of 'one-size-fits-all' ratios not accounting for the individual degree of risk diversification. As a consequence, the revised Basel II framework—being in an advanced implementation stage when the financial crisis 2007–09 erupted—sought to account for institutional differences in its second pillar, by incorporating the quality of internal risk management processes. Its third pillar defined disclosure standards meant to improve market discipline[51].

With regard to the implementation of the Basel Capital Accord, it is possible to highlight some general challenges for the international regulatory framework. An important aspect to consider is that elements of public sector regulation are simple to distinguish in theory, while the dividing lines blur when approaching implementation. In the complex environment of global financial markets, particular aspects—e.g. addressing solvency and liquidity issues through capital regulation; see Brunnermeier et al. (2009)—cannot be addressed separately, but will be heavily intertwined. Similarly, the effects of specific regulatory instruments will not be confined to only one aspect of regulation, but have further-reaching, sometimes unintended consequences. Without further discussion, we refer the reader to three particular challenges that we will come back to in our later discussion: (1) differentiating between institutional or functional approaches, determining the subject of regulation, see Goodhart et al. (1998) and Monkiewicz (2007); (2) the harmonization of national regulatory frameworks in globalized markets, see Walker (2001), Lannoo (2005) and van Aaken (2007); and (3) choices regarding the types of rules to be imposed, see Llewellyn (1999), Abbott and Snidal (2000), and Summer (2002).

[50] For similar arguments see Hellwig and Staub (1996), Staub (1998), or Goodhart (2008).

[51] Hellmann et al. (2000) discuss whether capital regulation as the main instrument of public regulation is to be sufficient to mitigate moral hazard in banking.

The second critical instrument in the regulatory framework is *emergency measures for crisis intervention.* These are necessary, for there will always be a residual risk of the financial system being prone to crises. As an example, authorities can decide to bail out financial institutions, with the central bank acting as lender of last resort (LOLR), or there are further monetary policy instruments available to correct temporary market disruptions, such as providing liquidity, or reducing interest rates[52].

Kaufman (2000) demonstrates that there is a critical trade-off tied to these instruments: any predefined mechanism—an explicit safety net or its anticipation—gives rise to a moral hazard problem and can cause excessive risk-taking in financial institutions, as they know that they will be bailed out upon failure; see also Llewellyn (1999). On the other hand, uncertainty regarding the existence of a safety net can exacerbate a crisis, since it leaves financial institutions vulnerable to different forms of bank runs; see Brunnermeier (2009)[53]. Against this background, Goodhart et al. (1998) argue that it is key for the effectiveness of regulatory structures to design a combination of instruments offering specific incentives but also incorporating adequate sanctions such as allowing for the failure of a financial institution[54]. As we will illustrate later, governmental interventions were crucial in the crisis—both positively and negatively—at certain stages. For an effective regulatory framework, the issue of bank failures and resulting governmental interventions will need to be addressed.

[52] Crockett and Cohen (2001) illuminate challenges that financial innovation poses to these traditional instruments and suggest potential extensions of instruments for crisis resolution.

[53] Keeley (1990) discusses implications of the design of safety net structures.

[54] As an example, Philippon and Schnabl (2009) highlight possible options in terms of banking recapitalization.

Chapter 3

Systemic analysis of the financial crisis 2007–09

This chapter presents a systemic analysis of the financial crisis 2007–09. The multiple steps of the analysis are of a qualitative and descriptive nature, based on a large number of in-depth reports and studies that have been published on the crisis[55]. The goal is to illustrate and explain aggregate dynamics in the financial system prior to and in the first stages of the financial crisis 2007–09. These views are complemented by anecdotal insights from the perspective of an individual financial institution.

The analysis helps us develop an understanding of the system's dynamics with regard to different views on the crisis evolution, which we refer to as narratives. A systemic perspective on the system dynamics is critical, as it highlights the links between these narratives, which focus primarily on isolated aspects of financial markets and systemic risks, so that the question how the crisis evolved can be answered in a more comprehensive manner.

From a forward-looking perspective, in view of insights regarding the governance of systemic risk in financial markets, this systemic analysis allows us to identify critical variables/drivers that influence the dynamics of the aggregate system. By focusing on these core variables, it can be possible to prevent that critical dynamics arise at all. Alternatively, other variables can contribute to mitigating the dynamics in order to navigate the overall system towards a more sustainable pattern, contributing to a better governance of systemic risk.

[55] The major studies this account bases on are: Bank for International Settlements (2008); Gorton (2008, 2009); International Monetary Fund (2008); Institute of International Finance (2008); Eidgenössische Bankenkommission (2008); Senior Supervisors Group (2008); Acharya and Richardson (2009); Brunnermeier (2009); De Larosière et al. (2009); Liedtke (2010); Financial Crisis Inquiry Commission (2010), as well as Levin and Coburn (2011). Lo (2012) provides a broad overview of studies of the crisis.

Yet, some preliminary remarks are in order to specify the boundaries of this analysis. The term 'financial system' is generally interpreted globally, although dynamics are most centered on financial institutions from industrialized countries. As we focus on aggregate dynamics there is no need for a differentiation. The term is meant to comprise the whole spectrum of financial market segments, and all aspects relevant in international financial transactions. With regard to economic developments, we feature the dynamics of the evolving bubble in US real estate markets. Certainly other market segments, such as leveraged buyouts[56], exhibited similar dynamics and also contributed to the crisis. The emerging real estate bubble was clearly not a distinct feature in the US alone, but can also be identified in other regions, e.g. in several European countries[57]. However, the dynamics in the US seem to be the most pronounced, and the bursting of the US bubble in mid-2007 is central, as it marks the starting point of the subprime crisis, which led to the 2007–09 financial crisis. Hence, by examining US real estate markets, we can greatly reduce the complexity and length of the subsequent explanations, while an inclusion of further segments would not have contributed to a better understanding of the crisis evolution.

Table 3: Episodes differentiated in the analysis

Episode	**Description**
Innovation and growth (before mid-2005)	Continuation of an extended period of economic growth often referred to as the 'Great Moderation'; see Bernanke (2004): environment with low interest rates in industrialized countries and strong economic growth in emerging market economies; manifold innovations in (structured) financial products and growing importance of non-bank financial institutions, as a result of scientific and technological advances that fundamentally altered risk management practices.
Diseconomies of risk (mid-2005 to mid-2007)	Decoupling of financial market dynamics from economic fundamentals: continued increases in MBS and CDO issuance, although US home sales and increases in real estate prices peak and delinquency rates increase; in the second half of 2005, first concerns about risks in US real estate (esp. subprime markets), e.g. Greenspan (2005) and International Monetary Fund (2005); strong competitiveness in financial dynamics and risk appetite remains strong.
Tipping point[58] (January 2007 to June 2007)	Increasing signs of deterioration in US mortgage markets (esp. subprime segment) as well as an imminent re-pricing of risk; bankruptcies of US mortgage lenders (e.g. New Century) and strong declines of indices related to subprime mortgage-based securities; first financial institutions issue profit warnings and are forced to support or close affiliated hedge funds or special purpose vehicles (SPVs).
Subprime crisis (June 2007 to September 2008)	Onset of subprime crisis marked on June 1, 2007[59]; start of vicious cycle: crisis spreads to different (higher-quality) market segments and stepwise aggravation with regard to declines in market prices, spikes in volatility, as well as interruptions of market liquidity; major international financial institutions bear losses and are forced to seek recapitalization; after several lender-of-last-resort (LOLR) interventions, crisis reaches higher dimension with Lehman Brothers breakdown on September 15, 2008[60].

[56]A detailed account, which also points out parallels to the evolution of the mortgage securitization market, is given in the Financial Crisis Inquiry Commission (2010), p. 174 sqq.

[57]Examples from other countries, such as the UK and Spain, as well as supporting data, are presented in the dissenting statements of the Financial Crisis Inquiry Commission (2010).

[58]Note that the time-windows of the 'diseconomies of risk' and the 'tipping point' episodes overlap. This is in order to highlight the turn of the cycle in financial markets in the six months prior to the crisis.

[59]This date has been determined by Nowak et al. (2009), who study a Markov-switching vector autoregression of bond market data and are thus able to endogenously determine the starting point of the crisis.

[60]Later aggravations such as the recession in the real economy and sovereign debt crisis are not covered.

Then the evolution of the crisis has to be differentiated into different episodes. This has also been the conclusion of many studies, such as Liedtke (2010), and the Bank for International Settlements (2009). Table 3 illustrates how we divide the timeline of events prior to and within the crisis into four episodes. This division along the time-dimension will serve as a reference point throughout later stages of our analysis, especially our empirical study (chapter 4). We acknowledge that it has been determined with the benefit of hindsight and therefore poses a selection bias. Yet, it helps us to develop a better understanding of the dynamics in the financial system during different stages of the economic cycle.

The analysis in this chapter proceeds in five steps: Following a descriptive summary of events (section 3.1), we introduce five narratives, which explain the crisis evolution from different perspectives (section 3.2). After that, in the line of Vester (2002) and Gomez and Probst (1995), we develop a system model of the crisis dynamics (section 3.3), which helps us to link the individual narratives to a comprehensive picture of the evolution of systemic risk. After clarifying the important distinction between the banking and insurance industries and their roles in the crisis (section 3.4), we conclude that the financial crisis 2007–09 has been the consequence of wide-ranging failures in financial market governance (section 3.5).

3.1 Summary of events

This section gives a brief account of major events leading to the financial crisis 2007–09. The timeline differentiates the different phases of the crisis evolution according to the description above. As many of the facts and events represent common knowledge, only specific facts and conclusions taken from other references are individually quoted. Although most readers will be familiar with the sequence of events, this section helps to illustrate fundamental dynamics as the basis of our system model (section 3.3).

3.1.1 Innovation and growth in financial markets

Towards the end of the last century, extensive structural changes occurred throughout global financial markets, as well as the real economy. This 'great moderation', as it has been referred to e.g. by Bernanke (2004), was driven by a variety of factors: commentators refer to advances in information technology; an increasing relevance of services in the economy; successful anti-inflation policies, which greatly reduced macroeconomic fluctuations; and gains from globalization. Nevertheless, financial markets were not immune to adverse shocks, such as the 1998 Asian and Russian crises, followed by the breakdown of

Long-term Capital Management (LTCM); the burst of the internet bubble; and, lastly, the 2001 terrorist attacks of 9/11 and the ensuing invasion of Iraq, followed by the 2002–03 recession in the US and Europe.

In this environment, central banks in developed countries, led by the US Federal Reserve (Fed), adapted loose monetary policies and kept interest rates at low levels for an extended period of time in order to stimulate economic activity. On June 25, 2003 the Fed dropped US interest rates to 1% and kept it at that level until June 30, 2004. This aggressive policy of stimulation coincided with an unprecedented period of economic growth in emerging market economies, especially China, Russia, India and Brazil (BRICs). The interaction of these factors supported a strong cyclical upswing in the global economy after 2003 and the benign economic conditions stimulated developments in global financial markets[61].

Structured credit products became very popular as an alternative form of investment, because these products offered more attractive yields than, for example, low-risk corporate/sovereign bonds, where yields generally declined. The strong macroeconomic dynamics created a vast supply of liquidity, and risk premiums decreased. Thus, it became attractive for financial market participants to improve profits by increasing leverage. The growth of structured credit products also had an influence on the business model of financial intermediaries. Instead of holding loans until maturity, a massively increasing portion of loans was now originated to be distributed as structured credit products. It was commonly believed that this growth of securitization would contribute to the distribution of risk throughout the system and, therefore, add to the resilience against shocks and financial crises; see Rajan (2005).

As a result of these combined forces, asset markets experienced another boom starting in 2003. One core market in this regard was US real estate, especially the residential segment[62]. House prices had been increasing steadily on a nation-wide basis and the environment of low interest-rates, combined with positive income perspectives, made mortgage-financed homeownership very attractive. The entry of new players to the mortgage-market—which began to compete with the government-sponsored enterprises Fannie Mae and Freddie Mac—fostered the expansion of innovative mortgage products (such as adjustable-rate-mortgages, ARM), as these institutions were trying to expand their market share. Furthermore, the 'affordable housing goals' advanced by the US Congress already since the 1980s contributed to the creation of the subprime-mortgage segment, which included borrowers of lower creditworthiness, and was literally

[61] Certainly, there is a somehow mutual stimulation between economic and financial market dynamics. However, causality is particularly hard to determine, see Bank for International Settlements (2002).

[62] A similar boom occurred in the commercial real estate sector, but because residential real estate markets had a more immediate relevance in the magnitude of the crisis, we largely exclude the commercial segment.

non-existent before the year 2000; see Financial Crisis Inquiry Commission (2010). These developments created additional demand for housing in the US and induced a construction boom. Consequently, house prices increased even further.

The interplay between dynamics in the real estate sector and financial markets created a 'virtuous cycle' in US residential mortgage markets: a self-enforcing dynamic of better mortgage conditions, higher real estate demand and stronger price increases; see Goldman Sachs (2007). Housing prices started to surge on a nation-wide basis. The extended availability of mortgages even to financially weaker segments of the US society was a core driver of these developments. Furthermore, the average duration until mortgages were refinanced decreased as homeowners were able to benefit from regularly re-financing their mortgages at improving conditions. Often they were able to increase the value of their mortgage according to gains in house value and obtain the difference as a cash-out[63].

The combination of growth opportunities in these specific market segments as well as generally low interest-rates and ample liquidity, further fostered the structural evolution in the financial sector, at the institutional as well as market level. Value chains experienced an episode of vertical disintegration. Partly, these developments also occurred in consequence of market deregulation[64]. Moreover, the entry of new players, who were often not closely regulated and thus attributed to the 'shadow financial system', contributed to the deepening of financial markets[65].

Growth dynamics became especially pronounced in the closely interconnected areas of asset-backed securities (ABS), credit-default swaps (CDS) and collateralized-debt obligations (CDO)[66]. Particularly, these products allowed (institutional) investors to realize higher yields, while ratings suggested a risk-profile similar to sovereign bonds. This major benefit of the securitization business, in combination with high market liquidity and low (risk-less) interest rates, accommodated the 'search for yield' in financial markets; see International Monetary Fund (2005).

Many of these structured finance products, notably derivatives, were traded over-the-counter (OTC) and thus outside centralized and regulated markets. Institutions of

[63]In fact, homeowners were able to reduce their equity portion of their house ownership against the mortgage value. Consequently, there was a broad increase in loan-to-value (LTV) ratios. This dynamics in real estate mortgage markets was also paralleled in other areas, such as LBOs and in a general dimension. As the general savings rate in the US was very low, there was an ongoing increase of household leverage, measured by the financial obligation ratio (FOR).

[64]As an example, over-the-counter derivatives were banned in the US after the breakdown of LTCM until the moratorium was lifted in December 2000 through the Commodity Futures Modernization Act, which dropped most restrictions and oversight provisions on derivatives. Subsequently, activity in this market increased exponentially; see Financial Crisis Inquiry Commission (2010).

[65]For a definition and detailed overview of the shadow financial system see Pozsar et al. (2010).

[66]The nomenclature of securitization products is relatively complex as it also involves different types and layers of securitization. Weaver (2007) gives an overview of most common product abbreviations. Furthermore, we omit an explanation of the securitization process for reasons of briefness. Rudolph (2009) points out the overall value added by securitization transactions. In reference to the crisis, sample transactions of securitization are reviewed in Financial Crisis Inquiry Commission (2010), pp. 71, 116 and 144.

the shadow financial system were often involved as counterparties in such transactions as they created demand for riskier tranches of these securities. However, there were no extensive disclosure obligations and the level of information about these institutions, and their risk profiles, remained very limited.

Overall, increasing disintermediation led to complexity and opaqueness of the financial system, making thorough risk assessments more difficult. This issue was mitigated by an increasing sophistication of quantitative risk management systems. In addition, ratings became a central standard, serving as an objective assessment of risk throughout all stages of the value chain. Rating agencies, similar to banks, applied highly sophisticated quantitative modeling procedures to assess the risks of a wide range of financial products.

The changing market structure and the competitive challenges drove changes to the microstructure of financial institutions. Regulatory developments gave rise to market-oriented approaches, and fair value accounting—through mark-to-market rules—allowed financial institutions a more direct participation in market movements. Consequently, an emphasis on (short-term) returns evolved, which was amplified by competitive pressures; see Rajan (2005).

On account of that, publicly quoted financial intermediaries did not only engage in search for yield by exploiting growth opportunities in structured finance, they also optimized returns by adjusting the structure of their balance sheets. According to the parameters defined by regulation, leverage increased for a wide range of financial institutions[67]. The fact that capital provision rules attributed lower capital surcharges to specific off balance sheet structures—which were also excluded from consolidation—induced opportunities to optimize important profitability ratios such as return-on-assets (RoA) or return-on-equity (RoE). Since money markets provided short-term funding at highly competitive spreads, institutions also increased the level of maturity transformation, e.g. by issuing commercial papers which had to be rolled over regularly, often weekly or even overnight.

3.1.2 Diseconomies of risk: financial market growth decouples from fundamentals

In response to stronger economic activity, the Federal Reserve initiated a gradual rise of interest rates starting at the end of June 2004. Regardless of this tightening, growth in US real estate markets continued until mid-2006 and mortgage financing conditions remained vastly unaffected, especially in the subprime segment. One factor that contributed to

[67] Note that this observation depends on the exact aggregate measured to calculate leverage; see Lo (2012), figure 1.

further growth was the increasing share of adjustable-rate-mortgages (ARM), often involving teaser-rates. With such products, homeowners would pay a low interest rate for the initial 2–3 years and afterwards, rates would reset to a higher level if homeowners had not refinanced the mortgage before[68].

In financial markets, strategies were strongly focused on growth. Institutions sought higher profits and expanded market shares, and they exploited new business opportunities to manage risks. Investment banking units of global banks competed with largely unregulated hedge funds, so compensation systems were aligned to enhance growth and ensure the retention of talent[69]. The increasing importance of ratings, which were highly valued by market participants as well as regulators, contributed to the notion that risks could be almost fully diversified throughout the global financial system. As a result, the search for yield became even more pronounced and—with positive feedback—further incited changes at the institutional and systemic level of financial markets.

With economic conditions still very favorable, the overall momentum of growth in financial markets increased. Issuance of structured products rose in all sectors and the demand for securities backed by residential mortgages or other assets increased constantly. To create more diversification benefits and liquidity, asset-backed securities were re-issued as collateralized debt obligations (CDOs)[70]. The surging demand for securitized products, such as residential mortgages, created a feedback mechanism into US real estate markets. Volumes in the subprime segments increased substantially as lending standards decreased and new products were created to include additional social groups of lower creditworthiness; see Dell'Ariccia et al. (2008). A second avenue to increase volumes of securitization was to add additional layers of securitization, such as CDO^2s which were created by bundling tranches of already existing CDOs. Alternatively, synthetic CDOs were not based on physical assets, but rather referenced the performance of existing pools or indices of mortgage-related securities[71].

The addition of new layers of securitized products was driven mainly by two considerations. First, it was a fact that many investors—large institutional investors such as pension funds etc.—were only allowed to invest in financial products with prime ratings (AAA). Through the multiple layers of securitization and a careful transaction design

[68] For a detailed overview of mortgage products see Financial Crisis Inquiry Commission (2010), p. 86.

[69] This has been the conclusion of many reports analyzing an institutional perspective of the crisis (section 3.3.4).

[70] The creation of CDOs is similar to the process of RMBS, the only difference being that a CDO consists of a pool of RMBS, of which each contains a pool of individual mortgages. The process of CDO creating is described in detail in Financial Crisis Inquiry Commission (2010), chapter 8.

[71] See e.g. Hellwig (2008). According to the definition given by SIFMA: 'Synthetic CDOs sell credit protection via CDS rather than purchase cash assets. Synthetic CDOs use CDS to synthetically replicate a cash flow CDO. Funded tranches require the deposit of cash to an SPV at the inception of the deal to collateralize portions of the SPV's potential swap obligations in the transaction; losses result in principal write-downs of the issued notes'.

(hedging certain risks) it was possible to maximize the portion receiving a AAA-rating[72]. Second, every origination of securities involved fees and commissions for investment banks. Thus, higher volumes implied higher earnings. This was similar to other segments of over-the-counter (OTC) derivatives, for which issuance increased sharply.

The growth in structured finance was accompanied by a steady growth of the global economy and an overall decline in market volatility. Thus, risk sensitivity continued to decline, at the same time that risk management systems seemed to confirm that resilience throughout financial markets and institutions was strong. With ongoing disintermediation and growing product complexity, market participants became specialists at managing risk portfolios covering only very specific parts of the value-chain. Because of the complexity, ratings moved into the center of risk assessment for investors, financial institutions and regulators, as they were commonly believed to enhance market transparency.

At the institutional level, an increasingly fierce competitive environment shifted the predominant strategic focus to growth and return. Financial institutions expanded off-balance sheet activities at a rapid pace and, in parallel, their dependence on commercial paper, and repo-markets, where most of these vehicles were financed, grew. These growth strategies were summarized by the notion of banks 'economizing' on their balance sheets, optimizing funding and balance sheet structures to maximize returns; see Hellwig (2008). Many institutions and internal departments entered carry trades, buying mortgage-related products that offered higher yields than the cost of internal funding[73].

Though there were no immediate 'red flags', concern started to mount in international institutions regarding the development of overshooting in global financial markets. From the second half of 2005, several institutions began to highlight critical developments as potential risks to financial stability. In December 2005, the International Monetary Fund (2005) stated in its Financial Market Update[74]:

> 'A turn in the interest rate and credit cycle could lead to distress for specific companies. Such disturbances in specific credits could be amplified through the credit derivative markets, including through collateralized debt obligations.
>
> Mortgage markets (subprime) are an area of concern as evidence builds that monetary tightening is finally slowing the US housing market. The proliferation of riskier mortgage lending to marginal borrowers will, in particular, make this market segment vulnerable to rising interest rates and

[72] As Weaver (2007) points out, more than 80% of the value of residential subprime mortgages could be turned into a AAA-rated tranche of a RMBS or CDO.

[73] Anecdotal evidence for these trends has been provided by UBS AG (2008)'s analysis of shareholder losses in the crisis and the subsequent report by Eidgenössische Bankenkommission (2008).

[74] Similar concerns were voiced by Greenspan (2005) and the Bank of England (2005). The International Monetary Fund (2009b) gives a comprehensive overview of internal/external warnings throughout this period.

> a cooling of the housing market. Moreover, the increasing inclusion of mortgage-related products in relatively untested CDOs may expose vulnerabilities in these instruments and lead to unexpected investor losses.'

Overall, the majority of commentators acknowledged that US real estate markets posed an issue. Due to fierce competition and the expansion of mortgage-markets to socially weaker groups, lending standards had eroded over time[75]. House price increases had started to weaken in 2005 and eventually prices peaked in early 2006. Furthermore, a slowing in the rate of construction permits issued in the second half of 2005 indicated that the boom could be coming to an end. In the same period, delinquency rates started to rise, especially in the subprime segment (figure 3, left panel). A vast share of these delinquencies was also related to fraud.

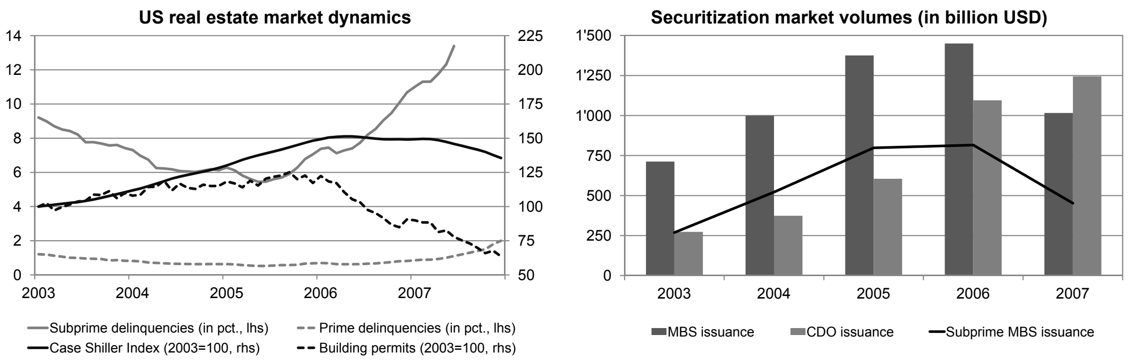

Figure 3: US real estate markets and securitization dynamics[76]

Financial market dynamics, however, remained strong and were almost unaffected by these changes. MBS issuance reached record levels in 2006 (figure 3, right panel). This observation is similar for the increasing share of subprime MBS issuance. The CDO issuance dynamic, which also exhibits extreme growth even in 2007, seems to start slightly later than for MBS products. Overall, most participants kept expanding their business activities, while only very few participants took the decision to withdraw from mortgage-related and other market segments[77].

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[75] Besides competitive dynamics, Dell'Ariccia et al. (2008) attribute the erosion of lending standard to the degree of financial innovation, with new riskier mortgage products, as well as the support by macro-factors: house prices, liquidity and interest rates. However, similar trends can be identified in other sectors. One sector with parallel dynamics is leveraged buyout (LBO) markets; see European Central Bank (2007). In LBO transactions, lending standards also increased dramatically, e.g. as loans included payment-in-kind (PIK), covenant-lite elements. Furthermore, inherent leverage and the portion of risky loan structures increased throughout the boom. However, leveraged loan markets included fewer but higher volume transactions. Thus, there might have been higher scrutiny because most of these transactions were directly overseen by boards.

[76] Delinquency data for variable rate mortgages derived from Mishkin (2007); Case-Shiller index (Composite 20) provided by Standard & Poor's; construction permits refer to New Privately Owned Housing Units Authorized by Building Permits in Permit-Issuing Places (seasonally adjusted rate) provided by US Census Bureau; MBS/CDO issuance data (Europe and US) derived from International Monetary Fund (2008) and subprime MBS issuance (US) derived from Bank for International Settlements (2009).

[77] According to the Financial Crisis Inquiry Commission (2010) investment company PIMCO is one of the few examples that largely withdrew from mortgage-related businesses. The Senior Supervisors Group (2008) points out that, in the early stages of the crisis, one can see an overall differentiation: financial institutions with better designed risk management

3.1.3 Tipping point: major breaks in the system turn the tide

Towards the end of 2006, signs of a deterioration in US real estate markets increased and delinquency rates gained momentum. According to the Financial Crisis Inquiry Commission (2010), roughly 60% of mortgages originated in 2007 became delinquent in the following three months. The International Monetary Fund (2008) states that delinquencies and foreclosures were concentrated in the subprime segment and in adjustable-rate mortgages, which were reset to higher interest rates after a certain period. This suggests that these initial spikes in foreclosures were largely driven by fraud, speculation, over-extension of borrowers and weak underwriting standards[78].

Throughout the first half of 2007, indications signaled that a repricing of risk was imminent[79]. Throughout the first quarter of 2007, mortgage-lenders reported tumbling profits and first subprime-lenders declared bankruptcy. On April 1, 2007 the bankruptcy of New Century, the largest subprime-lending institution, made worldwide news. Indices for subprime RMBS dropped more than one third during the first months of 2007. These dynamics quickly reverberated in investment bank units dealing with structured products related to US mortgages. Already in February 2007, HSBC issued a profit warning with regard to potential losses stemming from mortgage-related businesses in the US. In May 2007, UBS closed its hedge fund Dillon Reed Capital Management (section 3.3.4).

In early June 2007, which is regarded as the 'outbreak' of the crisis[80], Bear Stearns, being one of the leading investment banks in the mortgage segment, had to financially support one of two hedge funds that had suffered sharp losses from write-downs on mortgage-related securities, by injecting USD 3.2 billion. Parallel to these announcements rating agencies concluded reviews of mortgage-related securities that had been initiated because of the deteriorating market perspectives. Those reviews resulted in a wide-spread downgrading. Subsequently, markets were shaken by a first round of fire-sales and the deterioration in US subprime mortgage markets gradually spread to securities of higher-class assets.

practices were less exposed to US mortgage markets, because they were able to identify their true exposures and better adapt to the deteriorating market conditions in US real estate markets.

[78] However, the impact of deteriorating fundamental dynamics must not be underestimated: As house prices decreased, the refinancing of mortgages became increasingly difficult. Consequently, more and more mortages experienced resets to higher rates, which homeowners were often not able to afford, because they had overstretched their financial position. What had obviously added to the propensity to take on residential mortgage debt were regulations determining these loans as non-recourse: the bank could only seize the underlying asset (i.e. the house) if a mortgage went into foreclosure.

[79] A simple factiva.com search for the term 'subprime' throughout the first half of 2007 reveals that the amount of articles mentioning the term increased drastically from 3'000 articles in January/February to 10'000 articles in March/April. After a temporary decrease throughout May/June, coverage increased exponentially with 11'000 articles in July and 27'000 articles in August. Brunnermeier (2009) states that increases in mortgage defaults were first noted in February 2009.

[80] See for example Nowak et al. (2009), who determine the starting date of June 5, 2007.

3.1.4 The subprime crisis unfolds into a global financial and economic crisis

Following this initial period until June 2007, the culmination into a global financial crisis and economic recession involved several phases[81]. Most of these phases occurred as renewed surprises triggered abrupt movements in the markets, which became increasingly volatile and sensitive to new information. It is noteworthy that, nonetheless, the Dow Jones index reached a record high by mid-July 2007 (eventually peaking in October 2007). As a matter of fact, only a few commentators foresaw the true extent of the crisis at this early stage, especially that the crisis would be exacerbated to such a far-reaching extent by information effects and contagion.

The downgrades and first fire sales described in the previous section caused the crisis to spill over into other credit markets, such as mortgage-related securities with higher ratings. Transactions had to be delayed and financial institutions were left with a pipeline of assets acquired to be re-issued as SPVs. In the following months, risk exposures to these markets were disclosed for all forms of financial institutions: from smaller banks, such as the state-owned German Landesbanken, to the largest financial institutions in Europe and the US. This wide-spread exposure underscores the collective characteristic of the prior growth dynamics.

What came to the fore was that by investing in mortgage-related products investors, often highly leveraged, had taken tail-risk exposure without correctly accounting for it. The complexity of the products, including the multiple layers of securitization, as well as the legal uncertainties resulting from a possible resolution of these products—which were unstandardized and largely untested—added to the sudden risk-averseness. As investors tried to limit their exposure the market experienced liquidity disruptions[82].

Hellwig (2008) points out three core mechanisms that aggravated the situation in financial institutions: First, most of the exposure to structured credits and US real estate markets was concentrated in off balance sheet vehicles such as SPVs. These vehicles operated with extreme leverage and had only marginal cushions against losses. Second, they were financed largely by short-term debt. Because of this maturity mismatch, funding of these vehicles had to be rolled-over regularly by issuing (asset-backed) commercial paper. Third, fair value accounting rules allowed for invested securities being mark-to-market. This required a continuous adjustment of the accounted value according to market prices.

[81] The Bank for International Settlements (2008) identifies five stages subsequent to the period June/July 2007 until mid-2008, before the breakdown of Lehman Brothers.

[82] Brunnermeier (2009) points out that in this period notable increases in the TED spread highlight the severity of the culminating liquidity crisis.

The first wave of the crisis caused a fall in prices of underlying assets and money markets, where these vehicles were refinanced, dried up as the crisis unfolded. This created a disruption in refinancing these vehicles and it induced losses that often exceeded equity cushions. Lacking market liquidity and observable transactions, determination of the value of these securities became a challenging task and aggravated uncertainty. Attempting asset sales in order to limit losses and foster deleveraging, in fact, further aggravated the downward spiral.

Throughout the following period, the dynamic continued in cycles as the situation in US real estate markets further deteriorated and rating agencies downgraded larger chunks of securities (also higher asset classes). This added to uncertainty not only about the perspectives of real estate markets, but also regarding risks of structured finance products in general. Thus, a behavioral shift toward a totally risk-averse regime occurred in financial markets, which failed due to information frictions, such as adverse selection, and co-ordination problems, which arose e.g. due to wide-spread counterparty risks that were attached to structured products.

From the institutional perspective, international financial institutions successively reported write-downs and revealed exposures the extent to which was yet unknown. With only few exceptions all major institutions were collectively exposed to the critical market segments. Now off balance sheet vehicles threatened to collapse and sponsoring institutions were forced to provide support. The necessary consolidation of these vehicles on their balance sheets severely strained the supporting institutions by increasing leverage and, thus, requiring additional capital buffers. In some cases, such as the German Landesbanken, the institutions simply lacked the capacity to provide sufficient support. Hence, banks were forced to seek fresh capital to bolster capital buffers, which increased uncertainty and led to a run on the interbank market.

By August 2007, central banks announced their first liquidity injections into interbank markets and, following the bank-run on Northern Rock on September 14, 2007, the British Treasury announced a far-reaching deposit guarantee to prevent further runs. Throughout the first half of 2008, the near breakdown of Bear Stearns in March—a consequence of the liquidity crunch—marked another critical point of the crisis. After the Fed had stepped in as a lender-of-last-resort (LOLR) and provided bridge financing, Bear Stearns was sold to JP Morgan. As the market downturn continued, rating downgrades extended to monoline insurers who had provided extensive credit protection against mortgage-related securities. This triggered margin calls and, as they were unable to resolve the situation by raising additional capital, many of the major institutions, such as AMBAC and MBIA, failed.

In July, the downgrade of government-sponsored enterprises (GSEs) Fannie Mae and Freddie Mac, by far the largest mortgage agencies in the US, initiated a next phase of the crisis. The reaction of the US government, which by means of the Housing and Economic Recovery Act pledged to guarantee USD 300 billion of mortgages under certain conditions, did not suffice to calm market dynamics. In September, the US government seized control of Fannie Mae and Freddie Mac in order to prevent their collapse. Shortly afterwards, the decision of US authorities to allow Lehman Brothers to fail certainly marked the crucial point of the financial crisis.

Immediately after the failure, the liquidity of interbank markets as well as other credit markets dried up completely, causing an acute threat of a cascade of further failures in the banking sector[83]. The Fed and other central banks took unprecedented LOLR measures to stabilize markets. US investment banks gave up the special status they enjoyed under the Glass-Steagall Act in order to get access to Fed support. At the same time, central banks—through concerted interest rate cuts—tried to mitigate the economic implications of the crisis. By the end of 2008 it became clear that the major industrial economies had entered into a sharp recession, which led to further rounds of concerted stimulus programs. They were joined by the major emerging market economies, which were also affected by the recession. Commentators identify a leveling out of the financial crisis 2007–09 in the second quarter of 2009. However, in early 2010, the European sovereign debt crisis, starting in Greece, again shook financial markets and economies. Reinhart and Rogoff (2011) explain in detail the spillover from financial markets to sovereign debt[84]. At the time of writing, this combination of crises and risks in the financial system, the real economy, and sovereign debt is still not resolved. Volatility remains and financial institutions are still seeking to restore capital buffers.

3.2 Narratives on the causes of the crisis

The discussion on causes of the crisis was initiated in very early stages: in late 2007 different stakeholder groups presented a first round of comprehensive reports on specific aspects of the financial system and its institutions, which they believed was a core reason for the tremendous accumulation of risk throughout the system going widely unnoticed. Certainly, these initial analyses significantly underestimated the magnitude of the crisis and covered only fragments of what would be considered relevant in retrospect today.

However, reports were published by all stakeholder groups and it was not their sole objective to contribute to an understanding of events: they aimed to attribute responsi-

[83]The latest at this stage, the crisis had developed into a full-fledged systemic banking crisis, according to the definition of Laeven and Valencia (2008) given in our fundamentals chapter (section 2.2.1).

[84]Already in Reinhart and Rogoff (2009) they argue that contagion from the banking sector to sovereign debt are a common feature in the history of financial crises.

bility for the evolution of the crisis to specific stakeholders, as well as propose structural reforms. There were many contrasting opinions. One explicit example is the report of the Financial Crisis Inquiry Commission (2010) commissioned by the US Congress. In that report, published in January 2011, ten commission members representing both political parties failed to agree on one shared reasoning for the crisis. Instead, the report contains three analyses highlighting totally different causes. Lo (2012) illustrates the diversity of opinions in his comprehensive literature review on the crisis.

Elliott and Baily (2009) acknowledge this problem of differing opinions and offer a simple explanation. Financial crises such as the one from 2007–09 evolve through a complex network of interactions between fundamental, behavioral and other dynamics. Therefore, it will be impossible to provide 'the one' absolute explanation and any description of the crisis will necessarily abstract from the complex sequence of events. Instead, a relatively simple narrative is developed, biased by individual background and opinion, which determine the subjective process of selecting different pieces to support one's argument. Unavoidably, there will be an almost infinite variety of narratives, each arguing from a slightly different perspective and explaining specific aspects of the crisis. While certain narratives will overlap and share parts of their reasoning, they will contradict others at the same time.

Table 4: Overview on main narratives on the crisis

Narrative	Focus	Main driver of systemic risk
Chimerica (section 3.2.1)	Macroeconomic developments, esp. trade and capital flows between the US and China.	Overshooting due to high asset returns and low cost of capital, while rebalancing mechanisms (e.g. exchange rates) ineffective.
Public sector (section 3.2.2)	Public policies, esp. US housing (GSEs), interest rates (Fed), as well as regulatory and supervisory structures.	Public sector policies boost developments and fail to impose limits on critical dynamics (regulatory capture).
Minsky moment (section 3.2.3)	Behavioral dynamics in financial markets, esp. cyclicality of expectations and excuberance.	Endogenous dynamics of expectations fuel speculative market cycle and induce collective vulnerability in financial markets.
Moral hazard (section 3.2.4)	Competitive effects and agency problems, esp. information asymmetries and misaligned incentives in financial institutions.	Competitive pressures and compensation systems foster short-term risk-appetite with risks borne by investors and LOLR.
Collective surprise (section 3.2.5)	Limitations and flaws in common risk standards (e.g. ratings), and manifestation of risks of conditions.	Insufficiencies in standardized risk assessments (e.g. interdependencies of risks) allow for individual/aggregate overexposure.

Because most narratives include proposals for reforms, a competition develops: those narratives that become predominant and widely accepted will shape priorities for subsequent reforms. Looking at the variety of analyses that have been published on the financial crisis 2007–09, one especially overt contrast is the divide between blaming public sector institutions vis-à-vis the private sector. In our later conclusions (section 3.5), we will argue that responsibility has to be attributed to all stakeholders. In the following sections we briefly introduce five narratives (table 4) and relate them to the literature. Whereas one can certainly define different narratives or variations of ours, those introduced represent prominent positions in the ongoing debate about reforming the financial system.

3.2.1 Macroeconomic imbalances: Chimerica

As the title suggests, this narrative concentrates on macroeconomic causes of the financial crisis. It does not make direct reference to specific asset classes (such as US mortgage markets), but rather describes a wide-ranging increase of leveraging and mispricing of risk, which was abruptly corrected in the crisis. The term Chimerica, referring to the special relationship between the US and China, was initially proposed by Ferguson and Schularick (2007) and has since been adopted by many other commentators. Wolf (2008) presents a relatively similar explanation under the more general heading of 'global imbalances'.

This narrative contradicts those commentators who see failed macroeconomic policies at the heart of the explanation of the crisis (section 3.2.2). Instead, it argues that the special relation between the US and the Chinese economies poses a core reason for the massive mispricing of risk in financial markets. Underlying the dynamics was a dreadful combination of high returns and low cost of capital that is attributed more importance than other explanatory approaches such as excess liquidity created by central bank policies. An alternative view is the presumption that global asset scarcity was responsible for the mispricing of risk. This view is promoted by Rajan (2006), and Caballero et al. (2008) and suggests that emerging markets had only limited capacities to store value in local assets. As these economies were growing at very high rates, there was a strong flow of funds into the developed world and this caused an unsustainable boom cycle[85].

The core mechanism of the Chimerica narrative is that higher returns of capital were not offset by a parallel increase in capital cost, which one would expect due to supply constraints. Instead, studies show that the cost of capital measured by historical standards was exceptionally low during the pre-crisis period. Taking the example of corporate bond markets, this observation can be attributed to the fact that earnings grew much stronger than the cost of debt, thus providing corporations with opportunities to rapidly improve their financial positions. The crisis marks an abrupt rebalancing due to the failure of a gradual correction of this divergence.

The growing imbalances were a consequence of the joint economic development of the US and Chinese economies in terms of trade and capital flows. Huge imports by

[85] This somehow relates to the general observation that the home bias had declined in the pre-crisis period and, therefore, global investment opportunities were sought; see French and Poterba (1991), Coval and Moskowitz (1999). However, Ferguson and Schularick (2007) argue that emerging market assets grew at a rapid pace and also paid premiums that did not deviate substantially from fundamentals, which suggest a scarcity of investment opportunities.

the US from China generated massive Chinese trade surpluses while at the same time inflowing funds were channeled back into the US by building huge reserves of US treasury bonds. This build-up suppressed US risk-free rates as a lead indicator in global financial markets. The dynamic continued to play because there was no variable exchange rate between the two countries that would have fostered a gradual rebalancing[86]. In addition, the massive expansion of the Chinese labor force kept capacities relatively unconstrained, thus lowering the cost of production and further stimulating trade dynamics.

3.2.2 Flawed policies and regulation: public sector

This narrative focuses on the responsibility of the public sector in the emergence of systemic risk. A combination of three separate policy areas contributed to the overshooting of dynamics in financial markets, as well as failure to identifying (and consequently mitigating) the accumulation of risk in the financial system and its institutions. Though the general reasoning is different from the prior narrative, a major parallel exists since many versions of this narrative put developments in US financial markets at the center of the crisis evolution.

The narrative judges that promotion of the 'affordable housing goals' in the US created the problem in the subprime mortgage segment, with repercussions throughout US real estate markets in general. In this argument, some commentators go back as far as 1992 to the political intervention in government sponsored enterprises (GSEs) Fannie Mae and Freddie Mac[87]. The GSEs' primary mission was to purchase and securitize mortgages. Furthermore, they enhanced liquidity in secondary markets through purchases of mortgage-backed securities. The affordable housing goals forced the GSEs to expand the scope of their business towards non-prime borrowers.

An implicit governmental guarantee provided the GSEs with a competitive advantage vis-à-vis other institutions. This bias had two implications: first, the guarantee suppressed GSE funding rates and allowed them to expand to a 'too-big-to-fail' size. With MBS portfolios totaling about USD 1.4 trillion and being strongly interconnected throughout financial markets, a failure of these agencies would have exacerbated the crisis exponentially. Second, the guarantee supported the agencies' dominance, especially in the prime segment of US mortgage markets, and shifted competition to riskier market segments. As competition became more fierce throughout the years prior to the crisis,

[86] Moreover, Ferguson and Schularick (2007) highlight the fact that the Chinese economy was largely shielded from outside investments by a variety of protectionist measures. Partially, this was consequence of the 1997/98 Asian crisis.

[87] Financial Crisis Inquiry Commission (2010)'s dissenting statement, pp. 443. Note that there were further GSEs: Ginnie Mae or Indy Mac, who were, however, holding much smaller portfolios and are thus overlooked in most analyses.

the share of the subprime market grew. In consequence, the two agencies also expanded their activities in these segments, adding to the risks on their balance sheets[88].

Dell'Ariccia et al. (2008) show that competitive dynamics and innovation in US mortgage markets led to an overall decrease in lending standards over time and especially in the subprime segment[89]. Hence risks accumulated and—once the upward cycle of house prices halted—refinancing conditions deteriorated quickly. Borrowers were often unable to cover the necessary interest payments after variable rates were reset to higher levels.

The tremendous increase in loan-to-value (LTV) ratios can be regarded as a red-flag for the over-extension of credit[90]. Yet, although Greenspan (2005) remarked in his economic outlook that 'exotic forms of adjustable-rate mortgages are developments of particular concern', no regulatory action was taken to curb dynamics. As Franke and Krahnen (2008) and Ashcraft (2008) have pointed out, the originate-to-distribute model induced manifold frictions and agency problems throughout the value chain. This was highlighted through many incidences of fraudulent mortgage origination practices due to an insufficient supervision of institutions especially at the beginning of the mortgage securitization value-chain. However, it is also clearly an example of a lack in discipline and an overarching risk appetite on the business side. This is the subject of the moral hazard narrative (section 3.2.4).

A second widely debated topic of this narrative refers to the responsibility of the Fed's low-interest policy prior to the crisis in creating massive financial market liquidity and thus stimulating the 'search for yield', which in turn fostered the overall mispricing of risk[91]. Liedtke (2010) shows that, measured by the Taylor rule[92], the Fed's interest policy strongly deviated from the theoretical optimum throughout 2004–06 and, consequently, might have stimulated overshooting of dynamics in financial markets. However, it is impossible to prove the counter-factual argument that higher interest rates would have prevented the financial crisis without developing strong adverse effects on economic growth. Greenspan (2009) and others point out that, even after the Fed started raising interest rates in 2004, mortgage rates remained largely unaffected, especially in the subprime segment. Furthermore, they argue that though in the US there was a historic

[88] Mortgages from groups with lower credit scores were not among the primary businesses of the GSE's. The Financial Crisis Inquiry Commission (2010) argues that accounting scandals during 2004/5 diverted management attention and the agencies failed to expand their market share more aggressively. However, major purchases of subprime mortgages were being made in order to fulfill the affordable housing goals set by the US Congress.

[89] The unrelenting demand for mortgage-backed securities by financial institutions also contributed to this decline.

[90] Unlike the European system, US mortgages are non-recourse contracts. This means that if a mortgage goes into foreclosure, the bank can only seize (and sell) the underlying asset, but has no further recourse to the mortgage-holder. Hence, the risks for mortgage holders are limited to the equity tranche of a loan, which was decreasing prior to the crisis. This limited exposure is generally seen as a critical incentive for the boom in US real estate markets.

[91] After the Fed had decreased interest rates during 2001 to historically low levels, it kept these rates low until mid-2004, when rates were gradually increased.

[92] The Taylor rule calculates an 'optimal' monetary policy interest rate according to economic growth and inflation.

relationship between short-term interest rates and mortgage rates, long-term mortgage-rates were derived according to long-term interest rates, which are independent of the Fed's policies. Thus, the role of the Fed's policy is disputed and alternative views support the prior narrative of macroeconomic imbalances to explain liquidity and yield dynamics in financial markets.

A third point is that public sector narratives highlight flaws in the regulatory and supervisory framework of financial markets[93]. Note that this observation is not confined to the US, but applies to all major industrial countries. Specifically, it comments on the role of the regulatory system in the period prior to the crisis. The umbrella of regulation covers a wide range of issues that have been identified, even leaving aside fraudulent business practices at the very beginning of the mortgage value chain. Whereas some of these factors contributed to the extent of the boom and bust in financial markets, others exacerbated the crisis through pro-cyclical or contagious effects.

One clear shortcoming of the regulatory system prior to the crisis has been the national fragmentation of regulation vis-à-vis globalized financial institutions and markets. Though there was some cooperation among supervisory institutions of industrialized economies, this was obviously insufficient to identify the evolving interdependencies throughout the financial system, as well as the overall increase in systemic risk. Furthermore, it is noteworthy that regulation did not come close to covering financial markets in a comprehensive manner. Instead, regulatory structures were outpaced by globalization and innovation. The massive expansion of the shadow financial system implies that an increasing share of financial transactions was conducted outside the closely regulated sectors of financial markets.

Criticism regarding supervisory institutions points to the non-existence of macroprudential regulation, which would have been needed to identify the correlated build-up of risks in financial institutions and its implications on systemic risk. Regulatory oversight prior to the crisis focused primarily on the health of individual institutions ('microprudential' regulation)[94]. Nonetheless, there were also severe flaws at the microprudential level. Regulatory influence declined particularly as a result of increased market-based approaches to controlling financial markets[95]. Hellwig (2008), p. 55, refers to this overall dynamic—specific examples are the evolving acknowledgment of internal risk measures or ratings—as 'regulatory capture by sophistication'. A major implication was that the complexity of institutions increased tremendously after the millennium, causing substantial risks to be concealed[96]. This notion is further developed in the collective surprise

[93] For extensive remarks see International Monetary Fund (2009c), Hellwig (2008).

[94] For general remarks on regulation and supervision of financial markets see section 2.3.

[95] As an example, the ban on OTC derivatives was lifted in December 2000; see section 3.1.1.

[96] The institutional perspective in the crisis evolution will be illustrated in section 3.3.4.

narrative (section 3.2.5).

The decline in oversight of developments in financial institutions and the system overall, as well as incentives for institutions to engage in regulatory arbitrage, had numerous pro-cyclical effects that aggravated the crisis; see Brunnermeier (2009). After the market-oriented design of the second Basel capital accord, capital buffers were determined partially based upon the results of internal risk assessments and ratings (figure 4). Financial institutions then had incentives to remove securities from their balance sheets by building off-balance sheet vehicles (SPVs). Such vehicles had lower capital requirements and allowed a reduction in the size of the balance sheet, thus achieving a positive impact on return ratios (RoA, RoE). Besides, there were no extensive disclosure requirements and the vehicles could be financed with short-term commercial papers, adding to the maturity mismatch throughout the financial system.

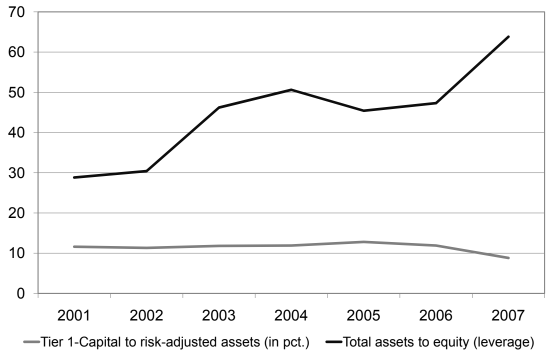

Figure 4: Development of capital ratios at UBS prior to the crisis[97]

In a similar manner, fair value accounting rules (mark-to-market) allowed financial institutions to directly benefit from rising asset prices during the boom. Risk-adjusted capital buffers seemed to be strong, while at the same time total capital buffers were decreasing. The perception of improved resilience against financial crises contributed in particular to the increasing leverage and the maturity mismatch within financial institutions, making them vulnerable to liquidity disruptions in money markets. Thus, the bust developed immediate repercussions in many areas, increasing uncertainty and adding to the momentum of the crisis. As regulators did not impose limits on the overall size or leverage of institutions, they became 'too-big-to-fail', forcing the public sector to act as a LOLR in order to prevent a further deepening[98].

[97] Data derived from UBS annual reports.

[98] However, these institutions—individually and collectively—threatened to outgrow the public capacity to bail them out. The subsequent sovereign debt crisis in Europe is, however, not part of our analysis.

3.2.3 A cyclical crisis with exuberance: Minsky moment

Comparing the common patterns of boom and bust cycles going back to the Dutch Tulip-crisis in the 17th century (section 2.2.2), the financial crisis of 2007–09 can also be described as an extreme occurrence of a speculative cycle and subsequent bust. This exuberant speculation is the basic hypothesis of this narrative[99]. Minsky (1977)'s financial instability hypothesis states that a stable equilibrium can only be temporary in a capitalist economy[100]. This view can be related to Haller (1999)'s more general concept of 'diseconomies of risk', in which he proposes that as a result of many dynamics having passed a certain stage of functional disintegration, further progress will be in concert with a disproportionate increase of risk.

At the beginning of a cyclical upswing, positive expectations regarding economic developments will increase investment. Because funding is fully elastic in the initial stages, cost of capital will remain stable and provide incentive for further investments, similar to the Chimerica narrative. Over time, as the cyclical dynamic gains momentum, funding will also be available for riskier projects. In general, Minsky differentiates between 'hedge finance' (very safe) and 'speculative finance' or 'Ponzi finance' for increasing risk[101].

With positive expectations, the boom eventually turns into euphoria and allows for the realization of a large share of Ponzi finance projects. Since these projects refer to purely speculative projects this stage has parallels to Shiller (1990)'s theory of irrational exuberance. As the upswing continues, there is a growing vulnerability to a decrease in the boom's momentum and increases in the cost of capital (interest rates). From a certain point onwards, the cost of capital must actually increase because capital supply is no longer fully elastic. Furthermore, some investors will start to take out profits. Once interest rates increase, which can also happen in consequence of an exogenous shock, speculative finance projects immediately turn into Ponzi finances. The cycle slows and expectations deteriorate. Ponzi finance projects can only cover their debt by an immediate sell-off—a collective fire-sale—which adversely affects prices. This Minsky moment is thus self-enforcing and will lead to a cyclical crisis.

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[99] Note that this view is somehow contested by Reinhart and Rogoff (2009), who point out many differences but also similarities to other crises. However, commentators commonly agree that speculative dynamics added to the magnitude of risks.

[100] Minsky (1977) argues that 'the essence of the financial instability hypothesis is that financial traumas, even onto debt deflation interactions, occur as a normal functioning result in a capitalist economy. This does not mean that a capitalist economy is always tottering on the brink of collapse'; p. 111.

[101] See section 2.2.2. 'Hedge finance' is a very safe structure. Expected cash flows exceed interest payments and thus the project has a positive present value. Secondly, 'speculative finance' describes projects where expected cash flows still exceed the cost of capital, but projects are sensitive to interest rate changes and have to be regularly refinanced. 'Ponzi finance' refers to projects where expected cash flows do not cover the cost of capital, but instead interest payments are paid from additional debt. Such projects will have a short term focus as owners seek to sell projects to realize price increases, which in turn cover debt and yield a profit.

The proposition of endogenous instability contradicts the efficient market hypothesis, which is an underlying assumption of the collective surprise narrative (section 3.2.5). It proposes that behavioral dynamics and exuberant expectations lead to a misjudgment of risk. Even though the crisis first evolved due to a dry-up of liquidity, this is only a symptom of over-extended credit markets which require a constant availability of funding. The narrative concentrates on developments in US mortgage-markets, where the evidence of speculation on housing prices and Ponzi projects is preeminent and the deterioration of lending standards is well documented; see Dell'Ariccia et al. (2008)[102]. In a broader context, the narrative can be related to the overall increase of maturity mismatch and leverage that occurred throughout the financial system; see Bank for International Settlements (2008).

3.2.4 Misaligned (collective) incentives: moral hazard

This narrative also refers to behavioral dynamics in the banking sector. Instead of referring to the exuberance of market participants, it suggests asymmetric incentives and (collective) moral hazard as sources of market misbehavior. The narrative has been fueled by observations of high bonuses in the banking sector and the golden parachutes of executive managers in the crisis, executives who were forced out of financial institutions on the brink of collapse. It covers a broad spectrum of criticism: misaligned risk appetite in consequence of competitive pressures or asymmetric incentives and (collective) moral hazard; and even accusations that conflicts of interest actively influenced behavior to the client's disadvantage. The relevance of moral hazard, at the collective level, as a source of systemic risk will be the core subject of our subsequent analysis.

In US mortgage markets, the originate-to-distribute (OTD) business model with its many frictions along the mortgage value chain[103] provided incentives to originate highly speculative or fraudulent mortgages[104]. Further along the value chain, there were few incentives to prudently assess risks of securities, because they were being passed on immediately under the OTD business model. Moreover, the manifold steps of securitization induced a focus on commissions and fee earnings. Hence, business dynamics were often driven by quantity rather than quality. In this regard, the public sector narrative has pointed out the shortcomings of regulation that enabled these dynamics and failed to mitigate them.

[102] Similar decreases of lending standards have been reported in other markets such as leveraged buy-outs; see European Central Bank (2007).

[103] See Ashcraft (2008) or Franke and Krahnen (2008) for an extensive overview.

[104] Common products in this regard are loans without any documentation, or so-called Ninja-loans (No income, no job or assets) or piggyback-loans (a combination of two mortgages eliminates the necessity of any down payment).

Charles Prince, former CEO of Citigroup, famously stated that 'when the music stops, in terms of liquidity, things will be complicated. But as long as the music is playing, you've got to get up and dance'[105]. This quote highlights the relevance of competitive dynamics in the financial sector and its collective implications. Following the 2002–03 recession, one consequence of competition was an overall focus on growth and return throughout financial markets. This has been often termed as the 'search for yield': the reason why institutions were inclined to take more risk. Compensation systems were aligned accordingly to foster individual risk appetite throughout the organization. Acharya and Richardson (2009), chapters 7–8, give a comprehensive overview of these compensation and governance issues and the further problems related to growth strategies[106]. Hellwig (2008), p. 34, points out that such fundamental 'flaws in governance' have to be distinguished from 'errors in judgment', which are encompassed in the subsequent collective surprise narrative. More generally, the limited liability of financial institutions effectively skewed payoff profiles and consequently increased the overall preference for risk. The more detailed institutional view (section 3.3.4) will show that these issues were widely spread throughout financial institutions.

Going forward, the collective implications of banks' behavior are very critical because they create a 'too-many-to-fail' problem and increase the probability of central bank intervention—as LOLR—in response to a crisis. With reference to the US Fed this issue has been called the 'Greenspan Put', see Diamond and Rajan (2009). This notion implies that, though the Fed would not decisively counteract asset bubbles, it would adjust its policies as soon as a potential bubble would burst. Such a moral hazard problem at the collective level also sheds critical light on the non-existence of macroprudential regulation. Thus, it makes another reference to the narrative arguing for a public sector responsibility in the crisis.

Lastly, the harshest version of this moral hazard narrative manifests as accusations of US authorities that some banks would have known about inherent risks of financial products related to subprime mortgage markets, but kept marketing these products to clients without effective disclosure nonetheless. As one example, Goldman Sachs has been accused that it conducted transactions with its clients while at the same time taking the opposite position in these deals. In that case, Goldman would have been acting under a clear conflict of interest, collecting major profits from the downfall of markets at the cost of its own clients. Such examples are stressed in the US Senate report by Levin and Coburn (2011) and supported by anecdotal evidence derived from internal documents. Although at the time of writing there have been no convictions, it sheds a very critical light on business practices and governance in the financial sector. The accusations have

[105] Interviewed by Financial Times on July 10, 2007.

[106] In addition see analyses by the Institute of International Finance (2008) and the Senior Supervisors Group (2008).

already had a strong influence in fueling the discussions about governance and regulation of financial institutions.

3.2.5 Risk management, complexity and vulnerability: collective surprise

This narrative suggests that the crisis—in its magnitude—occurred largely unexpectedly, as many of the relevant risks were concealed within the system or accumulated outside the scope of common risk assessments. According to Hellwig (1998), vast areas of risks developed as hidden aggregate exposures (section 2.2.3). A strong version of the narrative would even compare the crisis to the 'black swan' metaphor[107]. It attributes less importance to the endogenous evolution of systemic risk as a result of a boom cycle, but it takes a broader perspective closely related to Haller (1999) and his concept of 'risks of conditions' (section 2.1). From this perspective, a variety of endogenous or exogenous factors can trigger a systemic crisis by falsifying core assumptions for market interactions; consider for example the role of ratings in the financial crisis 2007–09.

In a similar manner, the International Monetary Fund (2008) points out a collective failure to appraise the level of leverage taken by a wide range of financial institutions and its associated risks of a disorderly unwinding. More generally, Hellwig (2008) refers to errors in judgment of risk—contrary to the moral hazard narrative—as being unavoidable. Continuing though, he states that there was certainly at least a combination of judgment errors and flaws in governance.

The relevance of the narrative is supported when looking at the significant underestimation of the extent of the crisis throughout its stages. In July 2007, Fed chairman Ben Bernanke described the problem as being confined to US mortgage markets. As he did not believe that there would be systemic repercussions, he estimated losses at around USD 50–100 billion[108]. Similarly, the narrative includes the fact that it took several reporting periods before financial institutions were able to fully disclose their exposure, which was scattered widely throughout many different departments [109]. Consequently, the crisis has often been divided into different phases, which are characterized by new spikes of uncertainty and market volatility; see Liedtke (2010).

Zimmermann (2008) discusses a basic problem of 'risk' being assessed (represented) by means of a consciously designed process, as an abstraction from reality. He says risk has to be regarded as a second-order observation (section 2.1), which is itself subject

[107]Such a sudden and unforeseeable realization of risk, possibly related to the 'sunspot theorem', would somehow contradict the previous narrative of a Minsky moment; see our preliminary remarks on systemic risk in section 2.2.

[108]Financial Times, July 26, 2007. See also comments by Hellwig (2008), and the International Monetary Fund (2008).

[109]The institutional perspective will elaborate more on that issue, see section 3.3.4

to the risk of flaws in its construction. Because many risk management instruments were largely standardized and ratings played a central role in markets' and regulators' perception of risks, any flaws—e.g. a negligence to account for complex counterparty risks of structured products—that were identified with hindsight automatically developed systemic repercussions. The manifestation of such risks of conditions with regard to risk management systems, ratings, etc. as well as its complexity, explains a major part of the tremendous information contagion in financial markets that aggravated the crisis.

Many studies of the crisis have focused specifically on organizational processes to appraise risk. The Institute of International Finance (2008) and the Senior Supervisors Group (2008) have conducted comprehensive assessments of industry-standards in risk-management and other related areas. These studies identify serious shortcomings in the design of risk management systems, which particularly overemphasized quantitative risk assessment instruments (e.g. VaR) and led to a serious misjudgment regarding the level of risk. Furthermore, an aggregated perspective on risks throughout the institution and analyses of interdependencies among different categories of risk were non-existent, or inadequate[110]. The assumption of an undisrupted functioning of markets, and especially a severe underestimation of liquidity risks, had disastrous consequences in the crisis. Senior management often did not have accurate information to enforce decisions and actually reduce risk taking. With regard to the moral hazard narrative, these reports also point toward a misalignment of risk appetite at all organizational levels, stating that on some occasions managers consciously encouraged risk taking, or at least lacked internal governance mechanisms to limit such behavior.

These flaws at the institutional level seem to be an almost immediate consequence of the tremendous increase in the complexity of the financial system in the years prior to the crisis, which contributed to the central relevance of ratings and quantitative risk-measures such as VaR. Though the shortcomings of these models had long been pointed out (section 2.1), these instruments conveyed a false sense of certainty to market participants. Several types of risks were only inadequately represented. This misconception about risk accelerated a self-affirming cycle: prior to the crisis, market volatility had decreased to very low levels for a historically long time due to the applications of these instruments. The correction came suddenly and with largely unexpected strength.

[110] Major findings of the internal report by UBS AG (2008) have been confirmed by the supervisory body, the Eidgenössische Bankenkommission (2008), who provides a detailed institutional analysis (section 3.3.4).

3.3 A system model of the crisis' dynamics

The system model is developed following the methodology of Vester (2002) and Gomez and Probst (1995), who offer a heuristic to approach and analyze dynamics of complex systems in a holistic manner[111]. The methodology applies similar steps as Gomez and Probst (1995), whereas they are more focused on complex problems arising in the context of managing a corporation. In comparison, the approach of Vester (2002) is applicable to a broader spectrum of complex systems and particularly involves the perspectives of different stakeholders, often building on 'fuzzy logics' among qualitative variables[112]. The methodology allows us to identify core drivers that strongly influence aggregate dynamics of a specific system—i.e. the financial system—and thus offer possible starting points to approach issues of regulation and governance in later stages of this thesis.

As Zimmermann (2001) points out, risks in the financial system are characterized by complex interdependencies. Interactions include non-linearities, time-lags and path-dependencies, which differ for distinct states of the system. Beyond that, say looking at the interaction between the financial system and the real economy, such interlinkages are bi-directional and make it hard to distinguish between cause and effect; see Bank for International Settlements (2002). Quantifications of such interlinkages must be highly critically regarded. Therefore, we do not attempt to develop a quantitative model of the financial system. This would extend beyond the scope of this research project.

Instead, our system model is purely qualitative and descriptive. It focuses on aggregate dynamics in the financial system and seeks to illustrate basic patterns of interaction within the complex network of different factors. This allows us to put the previously introduced narratives (section 3.2) into a broader perspective, and to draw conclusions regarding important drivers of the evolving diseconomies of risk, as well as critical factors facilitating the outbreak of the crisis. In that sense, the subsequent analysis can serve as a risk history for the events that were summarized previously (section 3.1); see Zimmermann (2001). From a forward-looking perspective the analysis can also help us identify those variables that might be able to navigate the dynamics of the financial system towards a more sustainable path and, hence, mitigate an overshooting and the evolution of systemic risk.

[111] The methodology involves nine steps. A (1) description of the system has already been given in the prior section. This section will (2) identify core variables and (3) assess their relevance in the overall system; (4) scrutinize the interaction of different drivers and (5) identify their role within the system; (6) conclude with an analysis of the overall network. The further steps, (7) cybernetics of individual scenarios, (8) scenario projections and policy tests are not conducted in this analysis. We only aspire to establish conclusions on the causes of the financial crisis 2007–09, but not to propose forward-looking policy recommendations. Therefore, any forward-looking analyses are omitted. Lastly, (9) we conclude this part with an overall evaluation of the system.

[112] Vester (2002) notes that this is in contrast to strictly quantitative approaches such as system dynamics; see Forrester (1994).

In the following subsections, we will define the system's boundaries and major subnetworks of our model (section 3.3.1). We will then introduce the individual variables and analyze their roles within the model (section 3.3.2), as well as patterns of interaction and core cycles (section 3.3.3). Lastly, we complement the analysis with anecdotal institutional insights from a case study of UBS AG (section 3.3.4).

3.3.1 Stakeholder perspectives and major subnetworks

In order to define the boundaries of the system to be incorporated in our model, it is first necessary to consider the stakeholder perspectives to be accounted for. The goal of our analysis is to contribute to the understanding of how systemic risk evolved in the 'diseconomies of risk' period from mid-2005 until mid-2007. More specifically, we want to draw possible conclusions for the governance of systemic risk. Therefore, in reference to our governance triangle (section 2.3), we incorporate the three stakeholder perspectives: the public sector, financial markets, and financial intermediaries (table 1 on page 25).

At the center of our model are dynamics of the global financial system. In order to develop a more comprehensive understanding of the crisis evolution, it is important to complement the model with a set of variables covering the development of mortgage-markets and the residential real estate market bubble in the US. Other regions or segments such as leveraged-buyout-markets, which were also identified as critical for systemic risk and the growth of structured finance, remain excluded, in line with our previous reasoning.

It is also important to note that the interplay between dynamics in the real economy and financial markets is not fully developed in our model. Although we include a subnetwork covering macroeconomic developments, this is regarded as largely exogenous. A singular differentiation is made among economic dynamics in the US, being strongly intertwined with mortgage markets as well as emerging market economies (EMEs), which exhibited much higher growth rates. These restrictions serve to reduce the complexity of the model. We are of the opinion that a more complex model structure would not render significant additional insights into the evolution of systemic risk in financial markets.

For the sake of simplicity, we do not differentiate among different countries, with regard to differences in the regulatory regimes and policies of their central banks. The financial crisis has highlighted that the dynamics exhibited strongly collective features: financial institutions from almost all of the industrialized world had built significant exposures to market segments, which were of relevance in the crisis. Thus, our systemic analyses focuses on commonalities and overall endogenous dynamics throughout financial markets and the individual stakeholder groups. This is fundamentally different from an

Table 5: Subnetworks of the model

No.	Subnetwork/Description
I.	**Behavioral dynamics and moral hazard** (blue coding) This subnetwork comprises core determinants of behavior, which pose specific incentives: e.g. compensation, goals set within financial intermediaries as well as attitudes towards risk and expectations. The consequence of their interplay is a certain pattern of behavior that influences the structure of financial institutions, the structure of financial markets, and overall macro-factors. The subnetwork relates to moral hazard as it comprises incentive structures within financial markets as well as participating institutions. Moreover, it includes specific factors that drive US mortgage markets. Moral hazard arises as incentives within financial institutions diverge from those of investors and suppose an overall information asymmetry between investors and financial intermediaries.
II.	**Financial system structure** (purple coding) The financial system is defined by the composition and organization of institutions along the intermediation value chain. It comprises the interplay between institutions inside and outside regulatory boundaries as well as the the growing specialization of financial intermediaries along the value chain. Apart from the institutional organization, it bundles developments and innovations from a product or market perspective, which are, however, not further differentiated. Clearly these structural changes gradually influence information availability throughout the financial system, which is a critical factor especially in a crisis situation.
III.	**Macroeconomic conditions** (green coding) The perspective of the real economy is considered an exogenous perspective in our model of the financial system. However, developments in the real economy are strongly intertwined with those in financial markets. As it was suggested in the ‘Chimerica’ narrative, it is important to differentiate between growth dynamics throughout the industrialized world—our focus is on the US—compared to Emerging Market Economies. An important factor to determine the state of financial market dynamics is the environment for financial transactions, in terms of liquidity and risk premiums. These macro factors complement this subnetwork describing overall conditions in the financial system or its state.
IV.	**Microstructure of financial institutions** (pink coding) The complex microstructure of financial institutions plus its development prior to the crisis are combined in a small, but critical subnetwork. The structure does not include organizational structures, but focuses on a balance sheet perspective. Hence, overall size of assets, financing and maturity structures, as well as ratios between equity and liabilities, and on- and off-balance sheet assets are important. Whereas the change in a positive market environment appears to be rather gradual, adverse market conditions can foster abrupt changes, thus inducing an overall vulnerability of financial institutions.
V.	**Public sector** (light green coding) Part of the public sector subnetwork is considered to be exogenous. This applies to those factors that have an influence primarily on developments in the real economy, or US mortgage markets specifically. Whereas this part actively influences dynamics within the network, a second part relates to regulatory structures including all types of rule-setting done by public authorities as well as activities of supervisory authorities. This is relevant when following the ‘public sector’ narrative, asking whether the public sector controlled dynamics effectively. A third part includes public sector interventions with sole but immediate influence in the financial system. Agents within the financial system will, however, not only react upon public sector actions, but align their expectations if specific actions are anticipated.
VI.	**Representation of risk** (orange coding) The representation of risk is an important subnetwork describing the foundation upon which financial market participants build their expectations. In reference to Haller (1999)’s risk model, the subnetwork provides information in terms of the first-level-objectivity, which is afterwards processed by financial market participants. We have already noted in the previous sections that the representation of risk changed fundamentally prior to the crisis. Whereas part of this development can be described as an endogenous dynamic, an important exogenous factor included in the subnetwork captures advances in the transformation process from uncertainty towards risk (section 2.1).
VII.	**US real estate markets (core bubble)** (yellow coding) Developments in US real estate markets describe an endogenous upward cycle that was amplified by the dynamics within the rest of the system. The main intent is to illustrate the interplay between the core bubble and wider financial markets, which has been researched in depth by Dell’Ariccia et al. (2008). We stated before that other market segments or geographical areas exhibited similar dynamics, so the cycle could be generally replaced within the network.

analysis focusing only on those cases (e.g. institutions) exhibiting unique patterns in the crisis.

The variables included in the final model are divided into seven subnetworks (table 5), while only a few variables remain as separate catalyzers. To better illustrate the model, the individual variables are color-coded in the full overview (figure 5, page 64) according to these subnetworks. As the titles chosen for the subnetworks suggest, there is a close relation to the narratives that were introduced in the previous section. In that sense, the model also helps us to illustrate the interdependence among the individual narratives that we consider critical for the evolution of systemic risk prior to the crisis.

The Chimerica narrative directly relates to the subnetwork of macroeconomic conditions and similarly, the public sector subnetwork mirrors the accordant narrative. The Minsky moment narrative is strongly referenced in the subnetwork of US real estate markets, but also relates to individual factors of the financial system as well as behavioral dynamics and moral hazard. The critical influence of incentives is included in the behavioral dynamics and moral hazard subnetwork, whereas the information efficiency—as a source for asymmetric information, but in a different way also at the core of the collective surprise narrative—is formed through the combination of the financial system, the representation of risk, and the financial institutions microstructure subnetworks.

3.3.2 Model variables and individual roles

As does Vester (2002), we limit the number of variables to fewer than 40. In order to minimize the number, we have combined variables capturing the microstructure of financial institutions as well as those variables describing the evolution of financial instruments and accordant innovations as one variable-block. This allows us to reduce the number of similar interconnections within the model and, thus, its complexity.

The full set of variables of our system model (table 6) includes 34 variables[113]. The numbering of the variables does not imply any prioritization, but simply orders seven subnetworks alphabetically. Whenever possible our variable titles refer to commonly used concepts and are described in a general manner. In order to illustrate their behavior within the model, we refer to indicators that could be used to measure the corresponding aggregate where adequate, or, otherwise, give the spectrum of values that an individual variable is assumed to reach within the dynamic model.

As we are describing aggregate dynamics of the financial system, our variables have to be understood as aggregate measures in reference to market segments or groups

[113]Due to both the narrow and broad references to the aforementioned studies, the variable set can be regarded as comprehensive. Therefore, we do not analyze the variable set according to Vester (2002)'s criteria matrix.

of institutions rather than resembling individual players and products. As argued before, it is our goal to highlight commonalities among institutions and over financial market segments, instead of focusing on individually diverging developments.

Table 6: Variable set of network model

No.	Variable/Description
I.	**Behavioral dynamics and moral hazard**
1.	**Compensation in financial institutions** (high vs. low participation) Extent to which corporate compensation schemes allowed employees/business units to participate in profits.
2.	**Competition in mortgage financing** (intense vs. low competition) Intensity of competition in US mortgage financing markets.
3.	**Incentives (mortgage market)** (high vs. low incentives) Level of incentives for US mortgage-brokers attached to origination volumes of new mortgages.
4.	**Return/growth focus in financial institutions** (high vs. low priority) Priority attributed within financial institutions to seizing new business opportunities in terms of growth and profitability as compared to a more conservative, risk-focused strategy approach.
5.	**Risk appetite** (high vs. low propensity) Aggregate propensity of market participants to enter risky transactions in consequence of expectations or individual incentives attached to these transactions.
6.	**Search for yield** (high vs. low propensity) Propensity of market participants to invest in higher-yielding financial instruments and accepting an implicitly/explicitly higher risk profile to earn a higher return.
II.	**Financial system structure**
7.	**Transparency** (transparent vs. complex structures) Availability of relevant information throughout financial markets as a prerequisite for efficient markets.
8.	**Disintermediation** (strong disintermediation vs. vertical integration) Level of disintermediation and specialization of market participants on specific fragments of the value chain.
9.	**Entry of non-agency mortgage brokers** (many markets entries vs. stable market environment) Number of new players (e.g. non-agency mortgage brokers) entering US mortgage markets and competing with GSEs esp. in lower-creditworthiness segments such as subprime.
10.	**Financial instruments and innovation** (high vs. low issuance volumes, prices) Development of derivatives, securitized products, CDOs and money markets in terms of new issues (volume), increases/decreases of prices or low/high spreads.
11.	**Shadow financial system** (increasing vs. decreasing share) Share of financial intermediation activities conducted outside the core regulatory framework; for a detailed classification regarding types of institutions and comparable activities see Pozsar et al. (2010).
III.	**Macroeconomic conditions**
12.	**EME economic dynamics** (strong vs. weak economic environment) Strength of economic dynamics (in terms of growth) in Emerging Market Economies and especially Asia.
13.	**Market liquidity** (high vs. low volume of market transactions) Aggregate volume of transactions in different segments of financial markets. Whereas high market liquidity implies low bid-ask spreads, lower levels of liquidity impair the functioning of markets as the spread increases.
14.	**Risk premiums** (high vs. low transaction premiums) Aggregate level of expected risk-return profiles for specific asset categories and spreads on debt securities or derivatives depending on maturity or other types of financial risks (e.g. market, credit and liquidity risk).
15.	**US economic dynamics** (strong vs. weak economic environment) Strength of economic dynamics (in terms of growth) in the US economy.
IV.	**Microstructure of financial institutions**
16.	**Financial institutions' microstructure** (high vs. low value of indicators) Aggregate developments of indicators (maturity mismatch, leverage, off balance sheet assets, overall size/assets) measuring the vulnerability of financial institutions towards external shocks, whereas a jointly higher level of these indicators implies higher vulnerability[114].
V.	**Public sector**
17.	**Governmental intervention** (high vs. low level of market intervention)

continues on next page...

[114]Note that a larger financial institution would generally indicate less vulnerability towards external shocks. However, combined with an increase in maturity mismatch, leverage, and off balance sheet assets, vulnerability is likely to increase. For a detailed theoretical analysis see Dell'Ariccia et al. (2010).

Table 6: Variable set of network model (continued)

No.	Variable/Description
	Intensity of intervention by public sector institutions in specific segments of financial markets through policies (e.g. affordable housing goals) or other forms of guarantees (e.g. GSEs). Furthermore, common expectations regarding LOLR-interventions of the public sector (e.g. central banks) in a crisis.
18.	**Monetary policy (interest rates)** (restrictive, high vs. expansionary, low interest rates) Exogenous factor describing interest rate policy followed by central banks (primarily US Fed) and other measures of monetary policy in order to stimulate/curb economic dynamics or mitigate crises.
19.	**Regulatory capture** (high vs. low influence of industry interest) Influence of financial institutions on regulatory/supervisory bodies to take decisions in their interest.
20.	**Tax incentives** (high vs. low tax exemptions on mortgage payments) Exogenous variable capturing impact of tax incentives created to stimulate home ownership.
VI.	**Representation of risk**
21.	**Fair value accounting** (broad vs. restricted application of fair value accounting principles) Scope of application allowing financial institutions to report specific asset classes at 'fair value' and thus participate directly in positive/negative movements of market prices[115].
22.	**Information, science and technology** (high vs. low advances in processing information) Exogenous factor capturing advances in science and technology that enabled ubiquitous information availability and fundamentally changed the processing of information/risk throughout the financial system.
23.	**Quantitative risk management focus** (high vs. low importance of quantitative risk assessments) Extent to which decision-making in financial institutions is based on quantitative risk models and statistical observations derived from market information.
24.	**Rating focus** (high vs. low importance of ratings) Common acceptance by all stakeholders of external ratings as a primary measure of risk for products throughout all stages of the financial intermediation value chain. A high importance implies a lower intensity of individual risk assessments.
VII.	**US real estate markets (core bubble)**
25.	**(Re-)financing conditions** (positive vs. negative conditions for mortgage (re-)financing) Overall conditions for (re-)financing mortgages related to real estate ownership, including mortgage availability, variety of offers, short-term incentives such as cash-outs, teaser-rates, etc.
26.	**Demand for houses** (high vs. low demand) Strength of demand in US residential real estate market.
27.	**House prices** (high vs. low absolute real estate prices) Countrywide price developments – Case-Shiller index – of US residential real estate (figure 3, page 40, left panel).
28.	**Household leverage (FOR)** (high vs. low household leverage) Homeowner financial obligations ratio as measured and published by US Fed[116].
29.	**Houses built** (high vs. low number of new houses) Quantity of new houses being built in the US and number of building permits (figure 3, page 40, left panel).
30.	**Lending standards** (strict vs. loose lending standards) Developments of indicators for lending standards in US mortgage markets, e.g. loan denial and loan-to-income rates, see Dell'Ariccia et al. (2008) for a detailed study.
31.	**Mortgage origination** (high vs. low volume of mortgages originated) Volume of mortgages being originated or refinanced.
	Further variables (catalyzers)
32.	**Credit losses/delinquencies** (strong credit performance vs. rising delinquency rate) Development of indicators on the performance of mortgage-based securities (e.g. delinquency rates, foreclosures (figure 3, page 40, left panel).
33.	**Demand for (mortgage-related) securities** (high vs. low demand) Development of indicators regarding demand for (mortgage-related) securities in financial markets, e.g. measured by issuance of RMBS by US mortgage brokers not held on the balance sheet after origination.
34.	**Fee earnings** (high vs. low share in total revenues) Development of the portion of origination fees and other commissions in total revenues of financial institutions as an indicator for the strategic importance of issuing business units.

With this definition of the individual variables, we now turn toward identifying the various interdependencies. These connections can be either positive, if the increase of one

[115]For a discussion of the role of fair value accounting in the crisis see Hellwig (2008).

[116]http://www.federalreserve.gov/releases/housedebt/

variable leads to an increase in another variable, or negative, if the increase of one variable causes a decrease of another. Furthermore, the interconnections can be differentiated by their strength, whether the induced change is proportionate or disproportionate, as well as time-dependent; whether the effect on another variable is immediate or lagging.

We have stated before that developing a quantitative model of the financial system would be an overly ambitious task, because many interdependencies of individual factors cannot be clearly identified. Even if a measurement of potential correlations between the development of specific variables was possible, this would not allow conclusions regarding the underlying drivers; see Manski (1995). As an example, we highlighted the strong interlinkage between the real economy and the financial sector, where we allow for bi-directional connections among several variables, accounting for (1) a direct feedback loop and (2) the fact that interdependence is ambiguous.

In a next step of developing the system model, we qualitatively estimate the influence among the variables by attributing values 0–3 for each interlinkage (table 7). Whereas a value of 0 implies that there is no influence, higher values represent a 1–disproportionally low, or lagged; 2–proportional; and 3–disproportionally high influence on the other variable. After all interdependencies have been assigned, the full system model can already be illustrated (figure 6 on page 67). The only information not following immediately from the assigned interdependency values is the algebraic sign of the connection.

Yet, before we turn to individual dynamics and core cycles, we can draw first conclusions with regard to the function of individual variables within the model. We can calculate the total active influence of a specific variable (active sum of interdependencies) as well as the total influence from other factors on a specific variable (passive sum). Furthermore, the P-value[117] helps us to prioritize the individual variables in terms of their criticality within the system, whereas the Q-value[118] indicates, whether a variable assumes an active or reactive role within the overall model. For completely exogenous variables, such as monetary policy (interest rates) (18.), tax incentives (20.) and information, science and technology (22.), the Q-value does not apply.

In order to better visualize the roles of individual variables within the model as well as their influence on the overall dynamics, we illustrate the correlation of active and passive sums in a matrix illustration (figure 5)[119]. This is analogous to Vester (2002), p. 235, who assigned different functional roles within the model to specific areas of the matrix. Four important groups of variables are worthwhile to highlight in more detail.

[117]The P-value is calculated as the product of active and passive sums.

[118]The Q-Value is calculated as the active sum divided by the passive sum.

[119]Note that the active and passive sum of financial instruments and innovation (10.) is higher than in the illustration.

Table 7: Interdependencies between individual variables

		Sum of interdependencies		Functional indicators		Influence on variable																																	
No.	Variable Name	Active[1]	Passive[2]	P-Val[3]	Q-Val[4]	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20.	21.	22.	23.	24.	25.	26.	27.	28.	29.	30.	31.	32.	33.	34.
1.	compensation in financial institutions	11	5	55	2.2		0	0	0	3	3	0	0	0	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2.	competition in mortgage financing	4	7	28	0.6	0		2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0
3.	incentives (mortgage market)	6	6	36	1.0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	0	0	0
4.	return/growth focus in financial institutions	16	12	192	1.3	3	0	0		3	3	0	0	0	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
5.	risk appetite	13	19	247	0.7	0	0	0	3		3	0	0	0	2	0	0	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6.	search for yield	7	14	98	0.5	0	0	0	0	0		0	0	0	3	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
7.	transparency	10	15	150	0.7	0	0	0	0	0	0		0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0
8.	disintermediation	13	6	78	2.2	0	0	2	2	0	0	3		2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
9.	entry of non-agency mortgage brokers	4	4	16	1.0	0	2	0	0	0	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
10.	financial instruments and innovation	26	29	754	0.9	0	0	0	0	2	0	3	2	0		3	0	2	0	0	2	0	0	2	0	1	0	3	2	0	0	0	0	0	0	0	0	2	2
11.	shadow financial system	16	7	112	2.3	0	0	0	0	0	1	2	3	0	3		0	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
12.	EME economic dynamics	7	2	14	3.5	0	0	0	0	0	0	0	0	0	0	0		3	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13.	liquidity	11	16	171	0.7	0	0	0	0	2	2	0	0	0	3	1	0		2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14.	risk premiums	6	14	84	0.4	0	0	0	2	0	2	0	0	0	2	0	0	0		0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15.	US economic dynamics	8	7	56	1.1	0	0	0	0	0	0	0	0	0	0	0	2	0	2		0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	2	0	0
16.	financial institutions' microstructure	9	18	2	0.5	0	0	0	0	0	0	2	0	0	2	0	0	0	0	0		2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
17.	governmental intervention	9	4	36	2.3	0	2	0	0	2	0	0	0	0	0	0	0	2	1	0	0		0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0
18.	monetary policy (interest rates)	8	0	0	n/a	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0		0	0	0	0	0	0	2	0	0	2	0	0	0	0	0	0
19.	regulatory capture	14	12	168	1.2	0	0	0	0	1	0	0	0	0	2	3	0	0	0	0	2	2	0		0	1	0	0	1	0	0	0	0	0	2	0	0	0	0
20.	tax incentives	2	0	0	n/a	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	2	0	0	0	0	0	0	0	0	0
21.	fair value accounting	10	6	60	1.7	0	0	0	2	0	0	2	0	0	0	0	0	0	2	0	2	0	0	0	0		0	2	0	0	0	0	0	0	0	0	0	0	0
22.	information, science and technology	10	0	0	n/a	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	2		3	2	0	0	0	0	0	0	0	0	0	0
23.	quantitative risk management focus	19	16	304	1.2	0	0	0	1	3	0	1	0	0	2	0	0	0	2	0	3	0	0	3	0	2	0		2	0	0	0	0	0	0	0	0	0	0
24.	rating focus	9	14	126	0.6	0	0	0	0	2	0	2	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2		0	0	0	0	0	0	0	0	0	0
25.	(re-)financing conditions	5	12	60	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0	3	2	0	0
26.	demand for houses	6	6	36	1.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		2	0	2	2	0	0	0	0
27.	house prices	6	2	12	3.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	2		0	0	2	0	0	0	0
28.	household leverage (FOR)	3	6	18	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	2	0		0	0	0	0	0	0
29.	houses built	2	2	4	1.0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0		0	0	0	0	0
30.	lending standards	2	13	26	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0		0	0	0	0
31.	mortgage origination	5	6	30	0.8	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	2	0	0		0	0	0
32.	credit losses/delinquencies	7	4	28	1.8	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0		3	0
33.	demand for (mortgage-related) securities	9	11	99	0.8	0	3	2	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0		0
34.	fee earnings	4	2	8	1.0	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

[1] Sum of active influences on other variables
[2] Sum of passive influences by other variables
[3] Criticality of variable within model (active sum * passive sum)
[4] Role of variable within model in terms of activeness vs. Reactiveness (active sum / passive sum)

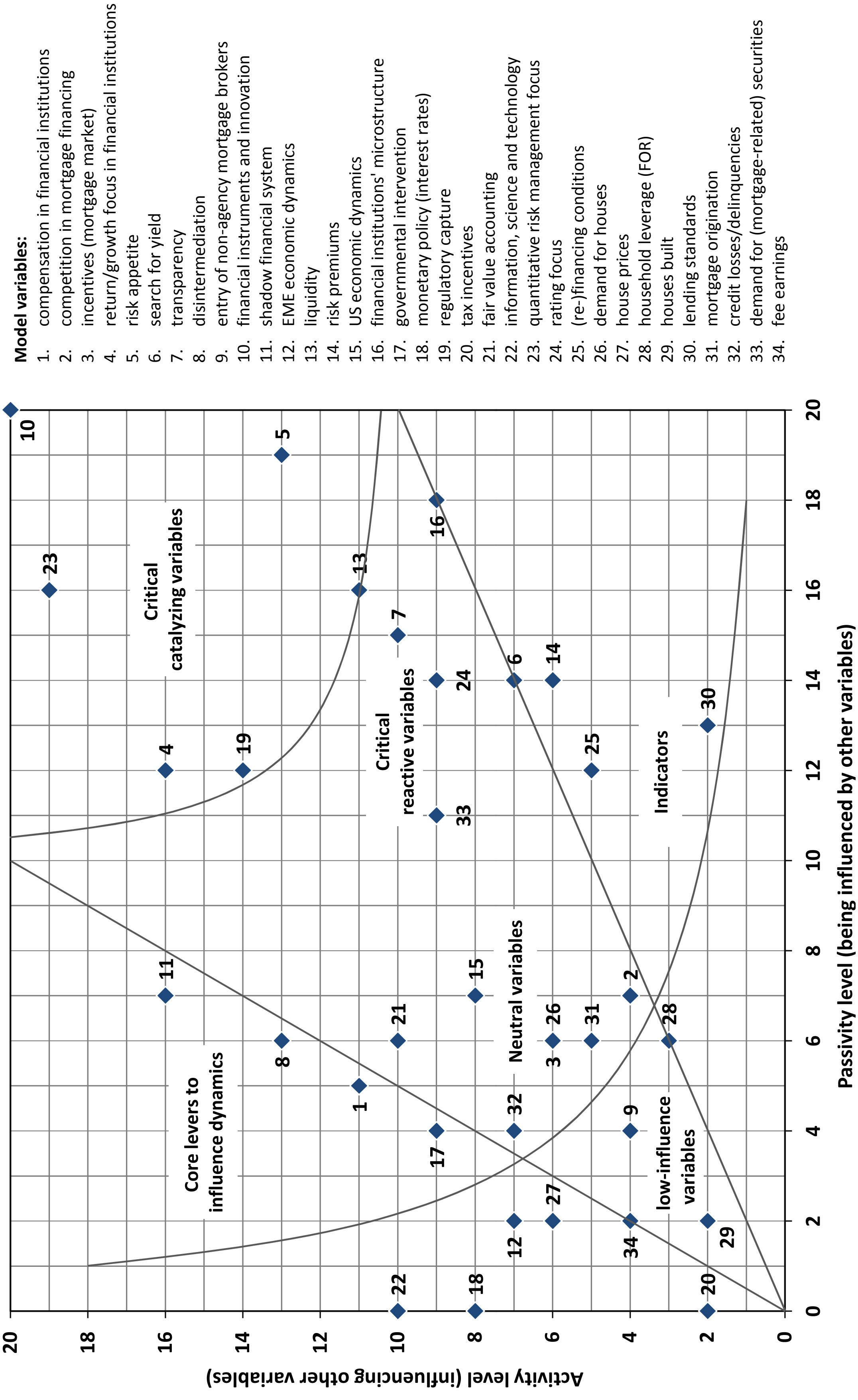

Figure 5: Roles and criticality of variables within the model

Critical catalyzing variables are characterized by both high active and passive sums of interdependencies, which imply strong interconnections with other variables. Hence, these variables have a dominant influence on the model dynamics. Starting with the highest criticality (P-value), this group comprises financial instruments and innovation (10.), quantitative risk management focus (23.), risk appetite (5.), return/growth focus of financial institutions (4.), and regulatory capture (19.). By their resulting Q-value, all variables but risk appetite, which is a reactive variable, actively drive the dynamics of the model.

The second group *critical reactive variables* is characterized by a comparably high P-value combined with a Q-value smaller than one and larger than one-half. This implies that these variables are heavily intertwined within the model, yet they tend to react sharply to changes of other variables, which they then transmit into the broader system. Again sorted by criticality, this group comprises liquidity (13.), financial institutions microstructure (16.), transparency (7.), rating focus (24.), and search for yield (6.). It must be noted that risk appetite (5.) also resembles a reactive variable, but with even greater criticality.

Variables which are even more reactive (lower Q-value), but at the same time exhibit a lower P-value, are attributed to the group of *indicators*. These variables can be valuable to measure model dynamics, whereas, due to their low active sum, they do not create a strong enough feedback loop that influences model dynamics. Among this group are risk premiums (14.), the total spread, which is dependent on market, liquidity and credit risks, that indicates the aggregate appraisal of risk in financial markets. Also, (re-)financing conditions (25.) and lending standards (30.) represent specific indicators for the state of the cycle in US mortgage markets. We suppose that for other market segments similar indicators could be found.

The last group with a strong and active influence within the model, *core levers*, comprise those variables which do not react strongly to changes of other variables, but instead actively shape the dynamics of the overall model. Variables assigned to this group, again in order of decreasing criticality, are shadow financial system (11.), disintermediation (8.), compensation in financial institutions (1.), and governmental intervention (17.). Information, science and technology (22.), and monetary policy (18.), which were modeled as completely exogenous, have a relatively strong and active influence on aggregate dynamics.

Overall, variables from the US real estate sector subnetwork exhibit a lower criticality within the model when compared to others. This might be considered an indication that the crisis was not only driven by exuberance in a single market, but, as we have stated before, similar exuberance occurred in other markets at the same time. The relatively low criticality of EME economic dynamics (12.) and US economic dynamics (15.) must be attributed to the limited and largely exogenous inclusion in our model, which resulted in a relatively low interlinkage with financial market variables[120].

3.3.3 Model dynamics and core cycles of interaction

Whereas the prior analyses led us to conclusions regarding the relevance of individual variables, the illustration of the full model (figure 6) can highlight core cycles that include more than two variables and thus drive the dynamics of the overall model. Whereas the illustration does not differentiate according to the strength of the bilateral interdependences, it highlights the algebraic sign of the connection by a continuous (positive) or dotted (negative influence) arrow.

A first cycle can be identified at the right hand side of the model in the US real estate sector subnetwork, involving demand for houses, house prices, lending standards, (re-)financing conditions, and mortgage origination. This cycle has been described by Goldman Sachs (2007) and many of the interconnections are supported by Dell'Ariccia et al. (2008)'s study of lending standards in US mortgage markets. Generally, the cycle resembles a self-enforcing upward or downward spiral, which involves a balancing as rising house prices will, gradually, suppress the demand for houses. Lending standards crucially influence the speed of the cycle, as they are also related to outside factors such as behavioral aspects of mortgage and financial markets. A similar observation applies for (re-)financing conditions, which is also affected by policies of the public sector subnetwork. This cycle will exhibit a dynamic that is close to the Minsky moment narrative. A break in (re-)financing conditions will leave many homeowners overstretched, as indicated by the rises of household leverage (FOR). Homeowners who rely on Ponzi financing are especially vulnerable to decreases in house prices; see Minsky (1977). A consequent selling spiral will exacerbate price decreases and accelerate the downward cycle.

Related to the role of behavioral dynamics and incentives in the evolution of systemic risk in financial markets is a second cycle at the top left of the system model, which can be described in reference to the moral hazard narrative. At the center of the cycle are return/growth focus in financial institutions and risk appetite, which are interlinked in both directions and thus self-enforcing. Directly, as well as through the design of compensation in financial institutions, these factors do influence the search for yield and the development of financial instruments and innovation. The factors are connected to market liquidity and risk premiums, which lead to a further acceleration of the dynamics. Another effect is created as the growth of financial instruments and innovation increases fee earnings through

[120]Yet, these interlinkages certainly exist, but would be very hard to estimate; see Bank for International Settlements (2002)

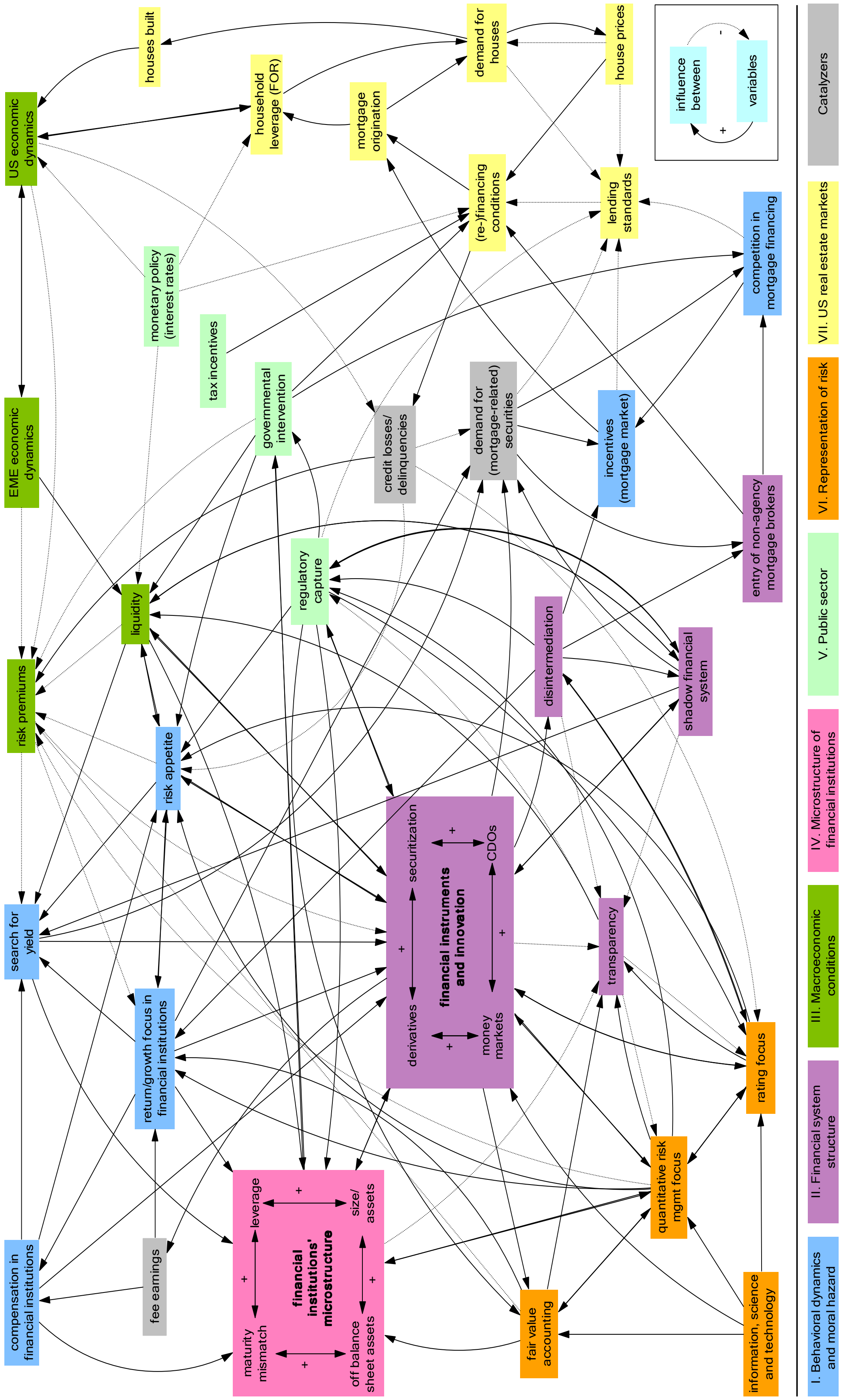

Figure 6: Integrated system model of the financial system

this channel, again, impacting the return/growth focus and compensation in financial institutions. As a reactive variable to this cycle, the financial institutions microstructure change over time, making those institutions more vulnerable to market interruptions in terms of liquidity and a potential flight to quality.

A third cycle which controls dynamics in financial markets is related to transparency as a balancing factor within the model. This cycle, in fact, exacerbates the vulnerability of financial markets to the previously mentioned disruptions. Naturally, changes in financial institutions microstructure and financial instruments and innovation, as well as ongoing disintermediation and a growing share of the shadow financial system, decrease transparency. The more complex environment will reduce liquidity in specific market segments, lead to higher risk premiums, and limit the risk appetite of market participants. This in turn should extenuate market dynamics. In the period prior to the crisis, major advances in the subnetwork representation of risk added to a pseudo-transparency and reduced its balancing role within the system. The critical impact of the quantitative risk management and rating focus is described in the collective surprise narrative. As the relevant risks were not adequately represented, or remained outside the scope of risk assessments, the overshooting of the dynamics were not mitigated—neither actively nor passively. There was a false belief in the macro efficiency of financial markets (section 2.2.3).

Fourth, the shadow financial system is closely connected to this cycle and encourages the growth of financial instruments and innovation. Many institutions attributed to the shadow financial system were able to enter higher-yielding transactions, and this added to the collective search for yield in the aggregate system. A crucial relationship exists between the shadow financial system and regulatory capture: With the growing importance of the shadow financial system, regulatory capture increased, and regulators were less able to control market dynamics. In turn, this reinforced the growth of the shadow financial system by opening further business opportunities to be exploited and built further momentum in the growth of financial instruments and innovation.

At last, although there are only few variables attributed to the public sector subnetwork, the criticality analysis has already highlighted that regulatory capture is in fact one of the most influential variables within the model. Furthermore, governmental intervention was identified as an active driver within the model. As was supposed in the public sector narrative (section 3.2.2), governmental intervention, as well as monetary policy, contributed to the initial momentum of the cycle in US mortgage and financial markets. As this momentum grew, the increasing regulatory capture led to a failure of the public sector to assume its role in limiting the dynamics and mitigating the development of systemic risk. Yet, it has to be noted that regulators also actively followed a market-oriented regulatory strategy; e.g. the Basel II framework explicitly acknowledges internal risk assessments and ratings to determine capital buffers.

While so far we have focused mainly on the positive dynamics within the model, an important issue to be considered is the timeline of the crisis evolution (section 3.1). It is important to first discuss which cycles drove the decoupling of the dynamics from fundamentals and led to the creation of systemic risk; and, second, the negative cycle has to be further elaborated as it runs differently, and much faster, than the positive cycle. Differentiating the positive and negative cycles allows us to show which variables might not have been the core drivers of the boom cycle but turn out to be crucial in the bust cycle.

The beginning of the boom cycle was based on benign macroeconomic conditions (US, EME economic dynamics), wide-spread, favorable monetary policy, and an ongoing boom in US real estate markets. From the financial market perspective, changes to the representation of risk, the wider application of fair value accounting as well as progressing disintermediation (OTD business model) created new potential to grow; see Liedtke (2010). As the cycle evolved, aggregate risk appetite gradually increased. This development was also driven by the growing number of shadow-financial institutions, that could, due to the weaker regulatory restrictions, create portfolios with higher risk profiles. In consequence, and in a continued low-interest rate environment, regulated financial institutions also increasingly searched for yield. At this stage, microstructural changes would have been already noticeable but not yet significant. However, the growth of the shadow financial system contributed to competitive dynamics in financial markets and added to the regulatory capture.

Whereas at this stage the cycle was still stable, several changes in underlying conditions and dynamics then induced diseconomies of risk and added to vulnerability in terms of systemic risk. In fact, financial market dynamics seem to have continuously decoupled from the real economy from mid-2005 until the 'subprime crisis' erupted. Initially, changes in monetary policy started to slow the cycle in US real estate markets. Further growth in this segment was driven by decreases in lending standards that allowed ever higher loan-to-value rates and, hence, did not limit a potential overstretching of borrowers; see Dell'Ariccia et al. (2008). Factors contributing to the decreasing lending standards were, besides endogenous factors in real estate markets, the competition in mortgage financing, and, more importantly, the steady high demand for MBS in financial markets.

In financial markets, critically growth in financial products and innovation during that period occurred in products segments, which were even more detached from their economic basis; e.g. synthetic CDOs that were based on indexes of mortgage securities rather than on these securities directly. This broadened the scope for growth in financial products, which eventually outpaced the growth of underlying assets.

Due to increasing regulatory capture, regulators were no longer able to limit aggregate dynamics. This was also due to the (national) fragmentation of the regulatory system vis-à-vis an ever more globalized financial system, which, at least partially, did not have the instruments, in terms of macroprudential regulation, in place to react in an adequate manner. It is noteworthy, however, that regulators did not respond to the risk appetite of individual institutions—microprudential regulation was extensive; see De Larosière et al. (2009)—or to changes in the microstructure of financial institutions. Hence, the public sector narrative also relates to the diseconomies of risk.

Similar to the public sector, investors did not adjust their behavior in reaction to this increasing vulnerability created throughout the financial system. It is important to account for the fact that the growth in financial products and innovation could only occur if there was sufficient demand for the originated products; only part of that demand could be created internally within the institutions. An explanation for this failure can be based on one of three of the narratives—(1) Minsky moment, (2) collective surprise, and (3) moral hazard—or a combination of all three.

An explanation from the perspective of the *Minsky moment narrative* focuses on positive expectations during the boom cycle, as an endogenous feedback process that lifts dynamics to a next stage. This supposes that negative signs from credit losses/delinquencies in US real estate markets were not strong enough to balance the growth in financial products and innovation. Therefore, risk appetite further increased and risk premiums remained suppressed, further contributing to the search for yield.

From the perspective of a *collective surprise narrative*, the containment of risk appetite and risk premiums derives from the flawed representation of risk and, especially, the quantitative risk management and rating focus, and the implications of fair value accounting. These, in turn, were initially boosted by advances in information, science and technology and later further affected by progressing disintermediation and transparency.

In terms of their explanatory power, any of these two narratives does not seem feasible individually, but rather only in combination. Result of the dynamics was a common belief close to 'this time is different', which implies the conviction that former limiting factors and observations of risk do not apply to the current situation, as innovations have made these risks obsolete; see Reinhart and Rogoff (2009). Hence, the overshooting of dynamics is supported by the majority of financial markets participants and systemic risk increased to an acute level.

A third possible explanation to determine the sources of systemic risks regards the importance attributed to these two narratives against the background of the *moral hazard narrative*. The moral hazard narrative emphasizes the role of a collective return/growth focus in financial institutions, in consequence of competitive dynamics, and its impact on the design of compensation in financial institutions. It implies a strong misalignment of incentives between financial institutions and external investors, which sustained the high risk appetite and had implications for risk premiums and the overall dynamics of the cycle. This moral hazard could apply individually, for traders, but collectively, as well, for groups of institutions. At its heart would be an information asymmetry that could be explained with similar factors as in the collective surprise. The difference is, however, that the moral hazard narrative suggests that there was a core group of institutions that somehow deliberately endangered the overall system.

In this regard, another pivotal issue is that warnings[121] by reputed internationally institutions such as the US Fed, the Bank of England, and the IMF (section 3.1.2) did not have an impact on the dynamics. One could argue that, due to decreasing transparency, these warnings were fragmented and could not adequately identify the dimension of risk that was building. However, one could also speak of deliberate decisions—due to behavioral incentives—to collectively ignore these warnings. Either way, no limits were imposed on the dynamics continuously escalating diseconomies of risk.

The evolving systemic risk can be best ascribed to a variety of factors in terms of vulnerability of the financial system and its institutions. As the following paragraphs will elaborate in detail, most of this vulnerability stemmed from risks of conditions (section 2.1.1): (1) the role of ratings; (2) the assumption of a continuous availability of liquidity; and (3) unforeseen coordination problems in an adverse market environment.

The first risk of conditions regards the dominant *role of ratings* as an indicator for risks. As credit losses/delinquencies continued to rise, in the first half of 2007 rating agencies initiated a wide-ranging review of mortgage securities, which resulted in downgrades for a tremendous number of securities; see Brunnermeier (2009). In our system model, this can be interpreted as a shock to the rating focus, exposing severe shortcomings and flaws of ratings. This had immediate repercussions in terms of a reversion of transparency into sudden complexity and questioning of the quantitative risk management focus within institutions.

Two important second-round effects of this shock were a sudden reappraisal of risk, in terms of reduced risk appetite and spikes in risk premiums, as well as coordination problems in several market segments, e.g. due to counterparty risks, that suddenly lacked liquidity. In addition, market volumes in mortgage-related financial products and innovation dropped sharply and demand for MBS stalled. This sudden shock, through a strong upward movement of lending standards and worsening (re-)financing conditions, finally sent the housing cycle into a negative spiral, aggravating the poor performance of MBS in terms of credit losses/delinquencies.

[121] A summary of early warnings is given by the International Monetary Fund (2009b).

As financial institutions and investors sought to limit their exposures to MBS a first flight-to-quality occurred, which caused price drops of financial products and innovations, and market liquidity almost completely dried up. The *assumption of a continuous availability of liquidity* posed a further risk of conditions, as many financial products and innovations, but, more critically, the financial institutions microstructure was widely exposed, due the high maturity mismatch in terms of financing[122].

Risk-adjusted capital buffers were then erased in real terms, and the liquidity crisis was complemented by solvency issues. This led to a further decrease of transparency, as trust among market participants was gone. Similarly, quantitative risk management models, ratings, and fair value accounting did not yield convincing results in the environment of illiquid markets. Hence, the crisis gained further momentum and gradually ended up as an endogenous downward spiral.

Overall, the sharp reappraisal of risk was determined not only by a correction of fundamentals, but also an aggravation of *coordination problems in an adverse market environment*. Due to the endogeneity of this cycle, only governmental intervention—largely exogenous and an active variable—was able to temper the momentum and break the cycle. These interventions occurred with different focus and in several intensities (section 3.1.4). By supplying liquidity and pledging support to financial markets and their institutions[123], regulators and central banks sought to moderate the adverse consequences of sudden risk aversion, i.e. extremely low risk appetite, and the flight-to-quality. Coordinated moves to cut interest rates (monetary policy) also aimed at stabilization of market liquidity, while at the same time supporting economic dynamics. Simultaneously, there should have been a positive impact on (re-)financing conditions in US real estate markets, which was, however, outweighed by the negative system dynamics.

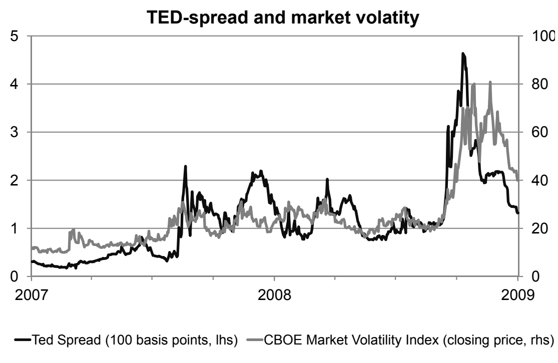

Figure 7: Development of TED-spread and volatility index in the crisis[124]

[122]Note that liquidity was one of the most critical reactive variables in our system model.

[123]These pledges included a comprehensive deposit insurance for banks in order to prevent depositor bank runs, similar to the one on Northern Rock in September 2007.

[124]Data obtained from Bloomberg.

These measures, however, were not sufficient to fully balance the endogenous dynamics of the crisis. Instead, they only prolonged the escalation of the crisis, which occurred throughout several phases, each igniting the endogenous dynamics and pushing the crisis to a higher level; see Liedtke (2010). This is shown by developments of the TED-spread, as an indicator of the severity of a liquidity crisis, as well as volatility indexes (figure 7); see Brunnermeier et al. (2009). As Bear Stearns was in danger of collapsing in March 2008, a governmental intervention by the US Fed provided bridge financing until the bank could be sold. In September 2008, the Fed refused to bail out Lehman Brothers, whose breakdown marks the end point of our analysis. That decision caused an ultimate climax of the crisis, driven by the factors that were described before. At this stage unprecedented governmental intervention had to take place in order to stabilize the dynamics of the system, and to prevent a wide-ranging failure of international financial institutions.

3.3.4 Insights from the institutional perspective

Our model of the financial system focuses on variables measuring aggregate dynamics throughout the system. This design was chosen due to the objective to highlight commonalities among institutions and financial market segments, instead of individual development of different institutions. Furthermore, this choice greatly reduces complexity. As a result, many variables, such as the return/growth focus in financial institutions or quantitative risk management focus, refer to the 'sum' of the behavior of many individual institutions. Variables such as the shadow financial system summarize developments of a large number of institutions, which offer a broad variety of services.

In this section, we complement the prior analysis with a bottom-up perspective: anecdotal insights from of UBS AG, Switzerland, which had tremendous exposure to subprime mortgage markets. The case of UBS is well documented through internal analysis of UBS AG (2008) and an external report by the Eidgenössische Bankenkommission (2008). It seems representative for other large and international financial institutions, as similar conclusions are made elsewhere, e.g. in the comprehensive report of the Financial Crisis Inquiry Commission (2010). Additional insights are drawn from reports by the Senior Supervisors Group (2008) and the Institute of International Finance (2008), containing extensive analysis of differences in risk management practices and other governance issues covering a variety of institutions[125].

[125] The Senior Supervisors Group (2008) shows that one can find differences among groups of institutions, and a number of financial institutions actually sought to limit exposure to US real estate markets from late 2006. Such institutions were also less affected in the initial phase of the crisis, but they shared other vulnerabilities with regard to leverage, maturity mismatch, or other areas of growth in financial instruments and innovation, which only came to the fore after the report had been published.

As the Eidgenössische Bankenkommission (2008) confirms, UBS management was not aware of its true exposures to US real estate markets until August 2007. Therefore, the case study seems to indicate a clear failure of risk management and strategy implementation. Until mid-2008 total losses related to US real estate markets amounted to USD 42.8 billion. Without major capital raises, as well as support by the Swiss National Bank to unload bad assets from the balance sheet, UBS would have almost certainly faced insolvency. A particularly striking fact is that exposures were not confined solely to the UBS investment bank, whose units were primarily dealing with these segments. Instead, significant exposures were spread throughout the whole organization.

The *Foreign Exchange and Cash Collateral Trading* unit—with the responsibility to ensure funding of UBS's balance sheet, serve as the central treasury and provide a single point of entry into short-term wholesale cash markets—added roughly USD 2 billion to UBS's total losses[126]. At certain times, this individual unit held an ABS portfolio of up to USD 30 billion[127], which resulted from the search for yield[128].

A major part of exposures was concentrated in a separate hedge fund, *Dillon Reed Capital Management* (DRCM), which was established in mid-2005 as an alternative investment business and acted separately from UBS until its re-integration in mid-2007. Headed by the former UBS investment banking head, it sought to diversify capital allocation through third-party investors, co-invest with the UBS investment bank in certain business segments, and support talent retention by offering a more competitive working environment[129]. Following various trading strategies, DRCM accumulated exposures to mortgage-related securities and also executed CDO transactions.

As highlighted by the analysis, oversight arrangements between DRCM and UBS were overly complex and governance structures inadequate. Different business lines of DRCM that involved different types of risk were overseen by different units within UBS and, a major conclusion from the analysis, the cooperation structure did not allow for an effective aggregation of risk at the group level. At the same time strategic objectives emphasized a return/growth focus, and behavioral incentives, e.g. in terms of compensation, were stronger than in the core bank.

The majority of exposure to US mortgage markets still evolved within the UBS investment bank. The unit taking the largest loss was the *CDO desk*, whose core business was the origination of CDOs, focusing on riskier (mezzanine) CDOs due to higher fee

[126]Effective write-downs in this business unit were probably much higher.

[127]This portfolio included primarily (residential/commercial) mortgage-related securities rated AAA or AA, but also securities from other areas such as car leasing, credit cards, student loans, etc.

[128]Besides other assumed advantages, the ABS products included in the portfolio offered more attractive yields as governmental bonds and, hence, a promising carry trade.

[129]However, the UBS investment bank unit experienced a major brain drain as a result of the separation.

earnings[130]. As underlying products for a CDO had to be collected in a warehouse before the final origination, the process naturally involved risk exposure in terms of market or liquidity risks. However, there were no notional limits imposed on the portfolio held in the warehouse. This proved to be detrimental in the crisis because, once market liquidity dried up and prices sharply declined, UBS had to take significant write-downs on MBS held in the CDO warehouse.

However, a different business line of the CDO desk created even higher exposure (roughly half of UBS' total losses). As funding was available within UBS at very low rates and without being risk-adjusted, the CDO desk identified a positive carry trade in holding highest-rated tranches of CDOs (super-senior). As spreads on these tranches were very low, there was little demand from outside investors; however, the carry trade would only add value if it was executed in high volumes. Hence, the CDO desk did not only retain super senior tranches of its own deals, but, additionally, bought externally, thus contributing to the demand of (mortgage-related) securities. The low levels of perceived risk on these trades could be further offset by hedges, often with monoline insurers as counterparties, which turned out to be ineffective. As risk assessments focused only on net exposures, the contribution to risk measures at the group level remained relatively low whereas gross exposures accumulated.

A major underlying factor that has been identified by UBS, was its strategic goal to enhance the positioning of its investment bank[131], which over-emphasized the growth/return focus within the organization[132]. The risk appetite within the organization became misaligned, through an aggressive compensation system. Thus, an evolving search for yield throughout the organization increased the volume of carry trades and securities' origination (to maximize fee earnings) as described above.

A second conclusion of UBS, supported by the Senior Supervisors Group (2008) report, demonstrates the collective surprise narrative at the institutional level. In many institutions, organizational change and specialization of institutional units—due to the ongoing disintermediation—occurred at such a high pace that governance and risk management systems were not able to correctly appraise the evolution of institutional microstructure and the reduction of transparency within those institutions.

Problems in the identification of risks derived especially from a fragmented firm-wide risk assessment, often aggregated through silos and only combined at the very top. Furthermore, most of the exposed institutions exhibited a strong rating focus even within

[130] For mezzanine CDOs, origination fees were up to 5 times higher than compared to high-grade CDOs.

[131] UBS and external consultants had identified competitive gaps in the investment bank in 2005. Strategic initiatives in response to these analyses, presented in 2006, included inter alia to exploit growth opportunities in securitized products, high-yield segments and structured credit.

[132] As the Senior Supervisors Group (2008) points out, other institutions that shared these strategic goals also fostered the growth of specific business lines that were heavily exposed in the crisis.

their internal risk models[133]. Clearly, these dynamics relate to the ongoing change of financial instruments and innovation, due to which some risks evolved outside the boundaries of the risk management system, such as liquidity risks of CDO warehouses[134]. In Haller (1999)'s terms one could again speak of a risk of conditions, because fundamental assumptions of risk management processes were proven inadequate[135].

Flaws in the design of risk management systems limited the responsiveness of exposed institutions to the deterioration of market conditions in US real estate markets. UBS senior management addressed the situation of this specific segment in September 2006, but did not take decisions on any actions to impose notional limits on these segments, nor to further analyze existing exposures to get a clearer picture. Such observations are not related to moral hazard but rather a false representation of risk, which importantly relates to the quantitative risk management and rating focus, conveying a false sense of certainty.

Overall, reports commenting on the institutional perspective also make references to the existence of moral hazard, strikingly similar to the moral hazard narrative, on several occasions. Levin and Coburn (2011) allege several banks acted under serious conflicts of interest and moral hazard prior to the crisis and exploited business opportunities at the clients' disadvantage. However, evidence for such behavior, up to the time of writing, appears to be more anecdotal than systematic. Nonetheless, it is clear the behavioral dynamics had a major influence at the individual and also at the institutional level, which then served as a transmission channel into the financial system.

3.4 The role of the insurance sector in the crisis

In our analysis we did not yet differentiate types of financial institutions. It is a fact, though, that the vast majority of insurance institutions—with American International Group (AIG) as one prominent exception—performed generally better in the financial crisis 2007–09 than most banking-oriented financial institutions. Overall, the contribution of the insurance sector to the evolution of systemic risk seems to be limited. However, the Geneva Association (2010), p. 1, concludes in its report on systemic risk in the insurance sector:

[133] In comparison, the Senior Supervisors Group (2008) points out that less exposed institutions mainly applied more rigorous internal risk measures.

[134] This conclusion clearly reaches further than Hellwig (2008)'s observation of errors in the judgment of risks.

[135] It has also to be noted that because of the low market volatility and the evolution of structured finance markets, UBS AG (2004) even adapted its VaR measures in the second half of 2004, causing a pro-cyclical decrease of VaR figures throughout UBS by more than 20%.

> '[...] the business model of the insurance industry is unfortunately not always sufficiently demarcated from the business model of other financial service providers such as banks. The way systemic risks are treated must, however, take account of precisely these specific characteristics of the business models and particular actions carried out by institutions.'

Against this background, this section briefly reviews the differences between banking and insurance and their implications on systemic risk. Starting with the traditional division among the business models of the two sectors, we illustrate the gradual convergence throughout the last decade. Overall, those insurance institutions that fostered a strategic alignment of their business model and became more interwoven with financial markets, accumulated similar exposure as banking-oriented financial institutions. On the contrary, the 'traditional' (re-)insurance business model proved to be largely resilient in the crisis.

3.4.1 Traditional divisions and convergence of banking and insurance

The business model and focus of the banking and insurance industry are naturally distinct in several regards. Whereas banks offer financial intermediation services, raising short-term funding and supplying longer-maturity loans for economic projects, insurance provides a mechanism for the pooling and transfer of financial consequences of (exogenous) risks. Traditional (primary) insurance providers focus on insuring life/health-related services or non-life segments, such as casualty and property damages[136]. Additionally, reinsurers provide a secondary layer of insurance for primary insurers and offer direct insurance for specific risks surpassing certain thresholds.

Insurance institutions retain and manage a large diversified pool of liabilities that are contingent on specific events causing financial damage. The overall ability to insure a certain type of risk is generally determined by specific criteria: most importantly, losses must be triggered randomly by independent, exogenous events and the insurer must be able to estimate the size of losses and corresponding probabilities ex ante in order to calculate a premium[137]; see Gruss (1978). This implies that the losses can be quantified ex post on specific criteria. After issuing primary insurance, the accordant institutions

[136] Composite insurers will often combine both segments, if regulatory provisions do not prevent them from doing so.

[137] This is similar to Knight (1921)'s differentiation of uncertainty and risk (section 2.1): Risks are constructed from uncertainty by attributing statistical probabilities. If that construction is impossible, one speaks of uncertainty, which cannot be insured. As additional principles, Gruss (1978) states mutuality (large number of people at risk), need (event leads to situation of financial need), economic viability (size of contingent financial need can be covered), and similarity of threat (all community members exposed to the same threat).

can purchase reinsurance by ceding a portion of their claims to reinsurers. This limits the primary insurer's exposure and transfers a specific part of the tail risk.

It is important to note that the structure of cash flows and the related risks of insurers are fundamentally different from banks. Banks borrow short-term—traditionally through deposits—and utilize these funds to conduct long-term transactions, such as lending to (non-)financial institutions in the real economy. This implies from the outset that all banks are exposed to a fundamental maturity mismatch: as deposits are first-come, first-serve liabilities, banks are naturally prone to bank runs[138], which occur in coordination problems because of an information shock. Risks on both the asset and liability sides are largely endogenous and can end up in a cyclical dynamic.

On the contrary, liabilities in the insurance sector are contingent and resemble specific future realizations of exogenous risks, which are generally funded by upfront premiums. Other than in banking, these upfront premiums are annuities being predefined by the insurance contract, according to the underlying risk characteristics of the transaction, and present stable flows of funds that can be accounted for. Similarly, payoff schemes for insurance events are predefined by the contract. Hence, the risk of a sudden withdrawal of funds is non-existent in traditional insurance contracts and, in a crisis situation, there will be no endogenous cycles, inducing pressure to sell relatively illiquid assets and possibly taking further losses. However, insurers are subject to solvency risks, if the contingent liabilities exceed economic capital. Solvency risk is dependent on investment results, as well as the volume of risk being underwritten as well as its (exogenous) realization.

The Group of Thirty (2006) summarizes several important differences of banking and insurance. Due to specific regulatory requirements, leverage in the insurance sector is generally lower than in banking. Received premiums have to be invested in a relatively safe portfolio of assets, of which a large portion is invested in highly liquid markets such as sovereign debt or real estate. The returns realized on these investments are retained to cover contingent liabilities and add to the institution's solvency. As a result, the risks of a liquidity squeeze are less significant than in banking. However, it poses a challenge to earn sufficient returns on such low-risk investments in an environment of decreasing yields on such assets categories.

These distinct features of the business models in banking and insurance imply totally different challenges with regard to risk management. Although risks in banking seem less diverse, the endogeneity of these risks and their multiple interconnections pose a major challenge for the risk assessments in the industry. Conversely, (re-)insurers need to assess

[138] In our fundamentals chapter (section 2.3), we have shown that public sector deposit guarantees, as an insurance, alleviate the risks of depositor bank runs. However, such runs can still occur in other market segments, as banks are dependent on other sources of short-term financing, e.g. commercial papers.

a wide variety of exogenous risks on the liability side, while at the same time accounting for the asset-related risk of their investments. Historically, much of the development of risk management instruments in financial markets was driven by the (re-)insurance industry. The overall variety of risks implies that insurers apply a multitude of tools. The arsenal of instruments for these assessments is not solely quantitatively oriented, but also complemented by qualitative approaches. Additionally, stress tests with very long time horizons ensure rigorous and ongoing reassessment of the insurability of specific risks and the solvency of the institution.

Since the mid-1990s, the insurance sector has faced a challenging business environment; see Group of Thirty (2006). As a result of generally low interest rates and risk premiums, returns on investments were low and equity market crashes, especially the bust of the dot.com bubble, impaired the value of investment portfolios throughout the insurance industry. At the same time, natural catastrophes such as hurricane Katrina in the US and the terrorist attacks in New York on September 11, 2001 triggered major insurance claims and caused industry-wide losses. Consequently, insurance markets softened in terms of underwriting performance a natural mechanism due to constraints of the industries' capacity.

These forces coincided with an overall increase of demand for insurance cover in traditional segments. Furthermore, innovation in financial instruments and developments of structured finance markets and derivatives, with highly liquid secondary markets, expanded the scope to manage and transfer low-frequency, high-impact risks in financial markets. In the classical insurance segments catastrophe-bonds were introduced to transfer risks that even went beyond reinsurers' capacities, or in general, to transfer risks by means of insurance-linked securities (ILS). Being perceived as 'masters of risk', many insurance institutions entered innovative segments related to transferring credit risks. Therefore, they engaged in a competition with investment banks which stimulated the convergence with the financial markets.

The evolution of large conglomerates, combining insurance with other financial services to realize cross-selling advantages and other synergies, further added to this convergence; see Geneva Association (2010). Specifically, these institutions set-up business units in innovative segments that underwrote large CDS portfolios or other forms of financial guarantees. Monoliners focused solely on guaranteeing and pooling credit risks. As a result of this phase of innovation and evolution of large complex financial institutions, overall market complexity grew strongly. New financial instruments allowed insurance institutions a more active management of risks. Several regulatory initiatives also had an impact on business practices in the sector with the goal to allow for a more comprehensive supervision of risk in these institutions in an international context. Similar to other areas of financial markets, rating agencies evolved as de facto regulating bodies in the insurance sector, too. They assumed a special role in the reinsurance sector as ratings were often referenced in business transactions, for example funding contracts that would contain rating-triggers.

Some commentators, such as the Group of Thirty (2006), have argued that especially regulatory initiatives in terms of internal compliance and risk management placed a very high regulatory burden on the insurance industry, making risk management a complex exercise consuming capacities that would have been needed to advance the adaptation of risk management instruments to the changing business environment. The perception that insurers had an exalted expertise in managing all types of risk ('masters of risk') allowed them to enter new business segments easily, but, instead might have caused a lack of scrutiny vis-à-vis these new instruments, related to a return/growth focus, as included in our system model. The positive feedback in terms of rating performance possibly contributed to this dynamic. This is similar to the collective surprise narrative, and the corresponding cycle that was described in our system model of financial markets, but also refers to behavioral dynamics and the critical role of (collective incentives).

3.4.2 Insurance institutions and their exposures in the crisis

The Geneva Association (2010) presents a detailed assessment of the performance of different insurance institutions in the financial crisis 2007–09. Prominently, the report highlights the different exposures that these institutions had entered in association with their business strategy. Yet, they did so mostly without comprehensively accounting for specific the implications on risk, which now did not only involve exogenous, but also endogenous types. Overall, however, the report confirms that the insurance sector, traditionally, had only limited exposure to the crisis, and the sources of systemic risk[139]. Contingent with our previous argument of a convergence between the insurance and the banking sector, the report mainly differentiates the balance of insurance and banking activities within corporations.

Due to the nature of the business model, insurance institutions were not strongly interwoven with those segments of financial markets being affected by the crisis (figure 8). However, already before the crisis, the Group of Thirty (2006) argued that securitization would broaden the interlinkage with financial markets and the sector would become more exposed to systemic risk. Furthermore, being among the largest institutional investors in

[139]The Group of Thirty (2006) concludes that a failure of a large (re-)insurer would not have significant systemic consequences in financial markets comparable to the failure of a major bank. A source of hidden aggregate exposures that is identified in the report is a 'reinsurance spiral', where multiple retrocession transactions and co-insurance treaties might induce hidden interconnectedness. However, this scenario seems to be very specific for insurance and could also be tackled through increased transparency and better information quality within the sector.

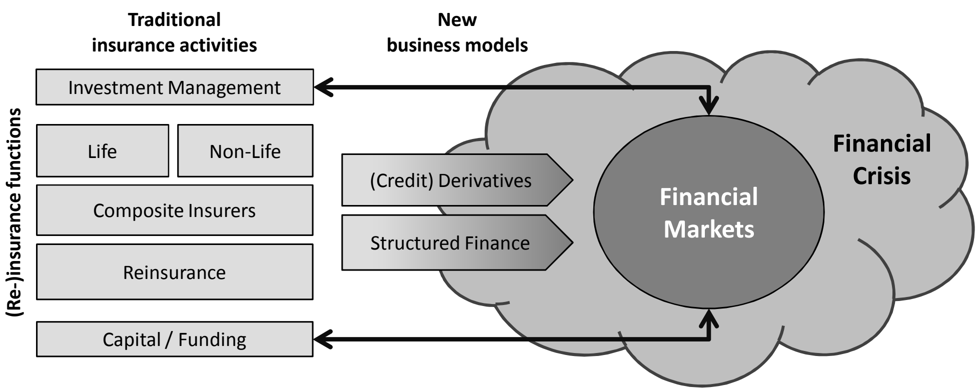

Figure 8: Channels of exposure of the (re-)insurance industry in the financial crisis 2007–09

financial markets, exposures on the asset side were natural, but typically these were limited by a rather conservative investment approach and regulatory provisions. It has to be noted the dot.com crisis had impaired equity holdings of many insurance institutions. On the liability side, besides general exposures in funding markets, the risks that were insured generally proved not to be correlated as long as credit risks of structured products had been underwritten, which turned out to be prone to liquidity disruptions as well as market risks[140]. For the 2007–09 financial crisis, the Geneva Association (2010) differentiates the exposures in the insurance industry for four groups, and additionally, the reinsurance industry has to be differentiated.

The first group, insurance *groups with none or only limited banking activities* proved to be largely unexposed in the crisis[141]. These institutions were only affected indirectly: they incurred losses due to illiquidity and price drops of specific assets, which were mark-to-market; they were exposed to overall spikes in volatility of financial markets (e.g. in regard to variable annuities); and they suffered from the liquidity crunch in their banking operations and the overall economic slowdown in late 2008. Some of these institutions had direct investment exposure to US housing markets or counterparty risks to defaulted banks such as Lehman Brothers. Japanese Yamato Life Insurance declared bankruptcy because of major losses on a subprime portfolio that it had built to realize higher yields. Analysts point out that this search for yield was developed to balance strategic disadvantages, such as a generally low level of operational efficiency.

The second group comprises *bank-insurance conglomerates*. Most of these insti-

[140] Note that securitization has also become a means to transfer other types of risk. As one example, it is used by the reinsurance sector to transfer (low-frequency, high-impact) disaster risks to financial markets (CAT-bonds). Investors benefit from additional diversification reducing the systematic risk of their portfolios. This sort of securitization was certainly also affected by general market dynamics and risk-aversion in the crisis, however, far less then asset-backed securities or other forms of structured finance related to credit risk transfer.

[141] Traditional insurers, that had no direct exposures to US real estate markets or other affected segments, might still be exposed in terms of directors & officers (D&O) liability insurance business that could materialize in the aftermath of the crisis. Such risks would become relevant if it would be proven that individual managers had neglected duties with regard to governance and business conduct and, thus, contributed to excessive risk-taking. However, as it would probably take years until insurers would have to finally pay out claims, there would be a long-enough timespan to account for these risks and build-up sufficient accruals; see Group of Thirty (2006).

tutions were heavily exposed in the banking division, from where problems spilled over into the insurance business, although their balance sheets were ring-fenced to allay this kind of contagion. Two large European corporations—Fortis and ING—had to receive government support to prevent a failure. Specifically in the case of ING, investigators acknowledge that vast parts of direct exposures from holding a portfolio of US residential mortgages resulted from regulatory requirements for its US banking business, which was forced to hold a certain portion of mortgages in its portfolio. Other conglomerates such as BNP Paribas, HSBC or Credit Agricole seem to have managed the crisis far better, particularly due to the fact that they maintained strong liquidity positions.

The third group refers to *large and complex financial institutions with wholesale banking operations*. Here, exposure was again mostly concentrated in the banking divisions that spilled over to the corporate level. The most prominent example of a near-failure in this group is American International Group (AIG). Although AIG was not exposed in its traditional insurance business, it had concentrated exposures in its financial products division, which had underwritten a huge portfolio of CDS linked to mortgage-related products. As the first tranches of these products were downgraded, counterparties forced AIG to hold a higher cash collateral for these products (margin call). Although the financial products division was only a small unit within AIG, its high leverage turned out to be detrimental to the overall corporation. As a matter of fact, supervisory institutions could have demanded the CDS portfolio to be reduced but, as liquidity risks of these products were not adequately identified, no such actions were taken. De Larosière et al. (2009) point out that there were also severe shortcomings in cooperation between the supervisory institutions responsible for the banking sector and those covering the insurance business[142].

The fourth group of insurance organization comprises *monoliners* focusing exclusively on *guaranteeing credit risk*. Initially, these institutions guaranteed primarily credit risks of (high-grade) municipality debt in order to enhance municipal credit capacities. However, they then gradually moved into other classes of high-rated securities and also underwrote CDS on asset-backed securities, though only those with AAA-ratings.

As ratings turned out to be inadequate and risks were not independent but correlated, monoliners such as Ambac and MBIA suffered severe losses from their CDS-pools and were downgraded by rating agencies. These downgrades triggered higher collateral requirements for their portfolios, but they were unable to raise capital in the adverse market environment[143]. Consequently, all counterparties had to realize losses on the

[142]The report furthermore points out that the distinction between regulatory approaches—the Basel Capital Accord in banking and the Solvency II regime in insurance—is necessary to account for the different business risks. However, due to the evolution of conglomerates covering both sectors, tight cooperation is required to ensure effective oversight.

[143]In fact, risks of these products were reassessed with hindsight and were not considered a viable investment.

CDS transactions conducted with these institutions (counterparty risks) causing systemic repercussions and further fueling the crisis. The Geneva Association (2010) concludes that the crisis has put into question the whole business model of monoline insurance in the area of credit risks, especially as potential correlations of risks in a market turmoil have been acknowledged.

A last observation refers to the reinsurance industry. Major reinsurers—Swiss Re being at the forefront—placed a strategic emphasis on securitization, as a major means of transferring risks into financial markets and fostering diversification. These kinds of transactions should add to overall insurance capacity and, from the individual company's point of view, helped to unload risks from their balance sheets and improve profitability. Risk management expertise was utilized in areas such as credit risks, and Swiss Re became engaged in CDS and other structured investment transactions designed to protect financial institutions from (endogenous) market risks. This shift towards investment banking-like operations also induced exposure to US mortgage markets and caused losses in the later crisis.

To conclude, the strategic repositioning of the (re-)insurance industry as the overall managers of financial risks prior to the crisis posed a critical development. Relating this development to our system model, a motif to be identified relates to a return/growth focus. The reasons for this were the combination of a low-interest rate environment reducing investment returns, the overall expansion of insurance demand, and the major potential for growth in innovative segments of financial markets such as derivatives and structured products. Certainly, this shift implied similar behavioral dynamics, as our model of the financial system.

In terms of risk, this repositioning implied an extension of the types of risks to be managed from traditionally exogenous risks to financial market risks that were endogenous and, thus, not necessarily independent. Furthermore, credit risks became intermingled with market and liquidity risks through the design of structured products. The implications of this extension were not adequately accounted for in risk models, which were characterized—similar to our model—by a predominant focus on quantitative risk management and ratings. As the analysis by the Geneva Association (2010) points out, regulators failed to impose limits on the convergence of both sectors, a primary problem being an insufficient coordination among the different supervisory agencies dealing with both sectors separately and under different regulatory provisions. This might be subsumed as a form of regulatory capture.

Those (re-)insurance institutions that had proactively repositioned themselves in financial market segments were more prone to the cyclical dynamics of the financial crisis

2007–09. In retrospect, the new businesses that were developed undermined fundamental principles of insurability as inherent risks were endogenous and exhibited significant correlation. Furthermore, the structured products, e.g. SPVs, were prone to liquidity interruptions, which were not accounted for adequately, and led to similar effects regarding the financial institutions microstructure. However, it needs to be emphasized that the traditional insurance business was much less affected by the crisis, and only by the channels mentioned above.

3.5 Chapter conclusions

This systemic analysis of the financial crisis 2007–09 helps us to draw some initial conclusions on the sources of systemic risk, picturing the crisis as a consequence of wide-ranging failures in market governance (see our 'governance triangle' framework, section 2.3.1). Systemic risk evolved gradually, because of a decoupling between dynamics in financial markets and the real economy. Even as the underlying positive cycle in the US real estate sector reverted did the positive dynamics in financial markets persist, creating increasing diseconomies of risk and adding to an overall vulnerability of the financial system. Our conclusions address four aspects in sequence: (1) interconnections of the individual narratives and stakeholder contributions to systemic risk; (2) a dynamic perspective in the governance triangle to develop a more comprehensive narrative on the crisis; (3) endogenous model dynamics and main condition risks manifesting in the crisis; and (4) critical variables and roles in our model, that can serve as focal points for regulatory reforms.

For possible explanations of the underlying forces of these dynamics, we first refer to five narratives, of which each offered distinctive reasons for the crisis evolution (table 4, section 3.2). Following Elliott and Baily (2009) we argue that any description of the crisis will necessarily abstract from the true complexity of events. Instead, biased by personal background and interest, a relatively simple narrative is developed to support the individual argument[144]. As the narratives also comprise conclusions regarding improvements to the design of the financial system, a struggle evolves, because only an authoritative narrative will shape priorities for reforms in response to the crisis.

Against this background, our system model of the crisis dynamics (section 3.3), the main analysis of this chapter, offers an integrated perspective on the causes of the crisis. Following on the methodologies of Vester (2002) and Gomez and Probst (1995), we develop a model of the financial system, which also allows us to assess *interconnections of the individual narratives and stakeholder contributions to systemic risk*. The results

[144]This relates to Taleb (2007), who notes in the context of his black swan conjecture that there will be desire ex post to establish a rational explanation of the events.

of our analysis emphasize that diseconomies of risk were driven primarily by a collective behavioral dynamic of expectations (Minsky moment) and incentives (moral hazard). However, systemic risk could only arise in combination with other weaknesses of the financial system. Central to these weaknesses was a biased representation of risk being commonly shared by all stakeholders (collective surprise). Especially, the strong focus on quantitative risk management, which was a consequence of ongoing disintermediation and tremendous increases in market complexity, as well as the crucial importance of ratings contributed to a false sense of certainty in financial markets.

Rendering of these weaknesses were failures of governance with regard to all three stakeholder groups, which we differentiate in the 'governance triangle'. All these groups—individually and jointly—could have contributed to better governance of financial markets but neglected to impose limits on the evolution of systemic risk:

- Regulators were unable to keep up with the high level of sophistication and growing complexity of financial markets and institutions. Existing regulatory structures did not prove to be effective in the crisis and, furthermore, the structural evolution of financial markets—globalization, disintermediation and the growth of the shadow financial system, as well as the convergence of banking and insurance—caused coordination problems for regulatory bodies. However, advances in science, information and technology allowed an improved and more transparent assessment of risks and seemingly mitigated the implicit moral hazard problem of financial intermediation. Regulators shifted towards a more market-oriented paradigm of regulation, which explicitly acknowledged private sector practices to assess risks as well as governance structures within the organization[145]. Consequently, they failed to impose any form of limits on the endogenous dynamics.
- Investors largely based their decisions on similar (quantitative) risk assessment methods as financial intermediaries. From their external perspective, ratings attained an even greater importance, especially for structured products[146]. These assessments created a pseudo-transparency and a false sense of certainty, spurring the search for yield also on the investors' side. Consequently, there was strong demand for riskier categories of innovative structured products (ABS, CDOs, etc.), which were regarded as safe investments. This demand added to the competitive dynamics among financial intermediaries and, in US real estate markets, contributed to the decline of lending standards.
- Financial intermediaries did not prevent the accumulation of risk within the organization. As our case study of UBS showed (section 3.3.4), the search for

[145] This shift also shaped the redesign of the Basel Capital Accord prior to the crisis in a fundamental way.
[146] This was often also due to regulatory requirements, e.g. for institutional investors.

yield was internalized through return/growth-oriented strategy alignments. Beyond that, the strong market dynamics also stimulated competition among financial intermediaries—in terms of a fight for market share and new business opportunities—which further contributed to the behavioral dynamics. Hence, scrutiny regarding risks was suppressed while, at the same time, structural developments within the organization impaired the ability to comprehensively assess and govern risk-taking within the institution. Financial institutions were, even as the crisis erupted, often not fully aware of the extent of their exposure as it had accumulated independently and in different divisions.

Based upon the results of the systemic analysis, we can, in a second step, offer a *dynamic perspective in the governance triangle to develop a more comprehensive narrative on the financial crisis 2007–09*. The starting point of this narrative is the great moderation, in which one can identify a *first shift in the equilibrium of financial market governance*. Throughout this period, many segments and markets in the financial system were liberalized and the equilibrium shifted towards private sector governance and self-regulation. This liberalization created new opportunities for financial intermediaries to expand their activities and realize profits: it was intertwined with ongoing globalization and economic growth; and financial innovations, especially in structured finance and derivatives, which introduced new methods of transferring specific risks throughout financial markets.

This shift was complemented by innovations in risk management systems, which were widely acknowledged to improve the institutional understanding of risk exposures and add to its stability. In order to create transparency and reduce the information asymmetry between investors and financial intermediaries, ratings were commonly believed to offer an external and objective assessment of risk. Although the financial system was not immune to instability during that period, even incidents such as the collapse of LTCM did not impair the dominance of (quantitative) risk management approaches. This period of fundamental-driven growth until mid-2005 is characterized by gradual shifts in the governance equilibrium, such as the extended use of fair accounting or Basel II, which mark transitions towards market-oriented regulation[147].

Over time, the degree of financial innovation, the disintermediation of value chains, and the non-standardized design of derivatives strongly increased the complexity in financial markets, causing a *second shift in financial market governance*. The growing sophistication of financial market participants contributed to regulatory capture and thus shifted the equilibrium further away from the public sector. Regulatory and supervisory

[147] Note that the regulatory framework imposed by the public sector was expanded during this period. However, these rules increasingly acknowledged internal governance provisions or risk assessments as well as market-driven instruments such as ratings, prices, etc.

agencies were no longer able to control dynamics in financial market. In fact, though this contradicts the common opinion prior to the crisis, financial innovations and their implicitly increasing complexities, aggravated the information asymmetry towards investors and, consequently, shifted the governance equilibrium towards financial intermediaries.

This second shift occurred in a market environment that became increasingly competitive, as financial intermediaries vied for market share and, through the interaction with the investor community, expectations regarding the performance of financial institutions continuously increased. Due to this dynamic, organizational strategies were positioned to reach ambitious short-term growth and return objectives. As we illustrate with the institutional perspective, risk management and governance structures were, similar to regulators, outpaced by organizational growth, leaving these systems unable to cope with the increasing complexities; they were unable to identify accumulating exposure, due to problems in the aggregation of risk assessments and pro-cyclical biases of the methodology.

The evolving behavioral dynamics within organizations were neither scrutinized nor addressed adequately. Instead, short-term incentives created a collective increase of risk-taking and the search for yield. A counterfactual argument might be that, if financial institutions would have had better information about their risk exposures, they would have probably sought to limit risk-taking in specific market segments such as US RMBS. Such action at the institutional level would have, aggregately, limited systemic risk. What the governance triangle helps us to understand is that, although the dynamics of diseconomies of risk might be regarded as confined primarily to the period of mid-2005 to mid-2007, the fundamental flaws in financial market governance evolved already before and were, in many aspects, even intended developments.

The main feature of our system model is to identify *endogenous model dynamics and main risks of conditions manifesting in the crisis.* Specifically, it shows how, without limiting effects of governance, there will be an endogenous overshooting of the dynamics in terms of systemic risk. Whereas part of this dynamic is naturally explained by the Minsky moment narrative and regards expectations and cost of capital[148], the presence of other behavioral factors and (collective) moral hazard aggravates the risk appetite of the majority of agents and thus influences developments. As we illustrate, this endogeneity of the system's dynamics is driven by a combination of different subnetworks and is self-enforcing in the positive as well as the negative cycle.

Systemic risk evolves in form of a collective vulnerability, which is broader than just expectations and financing as suggested by Minsky (1977). Instead there is a variety of risks of conditions, which, upon their manifestation, induce an abrupt change of the system's state, i.e. halt a positive cycle or enforce a negative spiral. One core

[148]Similar explanations are given by Kindleberger (1989); Reinhart and Rogoff (2009).

risk of conditions that we illustrate (section 3.3.3) is the pseudo-transparency that relied upon quantitative risk assessments and ratings for the complex environment of financial markets. Once transparency turned abruptly into complexity, as the collective surprise narrative suggests, it triggered a tremendous uncertainty, which evinced sudden spikes of risk-aversion[149]. Furthermore, massive coordination problems among market participants induced collective behavior and sharply reversed the system dynamics into a negative cycle.

The price spiral, which was transmitted through fair value accounting rules, coincided with a flight-to-quality, which added to contagion in terms of a liquidity dry-up in specific market segments. These two spirals then triggered new risks of conditions, related to capital buffers and maturity mismatch. As the stability of the world's largest financial institutions was shaken, uncertainty spread further and endogenously aggravated the crisis throughout the financial system. However, our distinction of the insurance sector business model (section 3.4) highlights that, although there were common channels of contagion, at least the traditional insurance model seemed to be largely resilient to these spirals. For financial intermediaries, however, the endogenous cycle became so strong, over different phases, that only massive intervention (LOLR) by the public sector—ongoing even today—has been able to contain the crisis in the financial system. With reference to Group of Ten (2001)'s distinction of sources of financial instability (section 2.2.3), institutional vulnerabilities due to the maturity mismatch, interdependencies among financial institutions, and information-based contagion jointly contributed to the crisis aggravation.

As it is our goal to conclude with a discussion of implications for the regulation of systemic risk (chapter 5), we can, at this stage, draw some basic conclusions to pick up on later in our discussion. First, the systemic analysis, especially when compared to the individual narratives, shows that a holistic perspective is needed to fully grasp the causes of the crisis. A similar approach, accounting for the contribution to governance of all stakeholders, will also be required when designing regulatory reforms in the aftermath of the crisis. De Larosière et al. (2009) conclude, para 39:

> '[...] the present crisis results from the complex interaction of market failures, global financial and monetary imbalances, inappropriate regulation, weak supervision and poor macroprudential oversight. It would be simplistic to believe therefore that these problems can be 'resolved' just by more regulation.'

The collective dimension of the critical dynamics highlights the challenge to establish macroprudential provisions within the regulatory framework (section 2.3), or to

[149] Risk-aversion is the negative of risk-appetite, which was included as a variable in our model.

address the collective behavior of market participants otherwise. In terms of specific aspects to be addressed, our assessment (figure 5) allows to identify *critical variables and roles in our model, as focal points for regulatory reforms.* Whereas a first approach to better regulate the system dynamics could target the active drivers of the system, a second option could aim at neutralizing catalyzers and reactive variables to direct dynamics towards a more sustainable pattern.

Developing dynamics, though possibly rather at an early stage, could be governed by focusing on financial products and innovation, quantitative risk management focus, regulatory capture, shadow financial system, or disintermediation. At a later stage of the cycle, especially to ease the abrupt shift of the system into a crisis dynamics, one could focus on liquidity, transparency, and the rating focus as reactive variables that still have a tremendous impact on the overall system. Similar goals could be achieved if the vulnerability in terms of financial institutions microstructure could be reduced.

An issue that must be addressed by the public sector regards governmental interventions in terms of LOLR measures in a crisis situation. Although the mechanism is excluded from our model, a fundamental crisis in the financial system will—through the credit channel—develop adverse effects on the real economy; this was also observed in the aftermath of the collapse of Lehman Brothers (section 3.1.4). From the governmental perspective, losses will, then, not only arise in the financial system but also the real economy, whereas additional cost might well be triggered in social welfare systems. A crisis intervention that can put the brakes on endogenous dynamics can be rational ex post, only after the crisis erupts. This time-inconsistency of governmental interventions (section 2.3) has to be accounted for. At the same time, the ex ante anticipation of such intervention poses powerful incentives in financial markets and can even enforce risk-taking. Given the time-inconsistency these incentives can also arise, although governments strictly exclude any intervention ex ante.

This leads us to a final set of distinctive variables, which will also be at the forefront of our subsequent analysis. Although we have argued that the failure of governance mechanisms throughout the financial system let the endogenous upward cycle unfold without limiting the dynamics, we have also accentuated the fact that there have been warnings on the accumulation of risk, with specific regard to the US real estate sector as well as to related segments of structured products[150].

In efficient markets the search for yield and risk appetite should have reacted to such warnings, yet, the majority of market participants collectively maintained their exposure and even increased it. Only very few individual agents withdrew from critical market

[150] See the International Monetary Fund (2005)'s warning regarding a cooling of US real estate markets and the untestedness of CDOs in late 2005 (section 3.1.2), as well as the summary in International Monetary Fund (2009b).

segments. Active drivers in this regard, are the return/growth focus and compensation in financial institutions, which determine incentives for risk-taking of institutions. The essential role of incentives is also highlighted by the moral hazard narrative, in relation with the collective surprise and Minsky moment narratives.

Our subsequent analysis focuses on drivers of collective behavior that potentially foster the evolution of systemic risk. Especially, it is of interest to analyze underlying incentive and information structures and to determine when such behavior can be related to collective moral hazard. This will allow us to draw conclusions on the relevance of the corresponding narrative. A second analysis sheds light on the empirical measurement of collective behavior. Such measurability would permit the imposition of limits on evolving dynamics, particularly through macroprudential regulation. Based on these insights, we can discuss the relevance of collective moral hazard as a source of systemic risks, and the implications for its governance of financial markets in the concluding chapter.

Chapter 4

Collective behavior of financial institutions

The main goal of this chapter is to contribute to the understanding of collective behavior and moral hazard in the financial system, as a source of systemic risk[151]. This is an important prerequisite to designing effective macroprudential regulation and to strengthening the governance of systemic risk in financial markets. *Our analysis comprises two features: it approaches collective behavior of financial institutions from both a theoretical and an empirical perspective.* Whereas a theoretical analysis delves into incentive structures at the collective level that induce collective behavior and systemic risk due to collective moral hazard, the empirical analysis focuses on the prospects of an empirical ex ante identification of systemic risk in financial markets. Jointly, these two parts establish a basis to conclude how to reflect issues of collective behavior and collective moral hazard in our governance triangle framework, as the basis for our concluding discussion of implications for the governance of systemic risk in the subsequent chapter.

The relevance of collective dynamics as a driver of systemic risk in the 2007–09 financial crisis has been highlighted in our prior systemic analysis and also by other analyses; see for example Brunnermeier et al. (2009) and Lord Turner (2009). Particularly, a collective behavioral dynamic in terms of risk appetite resulted in financial institutions building risk exposure to similar asset classes, sectors, and other factors such as liquidity. This dynamic was not actively addressed by regulation or by a revised assessment of risks, so the prolonged cycle exhibited diseconomies of risk. This in turn induced vulnerability

[151] We focus on ex ante aspects of systemic risk that are a consequence of the collective behavior of financial intermediaries. In research, a wide spectrum of many analysis elaborates on 'herding', which is often modeled as an ex post phenomenon. Consequently bank runs, which are also a form of collective behavior, remain outside the scope of our analysis. This boundary is also implied by the limitation to ex ante aspects of systemic risk since bank runs represent an ex post phenomenon that only occurs in response to a specific shock. This type of systemic risk is related to indirect interdependencies in terms of correlated risk exposures of financial institutions, e.g. holding specific types of assets, or through loans to specific sectors. Also see our comments in section 2.2.3 for the relation within the wider context of systemic risk.

in financial markets in terms of systemic risk. Against this background, the post-crisis discussion on reforms of the financial system devotes great attention to complementing the regulatory framework with macroprudential provisions, which in turn focus on endogenous risks that are dependent on collective behavior; see for example Goodhart (2008), Bank for International Settlements et al. (2009), De Larosière et al. (2009), Brunnermeier et al. (2009), Group of Thirty (2010).

Proposals for regulatory reforms concur with the methodology of Vester (2002), which takes a system theory perspective: on the one hand, reforms can tackle forces of the observed dynamics that induce systemic risk; on the other hand, they can aim at identifying adequate indicators and measurements of the dynamics, and impose (exogenous) regulation once a critical stage has been reached. Dow (2000) and Summer (2002) point out that the overall comprehension of systemic risk arising from collective behavior is sparse—both from theoretical and empirical perspectives.

In order to avoid an incomplete or misdirected design of macroprudential regulation, explanatory approaches of collective behavior in financial markets and their underlying impetus needs to be enhanced. Research has to further analyze to what extent the dynamics observed in the previous chapter are a consequence of coordination problems, or are intentional, when caused by collective forms of moral hazard. The same argument applies from an empirical perspective where effective measurements of collective behavior and thus systemic risk have yet to be defined. The two parts of our analysis—theoretical and empirical—aspire to each fill a part of these gaps.

The core contribution of our *theoretical analysis*, the first part of this chapter, is to the understanding of incentive structures at the collective level that induce collective behavior and systemic risk due to collective moral hazard[152]. We establish a microfoundation for collective behavior, as observed in the systemic analysis, by focusing on strategic complementarities—negative externalities in particular—that create incentives for collective behavior. The analysis formally elaborates on three model variations of Acharya and Yorulmazer (2008) and Acharya (2009), focusing on the interaction of banks and creditors, as well as effects of regulation. We also discuss the relation of our analysis to the wider literature, which illustrates further approaches to incentives for collective behavior, and how these could be integrated into our model.

Overall, the results from the theoretical analysis highlight that there seems to be an inherent bias in financial markets fostering collective behavior, to be explained by a wide-spectrum of approaches. The crux of this microfoundation of collective behavior and

[152]In the theoretical context (see section 4.1.1), systemic risk is defined as the probability of joint failure of financial institutions, which induces a deadweight loss for its creditors. Although there is—also without collective behavior—always a residual risk of joint failure, the overall probability increases as a result of collective behavior. The difference in the residual can be regarded as systemic risk resulting from collective behavior.

collective moral hazard lies in the fact that financial market participants do not internalize the impact of their joint actions at the systemic level. Though regulatory provisions can reverse critical incentives, they face fundamental challenges, particularly to account for the dynamics of financial markets.

The second part consists of an *empirical analysis* focusing on the prospects of an ex ante identification of systemic risk[153] in financial markets. We study the dynamics of correlations among international financial institutions prior to the financial crisis 2007–09, until the breakdown of Lehman Brothers in September 2008. The underlying rationale of our analysis is that collective behavior of financial institutions, which is considered a major source of systemic risk, increases interdependencies and, through market expectations, leads to rising levels of correlations. Our goal is to determine whether, prior to the crisis, one can find significant indications for increases of interdependencies. Any statistical evidence that systemic risk can be identified ex ante supports the argument for quantitative indicators of systemic risk as an important pillar of macroprudential regulation.

We find particularly strong evidence of positive increases in the trends of correlations among financial institutions from the US for what we define as the systemic core of our sample. In contrast, our results for the aggregate samples, focusing on the international context and the US, are ambiguous. An interesting aspect of our results is a compatibility with complex analyses such as Acharya et al. (2010b). This is in line with other studies as well, such as Drehmann and Tarashev (2011a,b), who argue that complex measurements can be reproduced with simple indicators. By applying simple measures, regulators would mitigate the risk of a false sense of certainty that might arise with more sophisticated, pseudo-accurate quantifications of systemic risk. Our conclusions contribute to the corresponding discussion as they also elaborate on statistical challenges to the measurement of systemic risk.

Together, the results from both parts add to the debate on the design of a governance framework for financial markets in the aftermath of the crisis. We propose an extension of the governance triangle introduced in section 2.3.1, to allow for a differentiation of different levels—systemic, institutional, and individual—and corresponding types of moral hazard, or other sources of systemic risk at these levels. Especially critical are two distinct information asymmetries that arise between the systemic and institutional levels, and institutional and individual levels. While the two-level framework can help to clarify the focus of regulatory measures, it also illustrates a problem of regulation at the systemic level to create an adequate impact at the individual level.

[153]From the econometric perspective (see section 4.2.2), systemic risk is measured by the correlation among stock returns (as the daily percentage change of stock prices) of pairwise financial institutions, with an increase of correlation signaling an increase of systemic risk and vice versa. Stock prices reflect investor expectations and, as financial institutions increase interdependencies through correlated exposures, there will be an alignment of these expectations. This is then reflected by an increase in correlation, indicating higher systematic risk among these institutions. This increases the risk of a shock reaching a systemic dimension.

Information frictions within financial institutions—at the institutional level they were highlighted by our institutional account of UBS (section 3.3.4)—create challenges for an ex ante identification of critical collective dynamics, particularly in a constantly changing market environment. From a systemic perspective further challenges for regulation are necessary to define adequate boundaries and to account for endogenous feedback within financial markets. For internal mechanisms of governance, it might be a valuable strategy to aim at reducing critical information asymmetries through regulation, thus enhancing market discipline. This will, at the same time, increase transparency, and create a stronger basis for the effective implementation of macroprudential policies.

4.1 Theoretical analysis of collective behavior, collective moral hazard and systemic risk

4.1.1 Introduction

From a theoretical perspective, a focus on collective behavior and endogenous risks in financial markets leads to a shift in how we think about the behavior of agents in financial markets, and specifically banks. Traditionally, banks have been regarded as rather independent agents, acting upon their individual incentives; see Borio (2003). The macroprudential perspective emphasizes the interaction among multiple agents in financial markets, whose incentives are closely interlinked and influence each other. Systemic risk is the probability of joint failure of financial institutions, which increases endogenously due to collective behavior as financial institutions are exposed to correlated risks. The focus of our theoretical analysis is, therefore, on strategic complementarities and different forms of externalities—e.g. due to market structures, expectations, or regulatory provisions—that induce incentives for collective behavior, and not just influence individual risk-taking; see Windram (2005).

There is vast research on collective behavior, often referred to as 'herding', and implying 'systematic erroneous decision-making (sub-optimal relative to the best aggregate choice) by entire populations', Devenow and Welch (1996), p. 604. The wide spectrum of models in this area (with rational actors[154])—extensive surveys are conducted by Devenow and Welch (1996), Bikhchandani and Sharma (2001) and Hirshleifer and Teoh

[154] We exclude behavioral approaches, for which comprehensive accounts of the literature can be found in De Bondt and Thaler (1994), Brunnermeier (2001) and Sewell (2008). Harsanyi (1967) introduces the notion of higher order beliefs which influence agents' decision-making, which is extended by Aumann (1992). Focusing on the perceived utility gain by agents, Shleifer et al. (2010) in their theory of salience present support for the assumptions that agents weigh high positive outcomes (with low probability) higher than the standard expected value. From a different perspective, Shiller (1990) argues for behavioral effects in consequence of feedback mechanisms in financial markets.

(2003)—can be clustered into several groups: bank runs (multiple equilibria)[155]; information cascades[156]; reputational concerns or short-termism[157]; relative performance and career concerns[158]; ex post reactions to a crisis/shock (rational contagion)[159]; and, lastly, linkage to asset prices (bubbles)[160].

In general, a large number of analyses of collective behavior focus on decision-making structures that are influenced by strategic complementarities: the individual decision of one agent is affected through various forms of externalities created by prior actions of other agents or anticipated subsequent ones. Collective behavior arises due to coordination problems or moral hazard at the individual level. In the majority of cases the outcome is inefficient, as it deviates from the first-best equilibrium.

Our analysis follows a different, less developed strand of literature emphasizing potential biases in the joint decision-making of financial intermediaries, as agents have incentives to coordinate on a specific combination of strategies, jointly maximizing their utility. We will argue in the subsequent section that such behavior be referred to as 'collective moral hazard'. Our systemic analysis and the moral hazard narrative have pointed out various indications for such behavior being relevant for the evolution of systemic risk in the 2007–09 financial crisis (section 3.5). Anecdotal accusations have been made by Levin and Coburn (2011). Similar indications can also be found in analyses of earlier financial crises; see Bank of England (2009).

Despite these observations calling for a deeper analysis of incentive structures at the collective level, Dow (2000) and Summer (2002) point out that research in this area is sparse, but there are important contributions by Acharya and Yorulmazer (2008), Acharya (2009) and Farhi and Tirole (2009), as well as Acharya and Yorulmazer (2007a,b). In different contexts, these analyses support the existence of collective incentives for financial institutions to actively coordinate their decision-making and intentionally maximize the correlation of exposure to specific risks[161]. Collective behavior allows the avoidance of negative externalities in the payoffs of financial institutions that could arise in a scenario of differentiation[162].

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[155] Seminal contributions on bank runs are Bryant (1980) and Diamond and Dybvig (1983). Comprehensive literature surveys of bank run models can be found in Calomiris and Gorton (1991) and Bhattacharya and Thakor (1993).

[156] Prominent contributions on information cascades are Bikhchandani et al. (1992), Banerjee (1992) and Hirshleifer et al. (1994). For an annotated bibliography see Bikhchandani et al. (1996).

[157] See major contributions of Scharfstein and Stein (1990), Rajan (1994), Zwiebel (1995) and Graham (1999)

[158] Such as prominently, Maug and Naik (1996), DeMarzo et al. (2004) and Dasgupta and Prat (2008).

[159] Corresponding models have been proposed by e.g. Kodres and Pritsker (2002) and Calvo and Mendoza (2000)

[160] See the seminal contribution of Avery and Zemsky (1998), Morris and Shin (1999), and recently Hott (2009)

[161] Whereas other herding models assume that collective behavior and externalities arise through time (sequential decision-making), these models focus on incentives for collective behavior in a simultaneous decision-making environment. It is not the observation of other actions that influences the individual decision of an agent, but the positive probability of a negative externality that leads to an active coordination of (simultaneous) decisions.

[162] From an aggregate welfare perspective, the differentiation scenario is the first-best equilibrium, as it minimizes the risk of joint failure of banks.

Effective macroprudential regulation needs to account for all types of coordination problems, as well as critical incentives at the individual and collective levels in financial markets. Yet, corresponding regulation needs to carefully consider the individual characteristics of a specific market failure. *Our core contribution is to the understanding of incentive structures at the collective level that induce collective behavior and systemic risk due to collective moral hazard.* Analysis in this regard allows us to establish a microfoundation for the collective behavior described in the systemic analysis (chapter 3). Furthermore, our results make a contribution to the debate on the design of a governance framework for financial markets in the aftermath of the crisis.

Applying our governance triangle to financial markets, we are interested in the interaction among financial intermediaries, investors, and regulators. Specifically, we ask for potential market failures among investors and financial intermediaries, and the corrective effect of regulatory provisions. The models of Acharya and Yorulmazer (2008) and Acharya (2009) focus on the interaction between creditors and banks in money markets[163]. Due to information asymmetry creditors can only imperfectly observe the actions taken by banks. The models come to the interesting conclusion that this interaction—through the interest channel of banks' borrowing—can cause negative externalities and induce incentives for collective behavior. In consequence banks induce systemic risk, which implies a deviation from the first-best equilibrium. We refer to this as collective moral hazard.

These results are conditional on a set of specific assumptions, such as the strong information asymmetry among both groups. There is a wide spectrum of possible adjustments to these models, analyzing the effects of changed assumptions for the results. We formally analyze the implications of three model variations for collective incentives inducing systemic risk[164]:

- *Creditor expectation changes and the impact of a capital buffer*: Acharya and Yorulmazer (2008) show that creditor expectation changes, assuming fixed money supply, can induce a negative externality upon which banks behave collectively and induce systemic risk. The main ingredient is the information asymmetry between creditors and banks. This could be tackled through regulation: we propose a capital buffer to be observed by creditors for each bank individually. Analyzing the hypothesis that the capital buffer reduces banks' incentives for collective behavior, we show that, for a robust set of assumptions, it even leads to a reversal and fosters the differentiation among banks instead. Yet, banks would never opt for a capital buffer voluntarily; it has to be enforced by regulation. The fact that

[163] As the models presented in the subsequent sections are variations of Acharya and Yorulmazer (2008) and Acharya (2009), and as we explain the core differences and adaptations in detail later, we defer a more detailed explanation of these models at this stage.

[164] Whereas many of the aforementioned contributions also discuss normative aspects such as optimal design of regulatory provisions, we limit ourselves to the positive analysis of collective incentives.

incentives are dependent on priors regarding the state of the economy, as well as banks' performances, presents a further challenge since corresponding regulation needs to account for these dynamics.

- *Money supply shocks with fixed externality*: Acharya (2009) presents a model which jointly analyzes the implications of individual and collective incentives for systemic risk, when the failure of a bank reduces money supply and can trigger an adverse effect for the prospects of other bank. While the choice of collective behavior critically depends on the potential externality, Acharya finds that banks will always maximize their investment risk, as there is no liability in the case of failure[165]. We show that critical incentives at the collective level can be replicated in a much simpler model environment, eliminating additional incentives at the individual level. The model assumes variable money supply but fixed creditor expectations, so the information effect of the capital buffer is not relevant for the analysis. An interesting feature that is highlighted by our results is that this supply channel can be regarded as dependent on the potential for consolidation in the banking sector. Higher prospects of consolidation reduce incentives for collective behavior.
- *Money supply shocks with dynamic externality and multiple, heterogeneous banks*: In this step, we expand the prior model, relaxing the assumption of two homogeneous banks, which is a convention to simplify the modeling. We are interested in the effects of an endogenous externality in such a more general scenario and analyze the hypothesis that, for multiple and heterogenous banks, an endogenous externality will affect incentives for collective behavior, developed by the prior model. Our results show that, without prior knowledge regarding the externality, and taking sequential decisions, the choice of collective behavior resembles a dominant strategy for all banks, which has features of the information cascade models of Bikhchandani et al. (1992). For heterogeneous banks, there will be a dynamic similar to their concept of 'fashion leaders'.

Our systemic analysis also suggests to elaborate on incentives due to relative effects—e.g. due to competition or other forms of relative incentives—as a source of collective behavior. Several interesting models, such as DeMarzo et al. (2004), Boyd and De Nicoló (2005), etc., seem worthwhile to explore in more detail, in terms of their underlying mechanisms and their relation to our analysis[166]. One specific example for a possible extension would be to account for a two-level principal-agent problem with both internal and external information asymmetries. This *discussion of our analysis in the wider con-*

[165] This characterization of incentives at the individual level resembles the standard moral hazard of financial intermediation due to the limited liability of bank managers; see appendix A.2.

[166] Hassan and Mertens (2011) elaborate on market sentiment and the impact of costly information on collective behavior. They find that systemic risk can be described as a tragedy of the commons problem.

text of the literature marks our second contribution, as it illustrates further approaches to incentives for collective behavior, and how these could be integrated in our model.

Overall, the results from our analysis and the discussion in the wider context of the literature highlight that there seems to be an inherent bias in financial markets for collective behavior. This bias can be explained by a wide-spectrum of approaches, relating to our findings in the systemic analysis of the 2007–09 financial crisis (chapter 3). As stated earlier, the crux of this microfoundation of collective behavior and collective moral hazard lies in the fact that financial market participants—banks in particular—do not internalize the impact of their joint actions at the systemic level. Regulatory provisions can eliminate incentives for collective behavior, but to be effective they need to tackle some important challenges, such as accounting for market dynamics, i.e., the effects on expectations that arise in an economic boom.

The remainder of this section is structured as follows: section 4.1.2 gives an overview on general considerations and introduces the basic model design which will be applied for the three steps of our analysis (sections 4.1.3, 4.1.4 and 4.1.5); further explanations of collective behavior are discussed in section 4.1.6; and, lastly, section 4.1.7 presents our conclusions. The results are discussed in the wider context of systemic risk, and with the findings of the empirical analysis (section 4.2) at the end of this chapter (section 4.3).

4.1.2 Model design

Preliminary considerations

These preliminary considerations, from a game theory perspective, serve to illustrate the mechanism of strategic complementarities that induces incentives for collective behavior. The application in a highly abstracted and simplified setting helps to explain the specific incentive structures leading to collective behavior, and also allows us to propose a general definition for the concept of collective moral hazard. Our later analysis will apply exactly the same mechanism of strategic complementarities in the context of the interaction between banks and creditors in money markets. Similarly, the later proof of collective moral hazard builds on these preliminary considerations.

From a game theory perspective, the problem of collective behavior of financial institutions and systemic risk can be transformed into a standard non-cooperative game, in which two homogeneous agents decide whether to behave collectively and pursue correlated strategies (S1–S1, S2–S2), or differentiate and pursue different strategies (S1–S2, S2–S1). Our focus is on the negative externalities which induce incentives for collective behavior among banks. Collective behavior gives rise to systemic risk as it increases the probability of the joint failure of banks, which gives rise to a deadweight loss[167]. We formally deduce the presence of collective moral hazard in appendix A.1.

Two agents simultaneously decide on their strategy (S1 or S2), both of which resemble lotteries[168]. Because the standard game context assumes perfect information, both agents know of the risk characteristics of these lotteries. Being rational and risk-neutral, they will consistently seek to maximize their expected returns[169]. As we will show later, our model boils down to a one-shot game, and the decision problem of both agents can be fully represented by the game matrix below (table 8)[170].

Table 8: Payoff matrix with externalities

		Agent B	
		S1	S2
Agent A	S1	10, 10	$10 + E$, $10 + E$
	S2	$10 + E$, $10 + E$	10, 10

For $E = 0$, both strategies yield identical expected returns and there are no strategic complementarities[171]. All strategy combinations represent (weak) Nash equilibria: the players are indifferent between both options as none yields a higher expected return. Consequently, agents play mixed strategies by randomizing over the set of available actions[172].

In this scenario, collective behavior would not be intentional but as a consequence of randomization. There is no collective moral hazard, but there is a coordination problem[173]. Following Aumann (1974, 1987)'s concept of correlated equilibria, one could

[167] Though in reality one might consider further sources of systemic risk, which could also affect uncorrelated strategies, we exclude such factors from this example as well as the later model.

[168] In this context such lotteries could stand for loan portfolios to specific sectors, for example.

[169] The assumption of risk neutrality assumes a linear utility function, which implies that agents will be indifferent among choices of a similar expected value, but with different risk characteristics. It also facilitates the analysis, as it is sufficient to analyze the maximization of expected returns with no further utility assumptions as, e.g., the extent of risk aversion. For risk-averse agents, the maximization of expected utility would concern a concave utility function, which would make second-order stochastic dominance (the implied risk measured by variance) relevant for decision-making.

[170] For reasons of simplicity, the following payoff matrices give absolute numbers as expected payoffs. The specific numbers are arbitrary and serve solely illustration purposes. Furthermore, the game matrix is symmetrical because agents are homogeneous. Heterogenous agents are considered in section 4.1.5.

[171] Such a scenario would arise if both strategies are assumed to resemble lotteries being identically independently distributed (iid). Therefore, taking loan portfolios of two sectors as an example again, these would have exactly identical risk characteristics. Assuming efficient markets, Avery and Zemsky (1998) show that a dominant strategy—in terms of a higher expected return—can exist only temporarily. In the long-run, price effects will weaken its predominance and, in equilibrium, both strategies, accounting for their risk/payoff characteristics, will yield the same expected return. Otherwise, there would be arbitrage and markets would not be efficient.

[172] As there are just two strategies, we can suppose that agent A will play strategy S1 with a probability p and S2 with probability $(1 - p)$. Similarly, agent B will play strategy S1 with probability q and S2 with probability $(1 - q)$. It is a common, though less general, assumption that agents randomize their strategies by tossing a fair coin and play S1 on heads and S2 on tails. This would imply $p = q = 0.5$. Hence, the probability of collective behavior becomes $P(\mathrm{S1}, \mathrm{S1}) + P(\mathrm{S2}, \mathrm{S2}) = pq + (1 - p)(1 - q)$.

[173] As both strategies are independently and identically distributed (iid), there will be no moral hazard at the individual level, either. See appendix A.2 for further explanation.

imagine a 'trusted authority'—in the financial sector, the central bank or a regulatory body—that ensures coordination between the two agents. This institution would toss a (fair) coin and use this signal to indicate a strategy suggestion to both agents[174]. Agents are indifferent between both strategies and have no incentive to deviate from this suggestion. Hence, the authority could effectively prevent collective behavior, and there is only residual systemic risk.

For any $E \neq 0$, the game exhibits strategic complementarities, and the strategy decision of one agent will directly affect the payoff of the other agent. For different strategies, agents' payoffs are affected by an externality being either positive or negative[175]. In such a coordination game without conflicting interest, agents will seek to coordinate their behavior in order to jointly maximize their payoffs. If it is assumed that $E > 0$ (positive externality) agents have an incentive for different strategies. The challenge is then to coordinate and jointly choose either S1–S2 or S2–S1.

For $E < 0$ (negative externality), the game has two Nash equilibria, S1–S1 and S2–S2[176]. Agents have a preference for collective behavior in order to maximize their payoffs, even though this choice induces systemic risk. As long as no coordination among the agents is allowed, agents will randomize their strategies. Hence, S1–S2 and S2–S1 are correlated equilibria. In contrast to $E = 0$, there is no role for a trusted authority because agents do have incentives to deviate from the suggested strategy. Agents would know that, following the suggestion, their payoff results in $10 + E < 10$, whereas by deviating they might be able to realize a larger payoff[177]. Due to symmetry, however, both agents have the same incentive to deviate from the authority's suggestion. Therefore, there will again be a form of randomization, just as in a non-cooperative game.

If, for the negative externality, we suppose that banks have opportunities for a tacit coordination of their choices, then they jointly opt for collective behavior and pursue the correlated strategies[178]. In doing so, they maximize their individual payoffs while at the same time adding to systemic risk, due to the increased probability of joint failure. In effect, this shared maximization causes a negative deviation from the first-best equilibrium. Then, the collective behavior of the agents resembles a moral hazard and, as the

[174] This information signal could be correlated to a fair coin toss. As one example, the institution would tell agent A (B) to choose strategy S1 (S2) on heads and strategy S2 (S1) on tails.

[175] Alternatively, one could imagine an externality for the choice of correlated strategies (collective behavior).

[176] The analysis of a positive externality is analogous to the assumption of a negative externality.

[177] On the contrary, if the externality is assumed to be positive, it would naturally provide incentives to follow diversified strategies. Therefore, the authority could again ensure coordination and keep systemic risk at a minimal level.

[178] Because of the large information asymmetry between banks and external stakeholders, such as depositors, creditors, investors or also regulators, the later model will assume that banks 'know' about the decision-making in the other bank, or there can be a tacit form of coordination which allows banks to coordinate their strategies. For example, such a tacit form of coordination could be knowledge about the prospects of certain growth sectors, or certain signals to endorse a certain asset class, etc. Such an action might be interpreted as an information signal for the other bank, revealing the probability of playing either strategy.

two agents need to coordinate their strategy decision, we speak of collective moral hazard; see appendix A.1 for a formal deduction.

This result relates to the original definition of the principal-agent problem at the individual level, as proposed by Jensen and Meckling (1976)[179]. Yet, due to the collective dimension the definition naturally refers to a group of agents. Banks induce additional risk that, due to the underlying information asymmetry, are borne solely by investors. Their joint behavior causes a deviation from the first-best equilibrium to be achieved by a central planner with the objective to maximize aggregate welfare. Generalizing these considerations we can state the following definition[180]:

Definition: The concept of collective moral hazard, in reference to the collective behavior of more than one utility-maximizing agent vis-à-vis a continuum of principals, applies upon the following conditions:

- a group of agents being in some contractual relationship to one or more principals that involves an information asymmetry;
- agents being able to tacitly coordinate their strategy decisions;
- agents, due to strategic complementarities, having collective incentives to pursue a specific combination of strategies within the available strategy space; and
- while this strategy combination jointly maximizes the individual expected utility of agents, it has adverse implications on the expected aggregate welfare due to an increase of systemic risk, or other effects that reduce aggregate welfare.

Model overview

The goal of this analysis is to elaborate on different mechanisms that give rise to negative externalities, and upon which banks have incentives to coordinate their behavior and pursue correlated strategies, consequently inducing systemic risk. We elaborate on two complementary mechanisms, where such incentives arise from the interaction in money markets, and through the interest rate channel: based on (1) creditor expectation changes and the effect of a capital buffer, and (2) money supply shocks, respectively. In addition, we focus on (3) implications for incentives, once assumptions—limiting the analysis to two homogeneous agents—are relaxed. We formally prove that the intentional choice of

[179] Jensen and Meckling (1976), p. 5, define the basic principal-agent relationship as a 'contract under which one or more persons [the principal(s)] engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent.'

[180] We are not aware of any formal definition of collective moral hazard. Dow (2000) proposes a non-technical definition in a much broader context. Acharya (2009) speaks of 'systemic moral hazard induced through "too-many-to-fail" guarantee' without giving a general definition. The basic conditions of our definition are similar to those of moral hazard at the individual level. It only relates to a group of agents, instead of individual ones.

collective behavior among banks, due to negative externalities, resembles collective moral hazard.

The basic model of our analysis has two periods. It contains two homogeneous banks (agents) and a continuum of creditors (principals) from which banks raise funds to be invested simultaneously in either of two strategies. The investment decisions of both banks determine whether there is systemic risk resulting from collective behavior that increases the probability of joint failure.

There is a fundamental information asymmetry between agents and principals. Although creditors know about the strategic options of banks, they cannot observe their behavior, but only the strategy outcome. Thinking about a loan portfolio, this can be interpreted as creditors observing systematic risk factors such as the overall state of the economy, but not any idiosyncratic factors of these portfolios. Hence, if creditors update their priors regarding the return expectations of banks, they infer their observations with regard to the systematic factor[181]. The assumption of a capital buffer (section 4.1.3), reduces the information asymmetry, as it allows creditors to observe an idiosyncratic information signal for each bank[182].

At the beginning of each period banks raise funds from creditors and invest these in one of two strategies with a one-period-maturity[183]. After investment returns are realized at the end of the period, creditors are repaid and, if the return of a bank's investment falls short of the necessary repayment to its creditors in any period, the bank fails and operations cease. In this case, creditors receive the liquidation value of the bank's assets, and that value is reduced due to a deadweight loss.

Observing the results of the first period, creditors adjust their lending conditions. Thereby they shift the money supply curve for banks[184]. As both investment strategies are assumed iid and constant for both periods, a negative externality can derive only from this change of the money supply curve after the first period. This is the focus of our analysis, and we elaborate on two complementary effects that induce strategic complementarities, because of which banks intentionally induce systemic risk, opting for collective behavior.

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[181] Acharya and Yorulmazer (2008), p. 220, state: 'This opaqueness about the bank balance sheet and realized returns is critical to our model. Given that a proportion of bank loans is in fact to small and medium-sized firms, usually unrated by rating agencies, we believe the assumption that such an unobservable common factor exists is a reasonable one.'

[182] Once we focus on money supply shocks, we assume expectations to be fixed. In this setting, the additional information signal of the capital buffer is not relevant for the analysis.

[183] Banks are assumed to be price takers and lend from creditors by a standard debt contract with a one period maturity. They have to align the borrowed amount to the interest rate required by creditors. The continuum of creditors, with homogeneous risk-preferences, can be regarded as a participant of say money markets that will set an interest rate according to their risk assessment. If the interest required by its creditors exceeds the expected returns from investing, banks will decide not to operate.

[184] This mechanism implies that, at the end of the second period, creditors have no more means to punish banks for their behavior in a future period.

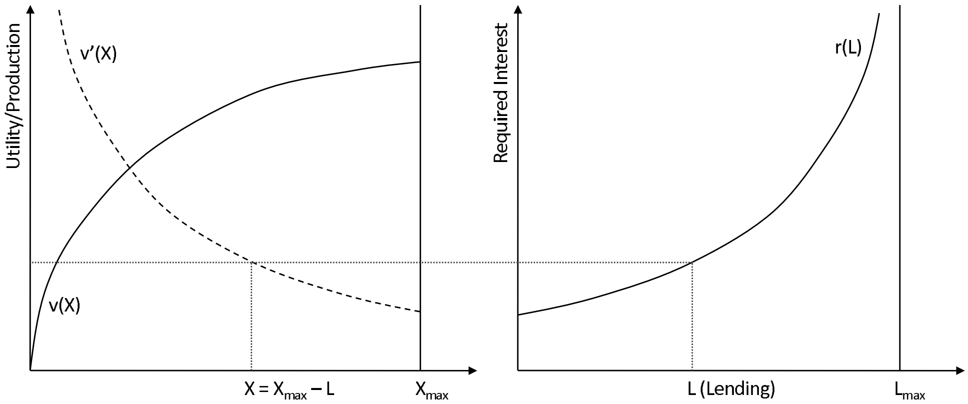


Figure 9: Creditors' utility and money supply

For creditors, with endowment X, we assume a decreasing marginal utility of wealth, which implies a concave utility function $v(X)$[185]. Therefore, creditors can be characterized as risk-averse and they will require higher interest rates r for higher amounts of lending L (figure 9). In the variable money supply setting of our supply shock model (section 4.1.4), creditors have an alternative investment opportunity with decreasing returns to scale, e.g. a project in the real economy. This does not affect the shape of the money supply curve to banks and is chosen to simplify the modeling.

As bank managers have only limited liability and do not bear the losses in case of a failure, they are assumed to be risk-neutral. To further facilitate the analysis, both banks are homogeneous by assumption, which implies that the decision problem is symmetric. In the extension to our model (section 4.1.5), we will discuss the robustness of our results for multiple and heterogenous agents.

Between the periods, the money supply equilibrium can change through two complementary effects (figure 10): a change of creditor expectations or a shock to money supply. Depending on banks' returns creditors can 'punish' banks by charging a higher interest rate. The strategic complementarity—in the form of a negative externality—arises as the performance of the second bank also has an effect on the interest rate of the first bank, and vice versa. This risk can be eliminated by opting for collective behavior, although this choice implies higher systemic risk, which is borne by the banks' creditors.

To reiterate, to facilitate the analysis, we analyze each effect separately: (1) elaborating on creditor expectation changes and the impact of a capital buffer (section 4.1.3) and, (2) money supply shocks with fixed externality (section 4.1.4). Lastly, we discuss the implications of relaxing some core assumptions, focusing on (3) money supply shocks

[185] Alternatively, a supposed liquidity or time-preference inherent in the utility would imply a similar result in terms of a concave shape of the utility function; see e.g. Farhi and Tirole (2009). However, in our simple model such an assumption is not necessary and a decreasing marginal utility of wealth is a basic economic assumption. For our comparison of different risk scenarios, it is not necessary to further specify absolute or relative risk aversion. The assumption that marginal utility is (strongly monotonous) decreasing in consumption is already sufficient.

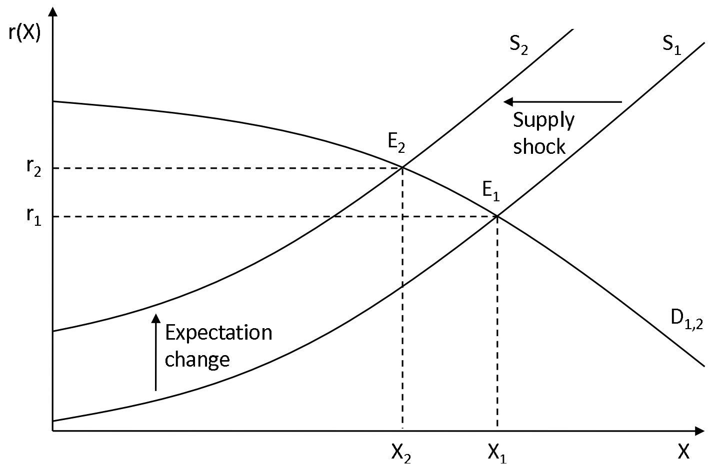


Figure 10: Model externalities and their impact on equilibrium lending

with dynamic externality and multiple, heterogenous banks (section 4.1.5). The following paragraphs comment on the relation of these individual steps of our analysis to the wider literature.

Related literature

Our model is directly related to other analyses modeling collective incentives created by lender-of-last-resort (LOLR) actions, or their anticipation, due to 'too-many-to-fail' issues. Even though it is not explicitly part of the regulatory framework, regulators or the central bank will be inclined to act as LOLR, if the potential cost of a joint failure of banks outweighs the cost of an intervention. This time-inconsistency creates critical collective incentives, which can be regarded as complementary to those developed in our model.

Acharya and Yorulmazer (2007b) study incentives in light of the allocation of the failing banks' assets, which can be acquired by surviving banks or outside investors. The strategic complementarity arises through the assumption that joint failure of banks reduces the efficiency of this allocation—outsiders are only willing to acquire the assets below their fundamental value—and increases the probability of being bailed out by authorities. As a counter incentive banks weigh possible benefits from a potential acquisition of businesses of the failed bank. In a two-bank environment, the predominant effect determines the choice of collective behavior or differentiation. Focusing on the normative aspects of interventions in a multiple bank environment, Acharya and Yorulmazer (2007a) analyze different forms of intervention mechanisms. The optimal policy, they argue, is for a liquidity provision to the surviving banks, discriminating against outsiders.

Farhi and Tirole (2009) analyze collective incentives for banks regarding the choice of leverage and maturity mismatch[186]. Strategic complementarities in banks' choices of leverage and maturity mismatch arise due to the fact that conceivable interest rate policy measures of the central bank—as LOLR—will be time-inconsistent and untargeted. Driven by institutions that are either unsophisticated or engaged in regulatory arbitrage, even sophisticated actors are enticed to build associated exposure to specific risk factors, such as asset classes, or market liquidity. This is because the common exposure increases the probability of an intervention by the central bank[187].

In the broader context of the literature on herding, specific elements and mechanisms of our models also relate to certain contributions that we will briefly describe in the following paragraphs. Like many models on herding, most prominently referring to the literature on bank runs, our model is also based on multiple equilibria in the choice of collective behavior or differentiation. The primary difference is that we have a stable equilibrium throughout the full model, which is determined ex ante. The standard assumption of a perfect Bayesian equilibrium implies that banks have all necessary information regarding the potential externality. In contrast, the instability of an equilibrium is an important feature of bank-run models, analyzing the shift to a run equilibrium, due to sunspot events, Diamond and Dybvig (1983); rational information, Gorton (1985); or liquidity needs in a crisis, Ennis and Keister (2009).

The second element of our model, the mechanism of the negative externality, can be related to analyses of (rational) contagion in financial markets. Kodres and Pritsker (2002) show how a transmission of asset movements across markets that do not share any common risk factors, can occur in a model where agents are fully rational[188]. The core ingredient of their model is the presence of variously informed groups of investors[189]. Contagion arises as informed investors respond to an idiosyncratic shock by rebalancing their portfolios across markets and corresponding risk factors, and as they respond to

[186]Their analysis confirms Diamond and Rajan (2009), who state that low interest rates set by the central bank induce a massive increase in leverage. Moreover, depending on the slope of the yield curve, as short-term debt is less expensive compared to long-term debt, there are further incentives to maximize the inherent maturity mismatch. Under a similar rationale, Rochet and Tirole (1996) analyze the role of interbank markets in allocating liquidity and as a potential source of systemic risk. They also find that incentives for banks are distorted due to a possible central bank intervention in the case of a crisis. This strongly reduces the core benefit of decentralized mutual lending—as compared to a system centralized at the central bank—and incentives for a peer monitoring among banks decrease.

[187]A very interesting finding concerns priorities of regulation in a heterogeneous bank environment, defined as a 'pecking order of regulation'. Assuming regulation to be costly, they show that it should be focused primarily on the largest institutions, as their failure has the largest economic implications and therefore increases the probability that the central bank changes its interest rate policies.

[188]As we do not assume any cost of information, our model is less related to Calvo and Mendoza (2000), who argue that the structural evolution of financial markets promotes contagion by weakening incentives for gathering costly information and, instead, participants imitate an arbitrary market portfolio. It would be a related and possibly interesting extension of our model to analyze the effects for banks' incentives if creditors could, individually, lower the information asymmetry to banks by obtaining costly information.

[189]Kannan and Köhler-Geib (2009) vary the share of informed investors, which Kodres and Pritsker (2002) assume to be fixed. This allows a differentiation between anticipated and surprise crises, when the latter affects expectations in terms of uncertainty, as investors have less confidence in the precision of their gathered information. Overall, the risk of a crisis, even without any fundamental contagion, is exacerbated.

actions of uninformed traders, due to price effects of their actions. As we will show, the negative externality of our model arises through the performance of the second bank, thus without influence of the first bank[190]. This can also be regarded as a sort of contagion; yet, it occurs as both banks are exposed to a systematic risk factor.

Third, the mechanism of collective moral hazard has to be differentiated from analyses of moral hazard at the individual level. In this regard, Scharfstein and Stein (1990) present a model, which is similar to Graham (1999)'s model of herding among investment newsletters. Agents behave collectively due to reputational concerns, since a bad performance of an individual agent, in comparison to other agents, cannot be exposed. Uncertainty about the agent's own ability gives rise to an incentive to 'hide' in the crowd. Zwiebel (1995) offers a more discerning model, in which good managers will outperform their peers by choosing innovative strategies, and only average managers engage in herding. In a different context, Rajan (1994) models incentives for banks to jointly adjust their credit policy based on economic conditions. There are incentives to write-down loans together with other banks in a bad economic environment. Overall, these analyses model collective behavior as agents fear to perform worse than their peers. This differs with the incentives of our model, which will affect even strongly performing banks. The fear is not that the bank itself performs badly, but that there are adverse effects due to the bad performance of the other bank.

In our extended model (section 4.1.5) we relax several assumptions, following the spirit of specific literature on collective behavior. First, we drop the assumption of perfect ex ante information and consider the case in which agents only receive an imperfect signal regarding the externality. This extension relates to analyses of herding due to informational cascades, as it has been analyzed originally by Bikhchandani et al. (1992), Banerjee (1992), and Welch (1992). Agents ignore their private information, since it is outweighed by the observed actions of prior agents. Such an informational cascade stops the aggregation of private signals and can imply a negative externality, if aggregated public information is not efficient[191].

Second, we assume a dynamic (endogenous) externality, which is inspired by analyses exploring potential effects of collective behavior on asset prices. These analyses assume that herding behavior leads to endogenous payoff effects, which regulate or enforce herding dynamics. Avery and Zemsky (1998) show that price effects will regulate herding behavior as far as traders are certain about specific aspects concerning the market environment,

[190] In the creditor expectation change model, the bad performance of the second bank has adverse effects on the expectations of the first bank's performance. In the money supply shock model the failure of one bank impacts the funding equilibrium by reducing the money supply.

[191] For a model in which the timing of information signals differs among agents, Hirshleifer et al. (1994) summarize the following implications of herding on informational cascades: Idiosyncrasy (poor aggregation of information); fragility (sensitivity to small informational shocks); simultaneity (delays followed by sudden action); paradoxicality (greater information does not necessarily increase welfare); and lastly path dependence (outcomes depend on the order of moves and information).

e.g. the occurrence of shocks. Once uncertainty becomes multi-dimensional, it becomes difficult to distinguish between erratic market movements due to herding, or adjustments in consequence of shocks. The result can be a significant short-term mispricing in terms of a bubble. In contrast, Morris and Shin (1999) illustrate a likely endogenous amplification of risk through correlated responses of agents. The risk of a joint reaction of multiple agents due to an information shock exacerbates its systemic dimension.

Our endogenous externality is rather in terms of Morris and Shin, as it leads to a self-enforcing dynamic: as more agents opt for collective behavior, the probability of the externality being negative increases and further agents will be inclined to choose collective behavior, as well. Taking the two assumptions together, we show that agents account for payoff implications of all possible cascades and, overall, collective behavior must be regarded as a dominant strategy in such a setting: that is, the risk of a negative externality strongly increases if the bank differentiates, but most other banks are part of a collective behavior cascade. In contrast, the option of collective behavior almost eliminates this risk.

4.1.3 Creditor expectation changes and the impact of a capital buffer

Acharya and Yorulmazer (2008) analyze creditor expectation changes as possible incentives for collective behavior in a two-bank model. They show that, if one bank performs worse than the other, there will be an information spillover that adversely affects the better performing bank in terms of interest rates. The origin of this spillover is an information asymmetry between creditors and banks: creditors can only observe banks' returns and infer from their observation regarding a systematic risk factor; however banks' risk is driven additionally by an idiosyncratic risk factor. Collective behavior offers banks with an option to eliminate this spillover, by maximizing the correlation of their exposure. At the same time, though, they will induce systemic risk.

Extending Acharya and Yorulmazer (2008), we foresee a capital buffer, reflecting an important regulatory provision existing in financial markets[192]. Banks are assumed to retain their first period profit to build a capital buffer as a cushion against losses in the second period. This extension follows the rationale of microprudential regulation and

[192] A further technical difference to the original model is the extent of the information asymmetry between banks and creditors. Acharya and Yorulmazer (2008) assume that creditors—upon collective behavior—will only receive one information signal from banks' returns. However, at the same time, they argue that creditors cannot observe the behavior of banks. Therefore, we change this assumption: Creditors, independent from the behavior of banks, always receive two information signals from the observed bank returns. This new assumption, which we consider more adequate, does not change the model results. However, it allows us to derive the effects for risk-neutral creditors, which is a broader assumption. We illustrate the technical differences in appendix A.3.

increases institutional stability. At the same time, this simple mechanism helps to decrease the information asymmetry between creditors and banks. As creditors observe the capital buffers, they receive an idiosyncratic information signal for each bank, in addition to the observed returns.

Our hypothesis that the capital buffer will reduce incentives for collective behavior is confirmed by our results, showing that this creates a counter incentive to collective behavior and can effectively eliminate collective moral hazard under certain assumptions. Analyzing the hypothesis that the capital buffer reduces banks' incentives for collective behavior, we show that, for a robust set of assumptions, it even leads to a reversal and fosters differentiation instead. Yet, banks would never opt for a capital buffer voluntarily. It has to be enforced by regulation. The fact that incentives are dependent on priors regarding the state of the economy, as well as banks' performance, presents a further challenge as regulation needs to account for these dynamics; see Hellwig (2008). Whereas in this section we describe only the intuition of the model's mechanisms and the resulting dynamics, a comprehensive presentation is included in appendix A.3.

As stated in the previous section, we analyze the interaction of risk-averse creditors (principal) and banks, which are led by risk-neutral managers (agents). After the first period, banks publish their results and, based on that, creditors adjust their expectations for the second period by Bayesian updating, since they can calculate posterior probabilities for the available strategies (iid) by taking into consideration the observed first period results, in addition to their priors. To facilitate our analysis, we allow for only a discrete distribution of returns (high, medium low, very low)[193]. In order to keep money supply constant over both periods, we rule out a bank's failure for the first period but do permit a failure in the second period[194].

The two available investment strategies for banks are assumed to be dependent on a systematic macro factor, the overall state of the economy, and an idiosyncratic component, e.g. the development of a specific sector or the competence of the banks' management in a specific business. As both strategies are iid, these factors are identical for both strategies. Whereas the macro factor (good/bad) can assume any probability between zero and one, the idiosyncratic component is conditional on the macro factor: if it is good (bad), the probability of a high (low) investment return will be greater than 0.5[195]. We refer to the

[193] Allowing for continuous returns would not change the results of our analysis. In order to specify the Bayesian updating process between the two periods, we would have to assume specific scenarios being analogous to the initial assumption of continuous returns.

[194] This is easily achieved by assuming the minimal return of the investment strategies to be equal to the necessary repayment to its creditors. Because banks cannot fail, and, hence, creditors are certain that there will be no loss in the first period, the interest rate in the first period is equal to zero. Although this is a strong assumption, it does not change the results of our model, as it only supposes a linear transformation (setting the basic interest rate to zero).

[195] If the macro factor is bad, the probability of a high investment return will be 1 minus the probability of a low investment return and, hence, smaller than 0.5.

total probability of a high return as α_0. The low return is differentiated as a medium low (L_M) with probability b, or very low return (L_L) with probability $(1 - b)$

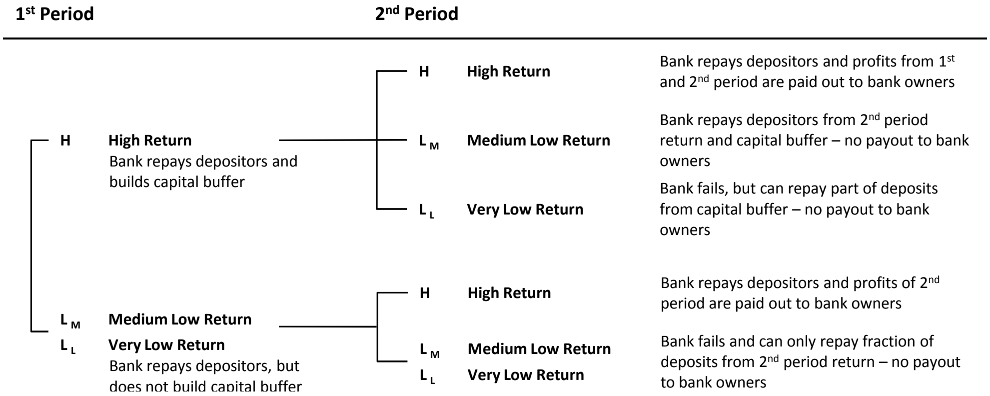


Figure 11: Overview on possible outcomes of (individual) bank returns and consequences

It is assumed that banks can build a capital buffer after the first period only if they realize a high return (figure 11). Otherwise, for both low returns, they do not build a capital buffer, but survive due to our prior assumption[196]. If banks build a capital buffer after the first period, they will be able to survive a medium low return in the second and will fail only due to a very low return. Otherwise, if a bank did not build a capital buffer after the first period, it is assumed to fail for both the medium and very low returns. The capital buffer implies a risk transfer from creditors to bank managers: the bank managers' payoff of the first period return becomes conditional on a high second period return, while creditors face a lower risk of the bank defaulting on their credit only if it has built a capital buffer.

Another aspect that influences the returns realized by banks comes from the assumption that both investment strategies have decreasing returns to scale, due to an increasing cost of identifying, originating and monitoring additional loans of a portfolio. Whereas the activity level of the two banks is constant by definition, this assumption implies that the cost—denoted by $c(\rho_{i,t})$—will be greater if banks collectively pursue the same investment strategy. Thus, it serves as a natural counter incentive to collective behavior. Banks, then, will always pursue different strategies in the second period[197].

After the first period, bank managers realize a profit only after a high return, with probability α_0. If the investment return is low, the entire proceeds will be distributed to the creditors of the bank. The profit, upon a high return, consists of the return minus

[196] To ensure survival, the very low return is set equal to the medium low return in the first period and the overall level is sufficient to repay creditors.

[197] The model is supposed to end after second period returns have been realized and distributed. The only relevant variables affecting banks' returns in the second period are (1) interest rates, but they have been set already after the first period, and (2) the cost component, which reduces returns only upon collective behavior. Therefore banks will never opt for correlated strategies in the second period.

the cost component $c(\rho_{i,t})$, as well as the required repayment to creditors[198]. Due to the capital buffer this profit is retained, and is contingent on realizing a high return in the second period, with probability α_1. If the bank realizes a low return in the second period, the retained profit is paid to the bank's creditors.

As the creditors observe both banks' results after the first period, they will rationally update their priors regarding the macro factor after this information signal[199]. From that they calculate the posterior probability of a high return in the second period. Depending on the choice of banks to collectively pursue the same strategies (s) or, instead, pursue different strategies (d), there can be a maximum of three scenarios at the end of the first period, because of the definition that the very low and medium low returns are only differentiated in the second period.

1. *Both banks realize a high return* (HH): this scenario occurs when both collective behavior or banks pursue different strategies. Both banks retain their profits and build a capital buffer as a cushion against future losses. Creditors update their priors regarding the macro factor and take into account that both banks will survive a medium low return in the second period. Depending on the behavior of banks, the interest rate required in the second period, is given as r_s^{HH} or r_d^{HH}.
2. *Both banks realize a low return* (LL): this scenario occurs when both collective behavior or banks pursue different strategies. By definition, the very low return is equal to the medium low return in the first period and the return suffices to repay the banks' creditors. However, banks do not build a capital buffer, which, besides the overall return, is taken into account by creditors when calculating the required interest rates for the second period, given as r_s^{LL} or r_d^{LL}.
3. *One bank realizes a high return and the other a low return* (HL/LH): this scenario can occur only if banks pursue different strategies. Because banks are homogeneous, this scenario is symmetrical and does not require a differentiation between HL and LH. Creditors first update their priors on the macro factor and then, for each bank individually, calculate the required interest rate for the second period. This rate is lower for the bank with the high return as it was able to build a capital buffer and will, therefore, survive a medium low return in the second period. Thus interest rates are given as $r_d^{\mathrm{HL,H}} < r_d^{\mathrm{HL,L}}$.

[198] This repayment is a sum of the initial funds that were raised plus an interest surcharge, which is zero in the first period due the fact that banks cannot fail.

[199] At this stage, we differ from Acharya and Yorulmazer (2008), who assume that creditors, observing returns in the case of collective behavior, do not receive an additional information signal from the second bank's return. Yet, if we suppose that creditors cannot monitor the decision of banks to behave collectively or not, they should not be able to distinguish this in the realization of returns. Altering this assumption does not change the results, and the implications are explained in detail in appendix A.3.

An important result from these scenarios, which depends on further assumptions, is a ranking of the individual interest rates[200], influenced by three effects:

- *Investment cost*: given collective behavior this cost will increase and reduce the return of banks. As creditors observe the lower return, they will assign a (slightly) lower probability of a high return in the second period, which leads to a higher interest rate when compared to the same scenario with different strategies.
- *Information contagion*: this occurs only in the third scenario as the low return of the other bank adversely affects the interest rate of the bank with the high return. Creditors update their priors regarding the state of the economy based on the observation of both returns. The bad performance of one bank will adversely affect these priors. The bank with the high return is punished, while the bank with the low return profits.
- *Capital buffer*: this decreases the interest rate for any individual bank that realizes a high return in the first period. While in the first scenario the interest rate decreases equally for both banks, in the third scenario, the bank with the high return will have to pay a much lower interest rate, compared to the bank with the low return, because it was able to build a capital buffer.

Bank managers already take into account this interest rate ranking when taking their investment decision in the first period. They calculate the probability of each scenario and link it to the corresponding interest rate for the second period. From this calculation they derive the expected interest rate for the second period, depending on whether they follow similar or different strategies. Leaving aside the capital buffer for a moment, the intuition develops as follows.

If banks pursue different strategies and one bank realizes a high return, while the other bank realizes a low one, Bayesian updating leads to a lower probability of a high return in the second period than if creditors would have observed only one high return. This information contagion implies an adverse effect on interest rates from the perspective of the bank with the high return, as it increases the interest rate for the subsequent period. The choice of collective behavior in the first period rules out the effect of the information contagion on interest rates. Thus, as bank managers coordinate and rule out this scenario through collective behavior, they have a means to actively influence the expected interest rate. At the same time though, collective behavior will increase their cost of investing.

Knowing these options, bank managers can calculate their expected total profits, as the sum of the expected profits from the first and the second period (figure 12), denoted as $E(\pi_i, 1) + E(\pi_i, 2)$. The choice to behave collectively or not influences this

[200] For detailed explanations see appendix A.3.

		2nd strategic choice	
		Collective behavior	Pursue different strategies
1st strategic choice	Establish Capital Buffer	$\max_i \quad E(\pi_i, 1)$ ①▼ ②▼ $+ E(\pi_i, 2)$ ③▲ ① Higher investment cost due to high correlation reduces expected profits ② Payout of profits contingent on high second-period return ③ Capital buffer decreases interest rates in case of high return	$\max_i \quad E(\pi_i, 1)$ ①▼ $+ E(\pi_i, 2)$ ②▼ ③▲ ① Payout of profits contingent on high second-period return ② Poor performance of other bank can induce information contagion ③ Capital buffer decreases interest rates in case of high return
	Payout profits from 1st period	$\max_i \quad E(\pi_i, 1)$ ①▼ $+ E(\pi_i, 2)$ ① Higher investment cost due to high correlation reduces expected profits	$\max_i \quad E(\pi_i, 1) + E(\pi_i, 2)$ ①▼ ① Poor performance of other bank can induce information contagion

Figure 12: Strategic choices of bank managers and impact on expected payoffs

calculation through the effects shown in figure 12. In general, if a positive probability of the third scenario increases the expected interest rate—as compared to the higher cost of investment—banks will opt for collective behavior, as this maximizes the total expected profit. Yet, as the capital buffer effect leads to a differentiation in the third scenario it, at least partially, offsets the effect from the information contagion. Thus, if the capital buffer effect is strong enough, banks will have an incentive to pursue different strategies to maximize their total expected profits.

Two major conclusions, which amplify the findings of Acharya and Yorulmazer (2008), can be drawn from this model of expectation changes. First, if one allows for a voluntary capital buffer (1st strategic choice in figure 12), bank managers never choose to build one. Because the payout of first-period-profits becomes contingent on a high return in the second period with the capital buffer, the overall expected payout is sharply reduced. In fact, the capital buffer implies a risk transfer from creditors to bank managers, and needs to be enforced by regulation. The positive effect of the capital buffer has to be considered against other complementary effects, which can, in turn, give rise to other risk factors[201]. Our second conclusion shows that for certain assumptions the capital buffer can effectively rule out incentives to behave collectively, from the information contagion effect (2nd strategic choice in figure 12). This confirms our hypothesis and importantly results from a lower information asymmetry between creditors and banks, which is in

[201] Hellmann et al. (2000) point out that although capital adequacy regulation reduces risk-taking incentives for banks, it has adverse complementary effects that have to be accounted for. Similarly, Farhi and Tirole (2009) argue that capital adequacy regulation has to be designed carefully to limit regulatory arbitrage, which would re-introduce certain risks.

contrast to Acharya and Yorulmazer (2008). Overall, the introduction of a capital buffer will always reduce the probability of banks behaving collectively and inducing systemic risk.

We still have to address why the intentional choice of collective behavior by banks would resemble collective moral hazard. It is straightforward that interest rates in the second period imply a transfer from banks to creditors, which compensates for risk. Next, we determine the consequences of collective behavior in terms of aggregate welfare and compare them with the first-best equilibrium that would be achieved by a central planner[202]. Remember that we ruled out the possibility of a failure in the first period. Therefore, there can be no deadweight loss to creditors. The variation of interest rates is not relevant from the aggregate perspective because it is a transfer between the groups within the overall aggregate. However, we have argued that collective behavior reduces the return on investing due to a higher cost factor. Through collective behavior, banks reduce aggregate welfare while maximizing their individual utility. This behavior can be characterized as collective moral hazard, according to our earlier definition (section 4.1.2).

The final aspect to consider is how different assumptions regarding the initial probabilities of macro and idiosyncratic factors affect incentives for collective behavior. In general, the information contagion (in the HL/LH scenario) obtains the highest values if the probability of a good economic state is low (figure 24 in appendix A.3). Our interpretation is that creditors feel confirmed in their negative outlook by the bad performance of one bank and accordingly judge a high return of the other bank as an outlier. As creditors become more certain about the presence of benign economic conditions, the information contagion generally decreases. However, the higher the probability that creditors assign a positive bank return in such a positive environment, the higher the impact of the information contagion. This observation pertains to creditors' expectations which, as they get stronger—e.g. in an economic boom or through competition—induce incentives for collective behavior[203].

Overall, our conclusions suggest a complementary explanation of herding as in Scharfstein and Stein (1990) Graham (1999), and Rajan (1994). It enhances the findings of Zwiebel (1995), who supposes that good managers will pursue differentiated strategies. In our results, if the capital buffer is not sufficient, even good managers will have an interest in all banks behaving collectively. The choice, however, is not based on individual incentives, but is taken jointly by all participating banks. Due to that collective behavior,

[202] It is assumed that the central planner puts equal weight on the welfare of both groups and that aggregate welfare is the simple sum of the welfare of both groups.

[203] Similarly, we could argue that the information contagion increases as creditors have lower confidence in banks' perspectives or management capabilities, because they weigh negative results stronger and as a confirmation of their prior expectations.

banks can together rule out the third scenario—one high and one low return (HL/LH)—at the end of the first period and prevent any information contagion. The capital buffer can be observed individually and generally reduces this incentive. Yet, it would have to be aligned dynamically if expectations changed because of a boom or competition. Otherwise, it will not be effective in mitigating the issue of systemic risk in the long run. We discuss these conclusions in conjunction with the other models in section 4.1.7, and in a wider context of systemic risk at the end of this chapter (section 4.3).

4.1.4 Money supply shocks with fixed externality

Acharya (2009) presents a model which analyzes the implications of both individual and collective incentives for systemic risk, when the failure of a bank reduces money supply and can set off an adverse effect for the prospects of the other bank. With regard to collective behavior, he finds that it critically depends on a potential negative externality, which is similar to the one that we develop below. On individual risk-taking incentives, he assumes that banks, in addition to the choice of interbank correlation, have an alternative investment opportunity through which they can adjust the riskiness of their portfolio. An important outcome shows that banks will always maximize investment risk, because they are not liable for potential losses on the investment and would profit from high returns.

The finding of individual moral hazard in banking due to limited liability has been widely developed in the literature; see seminal contributions of Jensen and Meckling (1976) and Stiglitz and Weiss (1981)[204]. As we are only interested in the collective dimension of incentives, we implement some technical adaptations to eliminate individual risk shifting from the bank managers' strategy space. The model confirms our hypothesis that the critical incentives at the collective level can be replicated in a much simpler model environment. Our results suggest that incentives for collective behavior are related to structural evolution in the banking sector, and they decrease if the prospects of consolidation in the sector are high. Our simplified model also develops the basis for our subsequent analysis of money supply shocks with dynamic externality and multiple, heterogenous agents (section 4.1.5).

Compared to the prior model of creditor expectation changes, the focus of this model is on the potential negative externalities arising from the money market equilibrium. We assume expectations to be constant throughout all model periods, while allowing the amount of bank borrowing to fluctuate because of certain effects which influence the money market equilibrium and can induce a negative externality. Due to the constancy of expectations, a capital buffer similar to the prior model, which had an important

[204] In appendix A.2, we give a brief overview on this incentive, comparing it to our initial considerations of our model.

information effect, is irrelevant in this model. As in the prior section, here we illustrate only major mechanisms and the resulting dynamics, whereas a formal presentation of the model is included in appendix A.4.

An important difference to the prior model is that the assumption for the first period, of lending being risk-free, is dropped. The possibility that banks can fail in both periods is a fundamental prerequisite for the central mechanism of the model. It is assumed that the failure of a bank causes two effects on the surviving bank in the second period:

- *Recessionary effect* (negative externality): the failure of a bank leads to a reduction in the aggregate supply of funds, due to liquidation losses or constraints to creditor mobility. The result is an increase in the market-clearing rate for deposits, which generally reduces profitability of the surviving bank.
- *Strategic benefit* (positive externality): the surviving bank can acquire a portion of the existing businesses or human capital from the failing bank. This increases profitability by reducing its investment cost.

The basic construct follows our initial considerations. Two banks, represented by their managers (agents), raise funds from a continuum of creditors (principals) in each of two periods. They subsequently invest in one of two strategies (iid) with a one-period maturity. For banks, again being homogeneous and run by risk-neutral managers, both investment strategies are defined as in the prior model; and the assumption of an investment cost, which increases upon collective behavior, is applied analogously[205]. Banks will never opt for collective behavior in the second period for reasons similar to the prior model.

A technical difference with the prior model is the fact that risk-averse creditors have an investment alternative to lending to banks, an investment which is risk-free and with decreasing returns-to-scale. For example, such an alternative could resemble a production opportunity in the real economy. Creditor expectations are assumed to be constant for both model periods. Then the optimal amount of lending is derived as an equilibrium: the money supply curve is determined by the creditors' overall endowment, their assessment of bank risk and the anticipated returns from the risk-free production alternative; the money demand curve, from the perspective of banks, can be derived by accounting for the cost of investing as well as the expected returns from both investment strategies. Additional assumptions ensure that supply and demand intersect and banks become active in the first period.

[205] As banks can now decide upon the level of their activity, the definition of the investment cost is anyhow more complex. It is now assumed that investment cost will be marginally increasing with the total activity in the accordant strategy. If both banks collectively pursue the same strategy, the cost will be disproportionally higher as the overall activity level increases.

At the end of the first period, the returns of the investment strategies are realized and banks repay the funds that were raised from creditors, as well as additional interest. If a bank's return is insufficient it fails and is subsequently liquidated, and creditors receive the liquidation value of the bank's assets. This liquidation value amounts to the investment return minus a deadweight loss, which marginally increases with the amount of assets to be liquidated. Hence, it will be disproportionally higher if both banks jointly fail. Similar to the prior model, we again have a maximum of three scenarios at the end of the first period:

1. *Both banks survive* (SS): this scenario occurs when collective behavior or banks pursue different strategies. If both banks survive all assumptions regarding cost and returns remain constant. The money supply does not change and the equilibrium of bank lending remains constant.
2. *Both banks fail* (FF): this scenario occurs when collective behavior or banks pursue different strategies. Creditors receive the liquidation value of the banks' assets, which is reduced due to the additional deadweight loss. As both banks are liquidated there will be no financial intermediation activity in the second period and creditors invest their total endowment in the risk-free production alternative.
3. *One bank survives and the other fails* (SF/FS): this scenario can only occur if banks pursue different strategies. Because banks are homogeneous, the scenario is symmetrical and does not require further differentiation between SF and FS. Whereas the failing bank is liquidated, the surviving bank continues its operations in the second period. However, the equilibrium of bank lending is affected by the two aforementioned effects: the recessionary effect and the strategic benefit. The total effect on the equilibrium, which is discussed in the subsequent paragraphs, determines potential incentives for banks to behave collectively or not.

Whereas the second period is analogous to the first period if both banks survive, and there is no intermediation activity if both banks fail, the interesting case is the third scenario, in which only one bank survives. Once we specify the two effects on the equilibrium of bank lending, it becomes clear that the recessionary effect reduces the aggregate supply of funds. It is assumed that not all creditors of the failing bank can migrate to the surviving bank due to some restrictions. From the perspective of the surviving bank one might assume that there will be constraints on the efficiency of extending its activities. Because of this reduction in aggregate money supply (the supply curve shifts to the left), the equilibrium interest rate—ceteris paribus—will be higher in the second period. This is even without the effect of creditor expectation changes (section 4.1.3), which applies complementarily.

With regard to the second effect, the strategic benefit assumes that the surviving bank can take over specific portions of the failing bank's existing business. This decreases the overall cost of investment, which is now determined only by the surviving bank's level of activity (the demand curve shifts up). These two effects have implications for the expected profit of the surviving bank. Depending on which effect exceeds the other, the overall impact of the other bank's failure will either be in the form of a negative externality—the recessionary effects exceed the strategic benefit—or otherwise, a positive externality.

When taking their investment decision in the first period, bank managers already think about maximizing their total expected profit from both periods. The interesting choice to be determined is whether banks decide jointly to collectively pursue the same strategies, or different ones. By behaving collectively in the first period, bank managers can rule out the probability of the third scenario, in which the other bank might fail. Instead, they would only jointly survive or fail, whereas, in the latter case, there is no payoff for bank owners.

	Expected 1st period return		**Expected 2nd period return**	
$\max\limits_{i}$	$v_{i,1}$ $i = s$: ▼	+	$P(R_{A,1} > r_1) \cdot v_2^{\mathrm{SS}}$	$+ \; P_i(\mathrm{FS}) \cdot (v_2^{\mathrm{FS}} - v_2^{\mathrm{SS}})$ $i = d$: ▲▼
	Increased cost of investment reduces payoff expectations for collective behavior.		Term independent of collective behavior.	The potential externality can have a positive or negative impact for different strategies.

Figure 13: Maximization problem of bank managers with a supply shock externality

The maximization problem of the bank managers (figure 13) boils down to the following considerations. If banks collectively pursue the same strategy in the first period, their investment return ($v_{i,1}$) is reduced due to the higher investment cost. This is similar to the prior model. Yet, the consideration regarding the second period is different. Since banks can fail in both periods now, one part of the expected second period return is defined as the expected profit upon a joint survival (v_2^{SS}) multiplied by the probability that the bank itself will survive, denoted as $P(R_{A,1} > r_1)$[206]. Added to this is the total externality resulting from the third scenario ($v_2^{\mathrm{FS}} - v_2^{\mathrm{SS}}$)[207] times the probability that one bank will fail, denoted as $P_i(\mathrm{FS})$. If the total externality is negative, the expected profit is reduced and bank managers will eliminate this probability by collectively pursuing the same strategy. Otherwise, if the failure of the other bank would lead to an increase of expected profits, the managers will maximize this probability by opting for differentiation.

[206] Naturally, one would add the expected payoffs for the joint (SS) and individual survival (SF/FS) scenarios, multiplied with their corresponding probability. To clarify the impact of the externality, this equation has been transformed so that the second part of the expected second period return illustrates the value of the externality.

[207] This externality is defined as the comparison of the continuation value of the bank in the third scenario to its continuation value in joint survival.

To prove that, in the event of a negative externality, banks' behavior resembles a collective moral hazard, we consider the aggregate welfare that would be achieved upon the decisions taken by a central planner. Since for direct proof the necessary assumptions regarding the individual cost and production functions would not allow for generality, we present an indirect proof focusing on the potential deadweight costs. These deadweight costs were defined as marginally increasing for the amount of assets to be liquidated.

The choice to collectively pursue the same strategy increases the probability for a joint failure of the banks, for which the deadweight loss is disproportionally higher than if only one bank fails. However, as this poses only a systemic risk, the situation can be described as constrained efficient[208]. The increased investment cost implies a decrease in aggregate welfare. Thus, collective behavior implies adverse effects on aggregate welfare. As in section 4.1.3, interest rates drop out of consideration as they are a transfer among the groups within the aggregate. As bank managers consider solely their individual expected profit, they do not internalize the potential cost of collective behavior in terms of systemic risk. Again, their behavior can be characterized as collective moral hazard.

The overall externality of this model, through the supply channel, is complementary to the expectation channel externality, which was illustrated in the prior model. Comparing the two, the supply channel is less affected by market dynamics, but influenced rather by the structural evolution of the industry. As an example, if banks foresee great potential for consolidation, they will opt for differentiation in order to profit from a potential failure of another bank. Otherwise, if banks expect that a failure will adversely affect dynamics in a specific market segment, e.g. that creditors will shift their investments towards other segments, they will even accept the higher cost of investment in order to minimize their exposure to the failure of the other bank, opting for collective behavior to suppress the negative externality. It has to be noted that the overall effect of industry structures and competition on the risk-taking of banks is disputed in the broader literature. Boyd and De Nicoló (2005) argue that the results are artifacts of the model; see also the discussion of Carletti and Hartmann (2002).

Our results on collective incentives replicate those of Acharya (2009), but in a simplified model structure. We further discuss these conclusions in conjunction with the other models in section 4.1.7, and in a wider context of systemic risk at the end of this chapter (section 4.3). Acharya (2009) extends his analysis to include the impact of capital buffers being targeted at individual banks. Although this is similar to the capital buffer in our prior model, it does not reveal anything further to reduce the information asymmetry between creditors and banks. Instead, it only achieves a reduction of banks' risk of failure, which is stable for both periods. His conclusion is that, although such a myopic buffer can

[208] Aggregate welfare can still reach the optimal value if there is no joint failure.

reduce individual incentives for risk-taking, it fails to address the collective dimension of incentives. Considering negative externalities arising through the money supply channel, only a capital buffer accounting for interbank correlation can be effective in reducing systemic risk, while, by focusing on creditor expectations (as in the prior model), already a myopic design of capital buffers can be effective[209].

4.1.5 Money supply shocks with dynamic externality and multiple, heterogenous banks

The prior models were based upon standard game assumptions, such as perfect ex ante information regarding the expected investment payoffs; similarly, externalities were crucial for the agents' incentives to behave collectively or not. Furthermore, the assumption of two homogeneous banks is common to simplify the modeling. It implies that the potential externality is discrete and can take only a specific value, both of which are known ex ante. In this step, we are interested in the effects of an endogenous externality, and in a more general scenario with multiple and heterogenous banks.

We analyze the hypothesis that, for multiple and possibly heterogenous banks, an endogenous externality will affect the incentives for collective behavior developed by the prior model. Our results show that, without prior knowledge regarding the externality, and taking sequential decisions, the choice of collective behavior resembles a dominant strategy for all banks. This shares similarities with the information cascade models of Bikhchandani et al. (1992). For heterogeneous banks, there will be a dynamic similar to their concept of 'fashion leaders'.

Building on the prior model, we consider a potentially negative externality that derives from a potential money supply shock. We relax the previous assumption and discuss the implications on our results in a sequence of three steps: (1) multiple banks do not receive perfect ex ante information regarding the (exogenous) externality; (2) the externality is determined endogenously, as multiple banks decide whether to behave collectively or differentiate; and (3) banks can be heterogenous.

Multiple banks without perfect ex ante information on the externality

We assume there is no perfect prior information regarding the externality, which is assumed to be exogenous. Instead, agents receive a private information signal, which reveals

[209]These contrasting results add to the discussion regarding incentive effects of regulation. Analyses related to ours also point towards other sources of negative externalities, which directly derive from regulatory provisions, or the anticipation of public sector interventions; see Acharya and Yorulmazer (2007a,b). Similarly, Farhi and Tirole (2009) show that the central bank's interest rate policy can also result in strategic complementarities that foster an increase of leverage and the maturity mismatch in the financial sector.

only the true externality with a certain probability. Decisions are taken sequentially, instead of simultaneously, and all prior actions can be observed. In a setting with more than two agents this adaptation introduces potential information cascades, as they have been originally analyzed by Bikhchandani et al. (1992), Banerjee (1992), and Welch (1992).

Each agent receives a private information signal ex ante, whether the externality is positive or negative. This signal hints at the true realization of the externality with a probability $p > 0.5$[210]. Deciding in sequence, the first agent only observes and consequently follows his private information signal. The second agent knows his own information signal but can observe the action taken by the first agent. Comparing these two signals, he will take the same action as the first agent, if his signal confirms the first agent's action, or randomize his action if the two pieces of information contradict each other.

The third agent in the sequence will observe the two signals from the prior agents in addition to his private one. All signals being equally weighted, if the two actions to be observed are similar, they will outweigh the agent's private information and he will mimic the action of the prior agents, ignoring his private information. But if the two prior actions are different, the third agent will decide solely based on his private information. Bikhchandani et al. (1992) show that once two agents have chosen one option over the other, the information conveyed from prior actions is always stronger than the private signal, and will start an information cascade in which all subsequent agents behave similarly.

As soon as such an information cascade has begun, aggregation of private signals stops and all agents follow the prior actions while not revealing their private information. Under these conditions, information aggregation is not always efficient and there would be a certain risk of wrong judgment on the externality. Although Bikhchandani et al. (1992) propose some slight adaptations—such as differences in the precision of the information signal or flexible sequences of decision-making—this will always, sooner or later, result in an information cascade, stopping the aggregation of private information. As a result, a residual risk of a 'wrong' cascade, e.g. banks behaving collectively although there would be a positive externality, will always remain[211].

[210] Furthermore, it has to be assumed that all signals are conditionally independent and the actions taken upon that signal reveal its true content.

[211] A similar issue, though in a slightly different context of financial markets, is illustrated by Hassan and Mertens (2011), who explore the impact of market sentiment on investor's decisions. They argue that some investors will follow market sentiment instead of deciding from their private information. By doing so, less private information is revealed, which in turn results in higher uncertainty regarding future states of financial markets. Consequently, it becomes beneficial for other investors to ignore their private information, and save the cost of obtaining it, and also follow market sentiment, which can be easily observed. This collective dynamic reduces the efficiency of information aggregation and can be described as a 'tragedy of the commons' problem.

Endogenous externality with multiple banks

Next, we relax the assumption of a constant externality in the supply shock model. For an environment of multiple banks, it seems reasonable to assume that the externality will vary according to the number of banks opting for collective behavior, or differentiation respectively. This extension is in the spirit of Avery and Zemsky (1998) and Morris and Shin (1999), who elaborate on the endogenous effects of dynamic payoff functions on herding behavior. Before, as a perfect Bayesian equilibrium, we assumed that the overall payoff function was unaffected by the behavior of the agent himself as well as all others. Such an absence of strategic elements allows us to consider a simple decision tree of banks with their related probabilities.

In a multiple agent environment, we now aim to endogenize the values of the strategic benefit, as well as the recessionary effect, according to the number of banks opting for collective behavior and the potential for failing jointly. We already assumed in our prior analysis that there were limits to the migration of creditors to the surviving bank and, similarly, to a bank's capabilities to take over existing business and human capital from the failing bank. We argued that there would be higher deadweight cost to the banks' liquidation value if the amount of assets to be liquidated would increase. Considering the development of the two effects for an increasing number of banks opting for collective behavior, the intuition is as follows (figure 14).

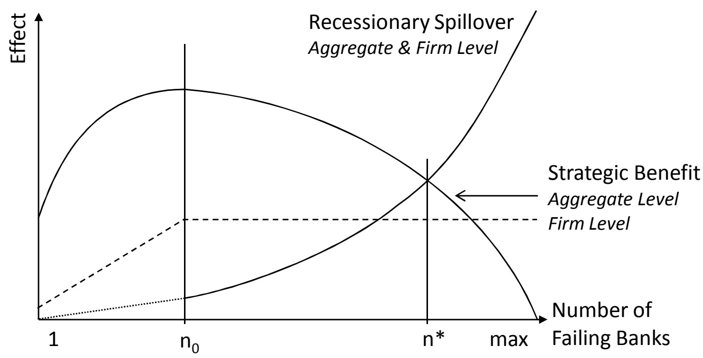


Figure 14: Dynamics of the externality for an increasing number of failing banks

If, in a multiple bank environment, only one bank fails, we can assume that the vast majority of its creditors will be able to migrate to one of the other surviving banks. It seems feasible that almost all parts of the failing bank can be sold to the surviving ones. As one might suppose a competition among the surviving banks to take over specific parts of existing businesses, the liquidation prices to be paid will be at fair value and the recessionary effect and deadweight loss can be almost eliminated; see Acharya and Yorulmazer (2007a)[212]. On the other hand, the strategic benefit at the firm level will be

[212] Certainly, there will be also information contagion in consequence of the failure so there will always be an adverse

relatively low, but considerable at the aggregate level. The total externality will take a low but positive value[213].

As the number of failing banks increases, possibly due to collective behavior, the strategic benefit at the firm level will continue to increase, similar to the aggregate level. However, for a critical threshold of failing banks (n_0) the surviving banks reach their capacity for integrating existing businesses from the failing banks. This implies that the strategic benefit at the firm level reaches saturation and is constant from this threshold onwards. As the number of surviving firms further decreases, the aggregate strategic benefit starts to decline. The same threshold is also critical for the recessionary effect, which will continue to increase as more and more assets of failing banks can only be liquidated at an increasing deadweight loss. The total externality, which was positive initially, will decrease with the number of failing banks and, for a second critical threshold ($n^\star$), be negative[214].

This endogenous definition of the externality depending on the number of failing banks has implications for a bank's decision whether to behave collectively or not[215]. Overall, the dynamic of the externality differs from Avery and Zemsky (1998), who show that, for simple uncertainty, price adjustments will limit incentives for collective behavior. Instead, it is more comparable to Morris and Shin (1999): feedback effects lead to an endogenous amplification and, hence, the dynamic becomes self-enforcing, as we will argue below.

Banks consider the risk of an evolving information cascade, as was illustrated before. The payoff of a bank therefore consists of the expected payoff if the bank rightfully anticipated a later cascade, plus the expected payoff if the bank ends up on the wrong side, e.g. it opts for collective behavior while almost all other banks choose different strategies.

If the bank opts for collective behavior, it will jointly survive or jointly fail with all other banks that behave collectively as well. The potential externality from the failure of banks that choose different strategies is positive with a relatively high probability, even if there was an information cascade fostering differentiation. This is because of the assumption that banks will not jointly fail in a differentiation cascade, since there still is differentiation among the participating banks. This is also why, should the bank opts

residual effect on the surviving banks.

[213] One could argue that in a banking system with many banks, a certain extent of consolidation will lead to higher efficiency and, hence, contribute to a higher aggregate welfare.

[214] For a formal presentation see appendix A.5.

[215] As we now assume the number of banks to be more than two, the strategy space has to be slightly adapted. The strategic options do not differentiate two investment options anymore. Instead, there are two strategies: collective behavior and differentiation. It is assumed that collective behavior resembles an investment in a specific sector, which is known to all banks. Differentiation implies investing in an arbitrary sector being only marginally correlated to the investments made by the other banks choosing differentiation, as well as those banks that opt for collective behavior.

for differentiation, it will be exposed to a relatively small number of failing banks if it rightfully anticipated the resulting information cascade.

However, if the cascade led to collective behavior instead, the differentiating bank would certainly be exposed to a negative externality if those banks opting for collective behavior jointly fail. Comparing the total expected payoffs from both options—collective behavior and differentiation—the bank will choose collective behavior over all potential information cascades in order to maximize its expected payoff. The risks of opting for differentiation, and subsequently being exposed to a joint failure as a result of a collective behavior cascade, outweigh any potential benefits of differentiation. Therefore, collective behavior can be considered the overall dominant strategy in such an extended supply shock model; see appendix A.5 for a formal deduction.

Heterogenous banks

Finally, we discuss the implications of relaxing our core assumption of banks being homogeneous. Although such an assumption simplifies the analytical procedure, it leaves aside the important aspect that banks are in fact heterogeneous; see Boyd et al. (2006). To highlight potential implications, we consider the following example of two heterogeneous banks: a large international bank and a regional mid-size bank[216].

The first intuition is that there will be an impact on potential externalities and the model can no longer be symmetrical. Clearly, if the large international bank fails, there will be a strong recessionary effect on the economy and the total externality certainly will be negative. The regional mid-size bank will be able to absorb only a relatively small portion of business and human capital from the large international bank[217]. In contrast, the implications of a failure of the regional mid-size bank while the large international institution remains in business can be considered to be less grave. The large international bank would likely be able to absorb most of the business of the failed bank and, notably, the regional mid-size bank has significantly fewer creditors than the large international bank. Thus, the recessionary spillover can be considered insignificant from the perspective of the large international bank. The same will probably be true for the strategic benefit, but overall one might assume a small positive, or no externality, respectively.

This finding has an important impact on the strategic complementarity of decision-making in both banks. The large international bank will almost certainly leave the decision of the regional mid-size bank unaccounted for, while the smaller bank, at its end, will strive for collective behavior in order to avoid an externality upon the failure of the larger bank.

[216] This resembles an arbitrary structure that was chosen only to highlight the case of heterogeneous agents.

[217] See e.g. Farhi and Tirole (2009). Adverse information effects in financial markets and further contagion mechanisms, which are not accounted for in our model, would even aggravate the impact of such a failure.

If, enlarging on the previous considerations, we allow for sequential decisions, the regional mid-size bank would try to let the large international bank decide first, and then align its strategy accordingly. For the large international bank the choice of the mid-size bank has a negligible impact on its decision-making process. It will not be problematic for the large international bank to decide first[218].

This phenomenon relates to Bikhchandani et al. (1992) and their theory of 'fashion leaders'. Agents with high precision signals will act upon their private information even if there is a cascade already ongoing. If these agents are allowed to choose the timing of their decisions, they will announce their strategies early. Once these are known, other agents will follow and ostensibly start a corresponding cascade based on the information revealed by these early movers[219]. The overall conjecture is that the larger bank's choice provides an important signal for smaller banks in a multiple bank environment. Though the decision initiating the cascade would doubtlessly be determined by very precise information regarding the individual strategy risk, the critical implications at the system level remain. Such a view might pose a rationale for regulation to focus on larger institutions, as it has been suggested by Farhi and Tirole (2009) in their 'pecking order' of regulation.

Considering the whole sequence of our extensions, we have shown that dropping the assumption of perfect ex ante knowledge regarding the externality, as well as a perfect Bayesian equilibrium with a constant payoff function, affects the incentives for collective behavior. This confirms our hypothesis. In fact, our extension even creates stronger incentives for collective behavior among banks; we have argued that collective behavior resembles a dominant strategy. The probability of a negative externality increases strongly in a collective behavior cascade. Hence, if a bank opts for differentiation but there is a collective behavior cascade, the risk of being exposed to a negative externality will be significantly higher, as compared to the option of collective behavior. Overall, the risks of a potential externality in consequence of joint failure of many banks outweigh the potential benefits from differentiation. For an environment with heterogenous banks, with reference to Bikhchandani et al. (1992), it can be supposed that larger banks will send relatively strong signals, which smaller banks will follow. The collective behavior, as the result of the different scenarios, induces systemic risk since it maximizes the probability of banks' joint failure.

[218]Apart from the decision sequence, we could assume that the large international bank has better information regarding available strategies; we mentioned the possibility to allow for a varying signal precision already in the first part of this section.

[219]Chamley and Gale (1994) study herding dynamics when decision-makers can choose their position in the line and derive the following results: (1) When period length is very short, there is a form of informational cascade, which results in a collapse of investment. (2) With increasing period length, the possibility of herding disappears. (3) As the number of players increases, the rate of investment and the information flow are eventually independent of the number of players; adding more players simply increases the number of players who delay their decision. (4) The time-profile of investment is extreme; a period of low investment is followed either by an investment surge or a collapse.

4.1.6 Discussion of further approaches to collective behavior

Our systemic analysis (chapter 3) also suggests elaborating on incentives due to relative effects—e.g. competition or other forms of relative incentives—as a source of collective behavior. Before turning to the discussion of our results of the theoretical analysis (section 4.1.7), this section briefly discusses further relevant approaches and corresponding models. Furthermore, we illustrate how effects can be related to our analysis. One specific example is the possible extension of our models accounting for a two-level principal-agent problem with both internal and external information asymmetries.

This discussion in the wider context of the literature marks the second contribution of the theoretical analysis, as it illustrates further ways to think of incentives for collective behavior, and how these could be reflected in our model. We discuss two major topics in sequence: (1) focusing on risk taking among banks and the impact of competition; and (2) elaborating on two-level moral hazard and the relative dimensions of incentives.

Risk taking among banks and the impact of competition

Though not formally based on concepts of collective moral hazard, the impact of competition on risk taking in the banking sector will also increase systemic risk and has a direct correlation to our research. We have argued that incentives in our creditor expectation change model (section 4.1.3) are potentially related to competitive dynamics. The overall debate on the link between risk taking and competition goes back to the influential study of Keeley (1990), who defines the 'charter-value hypothesis' as an explanation for a positive relation between competition and risk taking, and offers empirical support. He argues that market power of financial intermediaries mitigates risk taking, due to foregone future profits in the case of bankruptcy. Higher levels of competition reduce market power and lead to an erosion of profit margins. This decreases foregone profits in the case of bankruptcy and leads to higher risk taking incentives for financial intermediaries.

The hypothesis can be interpreted as a rationale to impose regulation in financial markets in order to limit the extent of risk taking in a competitive market environment. Hellmann et al. (2000) study the effects of regulatory provisions on risk-taking incentives and find that the imposition of capital requirements combined with deposit rate ceilings can effectively alleviate the risk-taking problem[220]. Focusing on industry structures, Allen and Gale (2001) argue that more monopolistic structures induce a form of corporate conservatism and, consequently, risk-taking declines.

[220]For specific assumptions, this policy can even be regarded optimal.

Many further studies have built on this hypothesis; selected references can be found in the comprehensive survey of Carletti and Hartmann (2002). Overall, results are ambiguous and indicate that the link between competition and risk-taking is not at all clear-cut. Specifically, empirical approaches to the issue have found dynamics which both support and contradict the charter-value hypothesis, as well as, that more competition reduces overall risk in the financial sector, adding to its stability.

A critical analysis seeking to bridge the underlying contradiction is Boyd and De Nicoló (2005). They claim that the positive link between competition and risk-taking is a mere artifact of underlying model assumptions. In fact, it is commonly assumed that banks compete in funding markets, but on the investment side face a simple portfolio choice with known distributions; this was also an assumption in our model. Once this portfolio choice is modeled as an optimal contracting problem and banks give loans to entrepreneurs who are subject to moral hazard, risk-taking incentives decline significantly. Nonetheless, their results suggest that the probability of failure increases in a more concentrated and less competitive environment[221]. In an extended version of their model—follow-up papers by Boyd et al. (2006) and Boyd et al. (2009)—the authors allow banks to hold a risk-free asset and show that competition can actually influence risk-taking both ways[222]. The overall direction of the link depends on the extent to which entrepreneurs increase the risk of their projects as banks raise interest rates. Such an effect has been studied in the seminal contribution of Stiglitz and Weiss (1981) for the context of credit rationing by banks.

It would be an interesting expansion of our model to analyze the impact on collective moral hazard in a model to be extended accordingly. A first presumption would be that collective behavior—in terms of loans in a specific segment—would increase the riskiness of these loans, because of the higher activity in the segment; more and potentially riskier projects receive financing. This would be a similar counter incentive to collective behavior as the investment cost that was assumed in the model. However, reactions of banks in terms of higher interest rates or collateral requirements might have further adverse selection effects, as also studied in Stiglitz and Weiss (1981). Hence, the overall counter incentive might be stronger than in the original model.

The negative externality through creditor expectation changes are likely to be similar to our model, as there is no reason to assume the information asymmetry between

[221] The authors show that without the assumption of a competitive loan market, banks' risk-taking can be reduced by a fixed cost of bankruptcy. As more competition decreases average firm size, marginal bankruptcy costs rise and thus reduce incentives for risk-taking.

[222] They present empirical evidence covering a broad-range of financial markets in the US as well as non-industrialized countries, which confirms the predictions of their model while rejecting predictions derived from the charter-value hypothesis. Part of their discussion involves the question whether competition is the adequate proxy for bank risk dynamics. De Nicoló and Kwast (2002) and De Nicoló et al. (2004) propose a set of empirical concentration measures, such as consolidation and conglomeration, which are related to but not similar to competition, and are and presumably better indicators to assess bank risk-taking.

creditors and banks to be lower in such a model. It would be intriguing to analyze the effects on the potential interest rate adjustment for the second period and its implications on risk taking in banks. Similarly, the effects on the money supply shock externality would need further analysis to determine how the equilibrium adjusts in such a setting. Yet, it seems reasonable to believe that such an extension could in fact reduce the incentives for collective behavior and lead to a reduction of systemic risk.

Two-level moral hazard and relative dimensions of incentives

Our models focused on the behavior of bank managers vis-à-vis creditors. Prior considerations suggest an extension with an added level of interaction outside the bank through the investment activities of banks; e.g. giving loans to entrepreneurs. Yet, a bank is always regarded as a single decision unit represented by its manager: a black box with one representative utility function. Clearly this representation is simplistic, considering a global financial institution with many geographical representations and hierarchical levels. As an alternative to a second level being external, it seems reasonable to augment the model with an internal dimension.

Such an amplification would relate to the conclusions from our institutional perspective included in the systemic analysis (section 3.3.4). Dow (2000), p. 20, argues that 'many instances of this collective moral hazard problem do not involve excessively strong incentives [...].' Further, he distinguishes between aggressive and passive corporate cultures. Whereas an aggressive culture encourages risk-taking in specific segments, a passive culture overemphasizes opportunities as compared to inherent risks of a specific strategy. At the system level, incentives can cause a collective overexposure, whereas no individual bank has an incentive to correct its strategy in order to reduce systemic risk. This observation is also a central issue of the debate concerning macroprudential regulation.

Following this line of thought, one could differentiate our definition of collective moral hazard from a similar concept, applying it in a broader sense. The issue is not that there are collective incentives to actively induce systemic risk, but rather that there will be an overshooting of collective dynamics due to the fact that there are no incentives for strategy alignment, even as aggregate risk reaches a critical systemic dimension. Such an explanatory approach has appeal when compared to our observations prior to the financial crisis 2007–09 (section 3.1.2). Overall, this point of view suggests that an important feature that has yet to be considered is the potential conflicts of interest within the bank itself.

In fact, one can argue that it is a major limitation of economic models that internal conflicts of interest and agency problems are left unaccounted for[223]. Yet, it seems clear that, although research in that direction might lead to revealing results, the complexity of corresponding models would increase exponentially. As a result of the number of necessary ex ante assumptions to specify, the model would strictly limit the generality of conclusions.

In one model description, we can assume banks with two hierarchical levels: while the basic relationship between bank managers and creditors remains unaffected, bank managers would no longer be directly responsible for investment decisions. Instead, this would be delegated internally to a trader. As a consequence, this sets up a two-level agency conflict: the first level, as analyzed previously, between creditors (principal) and bank managers (agent); and the second level between bank managers (principal) and traders (agent); see Schwarcz and Anabtawi (2011). It is clear that, even if the first-level agency conflict between creditors and bank managers could be resolved, the presence of the second-level conflict can still lead to collective behavior and, consequently, systemic risk. Any strategic complementarities at the second level could imply collective moral hazard, similar to our analysis.

In the two-level model, bank managers need to control the behavior of traders internally within the bank. Externally, creditors seek to uphold their interest vis-à-vis bank managers, by regulation if necessary. It is reasonable to assume that the internal information asymmetry should be significantly lower compared to the external one, since managers should have access to almost all information. However, it will be a challenging task to assess this information properly, due to a bank's complexity. From that perspective, strategic complementarities and moral hazard can also arise at the individual trader level, similar to our previous analysis. If bank managers, representing the institutional level, do not exercise adequate control, the institutional level serves as a transmission for collective moral hazard and systemic risk.

This conjecture is also true for the assumption that banks' investment choices consist of two strategies with identical, independent risk characteristics (iid). Such a setting should make banks indifferent between both strategies, and a central authority could ensure low interbank correlation. In the two-level model, and if traders would have a preference to behave collectively because of some negative externality, such coordination by a central authority would be impossible, even if there were no strategic complementarities at the institutional level.

If traders are assumed to work as profit centers—internally borrowing funds from the bank at a certain interest rate but keeping excess profits—such interaction would

[223] We have not modeled a potential agency conflict between managers and bank shareholders either. Nonetheless, it is clear that, compared to creditors, shareholders' interests are more aligned to managers because their profits are contingent on bank returns, whereas creditors receive only a fixed interest.

replicate the interaction between bank managers and creditors, as analyzed earlier. The externalities would be similar[224]. However, traders are not truly entrepreneurs, who distribute excess profits. Instead, though salaries are partially tied to their contribution to profits, there are many other discretionary factors influencing compensation. One such factor is the relative performance of traders, which can be a potential source of strategic complementarities—in the form of a negative externality—and thus pose as an incentive for collective behavior at the trader level.

In this regard, studies by Scharfstein and Stein (1990), as well as Graham (1999), mentioned before explain herding behavior as a consequence of reputational concerns[225]. In those models, agents have incentives to follow coordinated strategies because they can avoid potential adverse effects by virtue of performing worse than other agents: they can 'hide' in the crowd. Similar to the discussion before, any implications for systemic risk are not relevant for their individual decision-making. In reference to our prior analysis, it is worth noting that our strategic complementarities arise not for the agent performing worse, but even for the stronger-performing agent (section 4.1.3).

In a more general setting, DeMarzo et al. (2004) analyze implications on portfolio choices if an investor community competes for a scarce local resource. They show that 'competition for these resources leads investors to care about their relative wealth in the community. As a result, rational risk-averse investors have an incentive to herd and choose a portfolio similar to the rest of their community'. Consequently, and this is similar to our results, agents have no incentive to consider the aggregate effects of their actions. With this in mind, DeMarzo et al. (2004) show that such community effects can effectively induce price bubbles, as holding a diversified portfolio is not in the interest of individual agents. Instead diversification exhibits features of a public good.

A crucial ingredient in their model is the supposition of some frictions (incomplete markets) or a behavioral bias in the agents' behavior, because of which investment choices are in favor of local stocks[226]. The overall sequence of the model foresees that two types of agents build their wealth in the first period (by work or investment) and then compete for a (regionally) constrained good in the second period. While agents will hold a diversified market portfolio in a complete market equilibrium, they jointly shift towards a local portfolio and thus take unnecessary risks from the aggregate perspective once frictions are introduced to the model. The reason for this behavior is a preference for status, which is measured by the relative level of wealth in the community. Analyzing the robustness of this effect, DeMarzo et al. (2004) find that the dynamics will increase if either local

[224]This is again closely related to the findings of our institutional analysis of UBS (section 3.3.4).

[225]Following the basic definition of strategic complementarities, the utility of one agent for a certain outcome is, at least partially, dependent on the outcome for another agent.

[226]Such a home bias as been described by French and Poterba (1991) and Coval and Moskowitz (1999).

goods become more constrained or the overall wealth of the community rises. Moreover, local volatility has a positive effect on the correlation of dynamics similar to potential migration cost.

The core thesis of DeMarzo et al. (2004)—diversification as a public good—can be transferred to financial markets, where relative status is certainly a very important and relevant element for an agent's behavior. Several empirical studies, such as Brown et al. (1996) and Chevalier and Ellison (1997), have proposed that financial markets inherit dynamics of a tournament, targeting relative performance[227]. Most of these studies focus on risk-taking of specific types of agents, especially mutual fund managers. They find that managers of certain funds generally have incentives to adopt a certain risk structure. The strategic complementarity derives from the fact that funds compete for assets or are otherwise categorized as winners/losers[228].

Maug and Naik (1996) show that fund managers have in fact an incentive to minimize deviations from their peers, and even ignore potentially superior information, while pursuing strategies associated to those of other managers[229]. A similar result is derived by Dasgupta and Prat (2008), who show that a manager will never execute trades contrary to the market, due to career concerns and certain other assumptions.

This is also in the findings of Hassan and Mertens (2011), who model incentives to align decision-making to market sentiment as a tragedy of the commons problem. Their model is about the cost of information and its value, as compared to market sentiment, which is a bias in individual beliefs about future payoffs, and increases uncertainty. In an equilibrium with moderately dispersed information, market sentiment will cause uncertainty high enough to pose as an incentive to follow market sentiment, instead of obtaining additional information at a very low cost. The study concludes that information aggregation in financial markets is often not fully efficient and price bubbles can evolve[230].

Overall, the results of this research reveal an inherent bias in financial markets towards collective behavior, which can be explained by a variety of approaches. This is due to the relevance of relative performance factors on incentives, as they induce strategic complementarities. A major problem that has been exposed in our discussion of approaches to collective behavior is that systemic risk can arise because individual agents do not internalize the impact of their decision-making on systemic risk at the aggregate level. This poses a major challenge when reforming the governance framework in financial

[227] Directly testing the tendency of investment managers to herd, Lakonishok et al. (1992), however, do not find significant evidence for such behavior.

[228] Such a categorization also induces a specific dynamic to alter the risk profile of a fund during the year. Interim losers will have incentives to increase portfolio risk and try to catch up with interim winners, who focus on reducing portfolio volatility/risk.

[229] This is similar to our considerations of the supply shock externality for a multiple heterogeneous bank environment (section 4.1.5).

[230] Dasgupta and Prat (2008) also show that volatility decreases and market liquidity increases in view of these dynamics.

markets in response to the crisis. With regard to competition in financial markets, there is no clear-cut conclusion whether it contributes to the stability of financial markets or poses incentives for excessive risk taking, instead. Further analysis will be necessary to exactly determine relevant issues in this regard, as well as potential regulatory approaches to fix them.

4.1.7 Conclusions from the theoretical analysis

This analysis provides a theoretical microfoundation for collective behavior inducing systemic risk in financial markets, and being related to collective moral hazard. The analysis is inspired by our prior analysis of the financial crisis 2007–09, which identified the problem of collective behavior of financial institutions as an important source of systemic risk[231]. Surveying the literature, Dow (2000) and Summer (2002) point out that further research is needed on the collective dimension of incentives for risk taking in financial markets. Our first and crucial contribution is in this specific context, and to the understanding of incentive structures at the collective level which induce collective behavior and systemic risk due to collective moral hazard. Our second contribution complements the core analysis with a discussion in the wider context of the literature, illustrating further avenues to think of incentives for collective behavior, and how these could be integrated into our model.

We model incentive structures which arise through the interaction of creditors and banks in money markets, based on an information asymmetry between these two groups of agents. Our models focus on rational actors, while any behavioral explanations are excluded. The analysis delves into potential sources of strategic complementarities for banks and, specifically, negative externalities. With such externalities, bank managers can maximize their individual payoffs by jointly pursuing the same investment strategy. At the same time the collective behavior exposes banks to a correlated risk factor and induces systemic risk due to the increased probability of joint failure. The decision for collective behavior is intentional and the additional systemic risk is borne by banks' creditors. As it reduces aggregate welfare, the behavior resembles collective moral hazard. It is an important conclusion of our analysis that banks generally do not have incentives to account for the systemic implications of their actions. We formally analyze three forms of externalities separately, regarding collective incentives for banks' behavior and their robustness under relaxed model assumptions.

The first externality relates to creditor expectation changes and the impact of a capital buffer. Acharya and Yorulmazer (2008) show that interest rates are dependent on

[231] This behavior refers back to the moral hazard narrative (section 3.2.4) and supposes a misalignment of incentives in financial markets.

the joint performance of banks and, therefore, the first bank can be adversely affected by the bad performance of the second bank[232]. We expand their model, assuming that banks retain their first period profits in the form of a capital buffer to serve as a cushion against losses in the second period. As creditors observe the capital buffer for each bank individually, the information asymmetry between creditors and banks is reduced. This allows for a differentiation in the interest rate between the banks, and our hypothesis is that it will pose as a counter incentive to collective behavior.

This hypothesis is confirmed by our analysis and, for certain prior assumptions, the capital buffer fully reverses the negative externality and provides incentives for banks to differentiate. However, banks would never voluntarily opt for a capital buffer since they would bear additional risk that is otherwise borne by creditors. Therefore, market discipline can be exercised through the capital buffer, but must be enforced through regulation[233]. A second important insight from the model is that incentives are dynamic and will vary according to expectations regarding economic prospects. For example incentives for collective behavior increase in a boom period or through higher expectations in a competitive environment. Comparing our results to other analyses, the incentive structures seem similar to those of Scharfstein and Stein (1990). However, a major difference is that in our model even the potentially better performing bank has incentive to mimic the other bank in order to avoid a negative externality through the interest rate channel.

The second externality captures money supply shocks and at first is assumed to be constant, before this assumption is relaxed in the third step. Acharya (2009) analyzes individual and collective risk taking within the same model. Our hypothesis that collective incentives can be replicated in a much simpler model is confirmed by our analysis. A bank's failure after the first period implies adverse effects on the funding equilibrium: interest rates increase while, at the same time, the overall level of investment is reduced[234]. If this adverse effect is not fully balanced by a strategic benefit, banks pursue mutual strategies in order to rule out their individual survival: again a collective moral hazard. Compared to the expectation channel, this supply channel is influenced by the structural evolution of the industry. If there is potential for consolidation, the strategic benefit from a bank's failure will be high, which can create an effective counter incentive upon which banks will opt for differentiation[235]. An interesting finding, in reference to Acharya (2009), is that a capital buffer similar to that above will have no effect through the supply

[232] At the same time, the assumption that investment cost increases because of high interbank correlation presents a counter-incentive to herding.

[233] Concerning normative aspects of an optimal design of regulation, we refer the reader to analyses of Acharya (2009), Farhi and Tirole (2009), etc.

[234] This negative effect on the surviving bank is generally offset by the assumption that investment cost would decrease as the bank could take over either human capital or existing business from the failing bank.

[235] If they would fail together in consequence of collective behavior, they would have no chance to realize such a strategic benefit.

channel, but only if it specifically accounts for interbank correlation.

Third, we consider an endogenous externality as an extension of the second model, which relates to herding as a result of informational cascades. We allow for multiple and heterogenous banks and analyze the hypothesis that these more general assumptions will have an effect on incentives for collective behavior. We show that the externality will be certainly negative in a multiple bank environment once the number of failing banks surpasses a critical threshold. Banks bear the consequences of a potential failure of other banks. Without prior knowledge of the strategy of the remaining banks, the choice of collective behavior becomes a dominant strategy. It is rational from the ex ante perspective to opt for coordinated strategies in order to avoid a negative spillover[236]. With heterogeneous banks, larger institutions have to be regarded as 'fashion leaders' and their actions are a signal for smaller banks who postpone their decisions until the larger institutions have taken theirs. Overall, these extensions suggest that incentives for collective behavior will increase as we allow for multiple heterogenous banks in our model.

Our second examination connects our model to the wider literature, focusing on the effects of competition as well as the relative incentives that lead to collective behavior. Whereas the impact of competition on the risk taking of banks is debated controversially in the literature, the implications of relative incentives highlight other sources of externalities that will foster collective behavior.

An important element on incentives stemming from the relative level of wealth is explored by DeMarzo et al. (2004), who show how this induces incentives to hold highly-correlated portfolios. Then diversification at the system level exhibits features of a public good. Their model is constructed with some kind of friction, e.g. a bias towards local assets, but with no information effects. Another explanation, such as that of Hassan and Mertens (2011), shows that market sentiment can increase incentives for collective behavior. Hence, the issue of systemic risk can be compared to a tragedy of the commons. Due to a positive effect on uncertainty, investors are not willing to incur the cost of obtaining additional information. These explanatory approaches complement models that link collective behavior to reputational or other career-related concerns.

Such incentive structures, in addition to those developed in our model, appeal when considering an application to collective moral hazard in a broader sense. We propose this concept in reference to Dow (2000). In this case, an interesting enhancement to our model would be to open the black box of banks and allow for a two-level agency problem. As we describe, whereas extensions in terms of competition focus on an external information asymmetry, this would impose a second-level information asymmetry and moral hazard

[236] If there is a differentiation cascade the probability of a negative externality will be lower than for a collective behavior cascade.

within banks: between managers (principal) and traders (agent). Though a formalization of this issue poses a challenge, it would extend possible applications of the collective moral hazard theory: the central agency problem might be present within a bank, and could lead to collective behavior and systemic risk, even though the external conflict between creditors and banks (first level) has been resolved. Traders would have incentives for collective behavior, but, intentionally or not, managers fail to adequately control their behavior by means of internal corporate governance or compliance. A specific feature would be that incentives for collective behavior at the institutional level would not need to be very strong as they only serve for the transmission into the system.

Summing up, our discussion suggests that there is an inherent bias in financial markets fostering collective behavior. This bias can be explained by a wide spectrum of approaches, which are related to our findings in the systemic analysis of the 2007–09 financial crisis (chapter 3). We elaborate on various forms of negative externalities where collective behavior arises as a source of collective moral hazard: creditor expectations, money supply shocks, information cascades, fashion leaders, etc. and explore further links to competition or relative incentives. The core of this microfoundation of collective behavior and collective moral hazard rests in the fact that financial market participants—banks in particular—do not internalize the impact of their joint actions at the system level. As DeMarzo et al. (2004) point out, diversification has facets of a public good and has to be enforced externally. In the context of creditor expectations, we have illustrated how regulatory provisions can eliminate incentives for collective behavior. Yet, we have also pointed out challenges, such as the necessity of regulation accounting for market dynamics, e.g. the effects on expectations created in a boom; see Hellwig (2008). We will discuss our conclusions in the context of our overall analysis at the end of this chapter (section 4.3), together with the results from the subsequent empirical analysis.

4.2 Empirical analysis

4.2.1 Introduction

Turning from the incentives for collective behavior, research from an empirical perspective follows a more pragmatic rationale: if the existence or level of systemic risk can be empirically supported one will be able to impose regulatory measures for its reduction. The underlying drivers of systemic risk and a potential relation to collective behavior are less relevant. Yet, related assumptions determine methodological choices. The primary focus of research is on the appeal of an individual measure in offering statistically valid evidence of systemic risk, or even quantifying its level[237]. In this context, our empirical analysis focuses on the empirical measurement of systemic risk prior to the financial crisis 2007–09, and the underlying (statistical) challenges.

Naturally, the issue of systemic risk has received much attention in the aftermath of the crisis, especially in the burgeoning strand of literature on macroprudential regulation. Comprehensive reviews of recent advances can be found in Borio (2010), European Central Bank (2010), Drehmann and Tarashev (2011a,b), and Galati and Moessner (2011). Bisias et al. (2012) provide an in-depth overview of the wide spectrum of recent methodological approaches. In general, these can be divided into structural approaches to credit risk, such as Furfine (2003), Lehar (2005) or Elsinger et al. (2006), and reduced-form approaches—analyzing the statistical behavior of institutions' asset returns—examples being De Nicoló and Kwast (2002), Acharya et al. (2010b), Adrian and Brunnermeier (2010), and International Monetary Fund (2009a).

Both approaches face issues regarding the underlying data series, which weaken the statistical power of their results; see Lo (2012). Structural approaches require detailed information about asset/capital structures of financial institutions. Availability of such data is generally limited and data frequencies are relatively low. Further challenges are the adjustment, standardization and aggregation of the data, as item definitions are not necessarily consistent. In contrast, reduced-form approaches are based on the critical assumption of efficient markets, and that market prices reflect fair values. While data series are highly standardized and populated, any biases in the underlying time series—deviations from fair values—will inhibit the power of reduced-form approaches in the results, since they cannot be controlled for.

The majority of recent studies focuses on quantifying the level of systemic risk and comparing the contributions of individual institutions; see the overview of related literature (section 4.2.2). We argue that there is merit to conduct a much simpler analysis and our *core contribution is to the understanding of the prospects of an ex ante identification of systemic risk in financial markets, as well as the underlying challenges.* Any evidence that systemic risk can be identified ex-ante supports the argument for quantitative indicators of systemic risk, as an important pillar of macroprudential regulation. Beyond that, we reveal (statistical) challenges for such an identification. Such limiting factors have to be accounted for as potential risks of macroprudential regulation; see Galati and Moessner (2011). Whereas most analyses focus solely on the US, we extend our analysis to the international context, including Europe, and *analyze the hypothesis that there is empirical evidence for an increase of systemic risk prior to the financial crisis 2007–09.*

[237] In his survey of empirical research on social interactions, Manski (2000)'s makes the argument that the power of econometric methods to draw inferences about the nature of social interaction processes from solely observing the outcomes is sorely limited.

Following from the results of our systemic analysis of the crisis we focus on collective behavior. Our methodology seeks to address this specific type of systemic risk. We conjecture that collective behavior induces systemic risk through correlated exposures. The Group of Ten (2001) refers to these as 'interdependencies'. In turn, interdependencies provide indications of systemic risk. We measure interdependencies through the correlation of stock returns—as the daily percentage change of stock prices—among financial institutions and apply a two-step analysis focusing on the hypothesis that there is empirical evidence that (1) the level of interdependencies[238] increased prior to the crisis, and (2) there was a positive increase in the trend of interdepencies[239]. Following our earlier argument that the contribution of the insurance sector to systemic risk will be limited (section 3.4), we are also interested in any differences that can be identified in insurance and other financial institutions.

Our results are ambiguous: although we identify some evidence for increases of systemic risk prior to the crisis, these are neither particularly strong, nor applicable to the full samples. In the international context, a slight increase in the levels of interdependencies appears among European financial institutions, but not with the US. In the US context, there are indications of positive increases in the trends of interdependencies. These are particularly noticeable when concentrating on a systemic core of US financial institutions, defined in reference to Brownlees (2010). Similarly, those insurance institutions critically exposed in the crisis show strong ex ante increases of interdependencies with the rest of financial markets.

An interesting aspect of our results is a comparison to complex studies such as Acharya et al. (2010b), which is in line with Drehmann and Tarashev (2011a,b), who argue for a reproducibility of complex measurements with simple indicators. By applying simple measures, regulators would mitigate the risk of a false sense of certainty that might arise with more sophisticated, pseudo-accurate quantifications of systemic risk. Our conclusions contribute to the discussion of simple indicators vs. sophisticated quantifications of systemic risk, and also elaborate on the statistical challenges to the measurement of systemic risk.

The analysis of this section proceeds as follows: the overall focus, methodology, and sample of our analysis are introduced in section 4.2.2. Preliminary analysis and the estimation dynamic conditional correlations under the DCC-GARCH approach are presented in section 4.2.3. Afterwards we present our two main analyses of correlation levels (section 4.2.4) and time of correlations (section 4.2.5). Section 4.2.6 focuses on the insurance sector and its contribution to systemic risk, before we conclude in section 4.2.7.

[238] We refer to the 'level' of interdependencies as the average correlation measured for a specific time period. The measure and corresponding testing procedures are explained in more detail in the subsequent section.

[239] We refer to the 'trend' of interdependencies as a deterministic time trend that is measured for a specific time period. The measure and corresponding testing procedures are explained in more detail in the subsequent section.

4.2.2 Study approach, methodology and data

Study approach to systemic risk

The results of our systemic analysis, as well as other studies, have emphasized the importance of collective behavior as a source of systemic risk in the financial crisis 2007–09. We conjecture that collective behavior induces systemic risk as it leads to correlated exposures of financial institutions regarding specific asset classes, or other risk factors. This increases systematic risk throughout the financial system: there is higher probability of a large number of financial institutions being adversely affected by a shock, and hence there is greater potential for this shock to reach a systemic dimension[240]; see De Bandt and Hartmann (2000). Hellwig (1995) points out that even though individual exposures, in terms of maturity transformation or interest rates, may seem small, their interlinkage can cause formidable systematic risk in the financial system.

As cited in our fundamentals on systemic risk, the Group of Ten (2001) refers to correlated exposure to non-financial sectors, financial markets, or other risk factors as (indirect) 'interdependencies'. The report states that the extent of interdependencies among large and complex financial organizations needs to be assessed, as 'increased interdependencies are consistent with the view that systemic risk may have increased, because they suggest that a common shock would tend to be transmitted to many firms', p. 15. Hence, an increase of interdependencies can be interpreted as signaling a higher level of systemic risk and vice versa[241]. Empirically, the importance of such interdependencies as a source of systemic risk has also been discussed in empirical studies such as De Nicoló and Kwast (2002), Lehar (2005), Elsinger et al. (2006)[242].

For the period prior to the financial crisis 2007–09 we have described a dynamic of diseconomies of risk and argued that systemic risk evolved gradually. Obviously, there must have been an increase prior to the crisis. To determine the prospect of potential macroprudential provisions, it is of interest to determine whether this increase in systemic risk can be identified empirically. Thus, our hypothesis is:

MAIN HYPOTHESIS: There is empirical evidence of an increase of systemic risk prior to the financial crisis 2007–09.

[240] Whereas an investment strategy might be beneficial for an individual financial institution as it contributes to its diversification, it can be undesirable from the systemic perspective, due to the resulting interdependencies and systemic risk. This relates to our theoretical analysis in the previous section, where we were interested in underlying incentive structures upon which financial institutions choose correlated strategies.

[241] De Nicoló and Kwast (2002) argue that correlations are driven by developments of both direct interdependencies, as well as indirect ones. Therefore, we drop the distinction made by the Group of Ten (2001).

[242] In the context of cross-market linkages, Forbes and Rigobon (2002) measure 'interdependencies' as compared to contagion. Whereas they document significant interdependencies that are also present in a normal market environment, evidence on contagion in turbulent times is limited.

We measure interdependencies through the correlation of stock returns—as the daily percentage change in stock prices—among (publicly traded) financial institutions. Correlations are an adequate measure, as investors, observing an increase in interdependencies of two financial institutions, will adjust their return expectations according to the collective exposure to the underlying risk factors. Aggregated at the market level, these expectations are reflected in the stock prices of financial institutions and, econometrically, correlations of stock returns should increase due to the alignment of expectations[243]. Overall, the econometric definition of systemic risk for our study reads:

Definition: Systemic risk relates to interdependencies among financial institutions and is measured through the correlation of corresponding stock returns, as the daily percentage change in stock prices. An increase of correlation signals increasing systemic risk and vice versa.

This is in line with Forbes and Rigobon (2002), who point out that continued high levels of correlations (among markets) suggest strong interdependence, whereas one can only speak of contagion if there is a significant increase in the correlation only after a shock[244]. A similar approach is taken by De Nicoló and Kwast (2002), although we will argue later that our measure of correlations is methodologically superior.

There are three important aspects that have to be considered as potential limits to our approach. The first is the assumption of efficient markets, which applies to all reduced-form approaches. This assumption is necessary to exclude biases due to a low information-efficiency of financial markets or other behavioral biases, and allows us to establish the relation that increases in interdependencies will result in increasing correlations. Second, this relation has to be considered uni-directional, and there is no direct causality for the opposite direction; see Manski (2000). If we measure increases of correlations we can only infer that it was driven by rising interdependencies. Lastly, there are methodological challenges that can cause biases to correlation measures; see Forbes and Rigobon (2002) and Pukthuanthong and Roll (2009)[245]. These will be considered in the subsequent paragraphs.

[243] Khandani and Lo (2007) also emphasize that correlations, compared to more complex approaches to quantify systemic risk, can serve as a simple indicator of systemic risk. However, their measure of the 'degree of interconnectedness' focuses on the hedge fund industry and is calculated from public indices rather than the returns of individual institutions.

[244] Forbes and Rigobon (2002)'s criticism of the correlation measure only applies from a methodological perspective, as they show that unconditional measures of correlation will be biased due to the heteroskedasticity of the data.

[245] Further criticism on the methodology is voiced by the International Monetary Fund (2009a), pointing out that even dynamic conditional correlations cannot elucidate feedback effects and non-linearities in financial markets. Such non-linearities might be covered by embedding the methodology in a Markov-Switching model, similar to Chesnay and Jondeau (2001), Nowak et al. (2009), or International Monetary Fund (2009a).

Methodological considerations and hypotheses

To measure correlations, Forbes and Rigobon (2002) have pointed out that heteroskedasticity, a common feature in the time series of market returns, will cause a downward bias of unconditional correlation measures. This issue can be resolved by applying the generalized autoregressive conditional heteroscedasticity (GARCH) methodology, proposed in the seminal contributions of Engle (1982) and Bollerslev (1986). The wide spectrum of available models and extensions is surveyed in Bollerslev (2008). Univariate GARCH approaches allow us to account for the volatility clustering and model time-varying conditional variance to standardize the return series accordingly. Still, one has to consider Pukthuanthong and Roll (2009)'s findings that correlations can show a downward bias if the data series are conditioned by a factor model, due to differences in the proportional dependence on the factors included.

To model time-varying correlations of financial returns series—in a multivariate setting—Engle (2002)[246] proposes a model specification of dynamic conditional correlations (DCC-GARCH). He shows that, applied to large sets of financial market return series, the specification produces highly accurate results compared to other multivariate GARCH specifications. This has to be regarded in the context of other advantages, such as the simple two-step estimation process based on the maximum likelihood as well as the consistency of univariate and bivariate estimations[247]. The DCC-GARCH specification enhances Bollerslev (1990)'s constant conditional correlation measures, which are applied in Longin and Solnik (1995), De Nicoló and Kwast (2002), and International Monetary Fund (2009a).

To test our hypothesis that there is empirical evidence for an increase of systemic risk prior to the financial crisis 2007–09, we apply a sequence of two testing procedures which focus on exogenously defined time-windows; analogous to our systemic analysis (chapter 3). We acknowledge that this exogenous definition of the time-windows poses a selection bias and limits the generality of our analysis.

The *first testing procedure focuses on the overall level of interdependencies*, as measured by the mean of correlation for a specific time-window. Cappiello et al. (2006) present in detail the extended DCC-GARCH specification, accounting for possible structural breaks in mean. The rationale for this analysis is that the model fit to the data can be improved by allowing for structural breaks in mean—different levels of correlations—for pre-defined time-windows. Following this approach, Cappiello et al. (2006) analyze vari-

[246] Engle and Sheppard (2001) propose a prior version of this model.

[247] For an overview on the many different model specifications see Bauwens et al. (2006), Bollerslev (2008), Engle et al. (2008), or Silvennoinen and Teräsvirta (2008).

ous dynamics among international equities and government bonds[248]. Frank et al. (2008) analyze the link of market and funding illiquidity, based on the correlation of spread differentials in both markets[249]. Our analysis focuses on the period prior to the 2007–09 financial crisis and, in line with our main hypothesis, we can formulate our hypothesis for the analysis of structural breaks in mean of correlations as:

HYPOTHESIS 1: There is empirical evidence for an increase in the level of interdependencies prior to the financial crisis 2007–09.

Our *second testing procedure elaborates on deterministic time-trends of interdependencies*. Starting with the dynamic conditional correlation series produced by our models, we conduct the Phillips-Perron unit root test for a trend-stationary first-order autoregressive model, as proposed by Phillips and Perron (1988). This procedure is inspired by Pukthuanthong and Roll (2009), as well as—following a different methodology proposed by Vogelsang (1998); Bunzel and Vogelsang (2003)—studies by Bekaert et al. (2008), Bekaert et al. (2009) and Liow and Newell (2010). The test allows us to determine whether correlation dynamics exhibit a deterministic time trend for the individual time-windows. If this is the case, we can compare these time trends to draw conclusions on changes in the trend. Our hypothesis for this second testing procedure is, therefore:

HYPOTHESIS 2: There is empirical evidence for a positive increase in the trend of interdependencies prior to the financial crisis 2007–09.

If our subsequent analysis confirms of one of the two, or both hypotheses we interpret this in support of our main hypothesis that statistical evidence for an increase of systemic risk prior to the financial crisis 2007–09 can be established, either due to an early rise in the overall level of correlations, or by a positive increase in the trend. A rejection of both hypotheses would imply the conclusion that our methodology does not produce evidence for an early increase of systemic risk. As other studies (see below) document such early increases of systemic risk prior the crisis, this would suggest dismissing our underlying methodological assumption that correlations are an adequate measure of interdependencies and systemic risk.

Related literature

Our analysis and results relate to the broader context of (recent) contributions to the empirical measurement of systemic risk, and particularly those analyses following reduced-

[248]Cappiello et al. (2006) document asymmetric effects in correlations, as well as a structural break in the correlation of bond returns throughout Europe, subsequent to the introduction of a fixed-exchange rate regime.

[249]Frank et al. (2008) find the correlation to jump to a higher level with the start of the financial crisis.

form approaches and analyzing the statistical behavior of institutions' asset returns, often focusing on tail-risk behavior as indicators of systemic risk[250]. Four studies are particularly worthwhile to highlight in relation to ours.

The approach of our study is similar to De Nicoló and Kwast (2002), who also analyze trends of interdependencies among large and complex banking organizations for the time period of 1988–99 by applying a correlation measure. They find a significant positive trend, which they then link to industry consolidation through an elasticity measure. As their analysis of this consolidation elasticity exhibits substantial time variation, they conclude that interdependencies were driven by factors other than consolidation. In comparison to our study, their sample is much smaller and only contains US institutions. They apply a CCC-GARCH model based on rolling time-windows, which is subject to several biases, which are resolved in our DCC-GARCH specification.

Acharya et al. (2010b)[251] propose a combined structural and reduced-form approach focusing on the expected shortfall (ES) as a forecast of systemic risk[252]. Specifically, it measures the probability of individual institutions being undercapitalized conditional on the system being in distress. Companies with the highest marginal expected shortfall (MES)—a combination of an ex-ante leverage measure, a scaled pre-crisis measure of MES, and an adjustment term—are the most likely candidates to be systemically risky. Note that their analysis aims to establish a ranking of the individual institutions' contribution to systemic risk as a basis for regulatory taxation. Doing so requires the integration of further data into the analysis, as well as additional assumptions on their effects. This is beyond our focus on interdependencies for specific sections of financial markets, which requires only stock price data. With few exceptions, our US sample is similar to their analyses. However, they do not analyze trends in the international context.

A second prominent approach is 'CoVaR', Adrian and Brunnermeier (2010), applying a VaR approach to the financial system, conditional on its institutions being under distress[253]. The individual institution's contribution to systemic risk is defined as the difference of system VaR and CoVaR. The conditional measurement includes additional state variables, such as the slope of the yield curve, credit spreads, market volatility, reflecting tail risk dependence over time, which are then related to firm characteristics[254].

[250] De Vries (2005) also follows a reduced-form approach, modeling interlinkages of banks through interbank credit markets as a source of systemic risk. In the wider context of portfolio choice, Das and Uppal (2004) evaluate effects of systemic risk and find that losses result from diminished diversification, as well as—much more severe—from holding very leveraged positions.

[251] Their analysis is extended and improved methodologically by Brownlees and Engle (2010).

[252] Note that an extension of their MES measure by Brownlees and Engle (2010) proposes to use the DCC-GARCH methodology to get more accurate measures in a dynamic setting.

[253] As Drehmann and Tarashev (2011b) point out, this measure is different from the MES approach, as it assesses the institutional contribution to a system-wide distress situation. Vice versa, the MES analyzes the spillover of systemic events on individual institutions.

[254] Galati and Moessner (2011) draw attention to some issues of the methodology such as its crucial dependence on firm

Their modeling approach is different from the GARCH methodology. A potential drawback, compared to Acharya et al. (2010b), being the fact that CoVaR does not attribute greater weight to tail events, and aggregation is complicated.

The International Monetary Fund (2009a) analyzes the joint probability of default (jPoD) as a potential measure of systemic risk[255]. This measure calculates the stress dependence among financial institutions and is thus similar to our interdependencies. Aggregation to a Banking Stability Index (BSI) is their primary measure of systemic risk, which is applied to a wide spectrum of international financial institutions. The finding that this methodology only gives very short lead times highlights that it is more a measure of market stress than an ex-ante approach, allowing an early warning regarding critical trends in terms of systemic risk. Its use would be more suited for regulators to trigger interventions or other emergency measures than to implement targeted macroprudential regulation.

A major difference with the aforementioned studies is that our analysis solely aspires to establish statistical evidence for increases of systemic risk prior to the financial crisis 2007–09. To this end, the focus on correlation dynamics, as a simple measurement of systemic risk, is sufficient. Despite the resulting methodological differences, a core ingredient of the previous measures is the dynamic covariances among individual institutions or with aggregate indexes. Ceteris paribus, if the correlation among two corresponding time series increases—we interpret this as higher interdependencies and systemic risk—this should similarly result in higher covariance, and higher measures of systemic risk of these approaches. This consistency will be limited though, due to the additional variables and further adjustments.

Sample overview and timing

Our analysis of the dynamics of interdependencies focuses on two different samples: (1) the international sample, comprised of large financial institutions from Europe and the US in order to capture cross-regional dynamics of interdependencies; (2) the US sample contains only US financial institutions, differentiated by type and size, and allows us to consider cross-sectional dynamics of interdependencies. Overall, we can establish a time-series and cross-sectional perspective on systemic risk prior to the 2007–09 financial crisis; see Borio (2010).

As argued before, we use pair-wise correlations of stock market returns—the daily percentage changes in stock prices—as a proxy for interdependencies. An increase in

characteristics, i.e. size, leverage and maturity mismatch of individual institutions, as well as difficulties of an application in times of crises, in consequence of potential non-linearities.

[255] They apply a DCC-GARCH approach only for a preliminary cluster analysis in periods of market stress as compared to normal periods.

correlations signals an increase of interdependencies and, hence, an aggravation of systemic risk[256]. To avoid issues concerned with non-synchronous trading between different time zones, correlations among financial institutions from the US and Europe are calculated using weekly returns[257].

All return series are obtained as adjusted daily/weekly prices from DataStream[258] that are transformed into log-returns for the analysis. The sample period includes all trading days between January 1, 1990 and November 30, 2010, a maximum of 5'456 observations daily and 1'092 weekly returns[259]. Both samples are unbalanced and contain a potential survivorship-bias because not all institutions included in the samples were traded throughout the full time-period[260].

Univariate model estimations are based on the maximum number of observations available for individual institutions. Pair-wise correlations are derived for the time-window in which both stocks were traded. Whereas the full time-window is required to improve the estimations of the bivariate DCC-GARCH models[261], our analysis then focuses on a particular excerpt, the period prior to the subprime crisis. Time-windows have been defined in the systemic analysis (chapter 3). Throughout this study we will refer to three specific periods[262]: *48-months*, June 2003 to June 2005; *24-months*, June 2005 to June 2007; and *subprime crisis*, the onset of the subprime crisis in June 2007 until Lehman Brothers' failure on September 15, 2008.

As mentioned before, we acknowledge the selection bias, due to the exogenous definition of the time-windows. This issue is somehow mitigated as the individual periods have been defined in reference to other studies. Overcoming this selection bias poses an additional challenge for the ex ante identification of systemic risk, which will be discussed in our conclusions (section 4.2.7).

The *international sample* (table 9)[263] is constructed on the basis of analyses of systemically important financial institutions, published by the Federal Reserve (2009), and those institutions included in the IMF Monitoring for European LCFI Banks[264]. It

[256] A feasible alternative to equity returns would be to study CDS-spreads of financial institutions. Acharya et al. (2010b) find only minor variations of their results based on CDS quotes or equity returns.

[257] Using the non-synchronous daily stock market return causes a significant downward bias of calculated correlations. One possible solution to avoid this is to use high-frequency-data daily time-windows, in which all stocks are being traded. Alternatively, and we follow this convention, weekly stock returns are often used in order to mitigate synchronicity issues: see Cappiello et al. (2006), or Bekaert et al. (2008).

[258] As Datastream defines, prices taken at the close of market each trading day are adjusted for any subsequent capital actions, such as stock splits, stock dividends and rights issues.

[259] Prices are padded for days when there is no trading, but the series is not continued after going dead.

[260] Appendix B.1 contains a comprehensive breakdown of individual firms included in the sample.

[261] Although Brownlees et al. (2010) have shown that model factors can fluctuate over time, the model fit can be generally improved by choosing a wider time-window for estimating the uni- and bivariate GARCH models.

[262] All dates where only the month is given refer to the first day of that month.

[263] Comprehensive summary statistics are reported in in appendix B.1.

[264] LCFI stands for large-and-complex-financial institution. See Otker-robe et al. (2009) for a list of such financial institutions. Singular exceptions have been made because of ownership etc.

Table 9: International sample overview

Eurozone (EUR)			**Europe, not Eurozone (NEU)**			**United States (USA)**	
ABN AMRO[1]	ABN	NL	Barclays	BAR	GB	American International Group	AIG
Ageas (ex Fortis)	FOR	BE	Credit Suisse	CSG	CH	American Express	AEX
Alpha Bank	ALP	GR	Danske Bank	DAN	DK	Bank of America	BOA
Banca Monte dei Paschi	BMP	IT	DNB	DNB	NO	Bank of New York Mellon	BNY
Banco Popular Espanol	BPE	ES	Lloyds Banking Group	LLB	GB	BB&T	BBT
BBVA	BBV	ES	Nordea Bank	NOR	SE	Bear Stearns	BST
BNP Paribas	BNP	FR	Royal Bank of Scotland	RBS	GB	Capital One Financial	COF
Commerzbank	COM	DE	Svenska Handelsbanken	SVH	SE	Citigroup	CIT
Credit Agricole	CAG	FR	Swedbank	SWB	SE	Fifth Third Bank	FTG
Deutsche Bank	DEB	DE	UBS	UBS	CH	Goldman Sachs	GSG
Dexia	DEX	BE				JP Morgan Chase	JPM
Erste Group	ESG	AT				Keycorp	KEY
ING Group	ING	NL				Lehman Brothers	LEH
Intesa Sanpaolo	INT	IT				Merrill Lynch	MLL
KBC Group	KBC	BE				Metlife	MET
Natixis	NAT	FR				Morgan Stanley	MST
Santander	SAN	ES				PNC Financial Services	PNC
Societe Generale	SOC	FR				Regions Financial	REF
UBI Banca	UBI	IT				State Street	STS
Unicredit	UNI	IT				Suntrust Banks	SUN
						US Bancorp	USB
						Washington Mutual	WAM
						Wells Fargo	WEL

[1] Trading of stock terminated before November 30, 2010 (DataStream classification 'dead').

contains 53 international financial institutions which are divided into three major regional sections[265]: the Eurozone (EUR); institutions from geographical Europe but outside of the Eurozone (NEU); and lastly, US financial institutions (USA).

The separation into regional-sections allows us to study inter- as well as intra-regional trends of interdependencies. To enable focus on idiosyncratic pair-wise correlations, the international sample is controlled for the returns of national stock market indices, which allows us to exclude the systematic component of correlations. This is in line with Longin and Solnik (1995) and International Monetary Fund (2009a). Thus, the dataset is augmented with market index returns for individual stocks, which were also obtained from DataStream.

The *US sample* (table 10)[267] is constructed in reference to recent studies on measuring systemic risk conducted by Brownlees and Engle (2010) and Acharya et al. (2010b)[268]. This analogy also allows us to compare our results to these studies. The full sample consists of 90 US financial institutions, which will be distinguished in the later analysis by

[265] This division is analogue to Cappiello et al. (2006).

[266] The table reports clusters according to institutional type. The first column after the name reports the segmentation according to size (L=Large, M=Mid, S=Small). The second column reports abbreviations. One exception has been made for the type-cluster. According to DataStream classifications, Goldman Sachs should have been classified as 'Others'. Following Brownlees and Engle (2010), the institution has been classified as Broker-Dealer instead.

[267] Comprehensive summary statistics are reported in appendix B.1.

[268] The original sample used in these studies contains 94 financial institutions. However, four financial institutions (Ameriprise Financial, CBOT Holding, CIT Group, NYMEX Holdings) had to be excluded from the sample used in this analysis, because only a very limited number of observations for the relevant time period could be obtained for them. The number was too small to estimate the models applied in the later sections of this chapter. These institutions were included in the original study as it applies composite model estimations, which can also estimate models with very few observations.

Table 10: US sample overview[266]

Depositories (DEP)			**Insurance (INS)**			**Broker-Dealer (BRO)**		
Bank of America	L	BOA	AETNA	M	AET	AG Edwards[1]	S	AGE
Bank of New York Mellon	L	BNY	AFLAC	M	AFL	Bear Stearns[1]	S	BST
BB&T	M	BBT	ALLSTATE	M	ALL	Charles Schwab	M	CHS
Citigroup	L	CIT	AMBAC Financial Group	S	ABC	E-Trade Financial	S	ETR
Comerica	S	COM	American Int. Group	L	AIG	Goldman Sachs	L	GSG
Commerce Bancorp	S	CMB	AON	M	AON	Lehman Brothers	L	LEH
Hudson City Bancorp	S	HUD	ASSURANT	S	ASS	Merrill Lynch[1]	L	MLL
Huntington Bancshares	S	HUN	Berkshire Hathaway	L	BKH	Morgan Stanley	L	MST
JP Morgan Chase	L	JPM	Cigna	M	CIG	T Rowe Price	M	TRO
Keycorp	S	KEY	Cincinnati Financial	S	CIN	**Others (OTH)**		
M&T Bank	S	MTB	CNA Financial	S	CNA			
Marshall & Isley	S	MAI	Countrywide Financial[1]	S	CWF	American Capital	S	AMC
National City Bancorp[1]	M	NCB	Coventry Health Care	S	CVH	American Express	L	AEX
New York Community Banc.	M	NYC	Fidelity National[1]	S	FID	Blackrock	M	BLA
Northern Trust	S	NOT	Genworth Financial	M	GEN	Capital One Financial	M	COF
Peoples United Financial	S	PUF	Hartford Financial Ser.	M	HAR	CB Richard Ellis	S	CRE
PNC Financial	M	PNC	Health Net	S	HEN	CME Group	M	CME
Regions Financial	M	REG	Humana	M	HUM	Compass Bancshares[1]	S	COB
Sovereign Bancorp[1]	S	SOV	Lincoln National	M	LIN	Eaton Vance	S	EAT
St. Paul Bancorp[1]	S	SPB	Marsh & McLennan	M	MML	Fannie Mae	L	FME
State Street	L	STS	MBIA	S	MBI	Fifth Third Bancorp	M	FTB
Suntrust	M	SUN	Metlife	L	MET	Franklin Resources	M	FRE
Synovus Financial	S	SYN	Principal Financial	M	PRF	Freddie Mac	M	FMA
Unionbancal[1]	S	UBC	Progressive	M	PRO	H&R Block	S	HRB
US Bancorp	L	USB	Prudential	L	PRU	Intercontinental Ex.	M	IEX
Wachovia	L	WAC	Safeco[1]	S	SAF	Janus Capital	S	JAN
Washington Mutual	M	WAM	The Chubb	M	CHU	Legg Mason	S	LMA
Wells Fargo & Co.	L	WEL	Torchmark	S	TOR	NYSE Euronext	M	NYS
Western Union	M	WUN	United Health	L	UNH	sei Investments	S	SEI
Zions Bancorp	S	ZIO	Unum Group	S	UNU	slm Corp	S	SLM
			WR Berkeley	S	WRB	TD Ameritrade	M	TDA

[1] Trading of stock terminated before November 30, 2010 (DataStream classification 'dead').

their type and by the size of total assets[269].

This distinction allows us to study trends of interdependencies among US financial institutions according to their primary function (sector), or size respectively. Whereas the distinction by sectors is natural—certain activities of financial institutions are riskier than others—many recent studies of systemic risk, see e.g. De Nicoló and Kwast (2002), Brownlees (2010), and Drehmann and Tarashev (2011b), have noted a positive relationship in the size of financial institutions and their contribution to systemic risk.

Considering the statistical characteristics of the return series (table 11)[270], we easily identify standard properties of financial data. The data are generally leptokurtic with fat tails, and most sample sections show negative skewness, while only a few sections

[269] The sector of an institution is defined according to the FTA Group Level classifications from DataStream. Following Acharya et al. (2010b), we divide the included financial institutions into 'Broker-Dealer' (BRO), 'Depository' (DEP), 'Insurance' (INS) and 'Others' (OTH). Similarly, the size of an institution is determined on the basis of total assets as measured by Worldscope (field 02999). Any data not available from Worldscope was derived from Bloomberg or financial reporting documents dated before June 2007. The segmentation might not be fully accurate due to the volume of off balance sheet assets not included in the measure. However, there is no commonly accepted statistic including off balance sheet assets. By size, we cluster the sample into three sections: 19 'large' institutions (top 20% of the sample) with typically more the USD 30 billion of total assets; and, 32 'mid'-size institutions with total assets of USD 10–30 billion; lastly, 39 'small' institutions with total assets less than USD 10 billion.

[270] A comprehensive sample overview is included in appendix B.1.

Table 11: Sample summary statistics

Panel A: International sample

	Daily returns				Weekly returns			
	Full sample	**EUR**	**NEU**	**USA**	**Full sample**	**EUR**	**NEU**	**USA**
Companies	53	20	10	23	53	20	10	23
Avg. Obs.	4'763	4'432	4'778	5'044	952	886	955	1'008
Mean	1.29E-04	9.90E-05	1.66E-04	1.27E-04	6.55E-04	5.04E-04	8.61E-04	6.39E-04
Median	4.75E-04	3.43E-04	2.25E-04	2.80E-05	2.63E-03	2.15E-03	2.84E-03	2.61E-03
Std. Dev.	0.0179	0.0147	0.0165	0.0210	0.0377	0.0364	0.0392	0.0477
Skewness	-0.4652	0.0046	-0.1293	-0.7656	-0.7105	-0.6389	-1.7023	-1.0548
Kurtosis	26.00	15.00	20.81	32.25	14.26	11.08	23.50	19.24
JB[1]	53	20	10	23	53	20	10	23
LBQ[1]	53	20	10	23	50	19	9	22
Engle's LM[1]	47	20	9	18	48	18	9	21

Panel B: US sample

		Sections by type				Sections by size		
	Full sample	**BRO**	**DEP**	**INS**	**OTH**	**LRG**	**MID**	**SML**
Companies	90	9	30	31	20	19	32	39
Avg. Obs.	4'634	4'557	4'900	4'720	4'138	4'767	4'422	4'744
Mean	2.15E-05	7.63E-06	-2.02E-05	1.75E-05	9.01E-05	4.10E-05	5.08E-05	-1.15E-05
Median	3.08E-07	-1.52E-04	-4.03E-05	2.14E-04	1.48E-04	-1.57E-04	1.24E-04	1.87E-04
Std. Dev.	0.0164	0.0254	0.0180	0.0157	0.0181	0.0196	0.0166	0.0161
Skewness	-0.5227	-1.1238	-0.6135	-0.4256	-0.4768	-0.6058	-0.4776	-0.6682
Kurtosis	23.14	44.35	34.21	21.87	19.63	30.89	22.88	22.70
JB[1]	90	9	30	31	20	19	32	39
LBQ[1]	87	9	29	29	20	19	30	38
Engle's LM[1]	81	6	27	29	19	15	30	36

[1] Numbers of models for which null hypothesis was rejected at 5% significance level.

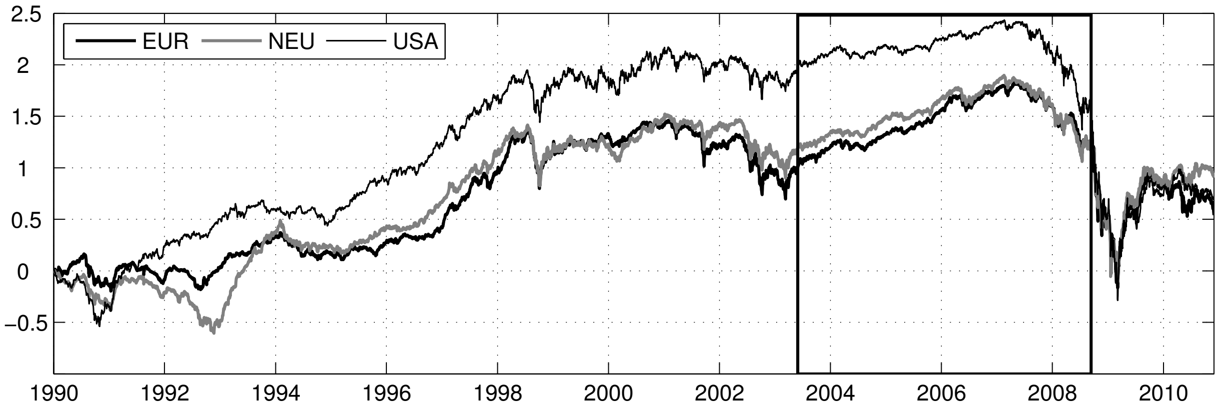
exhibit a slightly positive skewness. Looking at the data characteristics of individual institutions (appendix B.1), one can clearly distinguish those being heavily exposed in the financial crisis 2007–09. Strikingly, institutions such as AIG, Bear Stearns, Citigroup, Fannie Mae, Freddie Mac, Lehman Brothers, Morgan Stanley, Washington Mutual, etc. exhibit an extreme negative skewness and excess kurtosis due to their losses because of market turmoil.

The bottom rows of the panels report several pre-estimation tests to determine whether the GARCH methodology is applicable. All observed return series, despite singular exemptions, are highly non-normal and the Jarque-Bera test on normality can be rejected at a 1% significance level. Furthermore, the Ljung-Box-Pierce Q-test confirms a strong serial correlation in the (squared) return residuals. To test for ARCH-effects, we apply Engle's Lagrange-Multiplier test[271], which is robust to heteroscedasticity. The test generally confirms that the data exhibit volatility clustering and thus the GARCH methodology is applicable for the standardization of residual returns.

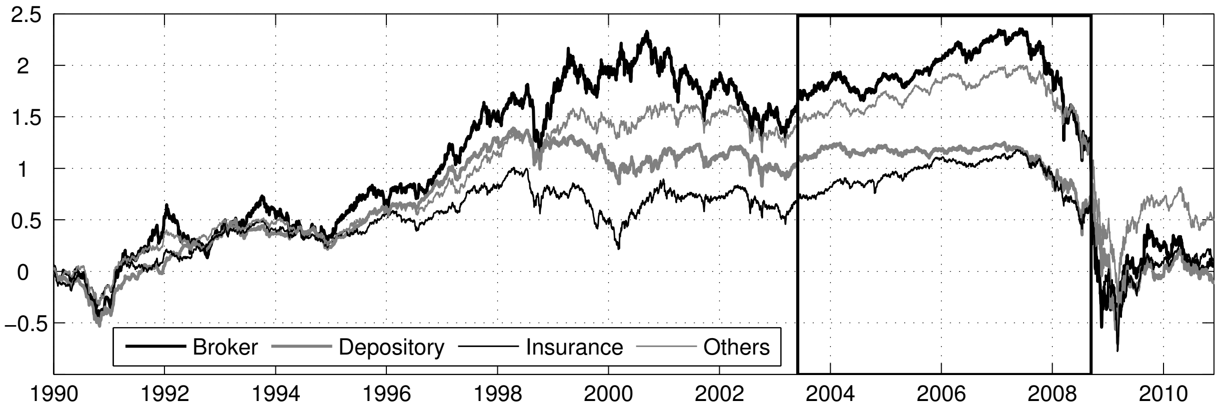
[271] Both tests are conducted for two lags, but are also largely significant for higher lag structures.

Figure 15: Cumulated median returns of samples (by sample and sections)

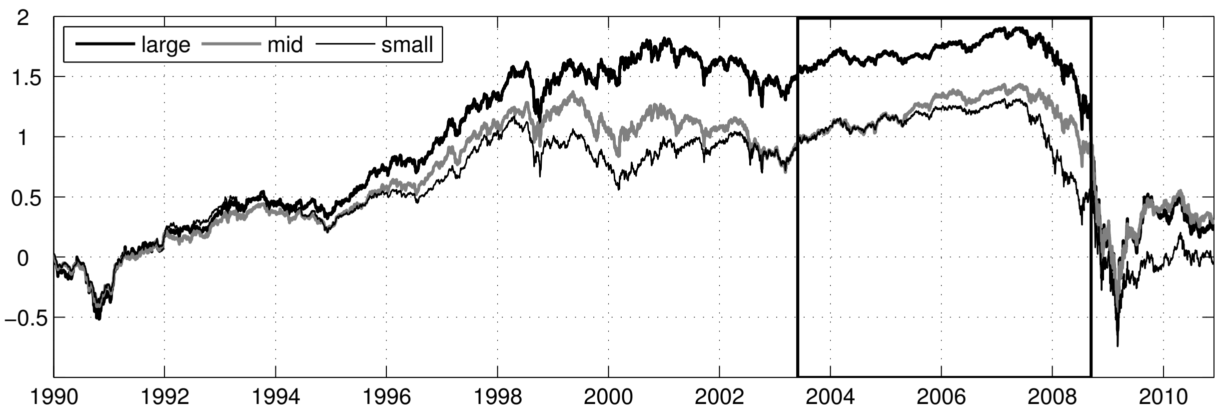
Panel A: International sample



Panel B: US sample (sections by type)



Panel C: US sample (sections by size)



The three panels of figure 15 show the cumulated (log-)returns of the two samples for the period from January 1990 to November 2010. All curves clearly show the major crises that occurred in financial markets during that period, although the impact varies for the individual sections. There is a clear dip of returns in 1998, which can be attributed to the breakdown of Long-term Capital Management (LTCM), coinciding with the Russian sovereign default and the Asian crisis. Shortly before 2002, there is another notable dip in the immediate aftermath of September 11, 2001, which is followed by bear markets as a result of the bursting New Economy bubble and the 2002–03 recession.

The marked box (June 2003 to September 2008) highlights the time-window of our analysis and begins with a relatively stable and uninterrupted path of growth, as no major events affected the benign economic environment. This trend slows significantly towards mid-2007[272] with the outbreak of the subprime crisis, and then turns into a sharp fall throughout all sections of the samples. Immediately following the end of the time-window, marked by the failure of Lehman Brothers (September 15, 2008), markets enter an even worse phase of turmoil and fall to levels even lower than 1990. With the beginning of 2009 markets show signs of a recovery.

Turning towards the sections of the international sample, the returns of European financial institutions (EUR, NEU) suggest a strong comovement. A singular exception is the period 1992–94, for which there is a distinct development due to the Scandinavian banking crisis that strongly affected the non-Eurozone section (NEU). Comparing the US and Europe, returns seem to move relatively in tandem, however, with a notably stronger performance of US financial institutions; Europe also suffered more from the 2002–03 recession. The observation of stronger dynamics for European institutions as compared with the US in the first half of the marked time-window can be attributed to the logarithmic scaling of returns.

For the US sample, the return pattern of the Broker-Dealer section is clearly distinct from the other segments. Cycles of growth and bust are stronger than in other sections and generally suggest higher volatility. This is especially conspicuous in the New Economy boom after 1999, where other sections even decline. Similarly, the dynamics of the Broker-Dealer section is distinct for the marked time-window. The increase of returns is higher than for the other sections. After the failure of Lehman Brothers, the crisis is also most pronounced in this section.

Dividing the US sample by the size of total assets there is a differentiation starting in 1995, and large institutions exhibit the strongest returns almost until the end of the sample period. In the aftermath of September 11, 2001, mid-size and small institutions show less participation in the New Economy boom. Throughout the period from mid-2003

[272] Cumulated returns peak during the period of May/June 2007.

to the onset of the subprime crisis all sections move in tandem. This comovement breaks down in early June 2007, and, after reaching the trough in early 2009, the following recovery is strongest for the mid-size and large institutions, whereas small institutions remain on the same level as 1990.

The subsequent analysis proceeds in several steps, for which methodology and, if necessary, supporting statistics are introduced at the beginning of each section. After a preliminary analysis of the data, which provides statistical support for the selection of the analysis framework (section 4.2.3), we present two approaches of analyzing interdependencies: first, we concentrate on structural breaks in the overall level of interdependencies for specific time-windows (section 4.2.4), and second, we analyze deterministic time-trends in interdependencies (section 4.2.5). We then highlight empirical insights—analogous to our systemic analysis—regarding the role of the insurance sector in the crisis (section 4.2.6), before we present our conclusions (section 4.2.7).

4.2.3 Preliminary analysis

This preliminary analysis derives time-varying correlations among the institutions in our samples. This is the basis to analyze our two hypotheses that there is evidence for an increase in the level (section 4.2.4), or the trend (section 4.2.5), of interdependencies prior to the financial crisis 2007–09. We derive correlations in a two-step procedure: (1) univariate conditional variance models are estimated for all institutions in our sample; (2) we conduct bivariate estimations of dynamic conditional correlation models for pairs of institutions. In each step, we briefly introduce the methodology, support its selection statistically, and then comment on the results.

Univariate estimation of conditional variance

In the first step, univariate GARCH models are estimated to standardize the residual returns of the individual time series by their time-varying conditional volatility. There are two important decisions to be taken when selecting the underlying model: first, one has to determine the lag structure of the model. Although a higher number of lags can increase the overall fit of the model to the data, it will reduce the estimations' significance and, therefore, implies a trade-off. Second, one has to make a choice regarding the underlying model, e.g. whether the direction of residual returns impacts volatility symmetrically or asymmetrically. Both choices can be illustrated by comparing the estimation results for the individual model structures. The maximized log-likelihood (LLF) of the estimations allows us to assess the overall fit of the model to the data, yet without accounting for the parsimony of the model description. This is included in the Akaike and Bayesian information criteria (AIC/BIC), which focus on both the optimized likelihood of the estimation as well as the number of parameters[273]. However, none of these criteria takes into account the significance of the conducted estimations, which needs to be assessed separately.

Table 12: Statistical criteria for model selection

		Int. Sample (D)[1]			**Int. Sample (W)**[1]			**US-sample**		
	(p,q)	**(1,1)**	**(2,1)**	**(2,2)**	**(1,1)**	**(2,1)**	**(2,2)**	**(1,1)**	**(2,1)**	**(2,2)**
Significance[2]	GARCH	**53/0**	46/2	3/1	**53/0**	26/4	6/4	**90/0**	70/3	18/1
	TARCH	**53/0**	43/3	9/0	**53/0**	24/5	5/2	89/0	56/6	10/2
LLF	GARCH	15'028	15'032	15'028	2'095	2'096	2'096	12'999	13'002	13'009
	TARCH	15'035	15'047	**15'049**	2'098	2'098	**2'100**	13'031	**13'035**	**13'035**
AIC	GARCH	-30'047	-30'055	-30'045	-4'182	-4'182	-4'180	-25'993	-25'997	-26'009
	TARCH	-30'060	**-30'082**	**-30'082**	**-4'186**	-4'185	-4'185	-26'055	**-26'061**	-26'057
BIC	GARCH	-30'021	-30'022	-30'006	-4'162	-4'157	-4'150	-25'973	-25'970	-25'976
	TARCH	-30'028	**-30'042**	-30'030	**-4'161**	-4'155	-4'145	**-26'028**	**-26'028**	-26'010

[1] Weekly data only apply to cross-sections of European and US financial institutions due to synchronicity issues.
[2] Number of significant model estimations at 1%/5%-levels.

Table 12 reports aggregate statistical criteria as the basis to select an adequate model for our sample[274]. It includes the medians of proforma estimations of Bollerslev (1986)'s standard GARCH and Glosten et al. (1993)'s asymmetric TARCH specification (also denoted as GJR-GARCH)[275], as well as of different lag structures (p,q)[276]. The table rows refer to the median estimation results of the GARCH/TARCH models in terms of significance, the maximized LLF, and the AIC/BIC criteria. The model specification preferred by the individual statistics is marked in bold.

It is easy to see that the asymmetric TARCH specification is generally superior to the symmetric GARCH model, especially for the US sample. This is despite that at least one further variable has to be estimated. In the context of stock market data, this result has also been confirmed by Engle and Ng (1993) and Cappiello et al. (2006)[277]. The information criteria mostly point towards a (2,1) or (2,2) lag structure, and for the international sample (W) as well as US sample, the TARCH(1,1) specification is preferred.

[273] The AIC/BIC focus on the minimal information loss and penalize less parsimonious model specifications; this is stronger for the BIC indicator. Comparing different models, the one with the minimal AIC/BIC value is preferred. As Zivot (2008) points out, GARCH(p,q) models of lower order are often preferred by AIC/BIC criteria for the reason of a higher numerical stability of the estimation results. Higher order GARCH(p,q) processes often exhibit several local maxima and minima.

[274] The detailed results for all data series can be found in appendix B.2.

[275] As Bollerslev (2008) and similarly Zivot (2008) point out, the TARCH specification is very close to other asymmetric specifications, such as Threshold GARCH models by Rabemananjara and Zakoian (1993) or EGARCH specifications. However, it must not be confused with the GARCH-t (also t-GARCH) specification, which is not asymmetric, but instead allows standardized residuals to belong to a t-distribution exhibiting fatter tails compared to other GARCH models.

[276] For the standard GARCH(1,1) model, three variables are estimated for the US sample and an additional variable in the return equation for the international sample. The TARCH(1,1) description contains leverage as an additional variable to be estimated. For higher lag structures the number of variables increases to a maximum of 9 for the international sample; if two lags of residuals are included in the variance equation, the TARCH model requires the estimation of two leverage variables.

[277] With a different methodological setup, Campbell and Hentschel (1992) obtain similar results. For bond returns, asymmetric specifications seem to be more adequate; see also Cappiello et al. (2006).

As these criteria do not account for the significance of model estimations[278] we must also consider the column which emphasizes the trade-off for lag structures higher than (1,1). As the initial univariate models are the basis for the subsequent bivariate estimations, we weight the robustness of estimations and then choose a TARCH(1,1) specification[279].

The *return model* of the TARCH(1,1) specification is defined in comparison to the standard GARCH specification in equation (4.1)[280]. For returns in the international context, regressions are controlled for national stock market returns and therefore the return equation is augmented with the respective national stock market index return, denoted as $r_{index_i,t}$, an explanatory variable. This extension is analogous to Longin and Solnik (1995) and the International Monetary Fund (2009a), who include a number of explanatory variables in the univariate models[281].

$$\begin{array}{ll} \text{General:} & r_{i,t} = c_i + \varepsilon_{i,t} \\ \text{International:} & r_{i,t} = c_i + \delta\, r_{index_i,t} + \varepsilon_{i,t} \end{array} \tag{4.1}$$

where $r_{i,t}$ denotes the log-return from our data series, which consists of a constant c_i and uncorrelated white noise disturbance $\varepsilon_{i,t}$, which we refer to as return residuals. It is assumed that $\varepsilon_{i,t} \sim$ TARCH(1,1)[282]. Thus, the variance equation (4.2) includes the first lag of squared return residuals ($\varepsilon^2_{i,t-1}$, ARCH) and the first lag of the conditional variance ($\sigma^2_{i,t-1}$, GARCH). The leverage variable γ_i of the TARCH specification allows us to consider asymmetric news effects on conditional variance, as analyzed in depth by Engle and Ng (1993).

The asymmetric specification of return residuals in the variance model follows from the observation that variance exhibits larger increases following bad rather than positive news. In the literature, this effect has been attributed predominantly to two effects: the leverage effect framed by Black (1976) and Christie (1982) suggests that volatility increases due to a higher debt-to-equity ratio following a negative shock; alternatively, Campbell and Hentschel (1992) point out that the asymmetric impact on volatility derives

[278] Focusing on the LLF results, one can also compare the individual lag structures by running likelihood ratio tests between the different structures with one, to compare the (1,1) and (2,1) specifications or 3 degrees of freedom; for the (1,1) and (2,2). This test confirms a better fit of the a higher lag structure, at the 5%-level, for roughly two-thirds of the international sample and half of the US sample. Yet, it neither accounts for the significance of the estimations nor the parsimony of the model specification.

[279] Furthermore, it can be seen from the table, that the distance to the TARCH(2,1) model in terms of AIC/BIC is relatively low and the additional information loss appears to be tolerable.

[280] Where necessary, variables are indexed by i to reference the i-th stock of the portfolio and t denoting time.

[281] A more general extension of the return equation is shown in Zivot (2008). Longin and Solnik (1995) include additional explanatory variables such as interest rates, etc., in the regressions. As the model fit in our analysis did not improve significantly upon the inclusion of further variables, these were excluded for reasons of a parsimonious model specification. Pukthuanthong and Roll (2009) point out that controlling for exogenous factors might cause a downward bias in correlation, due to the cross-sectional spread in factor loads of the explanatory term. However, as the cross-sectional spread of factors is constant, so should be the potential bias. Thus, we would still be able to document increases of correlations as indications for higher interdependencies and systemic risk.

[282] Because $\varepsilon_{i,t} \sim (0, \sigma_{r_{i,t}})$ the constant $c_i = \mu_{r_{i,t}}$ in equation (4.1).

from feedback effects. As a response to the initial volatility effect of a negative shock, risk premiums on stocks may increase and thus induce additional volatility[283].

In the first round of univariate estimations, residuals are standardized by their conditional volatility, so that $\varepsilon_{i,t} = \sigma_{i,t}\, z_{i,t}$ where the $z_{i,t} \sim (0,1)$, or standard Gaussian[284]. The *variance model* in the asymmetric TARCH(1,1) specification requires the estimation of three factors (α_i, β_i and γ_i) and is given as

$$\sigma_{i,t}^2 = w_i + (\alpha_i + I_{i,t-1}\,\gamma_i)\,\varepsilon_{i,t-1}^2 + \beta_i\,\sigma_{i,t-1}^2\ , \text{ where } I_{i,t} = \begin{cases} 0 & ; \varepsilon_{i,t} \geq 0 \\ 1 & ; \varepsilon_{i,t} < 0 \end{cases} \tag{4.2}$$

$I_{i,t}$ is a dummy variable that refers to the leverage effect and only takes a value of one if the return residual is negative[285]. Due to the constraint that $\alpha_i + \gamma_i/2 + \beta_i \leq 1$ conditional variances will be mean-reverting, or follow an integrated process[286], and the variance will fluctuate around the squared root of the unconditional variance $\sigma_i^2 := w_i/(1-\alpha_i - \gamma_i/2 - \beta_i)$.

For comparing the characteristics of individual GARCH processes—in both a uni- and multivariate setting—there are two relevant ratios, which will be referred to throughout the subsequent analysis. The *persistence* (of the i-th process), defined as $\pi_i = \alpha_i + \gamma_i/2 + \beta_i$, determines the dependence on the idiosyncratic variance evolution. For higher values of π_i, shocks to idiosyncratic variance will lead to a higher and slower reversal pattern of variance. Furthermore, the *smoothness*, defined as $\lambda_i = (\alpha_i + \gamma_i/2)/(\alpha_i + \gamma_i/2 + \beta_i)$, describes the roughness of the volatility path. For higher values of λ_i, the impact of shocks to idiosyncratic variance increases.

Table 13 summarizes the estimation results for the univariate TARCH(1,1) models. Panel A reports the results for the international sample (for weekly and daily observations) and panel B for the US sample (grouped by type and size respectively). The first rows of the individual panels show the number of models in each group, where all estimated factors are statistically significant at the 5%-level[287], as well as the median of the maximized

[283] Empirical studies, e.g. Bekaert and Wu (2000), have tried to disentangle the two effects empirically. Their study shows that one factor alone cannot explain the changes in volatility. Moreover, it has to be noted that the leverage effect obviously only applies to stock markets (equity) and not to bonds.

[284] As Cappiello et al. (2006) point out, while heteroscedastic return series can exhibit skewness and fat-tails, returns standardized by their estimated conditional standard deviation will be close to a normal distribution.

[285] The logical indicator $I_{i,t}$ allows conditional volatility to additionally increase by a factor of $\gamma_i\,\varepsilon_{i,t-1}^2$ upon negative news. Though it is a general constraint that all estimated factors have to be positive (or zero), only for the leverage factor is it defined that $\alpha_i + \gamma_i \geq 0$ and therefore γ_i can take negative values.

[286] A GARCH process is denoted as integrated if $\alpha_i + \gamma_i/2 + \beta_i = 1$. The fact that γ_i is divided by 2 in the equation derives from the assumption that $\varepsilon_{i,t}$ is normal and thus symmetric.

[287] The reported statistics show that the estimated models are statistically significant, with one single exception in the US sample: for the US-insurer Assurant the estimation of the ARCH coefficient failed as the time series is very short with only 1'777 observations and variance increased extremely in consequence of the crisis. As the company is small, the effect of its exclusion from further analyses can be assumed to be negligible.

Table 13: Sample statistics for univariate variance estimations (TARCH)

Panel A: Statistics for international sample

	Daily returns				Weekly returns			
	Full sample	**EUR**	**NEU**	**USA**	**Full sample**	**EUR**	**NEU**	**USA**
Significant	53/53	20/20	10/10	23/23	51/53	20/20	9/10	22/23
LLF	15'035	15'280	13'849	15'085	2'098	2'157	2'016	2'094
w^1	1.66E-06	1.78E-06	1.73E-06	1.52E-06	2.26E-05	2.07E-05	1.80E-05	2.75E-05
α^1	0.0541	0.0563	0.0749	0.0497	0.0693	0.0730	0.0552	0.0698
β^1	0.9302	0.9187	0.9244	0.9355	0.8780	0.8615	0.8918	0.8922
γ^1	0.0284	0.0141	0.0201	0.0337	0.0764	0.0914	0.0929	0.0565
Persistence[2]	0.9978	0.9947	0.9948	0.9992	0.9918	0.9880	0.9960	0.9919
Smoothness[2]	0.0688	0.0718	0.0728	0.0645	0.1126	0.1234	0.0981	0.1015

Panel B: Statistics for US sample

		Sections by type				Sections by size		
	Full sample	**BRO**	**DEP**	**INS**	**OTH**	**LRG**	**MID**	**SML**
Significant	89/90	9/9	30/30	30/31	20/20	19/19	32/32	38/39
LLF	13'031	11'734	13'898	13'386	12'802	13'483	12'927	13'278
w^1	4.13E-06	3.89E-06	3.51E-06	4.07E-06	6.71E-06	2.87E-06	4.37E-06	6.25E-06
α^1	0.0373	0.0229	0.0422	0.0439	0.0335	0.0228	0.0370	0.0469
β^1	0.9216	0.9426	0.9241	0.9119	0.9264	0.9425	0.9212	0.9130
γ^1	0.0611	0.0555	0.0537	0.0682	0.0539	0.0644	0.0649	0.0548
Persistence[2]	0.9946	0.9975	0.9956	0.9940	0.9925	0.9986	0.9935	0.9921
Smoothness[2]	0.0718	0.0550	0.0703	0.0839	0.0627	0.0550	0.0709	0.0792

[1] Median of estimated variable according to equation (4.2). Excludes estimations not significant at 5% level.
[2] Median of model persistence $\pi_i = \alpha_i + \gamma_i/2 + \beta_i$. Median of model smoothness $\lambda_i = (\alpha_i + \gamma_i/2)/(\alpha_i + \gamma_i/2 + \beta_i)$.

LLF[288]. The following rows of panels report the medians of the four variables that were estimated for each group, according to equation (4.2). The bottom rows report the median results of model persistence π and smoothness λ.

Test results for model misspecifications are reported in appendix B.3[289]. The Jarque-Bera test indicates that the standardized residuals $z_{i,t}$ are still non-normal, which is similar to the results of other studies, such as Cappiello et al. (2006). Yet, the standardized residuals are much closer to a standard Gaussian distribution for the vast majority of estimated models. They exhibit less negative skewness and a close-to-normal kurtosis. Engle's LM-test on ARCH effects fails to reject the null hypothesis of no ARCH effects for most of the series.

For the international sample, the medians of the estimated variables show that the leverage effect γ is strongest in the US, while shocks have a more symmetric impact

[288] The LLF-values are lower for those models estimated based on weekly observations, because fewer observations were available for the estimations and, hence, reduce the overall fit of the models. The fact that the estimated LLFs for the US sample are lower than the values reported for the international sample might be attributed to the higher number of time series with a relatively low number of observations in the US sample.

[289] A comprehensive reference and description of available tests can be found in Bauwens et al. (2006) as well as Zivot (2008). One simple method we apply is to run similar diagnostics on the standardized residuals $z_{i,t}$ as they were reported on the original data.

on volatility on European financial institutions (EUR, NEU), as the higher values of α suggest. Moreover, the impact of residual returns is stronger in European institutions, where the smoothness λ is higher than in the US. Similar to Zivot (2008)'s observation, our analysis also exhibits the stylized fact that model persistence π increases parallel to trading frequency and, therefore, is higher for daily observations. All models are very close to integrated GARCH processes[290].

Comparing the individual sections, the data of the US sample show that leverage is obviously lowest in the Broker-Dealer group. Distinguishing institutions by size, leverage also tends to be lower for small financial institutions and increases with size; this is also observed by Brownlees (2010). Whereas a similar observation applies to the estimated α (ARCH) of the Broker-Dealer group, the impact of lagged residuals on volatility is larger for small institutions and relatively symmetric; compare medians of estimated α and smoothness λ. The persistence of shocks to volatility obviously increases with size and, from the sector perspective, shows the highest levels for the Broker-Dealer group. However, as was observed in the international sample, all estimated models are close to an integrated process as the values of π being close to 1 show.

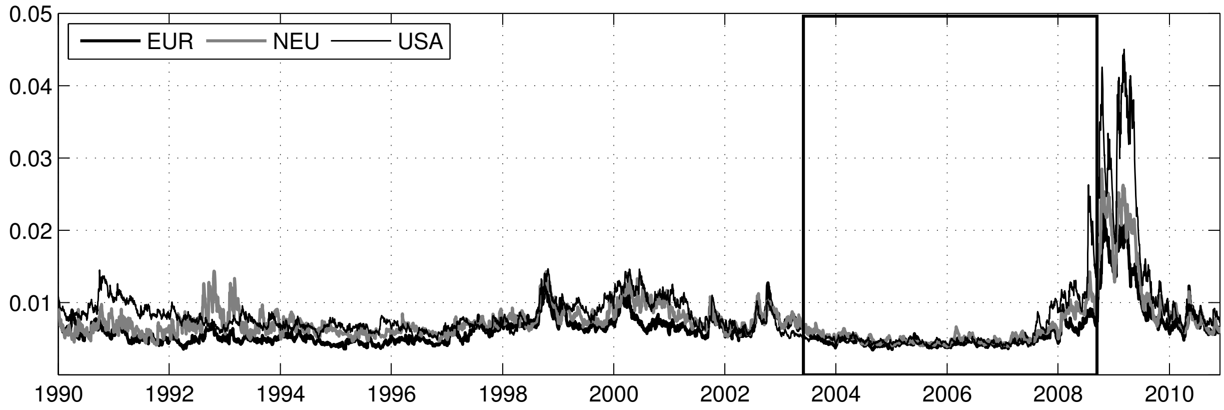
The three panels of figure 16 display the section-wise medians of conditional time-varying volatilities derived from the estimated TARCH(1,1) models. The highlighted box marks the time-window of our analysis. Unlike the cumulated median returns for the different sections (figure 15), conditional volatility does not show a similarly clear distinction and is sometimes hard to distinguish. However, some stylized facts are worthwhile noting: looking at the international sample (Panel A) one can find comparable crises outliers as they were described in the previous section. This underpins the general observation that volatility generally increases in times of crisis and these effects are even emphasized by the asymmetric model specification.

Towards the end of 1990 there is a spike in volatility in US financial institutions, which coincides with the first indications of an economic downturn prior to the recession in the US from July 1990 to March 1991. Furthermore, the Iraq invasion of Kuwait and consequent spikes in commodity prices plus other factors, added to the volatility in US markets, while reactions throughout Europe were less severe. Between 1992–94 volatility of European financial institutions from outside the Eurozone (NEU) increased due to the Scandinavian banking crisis. The general spikes around 1997–98 as a result of the Asian crisis, Russian default and breakdown of Long-term Capital Management (LTCM), as

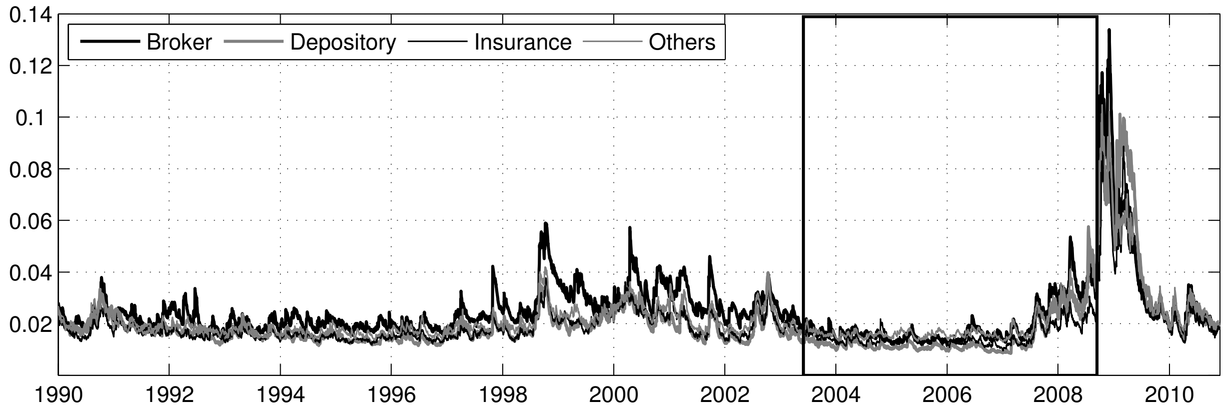
[290] As Engle (2001) points out, such integrated GARCH processes are applied for Value-at-Risk (VaR) calculations by RiskMetrics. Most studies, see e.g. Bekaert et al. (2009), find no permanent shifts of idiosyncratic volatility. Instead, shifts seem to be temporary and might also be described by a stationary mean-reverting process, which occasionally—e.g. in times of crises—shifts to a higher-mean, higher-variance regime. Bekaert et al. (2009) analyze these shifts by means of a Markov-Switching model, as it is also applied in Nowak et al. (2009), in order to endogenously determine the onset of the financial crisis.

Figure 16: Median conditional volatility of samples (by according sections)

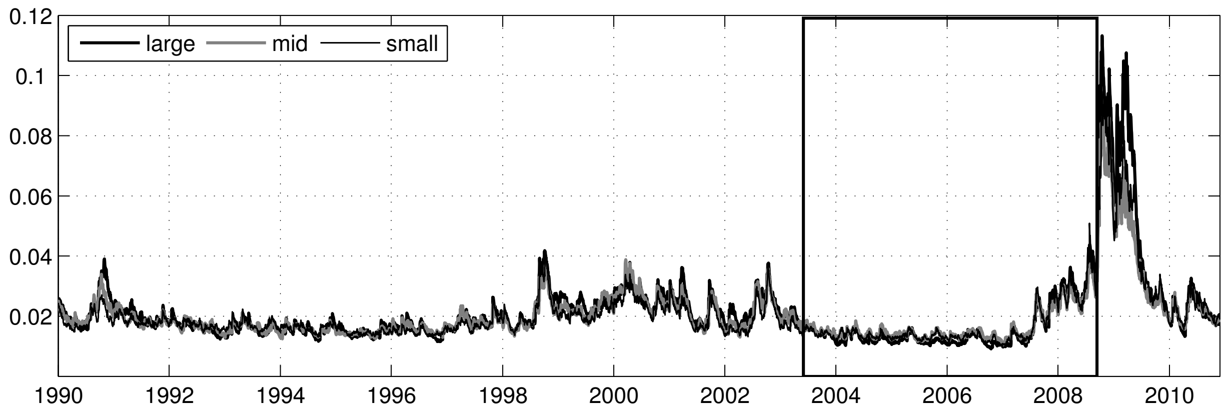
Panel A: International sample



Panel B: US sample (by type)



Panel C: US sample (by size)



well as the bust of the bubble in the New Economy, were most pronounced in the US, a phenomenon not unlike the much higher volatility in US markets following the failure of Lehman Brothers. The period from June 2003 to September 2008 exhibits an initial phase of very low volatility, for which the curves almost fully overlap. Only from the second half of 2007 does volatility start to increase sharply, eventually peaking after the failure of Lehman Brothers.

Regarding the volatility in the US sample for functional sections (Panel B), the Broker-Dealer group seems to be most exposed to jumps in conditional volatility, as it shows the strongest increases for the above-mentioned periods. This seems reasonable due to the fact that this group is comprised of the major US investment banks. Furthermore, the group is relatively small, containing only nine institutions, which leads to a smoothing of the dynamics by other individual institutions less exposed to market dynamics. However, there is almost no distinction in conditional volatilities in terms of size (Panel C), as the curves move close to each other.

Bivariate estimation of dynamic conditional correlations

As a second step, we estimate conditional correlations between pairs (i,j) of financial institutions. Table 14 shows the results of the Engle and Sheppard (2001) DCC-GARCH test, which is conducted to determine whether the dynamic conditional correlation (DCC-GARCH) specification outlined by Engle (2002)[291] is applicable. Engle (2002) shows that the DCC-GARCH model specification provides a very good approximation to a variety of time-varying correlation processes and is, in most cases, more accurate than other possible specifications[292]. Other advantages include the simple two-step estimation process based on the maximum likelihood, as well as the consistency between univariate and bivariate estimations[293].

Table 14: Results of test for DCC-GARCH specification

		Number of models for which H_0 was rejected (Significance level)				
	Models	*** (1%-level)	** (5%-level)	* (15%-level)	not rejected	time[1]
Int. Sample (D)[2]	688	598	27	20	43	0
Int. Sample (W)[2]	690	205	124	113	248	0
US-Sample	4'005	3'903	23	15	19	45

[1] Number of models dropped because overlap of time series too short.
[2] Only cross-sections between European and US financial institutions based on weekly (W) return series.

[291] Engle and Sheppard (2001) propose a prior version of this model.

[292] He compares the DCC-GARCH model to several other multivariate GARCH specifications, such as the Orthogonal, or principle component GARCH, as well as the scalar and diagonal BEKK GARCH. For a detailed analysis see Engle (2002), p. 6 sqq.

[293] For an overview of the many different model specifications, see Bollerslev (2008), Engle et al. (2008), or Silvennoinen and Teräsvirta (2008).

The test procedure requires only a consistent estimate of the Bollerslev's constant conditional correlation coefficient and can be implemented using a standard vector autoregression with two lags[294]. The results confirm that almost all pairs of the two samples exhibit dynamic correlations, and the null hypothesis (H_0) of constant correlation can be rejected[295].

Although Cappiello et al. (2006), with a dataset of global stock and bonds indexes, present a case for an asymmetric DCC model specification, this would significantly affect our estimations as a vast share would be rendered insignificant. Furthermore, the improvement in estimation results under the asymmetric specification is mostly not substantial for the remaining significant models[296].

A similar argument applies to the choice of the lag structure. It has to be noted that the amount of observations to which the model can be adjusted is generally lower than for the univariate estimations, because we use pairs of institutions for which the available observations do not always fully overlap. This already has an adverse effect on the estimation results. The parsimony of the model description is also quite important for the subsequent tests for structural breaks in mean. Therefore, we apply a symmetric DCC-GARCH(1,1) specification.

The DCC-GARCH(1,1) process models the time-varying correlation matrix denoted as $P_{ij,t}$ indirectly, by calculating a positive-definite pseudo correlation matrix $Q_{ij,t}$. See equation (4.4) below, which is then transformed into the *correlation matrix* $P_{ij,t}$ by defining[297]

$$P_{ij,t} = \mathrm{diag}(Q_{ij,t})^{-\frac{1}{2}}\, Q_{ij,t}\, \mathrm{diag}(Q_{ij,t})^{-\frac{1}{2}} \tag{4.3}$$

In order to ensure consistent estimates, the pseudo correlation matrix $Q_{ij,t}$ is formulated according to the cDCC-GARCH specification proposed by Aielli (2009), which is an adaptation of the standard DCC-model and offers an estimation procedure that is meaningful for all parameter specifications. Thus, it ensures consistent estimation results. For simplicity we will subsequently drop the distinction between the cDCC and DCC-specifications and consistently use the term DCC, while implying the Aielli-correction.

[294]The test hypothesis is generally similar to the tests proposed by Tse (2000) as well as the Bera and Kim (2002)'s information matrix-test, as it aims to reject the null hypothesis (H_0) of constant correlation. However, Engle and Sheppard (2001)'s test is generally more robust for different characteristics of the data.

[295]The only exception is the weekly cross-sections in the international sample between European and US financial institutions, where one third of the models does not reject the constant correlation hypothesis at a 15% significance level, or because there are too few observations available. Still, roughly half of the data series rejects the null hypothesis of constant correlation at the 5% level.

[296]As for the univariate models, there is a trade-off between the additional factor to be estimated and the increase in the maximized LLF of the estimated model. Whereas some studies cited in Cappiello et al. (2006) document an increase in correlation in a (negative) bear-market environment, this was not the case for our sample; see also Brownlees and Engle (2010). Furthermore, there will be an effect on market volatility.

[297]The $\mathrm{diag}(Q_t)$ operator refers to a matrix similar to Q_t, where all non-diagonal elements are set to zero.

Contrary to the univariate models, the bivariate specification is symmetric and, in scalar form, the *pseudo correlation matrix* is derived as

$$Q_{ij,t} = (1 - \alpha_{ij} - \beta_{ij})\, \bar{Q}_{ij} + \alpha_{ij}\, z^{\star}_{ij,t-1} z^{\star'}_{ij,t-1} + \beta_{ij}\, Q_{ij,t-1} \tag{4.4}$$

where $\bar{Q}_{ij}$ is the unconditional correlation matrix of the time-vectors of residuals z_i and z_j and similar to Bollerslev (1990)'s constant conditional correlation matrix. Moreover, $z^{\star}_t = z_t \sqrt{q_{ii,t}}$, where $q_{ii,t}$ refers to the diagonal element of the pseudo correlation matrix $Q_{ij,t}$[298]. Like the univariate specification of conditional variance, the estimated factors of the dynamic correlation model are by definition $\alpha_{ij} + \beta_{ij} \leq 1$ as well as $\alpha_{ij} \geq 0$ and $\beta_{ij} \geq 0$. Consequently, the process is again mean-reverting for the vast majority of estimation results or denoted as integrated if $\alpha_{ij} + \beta_{ij} = 1$. The measures of π_{ij} and λ_{ij} for persistence and smoothness are applied comparably to the univariate specification.

We estimate dynamic conditional correlations for each pair of financial institutions of our samples. In total, this is a maximum of 1'378 bivariate models for the international sample and 4'005 models for the US sample. As the return series for both institutions do not always fully overlap, the estimations are conducted with varying time-windows, for which returns of both institutions are available. We exclude those models from the later analysis, where the applicable time-window for estimations is shorter than the duration of the time-windows of our analysis, as defined in the previous section (24 months, appr. 500 observations)[299]. All model estimations where the estimated factors do not reach at least a 15% significance level are also excluded from further analysis.

Table 13 exhibits estimation results for all cross-sections of the samples[300]. The initial columns report the statistical significance of the models at the conventional limits. Overall, less than a fifth of estimated models in each subgroups had to be excluded, since estimations were either insignificant or the overlap of the time series was too short. Estimations of cross-sections between European and US financial institutions in the international sample pose an issue, which is a direct consequence of the weekly returns used to estimate these models to deal with potential synchronicity issues.

Looking at the estimated factors, the panels also report the 10% and 90% quantils of the estimations. As one would expect, the reported values are generally close to 0.01

[298] Because $Q_{ij,t}$ is a pseudo (non-standardized) correlation matrix, all diagonal elements are equal, though not necessarily equal to 1.

[299] It has to be noted, though, that for most of these models the estimated factors were largely insignificant anyway.

[300] The toolkit for formally evaluating the estimated DCC-GARCH models is relatively sparse, especially compared to the broad range of tests available for univariate models. As Silvennoinen and Teräsvirta (2008) point out, most of the numerous general misspecification tests apply only to univariate GARCH models and yet there have been no specific tests to evaluate the fit of dynamic conditional correlation GARCH models. Another issue that is pointed out by Zivot (2008) is the numerical accuracy of results; both in univariate and multivariate settings. Because the likelihood function has a multitude of local maxima, there might be slight variations resulting from different parametrization and estimation logarithms being used. However, the impact of such variations is only marginal and can thus be neglected.

Table 15: Sample statistics of bivariate model estimations (DCC-GARCH)

Panel A: Statistics for international sample

		Significance[1]			Estimated parameters[2]							
		***/**/*	dropped	LLF	α_{Q10}	α_{med}	α_{Q90}	β_{Q10}	β_{med}	β_{Q90}	Persist.	Smooth.
EUR	EUR	44/54/48	44/0	5'939	0.0034	**0.0083**	0.0206	0.8972	**0.9786**	0.9954	0.9901	0.0084
EUR	NEU	52/60/47	41/0	6'290	0.0030	**0.0061**	0.0189	0.8762	**0.9889**	0.9959	0.9955	0.0061
EUR	USA	24/57/107	178/94	617	0.0066	**0.0139**	0.0416	0.7125	**0.9700**	0.9874	0.9800	0.0145
NEU	NEU	14/18/8	5/0	5'695	0.0032	**0.0070**	0.0172	0.9589	**0.9888**	0.9962	0.9961	0.0070
NEU	USA	8/37/57	128/0	515	0.0078	**0.0160**	0.0387	0.7813	**0.9534**	0.9832	0.9703	0.0167
USA	USA	119/69/43	22/0	6'798	0.0048	**0.0108**	0.0230	0.9261	**0.9811**	0.9917	0.9924	0.0108

Panel B: Statistics for US sample

		Significance[1]			Estimated parameters[2]							
		***/**/*	dropped	LLF	α_{Q10}	α_{med}	α_{Q90}	β_{Q10}	β_{med}	β_{Q90}	Persist.	Smooth.
Cross-sections by type												
BRO	BRO	15/11/9	1/0	4'407	0.0135	**0.0191**	0.0315	0.9637	**0.9789**	0.9858	0.9981	0.0191
BRO	DEP	124/64/46	33/3	5'270	0.0105	**0.0181**	0.0259	0.9625	**0.9764**	0.9879	0.9963	0.0181
BRO	INS	123/72/48	36/0	4'461	0.0081	**0.0132**	0.0220	0.9517	**0.9784**	0.9876	0.9932	0.0132
BRO	OTH	73/53/31	22/1	3'559	0.0093	**0.0152**	0.0221	0.9549	**0.9812**	0.9879	0.9962	0.0153
DEP	DEP	217/79/76	59/4	6'700	0.0102	**0.0156**	0.0233	0.9688	**0.9802**	0.9876	0.9971	0.0156
DEP	INS	336/257/186	134/17	5'914	0.0065	**0.0107**	0.0186	0.9653	**0.9831**	0.9911	0.9953	0.0108
DEP	OTH	201/188/118	75/18	4'683	0.0081	**0.0133**	0.0199	0.9650	**0.9821**	0.9891	0.9956	0.0133
INS	INS	142/167/95	61/0	5'270	0.0069	**0.0113**	0.0206	0.9580	**0.9819**	0.9910	0.9942	0.0116
INS	OTH	212/179/132	96/1	4'070	0.0060	**0.0101**	0.0156	0.9700	**0.9862**	0.9922	0.9966	0.0101
OTH	OTH	57/56/52	24/1	2'937	0.0072	**0.0108**	0.0168	0.9667	**0.9854**	0.9906	0.9969	0.0110
Cross-sections by size												
LRG	LRG	64/18/7	2/0	6'174	0.0145	**0.0198**	0.0262	0.9571	**0.9696**	0.9787	0.9907	0.0200
LRG	MID	217/133/107	53/8	5'437	0.0101	**0.0168**	0.0242	0.9583	**0.9738**	0.9859	0.9931	0.0168
LRG	SML	280/149/65	48/4	5'918	0.0079	**0.0127**	0.0190	0.9691	**0.9822**	0.9893	0.9962	0.0128
MID	MID	186/174/157	140/9	3'876	0.0079	**0.0141**	0.0233	0.9440	**0.9789**	0.9894	0.9944	0.0141
MID	SML	491/407/315	210/20	4'927	0.0072	**0.0115**	0.0194	0.9646	**0.9832**	0.9905	0.9959	0.0117
SML	SML	262/245/142	88/4	5'481	0.0061	**0.0099**	0.0147	0.9780	**0.9872**	0.9926	0.9979	0.0099

[1] Models significant at ***=1% / **=5% / *=15% levels. Models dropped because insignificant / short time frame.
[2] Median and quantiles of significant parameter estimations according to equation (4.4).

for α and to 0.97 for β. These estimates can be regarded as an overall average for GARCH models in financial time series and have been confirmed by the majority of studies. The persistence of the model estimations shows, as do to the univariate estimations, that all models are close to integrated DCC-GARCH processes.

For the international sample, the dynamics of weekly (EUR–USA, NEU–USA) and daily models (all other cross-sections) do not allow a direct comparison because, generally, weekly estimations exhibit a less persistent and rougher description. As the quantiles show, the variation of model descriptions is much higher for the weekly return series. Comparing the daily models, one can note that the USA–USA cross-section describes a more volatile path of correlation, where the smoothness measure is higher than for the European cross-sections.

Looking at the US sample, it is interesting that the estimated models, especially within the Broker-Dealer group and the cross-section between Broker-Dealers and Depository Institutions, exhibit a rougher—that means more volatile—correlation path, as compared to the rest of the sample. This is a consequence of the higher smoothness of the estimated models. Likewise, the cross-sections of US financial institutions differentiated by size suggest that the roughness of correlation models increases with the size of the institutions (the value λ increases), while the persistence of the DCC-GARCH process decreases slightly.

Figures 17, 18 and 19 show excerpts of median correlation dynamics during the analysis time-window for all cross-sections of the two samples. As in our systemic analysis, we focus on correlations for the period of 48 months before the onset of the financial crisis 2007–09—determined as June 1, 2007 according to Aït-Sahalia et al. (2009)— and the dynamics of conditional correlations until the failure of Lehman Brothers on September 15, 2008. Within the international sample, the generally low level of correlations is striking, especially when compared to the US sample. This observation can be attributed to the fact that returns were conditioned on market returns in the univariate return equation (4.1), as an explanatory variable[301].

One feature that can be identified in both samples is the dramatic increase of conditional correlations after the start of the financial crisis, from June 2007 onwards. This event coincides with spikes in conditional volatilities of the univariate model estimations that were also observed starting mid-2007 (figure 16, page 155). Furthermore, it parallels the peak of cumulated median returns of the sample groups (figure 15, page 147). Such increases of correlations in a bearish market environment have been documented by many studies, e.g. Longin and Solnik (2001) and Kannan and Köhler-Geib (2009)[302], who analyze the extent of contagion and spillover effects in times of crises for a variety of contexts.

The correlations in the international sample indicate strong parallels with the dynamics between the individual cross-sections, in contrast to the US sample, which exhibits more variation. It demonstrates that correlation dynamics between Broker-Dealer institutions in the US sample show a significantly different picture when compared to the other curves (figure 18). First of all, the median correlations are on a much higher level than for the other cross-sections. This observation is similar for the cross-section of large US-institutions (figure 19).

[301] Comparing the lower correlation level of the US cross-section in the international sample with the average correlations of the larger US sample, one might attribute the difference to the criticism of Pukthuanthong and Roll (2009), who point out that due to different factor loads in an excess return model the correlation measure can exhibit a downward bias. However, one could also conclude that correlation in the US is to a large extent driven by overall market dynamics. An exclusion of the return variables from the return model of the international sample would generally increase the level of correlations, while at the same time increasing its variance.

[302] See also the notes in Cappiello et al. (2006) regarding analyses that document an increase in correlation in a (negative) bear-market environment as well as the references in section 2.2.3.

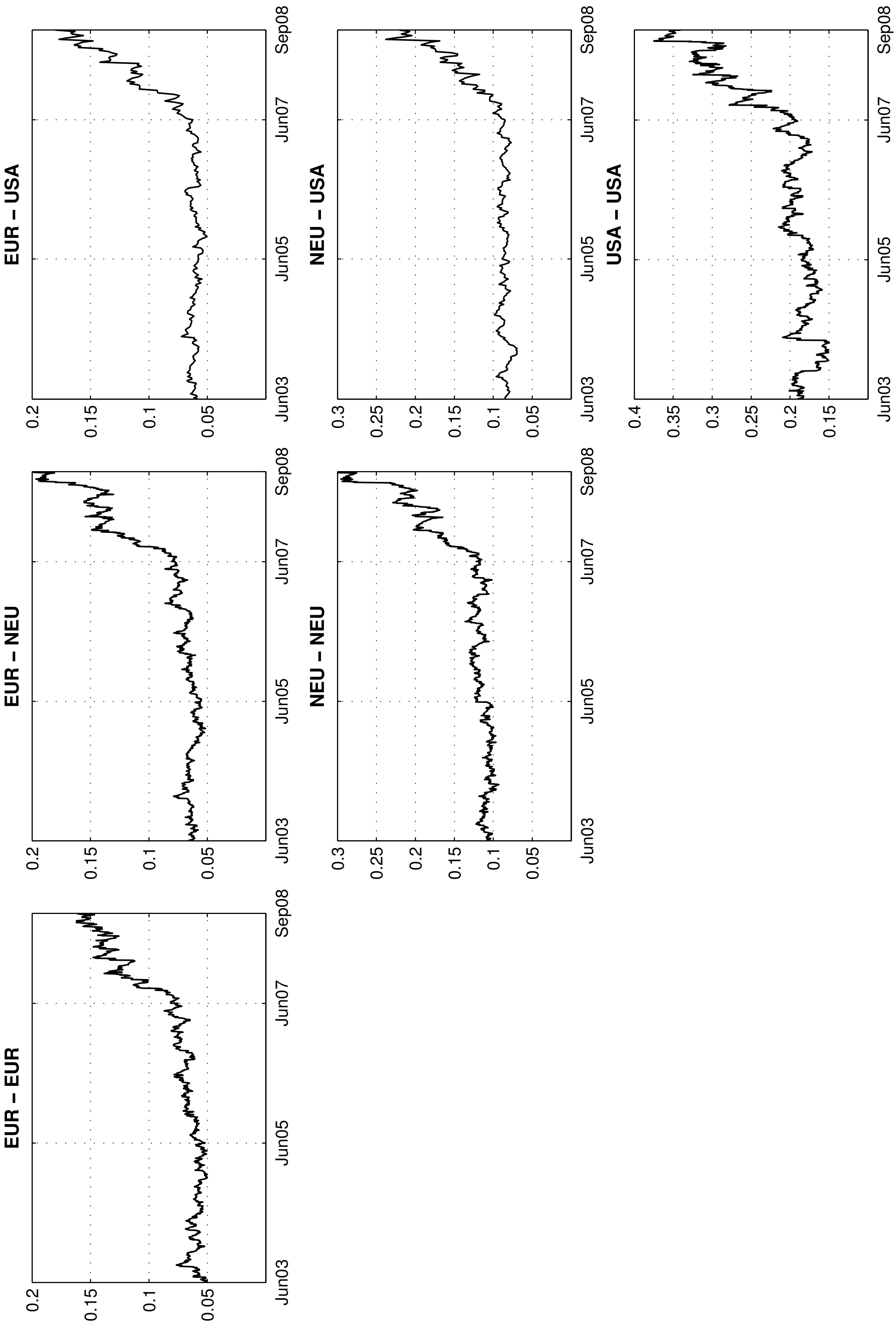


Figure 17: Dynamic conditional correlations for cross-sections of international sample

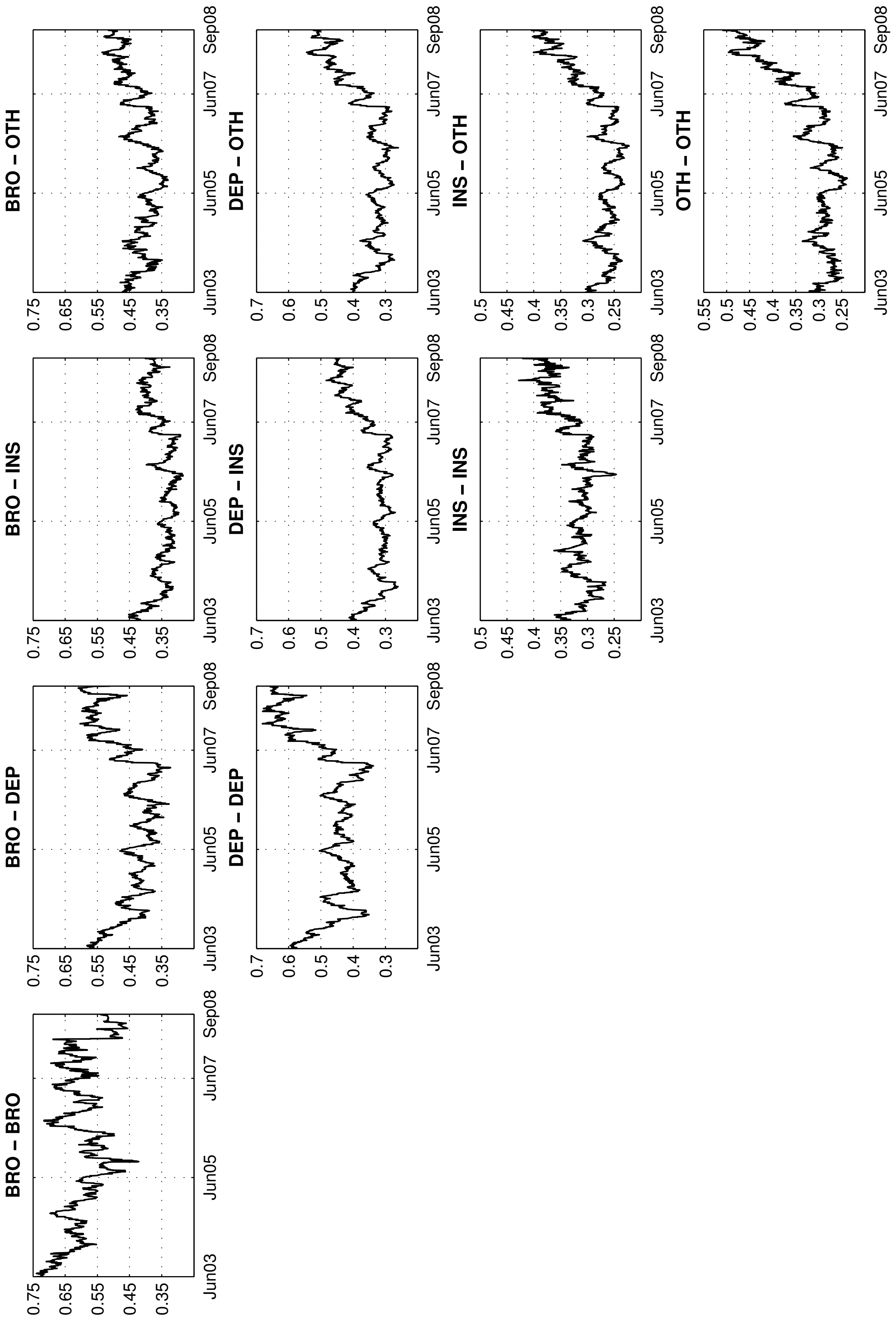


Figure 18: Dynamic conditional correlations for cross-sections of US sample (by type)

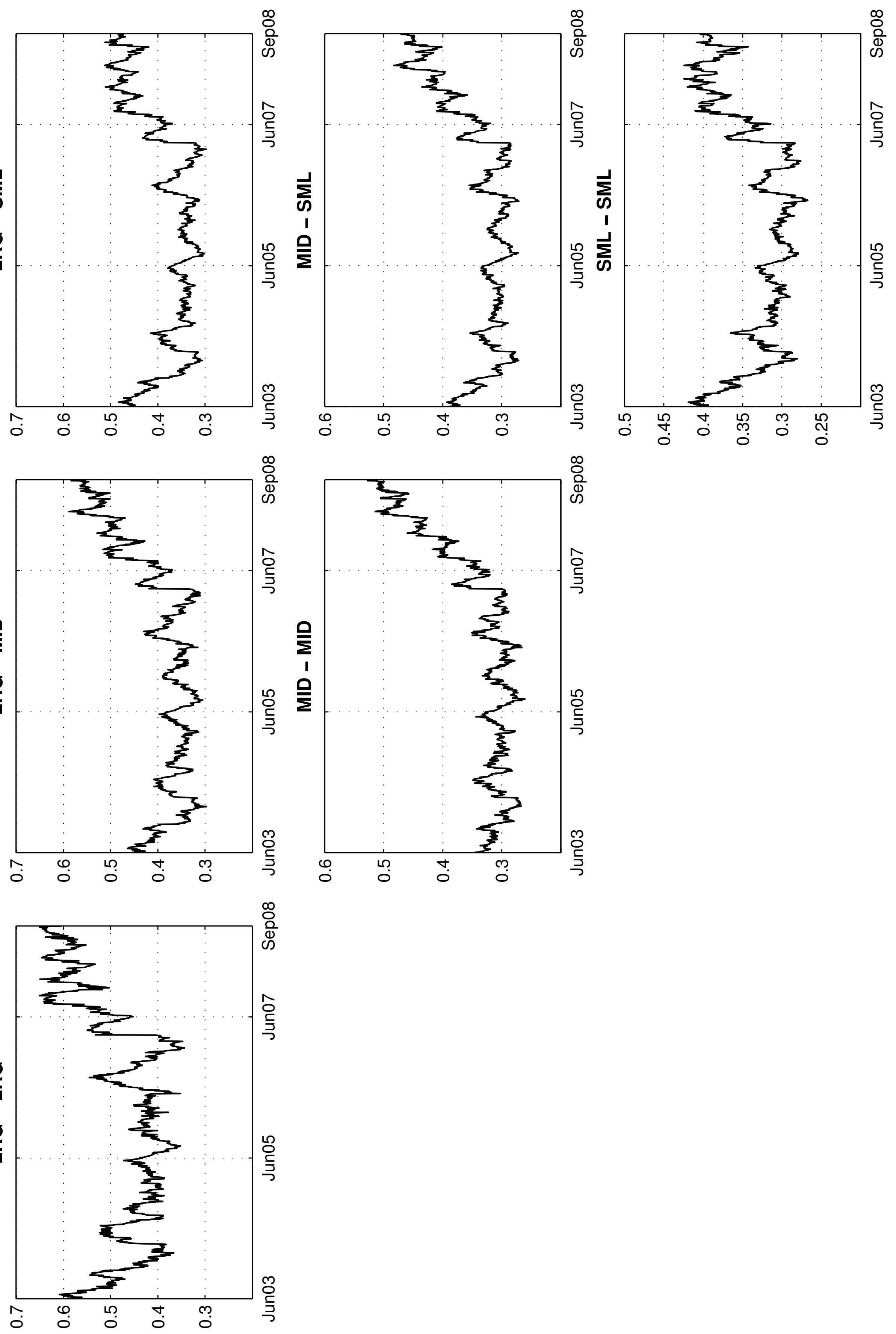


Figure 19: Dynamic conditional correlations for cross-sections of US sample (by size)

For all cross-sections, we discern a more or less pronounced spike in correlations already by mid-2006, which can also be seen in the volatility curves, although comparably small. This increase can be explained by an overall pullback in stock prices during the period of May–June 2006, which reflected greater uncertainty about risks to the economic outlook and policy responses; see the International Monetary Fund (2006). The sharp drop of correlations within the Broker-Dealer section in the crisis period coincides with the near breakdown and rescue of Bear Stearns, which is included in this section. As a result of the relatively low number of institutions in Broker-Dealer section, a reversal of some individual correlations with Bear Stearns has a strong impact on median correlations[303]. For all other cross-sections, we either see an increasing path of correlations subsequent to the onset of the crisis or, for some cross-sections, a jump in correlations to a higher level.

In the following sections we focus our analyses on the dynamics of correlations during the 24-months pre-crisis time-window, or the period June 2005 to June 2007. The prior 48-months time-window, as well as the subsequent subprime crisis time-windows, will be used for comparisons to the observed patterns. The question guiding our further analysis is whether there is statistical evidence for a pro-cyclical increase of correlations before the onset of the financial crisis 2007–09. Such increases would indicate stronger interdependencies among financial institutions and signal increased systemic risk. Certainly, as this preliminary analysis has shown, an increase does not have an equivalent impact as in the crisis itself. However, we are interested whether the levels or trends of correlations within the individual groups changed throughout the 24-months time-window.

A first look at the 2005–07 period throughout the different cross-sections suggests that correlations fluctuated around a relatively stable level. Nevertheless, there seem to be some indications of a positive trend of correlations in some of the cross-sections, e.g. Eurozone financial institutions (paired with Eurozone and broader Europe) and, in the US sample, the cross-sections of the Others (OTH) group compared with the rest of the sample. The following steps of the analysis will test the dynamic conditional correlation models regarding (i) structural breaks in the mean of correlations and (ii) underlying time-trends of correlations. Moreover, we will discuss correlations between selected individual institutions in order to highlight that partial trends—among smaller groups of institutions—are smoothed by the aggregation throughout a larger cross-section.

[303]This bias in the subprime crisis time-window is not relevant, because the analysis focuses mainly on the pre-crisis time-window. It can be noted that an exclusion of Bear Stearns would generally smooth correlation dynamics in the crisis period.

4.2.4 Structural breaks in the mean of correlations

To understand whether there is statistical evidence for a pro-cyclical increase in interdependencies among financial institutions prior to the financial crisis 2007–09, we now turn to the overall levels of correlations for the predefined time-windows and analyze our hypothesis.

HYPOTHESIS 1: There is empirical evidence for an increase in the level of interdependencies prior to the financial crisis 2007–09.

Cappiello et al. (2006) propose an extension of the DCC-GARCH structure, which allows us to test for structural breaks in the mean of correlations for exogenously defined time windows—also applied by Frank et al. (2008)—to study linkages between market and funding liquidity pressures in the crisis. Specifically, the test analyzes whether an extended model specification, including separate unconditional correlation matrices for the individual time-windows, significantly increases the models' fit to the data, as indicated by the maximized log-likelihood. The exogenous definition of the time windows poses a selection bias and limits the generality of this analysis[304].

Cappiello et al. (2006) also test for structural breaks in the dynamics of the models. However, these tests require the estimation of a whole set of variables for each applied time window[305]. The statistical significance of such a specification showed to be not viable for our samples. Similarly, Cappiello et al. (2006) fail to get significant results when testing for only one structural break in model dynamics. Another possible approach to model the dynamics of the variables over time would be to follow Brownlees et al. (2010), who re-estimate model variables over a rolling time-window. This methodology is applied primarily to forecast volatilities and no formal tests for changes in the level of correlations are available.

Starting from equation (4.4) of the previous section, the pseudo correlation matrix is now defined as[306]

$$Q_t = (1-\alpha_t-\beta_t)(\bar{Q}^\star(1-d_t)+\tilde{Q}d_t)+\alpha z^\star_{t-1}z^{\star\prime}_{t-1}+\beta Q_{t-1}\ ,\ \text{with } d_t = \begin{cases} 0 & \text{if } t < \tau \\ 1 & \text{if } t \geq \tau \end{cases} \tag{4.5}$$

[304]As the subsequent section will point out though, there are general procedures to test time series for structural breaks in mean or time trends. However, these are not applicable to our data because the curves show too strong volatility. To our knowledge, there is no direct procedure to endogenously test for breaks in mean or trend for a multivariate GARCH model specification.

[305]For the setup of this analysis, we would have to estimate 8 instead of 2 factors and for very short time-windows (with appr. 500 observations on a daily and 100 observations on a weekly basis).

[306]The indices ij denoting a specific pair of financial institutions have been omitted to simplify the equation.

$\bar{Q}^{\star}$, similar to $\bar{Q}$ in equation (4.4), denotes the unconditional correlation matrix of residual vectors $z^{\star}_{i,t}$ and $z^{\star}_{j,t}$, but only for $t < \tau$, where τ is an the exogenously defined point in time, for which a structural break in mean shall be tested. $\tilde{Q}$ marks the unconditional correlation matrix of $z^{\star}_{i,t}$ and $z^{\star}_{j,t}$ for $t \geq \tau$. We incorporate three exogenous time-windows in our test setup: from 48-months to 24-months prior to the crisis; 24-months until the onset of the crisis; and lastly from the onset of the subprime crisis in June 2007 until the breakdown of Lehman Brothers in September 2008. Then we re-run the model estimations for the new specification, with the definitions of $\bar{Q}^{\star}_{ij}$, $\tilde{Q}_{ij}$ and d_t adapted accordingly.

To determine if the DCC-GARCH specification allowing for structural breaks in the mean of dynamic conditional correlations provides a better fit than without a break in mean, we can compare the calculated maximized log-likelihoods of the estimations. We run a likelihood ratio test in order to analyze whether the less restricted model provides a better specification for the time series of our samples[307]. The test is conducted with the null hypothesis that the estimated break-models do not offer a better fit to the observed data as the maximized likelihood for the more restricted models without breaks in mean[308]. If the null hypothesis can be rejected, the structural break model provides a better description of the dynamic conditional correlations of the underlying time series. In that case we can compare correlation levels for the individual time-windows to draw conclusions on a potential increase prior to the financial crisis 2007–09.

The estimation results of the bivariate models, which allow for a structural break in mean—we will refer to this as the 'break-model'—are very similar to the prior estimation without structural breaks in mean, for both samples. Although there are marginal variations, the core observations for the different cross-sections remain. Therefore, we report only the estimated parameters in appendix B.5. In general, the break-models exhibit a slightly lower persistence and a rougher correlation dynamic (higher smoothness) although the differences are marginal. In terms of maximized log-likelihood, the break-model estimations are similar to the statistics of previous estimations. However more model estimations had to be excluded under the break-specification since variable estimations were not significant.

Table 16 summarizes the results of the analysis and shows a comparison between correlation levels for the 48-months and 24-months time-windows for the different cross-sections of both samples. The likelihood ratio test was only conducted for those models, where both estimated factors of the break-model were significant, while all other models were excluded. The significance column shows that the overall power of this type of

[307] The AIC and BIC criteria are not applicable because no additional factors are being estimated.

[308] The three restrictions imposed on the variables imply three degrees of freedom: $\bar{Q}^{\star} = \tilde{Q}_{win}$ with $win = 48, 24, \mathrm{SC}$. $\bar{Q}^{\star}$ is the long-run constant conditional correlation (CCC) estimator and $\tilde{Q}_{win}$ mark the according estimates for each of the three time-windows.

Table 16: Sample statistics for test of structural breaks in mean (48-months and 24-months time-windows)

Panel A: Statistics for international sample

		LLF	Significance[1]	Models Increase	Models Decrease	Increase[2] Δ_{Q10}	Increase[2] Δ_{med}	Increase[2] Δ_{Q90}	Decrease[2] Δ_{Q10}	Decrease[2] Δ_{med}	Decrease[2] Δ_{Q90}	$Q^\star$
EUR	EUR	7'674	49/118	30	19	0.01	**0.08**	0.24	-0.13	**-0.04**	-0.01	0.08
EUR	NEU	6'543	71/139	48	23	0.03	**0.06**	0.15	-0.09	**-0.05**	-0.01	0.08
EUR	USA	519	13/98	4	9	0.04	**0.12**	0.25	-0.24	**-0.15**	-0.06	0.04
NEU	NEU	5'685	19/35	9	10	0.00	**0.05**	0.12	-0.14	**-0.04**	0.00	0.09
NEU	USA	628	9/45	5	4	0.00	**0.07**	0.28	-0.30	**-0.13**	-0.01	0.09
USA	USA	6'837	65/205	36	29	0.01	**0.10**	0.20	-0.17	**-0.09**	-0.01	0.17

Panel B: Statistics for US sample

		LLF	Significance[1]	Models Increase	Models Decrease	Increase[2] Δ_{Q10}	Increase[2] Δ_{med}	Increase[2] Δ_{Q90}	Decrease[2] Δ_{Q10}	Decrease[2] Δ_{med}	Decrease[2] Δ_{Q90}	$Q^\star$
Cross-sections by type												
BRO	BRO	3'451	13/32	3	10	0.01	**0.05**	0.05	-0.14	**-0.07**	-0.03	0.51
BRO	DEP	5'975	56/236	14	42	0.02	**0.03**	0.14	-0.15	**-0.09**	-0.03	0.31
BRO	INS	4'206	67/229	16	51	0.01	**0.03**	0.08	-0.13	**-0.06**	-0.02	0.31
BRO	OTH	3'202	58/141	26	32	0.02	**0.08**	0.25	-0.16	**-0.08**	-0.01	0.38
DEP	DEP	6'901	121/357	74	47	0.01	**0.05**	0.18	-0.11	**-0.06**	-0.01	0.34
DEP	INS	5'843	195/730	100	95	0.01	**0.05**	0.13	-0.14	**-0.06**	-0.02	0.28
DEP	OTH	4'381	168/437	81	87	0.01	**0.07**	0.15	-0.18	**-0.09**	-0.01	0.31
INS	INS	5'126	116/370	47	69	0.01	**0.07**	0.14	-0.19	**-0.09**	-0.02	0.32
INS	OTH	3'548	145/452	71	74	0.02	**0.07**	0.17	-0.14	**-0.05**	-0.01	0.30
OTH	OTH	2'899	64/133	34	30	0.01	**0.09**	0.27	-0.18	**-0.07**	-0.03	0.34
Cross-sections by size												
LRG	LRG	5'678	17/173	10	7	0.01	**0.07**	0.18	-0.18	**-0.04**	-0.02	0.33
LRG	MID	4'865	137/468	63	74	0.01	**0.08**	0.22	-0.18	**-0.10**	-0.01	0.41
LRG	SML	5'590	180/639	98	82	0.01	**0.06**	0.12	-0.14	**-0.08**	-0.02	0.31
MID	MID	3'692	131/327	63	68	0.02	**0.08**	0.21	-0.17	**-0.07**	-0.02	0.42
MID	SML	5'063	349/904	151	198	0.01	**0.06**	0.15	-0.16	**-0.07**	-0.01	0.30
SML	SML	5'596	189/606	81	108	0.01	**0.04**	0.12	-0.13	**-0.06**	-0.01	0.25

[1] Models significant at 25% level (appr. half also significant at 5% level) / Total number of models.
[2] Median difference and quantiles of correlation estimates between the 48-months and 24-months time-windows.

analysis is not very high: the null hypothesis of the likelihood test was rejected for only less than half of the available models and only at a low significance boundary. Turning the attention to the correlation estimates for the different time-windows, the numbers given in the table only include those break-models, where the null hypothesis of the likelihood test could be rejected. The given correlation estimates for the individual time-windows equal Bollerslev's constant conditional correlation measure for a CCC-GARCH specification.

To determine whether such constant correlation estimates are appropriate for the individual time windows, we again conduct Engle's test for dynamic conditional correlation, separately for the residual returns (table 17). Contrary to prior test results for the full time series, we find that a large share of the models, especially of the international sample, does not exhibit dynamics in conditional correlations (see columns H_0) during the first two time-windows. The majority of models exhibits dynamic correlations only for the

Table 17: Results of DCC-Test for dynamic conditional correlation for individual time-windows

		48-months[1]					**24-months**[1]					**Subprime crisis**[1]				
	Models	***	**	*	H_0[2]	time[2]	***	**	*	H_0[2]	time[2]	***	**	*	H_0[2]	time[2]
Int. Sample (D)[3]	688	109	64	87	428	0	173	92	80	343	0	524	34	26	53	51
Int. Sample (W)[3]	690	1	8	36	645	0	1	21	26	642	0	207	84	74	325	0
US-Sample	4’005	3’127	71	24	18	765	3’170	177	71	68	519	3’250	77	68	91	519

[1] Number of models for which H_0 was rejected at ***=1% / **=5% / *=15% signicant levels.
[2] Number of models for which H_0 could not be rejected or time overlap of series was too short.
[3] (D) includes models based on daily, (W) models based on weekly returns (cross-sections EUR/NEU–USA).

third time-window, which captures the subprime crisis as the first phase of the financial crisis 2007–09. Consequently, the constant conditional correlation estimate provides us with an adequate approximation of correlation levels throughout the time-windows for the international sample, which we compare by their difference (increase/decrease) between the 48-months and the 24-months time-windows (table 16).

Again, for the international sample, correlation levels increased for a majority of models in the European cross-sections (EUR–EUR, EUR–NEU). This is similar to our earlier observation for the curves of dynamic conditional correlations (figure 17). For the other cross-sections there is a balance between increases and decreases[309]. For correlations among those US financial institutions included in the international sample there is a small majority of models showing an increase. The size of the increase is relatively small and fluctuates around 0.1, which for most cross-sections is a little more than the long-term average of correlation ($Q^{\star}$). The models showing decreases generally exhibit a lower decrease in correlation levels of a little more than 0.05[310].

For the US sample, the model allowing for structural breaks in mean shows a significant improvement for a much smaller portion, as compared to the international sample. This can be explained by the fact that there is a big share of pairs of US financial institutions that exhibit dynamic correlations[311], and therefore the derived constant correlation measures are less accurate[312].

Throughout most of the cross-sections of the US sample, the models suggest a balanced picture, or the majority shows decreases in correlation levels. Correlation estimates for decreases are slightly higher than for increases. However, the quantiles show that there is relatively high variation throughout some of the cross-sections. Comparing the

[309] The estimations of weekly models for the cross-sections between the US and Europe were largely insignificant. As a result of the smaller number of models, the table shows much more variation in these groups.

[310] It has to be noted that the cross-sections for weekly data are not directly comparable to those based on daily returns because frequency also has an impact on correlations.

[311] Unlike the international sample, Engle’s test on dynamic conditional correlation for the individual time windows rejected the null hypothesis of constancy of conditional correlations for the vast majority of institution pairs of the US sample for all time-windows; see appendix B.5 (table 31).

[312] A comparison of the volatility of correlations between the US and the international sample as observed in figures 17, 18 and 19, already pointed into the same direction.

deltas (Δ) between correlation estimates for the first two time-windows to the long-run correlation estimate $Q^{\star}$ indicates generally a higher level of correlations in the US. Breaking up the US sample by institutional size shows that the vast share of models for which the break analysis is significant lies in the cross-sections of mid- and small-size financial institutions.

A comparison of correlation levels between the first stages of the crisis with the 24-months pre-crisis time-window is reported in appendix B.5 (table 32). This comparison shows an overall increase for the vast majority of models. Only the Broker-Dealer section shows distortions, which, again, can be attributed to the inclusion of Bear Stearns in the sample. The fact that there is a strong increase in the deltas of the models, with an increase to numbers around 0.25, highlights the observation of a notable increase in correlation levels throughout financial crises, as was already discussed in the previous section. The bandwidth of increases as measured by the percentiles is similar to the comparison of the pre-crisis time-windows.

In summary, our test for structural breaks in the mean of correlations leads to ambiguous results in terms of our hypothesis. At first, the relatively low number of models, where we measured a significant increase of statistical power for the structural break-model, limits our ability to draw conclusions for the overall development of correlations in the two years prior to the onset of the financial crisis. This is especially true for the US sample, where correlations are shown to be more dynamic, compared to the international sample. Second, the overall balance of increases and decreases for the individual cross-sections is similar to the previous observation that dynamic conditional correlations seemed to be relatively stable during the pre-crisis time-window (figures 17, 18 and 19). The notion of a slight increase of correlations for European institutions was confirmed by this analysis, where a majority of significantly estimated models showed an increase of correlation levels.

However, the focus on median correlations for the full sample obviously leads to a smoothing of dynamics between those pairs of financial institutions, where correlations increased, and those which exhibit decreasing correlations; a similar conclusion is derived by Acharya et al. (2010b). In order to allow a better perspective on the evolution of correlations between the individual pairs of institutions, our next step expands the analysis by taking a dynamic perspective on correlations and analyzing the presence of time trends for the individual time windows.

4.2.5 Time trends in correlations

In this second step of our analysis, we formally test for time trends in correlation for the individual time-windows. As before, our motivation is to find statistical evidence for a pro-cyclical increase in interdependencies between financial institutions prior to the financial crisis 2007–09, analyzing the hypothesis:

Hypothesis 2: There is empirical evidence for a positive increase in the trend of interdependencies prior to the financial crisis 2007–09.

Inter alios Campbell et al. (2001), Bekaert et al. (2008) as well as Bekaert et al. (2009) and Liow and Newell (2010) follow a methodology proposed by Vogelsang (1998); Bunzel and Vogelsang (2003), who pose a powerful trend statistic, which is robust to serial correlation and other statistic artifacts[313]. They define a test statistic which is based on a simple regression for the relevant time series in the form $y_t = \alpha_0 + \alpha_1\, t + \varepsilon_t$. Pukthuanthong and Roll (2009) follow a similar regression approach, although their test does not apply the Vogelsang statistic.

For our analysis, must be noted that, though the test statistic is robust to a unit root and serial correlation in the error term, the regression model does not seem to be an optimal specification for our correlation series. Because of the DCC-GARCH description of correlation in equation (4.4), the correlation in period t generally depends on the correlation in period $t-1$. In addition, the vast majority of models estimates β_{ij} at values close to 1, thus confirming the presence of a unit root[314].

In view of these considerations we choose an alternative approach to Vogelsang, and follow Phillips and Perron (1988) by conducting the Phillips-Perron unit root test for a trend-stationary first-order autoregressive model. This test determines the underlying time series—the correlation between each pair of financial institutions—to be either a unit root process with a simple drift or, under the alternative description, a trend-stationary process. Thus, the test is based on a regression, which clearly accounts for the autoregressive nature of the process and is better suited for our data. Furthermore, the test statistic is robust to heteroscedasticity in the errors of the test equation[315]. The hypotheses of the test are:

$$\begin{aligned} H_0: &\quad y_t = c + y_{t-1} + \varepsilon_t \\ H_1: &\quad y_t = c + \phi\, y_{t-1} + \delta\, t + \varepsilon_t \end{aligned}$$

Interpreting the results, an acceptance of the null hypothesis implies that the residuals are pure white noise and therefore the conditional correlation series fluctuates

[313] An adapted version of this test by Sayginsoy and Vogelsang (2007) tests for structural breaks at an unknown date.

[314] The overall average for estimations of β_{ij} that has been confirmed by many studies ranges around 0.97.

[315] The test is similar to the augmented version of the Dickey and Fuller (1979) test for a unit root in a time series. This test can also be applied to test for a trend-stationary model. In order to account for a possibly higher order of autocorrelation in the data generating process, the augmented Dickey-Fuller test includes difference operators as lags in the regressions. In contrast, the Phillips-Perron procedure opts for a non-parametric correction of the test statistic.

randomly around its mean. However, the rejection of the null hypothesis implies that the residuals are trend-stationary and correlation dynamics exhibit a deterministic time trend. In an extension of the methodology, Perron (1989) and Perron (1993) describe a testing procedure for structural breaks in mean as well as in trend dynamics. Whereas the trend break date has to be identified exogenously in this approach, Kim and Perron (2009) advance the procedure so that breaks can be tested endogenously. This methodology poses a potential expansion of our study to overcome the selection bias due to the exogenous definition of the three time windows. However, those test results are strongly influenced by the volatility of the underlying time series and the analysis yields results only if this series exhibits relatively low volatility during the time period of the analysis, which is not the case here.

The test procedure is applied only to those DCC-GARCH models where all estimated factors were significant (section 4.2.3). If the null hypothesis can be rejected at conventional significance levels, we obtain a maximum of three trend coefficients for each series, one for each time window. By comparing the coefficients between the time windows we can draw conclusions about changes in the trends of correlation dynamics[316].

We report the test results for the individual sample groups in table 18[317]. The first column gives the total number of models for which the estimations of the DCC-GARCH models were significant, which is the maximum number of trend coefficients that we could obtain for each time-window[318]. The next three column groups report, for the three time windows, the number of models for which the null hypothesis was rejected, as well as the obtained results: the number of positive and negative trend coefficients, and the median coefficient. The last group of columns gives an overview of the difference in the trend coefficients between the 48-months and 24-months time-windows: the number of models, where a trend coefficient was obtained for both time-windows; and the median difference between the the trend coefficients of both time-windows with relevant quantiles[319].

Compared to the test for structural breaks in mean, it can be recognized immediately that a larger number of models rejecting the null hypothesis allows us to report on related coefficients. This is especially true for the US sample and confirms the prior indications of greater dynamics in conditional correlations. For the 48-months time-window, the number of positive and negative trend coefficients is fairly balanced, or skewed towards negative coefficients. In the 24-months time-window we derive a majority of positive trend

[316] The augmented Dickey and Fuller (1979) test generally yields similar results. The reported results are those based on the Phillips-Perron test, which needs no parametrization to correct for serial correlation in the underlying data series.

[317] To simplify the table, all estimated coefficients have been multiplied by 1'000.

[318] The number differs from the total number of models given in table 16 because this table reports the total number of significant model estimations allowing for a structural break in mean, and not for the standard DCC-model, which was reported in table 15.

[319] A similar analysis for changes between the 24-months pre-crisis and subprime crisis time-windows is reported in appendix B.6.

Table 18: Sample statistics for tests of time trend in correlation

Panel A: Statistics for international sample

			48-months[2]			24-months[2]			Subprime[2]			48-months − 24-months[3]			
		Models[1]	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	No.	Δ_{Q10}	Δ_{med}	Δ_{Q90}
EUR	EUR	146	29	43	-0.0010	41	30	0.0005	36	13	0.0079	47	-0.0055	**0.0008**	0.0112
EUR	NEU	159	25	41	-0.0010	34	31	0.0004	33	9	0.0128	44	-0.0085	**0.0011**	0.0088
EUR	USA	188	45	36	0.0064	43	23	0.0252	35	15	0.2565	42	-0.1420	**0.0182**	0.3000
NEU	NEU	40	6	5	0.0001	4	9	-0.0023	3	0	0.0390	6	-0.0061	**0.0014**	0.0118
NEU	USA	102	18	20	-0.0013	17	13	0.0211	35	3	0.5858	23	-0.1469	**0.0498**	0.2227
USA	USA	231	36	66	-0.0013	50	48	0.0002	75	7	0.0283	76	-0.0073	**0.0019**	0.0115

Panel B: Statistics for US sample

			48-months[2]			24-months[2]			Subprime[2]			48-months − 24-months[3]			
		Models[1]	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	No.	Δ_{Q10}	Δ_{med}	Δ_{Q90}
Groups by type															
BRO	BRO	35	0	7	-0.0040	12	0	0.0147	11	0	1.2443	5	0.0078	**0.0194**	0.0256
BRO	DEP	234	9	51	-0.0064	64	6	0.0066	75	7	0.0209	29	0.0050	**0.0115**	0.0351
BRO	INS	243	48	57	-0.0006	93	16	0.0055	72	22	0.0181	77	-0.0101	**0.0056**	0.0208
BRO	OTH	157	24	23	0.0005	55	1	0.0088	40	9	0.0356	36	0.0013	**0.0110**	0.0352
DEP	DEP	372	11	33	-0.0049	31	17	0.0023	65	20	0.0120	20	-0.0073	**0.0033**	0.0154
DEP	INS	779	125	115	0.0002	199	76	0.0038	163	66	0.0094	164	-0.0136	**0.0031**	0.0207
DEP	OTH	507	62	42	0.0009	159	19	0.0057	89	14	0.0219	75	-0.0037	**0.0039**	0.0193
INS	INS	404	93	90	0.0001	134	56	0.0039	86	34	0.0119	132	-0.0126	**0.0030**	0.0342
INS	OTH	523	82	79	0.0002	156	36	0.0052	107	25	0.0173	109	-0.0045	**0.0039**	0.0155
OTH	OTH	165	26	16	0.0013	56	3	0.0083	31	8	0.0254	27	-0.0009	**0.0062**	0.0153
Groups by size															
LRG	LRG	173	30	47	-0.0013	49	14	0.0075	51	13	0.0078	53	-0.0052	**0.0098**	0.0218
LRG	MID	518	110	92	0.0009	200	35	0.0054	157	45	0.0148	151	-0.0094	**0.0045**	0.0271
LRG	SML	684	85	100	-0.0007	159	45	0.0051	116	32	0.0156	119	-0.0059	**0.0060**	0.0189
MID	MID	372	82	41	0.0030	133	21	0.0053	115	20	0.0188	95	-0.0143	**0.0014**	0.0227
MID	SML	1023	140	147	-0.0003	286	78	0.0053	208	71	0.0186	198	-0.0092	**0.0047**	0.0215
SML	SML	649	33	86	-0.0039	132	37	0.0050	92	24	0.0245	58	-0.0033	**0.0056**	0.0325

[1] Total number of DCC-GARCH models that were significant.
[2] Number of models significant at 15% level with positive/negative trend and according median.
[3] Median and quantiles of difference in estimated δ between time windows.

coefficients for the US sample, while the international data still appear to be relatively balanced, even though the portion of positive coefficients has increased notably. As one would expect, the final analysis of the subprime crisis time-window shows a pronounced majority of positive trend coefficients, which are also of a much higher numerical value in comparison to the previous periods.

The notion that correlation trends already increased in the 24-months time-window is also supported by looking at the median coefficient values δ_{med}. While the median coefficients for the 48-months window are often negative, or at very low positive values, the 24-months time-window already suggests an increase, as all coefficients are higher than in the prior period. The non-Eurozone group (NEU) is a singular exception in this regard. A comparable observation is made by looking at the difference in trend coefficients between the two pre-crisis time-windows (Δ_{med}), which are positive throughout the complete sample[320]. However, the large difference between the quantiles suggests a high variation of these trends, which becomes even greater when comparing the 24-months pre-crisis correlation trends to the trends during the subprime crisis (appendix B.6).

Looking at individual cross-sections of the US sample (Δ_{med}), increasing dynamics seem to be strongest for those between the Broker-Dealer group and the rest of the sample (except the cross-section with insurers), and for those of the largest institutions included in the sample. The latter observation can be interpreted much like Acharya et al. (2010b), who argue that interdependencies among the largest financial institutions increased in the pre-crisis period. Looking at the cross-sections of depository and insurance institutions we observe a more diverse picture: the number of trend coefficients seems to be smaller and so are the median coefficients.

Summarizing this trend analysis, we were able to obtain better evidence supporting our hypothesis of a positive increase in the trends of correlations for the time-period of 24-months prior to the onset of the subprime crisis. However, the test for time trends in correlations has—like the test for structural breaks in mean—shows that this statement is only true for a portion of the sample. Looking at all financial institutions, the increase in correlations is balanced by other correlations where correlations either decrease, or the conducted tests do not yield statistically viable results. This is similar to Bekaert et al. (2008), who analyze stock return comovements for a sample of European countries. They identify only trends in comovements, focusing on a sub-section of large growth stocks, and comparing these to small value stocks, but not at the aggregate level.

The problem of extracting dynamics from a larger sample has also been looked at by Brownlees (2010), who proposes a hierarchical factor GARCH model to establish a dynamic connection between plain firm characteristics (size, leverage, distance-to-default and liquidity) and volatility dynamics during the subprime crisis. By developing a two-level GARCH framework, he is able to obtain a dynamic grouping of his sample and shows that there are strong links to volatility dynamics in these groups. His framework—at the first level—models returns of the sample as a function of a systematic component being driven by the observed firm characteristics, and complemented by an idiosyncratic shock. The second level is directly connected and is used to model the coefficients (factor load) for first level estimations. Thus it determines the dependence of a firm on the industry factor.

Brownlees concludes that leverage is the most influential factor in estimating volatility dynamics in his panel. To a large extent it explains variations in model persistence and smoothness according to the first level factor loading. With regard to the

[320] The high values of Δ_{med} for the cross-sections between the Eurozone and non-Eurozone, as well as the USA in the international sample are due to the weekly observations underlying the analysis. Therefore, a direct comparison to the other cross-sections (daily observations) is not adequate.

Table 19: Statistics for tests of time trend in correlation (selected institutions)

		48-months[2,3]			**24-months**[2,3]			**Subprime**[2,3]			**48-months − 24-months**[4]			
	Models[1]	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	No.	Δ_{25}	Δ_{med}	Δ_{75}
American Express	81	9	8	0.0000	18	3	0.0052	30	10	0.0067	12	-0.0035	**0.0000**	0.0048
Bear Stearns	77	14	16	0.0000	27	6	0.0055	4	17	-0.0140	33	0.0000	**0.0039**	0.0147
Citigroup	85	11	20	-0.0015	33	6	0.0034	25	6	0.0076	24	0.0000	**0.0027**	0.0123
Fannie Mae	67	31	23	0.0005	46	3	0.0069	4	7	0.0000	48	0.0017	**0.0061**	0.0092
Freddie Mae	71	56	13	0.0035	64	8	0.0054	5	21	-0.0161	69	-0.0020	**0.0022**	0.0061
Goldman Sachs	81	9	23	-0.0020	33	4	0.0060	29	8	0.0113	26	0.0028	**0.0096**	0.0136
JP Morgan Chase	80	3	11	-0.0007	19	2	0.0053	25	6	0.0076	11	0.0000	**0.0065**	0.0150
Lehman Brothers	74	12	22	-0.0013	29	2	0.0046	13	8	0.0019	23	-0.0002	**0.0070**	0.0114
Merrill Lynch	78	12	14	0.0000	24	4	0.0073	17	5	0.0052	20	0.0000	**0.0050**	0.0140
Morgan Stanley	84	11	23	-0.0024	33	2	0.0089	32	1	0.0131	23	0.0025	**0.0128**	0.0273
Washington Mutual	67	7	7	0.0000	14	0	0.0075	7	5	0.0000	12	0.0010	**0.0099**	0.0229

[1] Total number of DCC-GARCH models that were significant.
[2] Number of models significant at 15% level with positive/negative trend and according median.
[3] Median and quantiles of difference in estimated δ between time windows.

remaining variables, size proves to be an important factor to explain the overall exposure to systematic shocks, despite being less powerful. Finally, liquidity and distance-to-default have a negative impact on volatility, though on a much lower scale than the other factors. These results concur with other analyses, such as Drehmann and Tarashev (2011b), who conclude that there is a generally positive relation between the size of an institution and its measured contribution to systemic risk. Acharya et al. (2010b) apply the institutional leverage for 'fitting' their ranking of the systemic importance derived from the MES estimations.

For a period prior to the onset of the crisis[321], Brownlees looks at a subgroup of the largest 20% of institutions and ranks them according to their factor load. The results show that those companies, ranked highest by their factor loads, were hit especially hard during the financial crisis. He concludes that his factor loading measure might also be an ex ante indication of exposure to systematic shocks.

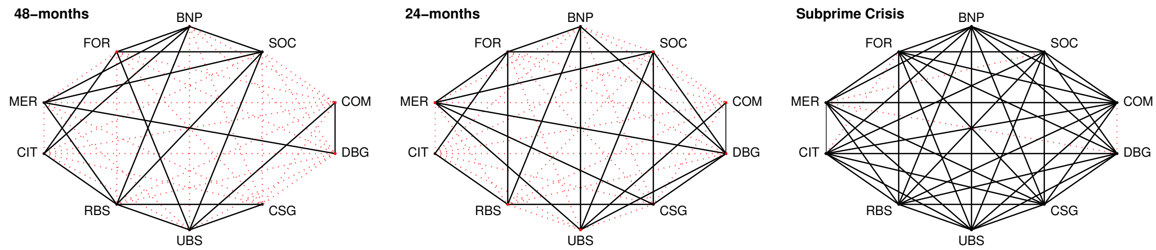
Comparing his approach to our analysis there is a clear-cut difference, as Brownlees focuses on volatility dynamics of individual financial institutions, while we analyze correlations between pairs of financial institutions. This leads to the question whether a similar approach would be applicable for our setting. Brownlees includes only US financial institutions in his sample, whereas we expand our perspective to the international context.

Nevertheless, we can apply his factor load-ranking to take a closer look at correlation dynamics in what might be called the 'systemic core' of the US sample. Table 19[322] displays the individual results of the trend analysis for those institutions that Brownlees ranks highest for the pre-crisis period[323]. Knowing about the tremendous exposures of

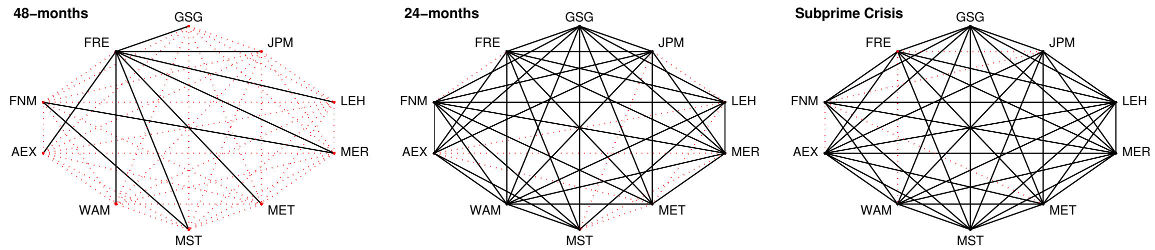
[321] Brownlees (2010) defines this period closely to our analysis from January 2005 to July 2007.
[322] To simplify the table, all estimated coefficients have again been multiplied by 1'000.
[323] Only exception is Wachovia, which has been excluded due to the merger with AG Edwards in early 2007.

Figure 20: Correlation trends for selected institutions for individual time-windows

Panel A: International sample



Panel B: US sample



some institutions in the financial crisis 2007–09, one would also expect Citigroup (ranked, but not among the top-ten) and Bear Stearns (not ranked due to size) to be included in this subgroup[324].

Table 19 clearly shows that there is an overall increase of correlation trend between the selected institutions and the rest of the sample. Compared with the former analysis of the whole sample, there is a much higher portion of positive trend coefficients in the 24-months time-window, while the numerical value of coefficients is at the same level as the results for the full sample. Similarly, the share of significant coefficients, compared to the total models, increase broadly for the selected institutions, which could be interpreted as generally stronger trend dynamics exhibited by these institutions.

Overall, these findings confirm the results of Brownlees (2010) that this group of companies shows a strong increase of interdependencies with the rest of the sample. It provides us with evidence to support our hypothesis, at least for the systemic core. It leads to the conclusion that these institutions induced a large share of the systemic risk that materialized during the financial crisis. It is also in line with Acharya et al. (2010b), who argue that institutions from the securities dealers and brokers section, as well as depository institutions with vast investment-banking activities added most to systemic risk in this specific period, but also generally.

[324] It has to be noted that the overall picture does not change if one includes Citigroup and Bear Stearns, instead of e.g. Metlife and American Express, which were the least exposed institutions in the financial crisis.

Narrowing our focus even further, we evidence the trends of interdependencies of the selected institutions of the 'systemic core' in figure 20 (Panel B)[325]. The lines indicate the numerical signs of the trends estimated for the individual time windows: a (black) solid line signals an increasing trend, and (red) dotted lines represent a negative trend coefficient[326]. What stands out immediately is that the contrast of trends for the two pre-crisis periods is indicating an overall reversal of correlation dynamics prior to the crisis during the 24-months time-window. Consequently, there was an overall increase of interdependencies among these institutions, which are considered systemically important.

For the period June 2003 to June 2005 (48-months), there is a decrease in correlations for almost the full sample. Only government-sponsored Fannie Mae and Freddie Mac show positive trends of correlations in relation to the other institutions of the systemic core. This dynamic is reversed in the 24-months pre-crisis window, where correlations mark a generally positive trend in the US sample[327]. The only exceptions are Fannie Mae and Freddie Mac, some correlations of American Express (with LEH, MER, MET), JP Morgan Chase (with MST, LEH), Metlife (with LEH, MST, AEX) and, lastly, Merrill Lynch and Morgan Stanley.

It would be speculative to attribute these exceptions to these institutions having less exposure during the crisis and, certainly, it would not be applicable to the interdependencies of Fannie Mae and Freddie Mac. However, it does not rule out the notion of a general increase of interdependencies among these systemically relevant US financial institutions in the run-up to the subprime crisis. As the illustration on the right of figure 20 (Panel B) shows, correlation trends increased (positive trend) throughout the subprime crisis. This is associated with the unraveling of exposures and information effects, as described in the fundamentals chapter (section 2.2.3), as well as previous comments on correlation dynamics in times of crisis.

To allow a comparison with the international sample, figure 20 (Panel A) presents a similar illustration for a set of European (EUR, NEU) financial institutions[328]. These institutions exclude financial institutions from the Mediterranean countries as well as Scandinavia, since they showed generally less exposure during the early stages of the financial crisis 2007–09. In addition, most US institutions were removed to avoid redun-

[325] The included institutions are similar to table 19 and include: Goldman Sachs (GSG), JP Morgan Chase (JPM), Lehman Brothers (LEH), Merrill Lynch (MER), Metlife (MET), Morgan Stanley (MST), Washington Mutual (WAM), American Express (AEX), Fannie Mae (FNM) and Freddie Mac (FRE).

[326] The primary source for correlation dynamics is the trend coefficients estimated in the previous step of our analysis. If these are not available, we report the difference between the estimated correlation levels from the models with a structural break in mean, or estimates derived from a robust regression of a simple linear time-trend model similar to Pukthuanthong and Roll (2009).

[327] Also trend coefficients and other measurements do increase numerically.

[328] Included institutions are: BNP Paribas (BNP), Societe Generale (SOC), Commerzbank (COM), Deutsche Bank (DBG), Credit Suisse (CSG), UBS, Royal Bank of Scotland (RBS), Ageas-Fortis (FOR), Dexia (DEX) and KBC Groep (KBC).

dancies, and because the analysis of correlations between US and European institutions was less significant due to the lower (weekly) data frequency.

It can be immediately seen that the dynamics during the subprime crisis are similar to those of the US sample. There is a generally positive trend throughout the whole group, with the singular exceptions of negative trends for Commerzbank with DBG and DEX. In the period prior to the crisis, the picture is more ambiguous in Europe than in the US. Considering the Royal Bank of Scotland (RBS), which was heavily exposed in the crisis, as an example, we see interdependencies increasing for the 48-months time window, although trends for the 24-months before the subprime crisis are negative. Nevertheless, KBC Groep (KBC), which was generally less threatened, shows broadly positive trends with other institutions throughout both time-windows. A similar case can be made for UBS, which, as described earlier (section 3.3.4), was also vulnerable to US residential mortgage markets.

It is problematic to draw parallels between the European and US samples. However, we have to bear in mind that the methodology applied to the international sample differs slightly from the US sample, since individual returns are conditioned on national market index returns by a simple factor model. By doing so, we control for aggregate trends of market correlation and focus on the idiosyncratic correlation among the institutions. The methodology is subject to Pukthuanthong and Roll (2009)'s criticism that asymmetries in the factor coefficients can cause a downward bias in the correlation measure.

Also, we have to account for the specifics of the subprime crisis, which began with the burst of the US real estate bubble, and then spread geographically and to other sectors. Therefore, we need to distinguish the exposures of European institutions. Only a few institutions, such as UBS, had prodigious exposure immediately linked to US real estate markets. Hence, though other institutions might have been laid open to like sectors, there was unlikely any strong interdependencies ex ante and correlations increased only in later stages, due to information contagion etc.

Lastly, one cannot ignore that European institutions represent a variety of countries, while the US sample focuses on just one market. Several studies, such as Bekaert et al. (2008) and Cappiello et al. (2006), have pointed out that, although there has been ongoing integration of European financial markets, the interdependencies of the European institutions are certainly not yet at the levels as those in the US. In fact, many factors remain that reduce institutional correlations across European borders[329].

[329] The observation that most of the cited studies of European financial markets focus on comovements or correlations of market indices as an aggregate measure, can be also attributed to this observation.

4.2.6 Interdependence of insurance and other financial institutions

In our systemic analysis, we introduced a differentiation between the banking and the insurance sector (section 3.4). We argued that the insurance and banking business models had to be distinguished as their implications on systemic risk were significantly different. In general, the contribution of traditional insurance institutions to systemic risk in financial markets should be relatively low, due to a lesser vulnerability to liquidity interruptions, and lower interdependencies throughout financial markets. Without contradicting this premise, we pointed to individual insurance institutions, such as AIG or monoline insurers Ambac and MBIA, which feigned impunity and have to be regarded as major contributors to systemic risk in the financial crisis 2007–09.

Table 20: Trends of interdependencies for insurance institutions in financial markets

		48-months[2,3]			**24-months**[2,3]			**Subprime**[2,3]			**48-months − 24-months**[4]			
	Models[1]	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	No.	Δ_{25}	Δ_{med}	Δ_{75}
AETNA	53	14	4	0.0018	12	6	0.0011	4	12	-0.0030	17	-0.0027	-0.0006	0.0020
AFLAC	49	9	4	0.0004	9	0	0.0044	8	4	0.0001	11	-0.0001	0.0000	0.0034
AIG	**53**	**2**	**22**	**-0.0076**	**24**	**7**	**0.0034**	**14**	**11**	**0.0007**	**23**	**0.0018**	**0.0147**	**0.0206**
AMBAC Financial	**55**	**3**	**14**	**-0.0016**	**10**	**0**	**0.0039**	**4**	**5**	**0.0000**	**8**	**0.0000**	**0.0051**	**0.0097**
AON	48	6	10	0.0000	31	2	0.0048	21	0	0.0214	21	0.0009	0.0074	0.0113
Berkshire Hathaway	54	22	9	0.0012	26	0	0.0082	2	4	0.0000	21	0.0011	0.0074	0.0130
Cigna	40	40	0	0.0132	30	9	0.0017	11	30	-0.0062	40	-0.0188	-0.0130	-0.0059
Genworth Financial	46	21	15	0.0001	42	1	0.0115	34	7	0.0086	38	-0.0013	0.0069	0.0269
Hartford Financial	52	7	19	-0.0032	26	7	0.0038	22	5	0.0073	25	0.0011	0.0074	0.0110
Humana	47	14	4	0.0012	15	9	0.0013	2	6	-0.0009	17	-0.0016	0.0000	0.0014
Lincoln National	53	1	5	0.0000	12	1	0.0073	12	2	0.0245	7	0.0000	0.0000	0.0134
Marsh & McLennan	54	0	4	0.0000	12	8	0.0003	20	1	0.0230	8	0.0000	0.0045	0.0125
MBIA	**53**	**0**	**25**	**-0.0101**	**11**	**0**	**0.0058**	**3**	**9**	**-0.0059**	**13**	**0.0056**	**0.0085**	**0.0150**
Metlife	45	3	22	-0.0046	15	1	0.0057	25	4	0.0133	17	0.0057	0.0101	0.0135
Principal Financial	48	7	21	-0.0032	35	2	0.0062	30	10	0.0066	29	0.0068	0.0107	0.0149
Progressive	55	9	4	0.0000	7	5	0.0000	9	1	0.0228	9	-0.0013	0.0000	0.0013
Prudential	42	18	18	0.0000	25	4	0.0052	26	4	0.0108	28	0.0001	0.0043	0.0123
The Chubb	52	18	7	0.0016	18	3	0.0027	22	1	0.0209	19	-0.0027	0.0000	0.0016
United Health	54	33	4	0.0023	10	28	-0.0011	7	12	-0.0026	36	-0.0071	-0.0042	-0.0005

[1] Total number of DCC-GARCH models that were significant.
[2] Number of models significant at 15% level with positive/negative trend and according median.
[3] Median and quantiles of difference in estimated δ between time windows.

In line with our prior analysis of the 'systemic core', table 20 reports the results for the analysis of time trends in dynamic conditional correlations, but only for (mid/large) insurance institutions within our sample[330]. Note that the table only includes correlations between insurance companies and financial institutions from different sectors. Hence, the table illustrates the evolution of interdependencies of the insurance sector and wider financial markets, while excluding dynamics within the sector.

Comparing the time trends of correlation between the 48-months and the 24-months time window, it stands out that many institutions of the sample already show

[330] For details on the sample structure please refer to table 18 on page 172.

increasing interdependencies in the period from June 2003 to June 2005 (48-months): there are more positive (δ_+) than negative (δ_-) trends and the median of all trends (δ_{med}) is mostly positive. In the two years prior to the crisis (24-months), these trends become generally more pronounced throughout the sample despite some exceptions. This observation on dynamics in interdependencies is even more notable for the three highly exposed companies—AIG, Ambac and MBIA—that are in bold for illustration purposes.

For these institutions which could be identified as systemically relevant insurance institutions from an ex post perspective, interdependencies with the rest of the financial sector mostly decrease throughout the 48-months time window, but then reverse to a strong increase for the two years prior to the crisis. Looking at the comparison of trend factors between the 48-months and 24-months time windows (last set of columns) specifically for AIG, we see that the median difference (Δ_{med}) reveals a strong increase of interdependencies which is higher than for all remaining institutions.

Overall, the finding underscores the presumption that individual insurance institutions fostered growth in business segments close to financial markets and, due to this convergence, interdependencies with other financial institutions increased. As a consequence, these insurers became exposed to (endogenous) systemic risk in financial markets and, at the same time, became a source of systemic risk themselves. This conclusion is similar to Brownlees (2010), who ranks AIG among those institutions being most exposed to the crisis dynamics. Interestingly, although their analysis is similar in nature, Acharya et al. (2010b) do not list AIG and Ambac, but only MBIA in their systemic risk ranking[331]. Generally, they conclude that in their estimate of systemic risk measures, institutions from the insurance sector are, overall, the least systemically risky.

4.2.7 Conclusions from the empirical analysis

We study dynamics of correlations among financial institutions prior to the financial crisis 2007–09 and until the breakdown of Lehman Brothers in September 2008. The underlying rationale of our analysis is that collective behavior of financial institutions, which is considered a major source of systemic risk, increases interdependencies and, through market expectations, leads to rising levels of correlations. Our goal is to determine whether, prior to the crisis, one can find significant indications for increases of interdependencies. Any statistical evidence that systemic risk can be identified ex ante supports the argument for quantitative indicators of systemic risk, as an important mainstay of macroprudential regulation. Our conclusions summarize our results, relate them to other analyses, and, finally, discuss statistical challenges to the identification of systemic risk.

[331] AIG is only included in the MES ranking based upon CDS data.

The focus of our study is on two samples of financial institutions, of which the first allowed us to track correlations in an international context and the second focused on interdependencies among US financial institutions, differentiated by type and size. With reference to time, we define three exogenous time windows: from June 2003 to June 2005 (48-months); from June 2005 to June 2007 (24-months); and from June 2007 to September 15, 2008 (subprime crisis). Hence, our analysis provides a cross-sectional as well as a time-series perspective on systemic risk, while it acknowledges that the exogenous time-windows—with the benefit of hindsight—imply a selection bias, which any forward-looking indicator of systemic risks would have to overcome; see Borio (2010).

In terms of methodology, we apply a bivariate DCC-GARCH specification to derive dynamic conditional correlations, pairwise for all institutions of both samples[332]. Such a reduced-form approach cannot be decisive in terms of causality, but only infer possible explanations from the results; see International Monetary Fund (2009a). Overall, the DCC-GARCH approach helps to gauge the extent of institutional interdependencies or the comovements among markets in normal as well as stressful periods in financial markets.

A first look at median correlations for the different cross-sections exhibits relatively stable correlation levels for the pre-crisis period; strong increases were noteworthy for the subprime crisis, stressing the presence of contagion, as analyzed by Longin and Solnik (2001) and Kannan and Köhler-Geib (2009)[333]. Subsequently, two statistical testing procedures are conducted to establish more specific evidence on trends in correlation dynamics. In the first step we focus on the level of correlations and, following Cappiello et al. (2006), analyze the hypothesis that there is empirical evidence for an increase in the level of interdependencies prior to the crisis. In the second step, our hypothesis is that there is empirical evidence for a positive increase in the trend of interdependencies prior to the crisis, and we apply the test statistic proposed by Phillips and Perron (1988) for a deterministic time-trend in correlations during the individual time-windows.

For the international sample, the overall results of both tests are generally balanced. Only for financial institutions of the Eurozone (EUR) with the rest of the sample do we find evidence for increasing correlations[334]. For the US sample the results of the test for structural breaks in mean are limited by the high volatility of correlations, with the

[332] A caveat to the explanatory power of stock market return correlations is that these are an external measurement and thus a potentially biased representation of institutional interdependencies. Additionally, one has to account for the methodological criticism of Pukthuanthong and Roll (2009) that the correlation measure might imply a downward bias. As we only focus on dynamics/trends of correlations, but without qualifying the overall level, this criticism is not applicable to our results. Furthermore, these limitations similarly apply to the major recent studies, e.g. International Monetary Fund (2009a), Adrian and Brunnermeier (2010), Acharya et al. (2010b), Brownlees (2010), etc.

[333] In contrast, Chesnay and Jondeau (2001) and Forbes and Rigobon (2002) argue that correlations are regime-independent and do not increase substantially in a crisis.

[334] While correlations within Europe (EUR, NEU) show to be more stable and the test for structural breaks in mean yields results, the Phillips-Perron test for a deterministic time-trend fits better for correlations dynamics between European and US financial institutions.

exception of depository institutions (DEP). Hence, the Phillips-Perron test yields better results and offers evidence that, looking at time trends in correlations, one can identify a trend break between the two pre-crisis time-windows: while time trends of correlations are balanced or mostly negative for the 48-months time-window, the majority of estimated trend variables is then positive for the 24-months pre-crisis period. This observation is especially significant for dynamics between the Broker-Dealer (BRO) segment and the large (LRG) financial institutions with the rest of the sample. However, these dynamics do not apply for the full cross-sections but only fractions of them.

Due to the fact that, in the aggregate samples we do not find particularly strong evidence for increasing interdependencies and rising levels of systemic risk prior to the crisis, we subsequently focus only on what we define as a 'systemic core' of financial institutions. This selection is made in reference to Brownlees (2010), who establishes a ranking of financial institutions according to their exposure to market dynamics. Once we narrow in on these systemically relevant institutions, the picture changes dramatically. For a group of ten institutions plus Bear Stearns as the leading investment bank in the mortgage securitization business, we show that correlations with the rest of the sample, and within the systemic core, generally increase prior to the crisis (24-months time-window), while for the previous time-window (48-months) correlation trends were mostly negative. Similarly, those insurance institutions critically exposed in the crisis show strong ex ante increases of interdependencies with the rest of the financial markets.

Summing up our results, we can partially confirm our main hypothesis as we identify statistic evidence for increasing interdependencies between specific subgroups of our samples prior to the crisis. Yet, the pure measurement of such dynamics does not allow any causal statements regarding the underlying drivers of systemic risk. It would be interesting to extend our analysis and try to link the observed dynamics of interdependencies to specific factors. This is done in a study by Bekaert et al. (2008), who relate increases in the comovement of markets to successive integration. De Nicoló and Kwast (2002) present evidence for consolidation as one driver of systemic risk among other unidentified ones.

Regarding our conclusion that interdependencies increase prior to the crisis, and are particularly strong for a systemic core of institutions, they are in line with those of the other studies that we referred to throughout this section, e.g. Acharya et al. (2010b), with their ranking of financial institutions in terms of their contribution to systemic risk is similar to ours. This is even though their methodology is much more sophisticated than ours, due to the fact that these studies aim to quantify the overall level of systemic risk as well as the institutional contribution[335].

[335] We have argued at the beginning that the fundamental ingredients to measure systemic risk, correlations in our study

Based on these comparative analyses Drehmann and Tarashev (2011a,b) argue that the differences in results among these more complex methodologies are to a large extent determined by methodology. More importantly, the observation that highly sophisticated methodologies do not yield substantially different results compared to simple indicators is also asserted by Drehmann and Tarashev (2011b) and Brownlees (2010), who show that plain variables such as leverage and asset size may serve as indicators for the systemic risk contribution of individual institutions[336].

Results coming from highly sophisticated methodologies in comparison to those derived from relatively simple indicators imply a trade-off for the design of macroprudential regulation. The adequate level of complexity and sophistication is set to become a tensely discussed issue. Furthermore, any sophisticated methodology will have to face intense scrutiny before regulators can consider their results as a basis for regulatory actions. One can argue rightfully that our correlation measure is constrained in its ability to detect systemic risk, since it fails to capture the 'fat-tailed' nature, and changes in the probability distribution of asset returns of key financial institutions, which are characteristic of systemic crises; see International Monetary Fund (2009a). However, correlations can certainly serve to identify potentially critical areas for which further analyses have to be conducted. Tarashev et al. (2009) point out that there can be no single indicator, but rather only a combination of factors can be effective in identifying critical developments.

The fact that results of highly complex studies can be somehow reproduced by much simpler indicators calls for further discussion. The trade-off is similar to risk-assessments at the institutional level: sophisticated approaches claim to produce a relatively accurate measure of specific realizations of systemic risk, especially focusing on the tail behavior of asset returns. Yet, there is a high risk—similar to our observation in the systemic analysis—that other realizations of systemic risk exist outside the boundaries of these models, and hence, the measures suggest a false sense of certainty. From that perspective, the much simpler indicators could help to identify potentially critical areas/developments for further analysis. The risk of neglecting aspects of systemic risk can only be mitigated by a multitude of perspectives on systemic risk being assessed in an integrated manner.

In terms of statistical challenges to the measurement of systemic risk, our study, and other methodologies are subject to similar limitations, and show that even ex post approaches to measuring systemic risk face the need to tackle two major limitations: any aggregate perspective causes a smoothing of dynamics, while only targeting a 'systemic

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and covariances in theirs, are by definition related. Variations in the results of Acharya et al. (2010b) derive predominantly due to the adjustment with further variables.

[336] De Nicoló and Kwast (2002) put forward the hypothesis that these large institutions may enjoy a safety-net subsidy higher than smaller banks, because they can be considered as too-big-to-discipline adequately (TBTDA).

core' of financial institutions exposes probable critical trends in interdependencies. Thus, any methodology needs to address the issue of limiting its focus to what is systemically relevant. The global dimension and integration of the financial system aggravate this challenge. Our analysis of the international sample stressed that it would be challenging to account for the global dimension of systemic risk, even if being able to identify critical trends in the US. For the latter, issues regarding methodology will need to be addressed.

Another difficulty with all approaches that have been developed after the crisis lies in the fact that a measurement of systemic risk has to be effective from an ex ante perspective, without being aimed at or optimized by the benefit of hindsight. This implies two concerns that weigh even more heavily than the prior issues: first, it will not be sufficient to simply identify a trend break or indications for increasing interdependencies. From an ex ante perspective, one would need a measurement that allows a qualification of such a trend and identifies whether it is temporary or persistent. This will be particularly hard as time-windows are continuous and cannot pinpoint specific periods. Consequently, as noted by the International Monetary Fund (2009a), advance notice regarding the risk of a systemic event might be very brief.

Second, any ex ante measurement would have to overcome the selection biases inherent in the analyses. Besides the time perspective, more sophisticated analyses often include state variables that seem to be specifically selected to capture certain aspects relevant in the 2007–09 financial crisis. It seems risky to assume that a future crisis would be triggered by similar types of risk. Even if these measures are relevant in the future, we must not neglect the fact that, from a system theory perspective, such a representation of systemic risk will have implications on the risk itself; see the fundamentals on risk (section 2.1.1). Therefore, a second-order observation for systemic risk would need to be identified to ensure an effective mitigation of systemic risk.

4.3 Chapter conclusions

The analyses of this chapter have explored collective behavior of financial institutions as an endogenous source of systemic risk both from theoretical and empirical perspectives. An enhanced understanding of the underlying drivers of collective behavior, and specifically the concept of collective moral hazard, as well as insights regarding possible approaches for its measurement, are crucial determinants for the adequate design of macroprudential regulation needed to address this specific kind of systemic risk. Our research design was motivated by our systemic analysis, and the basic approaches for influencing a system's dynamic proposed by Vester (2002).

This section briefly relates the results of both of our analyses to the context of the 2007–09 financial crisis. It advances the results of our systemic analysis towards some general considerations on collective behavior and moral hazard that are important to be considered when discussing the design of regulatory reforms in the aftermath of the crisis. Hence, it establishes a basis for our discussion of implications for the governance of systemic risk in the subsequent chapter.

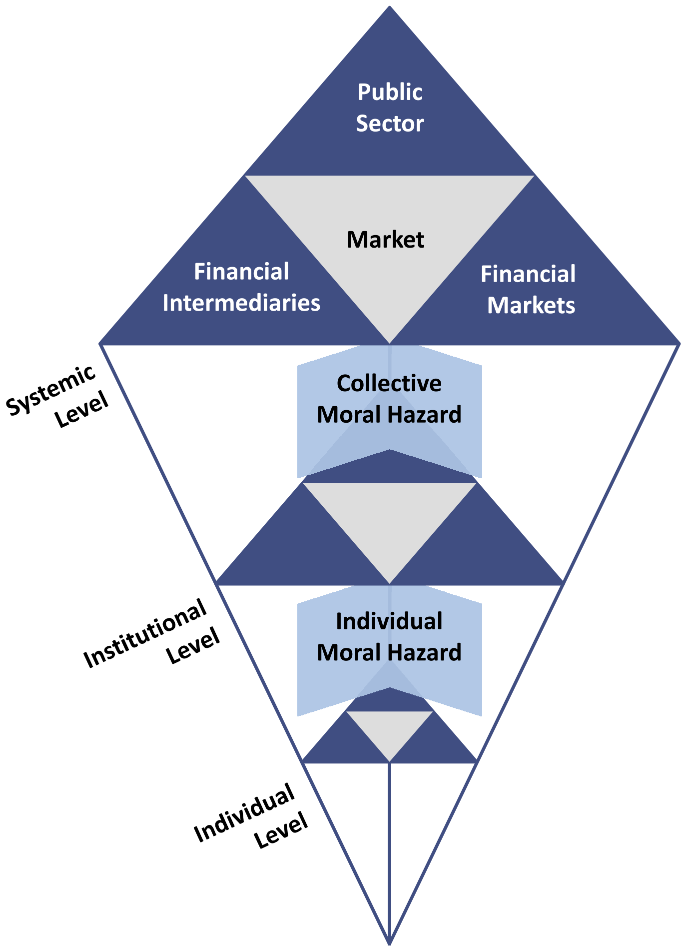

Figure 21: Extended governance triangle accounting for levels of moral hazard

The guiding concept to describe governance structures in financial markets is the governance triangle, presented in the fundamentals chapter (section 2.3). As a result of the systemic analysis we emphasized the evolution of an equilibrium within that framework from a dynamic perspective. Particularly, we described two major shifts that strongly influenced the governance equilibrium over time: first, the consequence of market liberalization; and second, increasing market complexity. These shifts relate to areas of the narratives that were reconciled by the comprehensive systemic approach. The analyses of collective behavior in financial markets in this chapter suggest a further differentiation within this framework (figure 21). This differentiation among levels is relevant to sources of systemic risk, and is now incorporated along the vertical axis of the governance triangle.

Starting at the top, the first differentiation applies between the systemic and institutional levels and is directly connected to the issue of systemic risk. It easily highlights the different approaches of micro- and macroprudential regulation (section 2.3). Microprudential regulation is primarily concerned with stability at the institutional level, as it builds on the rationale that institutional stability also minimizes risks at the systemic level. On the other hand, macroprudential regulation specifically accounts for endogenous dynamics of systemic risk and acknowledges that a group of financial institutions can be systemic in a herd; see Brunnermeier et al. (2009). It considers dynamics of risk at the systemic level to determine regulatory initiatives at the institutional level.

Our theoretical analysis has clearly shown that the interface between the institutional and systemic levels is particularly critical. This is because individual financial institutions have no incentives to account for the systemic effects of their (joint) actions. Therefore, diversification at the system level can be described as a public good; see DeMarzo et al. (2004). Our analysis of incentive structures underlying collective behavior has shown that the concept of collective moral hazard can explain for the evolution of the specific type of systemic risk—as a consequence of collective behavior—that we considered. The two models presented have demonstrated a mechanism that provides incentives for financial institutions to follow the same strategy and deliberately induce systemic risk, due to strategic complementarities in form of a negative externality. The information asymmetry between investors and financial institutions posed an important prerequisite for this externality, as investors had no means to observe banks' behavior and impose disciplinary measures.

The fact that these incentives are dynamic rather stable over time will be particularly challenging for regulation. They will change with the development of economic expectations, competitive dynamics, etc. Besides, even if banks face uncertainty regarding the externality, collective behavior will remain the dominant strategy and give rise to systemic risk. Furthermore, large institutions will assume the role of 'fashion leaders', whose strategies are mimicked by smaller institutions. These findings pose important limitations for regulatory policies targeted to reverse such incentive structures; we analyzed capital buffers, see Acharya (2009); Farhi and Tirole (2009) for further examination of the optimal design of such regulatory policies. The issue is also aggravated by the design of the public sector safety net, being potentially time-inconsistent in view of joint failure of financial institutions.

Whereas the allegation of collective moral hazard is relatively strong and harshly debated in the context of the financial crisis 2007–09, there are other explanations pointing toward systemic risk as a coordination problem which also have to be considered.

From that perspective, Hassan and Mertens (2011) describe the evolution of systemic risk as a 'tragedy of the commons' problem. Similarly, the collective surprise narrative (section 3.2.5) suggests information problems at the heart of developing systemic risk. Indeed, as Avery and Zemsky (1998) have shown, information problems in the form of multi-dimensional uncertainty can induce collective behavior and significant mispricing in financial markets, at least in the short-run.

The issue of information regarding risks in financial markets also relates to our empirical analysis, which aims to identify statistical evidence for an increase in institutional interdependencies as a source of systemic risk in an international and US context. Besides some general reservations whether measurements would be technically adequate, there is more deep-rooted concern about how the level of systemic risk can be qualified from an ex ante perspective. These concerns grow as we identify strong empirical evidence for increased interdependencies only when focusing on a 'systemic core' of financial institutions. Defining the boundaries of a systemic area in the wider financial system, as well as accounting for functional differences such as insurance institutions, will be a particularly challenging task without the benefit of hindsight.

Questions remain from a methodological perspective: Our study focuses on a relatively simple indicator of systemic risk but leads to results which are comparable to much more sophisticated reduced-form approaches such as Acharya et al. (2010b); Adrian and Brunnermeier (2010); Brownlees and Engle (2010). Drehmann and Tarashev (2011a,b) find that simple indicators such as size, leverage, etc. largely replicate the rankings of systemic risk produced by these studies. This makes clear that measuring systemic risk, at the interface of the systemic and institutional levels, is a risky undertaking, as complex methodologies can convey a false sense of certainty, while a subsequent systemic event might be triggered from factors outside the scope of these assessments. From a system perspective, the fact that a measurement of systemic risk will have an endogenous feedback on the system's dynamics has to be taken into account. Only an adequate second-order observation will determine to what extent the measurement of systemic risk poses a systemic risk by itself.

The problem of information regarding risk also reaches towards the lower part of the governance triangle in figure 21, which signifies the interface between the institutional and individual levels. One example demonstrating the importance of this interface was the case study of UBS (section 3.3.4), which reveals imprudent incentives and problems of information aggregation that effectively concealed the institutional exposure in US real estate markets. Yet, if risks are not adequately identified by financial institutions internally, identification of them from an external perspective, and at the system level, will be disproportionally more challenging.

The interface between the institutional and individual perspectives is relevant from the theoretical perspective, as it shows that the issue of collective moral hazard is complemented by traditional individual moral hazard issues within financial institutions, especially between the individual level (traders) and the institutional level (managers)[337]. The underlying rationale is that, because of inefficient governance structures or misaligned strategic objectives at the institutional level, (collective) actions can be taken by individual traders and are then channeled into the aggregate system.

This internal second-level problem complements the external moral hazard between banks managers and owners. Even if incentives between managers and investors are perfectly aligned, systemic risk might still arise once traders have incentives to pursue specific strategy combinations and induce correlated risks, without being adequately controlled by internal governance mechanisms. The institution serves as a meso-level for collective behavior in a two-level concept of collective moral hazard in a broader sense.

Overall, the relevance of specific drivers of collective behavior in the financial crisis 2007–09 is still a matter of debate, not unlike the relevance of underlying forms of collective moral hazard. Our analysis suggests that more research needs to be done to connect market dynamics to potential forms of market failures and identify the underlying (negative) externalities that induce collective behavior and give rise to systemic risk. Effective reforms to the regulatory framework need to be aimed at balancing specific sorts of externalities—e.g. by imposing regulatory externalities on collective behavior or otherwise enabling market discipline.

The differentiation of levels in the governance triangle and the accompanying moral hazard problems helps to clarify the focus of individual reform measures. At the interface of the systemic and the institutional levels, a salient issue is financial institutions not accounting for the aggregate impact of their action in the financial system. Other issues are the design of the public sector safety net and the time-inconsistency of related policies, which can be a source of collective moral hazard. To deal with the two-level concept of moral hazard, the main objective is to strengthen internal mechanisms of governance, through internal risk-control obligations or a redesign of compensation systems.

Possible reforms deduced from our theoretical models would be to (1) limit regulatory actions to setting minimum-standards, and (2) fostering information disclosure in order to tackle critical information asymmetries. This would allow external stakeholders of financial institutions to exert more discipline on financial institutions. At the same time, a better quality of information at the institutional level would create more transparency with regard to the risk exposure of individual institutions, and open new avenues

[337]The above-mentioned moral hazard between managers and investors probably arises at the institutional level. This conflict, however, arises among different stakeholder groups and thus is not differentiated in the vertical dimension.

for improving the measurement of systemic risk and implementing appropriate provisions to strengthen macroprudential regulation.

Chapter 5

Implications for the governance of systemic risk

As an immediate response to the financial crisis 2007–09 the G20, in November 2008, mandated major international bodies to identify shortcomings and propose reform measures to the regulatory framework of international financial markets. Since then, a variety of institutions have issued reports and papers: these include international institutions, special political committees, public think tanks, and representatives from academia[338]. The major slant of these contributions is the design of macroprudential regulation to tame (endogenous) systemic risks within financial markets and safeguard the stability of the global financial system.

This chapter discusses some critical issues connected to the design of macroprudential regulation against the background of the conclusions from our systemic analysis, as well as theoretical and empirical analyses of collective behavior among financial institutions. We do not claim this discussion to be comprehensive, but focus only on those aspects relevant from the perspective of our analyses[339]. We focus on the governance triangle, as it was already applied in our systemic analysis (chapter 3), and extended to different levels—systemic, institutional, and individual—in our analysis of collective behavior of financial institutions (chapter 4), to illustrate different types of moral hazard to be regarded as sources of systemic risk.

[338] Various corresponding reports have been issued by the Financial Stability Forum (FSF), Basel Committee for Banking Supervision (BCBS), International Monetary Fund (IMF), Senior Supervisors Group (2008), etc. and can be accessed online. Publications by private think tanks and other special committees include the Group of Thirty (2009, 2010, 2011), by Lord Turner (2009) in the UK, De Larosière et al. (2009) in the European Union, Brunnermeier et al. (2009), as well as the Institute of International Finance (2008). Last, representatives from academia have also intensively contributed to the debate; see e.g. Acharya and Richardson (2009) and Acharya et al. (2010a) amongst many others.

[339] It is not our goal to discuss the design and implementation of individual regulatory instruments. For such a discussion, we refer the reader to the aforementioned studies.

What sets us apart from the many existing discussions on these issues, the focal point of this thesis, is that *our argument draws from the results from a systemic analysis and combines these insights with our research on collective behavior of financial institutions.* The systemic analysis established an integrated model of different narratives on the crisis. It was particularly concerned with patterns of interaction in the financial system, such as feedback loops and the interaction of different variables, and the consequences for the evolving aggregate dynamics.

Against this background, we (1) argue there are significant reservations about how macroprudential regulation can effectively tackle the issue of systemic risk; and (2) highlight similar reservations for private sector governance, based on our prior conclusions on incentives for collective behavior. This is especially so as financial institutions have no incentives to account for the systemic implications of their (joint) actions. Our synthesis concludes that there is need for a broader understanding of governance, and for a more explicit discussion on the ratio of risk to return acceptable in society. Integrated sociological perspectives are needed in order to achieve a higher level of objectivity of risk. A more integrated approach, incorporating systemic and sociological aspects, brings to light an important element of research on systemic risk in financial markets.

Our systemic analysis shows that an equilibrium within the governance triangle will be dynamic. We pointed out two major shifts prior to the 2007–09 financial crisis: the first, from dominant public regulation towards private sector governance; and second, towards financial intermediaries, through the rising complexity of financial markets, products and institutions. The financial crisis 2007–09 will trigger a next shift in financial market governance, the direction of which has still to be determined. A proactive assessment of the governance equilibrium is important because, as the systemic analysis shows, imbalances or specific flaws will not immediately cause systemic risk, but rather pose a critical basis for its evolution. Ineffective governance of risk might again lead to a collective overemphasis of opportunities, a new 'this time is different' phenomenon, and could endogenously amplify to a level at which diseconomies of risk increase the vulnerability of the overall system.

The issue determining the governance equilibrium, comparing the above proposals for regulatory reforms, is the balance between the different stakeholder groups, specifically public sector regulation and private sector governance. In comparison to systemic instabilities tied to a dominance of private sector governance, an equilibrium dominated by public sector regulation can also have adverse consequences for financial market developments and for the real economy. It would constrain the potential for innovation and growth in financial markets, and might, through unintended consequences, even reduce the efficiency of capital allocation in the economy. This illustrates that trade-offs among the interests of the individual groups will be inherent in any governance equilibrium.

Our discussion is guided by the further observation that, while ultimate objectives of regulatory reforms—to safeguard the stability of the financial system—are easily agreed upon, more in-depth arguments on the design of measures of the individual stakeholder groups are fairly controversial. For macroprudential regulation, there is a gap between what reforms are supposed to achieve and their true effectiveness; see Borio (2010). Against this background, we focus specifically on limitations, and thus the risk-dimension, of individual stakeholder contributions to the governance of systemic risk: limits of macroprudential regulation by the public sector (section 5.1); and risks attached to private sector governance (section 5.2). Section 5.3 presents our synthesis.

5.1 Limits of macroprudential regulation

Although the term ‘macroprudential regulation’ evolved in the late 1970s there were only a few contributions prior to the financial crisis 2007–09; see Clement (2010). The discussion of how to regulate endogenous risks as being the consequence of the collective behavior of market participants only evolved subsequent to the crisis, from the conclusion that the regulatory focus was too much on microprudential regulation; see Group of Thirty (2010). Proposed macroprudential initiatives aim mainly to tackle two dimensions of systemic risk: the first goal is to identify and regulate critical trends in financial markets that can cause a pro-cylical bias and induce systemic risk; the second, that macroprudential policies are concerned with financial institutions not internalizing the potential cost of their failure at the systemic level. As Borio and Drehmann (2009), Lord Turner (2009) and the Group of Thirty (2010) point out, particular focus has to be on systemically important financial institutions (SIFIs).

To be effective, a macroprudential framework needs to be carefully designed. The Bank for International Settlements et al. (2011) has provided an extensive report to the G20, emphasizing three particular aspects to be considered[340]: (1) objectives, selecting the risks to be measured and their identification; (2) scope, defining the architecture of prudential arrangements; and (3) the set of powers, determining the institutional setup and necessary authority. Following this structure, we discuss the results of our analyses in the wider context of contributions to the ongoing debate.

[340]This categorization is similar to Borio and Drehmann (2009).

5.1.1 Identifying systemic risk

The primary challenge regarding the identification of systemic risk is highlighted by the initial quote from the International Monetary Fund (2009a), p. 113, that, due to its nature, systemic risk 'is difficult to define and quantify. Indeed, it is often viewed as a phenomenon that is there 'when we see it', reflecting a sense of a broad-based breakdown in the functioning of the financial system'. De Larosière et al. (2009) call for a 'through-the-cycle-approach' to measure systemic risk, which is an objective easily agreed upon, yet challenging to implement. Our empirical analysis makes a direct contribution to the debate on the potential identification of systemic risk. Overall, five major issues need to be considered.

The first issue relates to the *classification of systemic risk within the general context of risk*; see our fundamentals on systemic risk (2.2.3). It is the principal argument of Haller (2004) in his concept of diseconomies of risk that a systemic crisis will not necessarily start as a consequence of specific actions, but rather because of a growing vulnerability at the systemic level. A parallel distinction is between risks of actions and conditions. In our systemic analysis, we identified a set of reactive elements—liquidity, transparency, the rating focus, and institutional microstructure—being critical for the reversal of the system's dynamic and, ex post, highlighting sources of such vulnerabilities. The assessment of risks of conditions must follow a very different approach than for (ordinary) risks of actions. It poses a particularly challenging task as its sources are not yet well understood in the context of financial markets, and can possibly vary over time. This is not accounted for in the current proposals that we referenced in our empirical analysis.

Second, any measurement approach to systemic risk suffers from similar *constraints in terms of information efficiency*, as does risk management at the institutional level; see our fundamentals on measuring risk (section 2.1.2). The issue is further aggravated when considering the interface between the institutional and systemic level, which creates additional concerns of data aggregation to be tackled. Consequently, even the most sophisticated approaches to systemic risk will always incorporate residual errors. Measures building on reduced-form approaches, as referenced in our empirical study, rely on market information or aggregated expectations to identify systemic risk. Such methodologies will always be vulnerable to a collective surprise and lead-times to identify systemic risk can be short; see International Monetary Fund (2009a).

Third, there is a risk that *sophisticated quantifications of systemic risk convey a false sense of certainty.* This relates to the collective surprise narrative of our systemic analysis (section 3.2.5), and specifically to the role of ratings prior to the crisis. From a systemic perspective a pro-cyclical bias in information on financial market risks will spread into other measures, e.g. institutional risk models. This complicates the original bias[341]. The measurement of systemic risk can thus become a systemic risk itself, through this endogenous feedback loop. Similarly, one also has to account for the feedback of any representation of systemic risk in the financial system, as the measurement causes a reaction of the system's participants[342]. Based on this, Zimmermann (2008) calls for a second-order observation[343], to scrutinize the adequacy of any representation of risk in terms of potential circularities[344].

The fourth issue is that our empirical analysis argues that *simple indicators*, such as our correlation measure, can, to a large extent, replicate conclusions of more sophisticated approaches. The Group of Thirty (2010), similar to Drehmann and Tarashev (2011b), argues for simple indicators such as leverage, liquidity and measures of credit expansion. This calls for scrutiny of the necessary accuracy of systemic risk measures, see Zimmermann (2001), as it seems rather impossible to establish an accurate measurement of systemic risk. A focus on fuzzy measures or simple indicators would diminish the risk of a false sense of certainty. Our research design offers a potential strategy in this regard. Simple or fuzzy measures could serve as a first step to identify critical dynamics in the financial system. Through the combination with a systemic perspective one could further identify potential circularities. This would determine the focus of in-depth analyses, to be conducted as a second step, and to turn specifically to what drives systemic risk, e.g. collective behavior.

Last, it will be problematic that, in addition to defining an adequate measure of systemic risk, any *indicator will need to be qualified*. Hellwig (2008) points out that, in fact, regulators need to make a 'business judgment' whether the risks bound to an activity are desirable or not. This would elicit a strong market intervention, a discussion we will come back to later in this chapter. De Larosière et al. (2009) argue that such a judgment even contributes to collective moral hazard, as it increases expectations for a bailout, if the regulators' assessment turns out wrong and leads to a crisis. It remains to be seen to what extent macroprudential regulation can build on automatic stabilizers; see Borio and Drehmann (2009).

[341] Overall, the cyclicality of the financial system cannot be dealt with by static mechanisms of regulation; see Hellwig (2008). More research is needed to identify how regulation and governance can tackle these inherent characteristics of financial markets.

[342] Besides the issue of information-based contagion (section 2.2.3), our fundamentals highlighted the endogenous feedback of the measurement of risk to subsequent actions of market participants; see Morris and Shin (1999) and Danielsson et al. (2010), as well as section 2.1.2.

[343] von Foerster (1993) notes the problem of self-referentiality when analyzing a system from within, as it is affected by the system's dynamics. Only by observing the system from an exogenous position (second-order) can these develop an adequate representation.

[344] One relevant aspect in this regard is the close interaction of liquidity and credit risks, being particularly hard to distinguish; see Brunnermeier (2009).

5.1.2 Defining the perimeter of regulation

The second challenge to be tackled refers to the perimeter of macroprudential regulation. As one example, we have argued already in our systemic analysis that the traditional insurance business' contribution to systemic risk in the financial system is much lower than compared to other financial intermediaries[345]. Yet, the strategic alignment and convergence between both sectors led several insurance institutions to build extensive exposure to critical segments, particularly by underwriting CDS on securitized mortgage products. Risks of these products were not identified adequately by regulators, nor by financial institutions.

Thus, it becomes clear that a 'one-size-fits-all' approach to macroprudential regulation cannot be effective. The International Monetary Fund (2009c) and Brunnermeier et al. (2009) state that reforms to the regulatory framework of financial markets will have to carefully define the perimeter of regulation, including criteria to identify the SIFIs being subjected to more intense regulation; see Bank for International Settlements et al. (2009). This perimeter also has to account for functional or institutional differences, in terms of their individual contribution to systemic risk. Regulators need to reform institutional supervisory structures managing these differences but, at the same time, also deal with conglomerates that combine several activities[346].

From a general system theory perspective (see our systemic analysis in section 3.3), the selection of the system's boundaries is especially critical, as regulation can only target endogenous dynamics of this defined system. Any exogenous influences outside the boundaries of the regulatory framework cannot be affected. One example in the financial crisis 2007–09 is the shadow financial system. While being a critical endogenous factor in our model, it was exogenous to the regulatory system and, therefore, largely independent of regulatory provisions. In fact, regulatory provisions even contributed to the shift of specific financial intermediation activities to the shadow financial system. Our systemic analysis identified other critical variables driving the structural evolution of financial markets: in particular financial products and innovations, disintermediation, and the microstructure of financial institutions.

This signifies that the perimeter of regulation in financial markets has to be dynamic. Although Reinhart and Rogoff (2009) illustrate common patterns throughout financial crises at the system level, there is no stable link to the institutional level. In our empirical analysis, we are able to establish statistical evidence for increasing interdependencies of major insurance institutions—AIG, MBIA and Ambac—with the rest of

[345] Similarly, e.g. Acharya et al. (2010b) conclude that specific activities of financial intermediaries contribute less to systemic risk than others.

[346] Lord Turner (2009) argues that an effective design of interaction between regulatory bodies has yet to be developed and, as of today, we even lack understanding of the interaction among different regulatory bodies.

financial markets. Evidence also points to increasing interdependencies for a systemic core of financial institutions, to be potentially classified as SIFIs in a future regulatory framework. However, we argue that important challenges to identify systemic risk from an ex ante perspective need to be overcome. More sophisticated methodologies have been criticized for being heavily dependent on specific indicators relevant to the 2007–09 financial crisis; see Drehmann and Tarashev (2011a,b). While it already poses a struggle to identify systemically important parts in the financial system from a static ex ante position, a dynamic differentiation, accounting for a structural evolution, will be a disproportionally greater challenge.

Besides structural evolution, there will also be an endogenous response to a refined regulatory framework, similar to measurement of systemic risk. Specific activities will shift into less regulated parts of the system or even be driven outside of the regulatory perimeter. Minimizing potential 'regulatory arbitrage' will be a major task, taking into account the pace of innovation in financial markets. A system theory perspective, again, calls for a second-order observation to complement the regulatory framework and to account for potential feedback effects. Such an observation has to be continuous and carried out by an institution of a second order. In the global context—accounting for conflicting national interests—there are many reasons to doubt that the dynamic alignment of the regulatory perimeter can be effective.

5.1.3 Implementing effective macroprudential provisions

The final difficulty is how macroprudential provisions can be effectively implemented. For the financial crisis 2007–09 the International Monetary Fund (2009b) identifies a number of early warnings on evolving risks. Yet, as we conclude from our systemic analysis (section 3.5), these did not trigger reactions by any of the stakeholder groups integrated into our governance triangle. For the public sector, the failure to intervene might be attributed to increasing regulatory capture and other shortcomings of the framework that are shown in by our systemic analysis. For financial intermediaries, our theoretical analysis (section 4.1) led to the conclusion that there are no incentives to consider the consequences of their actions at the systemic level, in terms of systemic risk. We even point out the relevance of collective moral hazard as a source of systemic risk: incentive structures for which financial intermediaries intentionally opt for collective behavior and maximize the risk of joint failure. In this context, our discussion of macroprudential regulation must also focus on how to create effective counterincentives to collective behavior. We briefly comment on two particularly important regulatory instruments in this regard: (1) capital/liquidity buffers; and (2) governmental interventions as a lender-of-last-resort (LOLR).

One of the most important instruments of the regulatory framework in the financial system is *capital buffers*, being at the heart of the Basel Capital Accord. Our theoretical analysis incorporates a capital buffer as an idiosyncratic information signal that allows creditors to differentiate with regard to the risk of an individual bank's failure. We showed that it could effectively mitigate the collective moral hazard upon which banks behaved collectively and induce systemic risk. The rationale of a capital buffer, like the leverage ratio[347], is to control the evolution of a financial institution's microstructure and limit its inherent vulnerability. Whereas capital buffers provide a cushion against bankruptcy, liquidity buffers have been proposed to ease insolvency risks. For an effective implementation any form of a buffer needs to be carefully designed to tackle the right form of vulnerability and to dynamically account for cyclical developments.

The overall appeal of liquidity buffers is contested by Goodhart (2008) arguing that, as soon a liquidity buffer has to be drawn upon, underlying assets will turn illiquid, and the buffer becomes ineffective. Hellwig (2008) makes a comparable argument for capital buffers: once minimum standards are imposed, the buffer becomes obsolete and no longer fulfills its function, since capital must not fall below this minimum[348]. The Group of Thirty (2009)[349], p. 43, concludes that buffers would need to be defined as 'wide operating ranges, rather than minimum point estimates'[350].

The conclusions of our theoretical analysis emphasize another test for institutional capital/liquidity buffers, which is at the interface of the different levels in our expanded governance triangle. A regulatory imposition of buffers creates incentives at the institutional level to control developments at the systemic level. The juxtaposition of the institutional and individual levels can hardly be addressed externally. Our case study of UBS (section 3.3.4) demonstrates that the failure to implement differentiated capital surcharges within the organization—according to the riskiness of specific activities—importantly contributed to its risk exposure. Thus, the imposition of a capital buffer, at the juncture of the systemic and institutional levels, still requires complementary action within the institution.

Second, *governmental interventions* and specifically LOLR actions are instrumental to the macroprudential framework. Our systemic analysis, as well as the theoretical explanations of collective behavior, illustrate that the anticipation of LOLR interventions is particularly critical, as it gives rise to collective moral hazard. Banks then pursue

[347] A leverage ratio has for instance been implemented in Switzerland. A detailed description of measures implemented in Switzerland as a response to the 2007–09 financial crisis can be found Financial Stability Board (2012).

[348] See also similar arguments by Hellwig (1995); Hellwig and Staub (1996); Hellwig (2005).

[349] With regard to the design of capital/liquidity buffers, the Group of Thirty (2011) generally points out that further research is required regarding the inclusion and weighing of specific types of assets.

[350] Other commentators, such as Acharya et al. (2010a), propose other regulatory instruments, such as a taxation of specific bank activities, as an alternative to capital/liquidity buffers.

coordinated strategies to maximize the probability of a bailout. This is due to time-inconsistency from the regulator's perspective: a bailout will be less costly than the deadweight cost brought about by a joint failure of banks[351].

Hellwig (2008) explains that any stable set of rules for such interventions will necessarily imply anticipation of LOLR measures and thus collective moral hazard. Goodhart (2008) argues that the only strategy to limit this kind of moral hazard would be to design a bank insolvency regime that includes the expropriation of shareholder rights, at least to a certain degree[352]. Alternatively, the choice of discretionary measures will reduce banks' incentives but, at the same time, exacerbate market reactions and increase the risk of a panic, similar to after the failure of Lehman Brothers. A 'constructive ambiguity', as emphasized by De Larosière et al. (2009), offers to tackle both issues but seems particularly hard to implement. There has to be scrutiny of current proposals of living wills, allowing for an orderly resolution of failed institutions. Their implications in terms of spillover and information effects in financial markets are yet to be tested; see Group of Thirty (2011).

From an ex ante perspective, as mentioned earlier, it is important that macroprudential regulation requires some sort of business judgment by regulators, as they need to qualify the level of systemic risk (section 5.1.1). This would strengthen expectations of LOLR interventions in a crisis and exacerbate collective moral hazard. Acharya et al. (2010a) emphasize in their review of regulatory reforms that, despite their importance already in earlier financial crises, critical issues with regard to LOLR have not been addressed sufficiently, neither by implemented reforms nor by pending proposals. In the context of international financial institutions, an additional challenge stems from the fact that an effective cross-border resolution regime can only be surveilled internationally. Thus, a transfer of authority from national supervisors to an international body, which is a political challenge, is required; see Brunnermeier et al. (2009) and International Monetary Fund (2009c).

Overall, the missing alignment of strategies for regulatory reforms in the international context threatens to reduce the effectiveness of addressing systemic risk. The necessary set of regulatory powers claimed by proposals seems generally not achievable by implemented provisions; see Borio (2010)[353]. Due to long transition periods, e.g. Basel III being implemented fully only in 2019[354], reforms are set to suffer from a retrospective character: the structure of the financial system will have changed fundamentally by the

[351] Brunnermeier (2009) introduces a differentiation for desirable interventions on temporary effects such as liquidity interruptions and a threat of insolvency, as compared to undesirable interventions seeking to avoid the failure of any institution due to bankruptcy.

[352] See also the argument of Philippon and Schnabl (2009).

[353] Also compare as a concrete example the proposals for a macroprudential oversight institution made by De Larosière et al. (2009) and Group of Thirty (2010) with the adopted provisions of the European Commission (2009).

[354] A detailed implementation plan can be found in Basel Committee on Banking Supervision (2011), annex 4.

time of full implementation and the measures might be insufficient for tempering systemic risk, especially in the long run. Furthermore, inconsistencies at the international level foster regulatory arbitrage, with critical activities being shifted into a less restricted regulatory perimeter, instead of being limited in their effect; see International Monetary Fund (2009b).

To conclude, current reforms seek to tackle many aspects that were included in our system model individually but, importantly, they fail to address the critical interconnections and feedback loops within the financial system as well as its dynamics. This is the major contribution of our systemic analysis. An interesting aspect for further research would be to look at incentive effects of regulatory provisions at the collective level. This is required to fully understand the effects of regulatory provisions before and within a crisis; see Hellwig (2008). From a systemic perspective endogenous feedback on the dynamics within the financial system needs to be analyzed from a second-order perspective, also taking into account pivotal activities being lessened or shifted to just outside the regulatory perimeter. In its current form, macroprudential proposals seem to come with severe risks attached, and well-intentioned provisions might even contribute to renewed financial instability.

5.2 Perspectives of private sector governance

Considering our previous reservations regarding the effectiveness of macroprudential regulation one could make a strong case for strengthening private sector governance. In this section we argue that private sector governance is subject to similar reservations and its appeal to effectively tackle the issue of systemic risk in financial markets is limited, like public sector regulation.

Our argument proceeds in three steps that build on our prior analysis of collective behavior of financial institutions, as well as insights from the systemic analysis. Again, we discuss our findings against the background of the overall debate. First, we consider the rationale of enhancing private sector governance, before we turn to critical challenges in the second step. We conclude that the systemic dimension of risk will not be accounted for appropriately in decision-making at the institutional level and hence, the problem of systemic risk remains, even if mechanisms of governance are improved.

5.2.1 Basic rationale for enhancing private sector governance

As one example, the International Monetary Fund (2009b) points out that market discipline failed to limit risk-taking prior to the 2007–09 financial crisis due to falsely represented risks, combined with questionable incentive structures. Building on our systemic analysis, we can examine this argument in connection with the narratives on the evolution of the crisis (section 3.2). The systemic approach integrates these different narratives—each explaining the crisis evolution from different perspectives—into one common model and call attention to their interrelations. The collective surprise narrative suggests the presence of overall information frictions and biases in financial markets, as well as flaws in their interpretation; e.g. in the context of ratings. A reduced information efficiency in financial markets limited the potential to contain diseconomies of risk. A stronger interpretation is that the moral hazard narrative supposes that multiple information asymmetries—along the securitization value chain such frictions are identified by Ashcraft (2008) and Franke and Krahnen (2008)—gave rise to incentives for market participants to (collectively) build excessive exposure to specific market segments and exacerbated the issue of systemic risk.

Information frictions comprise a wide spectrum of biases in financial market information, as well as information asymmetries among different groups of actors; see for example Zimmermann (2007), Financial Stability Forum (2008), Goodhart (2008), Hellwig (2008), Institute of International Finance (2008), Brunnermeier et al. (2009), De Larosière et al. (2009), Group of Thirty (2009), or Lord Turner (2009). Examples underscored by these studies are: inadequate risk disclosures by financial institutions, especially regarding off-balance sheet exposures; pro-cyclicality issues in asset valuations and overall financial risk assessments; information frictions along the value chains of specific market segments; and an overall low transparency in specific financial market sectors causing coordination problems. Because of these frictions, evolving biases in the assessment of risk render mechanisms of private sector governance ineffective. Resulting coordination failures in financial markets induce systemic risk, being particularly critical in a downturn; in the context of the transfer of credit risk see Zimmermann (2007).

One basic strategy to enable private sector governance, as proposed by Brunnermeier et al. (2009), is to address these information frictions: to reduce the opaqueness of financial institutions and the complexity in market segments, e.g. derivatives, in order to enhance transparency throughout financial markets. Improving the efficiency of information will supposedly have positive effects on the effectiveness of private sector governance ex ante, and reduce exacerbating effects in a crisis. Clearly, such a strategy requires better knowledge of incentive structures in financial markets, in order to target information frictions of relevance to systemic risk.

This is a continuation of our theoretical analysis in the previous chapter, which models incentive structures underlying collective behavior as an important source of systemic risk, and shows that it can resemble an intentional choice, due to the presence of collective moral hazard. Incentives are biased through the information asymmetry among financial institutions and their creditors; we focus on the interaction in money markets. From the interaction between these two groups arise strategic complementarities, and potential negative externalities will impel collective behavior. Collective behavior induces additional systemic risk that is borne by banks' creditors, while banks' payoffs are jointly maximized. As the behavior is welfare-reducing from the aggregate perspective, it resembles collective moral hazard.

As we showed through our extension of a capital buffer in the creditor expectation change model, incentives can be tackled by reducing the information asymmetry mentioned earlier. The capital buffer provides creditors with an additional information signal, which is idiosyncratic for each bank. For a robust set of assumptions, the capital buffer even induces incentives for differentiation, fully eliminating the collective moral hazard problem. This result from our analysis adds an important contribution to the debate, supporting a possible enhancement of private sector governance.

Alternative explanations of collective behavior are also discussed in our analysis; e.g. competition or a tragedy of the commons explanation. Conflicts derive from the two-level problem that collective behavior can arise at the institutional level but also at the individual level, where the institutional level serves as a meso-level. An examination of the latter seems particularly challenging. Apart from collective moral hazard, we show how herding externalities—banks adjusting their behavior after observing prior actions of other banks—can induce collective behavior and systemic risk. Such biases to banks' decision-making reduce the efficiency of information aggregation. Avery and Zemsky (1998) and Hott (2009) show that they can cause significant mispricing in the short-run. Overall, we come to the conclusion that there is an inherent tendency in financial markets to take collective action, due to a variety of incentives or information shocks. Yet, the underlying mechanisms support the rationale for moderating their occurrence by improving information efficiency in financial markets.

5.2.2 Improving information efficiency in financial markets

There is a vast spectrum of proposals to enhance the information efficiency in financial markets. Reports issued by the Group of Thirty (2009) and De Larosière et al. (2009) call for extended disclosure of risks. For coordination problems in financial markets, reforms aim at adding disclosure standards for financial institutions and certain structured product markets, for over-the-counter (OTC) derivatives at a standardizing these products and establishing a centralized clearing institution. Thus, market transparency—in terms of information regarding market activity, trade prices, and related valuations—will be improved. Without commenting on individual proposals or instruments to be established, we argue that one has to acknowledge that improvements in the efficiency of information in financial markets do not automatically imply a reduction of systemic risk. There are some major problems—we highlight four particular ones—to be accounted for, as they still limit the effectiveness of private sector governance to tackle systemic risk.

The first issue to consider is the argument that, despite its positive effects, increased *transparency* can make the financial system prone to crisis. Sudden market corrections can occur as new information is revealed, increasing volatility; see Persaud (2000)[355]. Morris and Shin (2002) show that, if agents have private information, and additional public information, there are strategic complementarities and incentives for coordination that reduce aggregate welfare. An alternative explanation follows the argument of Akerlof (1970): if information structures are complex they can be processed only by more sophisticated agents, and adverse selection can lead to market interruptions[356].

A second observation is that many proposals foster a *standardization of information.* In highly intransparent market segments, such as OTC derivatives, in combination with a centralized clearing house, this will certainly help to ease information effects in a crisis and create more transparency for specific risk categories, e.g. counterparty risks; see Group of Thirty (2009). In contrast, standardization has to be investigated, as it could pose a risk of conditions. Our systemic analysis stresses how ratings—as standardized information on risk—suggest a false sense of certainty throughout financial markets. They attain relevance for decision-making in the market and regulatory context, and reduced incentives for independent risk assessments. Once the shortcoming of ratings become obvious there are tremendous information effects exacerbating the crisis, as the factual dependence on ratings first has to be overcome.

Therefore, while the enhancement of transparency regarding basic market information seems positive, standardization regarding the processing of information, particularly in the context of risk, seems more critical. This can produce a risk of conditions related to methodological challenges of assessing risks (see the fundamentals, section 2.1.2), as well as continuous innovation and the structural evolution of financial markets. Caution should also be applied to standardizing risk disclosures of financial institutions. Relevant provisions need to be dynamic, allowing for a potential strategy adjustment of financial institutions that might induce a bias. This again relates to a necessary second-order observation, to which we have already referred in the context of macroprudential regulation (section 5.1).

[355] This argument is also supported by the findings of Morris and Shin (2001) and Danielsson et al. (2010), who show the endogenous risks from VaR models. As a higher transparency, and negative information signals, can cause that several institutions sell an asset at the same time, this can cause additional sell-offs by other institutions, increasing market volatility.

[356] We previously refer to Avery and Zemsky (1998), who show that multi-dimensional uncertainty can lead to herding.

Strongly correlated is the third challenge to be addressed, the *pro-cyclicality* of financial markets; see Goodhart (2008). This relates to the Minsky moment narrative of our systemic analysis (section 3.2.3) and describes time-dependent biases in expectations and risks in an economic boom. Weaknesses in the context of the financial crisis 2007–09 were methodological shortcomings of risk assessments as well as dynamics of fair value accounting in the boom, and bust; see Hellwig (2008). The issue of pro-cyclicality is also connected to the notion of 'this time is different' introduced by Reinhart and Rogoff (2009). This refers to implicit risks stemming from the impact of innovation on expectations. Hellwig (2008) argues that once innovative financial products are made subject to adequate regulation, they might fade out of existence automatically, because they create no economic value.

Finally, the assessment of risk in financial markets in the private sector, just as in macroprudential regulation, can be improved only if risks are identified adequately at the institutional level, i.e. within the organization. This is an important result from our proposed *two-level extension of the governance triangle*, which appears in the conclusion of our analysis of collective behavior among financial institutions (section 4.3). Incidentally, this issue was also noted in our case study of UBS (section 3.3.4). Without going into further detail, an enhancement of private sector governance will require two-fold action. One, external mechanisms of governance affect overall behavior and strategic objectives of financial institutions, see Brunnermeier et al. (2009). The other is that mechanisms within financial institutions have to be improved so that management can exert adequate control over individual divisions/units and individual agents. We will argue later that there is merit to consider the sociological perspective on risk, as suggested by Zimmermann (2001), e.g. to assess the evolution of governance structures within the organization.

Despite these challenges, there is agreement among the many contributors to the debate that improvements to transparency in specific market segments is the first step to increase overall information efficiency in financial markets, allow a better assessment of risks, and limit coordination failures in an adverse market environment. However, one has to investigate any measures challenges in mind, as they can reinstitute risks of conditions. It seems crucial to understand that new instruments might suggest to market participants a false sense of certainty and bias behavior in financial markets—focusing only on the upside (chance) of transactions, instead of underlying risks. Such instruments would be risky themselves.

With regard to systemic risk, it is necessary to clarify that improvements to information efficiency will potentially limit risk-taking of individual institutions and help overcome some critical coordination problems. This will lead to the first but only indirect reduction of systemic risk in financial markets. For reasons that we argue in the subsequent section, the overall appeal of private sector governance to directly address systemic risk is subject to severe limitations.

5.2.3 Addressing systemic risk directly through private sector governance

The previous section points out that improvements to public sector governance will have a positive effect on systemic risk through an indirect causality: as better governance reduces risk-taking of individual institutions, it will lead to an aggregate reduction of systemic risk. In this section we focus on the appeal of private sector governance to directly address the issue of systemic risk. Our conclusion is that there are severe limitations because a direct positive effect of private sector governance on systemic risk seems to be an implausible assumption. Three particular aspects support our reasoning: (1) institutions cannot themselves identify systemic risk; (2) institutions have no incentives to account for systemic risk; and (3) the issue of contagion remains relevant, even if high-risk functions were to be separated from low-risk functions. Thus, the stable provision of financial intermediation has features of a public good, legitimizing a tighter regulatory framework.

The first question is *whether individual financial institutions can identify or measure systemic risk*. From a system perspective this seems implausible as, similar to prior arguments, an institution from within the system is not able to take a second-order perspective, identifying critical sources of systemic risk. This is because many aspects of systemic risk account for risks of condition, and are rather implicit; see our fundamentals on risk (section 2.1). Hellwig (2008), p. 52, states, ‘given the complexity and fluidity of the network of interbank relations, there is no way in which the quantitative risk model of an individual bank could satisfactorily take account of the institution’s exposure to systemic risk’. This points out the necessity for an external institution to provide a second-order perspective, perhaps a regulatory body.

The issue can be clarified more specifically by considering the complex interdependencies among financial institutions—sources of contagion after a shock—which are crucial elements within the institution; see Schwarcz and Anabtawi (2011). We pointed out in our discussion of the insurance industry that the case of AIG shows how an individual business that seems negligible in terms of size can still be sufficiently large and interconnected to cause the failure of the whole institution[357]. This relates to our concept of two-level moral hazard, and the corresponding extension of the governance triangle. The test is to account for separate aspects at the institutional and individual level in a comprehensive manner.

[357] Our institutional case study of UBS in the systemic analysis (section 3.3.4) highlights similar conclusions. Although losses were spread within UBS, the core exposure was concentrated in few organizational units.

Suppose that an accurate measurement of systemic risk would be possible. Then the issue becomes *incentives for individual financial institutions to account for systemic risk*. This directly connects to our theoretical analysis (section 4.1), where we show that financial institutions have, in fact, no incentives to account for the systemic impact of their actions. Whereas systemic risk is induced intentionally under collective moral hazard, our discussion of drivers of collective behavior shows that even without the presence of collective moral hazard, no individual bank has an economic incentive to withdraw from a critical strategy. And, no individual creditor would have incentive to force the institution to do so.

In support of this argument, DeMarzo et al. (2004) show that diversification at the system level exhibits features of a public good, particularly when relative performance matters, such as in a competitive environment. Therefore, incentives for financial institutions to align their behavior according to the level of systemic risk will need to be created through regulation; see e.g. Acharya et al. (2010b) or Tarashev et al. (2009)[358]. Again, the two-level problem has to be accounted for and focus has to be placed on risk management within financial institutions to allow an adequate identification, and the incentives to be created through regulation—either in terms of remuneration at the individual level, or taxation at the institutional level. However, such incentives cannot be created through private sector governance, as this would contradict basic assumptions of individual rationality and utility-maximization.

Last, one could argue for a *separation of high- and low-risk areas in financial markets*. Marketplaces for different attitudes to risk could be generally separated through regulation and investors would decide where to invest and exert governance. A low-risk area should be generally less prone to financial crisis. One example, which has been discussed in the aftermath of the recent crisis, is the concept of 'narrow banking'[359]. The imposition of limits on specific activities of certain kinds of financial institutions can be regarded as like means. Consider for example the 'Volcker rule'[360] or, for a broader focus, the leverage ratio that has been imposed in Switzerland.

Although the approach has certain appeal, positive effects on systemic risk will be limited due to contagion—see our fundamentals (section 2.2.3)—between the individual areas. Horizontal contagion among different segments can occur under comparable

[358] Acharya et al. (2010b) propose to measure the individual institution's contribution to systemic risk as a basis for taxation. Tarashev et al. (2009) propose a different approach—based on the concept of the Shapley value—to distribute an aggregate measurement of systemic risk across financial institutions.

[359] The narrow bank proposal was originally proposed by Simons in 1934, who argued in favor of a 100% buffer on deposits that should consist of liquid short-term assets; see Thakor (1996).

[360] The "Volcker rule", proposed by former Fed chairman Paul Volcker, seeks to limit the proprietary trading of banks. The rule imposes a factual limit on the risk-taking of banks, but also aims to mitigate potential conflicts of interest between banks and customers. The Levin and Coburn (2011) report alleged several banks to be selling financial products, while at the same time taking counter transactions, which were for their benefit but resulted in damage to the clients buying them. The rule was finally integrated into the Dodd-Frank Act in a less strong version, which has been criticized; see. e.g. Acharya et al. (2010a).

mechanisms, as the rational contagion in the model of Kodres and Pritsker (2002)[361]. It is feasible to believe that many investors would not invest all their endowment in a high-risk area, but instead build a portfolio covering different levels of risk. A crisis in the high-risk area causes rational rebalancing. The effects of the crisis in the high-risk segment are thus transmitted into low-risk segments. Furthermore, even high-risk areas will be interconnected with the real economy. Hence, vertical contagion will cause adverse consequences on the real economy, and overall welfare. Because of that LOLR issues, as discussed earlier, still remain.

Concluding from these considerations, then the potential of private sector governance to (directly) contribute to a reduction of systemic risk seems decidedly limited. An effective identification of systemic risk from the perspective of an individual financial institution is hardly possible, and even with accurate information, the institution would still need external incentives that foster a satisfactory reaction. These can only be created through regulation. Even if the issue is successfully tackled in certain market areas, interconnections with other areas and the presence of contagion can still cause a crisis of systemic proportions.

5.3 Synthesis: implications for the governance of systemic risk

The prior sections discuss limitations and potential risks of both public sector regulation and private sector governance. Certainly, the decision is not ‘either or’, but includes both sides complementarily. Private sector governance can (indirectly) contribute to a reduction of systemic risk, addressing risk-taking in both the individual and institutional contexts. This has to be augmented by public sector regulation, with stronger influence at the institutional and systemic levels. With the limitations of both approaches, the ultimate problem is where to strike the balance; see De Larosière et al. (2009). In the context of our governance triangle, this means a future governance equilibrium will evolve as a consequence of the financial crisis 2007–09[362].

An important observation is that an uninterrupted provision of financial intermediation is of pivotal importance for stable development in the real economy, and for the overall welfare of society; see the Group of Thirty (2009). Many studies of the history of

[361] In the model of Kodres and Pritsker (2002) contagion occurs among different geographical regions. Such a division can be transfered easily to an environment with market areas differentiated by risk instead of location.

[362] The systemic analysis (chapter 3) points out that the financial industry is one of the most intensely regulated sectors. However, we referred to shifts in the governance equilibrium, being (1) the ongoing liberalization, as well as (2) the consideration of private sector governance in the design of regulatory provisions, e.g. Basel II. Due to the increasing complexity of financial markets prior to the 2007–09 financial crisis, and the rising influence of the shadow financial system, we argue for an increasing importance of private sector governance, as compared to regulatory provisions.

financial crises (see our fundamentals, section 2.2.3), point out various negative spillover effects from financial crises into the wider economy. In contrast, the private sector argues that public regulation limits the ability of financial institutions to fulfill their primary function of financial intermediation at a maximum level. This alludes to the adverse effects of a tighter regulatory framework on economic growth and welfare benefits in society. Financial institutions are forced to limit the provision of credit to the real economy and thereby reduce economic activity. The exact impact of this mechanism is unclear though; see Bank for International Settlements (2002).

Overall, it has to be clear that financial intermediation—even in perfectly efficient markets being actively supervised by public authorities—always involves risk. Good regulation minimizes the residual risk, which is comparable to systematic risk in the capital asset pricing model (CAPM). Thus, regulation constitutes a trade-off between risk to return, the latter being interpreted broadly, e.g. as economic growth. In the financial crisis 2007–09, the issue is about the shift of the risk-return ratio implied by increasing 'diseconomies of risk'. This shift was not scrutinized adequately since all stakeholders commonly believed in a fundamentals-driven decline, while in fact the ratio was biased through an inadequate representation of risk.

After all, strong public sector intervention—e.g. massively increasing capital requirements—would be welcomed upon the conclusion that current levels of risk were intolerable. At the same time, adverse economic effects of such a tighter regulatory framework would have to be accepted as part of this specific scenario. The anticipation of welfare effects in future financial crises can generally legitimize a tighter regulatory framework as an ex ante measure. To allow better assessment, research will need to get out adverse consequences on economic growth for specific regulatory scenarios, and, counterfactually, avoid welfare costs due to the reduction of systemic risk.

In the societal context however, even a perfectly accurate measurement of (systemic) risk in the financial system will not allow policy makers to determine an adequate ratio of risk to return. Instead, a wider assessment is needed, integrating psychological and sociological factors, which reach a higher-level objectivity towards risk; compare Haller (1999)'s three-level model referenced in our fundamentals (section 2.1.3). With his concept of a 'risk-dialogue', Haller (1992) offers an interesting approach to explore in future research. The value of this approach is the contribution to a better understanding of the consequences of systemic risk in financial markets for the society, as well as the different attitudes towards risk. Grasping both aspects in greater clarity poses an important cornerstone for the satisfactory design of future governance equilibrium, not only addressing the issue of systemic risk, but also the profound societal effects of financial crises such as the one from 2007–09.

From a different perspective, reasoning on the ratio of risk to return points to an important aspect that has been implicit in the debate on regulatory reforms in the aftermath of the 2007–09 financial crisis, but has not been attributed the relevance that it deserves: one can argue for the stable provision of financial intermediation to be regarded as public good[363], generalizing the conclusion of DeMarzo et al. (2004). Here, the debate needs to look at how to guarantee an effective and stable provision of financial intermediation. One consideration is to which extent institutions providing financial intermediation shall be treated as a public utility, making them subject to tight regulation. This would shift the governance equilibrium towards the public sector and might create welfare losses, but, at the same time, may help to safeguard institutional and systemic soundness[364].

Apart from considering the ratio of risk to return, and the positioning of a future governance equilibrium, with multiple trade-offs for individual stakeholders involved, another contribution of this thesis is the symbiosis of a systemic approach with in-depth analysis of collective behavior of financial institutions, both theoretically and empirically. Overall, the results suggest the necessity for a perspective change with regard to systemic risk that is not reflected in the ongoing debate on reforming regulatory structures in the aftermath of the 2007–09 financial crisis. Three aspects, to which we already have referred throughout this chapter, are of particular relevance: (1) systemic risk has to be regarded as a truly 'systemic' phenomenon; (2) the perspective on governance needs to be broadened; and (3) the power of purely technical approaches to systemic risk is limited. Being summarized in the following paragraphs, these also present criticism of the current focus of research on systemic risk.

First, *systemic risk needs to be approached as a truly 'systemic phenomenon'*. Current proposals— especially on macroprudential regulation—seem to be too focused on individual forces in the financial crisis 2007–09, while neglecting the multitude of interconnections and circularities driving 'diseconomies of risk'. These dynamics are relevant sources of systemic risk, assessable only through systemic approaches; our systemic analysis makes a contribution in this regard. Already in our fundamentals on risk (section 2.1.1), we refer to the distinction of risks of actions and conditions introduced by Haller (1986). Interpreting systemic risk as a vulnerability, it has to be treated as a risk of conditions, and not risk of action, for which a fundamentally different approach is necessary that cannot be based on a purely probablistic assessment but must also account for psychological and sociological aspects, as well as critical interdependencies between individual dynamics in a comprehensive manner.

[363] Note though that financial services do not exhibit standard features of public goods. By definition a public good is characterized by non-excludability and non-rivalrous consumption; see the Concise Library of Economics at the Library of Economics and Liberty.

[364] A further aspect to be considered is that strong ex ante measures will also require an adequate LOLR system to be put in place. This will need complementary measures to deal with potential incentive distortions, and also requires further research.

Current proposals to measure systemic risk based on mostly a standard definition of risks cannot succeed in the long run. Instead, they might pose a systemic risk themselves, as vulnerability arises outside the scope of the proposed measures and suggest a false sense of certainty. Further, more endogenous feedback of these measures increase critical biases and dynamics that are not accounted for. These critical issues can only be tackled from a systemic perspective, by establishing a second-order observation to scrutinize the approach to risk; see Zimmermann (2008).

Second, the *interpretation of governance and its effects in financial markets has to be adapted*. Current proposals for reform are not sufficiently dynamic and risk being retrospective upon their full implementation. The financial system will remain highly dynamic in terms of innovation and structural changes, as well as constantly adapting to expectations. Therefore, any governance equilibrium will be emergent. We have underlined the major shifts prior to the crisis.

From one angle, this circles back to our prior call for a systemic perspective. Since all stakeholders contribute to the governance equilibrium, these shifts can only be assessed adequately by a higher-order perspective. A similar argument can be made regarding the characterization of the risk-return ratio, which poses a complex problem to be approached with methodologies related to system theory. As in our research design, such a perspective will help to identify important aspects to be researched in more depth, and to interpret the results in a wider context.

This view on governance also relates to the third aspect, that *the power of purely technical approaches to systemic risk is limited*. The governance triangle integrates the interaction of different stakeholders at different levels. From the economic perspective—rational and behavioral—stakeholders are agents whose actions are guided by available information, incentives, and expectations. In such a scenario, our theoretical analysis highlights various patterns of interaction where systemic risk is a consequence of collective moral hazard, inducing incentives for collective behavior among banks. However, a solely economic approach neglects sociological aspects of interaction among the different stakeholders, which are highly relevant for the governance of (systemic) risk.

Following the three-level risk model of Haller (1999), we argue that consensus for an acceptable rate of risk to return from the perspective of society needs to integrate sociological aspects, to achieve higher-order objectivity. Likewise, sociological aspects are relevant to understand the emergence of governance structures over time, due to the interaction of the different stakeholders. Zimmermann (2001) proposes various starting points for sociological research to determine patterns of risk-behavior within an institution as potential causes for failures of governance. One example is to analyze specific 'sociotops' through which individual agents can immunize themselves against internal control mechanisms; see Zimmermann (1999)[365].

Overall, these aspects bring up disparate questions to be addressed by future research on systemic risk. Research needs to better account for complex patterns of interaction in the financial system. System theory offers a variety of approaches to be explored. Beyond that, it seems relevant to aim at developing interdisciplinary approaches to explain financial market dynamics in a more holistic manner. One particular vein of future research should focus on the sociological dimension of risk in the financial system, to complement purely economic approaches.

Only by taking comprehensive aspects into consideration will we be able to gradually improve the understanding of systemic risk in financial markets and enhance its governance. This applies to any potential consensus on the ratio of risk to return. Regulatory reforms that neglect the relevance of a systemic perspective or sociological factors come attached with a serious risk that we will focus on mitigating only one possible realization of systemic risk, while diseconomies of risk evolve in a different area of the financial system, and the emerging vulnerability could reach the same level as that prior to the financial crisis 2007–09.

[365] In a different context, Laeven and Levine (2009) point out that researchers have not yet assessed how corporate governance mechanisms that are determined through ownership structures interact with the regulatory framework and whether they influence the risk-taking behavior of individual banks.

Chapter 6

Concluding remarks

The financial crisis 2007–09 shook the global financial system to its very core. Repercussions in the financial sector have been unprecedented and will influence the evolution of business models in banking and insurance for a long time to come. The resulting economic recession and sovereign debt crisis, triggered by the sharp reappraisal of risk are still felt today, as the recovery remains tenuous. Naturally, the crisis sparked intensive research as to its causes. The ongoing debate focuses on the elements of systemic risk, as well as proposals for reforms to the financial system and its regulatory framework, in order to temper the likelihood of a future occurrence of such magnitude.

Despite the sheer volume of research coming from many different kinds of institutions, there exists a fundamental limitation to these analyses, as they often focus on individual aspects and fail to account for interdependencies with other factors. In doing so, they neglect the intrinsic component of systemic risk, that is, the *systemic* aspect. The systemic dimension in our conceptual approach brings a new perspective to the debate. We hypothesize that the crisis cannot be explained through separated analyses of individual factors, but only by grasping their critical interdependencies.

When considering the governance of systemic risk in financial markets, we apply an integrated framework of the governance triangle to account for the complementarity of the individual stakeholder contributions, the public sector, investors and financial intermediaries, and not just the individual aspects of the regulatory framework. Our focus is on the relevance of collective behavior as a source of systemic risk, and how it relates to collective forms of moral hazard. We combine (1) the systemic analysis of the crisis evolution with (2) two in-depth research elements, underscoring the collective behavior of financial institutions from both theoretical and empirical perspectives. From that, we can derive some implications for the governance of systemic risk which specifically pinpoint the risks in proposed regulatory reforms.

In the *first step, the systemic analysis, we develop a system model of financial markets* to show that the many proposed explanations for the evolution of the crisis—we refer to these as narratives, focusing on macroeconomic developments, public sector policies, behavioral dynamics, competitive effects and agency problems, as well as biases in common risk standards—fail to capture its full scope. It can be explained only by zeroing in on interdependencies and their mutual feedback effects. Our analysis shows that the collective behavior of financial institutions constitutes a major source of systemic risk. Imposing limits to such collective behavior is the primary concern of the macroprudential regulation which has been commonly called for in the aftermath of the crisis. Collective behavior induces common exposures of financial institutions in terms of investments in similar forms of structured products, a high maturity mismatch, and extensive use of off-balance sheet vehicles to optimize balance sheet ratios, that increase systemic risk.

We demonstrate that the endogenous creation of growth in the financial system, from a certain stage onwards, induced diseconomies of risk and an overall vulnerability. One example is the quantitative risk models, e.g. ratings that created a pseudo-transparency on risk of increasingly complex financial products. Once the biases of these models became clear, the transparency abruptly turned into complexity and set off tremendous uncertainty, resulting in sudden risk-aversion and massive coordination problems. Markets turned illiquid, exposing the risks of a high maturity mismatch as well as weaknesses in accounting standards, which required functioning markets. Naturally, this cycle relates to the concept of risks of conditions, as proposed by Haller (1986), and our analysis emphasizes relevant reactive drivers such as market liquidity and risk appetite. Due to unfolding vulnerability, a shock in the US subprime mortgage markets, through various channels, quickly spilled over to other segments. Throughout different phases the crisis was exacerbated, putting the whole financial system on the brink of collapse.

In our *second step we focus on the collective behavior of financial institutions from both theoretical and empirical perspectives.* Theoretical research has two central explanations for (inefficient) collective behavior, describing it as a consequence of coordination problems, or due to moral hazard. In the debate on the crisis evolution, we explore the latter approach and the relevance of collective forms of moral hazard as a source of systemic risk.

Collective behavior is welfare-reducing and, for certain incentive structures, is related to collective moral hazard. The underlying incentives are dynamically dependent on economic prospects, competitive dynamics etc. The issue becomes more pronounced in a boom period, or because of higher expectations in a competitive environment. However, it can be modulated by reducing the information asymmetry between creditors and banks: we show this through a capital buffer, which must be enforced through regulation. Our models explain that incentives increase in a multiple-bank environment for a robust set of assumptions, as banks prefer to jointly follow similar strategies, but neglect to consider the systemic (risk) implications of their actions. Whereas our conclusion focuses mainly on collective moral hazard, it relates to DeMarzo et al. (2004) who argue, more generally, that diversification at the systemic level exhibits features of a public good.

From the empirical perspective, the measurement of collective dynamics, in terms of common exposures and interdependencies, is an important basis for macroprudential regulation. While from an aggregated perspective of our US and international samples indications for increasing interdependencies are generally weak, when we focus on a systemic core of US financial institutions. we obtain stronger evidence.

An interesting aspect of our results, based on a simple indicator of interdependencies, is that they are generally stack up with more sophisticated approaches; see Acharya et al. (2010b). This is in line with Drehmann and Tarashev (2011a,b), who point out that the added value of highly complex methodologies, as compared to simpler ones, still needs to be clarified. This is especially important when weighed against the risks of such sophisticated approaches, which may convey a false sense of certainty and cause a bias in financial market governance, similar to ratings. From the empirical analysis, we conclude that, particularly from an ex ante view, many statistical challenges have yet to be tackled to allow for an effective identification and qualification of systemic risk as a result of collective behavior.

Relating our systemic analysis to the two in-depth research modules, we conclude in the context of our governance triangle that we need not only to differentiate contributions of different stakeholder groups, but also at the systemic, institutional and individual levels. This is relevant in several regards. First, in terms of moral hazard, collective behavior can arise in two complementary contexts. At the interface of the institutional and systemic levels financial institutions do not account for the systemic implications of their actions. The interface of individual and institutional levels refers to agency problems within the organization being transmitted into the system. Second, in terms of information challenges, biases in the aggregation of information from the individual level to the institutional level will be directly transmitted into measures at the systemic level. Also, endogenous feedback—reactions to these measures of systemic risk—aggravate original biases and impair the ability to identify systemic risk ex ante. The appeal of macroprudential regulation, therefore, is limited, based on quantitative measures of systemic risk, as these themselves appear to be risky. Furthermore, the differentiation shows that proposals of regulatory reforms need to be clarified, in terms of their specific focus at these levels.

With regard to our findings in view of their implications for the prospects of the individual stakeholder contributions to the governance of systemic risk, we discuss the risk dimensions of proposed regulatory reforms. The discussion accentuates the limitations of macroprudential regulation and, similarly, instruments of private sector governance. Accepting that financial transactions are necessarily about allocating risk and that there will always be some contagion in a crisis, we identify a crucial aspect that needs to be discussed with greater clarity: the ratio of risk to return, at the macro level, that is acceptable from a societal perspective. This consideration has not yet been attributed the importance it deserves in the ongoing debate on reforming financial markets, even though it is implicit in most proposals. Regarding financial intermediation as a public good would lead to a discussion of the extent to which financial intermediaries should be regulated as public utility. Only then can we address the adequacy and effectiveness of regulatory structures to tackle systemic risk.

Overall, our analyses develop three important aspects to be taken into account for in future research on systemic risk in financial markets: (1) the specific characteristics of systemic risk, as a truly systemic phenomenon, and closely related to risks of conditions call for the further exploration of more integrated research designs such as ours; (2) the need for a comprehensive perspective on governance, involving all stakeholder contributions, as well as focusing on a dynamic other than static equilibrium, will help to identify challenges in the regulatory framework, where further analysis is necessary to understand the interaction of governance mechanisms implemented by the individual stakeholder groups; (3) the limitations of purely technical approaches to (systemic) risk highlight the imperative to elaborate on interdisciplinary methodologies. In a heterogenous society, a higher level of objectivity to risk has to be established that also takes into account psychological and sociological aspects; see Haller (1986). Our analysis presents a start in this direction, recognizing the systemic dimension as the key aspect of systemic risk.

The long history of financial crises suggests that it is unrealistic to believe that financial market risks and the occurrence of crises can ever be fully eliminated. Reinhart and Rogoff (2009) show how often the notion of ‘this time is different’ has been falsified. Although financial innovations allow for advances in managing individual aspects of risk, at the same time they often contribute to a systemic vulnerability of financial markets as a consequence of evolving diseconomies of risk. Acknowledging this ambiguity of financial innovations—entailing opportunities but also risks—seems to be a crucial first step to dealing with the issue of systemic risk in financial markets in a more sustainable way. In addition, the interconnectedness of financial markets with all areas of society highlights that the consideration cannot be limited to the financial system only, but needs to address the issue in a system of an ever higher order.

Appendices

Appendix A

Theoretical analysis: formal presentations

A.1 Collective moral hazard and systemic risk

To formally analyze collective moral hazard, we include the utility of creditors (principal), who provide funding to the bank (agent). With that, we consider the aggregate level of welfare from the perspective of a central planner ('trusted authority'), e.g. a central bank, which coordinates the agents' strategy choices in order to maximize aggregate utility. In the second step, we compare the first-best equilibrium of aggregate welfare to the resulting welfare once banks decide on their (joint) incentives.

To prove the presence of moral hazard, a very simple set of assumptions is sufficient. First, suppose both types of agents, bank managers and creditors, all have a simple linear utility function, which is increasing in consumption and supposes that all agents are risk-neutral[366]. For bank managers we define utility V for consumption x as $V(x) = x$ and similarly we set for creditors $U(x) = x$. Lastly, we assume that the central planner puts equal weight on the utility of both agents, and therefore $W = U + V$[367].

In our simple setting two homogeneous banks raise funds from homogeneous creditors. The banks then invest these funds in one of two risky strategies (iid), which yield a return R_i at the end of the period. Also at the end of the period, they must compensate creditors with a payment (incl. interest) of r. The strategy outcomes resemble lotteries, which either yield a high return $R_H \geq r$ or a low return $R_L < r$. For simplicity, we assume

[366]Often, creditors are characterized as risk-averse, which is a less general assumption than risk-neutrality.

[367]To assume aggregate welfare as the sum of creditors and bank managers welfare is a common convention. Farhi and Tirole (2009) assume that the central bank focuses primarily on creditor's utility, whereas bank managers' utility is assigned a variable weight of less than one, which reflects the political influence of the banking sector. Without changing the essence of our findings, such a mechanism would make our results even stronger.

that both returns occur with probability $P(R_H) = P(R_L) = p = 0.5$[368]. If a bank gets only the low return, which falls short of the necessary repayment, it is assumed to fail.

As was pointed out in the fundamentals chapter (section 2.2.3), the failure of a bank not only implies information effects in financial markets, but also price effects as bank assets have to be liquidated prematurely in order to repay creditors. Therefore, we assume that a failure leads to a deadweight loss $\delta(x)$ that marginally increases as the amount of assets involved in the failure increases. Consequently, the creditors of a failing bank are being repaid the full low return, reduced through a percental deadweight loss: $(1 - \delta(R_L)) \cdot R_L$. If the bank realizes the high high return, it repays its creditors and all excess returns are distributed to its managers.

At the end of the period, we can observe three possible scenarios, of which one scenario combines two symmetric ones, which do not need to be differentiated:

- Both banks survive (HH): All creditors are fully repaid and thus $U = 2r$; bank managers receive excess profits so that $V = 2(R_H - r)$; thus, $W^{\mathrm{HH}} = 2R_H$.
- One bank survives, while the other bank fails (HL, symmetrical to LH): One creditor group is fully repaid, while the other creditor group receives the low return minus deadweight loss $U = r + (1 - \delta(R_L))R_L$; the manager of the surviving bank receives the excess profits, whereas the other manager receives no payout and therefore $V = (R_H - r) + 0$; this implies $W^{\mathrm{HL}} = R_H + (1 - \delta(R_L))R_L$.
- Both banks fail (LL): All creditors receive the low return reduced by the deadweight loss, which is higher because of the joint failure and results in $U = 2(1-\delta(2R_L))R_L$; bank managers receive no payout and $V = 0$; thus, aggregate welfare $W^{\mathrm{LL}} = 2(1 - \delta(2R_L))R_L$.

The probabilities of these scenarios depend on the choice of banks to behave collectively and pursue the same strategies (s), or individually choosing different (d) strategies. They determine the level of interbank correlation and systemic risk:

Table 21: Probabilities of different scenarios

	Scenario HH	Scenario HL[1]	Scenario LL
Low correlation (d):	$P_d^{\mathrm{HH}} = p^2$	$P_d^{\mathrm{HL}} = 2p^2$	$P_d^{\mathrm{LL}} = p^2$
High correlation (s):	$P_s^{\mathrm{HH}} = p$	$P_s^{\mathrm{HL}} = 0$	$P_s^{\mathrm{LL}} = p$

[1] Note that the symmetry of HL/LH doubles the probability of this scenario.

With these assumptions, we can compare the expected aggregate utility for the case where the banks pursue correlated (s) or differentiated (d) strategies.

[368] It does not change our results if we would allow for $p \neq 0.5$, with $0 < p < 1$ and $P(R_H) = p$ and $P(R_L) = (1 - p)$.

$$
\begin{aligned}
E(W_d) &= P_d^{\mathrm{HH}} \cdot W^{\mathrm{HH}} + P_d^{\mathrm{HL}} \cdot W^{\mathrm{HL}} + P_d^{\mathrm{LL}} \cdot W^{\mathrm{LL}} \\
&= R_H + R_L - 0.5 \cdot \delta(R_L) - 0.5 \cdot \delta(2R_L) \\
E(W_s) &= P_s^{\mathrm{HH}} \cdot W^{\mathrm{HH}} + P_s^{\mathrm{HL}} \cdot W^{\mathrm{HL}} + P_s^{\mathrm{LL}} \cdot W^{\mathrm{LL}} \quad = R_H + R_L - \delta(2R_L)
\end{aligned}
$$

It is clear that $E(W_d) > E(W_s)$, because the expected deadweight loss is higher for the high interbank correlation scenario as $\delta(R_L) < \delta(2R_L)$[369]. This confirms the intuition that by pursuing correlated strategies banks maximize the risk of joint failure, which leads to a higher deadweight loss than for individual failure. Therefore, a central planner would ensure that banks pursue different strategies in order to maximize expected aggregate utility.

Hence, if banks intentionally decide to behave collectively in order to maximize their individual expected utility, they induce additional risk that is borne solely by creditors. As this leads to a deviation from the first-best equilibrium, chosen by a central planner, the behavior can be characterized as collective moral hazard. The collective dimension derives from the fact that banks can jointly maximize their individual expected utility only by following a specific combination in the strategy space. In addition, a deviation by one agent reduces the expected utility of the other agent.

A.2 Individual moral hazard and systemic risk

Compared to our definition of collective moral hazard, individual moral hazard can be accounted for in an individual preferences scenario (table 22), where both players have pure strategies, because strategy S1 yields a higher expected payoff than strategy S2. There are no strategic complementarities, which implies that the strategy decision of agent A does not affect the payoffs of agent B and vice versa. Consequently, S1–S1 is a strict Nash equilibrium as it mutually resembles the best response strategy for both agents. Yet, it induces collective behavior and increases systemic risk.

It is important to note that both agents decide solely upon their individual preferences in this scenario. There are no strategic complementarities, nor is there a collective dimension to the decision-making process[370]. As mentioned in our fundamentals chapter (section 2.2.3), such behavior can be classified as 'spurious herding', but not as collective

[369] A caveat has to be made for this comparison, as we do not include the externality that influences banks' behavior. As we show in our models (section 4.1), this externality resembles a transfer between bank managers and creditors. It is irrelevant then from an aggregate welfare perspective.

[370] Agents would even act in the same manner without knowing about other agents' actions.

Table 22: Payoff matrix with individual preferences

Individual Preferences		Agent B	
		S1	S2
Agent A	S1	15, 15	15, 10
	S2	10, 15	10, 10

moral hazard. A moral hazard could still arise in the traditional sense at the individual level, which would also have implications at the aggregate level of (systemic) risk. This refers to the classical agency problem in a 1:1–principal agent relation as it has been developed in the seminal contributions of Jensen and Meckling (1976) as well as Stiglitz and Weiss (1981).

To determine such individual moral hazard, we specify the expected payoffs for both strategies (S1 and S2). One possible explanation for the higher expected return of S1 could imply a loan portfolio to a highly innovative and growing sector, whereas S2 might reflect a loan portfolio to a traditional industry, which would yield lower returns. Because of the risk-neutrality assumption, agents would choose the strategy with the higher expected return, without accounting for risk characteristics of their choice[371].

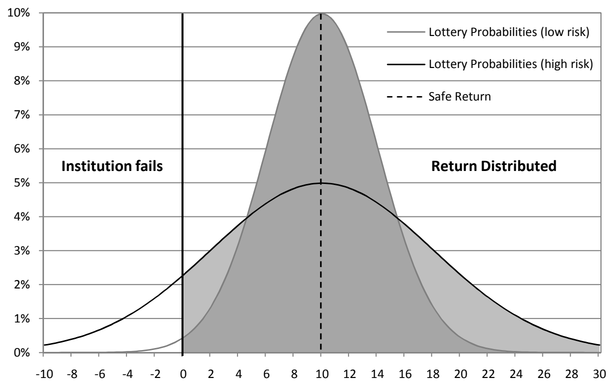

Figure 22: Impact of limited bank liability on risk-preferences

Individual moral hazard arises from the fact that a bank will not be liable for any losses. As soon as it cannot repay its creditors, it will fail and be liquidated. This skews bank managers' expectations of strategy returns. Assume that both of the aforementioned strategies have mean-preserving spreads (figure 22). Then, the overall expected returns from both strategies would be equal, but the innovative loan portfolio will possibly exhibit a higher variance of possible returns (risk).

[371] In a risk-averse setting, agents focus on the maximization of expected utility and conduct a transformation of return expectations by means of an increasing and concave utility function. As a result, the traditional loan portfolio might become more attractive, even when yielding a lower expected return than the innovative portfolio because of its second-order stochastic dominance.

With the additional assumption that a bank fails if the return falls below a critical threshold (zero in figure 22), and the bank manager has only a limited liability, all returns lower than this threshold—in terms of a lowest possible return—are excluded from the bank managers assessment of the strategy. For all these cases, he would earn no return and the bank would fail. Comparing the low risk lottery to the safe return, it comes clear that the banks' expected return from the lottery, which only includes the shaded area, is higher than the safe return. This extends to the high risk lottery, which even further increases the banks' expected returns because the upside increases asymmetrically because more of the bad results are being cut-off. The expected strategy returns from the perspective of the bank manager increase with the risk of the strategies.

As a consequence, risk-neutral bank managers will always exhibit a risk preference and the additional risk is borne by the bank's creditors, who cannot monitor the actions of the bank manager adequately due to an underlying information asymmetry[372]. Thus, there is no moral hazard at the collective level, only at the individual level. Collective behavior arises due to spurious herding or individual moral hazard and the consequence in terms of systemic risk are the same as before. However, the inherent moral hazard at the individual level can be addressed by microprudential regulatory provisions focusing on the risk taking of individual banks.

A.3 Creditor expectation changes and the impact of a capital buffer

This model focuses on the interaction of creditors (principals) and bank managers (agents) over two periods, and the potential negative externalities deriving from expectation changes with constant supply. There are three dates $t = 0, 1, 2$. Creditors have an endowment of $w = 1$ at the beginning of each period. They are by assumption risk-averse, due to a decreasing marginal utility of wealth, and thus with an increasing and concave utility function $u(w)$, for which $u(w) > 0$, $u'(w) > 0$, $u''(w) < 0$, $\forall w > 0$[373]. Creditors lend their endowment to banks at the interest rate r_t. Alternatively, they have access to a production technology, transferring one unit of consumption at date t into one unit of consumption at $t + 1$[374].

Two banks (A, B) with risk-neutral managers each borrow from a continuum of creditors. The assumption of risk-neutrality stems from the fact that managers have only a limited liability in case of failure and therefore cannot experience any welfare losses. All

[372] If bank managers were assumed to be risk-averse, this would not change the results.
[373] This assumption will be relaxed later. For normalization we define $u(0) = 0$, $u(1) = \bar{u}$.
[374] By assumption, this production technology has constant returns-to-scale.

lending is governed by a simple debt contract with a one-period maturity. Banks have access to the same production technology as creditors, or use the funds raised to pursue one of two risky strategies (S1, S2). These strategies can resemble a variety of strategic choices in different areas, e.g. investment strategies, financing or accounting decisions. Throughout this section, they will be referred to as loan portfolios to specific sectors.

The returns from the two risky strategies are random and denoted as $\tilde{R}_t$. To facilitate the analyses it is assumed that $\tilde{R}_t$ can take a discrete set of realizations limited to $\tilde{R}_t \in \{H_t, L_{\mathrm{M},t}, L_{\mathrm{L},t}\}$ with $H_t > L_{\mathrm{M},t} > L_{\mathrm{L},t}$[375]. The realization of strategy returns is determined through a systematic macro factor and an idiosyncratic component, which refers to an individual characteristic of the loan portfolios or the ability of managers to do business in a certain market segment. As both strategies are defined as iid, the idiosyncratic component is identical for both strategies.

The macro factor can be thought of as the overall state of the economy[376]. The probability of a good state is p and $(1-p)$ for a bad state, with $p \in [0;1]$. Furthermore, the idiosyncratic component attributes the following return probabilities: if the state of the economy is good (bad), the probability of a high (low) return is q with $q \in [0.5;1]$. Conversely, if the state of the economy is bad (good), the probability of a high (low) return is $(1-q)$. The low return is further divided into a medium low ($\mathrm{L_M}$) and very low return ($\mathrm{L_L}$). The medium low return is attributed a conditional probability $P_i(\mathrm{L_M}|\mathrm{L}) = b$ and the very low $P_i(\mathrm{L_L}|\mathrm{L}) = (1-b)$, respectively. Depending on those three probability assumptions, we can calculate the total probabilities of the individual returns (table 23).

Table 23: Return probabilities according to economic state

		Return		
		H	$\mathrm{L_M}$	$\mathrm{L_L}$
Economic State	good	pq	$p(1-q)b$	$p(1-q)(1-b)$
	bad	$(1-p)(1-q)$	$(1-p)qb$	$(1-p)q(1-b)$

Banks' profits are defined as excess returns after repaying creditors. For the first period, we define that if the bank has a low return—both medium and very low—all proceeds are paid to creditors and there is no profit for bank managers. This implies that first-period returns are by definition riskless with $L_{\mathrm{M},1} = L_{\mathrm{L},1} \geq r_0 + c(\rho_{s,1})$; for $c(\rho_{s,1})$ see below. The first period interest rate equals the original endowment and $r_0 = w = 1$[377].

[375] Though it is not analyzed in detail, the assumption of a discrete set of return realizations does not change the results of the analyses. It only serves the purpose to clarify the effects of the information contagion. Assuming continuous returns, the model could only be analyzed in a more complex manner and for a set of additional assumptions, which would in fact lead us back to discrete returns.

[376] The macro component can reflect any systematic component in the two loan portfolios.

[377] To ensure that banks are active in the first period and furthermore can choose both high and low correlation, it has to

When a high return is realized in the first period, profits are not immediately distributed to bank owners, but retained as a capital buffer instead. This capital buffer provides a cushion against potential future losses and enables banks to withstand a lower future return. Specifically, we assume that, with a capital buffer, a bank will be able to survive a medium low return in the second period, and it will fail only if it has the very low return.

The conditional probability b describes the proportion of low returns which are not sufficient to fully repay creditors, but by adding the capital buffer, allow for a full compensation of creditors' claims. It can be thought of as a Value-at-Risk (VaR) approach to determine the probability that a loss will remain under the threshold of the capital buffer. Instead, if a bank has a low return in the first period and cannot establish a capital buffer, it will fail in the second period for any low return $\mathrm{L_M}$ and $\mathrm{L_L}$.

In order to account for the effects of collective behavior, denoted by the interbank correlation $\rho_{i,t}$, the model differentiates two cases: if banks collectively pursue the same strategy then $i = s$, $\rho_{s,t} = 1$; or, if they choose different strategies $i = d$, $\rho_{d,t} = 0$. Banks are assumed to incur a transaction cost for both strategies, that is identifying or originating specific loans in their portfolio. This cost is assumed to be marginally increasing for the level of activity in one sector, and the cost will be disproportionally higher if both banks pursue correlated strategies. Consequently, profits for collective behavior are reduced by an additional proportion $\delta_s \in [0; 1]$ of the initial investment volume given through $c(\rho_{i,t})$, with $c(\rho_{s,t}) = \delta_s \cdot w$. Without impact for the analyses, the investment cost for differentiation can be set to $c(\rho_{d,t}) = 0$[378].

With the prior assumption that the medium low return ($\mathrm{L_M}$) equals the very low return ($\mathrm{L_L}$) in the first period, the expected profit for bank managers in the first period does not change in its overall value. However, it has to be acknowledged that, upon a high return, earnings are retained and only paid out after a second high return in the second period. Thus, the expected profit for bank managers from the first period is conditional on the probability of a high second-period return, denoted as α_1, and given as:

$$E(\pi_{i,1}) = \alpha_1 \cdot \alpha_0 \cdot (H_1 - c(\rho_{i,1}) - r_0) \tag{A.1}$$

be assumed that bank managers expect a non-negative return in the first and second periods in all scenarios. Therefore, it is assumed that $L_{\mathrm{M},1} = L_{\mathrm{L},1} \geq 1 + c(\rho_{s,1})$. If this assumption would not hold, banks would still become active by prior assumptions $H_1 > L_{\mathrm{M},1} = L_{\mathrm{L},1} \geq 1$, but the additional cost due to collective behavior $c(\rho_{s,1})$ might render them economically not viable. Thus, banks would always decide to pursue differentiation strategies and our analysis would be irrelevant.

[378] This definition serves the purpose of better illustrating the difference in expected payoffs to bank managers when deciding whether to pursue correlated or differentiation strategies. As we compare both cases, it is a simple linear transformation to set investment cost to zero for the low-correlation scenario, and it does not affect the overall difference in cost.

$$\text{with } \alpha_{0,1} = q + (1-p)(1-q),\ c(\rho_{i,1}) = \begin{cases} 0 & ; \rho_{d,1} = 0 \\ \delta_s \cdot w & ; \rho_{s,1} = 1 \end{cases} \text{ and } r_0 = 1$$

Possible states after first period and implications for interest rates

Using backward induction, we first focus on the analysis of the second period depending on the outcomes from the first period. The major difference is whether banks pursue the same strategies ($i = s$) or differentiation ($i = d$). Fundamental to the analysis is the information asymmetry between banks and creditors. The latter group is assumed to have no means of observing the strategy decisions of banks. The only information signal creditors receive are realized bank returns after each period. These are interpreted as a signal regarding the systematic factor. As Acharya and Yorulmazer (2008) argue, the extent of information revealed to creditors differs for the high- and low-correlation scenarios. Observing the two banks' returns, if they are perfectly correlated no further information is revealed, whereas it is in the low-correlation scenario. We will discuss the implications of changing this assumption at a later stage.

Creditors rationally update their priors regarding the overall state of the economy which persists in both periods. The posterior probabilities depend on the outcomes of the first period and are indexed according to the returns of both banks by $j \in \{\mathrm{HH, HL, LH, LL}\}$[379]. Additionally, the probability assumptions account for the capital buffer. In the case that the bank has a high return in the first period, creditors are repaid even if the bank suffers a medium-low return ($\mathrm{L_M}$) in the second period. If the bank has a low return in the first period it fails, even with a medium-low return in the second period.

For the case that both banks have a high return ($j = \mathrm{HH}$) because of collective behavior ($i = s$), creditors derive the posterior probability of a good economic state $P_s(\mathrm{G|HH})$ in the first step by Bayesian updating[380]. Second, they re-calculate the probability of a high bank return in the consecutive period denoted as α_s^{HH}, and they also account for the lower risk due to the capital buffer.

$$P_s(\mathrm{G|HH}) = \frac{pq}{pq + (1-p)(1-q)} \text{ and } P_s(\mathrm{B|HH}) = \frac{(1-p)(1-q)}{pq + (1-p)(1-q)} \tag{A.2}$$

[379] It is straightforward that, assuming collective behavior, the cases HL/LH cannot occur.

[380] Bayesian updating implies that $P(\mathrm{G|HH}) = (P(\mathrm{HH|G}) \cdot P(\mathrm{G}))\,/P(\mathrm{HH})$. All other probabilities can be derived analogously. At this point, we assume that creditors calculate the posterior probability of a good state of the economy depending on the overall probability of the bank's high (low) return in the first period.

$$\begin{aligned}\alpha_s^{\mathrm{HH}} &= P_s(\mathrm{G}|\mathrm{HH}) \cdot (q + (1-q)b) + P_s(\mathrm{B}|\mathrm{HH}) \cdot ((1-q) + qb) \\ &= \frac{1 - p + 2pq - (2-b)q + (1-b)q^2}{pq + (1-p)(1-q)}\end{aligned} \tag{A.3}$$

Based on this probability, creditors then determine the risk premium for lending to banks in the second period according to equation (A.4), which is similar for all scenarios[381]

$$r_{i,t}^{\mathrm{j}} = u^{-1}\left(\bar{u}/\alpha_i^{\mathrm{j}}\right) \tag{A.4}$$

If both banks have the high return ($j = \mathrm{HH}$) for different strategies ($i = d$), creditors follow an analogous procedure. Nevertheless, the return of the second bank reveals further information, once bank returns are no longer perfectly correlated[382]. Therefore, the Bayesian updating leads to:

$$P_d(\mathrm{G}|\mathrm{HH}) = \frac{pq^2}{pq^2 + (1-p)(1-q)^2} \text{ and } P_d(\mathrm{B}|\mathrm{HH}) = \frac{(1-p)(1-q)^2}{pq^2 + (1-p)(1-q)^2} \tag{A.5}$$

$$\begin{aligned}\alpha_d^{\mathrm{HH}} &= P_d(\mathrm{G}|\mathrm{HH}) \cdot (q + (1-q)b) + P_d(\mathrm{B}|\mathrm{HH}) \cdot ((1-q) + qb) \\ &= \frac{pq^2 \cdot (q + (1-q)b) + (1-p)(1-q)^2 \cdot ((1-q) + qb)}{pq^2 + (1-p)(1-q)^2}\end{aligned} \tag{A.6}$$

In the second possible scenario, one bank has the high return whereas the other bank only realizes the low return. As the medium and very low returns are by assumption equal in the first period, no additional differentiation has to be applied. The assumption of homogeneous banks further implies that the cases $j = \mathrm{HL}$ and $j = \mathrm{LH}$ are symmetrical and can be combined. This scenario does not need differentiation with regard to the banks' behavior, since it can occur only on differentiation. By choosing collective behavior in the first period, banks can effectively rule out this scenario and its second-period consequences. As the later analysis will show, the potential consequences of this scenario will become a crucial determinant for the choice of collective behavior in the first period. The Bayesian updating process of creditors occurs analogously to the first scenario, with:

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[381] Due to the assumption of risk-averse creditors, u represents a concave utility function. To obtain the risk premium we assume that creditors maximum utility $u(1) = \bar{u}$. This maximum is set equal to the expected utility from the interest payment $\alpha_0 \cdot u(r_{i,t}^j)$ and the resulting equation is solved for $r_{i,t}^j$.

[382] This feature of the model depends on the definition of returns and the information asymmetry. Assuming iid strategies, one might also consider the case in which creditors do get no additional information from the return of the other bank. This scenario is at a later stage of this section.

$$P_d(\mathrm{G}|\mathrm{HL}) = p \text{ and } P_d(\mathrm{B}|\mathrm{HL}) = (1-p) \tag{A.7}$$

Yet, a differentiation needs to be applied for the probability of a bank surviving the second period, due to a high return of a capital buffer. As the bank with the high return in the first period will build a capital buffer, the risk for creditors is lower than for the other bank. This distinction allows for an individual differentiation of borrowing cost between the two banks, since it can be observed by the creditors. Thus, if a bank has a high return in the first period, creditors assign an additional probability b for the case that the bank experiences a medium-low return and will still be able to repay its debt.

Creditors calculate the posterior probabilities of the two banks having a sufficiently high return in the second period in order to repay creditors. Because of the capital buffer, we differentiate posterior probabilities as $\alpha_d^{\mathrm{HL,H}}$ for the probability of the bank with a high return, and $\alpha_d^{\mathrm{HL,L}}$ for the bank with a low return.

$$\begin{aligned}\alpha_d^{\mathrm{HL,H}} &= P(\mathrm{G}|\mathrm{HL}) \cdot (q + (1-q)b) + P(\mathrm{B}|\mathrm{HL}) \cdot ((1-q) + qb) \\ &= p(q + (1-q)b) + (1-p)((1-p) + qb)\end{aligned} \tag{A.8}$$

$$\alpha_d^{\mathrm{HL,L}} = P(\mathrm{G}|\mathrm{HL}) \cdot q + P(\mathrm{B}|\mathrm{HL}) \cdot (1-q) = pq + (1-p)(1-q) = \alpha_0 \tag{A.9}$$

It is easy to show that $\alpha_d^{\mathrm{HL,H}} > \alpha_d^{\mathrm{HL,L}}$, and therefore $r_d^{\mathrm{HL,H}} < r_d^{\mathrm{HL,L}}$. If we would drop the assumption of a capital buffer, we could set $b = 0$. In this specific case, both banks would have to pay the same interest rate, equal to $\alpha_d^{\mathrm{HL,L}}$. This highlights that the capital buffer has a positive effect for the bank with the high return, since it leads to a decrease of the required interest rate.

The last possible scenario for bank returns at the end of the first period is that both banks have the low return and $j = \mathrm{LL}$. In this case, the distinction between collective behavior and differentiation applies analogously to $j = \mathrm{HH}$. As neither bank is able to build a capital buffer, the consideration of the probability of a medium-low return is irrelevant. If both banks pursue the same strategy ($i = s$), creditors update their beliefs regarding the probability of a good economic state and calculate the probability of a high second-period return by the following equations:

$$P_s(\mathrm{G}|\mathrm{LL}) = \frac{p(1-q)}{p(1-q) + (1-p)q} \text{ and } P_s(\mathrm{B}|\mathrm{LL}) = \frac{(1-p)q}{p(1-q) + (1-p)q} \tag{A.10}$$

$$\alpha_s^{\mathrm{LL}} = P_s(\mathrm{G}|\mathrm{LL}) \cdot q + P_s(\mathrm{B}|\mathrm{LL}) \cdot (1-q) = \frac{p(1-q)}{p(1-q)+(1-p)q} \tag{A.11}$$

On the other hand, if banks differentiated in the first period ($i = d$), creditors receive additional information from the return of the second bank and update their priors as follows:

$$P_d(\mathrm{G}|\mathrm{LL}) = \frac{p(1-q)^2}{p(1-q)^2+(1-p)q^2} \text{ and } P_d(\mathrm{B}|\mathrm{LL}) = \frac{(1-p)q^2}{p(1-q)^2+(1-p)q^2} \tag{A.12}$$

$$\alpha_d^{\mathrm{LL}} = P_d(\mathrm{G}|\mathrm{LL}) \cdot q + P_d(\mathrm{B}|\mathrm{LL}) \cdot (1-q) = \frac{pq(1-q)^2+(1-p)q^2(1-q)}{p(1-q)^2+(1-p)q^2} \tag{A.13}$$

Information contagion and consequences for banks strategic choices

To highlight the different effects encompassed in the model individually, we first consider the scenario of without the capital-buffer-effect, for $b = 0$. Figure 23 shows how posterior expectations of creditors regarding a high second-period return change, depending on the prior assumptions regarding the state of the economy (q fixed and p variable) and if the economic state is good (p fixed and q variable). Due to the definition of creditors' utility, there is a direct link between the posterior probability of a high return in the second period and the required risk premium for bank lending. Because of the assumption of risk-averse creditors, lower probabilities (higher risk) are attributed a larger premium than higher probabilities.

In the illustration, we can exhibit some individual dynamics of posterior probabilities α_i^j for different prior probability assumptions of p and q[383]. Each graph points out the dynamics of changing the assumption regarding one variable while holding the other variable constant. The top graphs exhibit posterior probabilities when holding the probability of a good economic state (p) constant, while varying the probability of having a high return in a good economic environment (q). The bottom graphs show the dynamics of varying the probability of a good economic state (p), while holding the probability of a high return in a good economic state (q) constant. A second aspect depicted by the graphs is the comparison (left to right) regarding the variation of the differences between α_i^j for low/high fixed values of p (first line of graphs) and q (second line).

[383] At this stage some brief comments on the prior probabilities α_0 seem adequate to allow a comparison. For a constant q, α_0 is increasing in the probability of a good economic state p. Keeping p constant, one has to differentiate between $p > 0.5$, for which α_0 is increasing in q. For all values of $p < 0.5$, α_0 is however decreasing in q. Lastly, for $p = 0.5$, $\alpha_0 = 0.5$ and constant at for all q.

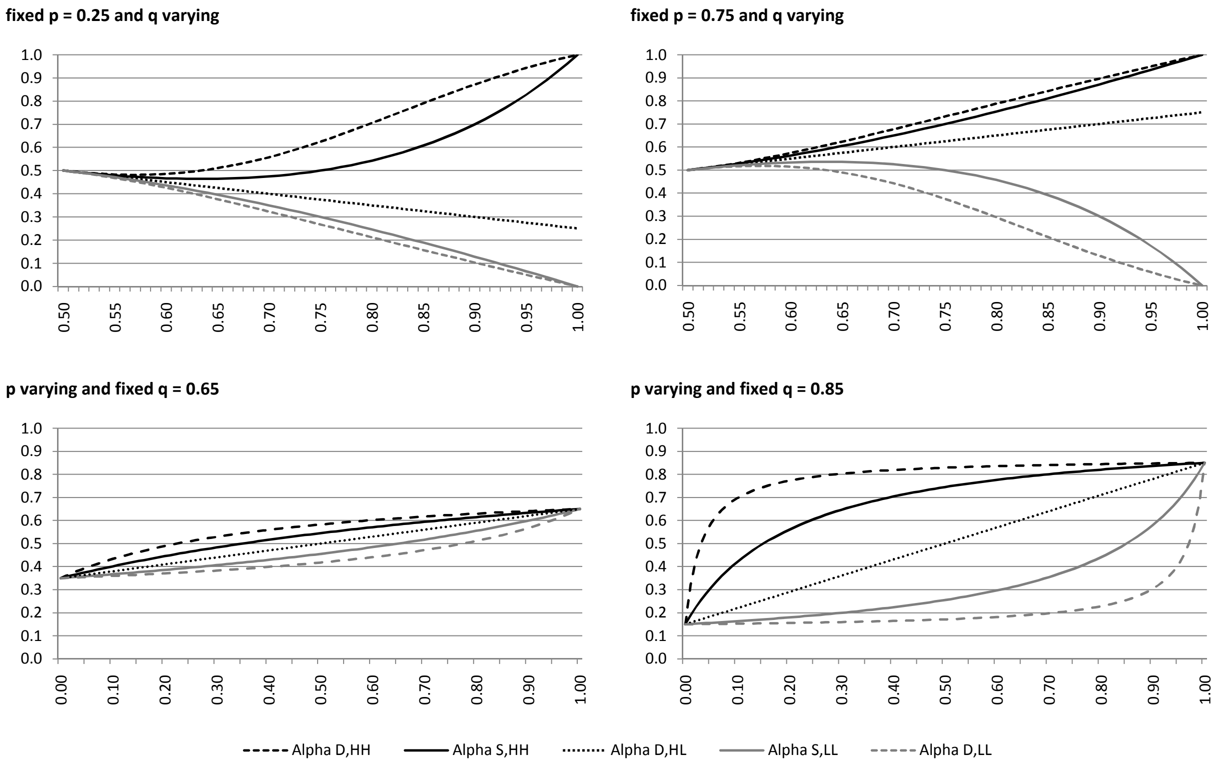


Figure 23: Posterior probabilities of a high second period return for different p, q

Whereas for constant p the difference between overall probabilities increases in q, the observation for a constant q is different: if q is held constant, the overall difference of posterior probabilities is most pronounced, as creditors are most uncertain regarding the state of the economy and $p \to 0.5$. Relevant for our analysis is the difference of α_d^{HH} to α_d^{HL}, which determines the interest rate change if both banks have a high return or one bank has a low return. Therefore, it illustrates the adverse effect on the bank with a high performance, if the other bank performs badly.

We can draw the following conclusions from the four panels in figure 23: For a constant p, the difference generally increases in q, as expectations regarding a positive performance of banks gets stronger. Setting p to higher values—creditors being more certain about the economic state—will decrease the overall difference for all values of q similar to a multiplier (compare the top graphs in figure 23 from left to right).

Furthermore, if we hold q constant, there is a value $p^\star < 0.5$ for which the difference between α_d^{HH} and α_d^{HL} reaches a maximum and then as $p \to 1$ decreases to zero again. Therefore, the adverse interest rate effect is higher as creditors' expectations regarding the economic state are lowered. A higher value of q—higher expectations regarding a positive bank performance—will increase the maximum difference between α_d^{HH} and α_d^{HL} and shift $p^\star \to 0$ (compare the bottom graphs in figure 23 from left to right).

These posterior probabilities directly translate into risk premiums. Hence, bank managers can calculate their expected payoffs in the second period contingent on the state at the end of the first period, as well as the second-period return. As the choice of collective behavior in the first period influences the risk premiums, it has to be accounted for through a differentiation of high and low interbank correlation.

If bank managers decide to pursue the same strategy in the first period ($i = s$), expected profits are given by the function below[384]. It has to be noted that profits larger than 0 are contingent on a high return from the second-period investment, denoted as $\tilde{R}_2 = H_2$.

$$\pi_{s,2}^{j} = \begin{cases} H_2 - c(\rho_{i,2}) - r_s^{\mathrm{HH}} & ; j = \mathrm{HH} \wedge \tilde{R}_2 = H_2 \wedge H_2 > c(\rho_{i,2}) + r_s^{\mathrm{HH}} \\ H_2 - c(\rho_{i,2}) - r_s^{\mathrm{LL}} & ; j = \mathrm{LL} \wedge \tilde{R}_2 = H_2 \wedge H_2 > c(\rho_{i,2}) + r_s^{\mathrm{LL}} \\ 0 & ; \text{all other cases} \end{cases} \tag{A.14}$$

In the alternative case of differentiation, the scenario in which one bank has a high return and the other bank a low return enters the equation. Thus, the expected payoff if banks invested in different industries ($i = d$) is given as in equation (A.15) below.

$$\pi_{d,2}^{j} = \begin{cases} H_2 - c(\rho_{i,2}) - r_d^{\mathrm{HH}} & ; j = \mathrm{HH} \wedge \tilde{R}_2 = H_2 \wedge H_2 > c(\rho_{i,2}) + r_d^{\mathrm{HH}} \\ H_2 - c(\rho_{i,2}) - r_d^{\mathrm{HL}} & ; j = \mathrm{HL, LH} \wedge \tilde{R}_2 = H_2 \wedge H_2 > c(\rho_{i,2}) + r_d^{\mathrm{HL}} \\ H_2 - c(\rho_{i,2}) - r_d^{\mathrm{LL}} & ; j = \mathrm{LL} \wedge \tilde{R}_2 = H_2 \wedge H_2 > c(\rho_{i,2}) + r_d^{\mathrm{LL}} \\ 0 & ; \text{all other cases} \end{cases} \tag{A.15}$$

Expected second-period payoffs are affected by two factors besides the random strategy returns. The risk premiums, which are required by creditors, are only dependent on banks pursuing the same or different strategies in the first period. Since the second period is the final model period, creditors have no means to charge bank managers other than this risk premium. Also, expected payoffs are adversely affected through the assumed cost of investment. As this cost is not affected by the outcomes after the first period, bank managers will always pursue differentiation strategies in the second period in order to minimize this investment cost. Therefore $c(\rho_{i,2}) = 0$ and for the second period $i = d$ and $\rho_{d,2} = 0$.

[384] Because the distinction is clear, time indices of the interest variable r are omitted to simplify the equation. Whereas r_0 refers to the initial interest rate, r_i^j refers to interest rates in the second period according to the realized returns in the prior period.

Another observation regarding expected payoffs for bank managers is that, with the cost of investment in the case of differentiation set to zero, if the high return in the second period falls short of the required risk premium ($H_2 < r_i^j$), there will be no bank activity in the second period. Instead, it is rational for creditors to put their endowment into storage as the banks are not able to sufficiently compensate for credit risk[385].

Critical for the maximization of total expected payoffs, as the sum from both periods, is the impact of the varying states at the end of the first period on the cost of the banks' borrowing in the second period. As was illustrated in equations (A.14) and (A.15), bank returns in the second period are directly affected by the results of both banks in the first period, and by their joint choice of collective behavior or differentiation. Figure 23 highlights a clear ranking of second-period risk premiums corresponding to the realization of first-period returns. This ranking derives from posterior probabilities of a high return in the second period and holds for all values of $p \in [0; 1]$ and $q \in [0.5; 1]$. Accordingly,

$$\alpha_d^{\mathrm{HH}} > \alpha_s^{\mathrm{HH}} > \alpha_d^{\mathrm{HL(LH)}} > \alpha_s^{\mathrm{LL}} > \alpha_d^{\mathrm{LL}} \tag{A.16}$$

$$r_d^{\mathrm{HH}} < r_s^{\mathrm{HH}} < r_d^{\mathrm{HL(LH)}} < r_s^{\mathrm{LL}} < r_d^{\mathrm{LL}} \tag{A.17}$$

This comparison, and especially the fact that $r_d^{\mathrm{HH}} < r_d^{\mathrm{HL(LH)}}$, shows that banks' borrowing costs can be adversely affected by the negative (low) performance of the other bank. Given that bank A (B) has a high return from the first period, its borrowing cost in the second period will decrease only if bank B (A) also realizes a high return. If bank B (A) realizes a low return instead, the probability will not change at all if $b = 0$, as $\alpha_d^{HL} = \alpha_0$. However, since second-period returns are risky, interest rates will rise. Furthermore, if the realization of a high return in the second period H_2 reaches a certain threshold and $r_d^{\mathrm{HH}} < H_2 < r_d^{\mathrm{HL(LH)}}$, the bank with a high return remains in business only if the other bank realizes a high return as well. Otherwise the low return of the other bank increases funding cost to an amount which renders the bank with the high return economically not viable in the second period.

In general, banks can effectively rule out the case in which one bank has a high return while the other realizes a low return by opting for collective behavior in the first period. The only two possible states after the first period with high interbank correlation are j = HH or j = LL. In reference to the remarks for our preliminary considerations (section 4.1.2), this introduces the strategic complementarity in the choices of banks.

[385] Also from the perspective of the bank manager it would not be rational to seek to borrow funds from creditors and invest them into risky strategies, since the expected payoff would be zero. Assuming that bank managers incur a non-pecuniary cost beyond boundaries of this model, they would have negative utility and thus would refrain from any intermediation activities.

However, it has to be taken into account that by opting for collective behavior, bank managers' expected payoffs are reduced as a result of an increase in the cost of investment.

In order to draw conclusions regarding the choice of interbank correlation, it is necessary to formally compare expected payoffs for the high/low interbank correlation scenarios, which include the two strategic complementarities described above. Bank managers seek to maximize the sum of expected payoffs from both periods by selecting the level of interbank correlation in the first period. Therefore,

$$\max_i E(\pi_{i,1}) + E(\pi_{i,2}), \text{ where} \tag{A.18}$$

$$\begin{aligned} E(\pi_{i,1}) = {} & \alpha_0 \cdot (H_1 - c(\rho_{i,1}) - r_0); \text{ and} \\ E(\pi_{i,2}) = {} & P_i(H_2, \mathrm{HH}) \cdot [H_2 - r_i^{\mathrm{HH}}] + 2 \cdot P_i(H_2, \mathrm{HL}) \cdot [H_2 - r_i^{\mathrm{HL}}] \\ & + P_i(H_2, \mathrm{LL}) \cdot [H_2 - r_i^{\mathrm{LL}}] \end{aligned}$$

The expected payoff in the first period corresponds to equation (A.1). Whereas the cost of investment corresponds to the level of interbank correlation in the first period, the riskless lending to banks implies $r_0 = 1$. For the second-period return, equation (A.18) implies that banks will choose low interbank correlation in the second period and thus $c(\rho_{i,2}) = 0$. Moreover, in the case of high interbank correlation ($i = s$): $P_s(H_2, \mathrm{HL}) = 0$.

Once more, the maximization problem can be looked at by applying backward induction. In the second period, since there are no cost of investment as a result of low interbank correlation, the bank managers' payoff expectations depend solely on the expected borrowing cost. Expected payoffs in the second period can be maximized by comparing the expected borrowing cost in the second period, which corresponds to the level of correlation in the first period. For both choices regarding correlation, expected borrowing cost are given as

$$E(r_i) = \sum_j P_i(H_2, j) \cdot r_i^j, \text{ and consequently}$$

$$E(r_s) = P_s(H_2, \mathrm{HH}) \cdot r_s^{\mathrm{HH}} + P_s(H_2, \mathrm{LL}) \cdot r_s^{\mathrm{LL}} \tag{A.19}$$

$$E(r_d) = P_d(H_2, \mathrm{HH}) \cdot r_d^{\mathrm{HH}} + 2 \cdot P_d(H_2, \mathrm{HL}) \cdot r_d^{\mathrm{LH}} + P_d(H_2, \mathrm{LL}) \cdot r_d^{\mathrm{LL}} \tag{A.20}$$

Proposition 1: From equations (A.19) and (A.20), as well as the risk-averseness of creditors, it follows that $E(r_d) > E(r_s)$[386]. This difference in the expected interest rates $E(r_s) - E(r_d)$, in the second period is defined as *information contagion*.

Similarly, it follows that the effect of the information contagion on borrowing rates in the second period is strong enough to induce banks to choose high interbank correlation in the first period in order to maximize second-period returns. The critical assumption, which causes the information contagion effect, is the risk-averseness of creditors.

Nonetheless, the proposition does not automatically imply that bank managers will always seek high interbank correlation in the first period. The investment cost in the first period $c(\rho_1)$, which increases to a value greater than zero as banks choose to behave collectively, can provide an effective counter incentive to collective behavior. In the end, bank managers compare the interest rate effect of the information contagion to the cost effect of high-interbank correlation. Therefore, it becomes clear that for every combination of p and q there is a critical value of $c(\rho_{s,1}) = \delta_d^\star \cdot w$, which marks the indifference boundary when choosing between high and low correlation.

Proposition 2: If $\delta_d < \delta_d^\star$, bank managers will maximize their total expected payoffs by choosing high interbank correlation. On the contrary, if $\delta_d > \delta_d^\star$, the implied increase of investment cost for banks serves as an effective counter incentive to herding, and banks pursue differentiation strategies.

Information contagion when creditors get no additional information if banks pursue differentiation strategies

An underlying assumption of the model until now regarded the information conveyed to creditors from observing bank returns. It was assumed that creditors receive additional information if both banks have a high return and banks pursue different strategies. Therefore $\alpha_d^{HH} > \alpha_s^{HH}$; compare equation (A.16) or figure 23.

It is important to note that information contagion occurs only for risk-averse creditors, because probabilities are transformed into risk premiums by a concave utility function. Otherwise, if creditors were assumed to be risk-neutral, as Acharya and Yorulmazer (2008) point out, there would be no information contagion effect and banks would have no incentives to behave collectively, neither in the first nor the second period. This observation results from the fact that $P(\mathrm{H}) = P_s(\mathrm{HH}) = P_d(\mathrm{HH}) + P_d(\mathrm{HL})$ and, therefore, if posterior probabilities were to be transformed applying a linear utility function, there

[386] The proof for this proposition is straightforward for the stated assumptions regarding p, q and risk-averse creditors, which leads to the ranking of interest rates in equation (A.17). Thus it is omitted.

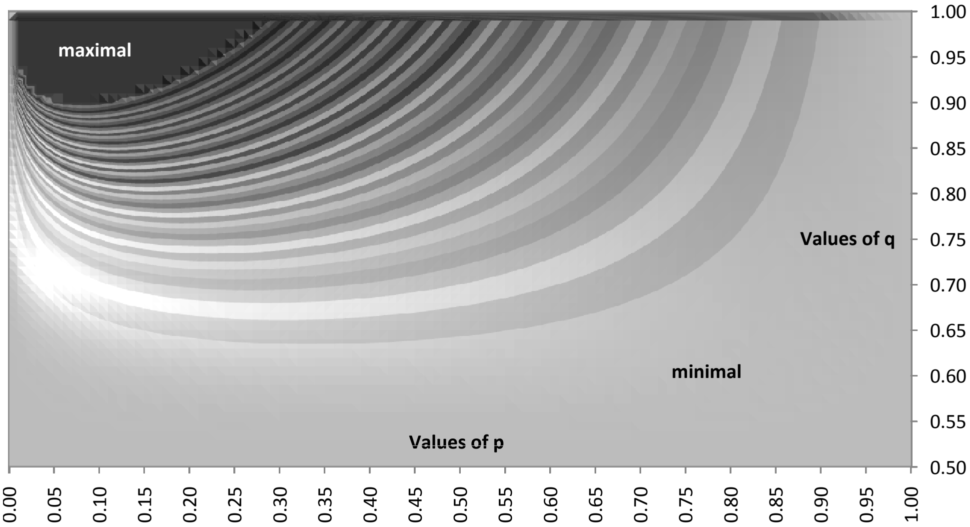


Figure 24: Degree of information contagion for different probability assumptions

would be no difference of the expected interest rates for the high and low interbank correlation scenarios. In that case, the only strategic complementarity would derive from the investment cost $c(\rho_{i,t})$ and, consequently, banks would have no incentive to pursue correlated strategies.

The whole picture changes once we adapt the level of information conveyed by the returns in both scenarios. Since both strategies are strictly iid, it would be a fair assumption that a high return of both banks for different strategies does not signal more information to creditors as it does for collective behavior; thus $\alpha_d^{\text{HH}} = \alpha_s^{\text{HH}}$. Such an adaptation would in fact assume a stronger information asymmetry between creditors and banks.

Following these considerations, figure 24 illustrates the difference of posterior probabilities for a high second-period return, while varying prior assumptions regarding p and q. Assuming risk-neutral creditors, the transformation of posterior probabilities into risk premiums is linear and does not affect proportions. However, as potential investment costs are not accounted for, the information contagion relates directly to the critical indifference boundary $\delta^{\star}$.

It is strikingly apparent from the figure that the extent of the information contagion is maximal for lower values of p and higher values of q. This is actually a combination for which the prior probability of a high return α_0 obtains the lowest possible values. We might interpret this observation in the sense that creditors feel confirmed in their negative outlook by the poor performance of the other bank, and accordingly judge the positive performance of the first bank as an outlier.

For increasing values of p, the information contagion decreases and obtains minimal values[387] as creditors are almost sure that the economic state is good, yet are ambiguous regarding their expectations for banks in a good economic environment. As creditors become more certain of high returns in a positive environment—e.g. they might have greater confidence in the banks' perspectives or management capabilities—the effect of information contagion again increases. Similarly, we could argue that the information contagion increases as creditors have less confidence in banks' perspectives or management capabilities, because they give negative results stronger weight and see them as confirmation of their prior expectations.

Effect of the capital buffer and consequences for banks strategic choices

From equation (A.3) it can be concluded that for any positive capital buffer effect—modeled as a positive probability of a medium-low return $b > 0$—the probability of a bank's survival in the second period increases:

$$\begin{gathered}\alpha_S^{\text{HH, Buffer}} > \alpha_S^{\text{HH, No buffer}} \\ \frac{1-p+2pq-(2-b)q+(1-b)q^2}{pq+(1-p)(1-q)} > \frac{pq^2+(1-p)(1-q)^2}{pq+(1-p)(1-q)};\ \forall b > 0\end{gathered} \tag{A.21}$$

Similar to our prior consideration, without the capital buffer bank managers seek to maximize their expected payoffs, which are affected by their choice regarding collective behavior in the first period, as well as the information contagion. Through the capital buffer the maximization problem is altered as follows: In the first period, the expected payoffs still depend on the choice regarding collective behavior; investment costs increase if banks pursue the same strategies. Moreover, the expected payoffs from the first period are conditional on a high return in the second period. Thus, if the bank realizes a low return ($\mathrm{L_M}$ or $\mathrm{L_L}$) in the second period, the capital buffer is used to cover creditor losses and there is no payout to bank managers.

The adverse effect of the information contagion, though, is now balanced by a positive effect due to the capital buffer. The extended decision problem for collective behavior or differentiation in the first period $i \in \{d, s\}$ is given as [388]:

$$\max_i E(\pi_{i,1}) + E(\pi_{i,2}),\ \text{where} \tag{A.22}$$

[387] Yet, the effect never reaches to zero.

[388] The equation for the expected second period return now includes the differentiation according to the individual bank return for j = HL/LH. In this case, the individual borrowing rate for the bank with the high return is lower than for the other bank, which had the low return.

$$\begin{aligned} E(\pi_{i,1}) = &\quad \alpha_1 \cdot \alpha_0 \cdot (H_1 - c(\rho_{i,1}) - r_0); \text{ as in equation (A.1) and} \\ E(\pi_{i,2}) = &\quad P_i(H_2, \mathrm{HH}) \cdot [H_2 - r_i^{\mathrm{HH}}] + P_i(H_2, \mathrm{HL}) \cdot [H_2 - r_i^{\mathrm{HL,H}}] + \\ &\quad P_i(H_2, \mathrm{HL}) \cdot [H_2 - r_i^{\mathrm{HL,L}}] + P_i(H_2, \mathrm{LL}) \cdot [H_2 - r_i^{\mathrm{LL}}] \end{aligned}$$

As was derived previously, the interest rates r_i^{LL} and $r_i^{\mathrm{HL,L}}$ equal the corresponding rates without the capital buffer. In addition, the interest rates for r_i^{HH} and $r_i^{\mathrm{HL,H}}$ are lowered by the capital buffer. As the probabilities of a high return from the perspective of banks remain unchanged in the second period, in comparison with the original model, it follows that $E^{\text{Buffer}}(\pi_{i,2}) > E^{\text{No buffer}}(\pi_{i,2})$ for all combinations of p, q and b.

From that perspective, the maximization problem again boils down to a comparison of the negative effect of collective behavior in the first period compared to the possible information contagion and capital buffer effect in the second period. In order to illustrate better insight into the capital buffer, there is merit in analyzing the impact of both effects for expected second period profits by comparing α_d^{HH} to $\alpha_d^{\mathrm{HL,H}}$. The question is whether there is a critical level of b, at which the information contagion is completely offset or even reversed by the capital buffer effect. Thus we set $\alpha_d^{\mathrm{HH}} \leq \alpha_d^{\mathrm{HL,H}}$ and thereby assume that creditors will assign an equal or higher probability to a bank's survival in the second period if the second bank performs worse, than if both banks have a high return in the first period. The resulting equation can be solved for b and is true for the condition that

$$b \geq \frac{2q-1}{p+q-1}, \ \forall b \leq 1 \tag{A.23}$$

Figure 25 shows the critical values for b, at which the capital buffer effect fully cancels out the information contagion and $\alpha_d^{\mathrm{HH}} = \alpha_d^{\mathrm{HL,H}}$; according to equation (A.23). For any b above this critical value (and with $b \leq 1$), the capital buffer effect is stronger[389] than the information contagion and thus $\alpha_d^{\mathrm{HH}} < \alpha_d^{\mathrm{HL,H}}$. It is clear from the illustration that the critical level of b is generally increasing in q and decreasing in p. Furthermore, for decreasing values of p there is an also a decreasing bound of q-values for which the critical level of b suffices the condition $b \in]0;1]$.

This can be explained as follows: as the probability of having a high return in good economic states generally increases, the effect of the capital buffer is marginalized

[389] Though the information contagion decreases the probability of a good economic state and thus a high return, the capital buffer increases the probability that a bank will survive although it only has a low return in the second period. The critical value of the probability assigned to the capital buffer represents the critical bound at which the second effect outweighs the first.

[390] Note that though by definition $p \in [0;1]$ the figure only includes values of $p \geq 0.5$. This is because for smaller values of p, there is no value of b within the critical bounds and for very small values of p there is no information contagion. Then there will be no incentives for banks to behave collectively, even if we would set $b = 0$.

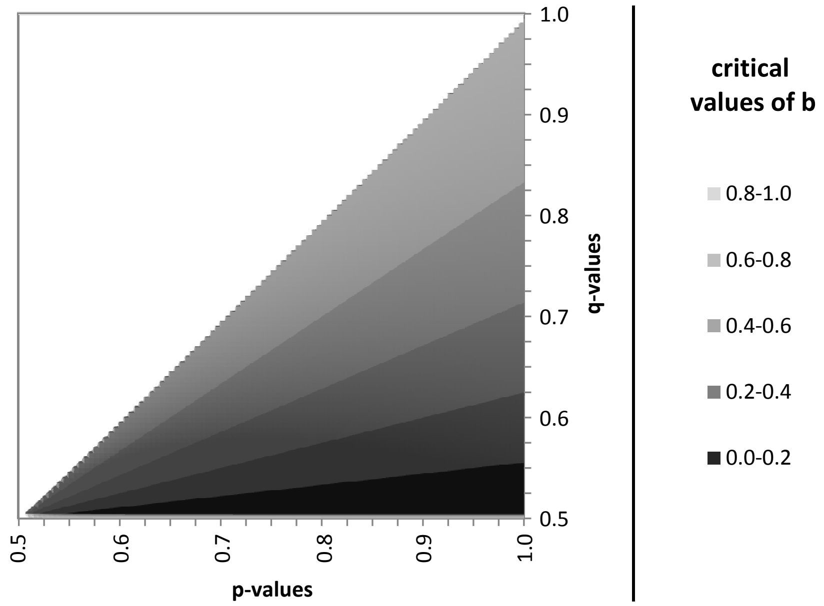


Figure 25: Critical values of b[390]

because the overall probability of a low return decreases. However, a higher probability of a good economic state diminishes the influence of the information contagion and hence already a low capital buffer level balances the negative externality. This shows that the capital buffer effect can rule out and even inverse incentives of the information contagion and thus allows for the following propositions.

Proposition 3: For any choice of collective behavior or differentiation, and probabilities p, q regarding the state of the economy and conditional returns, as long as $\frac{2q-1}{p+q-1} \leq 1$, there is at least one $b \in]0;1]$ for which $r_d^{HL,H} \leq r_d^{HH} < r_s^{HH} < r_d^{HL,L} = r_s^{HL} < r_s^{LL} < r_d^{LL}$:

$$\frac{2q-1}{p+q-1} \leq 1 \quad \Rightarrow \quad \exists b \in [0;1], \text{ for which} \quad E(\pi_{d,2}) \geq E(\pi_{s,2}) \tag{A.24}$$

Proposition 4: Even if proposition 3 does not apply because the condition of equation (A.24) is violated, there is a critical value of $\delta^\star$ at which the higher investment costs for collective behavior balance the overall effect of the information contagion, which is only partially mitigated by the capital buffer.

$$\frac{2q-1}{p+q-1} > 1 \quad \Rightarrow \quad \exists \delta^\star > 0, \text{ for which} \quad E(\pi_d) \geq E(\pi_s) \tag{A.25}$$

Collective behavior, systemic risk and collective moral hazard

We generally assume that collective behavior of banks induces systemic risk because the joint failure of banks implies a higher deadweight-loss for the overall economy. However, for this model we ruled out a failure of banks in the first period, and thus any deadweight loss. The presence of collective moral hazard in the choice of collective behavior can be proven similar to analyzing moral hazard at the individual level, by comparing the model outcome to the first-best equilibrium achieved by a central planning institution, e.g. a central bank. By coordinating bank managers' decisions, this institution maximizes the aggregate welfare, which can be measured as the sum of creditors' (denoted by V) and banks' utility (denoted by U).

Since first-period lending to banks is riskless, creditors receive a repayment including interest of $r_0 = 1$, which equals their original endowment. For the second period, first assuming no capital buffer effect, creditors demand an interest rate r_i^j, which corresponds to the state after the first period $j \in \{\text{HH, HL/LH, LL}\}$ and the relevant posterior probabilities of a high bank return in the second period. The expected welfare of creditors is given in equation (A.26). The expected profit of bank managers is given in equation (A.27), which is an adaptation of equation (A.18):

$$V = r_0 + \sum_j P(H_2, j) \cdot r_{i,2}^j \tag{A.26}$$

$$U = \alpha_0 \cdot (H_1 - c(\rho_{i,1}) - r_0) + \sum_j P(H_2, j) \cdot (H_2 - r_i^j) \tag{A.27}$$

According to our definition, the aggregated welfare is given as $W = V + U$, and with the definition $L_1 = r_0 + c(\rho_{i,0})$ transforms into:

$$W = \alpha_0 \cdot H_1 + (1 - \alpha_0) \cdot L_1 - c(\rho_{i,1}) + P(H_2) \cdot H_2 \tag{A.28}$$

Equation (A.28) shows that the overall welfare resembles the expected return in the first period, minus the potential investment cost in the case of high interbank correlation. Added to this is the value of a high return in the second period discounted by its probability. The fact that interest rates fully drop out of equation (A.28) illustrates that interest payments are simply a transfer of wealth from banks to their creditors. Therefore, the information contagion, which was captured by the different interest rates in the second period, only determines the level of wealth transfered from bank managers to creditors, but does not affect aggregate welfare.

Table 24: Strategic choices of bank managers and impact on expected payoffs

		2nd strategic choice (depending on δ, b)	
		Collective behavior	Pursue different strategies
1st strategic choice (depending on p, q)	Establish Capital Buffer	$\max_i \; E(\pi_i, 1)$ ①▼ ②▼ $+ E(\pi_i, 2)$ ③▲ ① Higher investment cost due to high correlation reduces expected profits ② Payout of profits contingent on high second-period return ③ Capital buffer decreases interest rates in case of high return	$\max_i \; E(\pi_i, 1)$ ①▼ $+ E(\pi_i, 2)$ ②▼ ③▲ ① Payout of profits contingent on high second-period return ② Poor performance of other bank can induce information contagion ③ Capital buffer decreases interest rates in case of high return
	Payout profits from 1st period	$\max_i \; E(\pi_i, 1)$ ①▼ $+ E(\pi_i, 2)$ ① Higher investment cost due to high correlation reduces expected profits	$\max_i \; E(\pi_i, 1) + E(\pi_i, 2)$ ①▼ ① Poor performance of other bank can induce information contagion

Nevertheless, assuming individual rationality and utility maximization, bank managers will strive to reduce this wealth transfer by opting for collective behavior in the first period. Equation (A.28) shows that this implies a decrease in overall welfare, because the cost of investment is higher if banks pursue correlated strategies. Therefore, while collective behavior might be rational from the individual manager's point of view, it represents a deviation from the first-best equilibrium, in which bank managers would always pursue different strategies. Consequently, collective behavior characterizes a collective moral hazard.

A further decision problem to be considered is whether it is rational at all for bank managers to retain their profits in the first period and establish a capital buffer to diminish potential information contagion effects. This comparison is critical, because the assumption of a capital buffer significantly changes the expected payoffs to bank managers, especially for the first period. The expected payout from the first period profit becomes conditional on the joint probability of a high return in the first and second periods, instead of only a high return in the first period. Thus, according to the values of δ, p, q, b, which are all assumed to be exogenous, bank managers have to maximize their expected payoffs in two steps: first, regarding the choice whether to build a capital buffer and potentially rule-out an information contagion or not to retain profits in the first period and optimize their profits; and, second, by deciding whether to opt for collective behavior or differentiation.

In conclusion, the decision problem of bank managers consists of four possible strategies (table 24). With regard to the initial presentation of possible returns and their consequences, the establishment of a capital buffer effectively represents a risk transfer from creditors to bank managers. This is an immediate consequence of the retention of excess profits in the first period. With the capital buffer, a payout of first-period excess returns is now conditional on a high return in the second period. If the bank does not realize a high return in the second period, the retained first period profits are distributed to mitigate creditor losses, but the bank manager receives no payout in this case. This risk transfer poses a very strong counter incentive for the voluntary establishment of a capital buffer by bank managers.

It thus seems unreasonable to assume that the positive effect of the capital buffer would marginalize the loss in expected payouts due to the capital retention, as explained above. Once banks can decide freely whether to establish a capital buffer or not, they will rationally vote for an immediate payout of profits from the first period. Furthermore, given the critical level of $\delta^{\star}$, which was derived in the original model, banks might pursue correlated strategies in order to rule out an information contagion in the second period.

The only solution to establish a capital buffer is thus an enforcement through regulation. If bank managers are forced to retain first-period profits as a cushion against future losses, the investment cost $\delta^{\star}$ would be comprehended by the capital buffer effect b. Since the capital buffer can effectively marginalize the adverse effects on banks' funding costs from the information contagion, it becomes more likely in this scenario that banks will not pursue correlated strategies, but will instead strive to differentiate.

This result shows that the imposition of a capital buffer can have positive effects as the level of interbank correlation and systemic risk decreases, while it does not imply any conclusions regarding the design of capital adequacy rules[391]. The main conclusion that can be drawn from this model is that, under certain assumptions regarding the appraisal of a capital buffer, the incentives for bank managers to pursue correlated strategies can be reversed to incentives to differentiate from the other banks. Thus, the positive effect does not primarily derive from an increased stability of the individual bank due to the (microprudential) capital buffer. Rather, the buffer enables the imposition of market discipline, which effectively leads to a reduction of systemic risk.

[391] Such policies are the subject of many other papers; for example Acharya (2001), Acharya (2009), Farhi and Tirole (2009), etc. The recent contribution of Tarashev et al. (2009) deals with systemic risk and capital adequacy rules in a more general manner and proposes to amend capital adequacy rules to account for bank externalities.

A.4 Money supply shocks with fixed externality

We analyze the interaction between bank managers and creditors for a two-period-model with three dates $t = 0,\ 1,\ 2$[392]. Each of two banks (A, B) raise funds from a continuum of creditors ($g \in \{A; B\}$) with an endowment $w_{g,t} > 0$ at the beginning of each period. The separation of creditors into two groups can resemble several assumptions, say as regionally specific groups. As in the prior model, creditors are by assumption risk-averse with a utility function $u(w)$ that is increasing and concave; therefore $u(w) > 0,\ u'(w) > 0,\ u''(w) < 0,\ \forall w > 0$.

New to the model is the variable money supply; the maximum money supply in each period is given as $W_t = w_{A,t} + w_{B,t}$. Creditors can pledge a portion of their endowment to banks by a simple debt contract with a maturity of one period. We refer to total lending to banks as $X_t = x_{A,t} + x_{B,t}$, where $x_{g,t} \leq w_{g,t}$. Alternatively, creditors can utilize their funds to produce goods in the real economy. This option is considered a safe investment in contrast to bank lending, because banks can fail in both periods. Underlying this safe investment is a standard neoclassical production function $f(w)$ with decreasing returns-to-scale, given as $f(w) > 0,\ f'(w) > 0,\ f''(w) < 0;\ \forall w > 0$[393].

Once banks have raised funds from creditors, they have a choice to pursue one of two possible risky strategies indexed by $h \in \{\mathrm{S1}; \mathrm{S2}\}$. Strategy returns R_t are assumed to be random and iid. In contrast to the previous model, we now allow for continuous returns with $R_t \sim N(R^\star, \sigma^\star)$[394]. The return distributions remain constant in both periods.

We again allow banks to endogenously determine the level of interbank correlation $\rho_{i,t}$ through some form of tacit coordination, which can result in the choice of collective behavior. Thus, interbank correlation is either assumed to be high if banks behave collectively and pursue the same strategy ($i = s, \rho_{s,t} = 1$), or low if they seek to differentiate ($i = d, \rho_{d,t} = 0$). The choice of collective behavior is directly linked to an investment cost $c_i(X_h)$, equation (A.29), that both banks incur and which is identical for both strategies. It is assumed that the total cost of investing in one strategy corresponds to the overall level of activity X_h[395] in this specific sector and imposes adverse scale effects:

[392] To reduce the complexity of the formulas, we refer to all variables relevant in the first period by time index 1 and index 2 for the second period.

[393] We apply two additional definitions in order to ensure that an equilibrium for bank lending exists: $f'(0) = \infty \wedge f'(w) \to 0$ for $w \to \infty$.

[394] In contrast to the original model by Acharya (2009), we assume variance $\sigma^\star$ to be fixed. Acharya allows σ to be endogenously determined by bank managers in order to illustrate individual risk-shifting dynamics: due to the limited liability, bank managers strive to maximize $\sigma = \sigma_{\max}$ and thus maximize risk. We already elaborated on this dynamic in appendix A.2.

[395] Whenever appropriate, we will later add a time-index denoting the activity level as $X_{h,t}$.

$$c_i(X_h) > 0, c_i'(X_h) > 0, c_i''(X_h) > 0, \text{ where } X_h = x_{A,h} + x_{B,h} \geq 0. \tag{A.29}$$

Consequently, the investment cost implies a similar counter incentive to collective behavior as in the expectation change model; only the definition has been adapted to account for the variable amount of bank lending. Since the overall activity in one sector is higher if banks opt for collective behavior, the investment cost rises to a disproportionally higher level than for differentiation strategies[396].

By the new assumption that banks can fail in both periods, they not only have to compensate creditors for a marginal loss in their production opportunity, but also must pay a risk premium on the borrowed funds. Generally, a bank is assumed to fail after the first period if the realized return after investment cost falls short of the required repayment to creditors. In this case, creditors are paid the full return $R_{g,t}$ of the respective bank, but might still incur a loss compared to the safe investment opportunity. Therefore, the expected return for creditors from lending to one bank is given in the equation below. The first term specifies the payoff if the banks' return was higher than the required interest rate, and the second term describes the payoff if the bank fails because of an insufficient return[397].

$$u_t(x_{g,t}, r_t) = \int_{r_t}^{r_{\max}} x_{g,t} \cdot r_t \cdot N(R^\star, \sigma^\star) dR + \int_0^{r_t} x_{g,t} \cdot R_{g,t} \cdot N(R^\star, \sigma^\star) dR \tag{A.30}$$

Accordingly, the interest rate r_t is determined in reference to the marginal product of the safe investment given in equations (A.31) and (A.32), which underscores that creditors not only consider their marginal loss in production, but also demand a risk premium for lending part of their endowment to banks[398].

$$r_t(x_{g,t}) = f'(W_t - X_t) \tag{A.31}$$

$$r_t(x_{g,t}) = \int_{r_t}^{r_{\max}} r_t \cdot N(R^\star, \sigma^\star) dR + \int_0^{r_t} R_{g,t} \cdot N(R^\star, \sigma^\star) dR \tag{A.32}$$

[396] Taking the choice of one strategy ($h = \mathrm{S1}$) as an example, it follows that if banks pursue the same strategies ($i = s$) that $x_{A,\mathrm{S1}} = x_{B,\mathrm{S1}} > 0$ and $x_{A,\mathrm{S2}} = x_{B,\mathrm{S2}} = 0$: $c_s = c(X_{\mathrm{S1}}) + c(X_{\mathrm{S2}} = 0)$. In contrast, we have the following activities for differentiation ($i = d$): $x_{A,\mathrm{S1}} > 0 \wedge x_{B,\mathrm{S1}} = 0$ and $x_{A,\mathrm{S2}} = 0 \wedge x_{B,\mathrm{S2}} > 0$ (or vice versa); consequently: $c_d = c(X_{\mathrm{S1}}) + c(X_{\mathrm{S2}})$. Due to the convexity of the function we can simply put for total cost $c_s > c_d$.

[397] Note that contrary to the expectation change model, r_t now applies as an interest rate and is therefore multiplied with the overall amount of lending.

[398] From the creditors' perspective, the expected bank repayment for a certain interest rate r_t must equal the marginal loss in the safe production opportunity. Note that while the expected bank repayment is defined at the individual level (lending to bank g an amount $x_{g,t}$), the marginal loss in the production opportunity depends on the available aggregate endowment after total lending $W_t - X_t$.

Both equations together determine the money supply curve in the model, and thus the basis for the decision of bank managers concerning the amount of funding to raise at a given interest rate. Banks are again assumed to be price takers. This establishes the basis for bank managers to invest in strategy $h \in \{\mathrm{S1}; \mathrm{S2}\}$. The expected strategy payoff for bank managers is given as:

$$v_t(x_{h,t}, r_t, X_h) = \int_{r_t}^{r_{\max}} x_{h,t} \cdot (R_{h,t} - r_t) \cdot N(R^\star, \sigma^\star) dR - c_i(X_{h,t}) \tag{A.33}$$

In order to ensure that banks become active in intermediation in the first period and that there will be an equilibrium in the funding market, it has to be assumed that $v_1(x_{g,1}, r_1, i) \geq 0$ for at least one $x_{g,1} > 0$. If the expected payoff for bank managers is negative, they would have no incentive to engage in intermediation and creditors would utilize all of their endowment in the safe-production opportunity. With this restriction, the banks' demand for funds can be derived from the first-order condition of equation (A.33), which identifies the profit maximum[399]:

$$\max_{x_{h,1}, X_h} \quad v_1(x_{h,1}, r_1, X_h) \quad \xrightarrow{v_1'(\cdot)=0} \quad \int_{r_1}^{r_{\max}} (R_{h,1} - r_1) \cdot N(R^\star, \sigma^\star) dR = c_i'(X_h, 1) \tag{A.34}$$

Equations (A.31), (A.32) and (A.34) define the equilibrium amount of lending and equilibrium interest rates at which creditors lend to banks[400]. Looking at this equilibrium, two remarks have to be made, which will be of relevance for later stages of the analysis. First, notice the impact collective behavior on the equilibrium condition, which materializes through the cost function. If banks opt for collective behavior, it follows from equation (A.29) that for $i = s$ equilibrium borrowing by banks will be lower compared to overall borrowing in the differentiation scenario[401]. Thus, by looking at one of the periods individually, there are no incentives for bank managers to behave collectively and pursue the same strategies.

[399] The first order condition implies that the marginal gains from one additional unit of investment are equal to the marginal cost of this additional unit.

[400] The equilibrium exists as a result of our additional assumptions regarding the production function: $f'(0) = \infty \wedge f'(w) \rightarrow 0$ for $w \rightarrow \infty$. Once the endowment w_t of creditors is large enough, there will be an amount $x_{g,t}$ for which the interest rate r_t defined by equations (A.31) and (A.32) suffices the condition laid down in equation (A.34). For a formal proof see Acharya (2001).

[401] As marginal costs of investing increase, the difference $(R_1 - r_1)$ has to increase in order to satisfy the first-order condition that expected marginal returns minus marginal cost of investment are zero. Since return expectations are constant with $R_t \sim N(R^\star, \sigma^\star)$, this can only be achieved by reducing the amount of lending and, in consequence of equation (A.31), the required interest rate for funding.

Possible states after the first period and implications for the funding equilibrium

After defining the funding equilibrium for banks, we shift the focus to potential states at the end of the first period and their implications for second-period funding. As in the expectation-change model, bank managers will have already accounted for potential second period effects while taking their strategy decisions in the first period. Looking at the first period individually, there are no incentives to follow correlated strategies. Such incentives will again arise from strategic complementarities that turn up in the second period.

Once strategy returns have been realized at the end of the first period, banks have to repay creditors' funds with the required interest r_1. If the strategy return on investment is insufficient, the bank is assumed to fail. Therefore, there can be two states for each bank, which relate to the return of the chosen strategy. For $R_{h,1} \geq r_1$ the bank will survive and, if $R_{h,1} < r_1$, the bank will fail. The case of collective behavior is special insofar as banks can only jointly survive/fail, but there can be no individual failure. The possible states and according effects at the beginning of the second period are:

- *Both banks survive* (j = SS): Given this scenario, there are no changes in the second period. All assumptions regarding cost and returns remain constant. There is no change in money supply and the equilibrium can be calculated as above.
- *Only one bank survives* (j = SF/FS): This case is only relevant if banks opt for differentiation in the first period[402]. The failure of a bank implies that it will be closed down and only one bank will remain active. There are two implications for the surviving bank in the second period:
    1. A *recessionary effect* due to a reduction in the maximum money supply as $W_2 = w_{A,2} + (1 - s) \cdot w_{B,2}$; for $s \in [0; 1]$. This assumption is reasonable, since creditors of the failing bank might require a portion of their endowment in the second period to cover their losses, or not all creditors may be able to migrate to the surviving bank in the other region. Also, from the perspective of the surviving bank, one might assume that the sudden inflow of new money can only be handled to a certain level because of structural rigidities, constrained investment capacities, etc.
    2. There is a *strategic benefit* for the surviving bank, as a result of the liquidation of the other bank. It can be assumed that this bank is able to take over certain

[402] As in the model before, this case applies if bank A survives and bank B fails or vice versa. Because of the homogeneity of banks, the analyses are symmetrical in both cases. Subsequently, it is assumed that bank A survived, while bank B failed after the first period.

asset portfolios or attract human capital from the failing bank, which in turn decreases its investment cost in the second period to $(1-\alpha) \cdot c(X_{h,t})$; for $\alpha \in [0;1]$[403].

- *Both banks fail* (j = FF): This case again applies to both collective behavior or differentiation. As both banks are liquidated upon their failure, there will be no financial intermediation in the second period. Creditors can utilize their funds only in the production opportunity. The welfare effects of a joint failure are discussed in the later analysis.

A first conclusion for the second period is that banks will never opt for collective behavior in the second period. There are no incentives if looking solely at one period of the model. Thus, because the second period is the final one, banks will seek to avoid the elevated investment cost because of collective behavior, and always pursue differentiation strategies[404].

A second evident observation regards the joint survival of banks (j = SS), in which the second period runs perfectly analogous to the first. As expectations are assumed constant, the funding equilibrium for banks is again given by the fixed-point system of equations (A.31), (A.32) and (A.34). The expected payoff for bank managers in the second period is given as[405]:

$$v_2^{\mathrm{SS}}(x_{h,2}, r_2) = \int_{r_2}^{r_{\max}} x_{h,2} \cdot (R_{h,2} - r_2) \cdot N(R^\star, \sigma^\star) dR - c(x_{h,2}) \tag{A.35}$$

More interesting is the scenario of an individual failure (j = SF/FS), in which the expected payoff for bank managers is affected by the recessionary effects as well as the strategic benefit. First, the recessionary benefit implies a reduction in the maximum money supply as $W_2 = w_{A,2} + (1-s) \cdot w_{B,2}$; with only one bank active, $X_2 = x_{g,2}$. This directly and negatively effects the money supply curve, which is now given by the following equations:

$$r_2(X_2) = f'(W_2 - X_2) \tag{A.36}$$

$$r_2(X_2) = \int_{r_2}^{r_{\max}} r_2 \cdot N(R^\star, \sigma^\star) dR + \int_0^{r_2} R_{g,2} \cdot N(R^\star, \sigma^\star) dR \tag{A.37}$$

[403] In order to achieve a positive impact of α we additionally assume that the increase of c due to the higher level of investment in one strategy in the second period is outweighed by the reduction $(1-\alpha)$.

[404] As a result, we drop the index for interbank correlation in the second period.

[405] Since bank managers always choose differentiation in the second period and for the case j = FS there is only one active bank, it follows that $X_{h,2} = x_{h,2}$.

Through the definition of $f'(w)$, the reduction of the total endowment raises the marginal loss in the production opportunity for equal levels of bank lending. Ceteris paribus, the equilibrium interest rate rises. However, bank managers adapt to this reduction in money supply and the new equilibrium is produced through the maximization of the adapted first order condition for the maximum profit. Equation (A.38) is adapted so that, while the interest level increases in consequence of equations (A.36) and (A.37), the cost of investment decreases by α capturing the strategic benefit of the surviving bank.

$$\max_{x_{h,2}} \quad v_2^{\mathrm{SF}}(x_{h,2}, r_2) \;\longrightarrow\; \int_{r_2}^{r_{\max}} (R_{h,2} - r_2) \cdot N(R^\star, \sigma^\star) dR = (1-\alpha) \cdot c'(x_{h,2}) \tag{A.38}$$

As both strategies S1 and S2 represent iid return distributions and only one bank remains in business, the choice of strategy is irrelevant. Therefore, the strategy index h can be dropped and the variable can be replaced by the total amount of borrowing. Moreover, there can be no collective behavior. The cost of investment is now directly determined by the level of borrowing of the surviving bank. Adapting equation (A.33), the new funding equilibrium implies an expected payoff to bank managers given through

$$v_2^{\mathrm{SF}}(X_2, r_2) = \int_{r_2}^{r_{\max}} X_2 \cdot (R_2 - r_2) \cdot N(R^\star, \sigma^\star) dR - (1-\alpha) \cdot c(X_2) \tag{A.39}$$

By comparing equations (A.35) and (A.39), it is possible draw conclusions on the overall effect of the externalities in the case that only one bank survives. The failure of the second bank after the first period induces a negative externality if $v_2^{\mathrm{SF}}(\cdot) < v_2^{\mathrm{SS}}(\cdot)$. Otherwise, if $v_2^{\mathrm{SF}}(\cdot) \geq v_2^{\mathrm{SS}}(\cdot)$, the impact of the other bank's failure is beneficial in terms of second-period payoffs to the surviving bank's manager.

We can describe the overall value of the externality by looking at $v_2^{\mathrm{SF}}(\cdot) - v_2^{\mathrm{SS}}(\cdot)$. From the assumptions in the model, we know that the extent of the recessionary spillover is determined by s, whereas a higher value of s implies a higher negative impact. In contrast, we have described the strategic benefit by α, with a higher value of α signaling a higher benefit for the surviving bank. Consequently, we can state

Proposition 1: For a given s, determining the recessionary benefit, there will be a critical level of $\alpha^\star$ where the two effects result in a positive externality and $v_2^{\mathrm{SS}}(\cdot) - v_2^{\mathrm{SF}}(\cdot) > 0, \forall \alpha > \alpha^\star$.

Proposition 2: For a given α, determining the strategic benefit, there will be a critical level of $s^\star$ where the two effects result in a negative externality and $v_2^{\mathrm{SS}}(\cdot) - v_2^{\mathrm{SF}}(\cdot) < 0, \forall s > s^\star$.

Impact of the externality and consequences for collective behavior

In order to analyze the effect of a positive/negative externality on the choice of collective behavior in the first period, it is important to account for the effect on investment cost in the first period, where we have already shown that it is higher for collective strategies ($i = s$) as $c_s > c_d$. Bank managers seek to maximize their expected returns from both periods and therefore consider the implications of these strategic complementarities. As the bank terminates its business in the case of failure, only those cases in which the bank survives after the first period ($j \in \{\mathrm{SS}, \mathrm{SF}\}$) are relevant for this assessment. The overall optimization problem from the perspective of bank A[406] is given as

$$\max_{x_{h,t},i} \; v_{i,1}(x_{h,1}, r_1, X_h) + P(\mathrm{SS}) \cdot v_2^{\mathrm{SS}}(x_{h,2}, r_2) + P_i(\mathrm{SF}) \cdot v_2^{\mathrm{SF}}(x_{h,2}, r_2), \text{ where} \tag{A.40}$$

$$P(\mathrm{SS}) = P(R_{A,1} > r_1, R_{B,1} > r_1) \text{ and } P_i(\mathrm{SF}) = P(R_{A,1} > r_1, R_{B,1} < r_1).$$

As the probability of a joint survival transforms to $P(\mathrm{SS}) = P(R_{A,1} > r_1) - P_i(\mathrm{SF})$[407], the decision problem can be rewritten, reducing the complexity of the equation by dropping the brackets with the functions' variables, as

$$\max_i \; v_{i,1} \; + \; P(R_{A,1} > r_1) \cdot v_2^{\mathrm{SS}} \; + P_i(\mathrm{SF}) \cdot (v_2^{\mathrm{SF}} - v_2^{\mathrm{SS}}) \tag{A.41}$$

The strategic choice to behave collectively or to differentiate affects the expected payoff for bank managers in both periods; figure 26 replicates equation (A.41) and highlights these two effects. In the first period, the choice of collective behavior implies that the expected return decreases because of higher investment cost. Looking at the second period, the left term is constant. The last term, however, is again dependent on collective behavior or differentiation. As it was described above, $v_1^{\mathrm{SF}} - v_1^{\mathrm{SS}}$ brings us to a conclusion about the overall value of the externality, which can be either positive or negative. The multiplier $P_i(\mathrm{SF})$ corresponds to the probability of one bank failing while the other bank

[406] Due to the homogeneity assumption, the analysis is analogous for bank B.

[407] Taking the perspective of one bank, the joint probability of survival is the probability that the bank itself will survive minus the probability that the bank will survive and the other bank will fail; consequently: $P(\mathrm{SS}) = P(R_{A,1} > r_1) - P(R_{A,1} > r_1, R_{B,1} < r_1) = P(R_{A,1} > r_1) - P_i(\mathrm{SF})$.

survives. As a consequence, banks can choose to pursue collective strategies and thereby effectively assign a zero-probability to this specific case: $P_s(\mathrm{SF}) = 0$ that would rule out any externality from their expected payoffs.

	Expected 1st period return		**Expected 2nd period return**	
$\max\limits_{i}$	$v_{i,1}$ $\quad$ $i = s$: ▼	+	$P(R_{A,1} > r_1) \cdot v_2^{\mathrm{SS}}$ +	$P_i(\mathrm{FS}) \cdot (v_2^{\mathrm{FS}} - v_2^{\mathrm{SS}})$ $\quad$ $i = d$: ▲▼
	Increased cost of investment reduces payoff expectations for collective behavior.		Term independent of collective behavior.	The potential externality can have a positive or negative impact for different strategies.

Figure 26: Maximization problem of bank managers with externalities

Just as in creditor expectation change model, here again bank managers will balance the expected implications of different outcomes on their expected payoffs from both periods. It is obvious that banks have an interest in assigning zero probability to the state of individual failure, if (a) the overall externality $(v_1^{\mathrm{FS}} - v_1^{\mathrm{SS}})$ is negative and (b) it outweighs the reduction of expected payoffs in the first period. If one of these two conditions does not hold, banks will opt for differentiation in the first period.

The increase in the cost of investment effectively serves as a counter incentive to collective behavior, as long as it is not outweighed by a potentially negative externality. Acharya (2009) defines the behavior of banks in response to a potentially negative externality as 'systemic risk-shifting'. On the other hand, if the strategic benefit is larger than the recessionary spillover, the expected externality will be positive and banks will have incentives to pursue differentiation strategies.

Collective behavior, systemic risk and collective moral hazard

To prove the presence of collective moral hazard in the banks' decision for collective behavior, we would have to compare the investment decisions of a central planning institution, which maximizes aggregated welfare, as the first-best equilibrium, with the aggregated level of welfare that results from the banks' decisions. However, for such a variable equilibrium the formal analysis is not possible without further assumptions regarding the production function $f(W-X)$, investment cost $c_i(X_h)$, expectations regarding the strategy return R and corresponding values of s and α. Yet the necessary number of assumptions would strongly limit the generality of our conclusions regarding aggregate welfare.

This problem is also recognized by Acharya (2009), who presents an indirect proof that correlated strategies in fact reduce aggregate welfare. His approach is to model deadweight costs of failure, which are dependent on the total amount of risky investment in the economy. Modeling the different scenarios, it is easy to show that ruling out the case of individual failure (j = FS/SF) by choosing high interbank correlation indeed increases expected deadweight cost compared to the low interbank correlation scenario. Interest rates again represent a simple transfer of wealth from banks to creditors and drop out of the aggregate analysis.

Because the maximization condition of bank managers contains only the cost of failure caused by the other bank (as part of the externality), they do not consider that a joint failure would disproportionally increase creditors' losses and that this risk is maximized by opting for collective behavior. Summing up, a central planner will always seek differentiation among banks. The joint choice of collective behavior, for the above-mentioned assumptions, resembles collective moral hazard.

A.5 Money supply shocks with dynamic externality and multiple, heterogenous banks

The supply shock externality consists of two effects: The strategic benefit captures a positive effect due to an increase in business as creditors of the failed bank migrate to the surviving one, and existing businesses or human capital can be integrated. This effect will be limited because of the potential integration cost, and rising complexity[408]. In contrast, the recessionary spillover consists of the potential liquidation cost and the price impact of fire sales, etc., that lead to a reduction in money supply.

We have assumed that a joint failure of two banks increases the externality since there can be no strategic benefit, but the recessionary spillover increases disproportionally. Transferring this observation to an environment with more than two banks, the intuition is as follows: if only one bank fails, the surviving banks will compete to acquire parts of its business and creditors can migrate to all other banks, which seek to expand in scale. Thus, all assets of the failing bank will be sold, and at fair value. Consequently, the recessionary spillover will be close to zero, consisting only of information effects[409] which will be outweighed by the strategic benefit.

Figure 14 of the main part (page 121) emphasizes the dynamics of both effects for an increasing number of failing banks n and highlights two critical thresholds regarding the externality. For threshold n_0, surviving banks reach individual saturation and will not acquire further assets from failing banks. This marks the peak of the aggregated strategic

[408] Returns-to-scale on the acquisitions are assumed to be decreasing in the size of the acquisition.

[409] It has to be remarked that with an increasing number of failing banks information effects arise, which were not formally accounted for in our model, but will give rise to a small recessionary spillover that is increasing with the number of failing banks; see our fundamentals (section 2.2.3).

benefit and, even if more banks fail, it will be not economically viable for the surviving banks to acquire all assets of the failing banks, since integration costs outweigh the benefits of an acquisition. Competition for liquidated assets declines and the recessionary spillover starts to increase[410]. The second threshold $n^\star$ marks the point at which the recessionary spillover exceeds the strategic benefit and the externality will be negative for a number of failing banks $n > n^\star$.

Equation (A.42) generalizes the strategic benefit, denoted as $(1-\alpha)\cdot c\,(x)\,;\alpha < 1$ in the original model. In reference to the number of failing banks n, $a(n)$ is defined as the aggregate of individual strategic benefits $\alpha(n)$ for all surviving banks. Because the strategic benefit at firm level reaches saturation for $n \geq n_0$ (dotted line in figure 14), it follows that $a(n) \to 0$ for $n \to n_{\max}$.

$$a(n) = (n_{\max} - n)\cdot\alpha(n),\ \text{where}\,\alpha(n) > 0,\ \alpha'(n) = \begin{cases} > 0 & ; n < n_0 \\ = 0 & ; n \geq n_0 \end{cases},\ \forall n > 0 \quad \text{(A.42)}$$

The recessionary spillover was originally defined as the decrease in money supply in the second period as $W_2 = w_{A,2} + (1-s)\cdot w_{B,2}$. The generalization in reference to n can be simply defined as[411]:

$$s(n) = \begin{cases} 0 & ; n \leq n_0 \\ > 0 & ; n > n_0 \end{cases},\ s'(n) > 0,\ s''(n) > 0,\ \forall n > n_0 \quad \text{(A.43)}$$

To model the strategy decisions in such a multiple bank environment, and with sequential decision-making, we also have to adapt the strategy space. This is because, strictly speaking, the first agent would not be able to behave collectively. We now assume that, prior to the first decision, banks decide on a collective strategy, which would induce interbank correlation and systemic risk, as well as a differentiation strategy, a broad subset of uncorrelated strategies under which banks differentiate from those banks opting for collective behavior, but similarly from those that differentiate as well.

The intuition regarding the externality is that, once a number $n > n^\star$ of banks pursues the collective strategy, it is individually rational for the other banks to follow this herd, because the externality from a failure of more than $n^\star$ banks is negative[412]. As we

[410] We might also assume that the aggregate strategic benefit reaches its peak only after the threshold, as not all banks reach the saturation level at the same time. However, still upholding the assumption of homogeneous banks it would be a contradiction.

[411] If we would consider an information externality, this would arise already as the first bank fails and it would increase upon consecutive failures of other banks. To account for this, equation (A.43) could be simply augmented with $\text{IE}(n) > 0$, $\text{IE}'(n) > 0$, $\text{IE}''(n) > 0$, $\forall n > 0$.

[412] This underlying rationale is somehow related to Allen and Gale (2008)'s analysis on contagion. They analyze spillovers on interbank loans. Their analysis shows that for a critical amount of losses on these loans, knock-on effects of a first failure will cause consecutive failures of other banks.

are interested only in the algebraic sign of the externality, and not its value, combining both equations, it can be denoted as

$$\text{Ext}(n) = \begin{cases} \geq 0 & ; n \leq n^\star \\ < 0 & ; n > n^\star \end{cases} \tag{A.44}$$

Interesting for our analysis are the implications of such a dynamic externality on banks' propensity to behave collectively. As it was stressed, information aggregation stops on an information cascade and a cascade is not always truly revealing. Since it can start very early in the decision sequence, the decisions of the first banks are highly important. Banks now account for the potential dynamics of the externality with regard to the number of failing banks. They are aware of the risk that choosing the wrong strategy could expose them to a negative externality if more than $n^\star$ banks fail. This case applies particularly for the scenario of the bank choosing to differentiate, while all other banks choose collective behavior.

The expected payoffs for the first bank choosing either collective behavior (C) or differentiation (D) are contingent on a later collective behavior (CC) or differentiation cascade (DC) and given by the following equations, which are adapted from equation (A.41)[413]. Note that 'Ext' in both equations only represents a negative externality. Hence, it is multiplied with the probability that the cascading banks fail and thus $n > n^\star$[414].

$$\begin{aligned} E(C) = {} & P(\text{CC}|C) \cdot V_2^{ss} \cdot P(R_1 > r) + \\ & P(\text{DC}|C) \cdot (V_2^{ss} \cdot P(R_1 > r) + \text{Ext}_{\text{DC}} \cdot P(R_1 > r, R_{\text{DC}} < r)) \end{aligned} \tag{A.45}$$

$$\begin{aligned} E(D) = {} & P(\text{CC}|D) \cdot (V_2^{ss} \cdot P(R_1 > r) + \text{Ext}_{\text{CC}} \cdot P(R_1 > r, R_{\text{CC}} < r)) + \\ & P(\text{DC}|D) \cdot (V_2^{ss} \cdot P(R_1 > r) + \text{Ext}_{\text{DC}} \cdot P(R_1 > r, R_{\text{DC}} < r)) \end{aligned} \tag{A.46}$$

For both strategies the expected payoffs consist of the expected value for rightfully anticipating the later cascade, plus the expected value if the bank's information was wrong and the bank is not part of the cascade. The individual payoffs correspond to the original model multiplied by the applicable probabilities. All those cases in which the bank itself fails are not relevant for its decision-making and drop out of the equations.

[413] By signaling its decision to subsequent banks, the first bank crucially influences other banks' decisions and thus positively affects the probability of being in the true cascade.

[414] In a differentiation cascade, the probability of the failure of a critical number of banks is certainly lower than for a correlation cascade, because banks still differentiate against each other and, therefore, the probabilities of realizing insufficient returns are independent.

It stands out from comparing both equations that the choice of a collective behavior strategy significantly changes the potential payoff. This is because, even if all banks in the collective behavior cascade fail, the first bank will fail as well and the subsequent externality is not relevant for its decision. Furthermore, if the bank chooses collective behavior but there is a differentiation cascade, the probability of a negative externality is much lower when compared to the collective behavior cascade. The picture changes when choosing a differentiation strategy: in this case, if there is a collective behavior cascade and many banks fail, the differentiating bank will certainly be exposed to a negative externality.

Comparing both choices with the assumption that $E(C) > E(D)$, we can eliminate the expected payoffs V_2^{SS} and the probability of the banks survival $P(R_1 > r)$. Assuming for simplicity that the externality takes a standard value for all cascades, this expression also drops from the equation[415]. Thus, the problem boils down to:

$$P(\mathrm{DC}|C) \cdot P(R_{\mathrm{DC}} < r) \ < \ P(\mathrm{CC}|D) \cdot P(R_{\mathrm{CC}} < r) + P(\mathrm{DC}|D) \cdot P(R_{\mathrm{DC}} < r) \quad \text{(A.47)}$$

and after dividing by the positive term on the left side of the equation we have[416]:

$$1 \ < \ \frac{P(R_{\mathrm{CC}} < r)}{P(R_{\mathrm{DC}} < r)} + \frac{P(\mathrm{DC}|D)}{P(\mathrm{DC}|C)}$$

This condition—$E(C) > E(D)$—is true if the sum on the right is greater than one. The first expression on the right compares the joint probability of failure, which is clearly higher for a correlation cascade (numerator) than for a differentiation cascade (denominator) and, hence, the first expression is greater than one. Since the probabilities in the second expression are by definition positive, the condition is already true and thus $E(C) > E(D)$[417].

In conclusion, the risks of choosing the differentiation strategy are significant, and the first (rational) bank manager can maximize expected payoffs by choosing collective behavior. Logically, this result also applies to the second and all subsequent banks.

[415]Because the Externality (Ext) is negative, its elimination (by division) changes the logical operator of the term in equation (A.47). If we would allow different negative values for the externality, this would not change our results, since the externality for the failure of a correlation cascade would certainly be higher than for a differentiation cascade. As more banks fail in a correlation cascade, this is implied by equations (A.42) and (A.43).

[416]Note that $P(\mathrm{DC}|C) = P(\mathrm{CC}|D)$ as both describe the probability of being in the wrong cascade.

[417]We can show that the second expression, which divides the probability to be in a right cascade (numerator) by the probability of being in a wrong cascade (denominator), is also greater than one. According to Bikhchandani et al. (1992), the probability of a cascade going in the direction of the first banks' decision is $P(\mathrm{DC}|D) = P(\mathrm{CC}|C)$ and larger than the probability that the cascade goes in the different direction $P(\mathrm{CC}|D) = P(\mathrm{DC}|C)$.

Therefore, the correlation strategy can be considered as the overall dominant strategy in this adapted form of the supply shock model[418].

[418]Our conclusions are similar to the result of another analysis by Acharya and Yorulmazer (2004), who model bank behavior in anticipation of potential public sector bailouts. The major difference is in the overall approach: banks in our model opt for collective behavior in order to avoid a potential externality; Acharya and Yorulmazer (2004) assume that for a joint failure of banks, the central bank will deviate from its no bailout policy and provide support. Thus, in anticipation of the bailout value, the collective behavior strategy becomes dominant in a multiple bank environment.

Appendix B

Empirical analysis: additional statistics

B.1 Detailed sample overview and summary statistics

Detailled sample statistics for individual financial institutions of the international sample (table 25) and the US sample (table 26). Summary statistics were given in table 11 on page 146. The last three columns of the tables report significance levels at which null hypothesis of Jarque-Bera (JB), Ljung-Box Q (LBQ) and Engle's LM-Test (LM) can be rejected.

Table 25: International sample overview

Company Name	ID	Cntry	Base Date	Obs.	Mean	Std.D.	Skew.	Kurt.	JB[2]	LBQ[2]	LM[2]
Eurozone (EUR)											
ABN AMRO[1]	ABN	NL	22.08.1990	4611	0.0005	0.0174	-0.06	9.85	***	***	***
Ageas (ex Fortis)	FOR	BE	01.01.1990	5455	-0.0002	0.0319	-18.96	892.90	***	***	***
Alpha Bank	ALP	GR	01.01.1990	5456	0.0004	0.0251	0.06	9.97	***	***	***
Banca Monte dei Paschi	BMP	IT	24.06.1999	2065	-0.0004	0.0193	0.02	6.66	***	***	***
Banco Popular Espanol	BPE	ES	01.01.1990	5456	0.0002	0.0176	0.39	10.53	***	***	***
BBVA	BBV	ES	01.01.1990	5456	0.0002	0.0200	0.12	10.63	***	***	***
BNP Paribas	BNP	FR	18.10.1993	4466	0.0002	0.0237	0.29	10.60	***	***	***
Commerzbank	COM	DE	01.01.1990	5456	-0.0002	0.0236	-0.24	16.34	***	***	***
Credit Agricole	CAG	FR	01.01.1990	5197	0.0001	0.0145	-0.75	33.68	***	***	***
Deutsche Bank	DEB	DE	01.01.1990	5456	0.0000	0.0214	0.14	13.74	***	***	***
Dexia	DEX	BE	19.11.1996	3660	-0.0002	0.0268	-0.28	27.71	***	***	***
Erste Group	ESG	AT	04.12.1997	3388	0.0003	0.0259	-0.21	11.68	***	***	***
ING Group	ING	NL	04.03.1991	5151	0.0001	0.0263	-0.03	21.64	***	***	***
Intesa Sanpaolo	INT	IT	01.01.1990	2065	0.0001	0.0236	0.20	9.03	***	***	***
KBC Group	KBC	BE	01.01.1990	5455	0.0002	0.0251	-0.06	37.96	***	***	**

Table 25: International sample overview (continued)

Company Name	ID	Cntry	Base Date	Obs.	Mean	Std.D.	Skew.	Kurt.	JB[2]	LBQ[2]	LM[2]
Natixis	NAT	FR	01.01.1990	5197	-0.0001	0.0235	0.65	22.95	***	***	***
Santander	SAN	ES	01.01.1990	5456	0.0002	0.0208	0.12	10.37	***	***	***
Societe Generale	SOC	FR	01.01.1990	5197	0.0001	0.0233	0.04	9.79	***	***	***
UBI Banca	UBI	IT	30.06.2003	1936	-0.0004	0.0176	-0.06	10.15	***	***	***
Unicredit	UNI	IT	01.01.1990	2065	0.0001	0.0235	0.58	12.52	***	***	***
Europe, but not within Eurozone (NEU)											
Barclays	BAR	GB	01.01.1990	5456	0.0002	0.0263	1.42	50.19	***	***	**
Credit Suisse	CSG	CH	01.01.1990	5456	0.0001	0.0228	0.15	13.33	***	***	***
Danske Bank	DAN	DK	01.01.1990	3892	0.0002	0.0180	-0.10	10.08	***	***	***
DNB	DNB	NO	23.09.1992	4744	0.0005	0.0239	0.16	16.56	***	***	***
Lloyds Banking Group	LLB	GB	28.12.1995	3893	-0.0003	0.0306	-0.91	39.82	***	***	**
Nordea Bank	NOR	SE	02.11.1995	3933	0.0005	0.0225	0.34	7.50	***	***	***
Royal Bank of Scotland	RBS	GB	01.01.1990	5456	-0.0001	0.0309	-8.77	312.79	***	***	*
Svenska Handelsbanken	SVH	SE	01.01.1990	5456	0.0004	0.0222	0.61	14.88	***	***	***
Swedbank	SWB	SE	09.06.1995	4037	0.0002	0.0241	-0.07	11.08	***	***	***
UBS	UBS	CH	01.01.1990	5456	0.0000	0.0214	0.15	17.81	***	***	***
United States of America (USA)											
American Express	AEX	US	01.01.1990	5456	0.0003	0.0238	0.05	10.15	***	***	***
American International Group	AIG	US	01.01.1990	5456	-0.0003	0.0358	-3.62	137.41	***	***	**
Bank of America	BOA	US	01.01.1990	5456	0.0000	0.0277	-0.30	31.57	***	***	***
Bank of New York Mellon	BNY	US	01.01.1990	5456	0.0003	0.0246	0.02	17.49	***	***	***
BB&T	BBT	US	01.01.1990	5456	0.0002	0.0215	0.17	19.13	***	***	***
Bear Stearns[1]	BST	US	01.01.1990	4804	0.0001	0.0368	-25.53	1309.11	***	***	–
Capital One Financial	COF	US	16.11.1994	4184	0.0005	0.0340	-1.07	22.75	***	***	***
Citigroup	CIT	US	01.01.1990	5456	0.0001	0.0304	-0.44	42.35	***	***	***
Fifth Third Bank	FTG	US	01.01.1990	5456	0.0002	0.0305	-0.34	69.66	***	***	***
Goldman Sachs	GSG	US	04.05.1999	3020	0.0003	0.0269	0.36	13.30	***	***	***
JP Morgan Chase	JPM	US	01.01.1990	5456	0.0002	0.0258	0.27	13.57	***	***	***
Keycorp	KEY	US	01.01.1990	5456	0.0000	0.0269	-0.45	45.18	***	***	***
Lehman Brothers[1]	LEH	US	02.05.1994	4326	-0.0011	0.0713	-12.62	661.78	***	***	*
Merrill Lynch[1]	MLL	US	01.01.1990	4957	0.0003	0.0282	-0.03	21.43	***	***	***
Metlife	MET	US	05.04.2000	2779	0.0003	0.0301	-0.32	23.09	***	***	***
Morgan Stanley	MST	US	23.02.1993	4635	0.0003	0.0317	1.28	48.11	***	***	*
PNC Financial Services	PNC	US	01.01.1990	5456	0.0002	0.0237	-1.23	64.02	***	***	***
Regions Financial	REF	US	01.01.1990	5456	-0.0001	0.0290	-0.58	51.64	***	***	***
State Street	STS	US	01.01.1990	5456	0.0004	0.0279	-5.79	206.89	***	***	*
Suntrust Banks	SUN	US	01.01.1990	5456	0.0001	0.0249	-0.38	28.65	***	***	***
US Bancorp	USB	US	01.01.1990	5456	0.0004	0.0223	0.20	18.35	***	***	***
Washington Mutual	WAM	US	01.01.1990	5456	-0.0008	0.0613	-13.67	538.95	***	***	–
Wells Fargo	WEL	US	01.01.1990	5456	0.0004	0.0240	0.77	26.78	***	***	***

[1] Trading of stock terminated before November 30, 2010 (DataStream classification ‘dead’).
[2] Significance levels: ***=1%, **=5%, *=15%.

Table 26: US-Sample overview

Company Name	ID	Size	Base Date	Obs	Mean	Std.D.	Skew.	Kurt.	JB[2]	LBQ[2]	LM[2]
Broker-Dealer (BRO)											
AG Edwards[1]	AGE	small	01.01.1990	4628	0.0000	0.0204	0.12	5.98	***	***	***
Bear Stearns[1]	BST	small	01.01.1990	4803	0.0000	0.0368	-25.53	1’309.11	***	***	–
Charles Schwab	CHS	mid	01.01.1990	5455	0.0000	0.0310	0.31	6.73	***	***	***

Table 26: US-Sample overview (continued)

Company Name	ID	Size	Base Date	Obs	Mean	Std.D.	Skew.	Kurt.	JB[2]	LBQ[2]	LM[2]
E-Trade Financial	ETR	small	16.08.1996	3726	0.0000	0.0517	-0.84	32.04	***	***	***
Goldman Sachs	GSG	large	04.05.1999	3019	0.0000	0.0269	0.36	13.30	***	***	***
Lehman Brothers	LEH	mid	02.05.1994	4325	0.0000	0.0713	-12.62	661.78	***	***	*
Merrill Lynch[1]	MLL	large	01.01.1990	4956	0.0000	0.0282	-0.03	21.43	***	***	***
Morgan Stanley	MST	large	23.02.1993	4634	0.0000	0.0317	1.28	48.11	***	***	*
T Rowe Price	TRO	mid	01.01.1990	5455	0.0000	0.0264	0.21	8.07	***	***	***
Depositories (DEP)											
Bank of America	BOA	large	01.01.1990	5455	0.0000	0.0277	-0.30	31.57	***	***	***
Bank of New York Mellon	BNY	large	01.01.1990	5455	0.0000	0.0246	0.02	17.49	***	***	***
BB&T	BBT	mid	01.01.1990	5455	0.0000	0.0215	0.17	19.13	***	***	***
Citigroup	CIT	large	01.01.1990	5455	0.0000	0.0304	-0.44	42.35	***	***	***
Comerica	COM	small	01.01.1990	5455	0.0000	0.0225	-0.14	16.78	***	***	***
Commerce Bancorp	CMB	small	01.01.1990	5455	0.0000	0.0155	0.12	13.81	***	***	***
Hudson City Bancorp	HUD	small	13.07.1999	2969	-0.0006	0.0175	-0.11	14.33	***	***	***
Huntington Bancshares	HUN	small	01.01.1990	5455	0.0000	0.0315	0.44	37.57	***	***	***
JP Morgan Chase	JPM	large	01.01.1990	5455	0.0000	0.0258	0.27	13.57	***	***	***
Keycorp	KEY	small	01.01.1990	5455	0.0000	0.0269	-0.45	45.18	***	***	***
M&T Bank	MTB	small	01.01.1990	5455	0.0000	0.0177	0.29	17.77	***	***	***
Marshall & Isley	MAI	small	01.01.1990	5455	0.0000	0.0269	-0.19	34.46	***	***	***
National City Bancorp[1]	NCB	mid	01.01.1990	3021	0.0000	0.0281	0.24	52.93	***	–	***
New York Community Bancorp	NYC	small	06.01.1994	4407	0.0000	0.0214	0.40	16.22	***	***	***
Northern Trust	NOT	mid	01.01.1990	5455	0.0000	0.0203	-0.15	10.11	***	***	***
Peoples United Financial	PUF	small	01.01.1990	5455	0.0000	0.0245	0.34	13.25	***	***	***
PNC Financial	PNC	mid	01.01.1990	5455	0.0000	0.0237	-1.23	64.02	***	***	***
Regions Financial	REG	mid	01.01.1990	5455	0.0000	0.0290	-0.58	51.64	***	***	***
Sovereign Bancorp[1]	SOV	small	01.01.1990	4977	0.0000	0.0342	-9.94	412.08	***	***	–
St. Paul Bancorp[1]	SPB	small	01.01.1990	2543	0.0000	0.0223	0.45	10.59	***	***	***
State Street	STS	mid	01.01.1990	5455	0.0000	0.0279	-5.79	206.89	***	***	*
Suntrust	SUN	mid	01.01.1990	5455	0.0000	0.0249	-0.38	28.65	***	***	***
Synovus Financial	SYN	small	01.01.1990	5455	0.0000	0.0274	-0.09	19.15	***	***	***
Unionbancal[1]	UBC	small	01.01.1990	4914	0.0000	0.0204	-1.02	28.64	***	***	***
US Bancorp	USB	large	01.01.1990	5455	0.0000	0.0223	0.20	18.35	***	***	***
Wachovia[1]	WAC	large	01.01.1990	3043	0.0000	0.0155	-0.34	16.22	***	***	***
Washington Mutual	WAM	mid	01.01.1990	5455	0.0000	0.0613	-13.67	538.95	***	***	–
Wells Fargo & Co.	WEL	large	01.01.1990	5455	0.0000	0.0240	0.77	26.78	***	***	***
Western Union	WUN	mid	20.09.2006	1093	0.0000	0.0260	-0.07	10.83	***	***	***
Zions Bancorp	ZIO	small	01.01.1990	5455	0.0000	0.0273	-0.13	21.50	***	***	***
Insurance (INS)											
AETNA	AET	mid	01.01.1990	5455	0.0000	0.0243	-4.62	132.89	***	-	***
AFLAC	AFL	mid	01.01.1990	5455	0.0000	0.0242	-1.03	38.86	***	***	***
ALLSTATE	ALL	mid	03.06.1993	4562	0.0000	0.0216	-0.63	20.44	***	***	***
AMBAC Financial Group	ABC	small	11.07.1991	5057	0.0000	0.0520	-1.94	74.45	***	***	***
American International Group	AIG	large	01.01.1990	5455	0.0000	0.0358	-3.62	137.41	***	***	**
AON	AON	mid	01.01.1990	5455	0.0000	0.0194	-2.28	55.43	***	***	***
ASSURANT	ASS	small	05.02.2004	1777	0.0000	0.0261	-0.80	23.21	***	***	***
Berkshire Hathaway	BKH	large	01.01.1990	5455	0.0000	0.0154	0.59	13.05	***	***	***
Cigna	CIG	mid	01.01.1990	5455	0.0000	0.0227	-2.02	50.94	***	***	***
Cincinnati Financial	CIN	small	01.01.1990	5455	0.0000	0.0184	-0.19	20.23	***	***	***
CNA Financial	CNA	small	01.01.1990	5455	0.0000	0.0215	-1.08	40.86	***	***	***
Countrywide Financial[1]	CWF	small	01.01.1990	4824	0.0000	0.0278	0.69	23.70	***	***	*
Coventry Health Care	CVH	small	17.04.1991	5118	0.0000	0.0379	-2.74	49.75	***	*	***
Fidelity National[1]	FID	small	01.01.1990	4397	0.0000	0.0227	-0.01	12.64	***	***	***
Genworth Financial	GEN	mid	25.05.2004	1699	0.0000	0.0600	0.01	51.16	***	***	**

Table 26: US-Sample overview (continued)

Company Name	ID	Size	Base Date	Obs	Mean	Std.D.	Skew.	Kurt.	JB[2]	LBQ[2]	LM[2]
Hartford Financial Services	HAR	mid	15.12.1995	3901	0.0000	0.0379	-0.43	87.33	***	***	***
Health Net	HEN	small	31.01.1994	4390	0.0000	0.0277	0.31	17.96	***	***	***
Humana	HUM	mid	01.01.1990	5455	0.0000	0.0281	-1.06	15.37	***	***	***
Lincoln National	LIN	mid	01.01.1990	5455	0.0000	0.0303	-1.35	59.96	***	***	***
Marsh & McLennan	MML	mid	01.01.1990	5455	0.0000	0.0179	-0.66	21.88	***	***	*
MBIA	MBI	small	01.01.1990	5455	0.0000	0.0344	-0.09	29.27	***	***	***
Metlife	MET	mid	05.04.2000	2778	0.0000	0.0301	-0.32	23.09	***	***	***
Principal Financial	PRF	mid	23.10.2001	2374	0.0000	0.0354	-0.37	25.40	***	***	***
Progressive	PRO	mid	01.01.1990	5455	0.0000	0.0200	0.04	18.38	***	***	***
Prudential	PRU	mid	13.12.2001	2337	0.0000	0.0341	-0.04	24.09	***	***	***
Safeco[1]	SAF	small	01.01.1990	4884	-0.0001	0.0166	-0.19	11.62	***	***	***
The Chubb	CHU	mid	01.01.1990	5455	0.0000	0.0175	0.41	10.75	***	***	***
Torchmark	TOR	small	01.01.1990	5455	0.0000	0.0191	-0.17	15.93	***	***	***
United Health	UNH	large	01.01.1990	5455	0.0000	0.0258	-0.92	23.04	***	***	***
Unum Group	UNU	small	01.01.1990	5455	0.0000	0.0272	-3.16	61.02	***	***	***
WR Berkeley	WRB	small	01.01.1990	5455	0.0000	0.0180	0.52	10.59	***	***	***
Others (OTH)											
American Capital	AMC	small	29.08.1997	3456	0.0000	0.0381	-1.08	38.54	***	***	***
American Express	AEX	large	01.01.1990	5455	0.0000	0.0238	0.05	10.15	***	***	***
Blackrock	BLA	mid	01.10.1999	2911	0.0000	0.0250	0.16	9.41	***	***	***
Capital One Financial	COF	mid	16.11.1994	4183	0.0000	0.0340	-1.07	22.75	***	***	***
CB Richard Ellis	CRE	small	10.06.2004	1687	0.0000	0.0476	0.80	21.06	***	***	***
CME Group	CME	mid	06.12.2002	2081	0.0000	0.0280	-0.29	10.98	***	***	***
Compass Bancshares[1]	COB	small	01.01.1990	4612	0.0000	0.0168	0.56	10.63	***	***	***
Eaton Vance	EAT	small	01.01.1990	5455	0.0000	0.0247	0.29	11.14	***	***	***
Fannie Mae	FME	mid	01.01.1990	5455	0.0000	0.0491	-17.42	847.53	***	**	*
Fifth Third Bancorp	FTB	mid	01.01.1990	5455	0.0000	0.0305	-0.34	69.66	***	***	***
Franklin Resources	FRE	mid	01.01.1990	5455	0.0000	0.0233	0.09	8.02	***	***	***
Freddie Mac	FMA	mid	01.01.1990	5455	0.0000	0.0468	-8.35	401.52	***	***	***
H&R Block	HRB	small	01.01.1990	5455	0.0000	0.0205	-0.40	11.88	***	***	***
Intercontinental Exchange	IEX	mid	16.11.2005	1313	0.0000	0.0401	0.19	10.52	***	***	***
Janus Capital	JAN	small	26.06.2000	2720	0.0000	0.0356	-0.09	9.99	***	***	***
Legg Mason	LMA	small	01.01.1990	5455	0.0000	0.0260	-0.32	16.06	***	***	***
NYSE Euronext	NYS	mid	12.08.2004	1642	0.0000	0.0357	1.55	25.68	***	***	***
sei Investments	SEI	small	01.01.1990	5455	0.0000	0.0255	0.09	8.21	***	***	***
slm Corp	SLM	small	01.01.1990	5455	0.0000	0.0290	-0.97	29.98	***	***	***
TD Ameritrade	TDA	mid	04.03.1997	3584	0.0000	0.0441	0.86	14.83	***	***	***

[1] Trading of stock terminated before November 30, 2010 (DataStream classification 'dead').
[2] Significance levels: ***=1%, **=5%, *=15%.

B.2 Statistical criteria for univariate model selection

Table 27: Model selection criteria for individual return series of international sample

	GARCH			TARCH			Preferred model specification (Criteria)		
	(1,1)	(2,1)	(2,2)	(1,1)	(2,1)	(2,2)	LLF	AIC	BIC
Eurozone Financial Institutions (EUR)									
ABN AMRO[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)

Table 27: Model selection criteria for individual return series of international sample (continued)

	GARCH			TARCH			Preferred model specification (Criteria)		
	(1,1)	(2,1)	(2,2)	(1,1)	(2,1)	(2,2)	LLF	AIC	BIC
Ageas (ex Fortis)	***	***	-	***	***	***	TARCH(2,2)	TARCH(2,2)	GARCH(2,1)
Alpha Bank	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	GARCH(1,1)
Banca Monte dei Paschi	***	**	-	***	**	-	TARCH(2,2)	GARCH(2,1)	GARCH(1,1)
Banco Popular Espanol	***	***	-	***	***	***	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
BBVA	***	***	*	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
BNP Paribas	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Commerzbank	***	***	-	***	***	-	TARCH(2,2)	GARCH(2,1)	GARCH(2,1)
Credit Agricole	***	***	-	***	***	***	TARCH(2,1)	TARCH(2,1)	GARCH(2,1)
Deutsche Bank	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	GARCH(2,1)
Dexia	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)
Erste Group	***	-	***	***	-	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
ING Group	***	***	-	***	***	-	TARCH(2,2)	GARCH(2,1)	GARCH(2,1)
Intesa Sanpaolo	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,1)
KBC Group	***	*	***	***	*	***	TARCH(2,2)	GARCH(1,1)	GARCH(1,1)
Natixis	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)
Santander	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,1)
Societe Generale	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
UBI Banca	***	-	-	***	-	-	TARCH(2,2)	GARCH(2,1)	GARCH(1,1)
Unicredit	***	***	-	***	**	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Europe, but not Eurozone Financial Institutions (NEU)									
Barclays	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Credit Suisse	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,1)
Danske Bank	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)
DNB	***	***	-	***	***	-	TARCH(2,2)	GARCH(2,1)	GARCH(2,1)
Lloyds Banking Group	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	GARCH(1,1)
Nordea Bank	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	GARCH(2,1)
Royal Bank of Scotland	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Svenska Handelsbanken	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Swedbank	***	***	-	***	***	-	TARCH(2,2)	GARCH(1,1)	GARCH(1,1)
UBS	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
US Financial Institutions (USA)									
American International Group	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
American Express	***	***	***	***	***	***	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Bank of America	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)
Bank of New York Mellon	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,1)
BB&T	***	***	-	***	***	-	TARCH(2,2)	GARCH(2,1)	GARCH(2,1)
Bear Stearns[1]	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Capital One Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
Citigroup	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Fifth Third Bank	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Goldman Sachs	***	*	-	***	*	-	TARCH(2,2)	GARCH(2,1)	GARCH(1,1)
JP Morgan Chase	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Keycorp	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Lehman Brothers[1]	***	***	**	***	*	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
Merrill Lynch[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Metlife	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	GARCH(1,1)
Morgan Stanley	***	***	-	***	**	***	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
PNC Financial Services	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Regions Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
State Street	***	-	-	***	-	***	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
Suntrust Banks	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
US Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)

Table 27: Model selection criteria for individual return series of international sample (continued)

	GARCH			**TARCH**			**Preferred model specification (Criteria)**		
	(1,1)	(2,1)	(2,2)	(1,1)	(2,1)	(2,2)	LLF	AIC	BIC
Washington Mutual	***	**	-	***	-	***	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Wells Fargo	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)

[1] Trading of stock terminated before November 30, 2010 (DataStream classification 'dead').

Table 28: Model selection criteria for individual return series of the US-Sample

	GARCH			**TARCH**			**Preferred model specification (Criteria)**		
	(1,1)	(2,1)	(2,2)	(1,1)	(2,1)	(2,2)	LLF	AIC	BIC
Broker-Dealer									
AG Edwards[1]	***	***	-	***	*	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Bear Stearns[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Charles Schwab	***	**	-	***	*	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
E-Trade Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Goldman Sachs	***	-	***	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Lehman Brothers	***	***	***	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
Merrill Lynch[1]	***	*	***	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Morgan Stanley	***	***	***	***	-	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
T Rowe Price	***	***	-	***	*	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Depositories									
Bank of America	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Bank of New York Mellon	***	***	-	***	-	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
BB&T	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Citigroup	***	***	-	***	**	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Comerica	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,1)
Commerce Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Hudson City Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Huntington Bancshares	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
JP Morgan Chase	***	***	-	***	-	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Keycorp	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(1,1)
M&T Bank	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Marshall & Isley	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
National City Bancorp[1]	***	-	-	***	***	-	TARCH(2,2)	GARCH(2,2)	GARCH(2,2)
New York Community Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Northern Trust	***	***	***	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Peoples United Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)
PNC Financial	***	***	***	***	***	***	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Regions Financial	***	***	-	***	**	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
Sovereign Bancorp[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
St. Paul Bancorp[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
State Street	***	***	-	***	**	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Suntrust	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Synovus Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Unionbancal[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
US Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Wachovia[1]	***	**	-	***	**	-	TARCH(2,2)	GARCH(2,1)	GARCH(1,1)
Washington Mutual	***	**	-	***	-	***	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Wells Fargo & Co.	***	***	-	***	*	**	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Western Union	***	-	-	***	-	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
Zions Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Insurance									

Table 28: Model selection criteria for individual return series of the US-Sample (continued)

	GARCH			TARCH			Preferred model specification (Criteria)		
	(1,1)	(2,1)	(2,2)	(1,1)	(2,1)	(2,2)	LLF	AIC	BIC
AETNA	***	-	***	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
AFLAC	***	***	-	***	*	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
ALLSTATE	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
AMBAC Financial Group	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
American International Group	***	***	***	***	-	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
AON	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
ASSURANT	***	-	-	-	-	-	TARCH(2,1)	TARCH(2,1)	TARCH(1,1)
Berkshire Hathaway	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Cigna	***	***	**	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Cincinnati Financial	***	***	-	***	***	***	TARCH(2,2)	TARCH(2,2)	GARCH(1,1)
CNA Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Countrywide Financial[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Coventry Health Care	***	***	-	***	***	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Fidelity National[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
Genworth Financial	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Hartford Financial Services	***	***	***	***	**	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Health Net	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Humana	***	***	***	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,1)
Lincoln National	***	***	***	***	**	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
Marsh & McLennan	***	***	-	***	***	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
MBIA	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Metlife	***	-	-	***	-	**	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
Principal Financial	***	***	-	***	-	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Progressive	***	*	***	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Prudential	***	-	-	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Safeco[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
The Chubb	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Torchmark	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
United Health	***	-	***	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
Unum Group	***	-	-	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
WR Berkeley	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Others									
American Capital	***	***	***	***	***	***	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
American Express	***	***	-	***	*	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Blackrock	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Capital One Financial	***	-	***	***	-	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
CB Richard Ellis	***	-	***	***	-	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
CME Group	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	GARCH(2,1)
Compass Bancshares[1]	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
Eaton Vance	***	***	***	***	***	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Fannie Mae	***	-	-	***	-	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
Fifth Third Bancorp	***	***	-	***	***	-	TARCH(2,2)	TARCH(1,1)	TARCH(1,1)
Franklin Resources	***	*	***	***	-	***	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Freddie Mac	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	TARCH(2,2)
H&R Block	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
Intercontinental Exchange	***	-	-	***	-	-	TARCH(2,2)	TARCH(2,1)	GARCH(1,1)
Janus Capital	***	-	-	***	-	-	TARCH(2,2)	TARCH(2,2)	TARCH(1,1)
Legg Mason	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(1,1)
NYSE Euronext	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	GARCH(2,1)
sei Investments	***	***	-	***	***	-	TARCH(2,1)	TARCH(2,1)	TARCH(2,1)
slm Corp	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,1)	TARCH(2,1)
TD Ameritrade	***	***	-	***	***	-	TARCH(2,2)	TARCH(2,2)	GARCH(2,1)

[1] Trading of stock terminated before November 30, 2010 (DataStream classification 'dead').

B.3 Mis-specification tests of univariate model estimations

Following Zivot (2008) and Bauwens et al. (2006) we concentrate on residual diagnostics and repeat the basic tests for non-normality and ARCH effects remaining for the individual the time series (appendix B.1). Though the data are still highly non-normal, excess kurtosis as well as negative skewness have been reduced significantly. Due to the standardization of the residuals mean and standard deviation are close to a standard gaussian distribution. Autocorrelation and ARCH effects are still evident, but only in a minor part of the sample.

Table 29: Summary statistics of mis-specification tests of univariate model estimations

Panel A: Statistics for International Sample

	Daily Returns				Weekly Returns			
	Full Sample	**EUR**	**NEU**	**USA**	**Full Sample**	**EUR**	**NEU**	**USA**
Mean	2.06E-03	7.23E-04	2.23E-03	3.37E-03	4.85E-04	-4.45E-04	-1.76E-04	4.85E-04
Median	2.84E-03	2.83E-03	5.09E-03	2.82E-03	-1.27E-02	-1.36E-02	-5.94E-03	-1.47E-02
Std. Dev.	1.0002	1.0003	0.9998	1.0015	1.0009	1.0010	0.9998	1.0005
Skewness	0.1172	0.1654	0.0689	-0.0102	-0.0575	-0.0097	-0.0034	-0.2049
Kurtosis	7.92	7.09	7.52	8.27	5.29	4.70	5.53	5.47
JB[1]	53	20	10	23	52	19	10	23
LBQ[1]	28	11	4	13	2	0	0	2
Engle's LM[1]	19	9	3	7	2	0	0	2

Panel B: Statistics for US Sample

		by Type				by Size		
	Full Sample	**BRO**	**DEP**	**INS**	**OTH**	**LRG**	**MID**	**SML**
Mean	1.49E-03	1.58E-03	2.51E-03	6.90E-04	2.21E-03	2.13E-03	9.35E-04	9.18E-04
Median	-1.41E-02	-1.34E-02	-1.62E-02	-1.11E-02	-1.90E-02	-1.40E-02	-1.40E-02	-1.42E-02
Std. Dev.	1.0000	1.0000	0.9997	1.0000	1.0003	1.0000	1.0000	0.9999
Skewness	-0.0049	0.0733	0.0648	-0.1221	0.0157	0.0560	-0.1106	-0.0021
Kurtosis	7.45	6.50	7.49	8.12	7.15	7.06	7.09	7.50
JB[1]	90	9	30	31	20	19	32	39
LBQ[1]	25	4	7	9	5	3	11	11
Engle's LM[1]	25	4	7	9	5	3	11	11

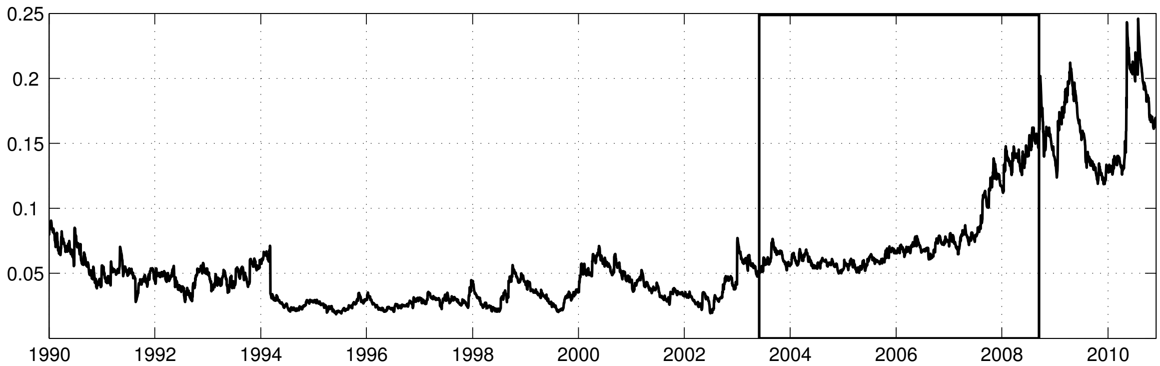
[1] Numbers of models for which null hypothesis was rejected at 5% significance level.

B.4 Long-run correlations for sample cross-sections

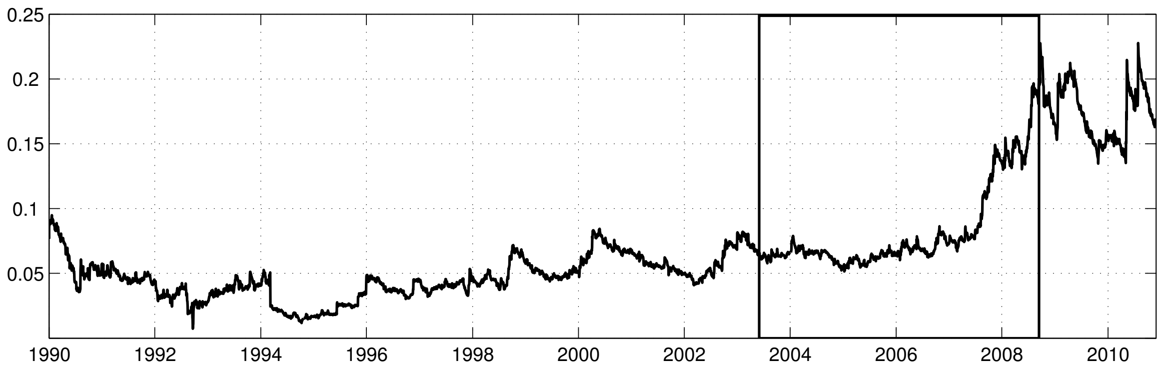
Sudden spikes/drops of median correlations, especially in the US sample, occur due to changes in the underlying dataset. This is since the sample is unbalanced and for some financial institutions, data were not for the full sample period.

Figure 27: Long-run correlations for international sample

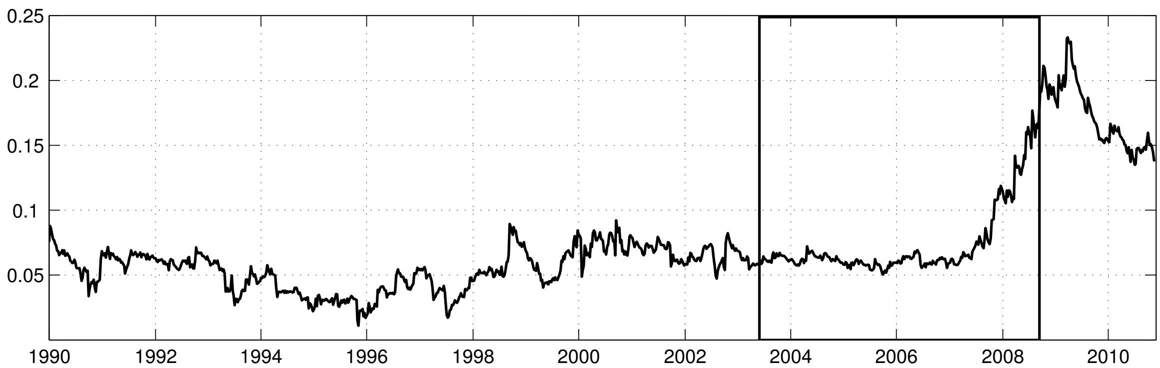
Panel A: EUR – EUR



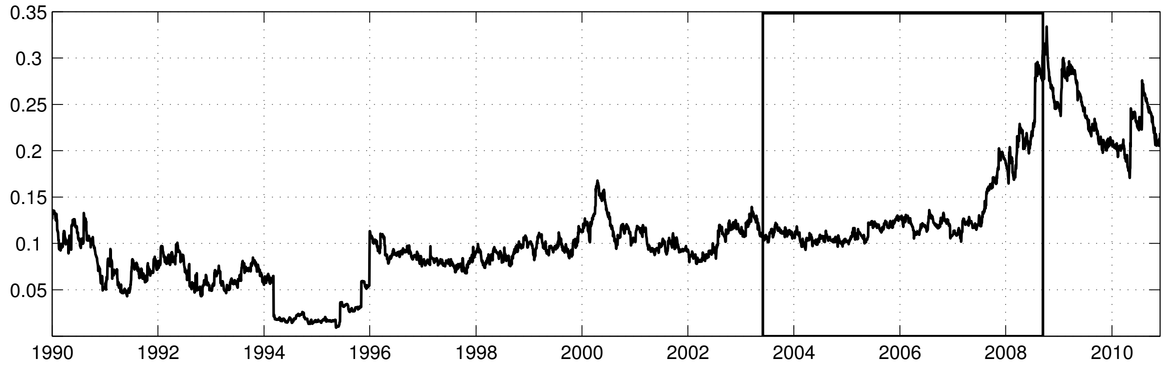
Panel B: EUR – NEU



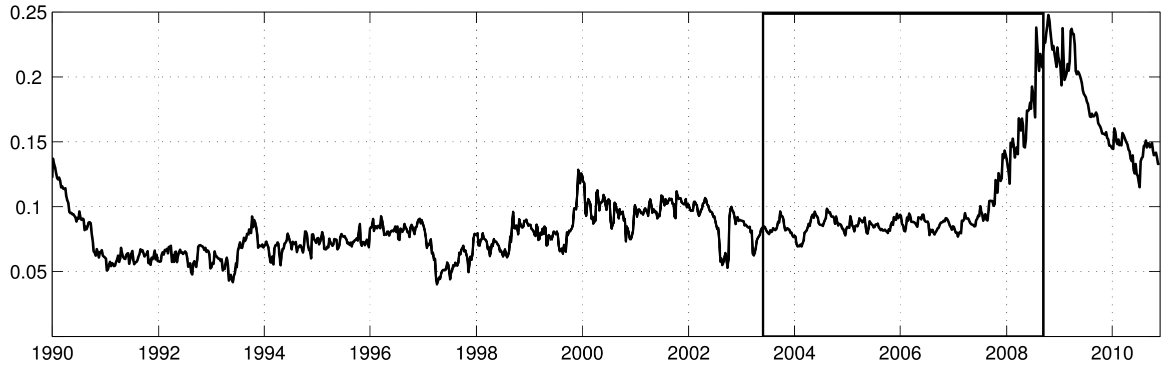
Panel C: EUR – USA



Panel D: NEU – NEU



Panel E: NEU – USA



Panel B: USA – USA

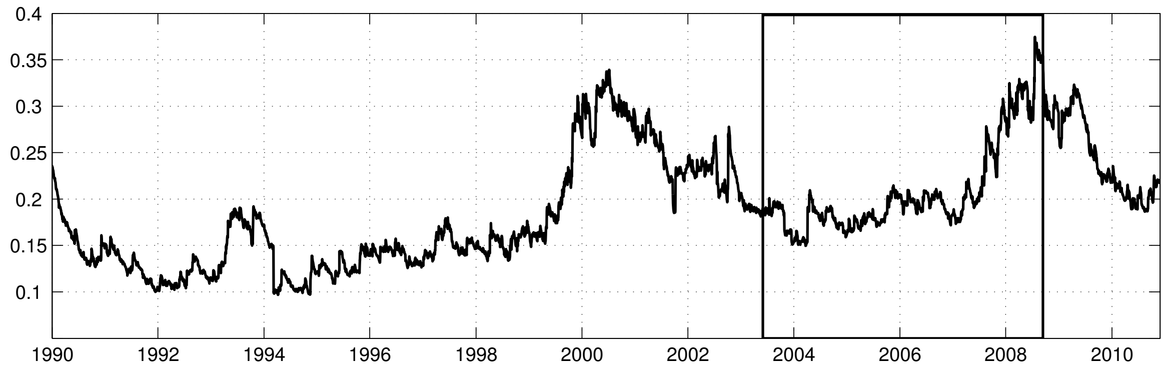
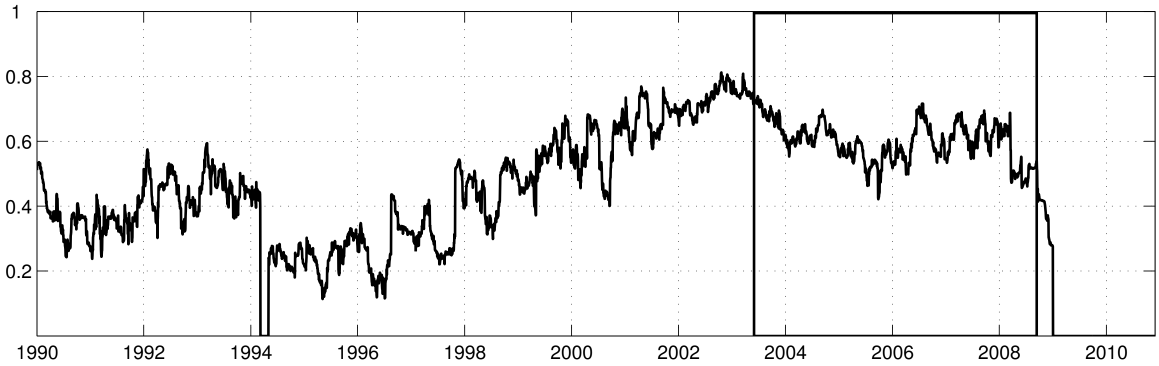
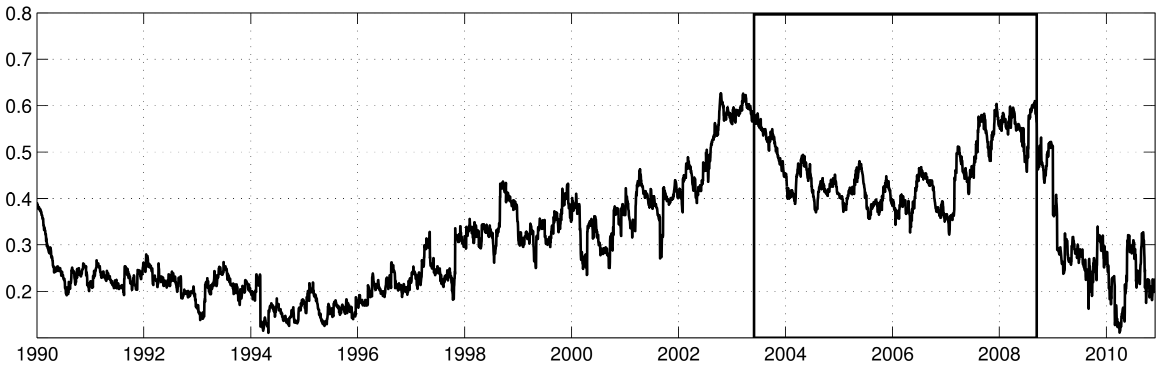


Figure 28: Long-run correlations for US sample (by type)

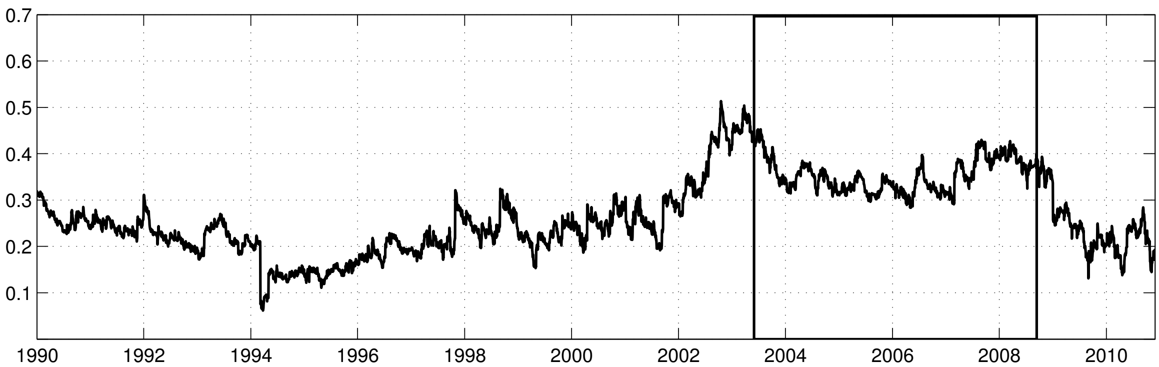
Panel A: BRO – BRO



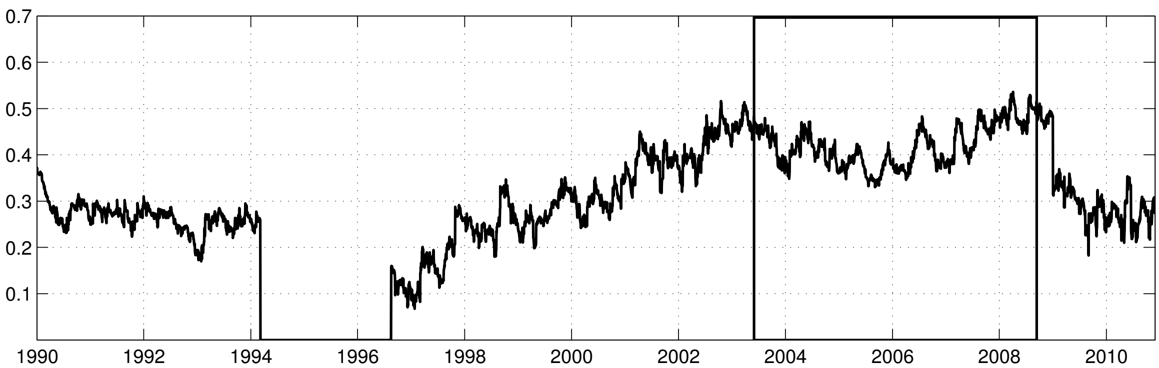
Panel B: BRO – DEP



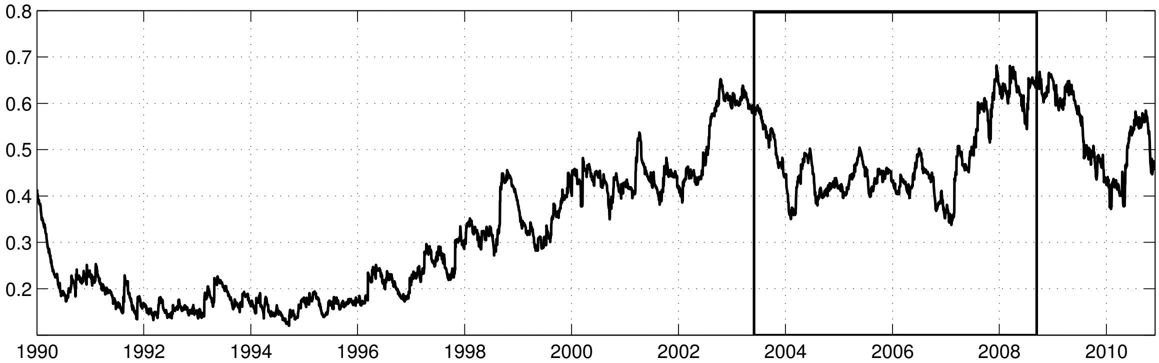
Panel C: BRO – INS



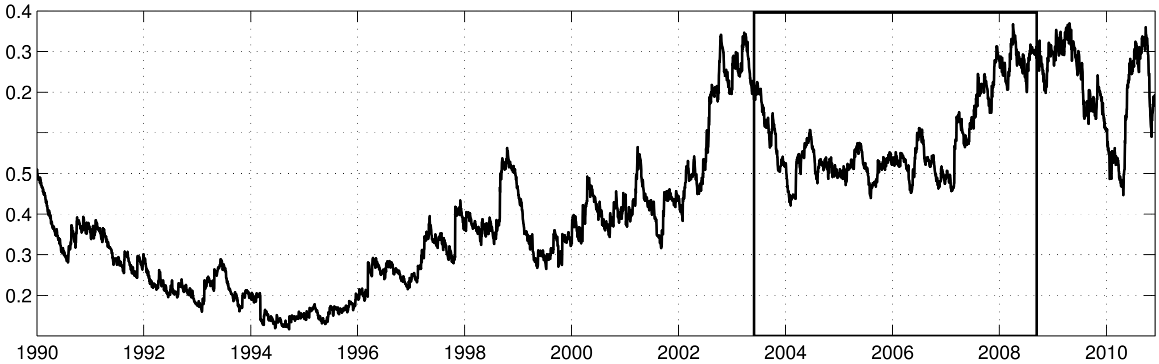
Panel D: BRO – OTH



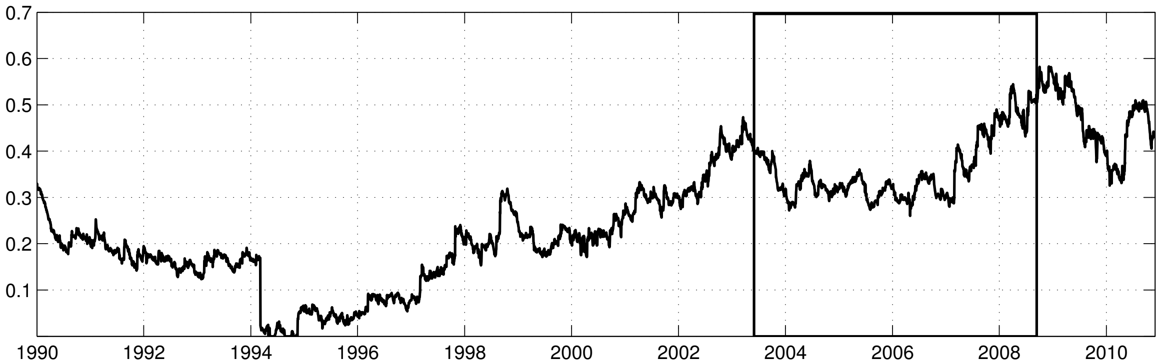
Panel E: DEP – DEP



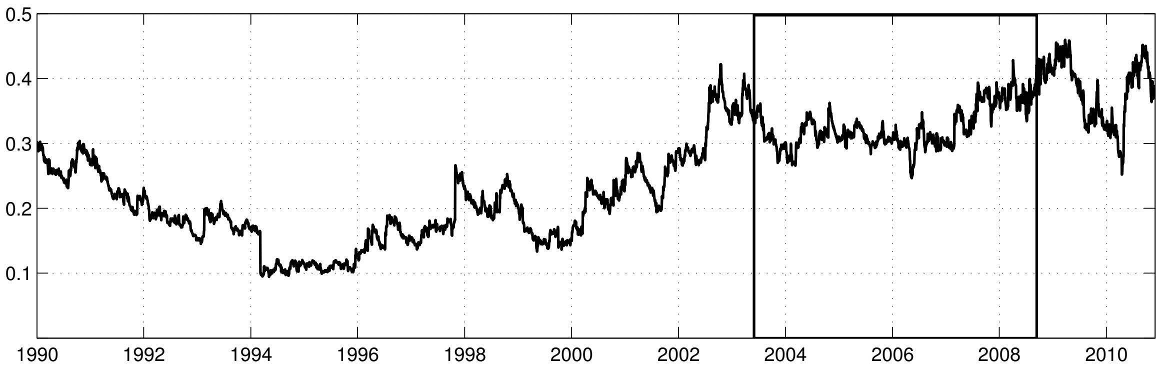
Panel F: DEP – INS



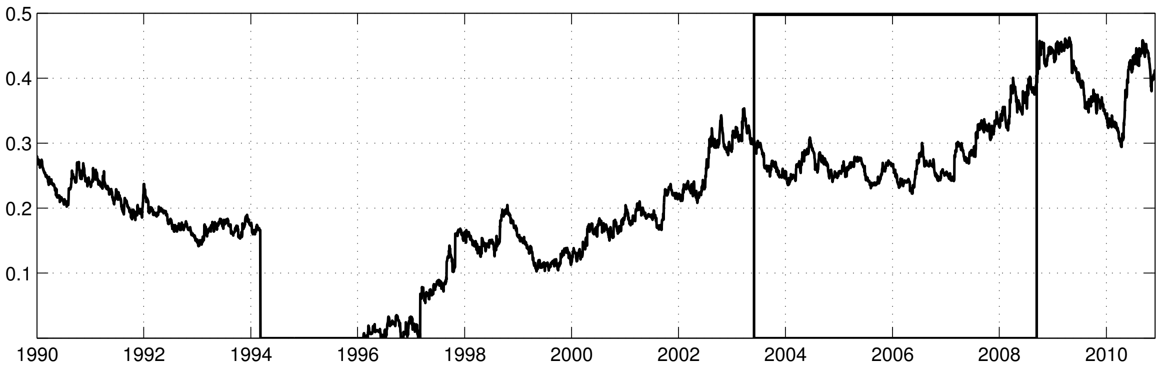
Panel G: DEP – OTH



Panel H: INS – INS



Panel I: INS – OTH



Panel J: OTH – OTH

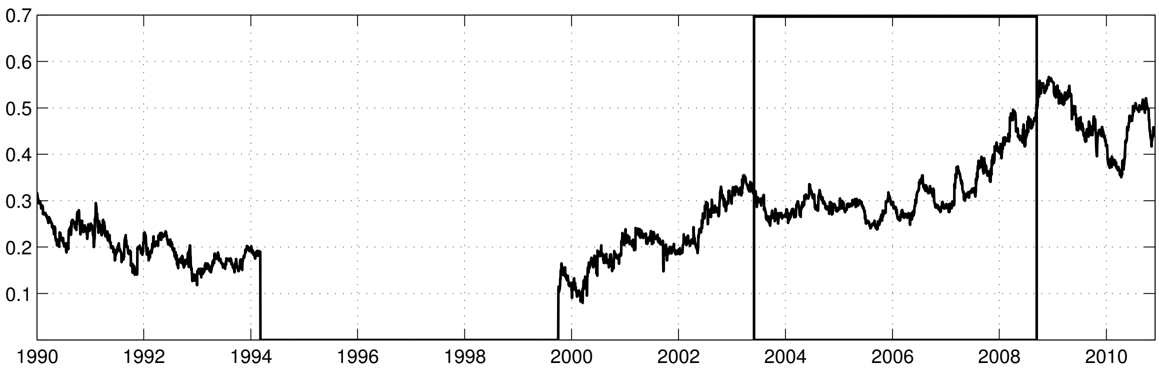
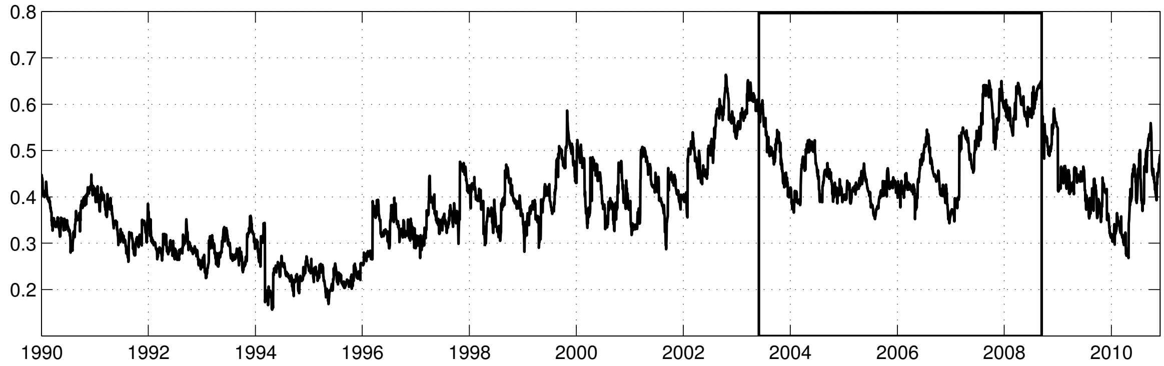
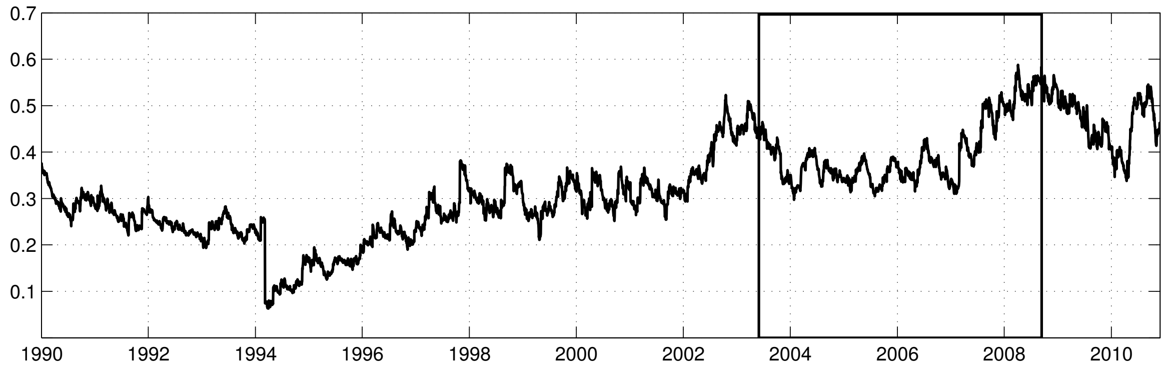


Figure 29: Long-run correlations for US sample (by size)

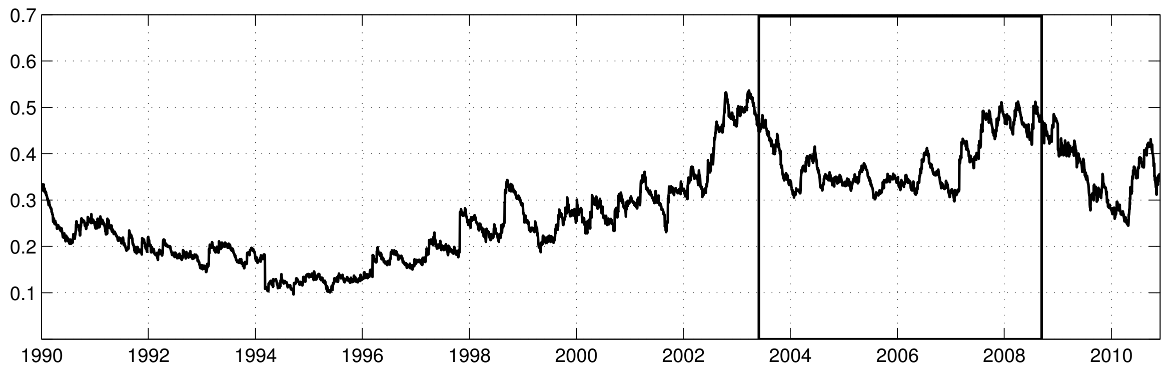
Panel A: LRG – LRG



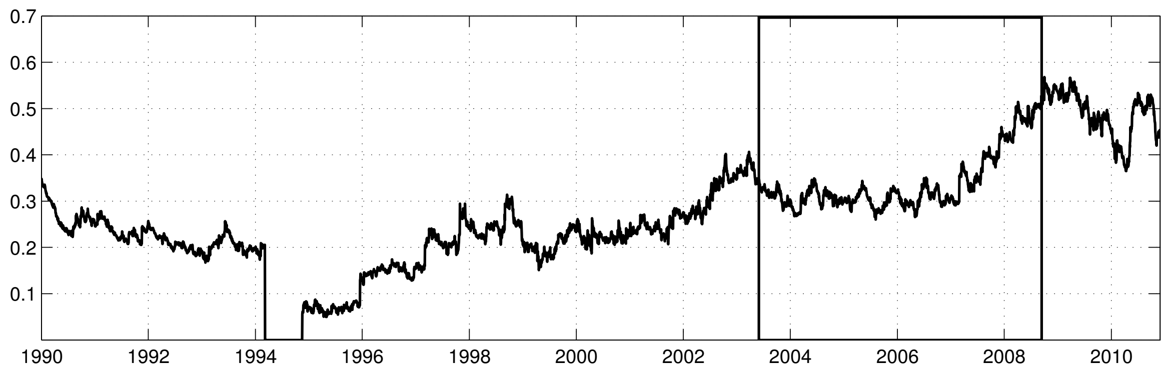
Panel B: LRG – MID



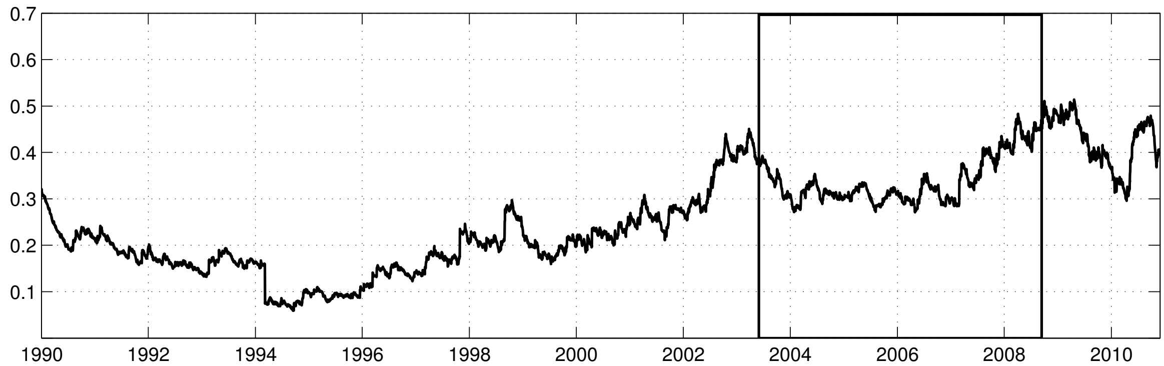
Panel C: LRG – SML



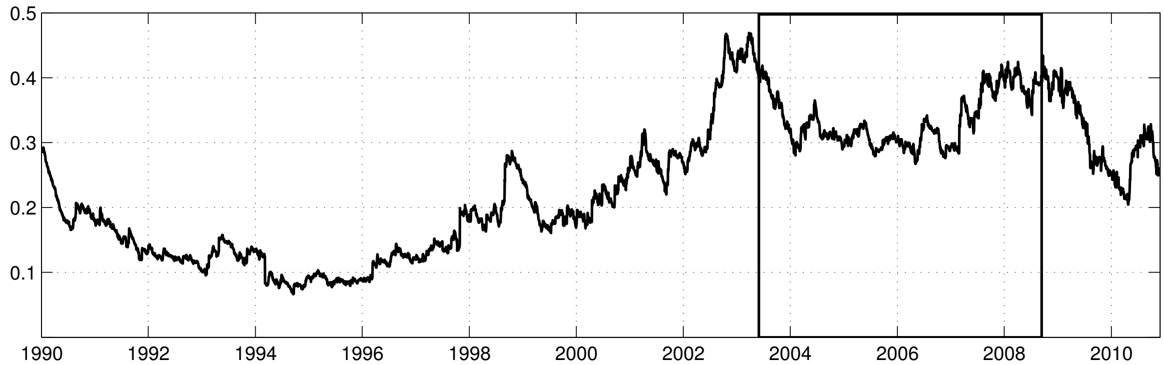
Panel D: MID – MID



Panel E: MID – SML



Panel F: SML – SML



B.5 Estimation results of models with structural breaks in mean

Table 30: Sample statistics for bivariate model estimations with structural break in mean

Panel A: Statistics for International sample

		Significance[1]			Estimated Parameters[2,3]							
		***/**/*	dropped	LLF	α_{med}	β_{med}	$\bar{Q}_{\mathrm{LT}}$	$\bar{Q}_{48}$	$\bar{Q}_{24}$	$\bar{Q}_{\mathrm{SC}}$	Persist.	Smooth.
EUR	EUR	39/36/43	72/0	5'476	0.0124	0.9134	0.0934	0.0239	0.0557	0.1683	0.9258	0.0255
EUR	NEU	30/57/52	61/0	6'016	0.0111	0.9120	0.0851	0.0325	0.0605	0.2193	0.9231	0.0208
EUR	USA	13/28/57	268/94	558	0.0150	0.8550	0.0546	0.0510	0.0436	0.1849	0.8699	0.0648
NEU	NEU	13/12/10	10/0	6'197	0.0099	0.9375	0.1141	0.0882	0.0999	0.3137	0.9474	0.0128
NEU	USA	3/16/26	185/0	472	0.0172	0.8113	0.0639	0.0514	0.0636	0.2175	0.8285	0.0996
USA	USA	88/58/59	48/0	6'339	0.0123	0.9427	0.1947	0.1431	0.1695	0.3903	0.9550	0.0138

Panel B: Statistics for US sample

		Significance[1]			Estimated Parameters[2,3]							
		***/**/*	dropped	LLF	α_{med}	β_{med}	$\bar{Q}_{\mathrm{LT}}$	$\bar{Q}_{48}$	$\bar{Q}_{24}$	$\bar{Q}_{\mathrm{SC}}$	Persist.	Smooth.
cross-sections by type												
BRO	BRO	20/8/4	4/0	4'295	0.0259	0.9475	0.5100	0.6292	0.5949	0.6262	0.9735	0.0278
BRO	DEP	125/73/38	31/3	4'865	0.0211	0.9534	0.3372	0.4178	0.3772	0.5691	0.9745	0.0227
BRO	INS	121/66/42	50/0	4'434	0.0177	0.9335	0.3147	0.3404	0.3159	0.4480	0.9512	0.0204
BRO	OTH	74/44/23	38/1	4'011	0.0194	0.9342	0.3889	0.4058	0.3946	0.5476	0.9536	0.0218
DEP	DEP	202/95/60	74/4	6'167	0.0184	0.9528	0.3389	0.3908	0.3984	0.5917	0.9713	0.0211
DEP	INS	305/252/173	183/17	5'610	0.0153	0.9451	0.2913	0.2935	0.2880	0.4340	0.9604	0.0173
DEP	OTH	169/157/111	145/18	4'862	0.0168	0.9509	0.3345	0.3188	0.3053	0.5230	0.9677	0.0182
INS	INS	144/130/96	95/0	5'222	0.0166	0.9433	0.3314	0.3163	0.2874	0.3958	0.9599	0.0185
INS	OTH	181/128/143	167/1	4'456	0.0157	0.9314	0.3098	0.2560	0.2510	0.4231	0.9470	0.0190
OTH	OTH	39/47/47	56/1	3'836	0.0149	0.9418	0.3678	0.2866	0.2878	0.5083	0.9567	0.0165
cross-sections by size												
LRG	LRG	61/16/10	4/0	5'934	0.0206	0.9661	0.4149	0.3644	0.3574	0.5096	0.9867	0.0209
LRG	MID	206/143/72	89/8	5'150	0.0202	0.9380	0.3842	0.3397	0.3339	0.5154	0.9583	0.0223
LRG	SML	256/135/78	73/4	5'567	0.0156	0.9603	0.3043	0.3403	0.3233	0.4763	0.9758	0.0172
MID	MID	158/160/142	197/9	4'433	0.0205	0.9090	0.3851	0.3126	0.3193	0.5138	0.9296	0.0250
MID	SML	443/340/291	349/20	4'879	0.0169	0.9395	0.3161	0.3214	0.3090	0.4754	0.9564	0.0192
SML	SML	256/206/144	131/4	5'231	0.0127	0.9656	0.2591	0.3210	0.2937	0.4364	0.9783	0.0138

[1] Models significant at ***=1% / **=5% / *=15% levels. Models dropped because insignificant / short time frame.
[2] Medians of significant parameter estimations (α, β) according to equation (4.5) in section 4.2.4.
[3] Values of $\bar{Q}$ refer to median CCC-estimator for corresponding time-windows (LT=long-term; SC=subprime crisis).

Table 31: Results of test for DCC-GARCH specification for individual time-windows

Panel A: Statistics for international sample

	Models	48-months[1]					24-months[1]					Subprime crisis[1]				
		***	**	*	H_0[2]	time[2]	***	**	*	H_0[2]	time[2]	***	**	*	H_0[2]	time[2]
EUR EUR	190	12	11	17	150	0	24	23	18	125	0	108	15	18	30	19
EUR NEU	200	4	15	22	159	0	26	21	34	119	0	146	14	7	23	10
EUR USA	460	1	7	23	429	0	1	13	16	430	0	125	68	58	209	0
NEU NEU	45	8	3	7	27	0	10	7	3	25	0	44	1	0	0	0
NEU USA	230	0	1	13	216	0	0	8	10	212	0	82	16	16	116	0
USA USA	253	85	35	41	92	0	113	41	25	74	0	226	4	1	0	22

Panel B: Statistics for US sample

	Models	48-months[1]					24-months[1]					Subprime crisis[1]				
		***	**	*	H_0[2]	time[2]	***	**	*	H_0[2]	time[2]	***	**	*	H_0[2]	time[2]
Sections by Type																
BRO BRO	36	36	0	0	0	0	36	0	0	0	0	28	0	0	0	8
BRO DEP	270	234	0	0	0	36	234	0	0	0	36	215	0	1	0	54
BRO INS	279	250	6	4	1	18	256	10	2	2	9	217	8	7	8	39
BRO OTH	180	153	0	0	0	27	171	0	0	0	9	152	0	0	0	28
DEP DEP	435	325	0	0	0	110	325	0	0	0	110	351	0	0	0	84
DEP INS	930	734	15	4	1	176	679	56	18	27	150	718	23	27	42	120
DEP OTH	600	437	4	1	0	158	473	17	2	2	106	513	0	0	0	87
INS INS	465	382	18	3	3	59	357	38	21	19	30	381	23	15	16	30
INS OTH	620	445	26	10	12	127	478	48	27	17	50	504	23	18	25	50
OTH OTH	190	131	2	2	1	54	161	8	1	1	19	171	0	0	0	19
Sections by Size																
LRG LRG	91	73	4	1	0	13	67	5	2	4	13	75	2	1	0	13
LRG MID	518	394	9	6	7	102	389	25	13	15	76	437	15	7	9	50
LRG SML	546	442	20	4	2	78	427	24	12	18	65	412	18	16	9	91
MID MID	666	479	13	1	3	170	525	21	7	8	105	606	10	5	9	36
MID SML	1'443	1'122	18	8	4	291	1'156	64	23	15	185	1'175	20	25	40	183
SML SML	741	617	7	4	2	111	606	38	14	8	75	545	12	14	24	146

[1] Number of models for which H_0 was rejected at ***=1% / **=5% / *=15% signicant levels.
[2] Number of models for which H_0 could not be rejected or time overlap of series was too short.
[3] (D) includes models based on daily, (W) models based on weekly returns (cross-sections EUR/NEU–USA).

Table 32: Sample statistics for tests of structural break in mean (subprime crisis time-window)

Panel A: Statistics for International sample

		LLF	Significance[1]	Models: Increase	Models: Decrease	Increase[2]: Δ_{Q10}	Increase[2]: Δ_{med}	Increase[2]: Δ_{Q90}	Decrease[2]: Δ_{Q10}	Decrease[2]: Δ_{med}	Decrease[2]: Δ_{Q90}	$Q^\star$
EUR	EUR	7'674	49/118	43	6	0.07	**0.20**	0.33	-0.31	**-0.16**	0.00	0.08
EUR	NEU	6'543	71/139	68	3	0.10	**0.24**	0.36	-0.34	**-0.14**	-0.03	0.08
EUR	USA	519	13/98	11	2	0.19	**0.40**	0.48	-0.26	**-0.19**	-0.12	0.04
NEU	NEU	5'685	19/35	18	1	0.10	**0.25**	0.45	-0.01	**-0.01**	-0.01	0.09
NEU	USA	628	9/45	8	1	0.20	**0.40**	0.55	-0.01	**-0.01**	-0.01	0.09
USA	USA	6'837	65/205	62	3	0.17	**0.28**	0.38	-0.13	**-0.02**	-0.01	0.17

Panel B: Statistics for US Sample

		LLF	Significance[1]	No. of models: Increase	No. of models: Decrease	Increase[2]: Δ_{25}	Increase[2]: Δ_{med}	Increase[2]: Δ_{75}	Decrease[2]: Δ_{25}	Decrease[2]: Δ_{med}	Decrease[2]: Δ_{75}	$Q^\star$
Groups by type												
BRO	BRO	3'451	13/32	5	8	0.09	**0.18**	0.24	-0.25	**-0.12**	-0.08	0.51
BRO	DEP	5'975	56/236	52	4	0.05	**0.26**	0.38	-0.06	**-0.04**	-0.04	0.31
BRO	INS	4'206	67/229	44	23	0.13	**0.29**	0.37	-0.23	**-0.09**	-0.02	0.31
BRO	OTH	3'202	58/141	49	9	0.06	**0.22**	0.34	-0.18	**-0.05**	0.00	0.38
DEP	DEP	6'901	121/357	121	0	0.11	**0.23**	0.34	-	**-**	-	0.34
DEP	INS	5'843	195/730	166	29	0.08	**0.25**	0.35	-0.21	**-0.06**	-0.01	0.28
DEP	OTH	4'381	168/437	155	13	0.12	**0.29**	0.40	-0.11	**-0.06**	-0.01	0.31
INS	INS	5'126	116/370	90	26	0.07	**0.19**	0.40	-0.25	**-0.13**	-0.03	0.32
INS	OTH	3'548	145/452	121	24	0.13	**0.28**	0.40	-0.17	**-0.06**	-0.01	0.30
OTH	OTH	2'899	64/133	58	6	0.12	**0.28**	0.39	-0.10	**-0.07**	-0.03	0.34
Groups by size												
LRG	LRG	5'678	17/173	11	6	0.12	**0.22**	0.41	-0.16	**-0.06**	-0.01	0.33
LRG	MID	4'865	137/468	120	17	0.12	**0.27**	0.39	-0.12	**-0.07**	-0.03	0.41
LRG	SML	5'590	180/639	145	35	0.08	**0.22**	0.36	-0.23	**-0.05**	-0.01	0.31
MID	MID	3'692	131/327	122	9	0.15	**0.29**	0.40	-0.14	**-0.06**	-0.01	0.42
MID	SML	5'063	349/904	306	43	0.09	**0.25**	0.39	-0.21	**-0.10**	-0.03	0.30
SML	SML	5'596	189/606	157	32	0.08	**0.25**	0.36	-0.25	**-0.08**	-0.01	0.25

[1] Models significant at 25% level (appr. half also significant at 5% level) / Total number of models.
[2] Median difference and quantiles of correlation estimates between the 24-months time-window and subprime crisis.

B.6 Analysis of time trends in correlations

Table 33: Sample statistics for tests of time trend in correlation (crisis time-window)

Panel A: Statistics for International sample

			48-months[2]			**24-months**[2]			**Subprime**[2]			**24-months − Subprime**[3]			
		Models[1]	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	No.	Δ_{Q10}	Δ_{med}	Δ_{Q90}
EUR	EUR	146	29	43	-0.0010	41	30	0.0005	36	13	0.0079	39	-0.0207	**0.0057**	0.0344
EUR	NEU	159	25	41	-0.0010	34	31	0.0004	33	9	0.0128	30	-0.0135	**0.0052**	0.0329
EUR	USA	188	45	36	0.0064	43	23	0.0252	35	15	0.2565	27	-0.3673	**-0.0390**	0.6004
NEU	NEU	40	6	5	0.0001	4	9	-0.0023	3	0	0.0390	2	0.0297	**0.0330**	0.0363
NEU	USA	102	18	20	-0.0013	17	13	0.0211	35	3	0.5858	15	-0.0861	**0.4688**	1.3824
USA	USA	231	36	66	-0.0013	50	48	0.0002	75	7	0.0283	52	-0.0052	**0.0186**	0.0584

Panel B: Statistics for US sample

			48-months[2]			**24-months**[2]			**Subprime**[2]			**48-months − 24-months**[3]			
		Models[1]	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	δ_+	δ_-	δ_{med}	No.	Δ_{Q10}	Δ_{med}	Δ_{Q90}
Groups by type															
BRO	BRO	35	0	7	-0.0040	12	0	0.0147	11	0	1.2443	6	1.2984	**2.2342**	4.5512
BRO	DEP	234	9	51	-0.0064	64	6	0.0066	75	7	0.0209	33	-0.0126	**0.0075**	2.1652
BRO	INS	243	48	57	-0.0006	93	16	0.0055	72	22	0.0181	66	-0.0208	**0.0089**	1.4779
BRO	OTH	157	24	23	0.0005	55	1	0.0088	40	9	0.0356	24	-0.0433	**0.0121**	1.4480
DEP	DEP	372	11	33	-0.0049	31	17	0.0023	65	20	0.0120	19	-0.0545	**0.0082**	0.0235
DEP	INS	779	125	115	0.0002	199	76	0.0038	163	66	0.0094	144	-0.0199	**0.0006**	0.0232
DEP	OTH	507	62	42	0.0009	159	19	0.0057	89	14	0.0219	56	-0.0221	**0.0125**	0.0339
INS	INS	404	93	90	0.0001	134	56	0.0039	86	34	0.0119	93	-0.0217	**0.0056**	0.0272
INS	OTH	523	82	79	0.0002	156	36	0.0052	107	25	0.0173	72	-0.0179	**0.0089**	0.0470
OTH	OTH	165	26	16	0.0013	56	3	0.0083	31	8	0.0254	24	-0.0256	**0.0000**	0.0465
Groups by size															
LRG	LRG	173	30	47	-0.0013	49	14	0.0075	51	13	0.0078	30	-0.0142	**0.0018**	0.0148
LRG	MID	518	110	92	0.0009	200	35	0.0054	157	45	0.0148	119	-0.0120	**0.0067**	0.0319
LRG	SML	684	85	100	-0.0007	159	45	0.0051	116	32	0.0156	77	-0.0200	**0.0065**	1.9685
MID	MID	372	82	41	0.0030	133	21	0.0053	115	20	0.0188	86	-0.0178	**0.0067**	0.0383
MID	SML	1023	140	147	-0.0003	286	78	0.0053	208	71	0.0186	167	-0.0266	**0.0047**	0.2986
SML	SML	649	33	86	-0.0039	132	37	0.0050	92	24	0.0245	58	-0.0331	**0.0077**	1.1515

[1] Total number of DCC-GARCH models that were significant.
[2] Number of models significant at 15% level with positive/negative trend and according median.
[3] Median and quantiles of difference in estimated δ between time windows.

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Curriculum Vitae

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