Essays in Small Business Finance

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St.Gallen, October 22, 2019

The President:

Prof. Dr. Thomas Bieger

To my wife and my parents

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Hannes Mettler

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Summary

This dissertation is comprised of three papers related to the subject of small business finance. The aim of this thesis is to expand the existing literature on the use of bank debt by SMEs and the relevance of the SMEs' credit risk assessments by banks.

The first chapter deals with the question to what extent residential real estate is used as collateral for investments in small businesses. First, credit growth and investments of firms in high versus low price growth regions are compared. In this setting, firms who hold residential real estate collateral are compared to those which do not. Second, firm funding by owners in high versus low price growth regions are compared. The results suggest that firms that experienced a substantial increase in collateral value – either directly or indirectly through their owners – experience an increase in firm funding and business investments. These collateral channel effects predominantly stem from the period after the financial crisis of 2008.

The second chapter investigates to what extent the bank's credit risk assessment of an SME has an influence on its financing costs. The analysis documents that banks apply a risk-adjusted pricing strategy for first-time borrowers with unsecured bank loans. Analyzing rating changes during the credit relationship shows that the rating transitions of SMEs result in changes in financing costs in the following financial year. In particular, persistent rating changes in the same direction and rating reversals trigger a larger change in financing costs as compared to firms with no previous rating change. Furthermore, SMEs with high credit risk systematically report lower financing costs than a pure credit risk perspective would suggest.

The third chapter examines how SMEs credit ratings migrate over time. The analysis documents a significant path dependency in bank-internal credit ratings of SMEs: Rating changes reverse over time. The results show that the rating reversals are persistent across industry affiliation and also independent of the number of rating classes. Furthermore, qualitative risk assessments by loan officers do not materially change this rating reversal effect. Only larger SMEs show slightly fewer reversals when compared to the smallest firms.

Zusammenfassung

Diese Dissertation untersucht drei Themenstellungen im Bereich der Finanzierung von kleinen und mittleren Unternehmen (KMU). Das Ziel dieser Dissertation ist, die vorhandene Literatur zur Verwendung von Bankverbindlichkeiten durch KMU und zur Relevanz von Kreditrisikoeinschätzungen von Banken über KMU zu erweitern.

Das erste Kapitel beschäftigt sich mit der Frage, inwieweit Wohnimmobilien als Sicherheit für Investitionen von KMU genutzt werden. Zunächst werden das Kreditwachstum und die Investitionen von Unternehmen in Regionen mit hohem und niedrigem Preiswachstum verglichen. Dabei werden KMU, die Wohnimmobilien halten mit KMU ohne Wohnliegenschaften verglichen. Des weiteren wird die Entwicklung der Eigenfinanzierung nach Regionen verglichen, da Eigentümer von KMU oft privat Wohnliegenschaften halten. Die Ergebnisse zeigen, dass KMU, deren Wohnliegenschaften aufgewertet wurden, eine Zunahme der Unternehmensfinanzierung und der Investitionen verzeichnen. Diese Effekte stammen überwiegend aus der Zeit nach der Finanzkrise 2008.

Das zweite Kapitel untersucht die Frage, welchen Einfluss die Kreditrisikoeinschätzung der Bank auf die Finanzierungskosten von KMU hat. Die Analyse zeigt, dass Banken eine risikoadjustierte Preisstrategie für Erstkreditnehmer mit Blankokrediten anwenden. Die Analyse der Ratingveränderungen während des Kreditverhältnisses zeigt, dass die Veränderung von KMU Ratings zu Änderungen der Finanzierungskosten im folgenden Geschäftsjahr führen. Insbesondere aufeinanderfolgende Ratingänderungen in die gleiche Richtung sowie Ratingreversionen führen zu einer stärkeren Veränderung der Finanzierungskosten im Vergleich zu Unternehmen ohne vorherige Ratingänderung. Des weiteren haben KMU mit hohem Kreditrisiko systematisch niedrigere Finanzierungskosten, als dies aus einer reinen Kreditrisikoperspektive zu erwarten wäre.

Das dritte Kapitel untersucht, wie sich die Kreditratings von KMU über die Zeit verändern. Bei den bankinternen Ratings von KMU dokumentieren wir eine signifikante Pfadabhängigkeit: Ratingänderungen kehren sich mit der Zeit um. Unsere Ergebnisse zeigen, dass die Ratingreversionen branchenübergreifend und unabhängig von der Anzahl der Ratingklassen bestehen bleiben. Darüber hinaus ändert die qualitative Risikobewertung nach Ermessen von Kreditrisikospezialisten den Effekt der Ratingreversionen nicht wesentlich. Nur grössere KMU weisen im Vergleich zu den kleinsten Unternehmen etwas weniger Ratingreversionen auf.

Chapter 1
The Real Estate Collateral Channel in SME Finance: Evidence from Switzerland

Hannes Mettler*

Abstract

I examine to what extent small businesses owners use residential real estate as collateral for investments in their firm. The analysis is based on annual financial statements of small firms in Switzerland over the period 2002-2014. In a first step I compare credit growth and investments of firms in high versus low price growth regions and hereby compare firms who hold residential real estate collateral to those which do not. In a second step, I compare firm funding by owners (equity and shareholder liability) and firm investments of firms in high versus low price growth regions. I find evidence that firms that experienced a substantial increase in collateral value - either directly or indirectly through their owners - report an increase in firm funding and business investments. The results show that these collateral channel effects predominantly stem from the period after the financial crisis of 2008.

Keywords: Collateral Channel, Small Business Finance

JEL classification numbers: D22, G21, G31

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1.1 Introduction

In the wake of the 2007-2009 financial crisis the role of real-estate collateral in small business finance has received increased attention. On the one hand, increasing real estate prices are seen as a key driver of firm borrowing and investment prior to the crisis. On the other hand, there are concerns that in the aftermath of the crisis small businesses – and especially those without real estate – have experienced credit constraints (OECD, 2014). Over the last 16 years, residential real estate prices in Switzerland increased significantly. On average, the prices of apartments doubled, and house prices increased by 50% in this period. Has this increase in real estate prices also affected small business finance and investment? In Switzerland, collateralized debt, especially real estate collateral, is widely used in SME finance: 74% of bank lending to SMEs are mortgages (SNB, 2015). Following this observation, it appears likely that small firms make use of increased collateral values to increase their bank funding and investment.

The interaction between real estate values, credit and investments are summarized in the term *collateral channel*. Its theoretical foundation stems from the models of Barro (1976) and Stiglitz & Weiss (1981). They show that pledging collateral alleviates information asymmetries between banks and firms and enhances a firm's financial capacity. Kiyotaki & Moore (1997) highlight that an increase in the value of collateralized assets leads to a higher debt capacity of a firm and vice versa (Shleifer & Vishny, 1992). Hence, this effect is a major suspect for credit boom and bust leading to the Great Depression in the United States (Bernanke, 1983). The collateral channel also raises the question of whether firms or individuals face credit constraints (Bernanke & Gertler, 1989).

In this paper, I study the usage of the *collateral channel* by small businesses in Switzerland. I combine unique financial data, providing detailed annual information on firm funding (bank loans, equity, shareholder loans) and investments, with information on local house price growth across 65 regions within Switzerland over the period 2002-2014. In order to analyze the collateral channel over time, I split the data set into two balanced panels of equal length: 2002-2008 and 2008-2014. The Swiss residential real estate price development is an ideal setup for studying a collateral value effect, because either the firm itself or their entrepreneur are most likely to hold residential property and experience the asset increase (Schmalz et al., 2017). To the best of my knowledge, this is the first paper that empirically contributes to a better understanding of the collateral channel in Switzerland using proprietary data.

My empirical strategy follows Chaney et al. (2012) and Schmalz et al. (2017). Chaney et al. (2012) examine how the variation in real estate price growth across regions in the US affects the investment behavior of US corporations during 1993-2007. Schmalz et al. (2017) examine how variations in house price growth across regions in France influence entrepreneurial activity in 1990-2002. Both papers find the collateral channel effect and disentangle it for example from regional demand effects by relying on a difference-in-differences strategy. They compare funding and investment for real estate owners to that for non-owners. In the first part of my analysis I compare mortgages and investments of firms which report residential real estate on their balance sheet (RRE owners) to those which do not and relate this difference to the residential real estate dynamics across 65 regions in the sample.

The funding of small firms and the private finances of their owners are often closely interlinked. Previous evidence shows that particularly entrepreneurs may take on private debt (e.g. mortgages) to finance their business activities (Bahaj et al., 2016; Schmalz et al., 2017). This is based on the strong correlation between entrepreneurial wealth and the propensity to invest in their own business (Evans & Jovanovic, 1989; Evans & Leighton, 1989; Holtz-Eakin et al., 1993). Entrepreneurs which experienced a large price increase of their private homes are more likely to invest in their firms. I therefore compare the funding by firm owners (equity, shareholder liability) and investments of firms in high price growth regions versus firms in low price regions. To the best of my knowledge, except for Schmalz et al. (2017) and Bahaj et al.(2016), there are no studies that have analyzed the collateral channel simultaneously from the entrepreneur’s and firm’s perspectives.

Overall, my results suggest that there are substantial collateral channel effects between 2008 and 2014 by firms which own RRE property as well as by entrepreneurs in high price regions who use their private homes to fund their firms. In the period 2002-2008 there is no evidence of this residential real estate channel.

My paper contributes to the literature on the relationship between economic activity and asset prices. In my first set of results I find evidence that SMEs which experienced a higher real estate price increase, expand their mortgage borrowing more than firms in regions with less real estate price growth. A 1%-point increase in RRE price growth leads to a 0.29%-point increase in mortgage growth by RRE owners relative to non-owners. This relation is stable using multiple control variables and several robustness tests. My finding on bank funding is consistent with those found for the United States by Chaney et al. (2012) and for European countries by Bahaj et al. (2016) and Banerjee & Blickle (2016). Chaney et al. (2012) show that during 1993 to 2007, large US corporations that held real estate made larger debt issuances. A $1 increase in collateral value raised debt issues by $0.095. Obviously, the relation between collateral values and debt issues is distinctively weaker than in Switzerland, which can be partially attributed to different firm types as SMEs are typically financially more constrained than large firms. Compared to other European countries, my finding for Switzerland is quantitatively similar to those found by Banerjee & Blickle (2016) for France (0.06%) and the United Kingdom (0.14%).

My paper extends the existing literature on the lending collateral channel by differentiating between non-business-related investments (i.e. residential properties) and business investments which only includes investments in productive capacity. As I am interested in whether or not the SME uses the collateral increase for changes in the productive capacity, I focus on business investments. I find support that the business investment rate of RRE owners is positively influenced by the collateral value increase. While non-owners show declining investment rates from 2008 to 2014, RRE owners' investment rates remained stable or even increased. A 1%-point increase in RRE price growth leads to a 0.18%-point increase in business investment growth by RRE owners relative to non-owner. My finding is consistent with those of Chaney et al. (2012), Bahaj et al. (2016) and Banerjee & Blickle (2016). They all show that an increase in collateral value of real estate assets leads the respective company to increase its investments. Using the land market collapse in Japan as natural experiment, Gan (2007a) shows the same finding but in reverse.

In my second set of results, I contribute to the literature on the role of privately owned collateral in doing business. My result show that firms in high price growth regions report significantly higher growth in paid-in equity as compared to SMEs in low price regions. This suggests that, entrepreneurs increase their private mortgages to inject equity into their firms. To capture only equity transfers by entrepreneurs without yearly P&L-effects, my analysis relies on paid-in equity excluding retained earnings.

On average a firm in a region with high price growth shows approx. 70% more paid-in equity growth as compared to firms in a low price region. My finding concurs with those of Schmalz et al. (2017). They show that homeowners in France who experience an increase in their home values are more likely to start or keep their own firm and maintain larger firms with respect to employment, sales and assets. Similarly, Adelino et al. (2015)

find that areas in the United States with rising house prices experience a significantly larger increase in the number of new small businesses as compared to areas without an increase in house prices.

The remainder of this chapter is organized as follows. Section 1.2 provides an overview of the residential real estate market as well as the SME financing channels. Furthermore, section 1.2 elaborates on the research hypotheses. Section 1.3 gives an overview of the datasets used in the empirical section. Section 1.4 shows the empirical strategy and the results from the perspective of the SME itself whereas section 1.5 presents the empirical strategy and results from the entrepreneur's point of view. Section 1.6 concludes the findings.

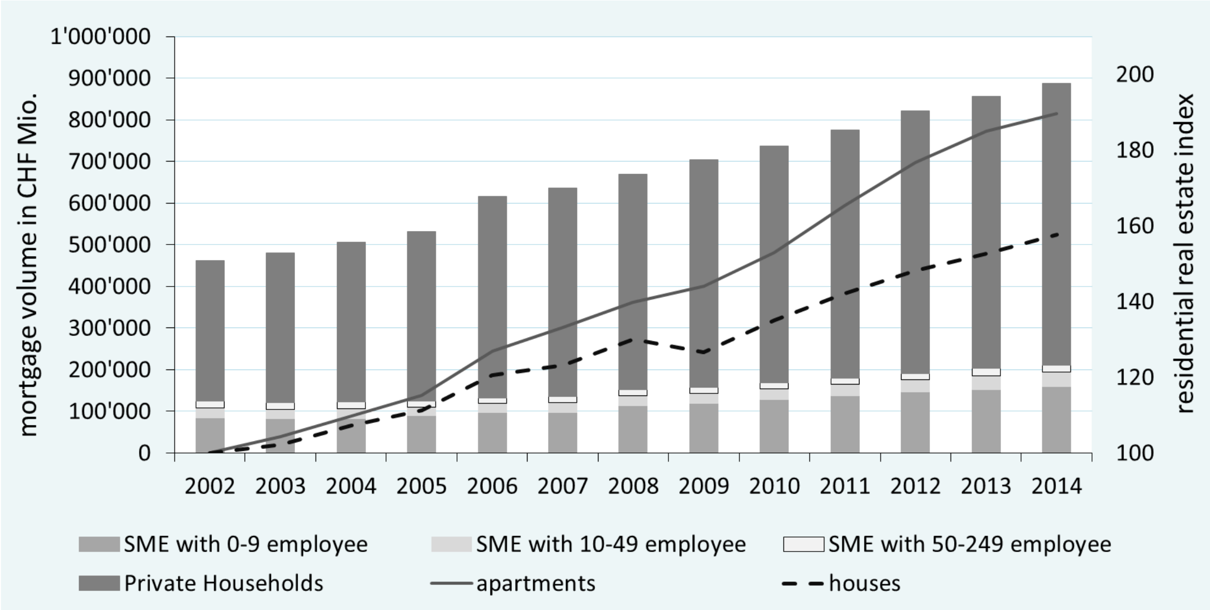
1.2 Institutional Background

1.2.1 The Swiss Real Estate and Mortgage Market

Between 2000 and 2014 residential real estate prices increased by 74% on average across Switzerland. At the same time, the outstanding total mortgage volume increased significantly from CHF 473 bn in 2002 to CHF 897 bn in 2014 (SNB, 2016). Mortgages to private households increased by CHF 337 bn (100%) and mortgages to SME by CHF 88 bn (71%) in these 12 years. This development has attracted the concern of banks and their supervisor, the FINMA[1], as well as the SNB[2], fearing that a real estate crisis similar to that of 1990 might emerge (Bosley, 2014). Due to the strong growth in both mortgages and real estate prices, FINMA and SNB took various actions aimed at protecting the financial sector and cooling down the residential real estate market (i.e., implementing a countercyclical capital buffer; SNB, 2014). Figure 1.1 shows the outstanding mortgages to SMEs and private households in comparison to the residential real estate prices. The mortgage volume includes all types of properties as there is no more granular information available. Figure 1.1 shows that residential real estate prices strongly correlate with both, SME and private households mortgage volumes.

[1] FINMA: Swiss Financial Market Supervisory Authority
[2] SNB: Swiss National Bank

Figure 1.1: SME and Private Households Mortgage Volume with Residential Real Estate Price Index



Notes: The graph plots the mortgage volume of SME and Private Households (all property types) with the residential real estate price indices of apartments and houses in Switzerland from 2002-2014. *Source:* SNB and W&P.

For SMEs and entrepreneurs alike, access to a mortgage or an increase in an existing mortgage depends mainly on the creditworthiness of the borrower and the value of the real estate property. The two main limiting factors are the loan-to-value ratio (LTV) and the affordability of paying the interest rate (debt service). The latter is differently calculated depending on the borrower type. If a corporate appears as borrower, banks assess the net operating income in respect to the debt service (debt service coverage ratio) and the debt capacity. Similarly the entrepreneur's income is relevant if the entrepreneur act as borrower itself (loan-to-income ratio). In Switzerland, bank credit policies state an upper LTV of 80% for residential real estate properties. This is independent of the borrower type. Due to conservative lending practices, the average LTV is less than 66% (Brown, 2006). Therefore, a residential property owner may ask for a mortgage whenever he or she has an LTV of less than 80% and is still able to pay the mortgage interest. Because of the LTV as a relative measure, whenever the real estate prices increase substantially, a borrower (SME or entrepreneur) may theoretically ask for an increase of their mortgage. Particularly for self-used homes, banks use hedonic models to calculate the property value. In these models, the paid prices of recent transactions are the main driver.

There are important differences compared to commercial real estate. First, there are different upper LTVs depending on the subtypes of commercial properties (i.e., office, industrial, department store). Second, the valuation depends mainly on the rental income and assessment of real estate valuation expert.

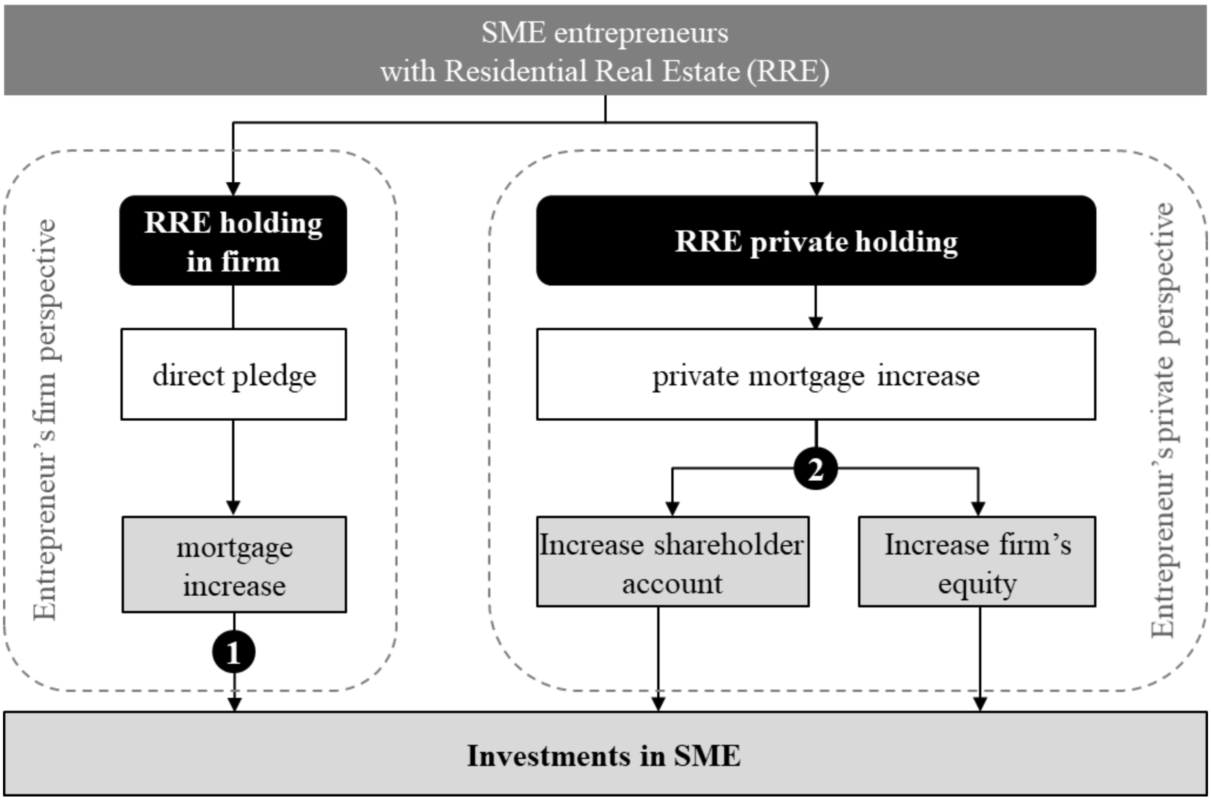
1.2.2 SME Financing with Residential Real Estate Collateral

Because of the financial interdependence between entrepreneurs and their firms, the private as well as the firm's perspective are both relevant. There are mainly two different channels for how residential real estate (RRE) growth may materialize in increased mortgages and eventually in higher investments[3]. Figure 1.2 shows these channels from the entrepreneur's and the firm's perspective.

(1) RRE held by firms: Firm's mortgage increase secured by RRE collateral

(2) RRE held by entrepreneurs: Shareholder liability or firm's equity increase through private mortgages

Figure 1.2: Collateral Channels



Notes: Own illustration.

[3] Bank credit policies foresee that any kind of misuse of the loan purpose should be prevented (i.e., mortgage proceeds should be solely used for investments in the same property). However, banks also confirm that there are exceptions if the LTV-ratio on the property is sufficiently low. Furthermore, in the prevailing competitive retail market with increasing residential real estate prices, a mortgage request by an entrepreneur with a reasonable LTV-ratio on his real estate will most likely not be rejected.

Channel (1) “RRE held by firms” in figure 1.2 shows the case of an SME pledging its residential real estate in order to increase an existing or apply for a new mortgage. The mechanism of channel (1) is straightforward and is analyzed among others by Chaney et al. (2012). There are different reasons whether the entrepreneur holds his or her private home within the firm or privately.[4] In addition to the entrepreneur’s home, there could be also other residential real estate properties that are not relevant to the business and are mainly purchased from a return perspective for rental purposes. According to experts, these properties are usually held by the firm itself due to tax reasons.

If the residential real estate is held by the entrepreneurs rather than within the firm, these properties can serve as collateral for investments in the firm as well. Entrepreneurs may ask for a mortgage from the bank and transfer the cash to the firm. This is channel (2) “RRE held by entrepreneurs”. Technically this process is done by either increasing the firm’s equity or the shareholder liabilities.[5] Among others, channel (2) is analyzed by Schmalz et al. (2017).

To answer my research questions, I deduce three relevant hypotheses. These hypotheses are based on the theoretical foundations in Kiyotaki & Moore (1997), Barro (1976), and Stiglitz & Weiss (1981) and on the recent empirical results of Schmalz et al. (2017), Bahaj et al. (2016), Banerjee & Blickle (2016), Adelino et al. (2015) and Chaney et al. (2012). In this paper, H1 and H2 refer to the amplifying effect of real estate as collateral channel by influencing the debt level of firms and entrepreneurs:

H1: “Mortgages”:	SMEs use the residential real estate growth to increase their mortgages.
H2: “Equity/Shareholder Liability”:	Entrepreneurs use the RRE growth to increase their private mortgages and subsequently use the proceeds for the firm by increasing the firm’s equity or the shareholder liabilities (channel 2).

H3 is based on the intensive margin analysis and its impact on investment behavior, as shown in the theoretical and empirical literature described above. Because of the detailed balance sheet data, it is possible to disentangle total investments into business (i.e.,

[4] From a tax perspective, there are some advantages if the property is held within the firm, such as the possibility of depreciation on private homes, but there are also tax disadvantages in case the firm should be sold. In addition, an entrepreneur may hold his home for economic or other personal reasons within the firm. Bank experts believe that the entrepreneurs’ homes are more likely held privately.

[5] As an alternative to channel (2), it is possible that an entrepreneur pledges the privately held property in favor of the firm (third-party-pledge). In this case, the firm’s record will show a business loan instead of a mortgage.

productive capacity, business equipment) and investments in non-business assets (i.e., RRE). H3 subsumes the impact on the investment behavior regarding productive business investments.

H3: "Investments": SMEs or entrepreneurs which experienced an increase in RRE collateral value invest more in productive assets (i.e., PPE) of their firm.

1.3 Data

My analysis is based on two proprietary datasets. The first dataset contains financial statements of Swiss SMEs, which are provided by seven Swiss banks located in Northwestern, Central and Eastern Switzerland. This unique dataset has not been used in any empirical paper related to the collateral channel. The second data set comprises regional real estate price data provided by Wüest & Partner, which are widely used by academic researchers and research departments of banks.

1.3.1 SME Accounting Data

The accounting dataset comprises 74,992 yearly financial statements of 12,415 unique SMEs for a period of 13 years between 2002 and 2014. These SMEs are located in 90 of a total of 106 MS-regions[6] across Switzerland. The financial statements are collected by banks using an identical software ensuring that the structure of the financial statements are the same. This is an unbalanced panel. Not all SMEs have financial statements for all 13 years. Missing financial statements can have various reasons, such as the SME went bankrupt or it simply ceased to provide financial statements to banks. The dataset includes the entire balance sheet (i.e., property plant and equipment (PPE), receivables, payables mortgages, equity, etc.), profit and loss (i.e., sales, EBITDA, depreciation, etc.) as well as some basic characteristics of the SME (i.e., number of employees, legal form, industry and MS-region). There is a possible selection bias in this data set, given that only SMEs with a credit relationship with a bank or SMEs that at least applied for a loan are included.

Critical to the empirical design of this study is the relation between the SME and the residential real estate. Therefore, the location of an SME is key information that is available in the dataset with the MS-region code of each SME. All pure real estate firms are

[6] MS-regions: The Swiss Federal Statistical Office (BFS) has divided Switzerland into 106 homogenous Mobilité Spatiale (MS)-regions, which are widely used for spatial analysis.

eliminated from the sample; hence, residential real estate holdings should have no business purpose. All firms in this dataset are restricted to less than 250 employees and less than CHF 300 Mio. in total assets. Appendix A1 provides a list of all exclusions (i.e., sample construction).

In reference to the empirical strategy, which will be introduced in sections 1.4 and 1.5, the available financial statements are restricted to a *balanced panel*. Considering the entire time period from *2002-2014*, the *balanced panel* ends up with only 1,110 firms in 38 MS-regions. Due to the small sample size, this full panel is not used for the analysis. Instead, splitting the entire time window into two periods of equal length (seven years), results in 2,461 firms in 54 MS-regions for the *2002-2008* panel and 2,474 in 65 MS-regions for the *2008-2014* panel. In this case, the cutoff year between these sub-samples coincides with the global financial crisis in 2007/2008. Summary statistics of the balanced panels are shown in table 1.1 (more summary statistics in appendix A4 and A11; variable definitions in appendix A2).

Based on the research questions and hypotheses, there are four variables derived from the financing channels 1 and 2 (section 1.2.2) that are of interest. These dependent variables are expressed as average of yearly changes over the panel period. I define *mortgage growth* as the annual change in the balance sheet position "mortgages" divided by mortgages lagged by one year. *Business investment growth* is defined as the change in total fixed assets plus depreciation divided by the lagged total fixed assets. Due to the detailed balance sheet information, non-business-related investments such as residential properties are explicitly excluded in this calculation and *business investment growth* only includes investments in productive capacity. In order to capture channel 2, *equity growth* is defined as the change in paid-in capital (i.e. common stocks) divided by lagged paid-in equity. This definition excludes retained earnings and isolates the payments from the firm's owners which I am interested in. *Shareholder liability growth* is defined as annual change in shareholder liabilities divided by one year lagged shareholder liability.

Table 1.1 summarizes some of the univariate characteristics of both panel periods. 43% of all SMEs in the *2002-2008* panel (resp. 44% in the *2008-2014* panel) do not have a mortgage. This is also why mortgages grow by 1-2% on average per year in the samples[7].

[7] Table 1.1 includes firms without mortgages. Using only firms that reported mortgages (43% of all firms in 2002; 44% of all firms in 2008), the mortgage growth rate would be 3.1% (2002-2008) and 4.4% (2008-2014) which is comparable to the SNB data (annual growth rate of 4.6%) from figure 1.1. Robustness section 1.4.2.3 shows the regression analysis using only firms that reported mortgages (intensive margin).

Investments in productive business assets grow around 7-9% p.a. of the book value of total fixed assets. Due to its definition, paid-in equity is rarely negative for SME. Only 1% of firms decreased their common stocks. However, only 6% of the firms increased their paid-in equity. This leads to an annual growth rate of paid-in equity of 2-3%. Shareholder liability showed unsteady developments with a negative growth rate between *2002-2008* and increasing shareholder liabilities in *2008-2014*. Except for the variable *business investment growth*, all other dependent variables are highly sporadic, which reflects that many firms increase their mortgages, equity or shareholder liability in a single year and no more in the next years.

Table 1.1: Panel Summary Statistics

standardized variables (mean)	balanced panel 2002-2008			balanced panel 2008-2014		
Number of firms		2,461			2,474	
Variables of interest (dependent variables)	Mean	Standard deviation	Median	Mean	Standard deviation	Median
Mortgage Growth	0.01	0.39	0.00	0.02	0.44	0.00
Business Investment Growth	0.08	0.29	0.03	0.09	0.36	0.03
Equity (paid in) Growth	0.03	0.39	0.00	0.02	0.50	0.00
Shareholder Liability Growth	-0.01	0.45	0.00	0.01	0.51	0.00
Number of firms						
Reporting Mortgages		1,405			1,396	
Reporting Business Assets		2,461			2,474	
Reporting Equity		2,461			2,474	
Reporting Shareholder Liability		585			666	
Firm's characteristic variables (controls)	Mean	Standard deviation	Median	Mean	Standard deviation	Median
Log of Total Assets	7.72	1.42	7.66	7.94	1.35	7.87
PPE_share	0.44	0.29	0.44	0.47	0.30	0.48
Debt_share	0.23	0.30	0.13	0.26	0.31	0.21
Equity Ratio	0.35	0.20	0.32	0.38	0.21	0.36
Return on Assets (RoA)	0.10	0.12	0.08	0.12	0.13	0.09
Return on Sales (RoS)	0.09	0.29	0.06	0.11	0.28	0.07
Return on Equity (RoE)	0.05	1.72	0.05	0.10	1.82	0.08
Number of Employees	21	32	9	24	34	10

Notes: This table depicts summary characteristics for the variables used in the analysis. The information is represented for the balanced panels 2002-2008 and 2008-2014. Dependent variables are shown as yearly changes. Control variables are shown as yearly standardized values. Additional controls, such as industry or region dummies are omitted for brevity. Holding mortgages, business assets, equity and shareholder liability is defined in the first year of each period.

SMEs may hold different types of real estate properties. Table 1.2 shows the main real estate categories and their distributions. From 2,461 firms of the *2002-2008* panel, there are 437 SMEs (18%) that hold RRE. Similarly, there are 363 firms (15%) holding RRE within the 2,474 firms of the *2008-2014* panel. It is not surprising that only 15-18% of the firms hold RRE, as this is not their core business. By sample construction real estate firms (= real estate as business purpose such as rent, buy and sell properties) are excluded (details see Appendix A1). Therefore, residential real estate holding should serve no business purpose.

Table 1.2: Type of Real Estate Ownership

Share of firms		balanced panel 2002-2008	balanced panel 2008-2014
Number of firms		2,461	2,474
Holding no real estate	(Non-owner)	36%	34%
Holding commercial property	(CRE-owner)	46%	51%
Holding residential real estate	(RRE-owner)	5%	3%
Holding commercial and residential properties	(CRE and RRE-Owner)	13%	12%

Notes: The table presents different types of real estate ownerships. The abbrevations in brackets are used in the following analyses. Real estate ownership is defined in the first year of each period.

There are two main reasons why this analysis focuses only on residential real estate collateral. First, residential real estate prices in Switzerland experienced a unique substantial price increase during the recent 15 years. Contrary to that, commercial real estate prices developed unsteady within a range of +10% and -10% on average. Due to the unstable commercial price development and the higher credit risk of commercial properties, banks are less likely to increase a mortgage on a commercial real estate as compared to a residential property. It is important to note, however, that this does not imply that collateral effects from residential real estate are more important than from commercial properties. Second, the historic development of residential real estate prices does not only have an impact on private persons and real estate investment firms but also on productive SMEs with no direct affiliation to the residential real estate market.

Appendix A4 shows the summary statistics of the two samples, but separated by companies owning residential property and those having no residential real estate. SMEs that report residential real estate are slightly larger than SMEs without residential property.

1.3.2 Real Estate Data

This dataset contains the quarterly transaction price indices for the residential real estate category "self-used apartments" from 2002 to 2014. The transaction prices are reported by banks on a regional level and pooled by the financial provider Wüest & Partner, Switzerland. Each of the 106 Mobilité Spatiale (MS)-regions in Switzerland receives an individual price index for a standard apartment.

Based on the accounting sample periods used, the RE price index is employed for *2002-2008* for each of the 54 MS-regions where firms are located. Equally for the *2008-2014* panel, each of the 65 MS-regions, where the accounting data shows a firm entry, receive a RE price index. Table 1.3 summarizes the price distribution of both time periods. The price regions are categorized into "*low price growth*" and "*high price growth*" regions, using the mean of the price development as the cutoff value to distinguish between low and high price growth. The strongest growth between 2002 and 2008 amount to 165.96 index-points (2002 is set to 100). After the financial crisis the price index peaked in 2014 at 167.31 index-points (2008 = 100).

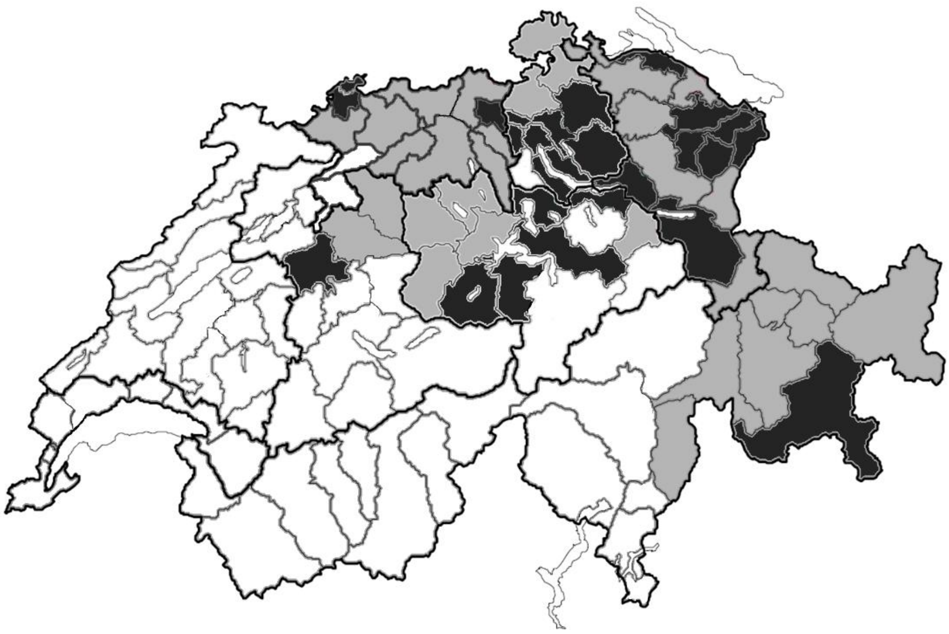
Table 1.3: RE Price Index Distribution

Parameter	2002-2008 Price index in 2008	2002-2008 Number of firms (accounting data)	2008-2014 Price index in 2014	2008-2014 Number of firms (accounting data)
Starting year = 100	2002		2008	
minimum	99.68	low price growth: 1'514	125.57	low price growth: 1'696
25%-Quantil	123.70		136.38	
50%-Quantil	127.73		141.29	
75%-Quantil	133.05	high price growth: 960	147.30	high price growth: 765
maximum	165.96		167.31	
mean (cutoff value)	129.64		142.15	

Notes: The table presents the distribution of the transaction price indices "residential real estate (self-used apartments) of 54 MS regions in 2002-2008 and 65 MS-regions in 2008-2014.

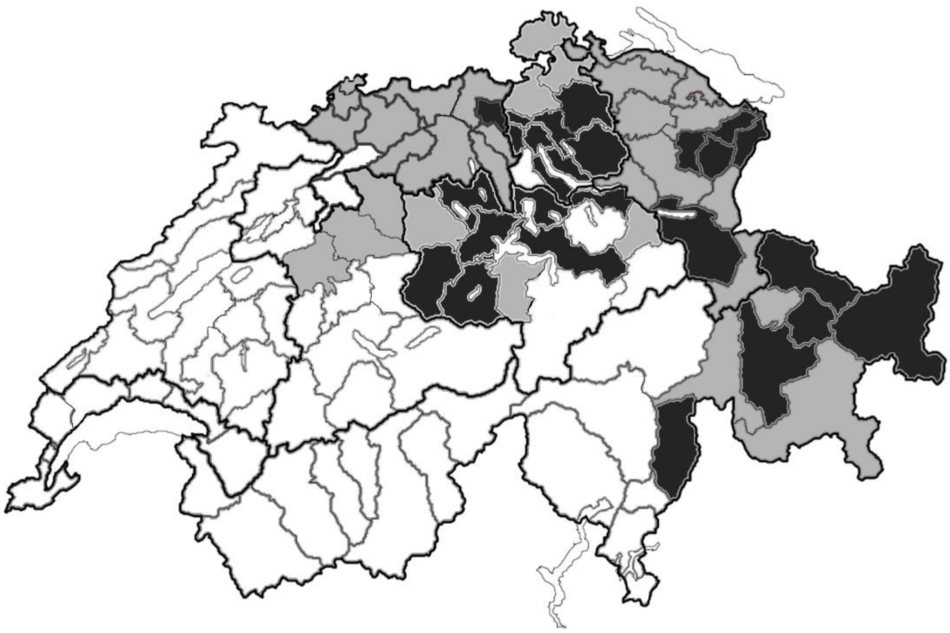
For visualization purposes, the low and high price growth regions for 2002-2008 are shown in figure 1.3 and for 2008-2014 in figure 1.4. (Appendix A5 illustrates the residential real estate price dynamics of the MS regions split by the two growth categories). These figures show that many regions have high resp. low price growth in both periods. Regions which are colored white are not in the analysis due to the lack of firm-level accounting data.

Figure1.3: Geographical classification after BFS and Monitoring-Regions 2002-2008



Notes: The figure shows the 54 MS-regions with low price growth (grey) with a price increase between 99.68% - 129.64% and high price growth (black) with a price increase from 129.64% to 165.96%.

Figure 1.4: Geographical classification after BFS and Monitoring-Regions 2008-2014



Notes: The figure shows the 65 MS-regions with low price growth (grey) with a price increase between 125.57% - 142.15% and high price growth (black) with a price increase from 142.15% to 167.31%.

1.4 Residential Real Estate held by Firms

This section covers the first channel as explained in section 1.2.2, where SMEs hold pledgeable residential real estate in their accounts.

1.4.1 Empirical Strategy

My aim is to identify the causal relationship between residential property collateral value growth on a firm's behavior. I mainly follow the empirical methodologies by Chaney et al. (2012) and Schmalz et al. (2017), which are both akin to a difference-in-differences strategy. The main difference lies in the regression set up: Chaney et al. (2012) use a panel model with firm and year fixed effects over a period of 14 years. Considering the intensive margin, Schmalz et al. (2017) implement a cross sectional approach with its independent variables five years later. My research design is based on the cross-sectional approach, which compares the behavior of SMEs holding residential real estate (RRE owner) and SMEs without residential property (non-owner) within the same region and relates this difference to the real estate price dynamics observed across different regions within Switzerland. The identification strategy is based upon the idea that when residential prices rise, RRE owners experience an increase in the value of available collateral. This increase in collateral value may have an impact on the behavior of RRE owners.

Regression model (1) estimates the impact of residential real estate growth on SME debt issuances and investments. SMEs with RRE property are the treated group. SMEs without RRE serve as the control group. The treatment is the development of residential real estate prices in a certain region. The regression model (1) is estimated twice: for the *2002-2008 balanced panel* and the *2008-2014 balanced panel*. The regression variables correspond to the explained variables in the accounting data in section 1.3.1.

Let *i* be an SME and *l* its location:

$$\Delta Y_i^l = \alpha + \beta \cdot Owner_i^l \times \Delta p^l + \theta \cdot Owner_i^l + \zeta \cdot \Delta p^l + \gamma \cdot controls_i + \tau \cdot controls_i \times \Delta p^l + \delta_l + \varepsilon_{i,l} \tag{1}$$

$$\Delta Y_i^l \coloneqq \Delta MORTG_i^l \tag{1.1}$$

$$\Delta BINV_i^l \tag{1.2}$$

where $\Delta MORTG_i^l$ and $\Delta BINV_i^l$ are the average growth of mortgages and business investments of the four recent years of each panel (*2004-2008,* resp. *2010-2014*). The first two years of each panel are not considered for the dependent variables because of the time elapsing between the experienced price increase and materialization in mortgage demand (i.e., mortgage requests and credit approval process at banks). $Owner_i^l$ is a dummy equal to 1 if the SME owns RRE (= RRE owner) in *2002* or *2008*, respectively. δ_l are region fixed effects where l is a MS-region. Δp^l is the cumulative residential real estate growth in region l over the first four years of each panel (*2002-2006, 2008-2012*, respectively), standardized to residential real estate price in *2002* or *2008*.

$Controls_i$ include PPE, debt and equity (defined as ratios to total assets) as well as the log of total assets and profitability financials (RoA, RoS and RoE) for firm i in *2002* or *2008*, respectively. All control variables are calculated as mean of the entire panel period. The variation across the two panel periods is relatively similar (see table 1.1 for details). All SMEs report mean total assets of CHF 2-3 Mio., similar leverage levels and comparable profitability across the two periods. The mean firm has 21-24 employees.

The aim of control variables, their interaction with cumulative RRE price growth and fixed effects is to difference out all unintended effects. The interaction of control variables with the cumulative residential real estate growth should alleviate the concern that heterogeneity across RRE owners and non-owners is driving the results. This interaction controls for the overall impact of the real estate cycle, irrespective of whether a firm owns real estate. Regional fixed effects δ_l control for different real estate developments and unobserved variables within a region l where an SME is based. This will also control for local investment opportunities.

The interaction of the dummy variable $Owner_i^l$ and the cumulative RRE price growth Δp^l is of main interest. Its coefficient β captures the causality of holding RRE in regions with high price growth and SME activity and what magnitude this effect has. The estimation relies on the comparison to non-owners. Owners and non-owners face the same local shocks to economic activity. Therefore, the within-region comparison of debt issuance and investments between property holders and non-holders allows for differentiating between local economic shocks that may drive real estate prices, debt issuance and investments. Based on this empirical strategy, the cross-sectional variation in RRE growth between the MS regions is used to identify the collateral channel effect. β is identified by comparing the difference in SME activity between RRE owners and non-owners across these regions with different RRE-price growth developments.

A positive β shows that RRE owners issue more debt and invest more than non-RRE owners dependent on the price development in the region. Equation (1.1) $\Delta MORTG_i^l$ relates directly to hypothesis H1:

H1: "Mortgages": $H1_0$: $\beta = 0$ RRE collateral increases do not affect mortgage issuance.

$H1_A$: $\beta > 0$ RRE collateral value increases affect mortgage issuance.

Equation (1.2) $\Delta BINV_i^l$ covers the investment activity into productive capacity by a firm and relates to hypothesis H3:

H3: "Investments": $H3_0$: $\beta = 0$ RRE collateral values do not affect investment behavior.

$H3_A$: $\beta > 0$ RRE collateral values affect investment behavior.

The measurement of SMEs with residential real estate is crucial to the empirical strategy pursued. Therefore, the measurement strategy is explained in more detail. Accounting data is used to determine whether an SME holds RRE. The balance sheet contains an item "*residential property*", with no further classification. Hence, it is not possible to distinguish between residential property for rent (income-producing real estate; IPRE) and the entrepreneur's home (house or apartment). This lack of residential property type identification leads to the question which real estate data will be used. According to bank and tax expert discussions, small firms in particular may hold properties with mixed usage or semi-detached houses, where one part is for residential use (i.e., apartment of entrepreneur) and another part is the firm itself (commercial purpose). This view is further supported by the financial statements. The residential real estate reported in the financial statements (appendix A4) shows a median value of CHF 787,000 as compared to a typical private home (apartment or house) of approximately CHF 1 Mio. This might suggest that there are more private homes (house or apartment) than IPREs because the value of IPREs are substantially larger. A medium-sized residential property building for rental purposes easily amounts to CHF 3 Mio. or even more. Therefore, I use transaction prices for apartments from the Wüest & Partner database.

In addition to the property subtype, the property location raises questions as well. This information is also not available from the financial statements. From the financial statements data, only the location of the SME is available. However, there are two reasons to assume that the properties are mostly located in the same MS-region as the SMEs. First, SMEs have regional roots. Second, if the residential property is the private home, then the entrepreneurs typically work somewhere close, mostly in the same town or even in the same building (mixed-used property). Among others, Chaney et al. 2012 use the headquarters of larger firms as an approximation for their location.

One drawback with accounting data is that the reported property value of residential real estate cannot be used for this research. This drawback is rooted to a particularity in the local accounting standards stated in the "Code of Obligations" (Obligationenrecht) in Switzerland, which is widely used by SMEs. Based on these accounting standards, SMEs are allowed to build up hidden reserves in their balance sheet. This is not congruent with the true and fair view, known from Swiss GAAP FER and IFRS. SMEs often depreciate their property, plant and equipment (PPE) much more than needed or economically true. Thus, the (real estate) value in PPE neither reflects the market value nor the historical value (KPMG, 2013).

1.4.2 Results

1.4.2.1 Univariate Evidence

Table 1.4 shows the defined dependent variables mortgage and business investment growth split by the aforementioned real estate price growth categories and whether the SME holds RRE or not.

Table 1.4: Univariate Evidence of Firm Behavior 2008-2014

2008-2014	RRE owner			Non-owner		
	high price region (mean)	low price region (mean)	Δ (high - low)	high price region (mean)	low price region (mean)	Δ (high - low)
Mortgage Growth $(\Delta MORTG_i^l)$	0.05	0.02	0.03	0.01	0.01	0.00
Business Investment Growth $(\Delta BINV_i^l)$	0.08	0.06	0.02	0.08	0.09	-0.01

Notes: The table reports the dependent variables from equation (1) for the panel 2008-2014, split by RRE price growth regions and RRE ownership.

RRE owners in high price regions significantly increased their mortgages to a larger extent than RRE owners in low price regions and non-owners, which supports the research hypothesis H1. Note that non-owners mortgage issues stem from commercial real estate properties as discussed in section 1.3.1. In line with the investment hypothesis H3, RRE owners in high price regions invest more in productive capacity than RRE owners in low price regions. This indicates that RRE owners use the substantial collateral value increase.

While there is evidence that the collateral channel is working after 2008, the results for panel *2002-2008*, as reported in table 1.5, show no such indication. Contrary to the post-crisis findings, mortgage growth shows just a minor positive difference between RRE owners in high versus low price regions. Furthermore, non-owners in low price regions show the highest mortgage growth rate. Similarly, non-owners in low price regions show the highest business investment growth.

Table 1.5: Univariate Evidence of Firm Behavior 2002-2008

2002-2008	RRE owner			Non-owner		
	high price region (mean)	low price region (mean)	Δ (high - low)	high price region (mean)	low price region (mean)	Δ (high - low)
Mortgage Growth $(\Delta MORTG_i^l)$	0.00	-0.01	0.01	0.00	0.01	-0.01
Business Investment Growth $(\Delta BINV_i^l)$	0.05	0.05	0.00	0.08	0.09	-0.01

Notes: The table reports the dependent variables from equation (1) for the panel 2002-2008, split by RRE price growth regions and RRE ownership.

1.4.2.2 Multivariate Evidence

Table 1.6 reports the estimates of β in equations (1.1) and (1.2), derived in section 1.4.1. In a first step, all regressions are run without control variables but with region fixed effects and afterwards stepwise with the entire set of control variables and their interaction with the cumulative real estate prices. The estimation of the linear regressions for the *balanced panel 2008-2014* goes along with the univariate results. For this time period, there is evidence that the collateral channel was used.

Table 1.6: Regression Results Firm Perspective 2008-2014

2008-2014	Mortgage Growth ($\Delta MORTG_i^l$) (1.1)			Business Investment Growth ($\Delta BINV_i^l$) (1.2)		
Owner x Δp	0.276*	0.282*	0.287*	0.196**	0.194**	0.176**
	(0.17)	(0.17)	(0.17)	(0.1)	(0.09)	(0.09)
Owner	-0.048	-0.043	-0.044	-0.068	-0.045	-0.040
	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	2,474	2,474	2,474	2,474	2,474	2,474
Adj. R2	0.00	0.00	0.00	0.00	0.10	0.10
Root MSE	0.22	0.22	0.22	0.13	0.12	0.12

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (1). Dependent variables are the average of annual mortgage growth (1.1) and business investment growth (1.2) between 2008 and 2014. Δp is the cumulative residential real estate price for the first 4 years. Control variables are explained in section 1.4.1. The sample consists of a balanced panel of 2'474 SMEs located in 65 MS-regions that reported their financial statements between 2008 and 2014. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

The estimates of β for the dependent variable *mortgage growth* of equation (1.1) are positive and statistically significant at the 10% confidence level across all specifications. This point estimate is also stable across specifications. The estimation of (1.1) supports the hypothesis that SMEs holding RRE use the collateral increase to issue higher mortgages. A 1%-point increase in RRE price growth leads to a 0.29%-point increase in mortgage growth by RRE owners as compared to non-owners. Using two firms in two different regions illustrates this effect. Comparing a firm in a low price region with 36% price growth (25%-quantile) with a firm in a high price region with 47% price growth (75%-quantile). In the high price region, the difference in the mortgage growth rate between RRE owners and non-owners is 3.2%-points larger than in the low price region ([47%-36%]*0.29).

The estimation of equation (1.2) shows a positive and statistically significant relation between *business investment growth* and RE price developments dependent on RRE holdings. This supports the hypothesis that RRE-holdings influence the investment dynamics during the boom phase for real estate prices. A 1%-point increase in RRE price growth leads to a 0.18%-point increase in business investments by RRE owners relative to non-owners. Again, I compare a firm in a low price region with a price growth of 36% with a firm in a high price region and 47% in price growth. The difference in the business investment growth rate between RRE owners and non-owners in the high price growth is 2%-points larger than in the low price region. Using an average SME as example illustrates the effect: In 2008 to 2014 the mean of yearly business investments with respect to business core assets is 7% (Appendix A4). Assuming an RRE owner with CHF 3 Mio. in total assets and CHF 2 Mio. in business assets, she/he will invest CHF 140,000 p.a. in business assets. I use the difference of 2%-point as calculated above between owner and non-owners in a high versus low price growth region. This means an annual difference of CHF 40'000 in business investments for an average SME.

The estimation of the linear regressions for the balanced panel *2002-2008* support the findings from the univariate analysis as well. In this time period, there is no evidence of the collateral channel usage. Table 1.7 reports the estimates for β in equations (1.1) and (1.2). Neither *mortgage* (1.1), nor *business investment growth* (1.2) show any statistical significance. It appears that changes in mortgages and business investments do not primarily depend on the RRE ownership and real estate prices.

Table 1.7: Regression Results Firm Perspective 2002-2008

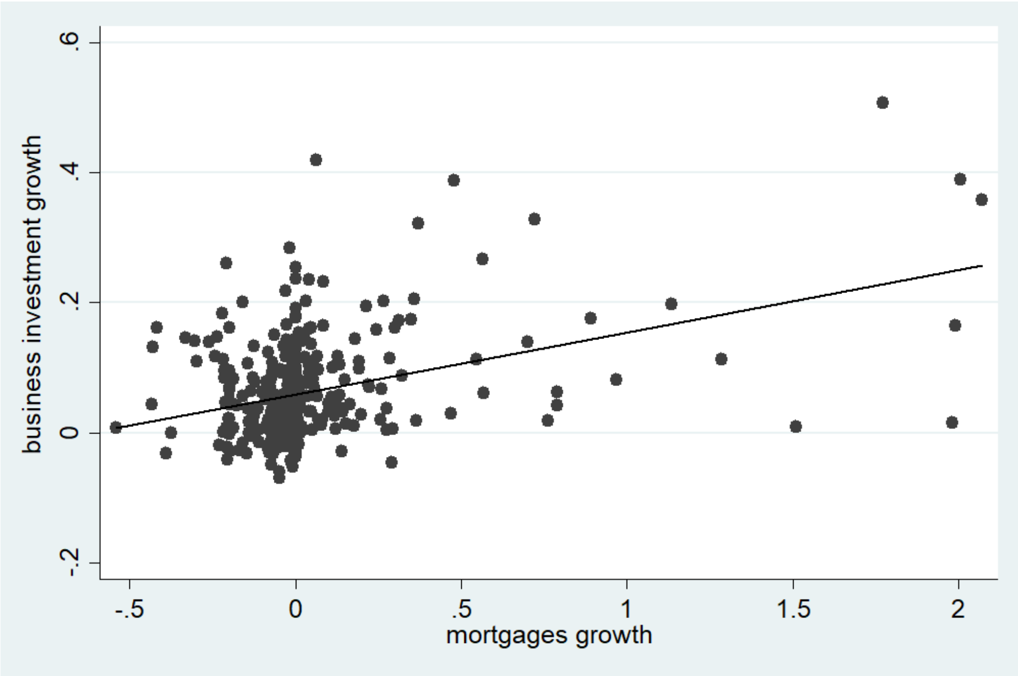
2002-2008	Mortgage Growth $(\Delta MORTG_i^l)$ (1.1)			Business Investment Growth $(\Delta BINV_i^l)$ (1.2)		
Owner x Δp	-0.416 (0.21)	-0.413 (0.21)	-0.430 (0.22)	0.087 (0.17)	0.099 (0.16)	0.058 (0.16)
Owner	0.059 (0.04)	0.061 (0.04)	0.065 (0.04)	-0.055 (0.03)	-0.036 (0.03)	-0.018 (0.03)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	2,461	2,461	2,461	2,461	2,461	2,461
Adj. R2	0.00	-0.01	-0.01	0.20	0.27	0.27
Root MSE	0.17	0.17	0.17	0.13	0.12	0.12

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (1). Dependent variables are the average of annual mortgage growth (1.1) and business investment growth (1.2) between 2002 and 2008. Δp is the cumulative residential real estate price for the first 4 years. Control variables are explained in section 1.4.1. The sample consists of a balanced panel of 2'461 SMEs located in 54 MS-regions that reported their financial statements between 2002 and 2008. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

One reason for the insignificance of equations (1.1) might be better access to financing for SMEs through banks before the financial crisis. This theory supports the concerns about credit constraints for SMEs (OECD, 2014). Time itself may explain the insignificance of (1.1) as well. Only after a long time period of steady real estate increase, RRE owners may systematically use the collateral channel and ask for higher mortgages which lead to significance of (1.1) in the *2008-2014* panel. The significantly declining EUR/CHF rate after 2008 may have had an impact on the collateral usage as well as export oriented firms became more cost sensitive. Hence, the use of residential collateral is favored over commercial mortgages or unsecured bank loans, due to the lower loan rate. Another explanation might be the state of the economy itself. Between *2002* and *2008*, the GDP of Switzerland increased by 26% compared to only 9% for the time period between *2008* and *2014*. The positive economic environment before 2008 may have influenced investments independent of RRE ownership.

The results from equation (1) imply a potential connection in *2008-2014* between raising mortgages and business investments dependent on RRE growth whereas in *2002-2008* there is none. However, given equation (1), the relation between the mortgage increases and business investments is not directly observable. This is intentional and based on the time lag between funding and investments. Therefore, equation (1.2) shows the gross effect of RE prices on business investments dependent on whether or not a company is holding RRE property. The positive effect of RE price increases on business investments derives not only from mortgage increases. Banks may allow deferring mortgage amortizations due to the RRE increase, which, in turn, may have a positive impact on business investments. In order to analyze a potential direct relation between mortgage funding and investments in productive capacity, I use a sub-sample of all RRE-owners in 2008 for the *2008-2014* panel. Figure 1.5 shows the relation between the two dependent variables *mortgage growth* and *business investment growth*.

Figure 1.5: Relation between Mortgage Growth and Business Investment Growth



Notes: This figure shows a scatter plot of the dependent variables mortgage growth $(\Delta MORTG_i^l)$ and business investment growth $(\Delta BINV_i^l)$ from equation (1). The sample is restricted to RRE-owners in 2008 of the 2008-2014 panel. A linear regression (OLS) of both variables results in an adjusted R2 of 0.16 and positive β which is significant at the 1% level.

Regressing *mortgage growth* on *business investment growth* with a linear regression (OLS) results in a positive and highly significant β of the *mortgage growth* and vice-versa. The Pearson correlation coefficient is 0.21. This emphasizes that there is a positive correlation and connection between funding by mortgages and investing in productive capacity, supporting H1 and H3.

1.4.2.3 Robustness

Bank loans can be divided into mortgages (collateralized by real estate), bank loans collateralized by other securities and unsecured bank loans. If SMEs use the residential collateral channel, bank loans excluding mortgages will be unaffected by the real estate price development. Therefore, I use a new outcome variable *other bank loans growth* $(\Delta BAKL_i^l)$ equally defined as mortgage growth rate, which includes the unsecured and non-real estate collateralized loans to firms. Based on equation (1), appendix A6 shows the results of equation (1.1) with $\Delta BAKL_i^l$ as dependent variable. All specifications show insignificant coefficients for *other bank loans growth*, which further verify H1. This supports my main finding that RRE owners use their collateral growth to expand their mortgage borrowing.

As already mentioned in section 1.3.1, there are many SMEs which hold commercial real estate (CRE owners). Mortgage growth and business investments may be driven by commercial real estate collateral. To ensure the robustness of the previous results, I use the same equation (1) but compare CRE owners with non-CRE owners. Therefore, I replace the residential ownership $(Owner_i^l)$ with commercial ownership $(CREowner_i^l)$. Again, the coefficient β captures the relation of holding CRE and residential real estate price growth on mortgage growth and business investments. Appendix A7 shows all estimated regressions. Neither *mortgage* (1.1), nor *business investment growth* (1.2), nor *other bank loans* (1.3) show a significant positive relation to commercial property owners interacted with real estate prices. This result supports H1 and H3, that residential real estate prices influence residential property owners.

Despite the many control variables, the observation that mortgages and investments of RRE owners are influenced by RE prices may be driven by other unobserved variables. To further address this concern, I use a sub-sample of the *2008-2014* panel, matching all 363 RRE owners with similar non-owners. Matching criteria are industry affiliation and total assets (firm size). There are 648 firms of similar size as measured by total assets within the same industry, that serve as a new control group. Using this sub-sample, all dependent variables (1.1) to (1.3) of equation (1) are estimated again. Appendix A8 shows all estimated regressions. Using this more restrictive approach, the estimates of β for *mortgage growth* (1.1) and *business investment growth* (1.2) are still positive and statistically significant, supporting the existing results. Compared to table 1.7, this matched sub-sample indicates a larger magnitude of the collateral effect for dependent mortgage demand (1.1) as well as a larger effect on the change in business investments (1.2).

So far, the methodology is based on a cross-sectional approach as used by Schmalz et al. (2017). Following Chaney et al. (2012), I introduce a panel fixed effects model to further analyze the robustness of the findings. Contrary to Chaney et al. (2012), I use an owner dummy variable interacted with the real estate price change instead of the market value of the property itself. Furthermore, the owner dummy variable is lagged due to the time elapsing between the experienced price increase and materialization in mortgage demand. Appendix A9 shows the estimated results of equation (3). Again, mortgage growth is positively influenced by real estate prices for those firms that own RRE. This finding is stable across different specifications and significant at the 5% level. Compared to the results of equation (1), the magnitude of β is higher. Furthermore, the panel regression indicates that real estate prices are positively and statistically significant related to the *business investment growth*. RRE owners increase their business investments to a larger extent if they experience a higher RE price. Accordingly, this yearly panel analysis support the existing results.

The main analysis does not differentiate between intensive and extensive margin. In order to analyze the intensive margin, I replicate my main findings in table 1.6 (2008-2014 sample) using equation (1) and only firms that report a mortgage in 2008. Appendix A10 shows the estimated coefficients. The magnitude of β for both dependent variables *mortgage growth* (1.1) and *business investment growth* (1.2) are higher. Compared to the main results in table 1.6, the statistical significance is the same or higher.

1.5 Residential Real Estate held by Entrepreneurs

Not all entrepreneurs hold their residential properties, especially their private homes, in the companies' financial records. Using the entrepreneur's private homes as collateral for firm investments is the second channel explained in section 1.2.2.

1.5.1 Empirical Strategy

The second goal of this research paper is to identify the causal effect of privately held residential property and its collateral value growth on an entrepreneur's investment in the firm and the firm's business investments. The empirical strategy is based on the assumption that if an entrepreneur faces a substantial value increase in their private home, the entrepreneur may support his own firm with a loan, and this *"shareholder liability"* materializes in the financial statement of the firm. Alternatively, the entrepreneur may directly increase the *"equity"* of the firm with the proceeds from the private mortgage. Hence, I am interested in paid-in equity (i.e. common capital) excluding retained earnings. The willingness of an entrepreneur to support its own SME with private funds is based on the strong correlation between entrepreneurial wealth and the propensity to start or keep a business (i.e., Evans & Jovanovic, 1989; Holtz-Eakin et al., 1993; Schmalz et al., 2017). Following this intuition, it is most likely that a substantive share of entrepreneurs possesses residential real estate. However, the main concern about the identification is the missing private information of the entrepreneurs' residential holdings and determining whether some proceeds of the private mortgage were used by the firm. Schmalz et al. 2017 used proprietary data stemming from a panel survey (French Labor Force Survey) where people had to fill in whether they owned property or not. Similarly Bahaj et al. 2016 used proprietary data which included the mortgage origination details with the borrowers' date of birth which they matched with the SME directors birth date. In Switzerland, neither panel survey data from entrepreneurs nor mortgage origination data that contains this information is available. Due to the missing information of the firms' entrepreneurs holding residential real estate privately, my analysis focuses on the differences between firms in low price growth regions with firms in high price growth regions. Similar to the empirical strategy of the firm perspective in section 1.4, I assume that the private property of the entrepreneur is located in the same MS-region as the firm.

The linear regression model (2) estimates the impact of residential real estate growth on *paid-in equity*, *shareholder liability* and *business investment growth*. For this regression, I use both balanced panels (*2002-2008; 2008-2014*). Let *i* be an SME, *l* its location:

$$\Delta Y_i^l = \alpha + \beta \cdot priceRegion^l + \theta \cdot controls_i + \varepsilon_{i,l} \tag{2}$$

$$\Delta Y_i^l \coloneqq \Delta EQTY_i^l \tag{2.1}$$

$$\Delta SHLIAB_i^l \tag{2.2}$$

$$\Delta BINV_i^l \tag{2.3}$$

where $\Delta EQTY_i^l$, $\Delta SHLIAB_i^l$ and $\Delta BINV_i^l$ are the average growth of paid-in equity, shareholder liability and business investments of the four most recent years for each panel (*2004-2008* and *2010-2014*). Again, the first two years of each panel are not considered for the dependent variables because of the time elapsing between the experienced price increase and materialization in the balance sheet. $PriceRegion^l$ is a dummy equal to one if the SME is based in a high price growth region (dependent on the MS-region *l*), using the aforementioned price regions (section 1.3.2). $Controls_i$ include the log of total assets, the equity ratio, return on assets and return on equity for firm *i* in *2002* as well as *2008*.

The dummy variable $priceRegion^l$ is the main variable of interest. The coefficient β shows whether a firm in a high price growth region increases its paid-in equity or shareholder liability to a larger extent than a SME in a low price growth region. The estimation relies on the comparison of low versus high price growth regions. Therefore, equations (2.1) and (2.2) are related to the hypothesis in section 1.2 as follows:

H2: "Equity / Shareholder Liability":	H2$_0$: $\beta = 0$	Entrepreneurs of small firms do not increase private mortgages dependent on the RRE price to raise firm capital.
	H2$_A$: $\beta > 0$	Entrepreneurs of small firms use the RRE price increase to raise private mortgages and transfer the funds to the firm.

1.5.2 Results

1.5.2.1 Univariate Evidence

Table 1.8 compares the differences between low and high price regions for all three dependent variables in the 2008-2014 panel. The share of firms which increased these variables are shown in italics. Despite the very small differences, all three variables show systematically higher averages for firms in the high price regions. The same is true for the share of firms which raised paid-in equity. In high price regions there are 2.1% more firms that increased their equity than in low price regions. This supports the empirical strategy that firms in high price regions profit from entrepreneurial activity which may be related to the collateral increase of private homes in the 2008-2014 panel.

Table 1.8: Univariate Evidence of Entrepreneur Behavior 2008-2014

2008-2014	high price region (mean)	low price region (mean)	Δ (high - low)
Equity (paid-in) Growth $(\Delta EQTY_i^l)$	0.03	0.01	0.02
Share of firms which raised *paid-in equity*	*13.7%*	*11.6%*	*2.1%*
Shareholder Liability Growth $(\Delta SHLIAB_i^l)$	0.01	0.00	0.01
Share of firms which increased *shareholder liability*	*12.8%*	*13.4%*	*-0.6%*
Business Investment Growth $(\Delta BINV_i^l)$	0.09	0.08	0.01
Share of firms which increased *business investments*	*89.8%*	*89.9%*	*0%*

Notes: The table reports the dependent variables from equation (2) split into the RRE price growth regions of panel 2008-2014.

Table 1.9 shows the dependent variables by price regions for the *2002-2008* panel. Similarly to the firm collateral channel 1 in the firm perspective (section 1.4.1), there is no indication of obvious usage of the collateral channel 2 in the pre-crisis panel. No dependent variables show any positive difference between high versus low price growth regions.

Table 1.9: Univariate Evidence of Entrepreneur Behavior 2002-2008

2002-2008	high price region (mean)	low price region (mean)	Δ (high - low)
Equity (paid-in) Growth $(\Delta EQTY_i^l)$	0.02	0.02	0.00
Share of firms which raised *paid-in equity*	*11.9%*	*13.7%*	*-1.8%*
Shareholder Liability Growth $(\Delta SHLIAB_i^l)$	-0.01	-0.01	0.00
Share of firms which increased *shareholder liability*	*12.7%*	*10.3%*	*2.4%*
Business Investment Growth $(\Delta BINV_i^l)$	0.07	0.07	0.00
Share of firms which increased *business investments*	*91.0%*	*90.4%*	*0.6%*

Notes: The table reports the dependent variables from equation (2) split into the RRE price growth regions of panel 2002-2008.

1.5.2.2 Multivariate Evidence

This section reports the results of regressions (2.1) to (2.3) as derived in section 1.5.1. Table 1.10 and table 1.11 report the estimates for β in equations (2.1) to (2.3) for the two different time periods. In the first step, all regressions are run without any control variables. In the second step, all regressions are run with the entire set of control variables. The results correspond with those in the univariate analysis.

Table 1.10: Regression Results Entrepreneur Perspective 2008-2014

2008-2014	Equity Growth $(\Delta EQTY_i^l)$ (2.1)		Shareholder Liability Growth $(\Delta SHLIAB_i^l)$ (2.2)		Business Investment Growth $(\Delta BINV_i^l)$ (2.3)	
HighPriceRegion (dummy=1)	0.017** (0.01)	0.014* (0.01)	0.008 (0.01)	0.008 (0.01)	0.003 (0.01)	0.002 (0.01)
Controls	no	yes	no	yes	no	yes
Observations	2,474	2,474	2,474	2,474	2,474	2,474
Adj. R2	0.00	0.05	0.00	0.00	0.00	0.12
Root MSE	0.23	0.23	0.22	0.22	0.13	0.12

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (2). Dependent variables are the average of paid-in equity growth (2.1), shareholder liability growth (2.2) and business investment growth (2.3) between 2008 and 2014. Control variables are explained in section 1.5.1. The sample consists of a balanced panel 2008-2014 with 2'474 SMEs located in 65 MS-regions. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

The estimate of β for the dependent variable *equity growth* (2.1) is positive, stable and statistically significant at the 10% confidence level for the panel *2008-2014*. This indicates that entrepreneurs use the collateral increase of privately held RRE to issue higher private mortgages and then transfer these funds to the equity of the company. Comparing two firms illustrate the differences. SMEs on average reported a mean equity growth of 0.02. A firm in a high price region shows 0.014 more equity growth than a firm in a low price region. On average this translates to approx. 70% more funds to equity in high price regions. Although *shareholder liability* (2.2) and *business investment growth* (2.3) are positively related to high price regions, these coefficients are not significantly different from zero on the required confidence level.

Similar to the univariate analysis and firm perspective (section 1.4), table 1.11 shows neither statistical significance nor a stable positive relation for the dependent variables of the pre-crisis data sample *2002-2008*. The same economic reasons as for channel 1 (section 1.4.2.2) potentially support these findings. Access to other funding sources might have been easier accessible in the pre-crisis period or cost sensitivity of firms in terms of loan rates was lower before 2008.

Table 1.11: Regression Results Entrepreneur Perspective 2002-2008

2002-2008	Equity Growth $(\Delta EQTY_i^l)$ (2.1)		Shareholder Liability Growth $(\Delta SHLIAB_i^l)$ (2.2)		Business Investment Growth $(\Delta BINV_i^l)$ (2.3)	
High Price Region (dummy=1)	-0.0062 (0.01)	-0.004 (0.01)	0.001 (0.01)	0.001 (0.01)	-0.005 (0.01)	0.000 (0.01)
Controls	no	yes	no	yes	no	yes
Observations	2,461	2,461	2,461	2,461	2,461	2,461
Adj. R2	0.00	0.01	0.00	0.00	0.00	0.11
Root MSE	0.21	0.21	0.22	0.22	0.14	0.14

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (2). Dependent variables are the average of paid-in equity growth (2.1), shareholder liability growth (2.2) and business investment growth (2.3) between 2002 and 2008. Control variables are explained in section 1.5.1. The sample consists of a balanced panel 2002-2008 with 2'461 SMEs located in 54 MS-regions. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

Not all firms report shareholder liabilities. In order to analyze the intensive margin, I replicate my main findings in table 1.10 (2008-2014 sample) using equation (2) and only firms that report shareholder liability in 2008. Appendix A12 shows the estimated coefficients. The magnitude of β for both dependent variables *shareholder liability growth* (2.2) and *business investment growth* (2.3) are slightly higher compared to the main analysis (table 1.10). Furthermore, the relation between *shareholder liability growth* and high price regions is statistical significant at the 10 percent level.

1.5.2.3 Alternative Specification

Based on the strong correlation between entrepreneurial wealth and the propensity to start or keep a business (i.e., Evans & Jovanovic, 1989; Holtz-Eakin et al., 1993; Schmalz et al., 2017), the question arises, what drives the willingness of entrepreneurs to invest private funds into their firms. The differentiation between the legal forms of firms is an important perspective for entrepreneurs. Many Swiss SMEs have limited liability companies such as Ltd. (“AG”) or LLC (“GmbH”). However, the smallest companies and “*one man businesses*” are often sole proprietorship (“Einzelfirma”) companies. In the case of limited companies, assets such as private homes and other real estate properties are clearly separated between private wealth and the firm’s wealth. This is not the case for the sole proprietorship, where the proprietor is liable with the entire private wealth for the firm’s activity. The interdependence between entrepreneur and sole proprietorships is much higher than for other legal forms.

Therefore, based on the high interdependence in sole proprietorships, these entrepreneurs are more likely to invest in their firms using private mortgages. Following this assumption, the balanced sample *2008-2014* is split by the legal form “sole proprietorships”. In total, there are 318 sole proprietorships of 2,474 firm in the sample. I use a similar difference-in-difference approach as from the firm perspective (section 1.4.1). The main differences from equation (1) are the interaction term and the dependent variables. The interaction term consists of two independent dummy variables. $(SoleProprietor_{i,t})$ takes the value one if it is a sole proprietorship and zero otherwise. $(priceRegion^{l})$ equals one if the SME is located in a high price growth region and zero otherwise.

The identification strategy is based upon the idea that when the SME is in a high price region, sole proprietorships experience a substantial increase in the value of available collateral. This increase may be used by the entrepreneur to raise its equity and invest into the firm. Shareholder liabilities are unlikely to be used by an entrepreneur of a sole proprietorship, because the proprietor is liable with its private wealth anyway. Therefore, this debt financing instrument is equal to the character of equity in terms of financial risk taking. That is why only 8 of 318 sole proprietorships used shareholder liability as financing instrument. Based on these considerations, I write:

$$\begin{aligned}\Delta Y_i^l \quad &= \quad \alpha + \beta \cdot SoleProprietor_{i,t} \times priceRegion^l \\ &\quad + \theta \cdot SoleProprietor_{i,t} + \zeta \cdot priceRegion^l \\ &\quad + \gamma \cdot controls_{i,t} + \tau \cdot controls_{i,t} \times \Delta p^l_{t\rightarrow(t+4)} + \delta_l + \varepsilon_{i,l}\end{aligned} \tag{4}$$

$$\Delta Y_i^l \quad \coloneqq \quad \left(\Delta EQTY_{i,t}^l;\ \Delta BINV_{i,t}^l\right) \tag{4.1; 4.2}$$

Appendix A13 shows all estimated regressions for equation (4). *Paid-in equity growth* (4.1) is substantially larger for proprietors in high price regions as compared to other companies (i.e. limited liability companies) in low price regions. When comparing a proprietor in a high price region with a limited liability company in a low price region, the difference in the *paid-in equity growth* between these firms is 11.1%-points larger. Beside this supportive result for H2, there is no statistical evidence that these funds are primarily used for business investments. There is a positive relation of the interacted sole proprietorships in a high price region with *business investment growth* (4.2), but its coefficient is not significantly different from zero.

1.6 Conclusion

This research paper studies whether and to what extent residential real estate is used as collateral and how it influences the investment behavior of Swiss SMEs. I find evidence that both, privately held residential real estate of entrepreneurs and real estate held by SMEs, are used to increase mortgages and invest in productive capacity of the firm in the period from 2008 to 2014. RRE owners demand significantly higher mortgages than non-owners. Furthermore, firms in high price growth regions, whose entrepreneurs face a larger increase of their potential residential property, report a significantly higher paid-in equity growth as compared to SMEs in low price growth regions. This is strong evidence that entrepreneurs use their privately owned homes as collateral to fund their own firms with additional equity. This positive relation between high price growth and paid-in equity is even stronger for sole proprietorships.

In terms of investment activity, there is ample evidence that holding RRE and its price increase positively influence business investments. It seems that holding RRE is a “security margin” for SMEs and entrepreneurs, trying to maintain or even raise their productive investment levels across time. Firms without such a "security margin" report lower business investment rate in uncertain times (i.e., the financial crisis).

For the period 2002-2008, there is no evidence of the residential real estate channel. Access to other funding sources may have been more easy or investments may have been more independent to real estate prices due to the strong and positive economic expansion in this time period. On the other hand, increasing cost sensitivity of export oriented SMEs due to the decline of EUR/CHF-exchange rate after 2008, may have fostered the demand for cheaper residential mortgages.

Understanding the impact of real estate developments on bank funding and investments by SMEs may further help to anticipate the effects that changes in residential real estate prices have on the SME economy. In 2016, residential real estate prices began to remain at constant levels or even decrease slightly. Based on this research paper's results, a decrease in residential real estate may negatively influence the SMEs' business investments through the collateral channel.

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1.8 Appendix

A1: Sample Construction

A1.1: Observation Exclusion

After the exclusions of certain financial statements and firms described below, I end up with an *unbalanced* panel of firms from four banks which consist of 12'415 unique SMEs, containing a total of 74'992 financial statements and firm years. For the purpose of this paper, the financial statements with the following characteristics were dropped:

1) Consolidated financial statements	7'723
2) Financial statements without EBITDA	3'164
3) Financial statements with other currency than CHF	161
4) Financial statements with US GAAP, IFRS, others	600
5) Financial statements with Total Assets CHF >300 Mio.	2'018
6) Financial statements with Total Liabilities and Equity CHF >300 Mio.	2
7) Financial statements with Equity CHF <0	6'668
8) Pure real estate firms (real estate as business purpose such as rent, buy and sell properties)	13'985
9) Financial statements with more than 250 employees	1'283
10) Financial statements with FY = 2015	324
11) Financial statements with Equity > Total Assets	3'095
12) Financial statements with imbalance between assets and liabilities	251
13) Financial statements with P+L (sales) < CHF 100'000	998
14) Financial statements duplicate	1'072
15) Financial statements bank internally not 4-eyes checked	19'112

A1.2: SME Accounting Data Overview

FY	Number of Financial Statements unbalanced panel (full sample)	Balanced panel 2002-2014 (sub-sample)	Balanced panel 2002-2008 (sub-sample)	Balanced panel 2008-2014 (sub-sample)
2002	3'900	1'110	2'461	--
2003	4'113	1'110	2'461	--
2004	4'364	1'110	2'461	--
2005	5'702	1'110	2'461	--
2006	5'822	1'110	2'461	--
2007	6'038	1'110	2'461	--
2008	6'334	1'110	2'461	2'474
2009	6'712	1'110	--	2'474
2010	6'786	1'110	--	2'474
2011	6'963	1'110	--	2'474
2012	6'946	1'110	--	2'474
2013	6'567	1'110	--	2'474
2014	4'745	1'110	--	2'474
Firms	12’415	1'110	2'461	2'474
MS-regions	90	38	54	65

Notes: The table presents the distribution of the financial statements in the SME’s accounting data.

A2: Variable Definition

Variable	Definition
Total Assets	Total assets
Other Bank Loan	short and longterm bank loans
Mortgages	Mortgages (real estate collateralized bank loan)
Shareholder Liability	Shareholder liabilities
EBITDA	Earnings before interest tax and depreciation
longterm assets	Property plant and equipment + investments + other longterm assets
Business Investments	longterm assets without non-business assets
Return on Sales (RoS)	EBITDA / sales
Return on Assets (RoA)	EBITDA / total assets
Return on Equity (RoE)	(profit or loss) / equity
EquityRatio	Equity / total assets

Standardized Variable	Definition
Mortgage Growth	See next section A2.1
Other Bank Loans Growth	
Business Investment Growth	
Equity (paid in) Growth	
Shareholder Liability Growth	

Log of Total Assets	Logarithm of total assets
PPE_TA	Property plant and equipment / lagged total assets
Debt_TA	Interest bearing debt (i.e. mortgages, bank loans) / lagged total assets
Mortgage_TA	Mortgages / lagged total assets
ShareholderLiability_TA	Shareholder liabilities / lagged total assets
ResidentialProperty_TA	Book value of residential real estate / lagged total assets

A2.1: Variables used in regression model in section 1.4:

Equation (1) with time notation for the corresponding *2008-2014* panel.

$$\Delta Y^l_{i,(2010\rightarrow 2014)} = \alpha + \beta \cdot Owner_{i,2008} \times \Delta p^l_{(2008\rightarrow 2012)} + \theta \cdot Owner_{i,2008} + \zeta \cdot \Delta p^l_{(2008\rightarrow 2012)} + \gamma \cdot controls_{i,2008} + \tau \cdot controls_{i,2008} \times \Delta p^l_{(2008\rightarrow 2012)} + \delta_l + \varepsilon_{i,l} \quad (1)$$

$$\Delta Y^l_{i,(2010\rightarrow 2014)} \coloneqq \Delta MORTG^l_{i,(2010\rightarrow 2014)} \quad (1.1)$$

$$\Delta BINV^l_{i,(2010\rightarrow 2014)} \quad (1.2)$$

$$\Delta BAKL^l_{i,(2010\rightarrow 2014)} \quad (1.3)$$

The following variable definitions correspond to the *2008-2014* panel. The same definitions apply for the *2002-2008* panel analysis.

$$\Delta MORTG^l_{i,(2010\rightarrow 2014)} = \left[\sum_{t=1}^{4}\left(\frac{mortgages^l_{i,(2009+t+1)} - mortgages^l_{i,(2009+t)}}{mortgages^l_{i,(2009+t)}}\right)\right] * \frac{1}{4}$$

= average of mortgage growth over 4 years (2010-2014), standardized to lagged mortgages

$$\Delta BAKL^l_{i,(2010\rightarrow 2014)} = \left[\sum_{t=1}^{4}\left(\frac{otherBankloans^l_{i,(2009+t+1)} - otherBankloans^l_{i,(2009+t)}}{otherBankloans^l_{i,(2009+t)}}\right)\right] * \frac{1}{4}$$

= average of bank loan growth over 4 years (2010-2014), standardized to lagged bank loans

$$\Delta BINV^l_{i,(2010\rightarrow 2014)} = \left[\sum_{t=1}^{4}\left(\frac{businessInvestments^l_{i,(2009+t+1)} - businessInvestments^l_{i,(2009+t)}}{businessAssets^l_{i,(2009+t)}}\right)\right] * \frac{1}{4}$$

= average of business investment growth over 4 years (2010-2014), standardized to lagged business assets (=total fixed assets without non-business-assets).

$$businessInvestments^l_{i,(2010)} = \left(businessAssets_{i,(2010)} - busAssets_{i,(2009)} + business\_depreciation_{i,(2010)}\right)$$

$Owner_{i,2008}$ = dummy variable, 1 = SME owns RRE (RRE-owner), 0 = no RRE

δ_l = region fixed effects where *l* is a MS-region

$$\Delta p^l_{(2008\rightarrow 2012)} = \frac{RE\_price\_index^l_{(2012)} - RE\_price\_index^l_{(2008)}}{RE\_price\_index^l_{(2008)}}$$

= cumulative residential real estate growth in region *l* over 4 years (2008-2012) standardized to residential real estate price at time *t*

$controls_{i,2008}$ = log of total assets, equity ratio, return on assets, return on equity

$\varepsilon_{i,l}$ = error term is clustered at the location and firm level

A2.2: Variables used in regression models in section 1.5:

The following variable definitions correspond to the *2008-2014* panel. The same definitions apply for the *2002-2008* panel analysis.

$$\Delta EQTY_{i,(2010\rightarrow 2014)}^{l} = \left[\sum_{t=1}^{4}\left(\frac{paid\_inEquity_{i,(2009+t+1)}^{l} - paid\_inEquity_{i,(2009+t)}^{l}}{paid\_inEquity_{i,(2009+t)}^{l}}\right)\right] * \frac{1}{4}$$

= average of paid-in equity growth over 4 years (2010-2014), standardized to lagged paid-in equity

$$\Delta SHLIAB_{i,(2010\rightarrow 2014)}^{l} = \left[\sum_{t=1}^{4}\left(\frac{ShareholderLiability_{i,(2009+t+1)}^{l} - ShareholderLiability_{i,(2009+t)}^{l}}{ShareholderLiability_{i,(2009+t)}^{l}}\right)\right] * \frac{1}{4}$$

= average of shareholder liability growth over 4 years (2010-2014), standardized to lagged paid-in equity

$controls_{i,2008}$ = log of total assets, equity ratio, return on assets, return on equity

A3: Geographical Classification after BFS

MS-Regionen 1- 106

1 Zürich
2 Glattal-Furttal
3 Limmattal
4 Knonaueramt
5 Zimmerberg
6 Pfannenstiel
7 Zürcher Oberland
8 Winterthur
9 Weinland
10 Zürcher Unterland
11 Bern
12 Erlach-Seeland
13 Biel/Bienne
14 Jura bernois
15 Oberaargau
16 Burgdorf
17 Oberes Emmental
18 Aaretal
19 Schwarzwasser
20 Thun
21 Saanen-Obersimmental
22 Kandertal
23 Oberland-Ost
24 Grenchen
25 Laufental
26 Luzern
27 Sursee-Seetal
28 Willisau
29 Entlebuch
30 Uri
31 Innerschwyz
32 Einsiedeln
33 March
34 Sarneraatal
35 Nidwalden
36 Glarner Unterland
37 Glarner Hinterland
38 Zug
39 La Sarine
40 La Gruyère
41 Sense
42 Murten/Morat
43 Glâne-Veveyse
44 Olten
45 Thal
46 Solothurn
47 Basel-Stadt
48 Unteres Baselbiet
49 Oberes Baselbiet
50 Schaffhausen
51 Appenzell A.Rh.
52 Appenzell I.Rh.
53 St.Gallen
54 Rheintal
55 Werdenberg
56 Sarganserland
57 Linthgebiet
58 Toggenburg
59 Wil
60 Chur
61 Prättigau
62 Davos
63 Schanfigg
64 Mittelbünden
65 Viamala
66 Surselva
67 Engiadina Bassa
68 Oberengadin
69 Mesolcina
70 Aarau
71 Brugg-Zurzach
72 Baden
73 Mutschellen
74 Freiamt
75 Fricktal
76 Thurtal
77 Untersee
78 Oberthurgau
79 Tre Valli
80 Locarno
81 Bellinzona
82 Lugano
83 Mendrisio
84 Lausanne
85 Morges
86 Nyon
87 Vevey
88 Aigle
89 Pays d'Enhaut
90 Gros-de-Vaud
91 Yverdon
92 La Vallée
93 La Broye
94 Goms
95 Brig
96 Visp
97 Leuk
98 Sierre
99 Sion
100 Martigny
101 Monthey
102 Neuchâtel
103 La Chaux-de-Fonds
104 Val-de-Travers
105 Genève
106 Jura

A4: Summary Statistics Firm Perspective: RRE vs non-RRE owner

A4.1 2002-2008 Balanced Panel

Summary Statistics: **RRE-owner** (number of firms: 437)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Mortgage Growth	-0.0064	0.3244	-0.0402	-0.0067	0.0000	3'059
Other Bank Loans Growth	0.0073	0.4089	0.0000	0.0000	0.0000	3'059
Business Investment Growth	0.0396	0.1206	0.0000	0.0129	0.0481	3'059
Equity (paid in) Growth	0.0394	0.3913	0.0000	0.0000	0.0000	3'038
Shareholder Liability Growth	-0.0141	0.3219	0.0000	0.0000	0.0000	3'059
Log of Total Assets	8.2459	1.1366	7.4708	8.1548	9.0105	3'059
PPE_TA	0.3756	0.2481	0.1576	0.3698	0.5566	3'059
Debt_TA	0.3403	0.2706	0.0910	0.3408	0.5252	3'059
Mortgage_TA	0.3237	0.2622	0.0314	0.3243	0.5091	3'059
ShareholderLiability_TA	0.0260	0.0651	0.0000	0.0000	0.0078	3'059
ResidentialProperty_TA	0.2785	0.2516	0.0586	0.2172	0.4409	3'059
Equity Ratio	0.2986	0.1733	0.1667	0.2632	0.4060	3'059
Return on Assets (RoA)	0.0700	0.0851	0.0255	0.0587	0.1007	3'059
Return on Sales (RoS)	0.0841	0.1860	0.0275	0.0609	0.1095	3'059
Return on Equity (RoE)	0.0676	0.4018	0.0032	0.0433	0.1270	3'059
Number of employees	26	35	5	13	29	3'059

Notes: The table presents summary statistics for firms which own residential real estate. The sample period is 2002-2008.

Summary Statistics: **RRE-non-owner** (number of firms: 2'024)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Mortgage Growth	0.0058	0.3650	-0.0194	0.0000	0.0000	14'168
Other Bank Loans Growth	0.0054	0.3373	0.0000	0.0000	0.0000	14'168
Business Investment Growth	0.0758	0.2907	0.0000	0.0219	0.0754	14'168
Equity (paid in) Growth	0.0224	0.3511	0.0000	0.0000	0.0000	14'168
Shareholder Liability Growth	-0.0026	0.4393	0.0000	0.0000	0.0000	14'168
Log of Total Assets	7.6095	1.4463	6.6053	7.5186	8.5734	14'168
PPE_TA	0.4599	0.2941	0.1810	0.4668	0.7123	14'168
Debt_TA	0.2099	0.3027	0.0000	0.0041	0.3988	14'168
Mortgage_TA	0.1898	0.2874	0.0000	0.0000	0.3759	14'168
ShareholderLiability_TA	0.0356	0.0935	0.0000	0.0000	0.0000	14'168
Equity Ratio	0.3606	0.2069	0.2038	0.3268	0.4879	14'168
Return on Assets (RoA)	0.1107	0.1270	0.0463	0.0903	0.1588	14'168
Return on Sales (RoS)	0.0878	0.3094	0.0282	0.0624	0.1183	14'168
Return on Equity (RoE)	0.0488	1.8922	0.0036	0.0579	0.1724	14'168
Number of employees	21	32	3	10	22	14'168

Notes: The table presents summary statistics for firms which do not own residential real estate. The sample period is 2002-2008.

A4.2 2002-2008 Balanced Panel: restricted to 2002

Summary Statistics: **RRE-owner, restricted to financial year 2002** (number of firms: 437)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Log of Total Assets	8.2459	1.0976	7.4989	8.1371	8.9960	437
PPE_TA	0.3676	0.2359	0.1608	0.3682	0.5417	437
Debt_TA	0.0000	0.0000	0.0000	0.0000	0.0000	437
Mortgage_TA	0.0000	0.0000	0.0000	0.0000	0.0000	437
ShareholderLiability_TA	0.0243	0.0616	0.0000	0.0000	0.0014	437
ResidentialProperty_TA	0.3212	0.2371	0.1212	0.2845	0.4600	437
Equity Ratio	0.2706	0.1658	0.1511	0.2442	0.3615	437
Return on Assets (RoA)	0.0680	0.0667	0.0276	0.0617	0.0984	437
Return on Sales (RoS)	0.0926	0.1895	0.0337	0.0695	0.1164	437
Return on Equity (RoE)	0.0499	0.4865	0.0000	0.0288	0.0969	437
Number of employees	25	34	5	12	27	437

Notes: The table presents summary statistics for firms which own residential real estate. The sample period is 2002.

Summary Statistics: **RRE-non-owner, restricted to financial year 2002** (number of firms: 2’024)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Log of Total Assets	7.6049	1.4325	6.4983	7.5224	8.4736	2'024
PPE_TA	0.4823	0.2926	0.2025	0.5005	0.7347	2'024
Debt_TA	0.0000	0.0000	0.0000	0.0000	0.0000	2'024
Mortgage_TA	0.0000	0.0000	0.0000	0.0000	0.0000	2'024
ShareholderLiability_TA	0.0362	0.0952	0.0000	0.0000	0.0000	2'024
Equity Ratio	0.3454	0.2038	0.1945	0.3084	0.4630	2'024
Return on Assets (RoA)	0.1119	0.1335	0.0473	0.0917	0.1588	2'024
Return on Sales (RoS)	0.0928	0.1501	0.0305	0.0662	0.1214	2'024
Return on Equity (RoE)	0.0451	0.9283	0.0000	0.0409	0.1554	2'024
Number of employees	20	31	3	10	20	2'024

Notes: The table presents summary statistics for firms which do not own residential real estate. The sample period is 2002.

A4.3 2008-2014 Balanced Panel

Summary Statistics: **RRE-owner** (number of firms: 363)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Mortgage Growth	0.0269	0.6275	-0.0414	-0.0042	0.0000	2'541
Other Bank Loans Growth	0.0100	0.3015	0.0000	0.0000	0.0000	2'541
Business Investment Growth	0.0653	0.1777	0.0050	0.0291	0.0851	2'541
Equity (paid in) Growth	0.0126	0.1325	0.0000	0.0000	0.0000	2'541
Shareholder Liability Growth	0.0093	0.6116	0.0000	0.0000	0.0000	2'541
Log of Total Assets	8.5058	1.1010	7.7138	8.4158	9.1910	2'541
PPE_TA	0.4300	0.2582	0.2212	0.4237	0.6269	2'541
Debt_TA	0.3468	0.2507	0.1628	0.3404	0.5023	2'541
Mortgage_TA	0.3223	0.2508	0.1258	0.3182	0.4787	2'541
ShareholderLiability_TA	0.0286	0.0761	0.0000	0.0000	0.0169	2'541
ResidentialProperty_TA	0.1959	0.2247	0.0079	0.1212	0.2972	2'541
Equity Ratio	0.3639	0.1831	0.2238	0.3452	0.4822	2'541
Return on Assets (RoA)	0.0898	0.0845	0.0385	0.0748	0.1267	2'541
Return on Sales (RoS)	0.1189	0.1711	0.0422	0.0800	0.1453	2'541
Return on Equity (RoE)	0.1223	0.3056	0.0158	0.0770	0.1818	2'541
Number of employees	27	36	7	12	35	2'541

Notes: The table presents summary statistics for firms which own residential real estate. The sample period is 2008-2014.

Summary Statistics: **RRE-non-owner** (number of firms: 2’111)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Mortgage Growth	0.0136	0.4031	-0.0214	0.0000	0.0000	14'777
Other Bank Loans Growth	0.0053	0.3281	0.0000	0.0000	0.0000	14'777
Business Investment Growth	0.0936	0.3853	0.0046	0.0310	0.0940	14'777
Equity (paid in) Growth	0.0213	0.5344	0.0000	0.0000	0.0000	14'777
Shareholder Liability Growth	0.0071	0.4963	0.0000	0.0000	0.0000	14'777
Log of Total Assets	7.8400	1.3669	6.9207	7.7660	8.7218	14'777
PPE_TA	0.4725	0.3021	0.1866	0.4885	0.7363	14'777
Debt_TA	0.2410	0.3205	0.0000	0.1778	0.4193	14'777
Mortgage_TA	0.2077	0.3101	0.0000	0.0709	0.3831	14'777
ShareholderLiability_TA	0.0365	0.0909	0.0000	0.0000	0.0062	14'777
Equity Ratio	0.3851	0.2084	0.2246	0.3582	0.5228	14'777
Return on Assets (RoA)	0.1213	0.1327	0.0461	0.0942	0.1719	14'777
Return on Sales (RoS)	0.1119	0.2958	0.0321	0.0731	0.1412	14'777
Return on Equity (RoE)	0.0981	1.9635	0.0076	0.0759	0.2098	14'777
Number of employees	24	34	4	10	26	14'777

Notes: The table presents summary statistics for firms which do not own residential real estate. The sample period is 2008-2014.

A4.4 2008-2014 Balanced Panel restricted to 2008

Summary Statistics: **RRE-owner, restricted to financial year 2008** (number of firms: 363)

These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

variable	mean	sd	p25	p50	p75	n
Log of Total Assets	8.4433	1.0764	7.6549	8.3699	9.0865	363
PPE_TA	0.4115	0.2479	0.2152	0.4093	0.5816	363
Debt_TA	0.3719	0.2597	0.1982	0.3593	0.5108	363
Mortgage_TA	0.3464	0.2588	0.1548	0.3442	0.4994	363
ShareholderLiability_TA	0.0311	0.0843	0.0000	0.0000	0.0233	363
ResidentialProperty_TA	0.2460	0.2224	0.0737	0.1796	0.3426	363
Equity Ratio	0.3369	0.1712	0.1980	0.3242	0.4543	363
Return on Assets (RoA)	0.0834	0.0776	0.0338	0.0718	0.1226	363
Return on Sales (RoS)	0.1073	0.1327	0.0402	0.0723	0.1342	363
Return on Equity (RoE)	0.1035	0.3211	0.0143	0.0669	0.1542	363
Number of employees	27	33	7	12	35	363

Notes: The table presents summary statistics for firms which own residential real estate. The sample period is 2008.

Summary Statistics: **RRE-non-owner, restricted to financial year 2008** (number of firms: 2’111)

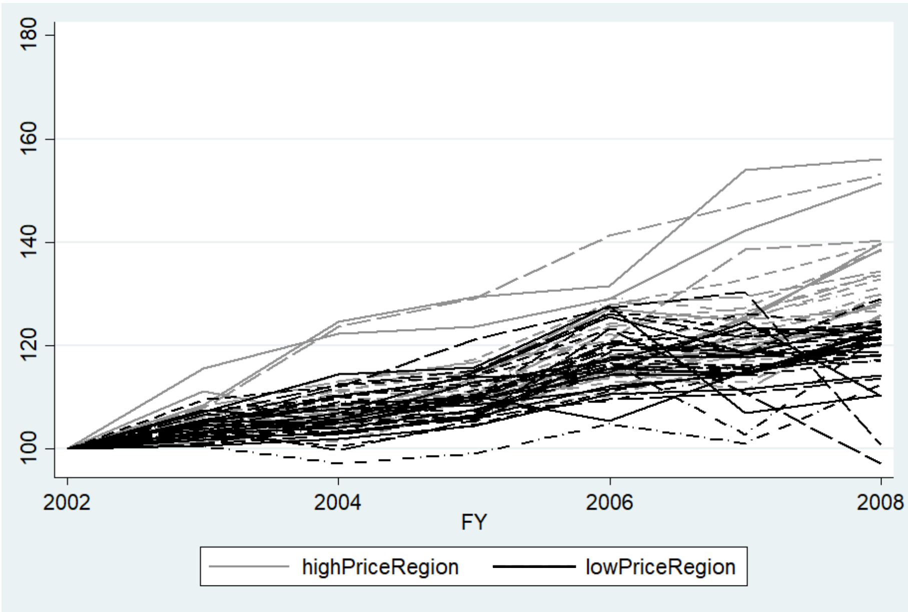
These values are based on the yearly financial statements, normalized by one year lagged total assets (TA).

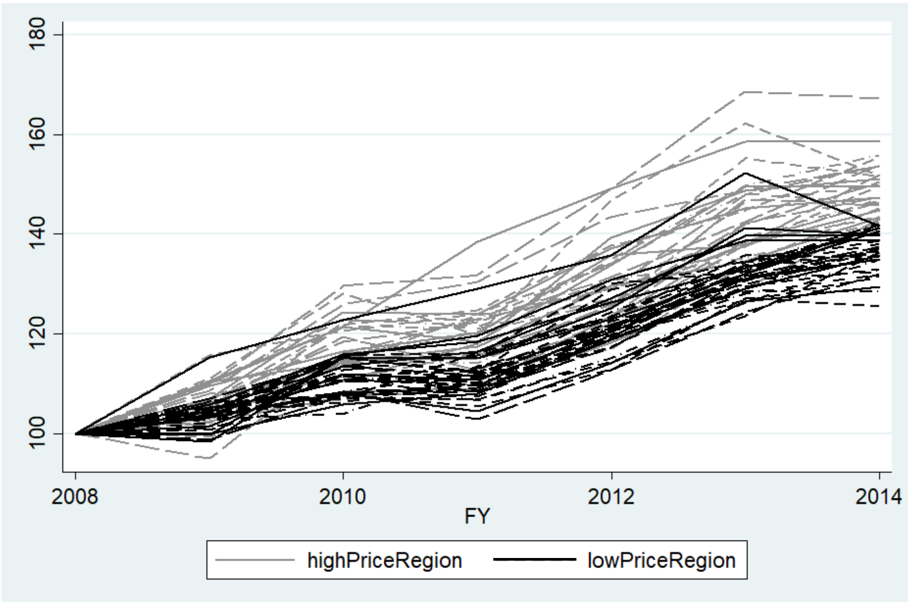
variable	mean	sd	p25	p50	p75	n
Log of Total Assets	7.8357	1.3857	6.8233	7.8483	8.6205	2'111
PPE_TA	0.4705	0.3055	0.1803	0.4824	0.7427	2'111
Debt_TA	0.2434	0.4688	0.0000	0.1342	0.4108	2'111
Mortgage_TA	0.2060	0.4560	0.0000	0.0000	0.3659	2'111
ShareholderLiability_TA	0.0371	0.0926	0.0000	0.0000	0.0096	2'111
Equity Ratio	0.3707	0.2059	0.2132	0.3429	0.5000	2'111
Return on Assets (RoA)	0.1324	0.1350	0.0555	0.1042	0.1827	2'111
Return on Sales (RoS)	0.1083	0.1425	0.0354	0.0736	0.1414	2'111
Return on Equity (RoE)	0.1409	0.4900	0.0136	0.0859	0.2273	2'111
Number of employees	23	32	4	10	28	2'111

Notes: The table presents summary statistics for firms which do not own residential real estate. The sample period is 2008.

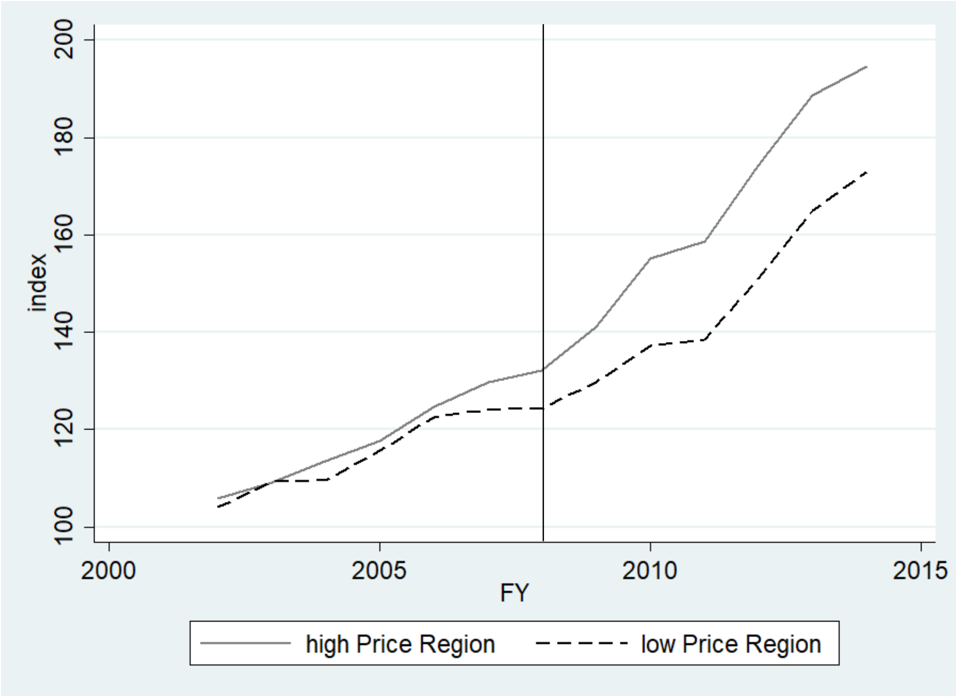
A5: Residential Real Estate Price Growth by Growth Categories

Apartment Price Development of MS Regions by Price Growth Category





Notes: The upper figure shows 54 resp. 65 MS-regions where firms from the balanced panel in the respective time period are based. Source: Wüest&Partner



Notes: The upper figure shows the mean of the two growth categories based on the MS-regions where firms from the balanced panels in the respective time period are based. The line in 2008 indicate the panel split introduced in section 1.3.1. Source: Wüest&Partner.

A6: Business Bank Loans Regression Results (Firm Perspective)

Regression Results Firm Perspective 2008-2014

2008-2014	other Bank Loans Growth $(\Delta BAKL_i^l)$ (1.1)		
Owner x Δp	-0.068 (0.12)	-0.069 (0.12)	-0.086 (0.12)
Owner	0.021 (0.03)	0.022 (0.03)	0.027 (0.03)
Controls	no	yes	yes
Controls x Δp	no	no	yes
Region Fixed Effects	yes	yes	yes
Observations	2,474	2,474	2,474
Adj. R2	-0.01	-0.01	-0.01
Root MSE	0.16	0.16	0.16

Regression Results Firm Perspective 2002-2008

2002-2008	other Bank Loans Growth $(\Delta BAKL_i^l)$ (1.1)		
Owner x Δp	-0.021 (0.23)	-0.013 (0.23)	-0.110 (0.24)
Owner	-0.003 (0.04)	-0.004 (0.04)	0.014 (0.04)
Controls	no	yes	yes
Controls x Δp	no	no	yes
Region Fixed Effects	yes	yes	yes
Observations	2,461	2,461	2,461
Adj. R2	0.00	0.00	0.01
Root MSE	0.18	0.18	0.18

Notes: The table reports the estimates of several linear regressions based on equation (1). Dependent variable is other bank loans growth (1.1). If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A7: Commercial Owners Results (Firm Perspective)

Regression Results for Commercial Owners 2008-2014

2008-2014	Mortgage Growth $(\Delta MORTG_i^l)$ (1.1)			Business Investment Growth $(\Delta BINV_i^l)$ (1.2)		
CREowner x Δp	-0.089 (0.1)	-0.074 (0.1)	-0.1026 (0.12)	0.0899 (0.06)	0.0867 (0.06)	0.0465 (0.07)
CREowner	0.032 (0.03)	0.047* (0.03)	0.055* (0.03)	-0.064 (0.02)	-0.034 (0.02)	-0.024 (0.02)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	2,474	2,474	2,474	2,474	2,474	2,474
Adj. R2	-0.01	0.00	0.00	0.02	0.10	0.10
Root MSE	0.22	0.22	0.22	0.12	0.12	0.12

2008-2014	other Bank Loans Growth $(\Delta BAKL_i^l)$ (1.1)		
CREowner x Δp	-0.021 (0.08)	-0.026 (0.08)	-0.064 (0.09)
CREowner	0.003 (0.02)	0.003 (0.02)	0.013 (0.02)
Controls	no	yes	yes
Controls x Δp	no	no	yes
Region Fixed Effects	yes	yes	yes
Observations	2,474	2,474	2,474
Adj. R2	-0.01	-0.01	-0.01
Root MSE	0.16	0.16	0.16

Notes: The table reports the estimates of several linear regressions based on equation (1) but with commercial real estate owners (CRE) as ownership (dummy) variable for the panel 2008-2014. There are 1'550 CRE-owners. Dependent variable are mortgage (1.1), other bank loans (1.1) and business investment growth (1.2). If a coefficient is statistically significantly different from zero, it is shown with an asterisk:
*** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A8: Matching Sample Results (Firm Perspective)

Regression Results for Matched Firms 2008-2014

2008-2014	Mortgage Growth ($\Delta MORTG_i^l$) (1.1)			Business Investment Growth ($\Delta BINV_i^l$) (1.2)		
Owner x Δp	0.307* (0.19)	0.341* (0.19)	0.502** (0.21)	0.212** (0.09)	0.232*** (0.09)	0.282*** (0.1)
Owner	-0.069 (0.05)	-0.058 (0.05)	-0.099 (0.06)	-0.067 (0.02)	-0.051 (0.02)	-0.065 (0.03)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	1’011	1’011	1’011	1’011	1’011	1’011
Adj. R2	0.01	0.02	0.02	0.01	0.07	0.07
Root MSE	0.21	0.21	0.21	0.10	0.10	0.10

2008-2014	other Bank Loans Growth ($\Delta BAKL_i^l$) (1.1)		
Owner x Δp	-0.035 (0.12)	-0.035 (0.12)	-0.014 (0.14)
Owner	0.014 (0.03)	0.013 (0.03)	0.006 (0.04)
Controls	no	yes	yes
Controls x Δp	no	no	yes
Region Fixed Effects	yes	yes	yes
Observations	1’011	1’011	1’011
Adj. R2	-0.02	-0.03	-0.03
Root MSE	0.14	0.14	0.14

Notes: The table reports the estimates of several linear regressions based on equation (1) using a matched sub-sample of the panel 2008-2014. All 363 RRE-owners are matched by industry and total assets to non-owners. Dependent variable are mortgage (1.1), other bank loans (1.1) and business investment growth (1.2). If a coefficient is statistically significantly different from zero, it is shown with an asterisk:
*** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A9: Panel Regression Results (Firm Perspective)

Following Chaney et al. (2012), I introduce a panel fixed effects model. Contrary to Chaney et al. (2012), I use an owner dummy variable interacted with the real estate price change instead of the market value of the property itself. Furthermore, the owner dummy variable is lagged due to the time elapsing between the experienced price increase and materialization in mortgage demand. Based on these considerations, I write the following:

$$\begin{aligned}\Delta Y^{l}_{i,(t-1)\to(t)} \quad = \quad & \alpha + \zeta_i + \delta_t + \beta \cdot Owner_{i,(t-3)} \times \Delta p^{l}_{(t-3)\to(t-1)} \\ & + \theta \cdot Owner_{i,(t-3)} + \zeta \cdot \Delta p^{l}_{(t-3)\to(t-1)} \\ & + \gamma \cdot controls_{i,t} + \tau \cdot controls_{i,t} \times \Delta p^{l}_{(t-3)\to(t-1)} + \varepsilon_{i,l}\end{aligned} \tag{3}$$

$$\Delta Y^{l}_{i,(t-1)\to(t)} \quad \coloneqq \quad \left(\Delta MORTG^{l}_{i,(t-1)\to(t)};\ \Delta BINV^{l}_{i,(t-1)\to(t)};\ \Delta BAKL^{l}_{i,(t-1)\to(t)}\right) \tag{3.1-3.3}$$

where $\Delta Y^{l}_{i,(t-1)\to(t)}$ represents the three known dependent variables, and ζ_i are firm fixed effects.

Panel Regression Results Firm Perspective 2008-2014

2008-2014	Mortgage Growth $(\Delta MORTG_i^l)$ (3.1)			Business Investment Growth $(\Delta BINV_i^l)$ (3.2)		
Owner x Δp	0.324** (0.16)	0.324** (0.16)	0.381** (0.16)	0.232* (0.13)	0.264** (0.13)	0.297** (0.13)
Owner	-0.008 (0.02)	-0.018 (0.02)	-0.024 (0.02)	-0.064 (0.03)	-0.083 (0.03)	-0.086 (0.03)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	17'318	17'318	17'318	17'318	17'318	17'318
Adj. R2	0.00	0.00	0.00	-0.16	-0.13	-0.13
Root MSE	0.44	0.44	0.44	0.36	0.35	0.35

2008-2014	other Bank Loans Growth $(\Delta BAKL_i^l)$ (3.3)		
Owner x Δp	0.028 (0.03)	0.033 (0.03)	0.021 (0.03)
Owner	0.002 (0.01)	0.000 (0.01)	0.001 (0.01)
Controls	no	yes	yes
Controls x Δp	no	no	yes
Firm Fixed Effects	yes	yes	yes
Region Fixed Effects	yes	yes	yes
Observations	17'318	17'318	17'318
Adj. R2	-0.17	-0.16	-0.16
Root MSE	0.08	0.08	0.08

Notes: The table reports the estimates of several panel regressions based on equation (3). Dependent variable are mortgage (3.1), other bank loans (3.3) and business investment growth (3.2). Independent variable p is the lagged residential real estate price. Control variables are explained in section 1.4.1. The sample consists of a balanced panel of 2'474 SMEs located in 65 MS-regions and reported their 17'318 financial statements between 2008 and 2014. Standard errors are shown in parentheses and are clustered at the firm level. If a coefficient is statistically significantly different from 0, it is shown with an asterisk:
*** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A10: Intensive Margin (Firm Perspective)

Regression Results for Intensive Margin 2008-2014

Only firms reporting mortgages in 2008

2008-2014	Mortgage Growth $(\Delta MORTG_i^l)$ (1.1)			Business Investment Growth $(\Delta BINV_i^l)$ (1.2)		
Owner x Δp	0.381* (0.24)	0.385* (0.24)	0.393* (0.24)	0.205*** (0.07)	0.208*** (0.07)	0.208*** (0.07)
Owner	-0.074 (0.06)	-0.069 (0.04)	-0.072 (0.04)	-0.049 (0.018)	-0.042 (0.018)	-0.041 (0.02)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	1,396	1,396	1,396	1,396	1,396	1,396
Adj. R2	0.00	0.00	0.00	0.02	0.10	0.10
Root MSE	0.27	0.27	0.27	0.08	0.08	0.08

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (1). Dependent variables are the average of annual mortgage growth (1.1) and business investment growth (1.2) between 2008 and 2014. Δp is the cumulative residential real estate price for the first 4 years. Control variables are explained in section 1.4.1. The sample is based upon the balanced panel of SME (2008 and 2014) but restricted to firms which reported a mortgage in 2008. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A11: Summary Statistics Entrepreneur Perspective: HighPriceRegion vs LowPriceRegion

2002-2008: Balanced Panel

Summary Statistics: **HighPriceRegion** (number of firms: 765)

variable	mean	sd	p25	p50	p75	N
Mortgage Growth	0.0036	0.3420	-0.0234	0.0000	0.0000	5'355
Other Bank Loans Growth	0.0119	0.4016	0.0000	0.0000	0.0000	5'355
Business Investment Growth	0.0747	0.2599	0.0000	0.0186	0.0661	5'355
Equity (paid in) Growth	0.0193	0.4050	0.0000	0.0000	0.0000	5'355
Shareholder Liability Growth	-0.0044	0.4678	0.0000	0.0000	0.0000	5'355
Log of Total Assets	7.9117	1.3800	6.9735	7.8336	8.8420	5'355
PPE_TA	0.4408	0.2799	0.1845	0.4430	0.6681	5'355
Debt_TA	0.2453	0.2951	0.0000	0.1759	0.4496	5'355
Mortgage_TA	0.2273	0.2867	0.0000	0.1231	0.4252	5'355
ShareholderLiability_TA	0.0435	0.1060	0.0000	0.0000	0.0194	5'355
Equity Ratio	0.3265	0.1964	0.1744	0.2920	0.4405	5'355
Return on Assets (RoA)	0.1003	0.1165	0.0383	0.0810	0.1415	5'355
Return on Sales (RoS)	0.0821	0.1257	0.0270	0.0591	0.1101	5'355
Return on Equity (RoE)	0.0692	1.2320	0.0057	0.0584	0.1655	5'355
Number of Employees	24	35	4	10	26	5'355

Notes: The table presents summary statistics of firms which are based in a high price growth region. The sample period is 2008-2014.

Summary Statistics: **LowPriceRegion** (number of firms: 1’696)

variable	mean	sd	p25	p50	p75	N
Mortgage Growth	0.0037	0.3652	-0.0255	0.0000	0.0000	11'872
Other Bank Loans Growth	0.0029	0.3256	0.0000	0.0000	0.0000	11'872
Business Investment Growth	0.0715	0.2727	0.0000	0.0205	0.0724	11'872
Equity (paid in) Growth	0.0242	0.3355	0.0000	0.0000	0.0000	11'872
Shareholder Liability Growth	-0.0047	0.3979	0.0000	0.0000	0.0000	11'872
Log of Total Assets	7.6371	1.4257	6.6554	7.5954	8.5897	11'872
PPE_TA	0.4468	0.2920	0.1699	0.4423	0.6968	11'872
Debt_TA	0.2276	0.3040	0.0000	0.1028	0.4196	11'872
Mortgage_TA	0.2073	0.2879	0.0000	0.0000	0.4005	11'872
ShareholderLiability_TA	0.0295	0.0800	0.0000	0.0000	0.0000	11'872
Equity Ratio	0.3601	0.2046	0.2054	0.3266	0.4868	11'872
Return on Assets (RoA)	0.1048	0.1238	0.0426	0.0848	0.1499	11'872
Return on Sales (RoS)	0.0894	0.3406	0.0287	0.0635	0.1201	11'872
Return on Equity (RoE)	0.0444	1.9052	0.0025	0.0533	0.1628	11'872
Number of Employees	20	31	3	8	21	11'872

Notes: The table presents summary statistics of firms which are based in a low price growth region. The sample period is 2008-2014.

2008-2014: Balanced Panel

Summary Statistics: **HighPriceRegion** (number of firms: 960)

variable	mean	sd	p25	p50	p75	N
Mortgage Growth	0.0188	0.4650	-0.0221	0.0000	0.0000	6'720
Other Bank Loans Growth	0.0072	0.3527	0.0000	0.0000	0.0000	6'720
Business Investment Growth	0.0906	0.4348	0.0037	0.0303	0.0956	6'720
Equity (paid in) Growth	0.0289	0.7248	0.0000	0.0000	0.0000	6'720
Shareholder Liability Growth	0.0114	0.4976	0.0000	0.0000	0.0000	6'720
Log of Total Assets	7.8158	1.4551	6.8063	7.7818	8.7510	6'720
PPE_TA	0.4519	0.3092	0.1566	0.4461	0.7246	6'720
Debt_TA	0.2407	0.3263	0.0000	0.1723	0.4281	6'720
Mortgage_TA	0.2067	0.3157	0.0000	0.0562	0.3936	6'720
ShareholderLiability_TA	0.0317	0.0814	0.0000	0.0000	0.0014	6'720
Equity Ratio	0.3777	0.2131	0.2115	0.3459	0.5096	6'720
Return on Assets (RoA)	0.1166	0.1341	0.0434	0.0901	0.1666	6'720
Return on Sales (RoS)	0.1179	0.4046	0.0299	0.0705	0.1407	6'720
Return on Equity (RoE)	0.1125	2.1792	0.0073	0.0705	0.2045	6'720
Number of Employees	24	35	4	10	28	6'720

Notes: The table presents summary statistics of firms which are based in a high price growth region. The sample period is 2008-2014.

Summary Statistics: **LowPriceRegion** (number of firms: 1'514)

variable	mean	sd	p25	p50	p75	N
Mortgage Growth	0.0135	0.4289	-0.0278	0.0000	0.0000	10'598
Other Bank Loans Growth	0.0052	0.3049	0.0000	0.0000	0.0000	10'598
Business Investment Growth	0.0809	0.3081	0.0052	0.0307	0.0907	10'598
Equity (paid in) Growth	0.0125	0.2637	0.0000	0.0000	0.0000	10'598
Shareholder Liability Growth	0.0048	0.5254	0.0000	0.0000	0.0000	10'598
Log of Total Assets	8.0150	1.2761	7.1869	7.9224	8.8346	10'598
PPE_TA	0.4753	0.2878	0.2145	0.4923	0.7205	10'598
Debt_TA	0.2665	0.3046	0.0000	0.2284	0.4416	10'598
Mortgage_TA	0.2359	0.2972	0.0000	0.1775	0.4094	10'598
ShareholderLiability_TA	0.0377	0.0933	0.0000	0.0000	0.0144	10'598
Equity Ratio	0.3847	0.1997	0.2320	0.3643	0.5183	10'598
Return on Assets (RoA)	0.1167	0.1227	0.0454	0.0909	0.1625	10'598
Return on Sales (RoS)	0.1097	0.1589	0.0354	0.0769	0.1422	10'598
Return on Equity (RoE)	0.0947	1.5451	0.0098	0.0798	0.2053	10'598
Number of Employees	24	34	5	11	28	10'598

Notes: The table presents summary statistics of firms which are based in a low price growth region. The sample period is 2008-2014.

A12: Intensive Margin (Entrepreneur Perspective)

Regression Results for Intensive Margin 2008-2014

Only firms reporting shareholder liability in 2008

2008-2014	Equity Growth $(\Delta EQTY_i^l)$ (2.1)		Shareholder Liability Growth $(\Delta SHLIAB_i^l)$ (2.2)		Business Investment Growth $(\Delta BINV_i^l)$ (2.3)	
HighPriceRegion (dummy=1)	0.014** (0.01)	0.013** (0.01)	0.05* (0.03)	0.05* (0.03)	0.01 (0.01)	0.01 (0.01)
Controls	no	yes	no	yes	no	yes
Observations	666	666	666	666	666	666
Adj. R2	0.00	0.02	0.00	0.00	0.00	0.19
Root MSE	0.07	0.07	0.36	0.36	0.10	0.10

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (2). Dependent variables are the average of paid-in equity growth (2.1), shareholder liability growth (2.2) and business investment growth (2.3) between 2008 and 2014. Control variables are explained in section 1.5.1. The sample is based upon the balanced panel of SME (2008 and 2014) but restricted to firms which reported shareholder liabilities in 2008. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A13: Sole Proprietors Results (Entrepreneur Perspective)

Regression Results Sole Proprietorships 2008-2014

2008-2014	Equity Growth $(\Delta EQTY_i^l)$ (4.1)			Business Investment Growth $(\Delta BINV_i^l)$ (4.2)		
SoleProp x highPriceRegion	0.059*** (0.01)	0.109*** (0.01)	0.111*** (0.009)	0.000 (0.02)	0.029 (0.08)	0.007 (0.09)
SoleProprietor	0.053*** (0.01)	-0.003 (0.1)	0.006 (0.1)	0.004 (0.01)	0.0061 (0.02)	-0.003 (0.02)
Controls	no	yes	yes	no	yes	yes
Controls x Δp	no	no	yes	no	no	yes
Region Fixed Effects	yes	yes	yes	yes	yes	yes
Observations	2,474	2,474	2,474	2,474	2,474	2,474
Adj. R2	0.08	0.08	0.08	0.00	0.13	0.10
Root MSE	0.09	0.09	0.09	0.13	0.10	0.12

Notes: The table reports the estimates of several linear regression models based on equation (4). Dependent variables are equity and business investment growth between 2008-2014. HighPriceRegion is a dummy variable, that equal 1 if the SME is located in a high price region and 0 otherwise. Control variables are explained in section 1.5.1. The samples consist of a balanced panel 2008-2014 with 2'474 SMEs located in 65 MS-regions. Standard errors are shown in parentheses and are clustered at the region-by-ownership level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk:
*** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

A14: List of abbreviations

FINMA	Swiss Financial Market Supervisory Authority
IPRE	Income-producing real estate
LTV	Loan-to-value
MS	Mobilité Spatiale
PPE	Property plant and equipment
RE	Real estate
RRE	Residential real estate
SME	Small and medium-sized enterprises
SNB	Swiss National Bank
W&P	Wüest and Partner

Chapter 2
Credit Risk and Financing Costs of SMEs: Evidence from Switzerland

Hannes Mettler*

Abstract

This paper examines to what extent a bank's credit risk assessment relates to the financing costs of SMEs. The analysis is based on bank internal credit ratings and detailed accounting information from SMEs in Switzerland from 2002 to 2015. The study analyzes the relationship for first-time borrowers and shows that banks apply a risk-adjusted pricing strategy for firms with unsecured credit lines and/or investment loans, but not necessarily for firms with mortgages. Analyzing rating changes during the credit relationship, I show that the rating transitions of SMEs result in changes in financing costs in the following financial year. Furthermore, there is strong evidence that the rating path plays an important role in pricing. Persistent rating changes in the same direction, as well as rating reversals, trigger a larger change in financing costs compared to firms with no previous rating change. My analysis also shows that the financing costs of SMEs with poor credit ratings are substantially lower than the probability of default would suggest.

Keywords: Credit Risk Pricing, Risk Adjusted Pricing, Small Business Finance, SME

JEL classification numbers: D22, G21, G31, L25

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2.1 Introduction

In most countries, bank loans are the primary source of external funding for small and medium sized enterprises (SMEs), as it is for Swiss SMEs (SECO, 2018).[1] Therefore, SME lending is a key business segment for banks in developed countries. History shows that credit losses in the SME lending business have repeatedly deflated the profitability of banks, i.e., in Switzerland during the 1990 real estate crisis or in the United States after the financial crisis 2008 (Chen, Hanson & Stein, 2017; Lüscher, 2015). It is expected that banks consider potential credit losses in their loan rate setting for SME loans. In particular, with the tightening of banks' profitability due to the low interest rate environment in recent years, the importance of adequate loan pricing (i.e., riskier firms have to pay more) has further increased.

Credit risk is an important component in loan pricing (BIS, 2006; Bluhm et al, 2003; Dietsch et al. 2002; Altman, 1968). Risk-adjusted pricing (RAP) is well known in the syndicated loan and bond market. In bank lending, transactional lending (e.g., consumer credit) typically uses a pricing strategy based on risk-adjusted pricing. However, theoretical and empirical studies show that risk-adjusted pricing is not fully applied in SME lending, where the relationship between banks and small businesses plays an active role (Petersen & Rajan, 1995; Boot & Thakor, 1994; Sharpe, 1990; Bharath et al., 2011; Kysucky & Norden, 2015; Cerqueiro et al., 2011).

In this paper, I study the relationship between the bank's internal credit risk assessment and the SME's financing costs. I use a unique dataset that consists of SMEs' annual financial statements and the corresponding internal credit risk assessments by regional banks. Based on the risk-adjusted pricing model, my empirical strategy isolates the impact of the available credit ratings on the bank financing costs of the firm (i.e., interest rate and fees). The aim is to identify and quantify the correlation between the initial allocated credit rating and SME's financing costs as well as to study the impact of changes in the credit rating. Therefore, this study is split into a cross-sectional analysis and a panel analysis. To my knowledge, this is the first study that shows the impact of internal bank ratings on SMEs' financing costs in Switzerland.

Overall, my results show that the role of the borrower's credit rating is more important for the pricing of unsecured bank loans than for mortgages. There is strong statistical

[1] Outstanding credit lines to SMEs amount to CHF 403 billion in 2015, or 63% of Swiss GDP.

evidence that banks apply a risk-adjusted pricing strategy for unsecured credit lines and investment loans of first-time borrowers. The difference between the best and worst initial ratings is 210 bp (mean). My results also show the relevance of collateral. While firms with only unsecured credit lines and investment loans report mean financing costs of 398 bp, firms reporting only mortgages show a mean financing cost of 268 bp. Furthermore, there is a positive relationship between the qualitative credit risk assessment by credit risk officers and the financing costs. Despite the moderate magnitude of approx. 20 bp, these qualitative risk assessments are relevant for the final loan rates.

My second set of findings is based on a panel analysis of SME credit lines. In accordance with the RAP strategy, I find evidence that rating transitions trigger changes in the financing costs of existing credit lines in the following financial year. Up- and downgrades lead to changes of similar magnitude. A transition of at least two rating grades triggers a change in the financing costs of +/-50 bp. This symmetric pricing behavior does not hold for firms with a rating change in the previous year. There is strong evidence that the rating path plays an important role in the pricing policies of banks. A firm that received two consecutive rating transitions reported a higher magnitude of change in financing costs compared to firms without a rating change in the year before. Furthermore, there is a significant difference if the firm's subsequent rating transition is in the same direction versus the case of a rating reversal (up and down; down and up). Two subsequent rating upgrades trigger the largest magnitude of change in financing costs (-190 bp) compared to firms with other rating paths.

In recent years, there has been a growing discussion on which bank loans remain in the bank credit market and which will be superseded by crowd lending platforms. My results show that banks offer relatively comfortable conditions compared with crowd lending rates. Furthermore, my findings suggest that SMEs with very weak credit ratings do not have to pay the full risk premium compared to the loan rates of SMEs with good credit ratings.

This paper contributes to two strands of literature: First, I contribute to the wide literature of the industrial organization approach to banking in terms of the loan rate setting process. In the presence of market competition, if banks have to break even in each accounting period, they must hold risk-adjusted returns constant by charging higher interest rates on lending when the borrower's returns exhibit greater uncertainty (Petersen & Rajan, 1995; Ryan et al., 2014). To my knowledge, there is only one paper that analyzes the banks' usage of RAP at the single loan level. Machauer & Weber (1998) show that the loan interest rate premiums of credit lines are positively related to borrower credit ratings. However, there was no evidence for an appropriate adjustment of loan terms to rating changes. Machauer & Weber (1998) use credit data from five German banks between 1992 and 1996. Using aggregated bank data from 12 European countries between 1989 and 1999, Nys (2003) also shows a positive relation between credit risk and the interest margin for Belgium and Germany, Netherlands and Portugal. In this paper, I document the existence of risk-adjusted pricing at the firm level for credit lines and investment loans of first-time borrowers. Furthermore, I show that there is no such relation for firms reporting mortgages. Contrary to Machauer & Weber (1998), I show that financing costs change in the case of rating transitions. My results suggest that the relation between credit risk and financing costs is less "sticky" than the existing literature on the pass-through of market rates suggests (Berger & Udell, 1992; Illes et al., 2015; Garriga, 2006; Berger et al., 2004; Degryse & Ongena, 2005).

Second, I contribute to the literature on relationship banking, which is able to explain why a bank may deviate from a pure risk-adjusted pricing strategy. The depth and duration of the relationship between the bank and the borrower is utilized as a measure of "information production", which is a way to mitigate information asymmetries and may result in favorable lending rates (Boot & Thakor, 1994; Petersen & Rajan, 1995; Bharath et al, 2011; Cenni et al, 2015). Kysucky & Norden (2015) report that long-lasting, exclusive and synergy-creating bank relationships are associated with lower loan rates. Another study by Cerquiro & Ongena (2011) shows that loan officers use their discretion in the loan rate setting. Furthermore, Brown et al. (2012) show that credit risk officers tend to smooth rating changes. They argue that loan officers are possibly reluctant to communicate interest rate changes. The role of collateral is also studied in the relationship banking literature. Among others, Matias & Duarte (1998) and Jimenez et al. (2004) show that collateral reduces bank loan rates. I extend this strand of literature by documenting that banks follow a pricing policy in favor of the client's rating history. Banks smooth a negative rating impact on the loan rate and use the opportunity of an upward path to pro-actively offer better loan rates to further tighten the relationship with the client. Furthermore, the large dispersion of financing costs per rating class supports the results by Cerquiro & Ongena (2011) that loan officers use their "discretion". Finally, I show that banks mostly deviate from pure risk-adjusted pricing for SMEs with very poor credit ratings.

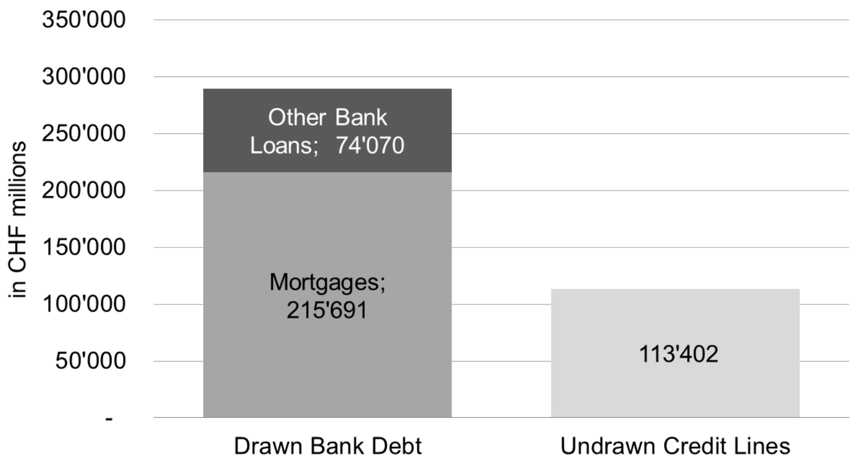
The remainder of this paper is organized as follows. Section 2.2 provides an overview of the Swiss SME loan market, credit ratings, and determinants of loan rates and develops the hypotheses. Section 2.3 provides an overview of the data. Section 2.4 shows the empirical strategy and the results from the cross-sectional analysis of the initial credit risk pricing, while section 2.5 presents the empirical strategy and results from the rating change panel analysis. Section 2.6 analyzes the potential subsidization of SME financing costs, and section 2.7 concludes the findings.

2.2 Institutional Background

2.2.1 SME Financing in Switzerland

Figure 2.1 shows the bank lending volume to SMEs, divided into loan and usage types in 2016. Overall, the credit volume amounts to CHF 290 bn drawn loans to SMEs, which is 43% of the Swiss GDP. The utilization of mortgages represents the largest share and is increasing. There is a positive correlation with increasing real estate prices. Over the last decade, the credit volume to SMEs increased by 40% (CHF 206 bn in 2002). However, the significantly increasing residential real estate prices led to much more growth in the residential real estate mortgages market. Mortgage lending to private households increased by 112% to CHF 715 bn in 2016 (CHF 338 bn in 2002). Clearly, banks are more willing to lend against real estate collateral, and in much higher amounts if it is residential real estate.

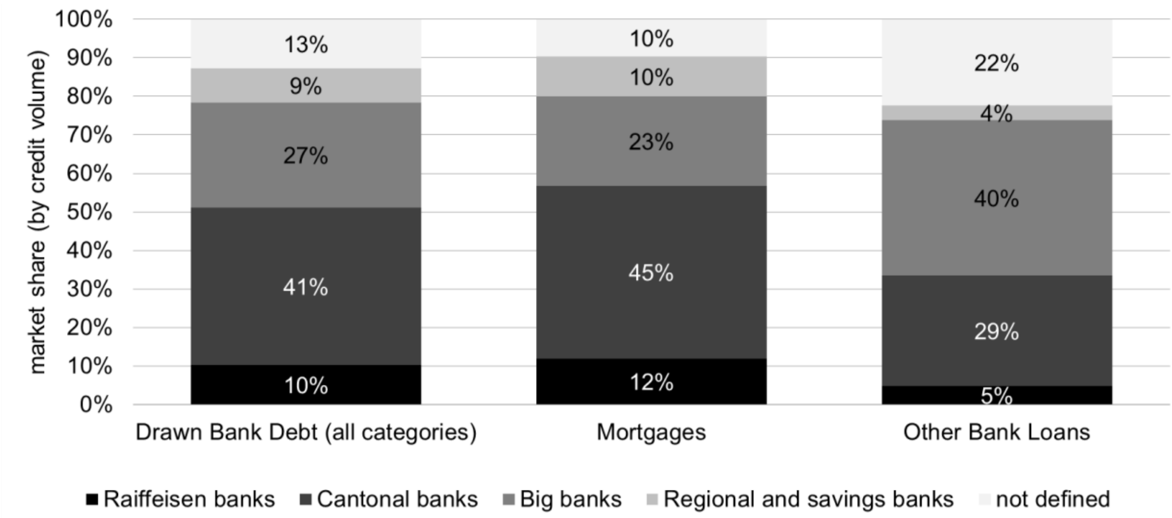
Figure 2.1: Lending to Borrowers Domiciled in Switzerland



Source: SNB. 2017. Credit volume survey (SNB KRED) per 31.12.2016.

Figure 2.2 shows the market shares in the SME loan market. In Switzerland, there is no price monopoly for a single bank. However, the market structure in SME lending can be divided into three main banking groups. Cantonal banks report a share of 41% in terms of the overall credit volume to SMEs. Second, the two big banks, UBS and CS, amount up to 27%. The residual is shared between regional/savings and Raiffeisen banks. This somewhat oligopolistic structure may provide a certain amount of market power to a lending bank. The data for this research paper stem from cantonal and regional/savings banks.

Figure 2.2: Market Shares in the SME Loan Market

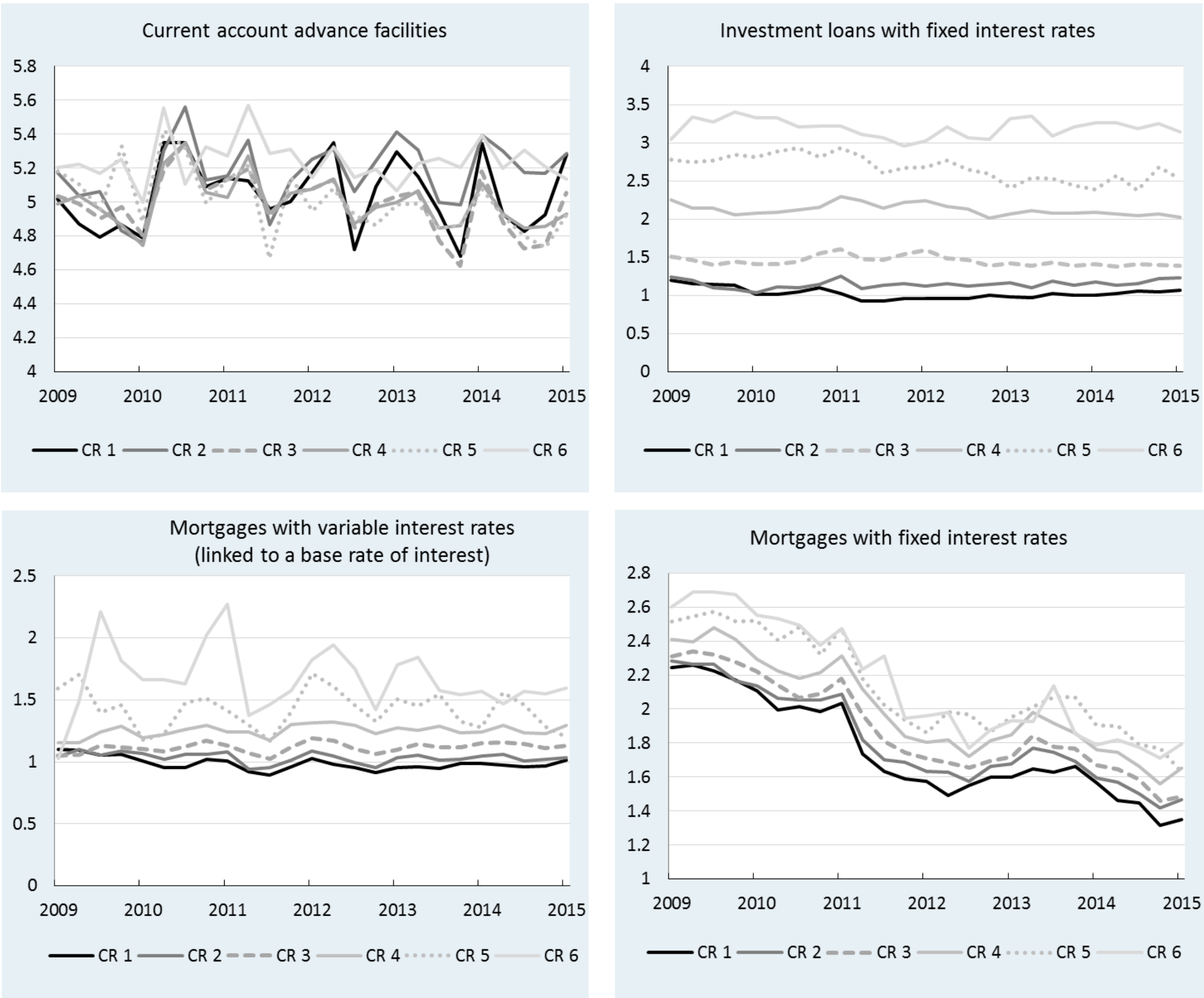


Source: SNB. 2017. Share of credit volume (utilization) by banks in Switzerland per 31.12.2016. Due to the SNB survey (KRED) there is a residual category "not defined".

The lending rate statistics (KREDZ) of the Swiss National Bank (SNB) starting from 2009 are the only publicly available data on corporate loan rates with a link to credit risk in Switzerland. These statistics show lending rates on new loan agreements by either product type, maturity or loan amount; each category is divided into six credit risk classes according to their expected loss. Figure 2.3 shows all credit risk and loan rate relations by product type. However, these statistics cannot be restricted to SMEs only. The split-up by product type shows different relations between credit risk class and loan rates. Investment loans show higher loan rates for poor credit risk classes, which is consistent with the expected behavior of risk-adjusted pricing. Mortgages with fixed interest rates do not fully follow this risk ranking pricing. Completely opposite to the idea of RAP are current account facilities, which show no dependence of the interest rate on credit risk.

Furthermore, it is noticeable that although the refinancing costs decreased over the entire time period, fixed interest rate mortgages have fallen as well but investment loans did not.

Figure 2.3: Lending Rates on New Loan Agreements by Product and Credit Risk Category



Source: SNB. 2015. Notes: CR stands for credit risk and is defined as expected loss in % of exposure [EL in % of exposure]. CR 1 = [0.0-0.05], CR 2 = [0.05-0.1], CR 3 = [0.1-0.3], CR 4 = [0.3-0.7], CR 5 = [0.7-1], CR 6 = [1.0-8.0]

In reference to Basel II and the existing literature on the expected loss (EL) framework (i.e., Bernet, 2003; Ravara et al. 2004), the probability of default (PD) is a main component of credit risk (Ayadi, 2005). SMEs are usually assigned their PD by bank internal rating models. In terms of measuring defaults there are two different approaches of PD modelling: point-in-time (PIT) and through-the-cycle (TTC). A PIT PD assesses the likelihood of default at a point in time. Therefore, the borrower will move up or down rating classes through the economic cycle. In a TTC framework a PD reflects the average default rate for a particular borrower over an economic cycle and ignore short term changes to a borrower's PD. Usually each rating class is associated with a PD. The PD is estimated using ex post default data and statistical models (Ravara et al., 2004). The accuracy of the PD strongly depends on the availability of a sufficiently large historical set of default data.

2.2.2 Determinants of Loan Rates

Banks use their individual pricing models and strategies. However, since Basel II, they all refer, more or less, back to the risk-adjusted pricing (RAP) framework, first introduced in the late nineties. This was the time when banks started introducing RAP for business loans, which would factor the individual credit risk into the loans' interest rates. In Switzerland, RAP was amplified in the aftermath of severe loan defaults during the 1990s and the introduction of Basel II (i.e., Ammann, 2001; Ammann et al., 1999; Grunert, et al. 2002; Ayadi, 2005). The literature (i.e., Dietrich, 2008; Ayadi, 2005; Dietsch & Petey, 2002) and the banks themselves (CS, 2003) state the components of the pricing scheme in the loan price model: (i) risk costs, (ii) capital costs, (iii) operational costs, and (iv) funding costs. While (iii) operational and (iv) funding costs are mainly bank specific, the differentiating components in terms of credit risk are (i) risk costs and (ii) capital costs. These cost types relate directly to credit risk.

In contrast to the sophisticated internal rating-based approach (IRB), which takes the individual SME credit risk into account, the standardized approach for credit risk (SA) accepts risk weights (RWA) lower than 100%, mainly in two circumstances. First, if the loan is classified as retail business (i.e., loan amount CHF <1 Mio.). Second, if the loan is secured by residential real estate or marketable securities (i.e., traded shares, bonds). In Switzerland, there are only four banks using the internal rating-based approach (IRB) that are permitted to use more individual risk weights. Therefore, the main driver in the SME-RAP of regional and cantonal banks in the underlying data should be (i) risk costs.

Based on Basel II, risk costs are usually calculated with an expected loss approach (EL), which is a multiplication of the (i) probability of default (PD), (ii) loss given default (LGD) and (iii) exposure at default (EAD). The PD depends solely on the borrower. It is derived by calculating a credit rating of the respective firm (see section 2.2). The LGD component depends on the collateral. Among others, Matias & Duarte (1998) analyzed the role of collateral in credit risk pricing. They show that collateral plays an important role and is negatively related to loan rates. Credit lines and investment loans are mostly unsecured. Marketable securities such as bonds or mutual funds that may serve as collateral are only rarely used in SME financing, as the business purposes of SMEs are unlikely to involve investing and managing mutual funds or bonds. On the other hand, real estate properties are widely used as collateral in SME financing. Mortgages are usually collateralized by the commercial properties of the SME. Due to tax or private reasons of the entrepreneurs, SMEs may hold residential properties with no business-related purpose and report a mortgage in their financial statements. Table 2.1 summarizes all RAP components.

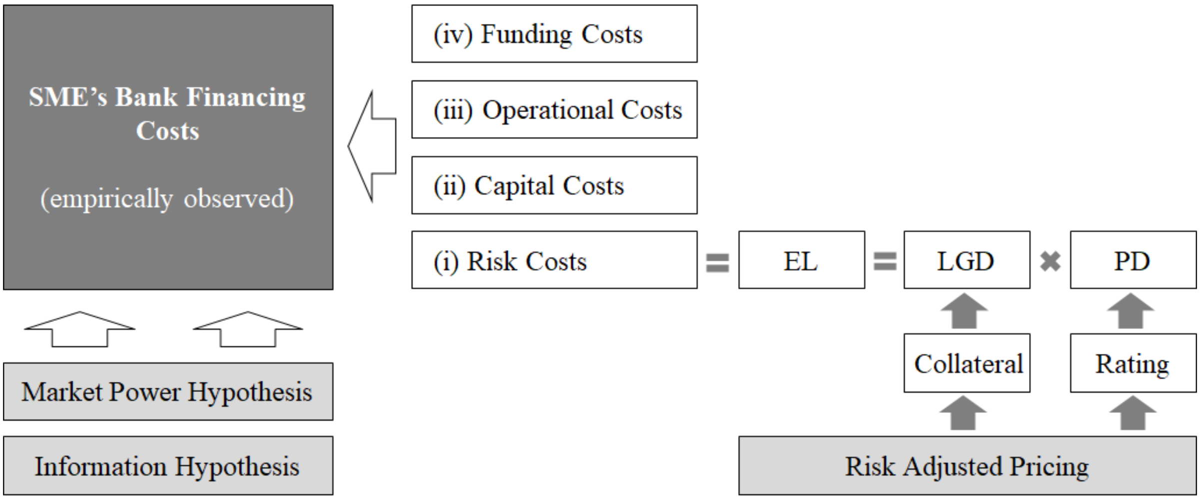
Table 2.1: RAP Components

(iv) Funding costs = costs of refinancing the bank debt granted to the SME - depend on refinancing costs of bank (Behr & Guettler, 2004) - depend on loan duration - in contrast to syndication loans for large corporates, in retail banking, funding costs are often not pegged to market rates (i.e. LIBOR as funding costs)
(iii) Operating costs = costs for application, screening, monitoring, booking - depend on loan amount because of fixed costs for every loan transaction (Durkin & Elliehausen, 1998; Dietrich, 2012)
(ii) Capital costs = costs of regulatory required capital for loan transactions - depend on collateral type and loan amount if the bank use the BIS Standardized Approach for Credit Risk (SA)
(i) Risk costs = expected loss - depend on PD (credit rating) and LGD (collateral type)

Notes: This table summarizes the components of a risk-adjusted pricing scheme. Own illustration.

Despite this pricing scheme, loan rates may be influenced by the market structure as well as the behavior of the banks themselves. The empirical results regarding relationship banking and industrial organization are mixed. However, neither the information hypothesis from the relationship banking literature (i.e., Petersen & Rajan, 1995) nor the market power theory from the industrial organization literature (i.e., Klein, 1971; Monti, 1972; Karagiannis et al., 2010; Montoriol, 2006; Berger et al., 2004) is necessarily controversial to risk-adjusted pricing. Thus, beside the collateral, the PD is the main variable of the credit risk reflected in the bank financing costs. Figure 2.4 summarizes the related plausible determinants of the loan rate.

Figure 2.4: Loan Rate Components and their Relations



Notes: Own illustration.

2.2.3 Development of Hypotheses

Industrial organization (IO) theory provides a theoretical background for analyzing the relationship between borrower rating changes and SME loan rate pricing. In the presence of market competition, if banks have to break even in each accounting period, they must hold risk-adjusted returns constant by charging higher interest rates on lending when the borrower's returns exhibit greater uncertainty (Petersen & Rajan, 1995; Ryan et al., 2014). There are many textbooks (among other Bessis, 2010; Bluhm et al. 2003) but only a few empirical studies (Machauer & Weber, 1998, Dietsch & Petey, 2002; Nys, 2003; Dietrich, 2008) that address this expectation of a positive relation between credit rating and loan rate for SME. Therefore, the first hypothesis states the following:

H1: "Risk-adjusted Pricing": Credit risk measured by credit ratings is positively related to financing costs.

Credit risk assessment of a bank is usually divided into two parts. There is a quantitative rating model and the qualitative risk assessment by a credit risk officer. Brown et al. (2012) report that credit risk officers smooth credit ratings. One reason for this smoothing could be the reluctance to communicate interest rate changes. Based on this line of argument, the rating adjustment by credit risk officers should be positively related to loan rates. Furthermore, Cerqueiro et al. (2011) analyze the dispersion in interest rates on SME bank loans. They associate this dispersion with the loan officers' use of "discretion" in the loan rate setting process. The loan officers' "discretion" is most relevant if loans are small and unsecured, firms are small and opaque, the firm operates in a large and highly concentrated banking market or if the firm is located distantly from the lender. These findings suggest that credit risk officers possess a certain power to directly or indirectly amend the loan rates:

H2: "Qualitative Risk Assessment": Credit risk officers use their discretion to influence loan rates. This adjustment is reflected in a positive relationship between the qualitative rating and financing costs.

Following the market power theory from the IO, banks exercise their power to adjust the loan and deposit rates in their favor (i.e., Kim & Ongena, 2009; Weth (2002); Karagiannis et al., 2010). Based on this assumption and the Swiss lending market structure, described in section 2.1, Swiss banks will most likely increase (decrease) loan rates (deposit rates) whenever possible. However, independent of the market structure, there is some evidence that banks adjust loan rates asymmetrically, i.e., they increase interest in the case of a downgrade, while, alternatively, to keep its earnings stable, they do not change the credit spread if the firm's rating remains stable or upgrades. Under certain market conditions, the transmission channel of market rates to loan (deposit) rates serves as a second explanation for asymmetric loan price behavior by banks. There is empirical evidence of a "sticky" pass-through of market rates (Berger & Udell, 1992; Hannah & Berger, 1991). There is empirical evidence that lending rates are rigid downwards and that the deposit rates are rigid upwards, which is in line with the predictions derived from IO models. (Freixas & Rochet, 2008; Berger & Udell, 1992; Illes et al., 2015; Garriga, 2006; Berger et al., 2004; Degryse & Ongena, 2005) Summarizing the market power theory and the pass-through argumentation leads to H3:

H3: "Rating Change Pricing Policy": Banks follow an asymmetric setting of loan rates: Banks impose downgraded firms with higher financing costs, whereas firms with improved ratings do not receive a change in financing costs.

2.3 Data

The dataset comprises 121,702 nonpublic annual financial statements of 30,033 unique SMEs that were collected by 24 Swiss banks during the period 2002 to 2015. Each bank is a regionally focused commercial bank. The dataset includes the entire balance sheet (i.e., property plant and equipment (PPE), receivables, payables mortgages, equity, etc.), profit and loss (i.e., sales, EBITDA, depreciation, etc.) as well as some basic characteristics of the SME (i.e., number of employees, legal form and industry). Not all 24 banks provided financial statements for the entire time period.[2]

Furthermore, for each financial statement, the dataset shows three internal ratings used by the banks. The first rating reflects the probability of default of the SME, calculated with a software program, based on a mathematical-statistical model. The second rating is requested by the credit relationship manager. The third rating is the final rating that is ultimately approved by credit risk officers. In this context, credit risk officers represent not only an additional validation but independently assess the credit risk without factoring in any client relationships. All three rating types are expressed on an ordinal scale {1,2,3,4,5,6,7,8,9,10}, where {1} denotes the best and {10} the worst (close to default) rating.

All banks in the sample use the same software to enter the financial statements and the same rating model; the provider is an external firm that specializes in credit risk solutions. This common rating approach is a mathematical-statistical model, and its calculation is based on the financial statements of the SME (primary score) with an industry/sector comparison (secondary score). It is a hybrid PIT-TTC model. Thus, qualitative assessments by credit relationship managers or credit risk officers are reflected in the difference between the calculated and applied or approved ratings.

The dataset used in the study is an unbalanced panel. Most SMEs did not report financial statements for all 14 years. There are various reasons: i.e., the SME became a new client during this time, the SME went bankrupt or it simply changed the bank relation. The dataset construction is shown in appendix A2 and the summary statistics of the entire dataset in appendix A3. The relevant subsamples are reported in the respective sections 2.4 and 2.5.

[2] In 2002, only eight banks provided data. The number of banks steadily increases to 24 banks in 2015.

2.3.1 Bank Loan Types

Due to the various different definitions of loan types, table 2.2 summaries the terms used in this study. All firms in the dataset have a lending relationship with a bank. The data sample is not restricted to a certain loan type. Overall, bank loans can be classified into credit lines, investment loans and mortgages.

Table 2.2: Accounting Data Definition

Term used in this Paper	Balance sheet item	Description	Collateral
Credit lines[3]	Short term bank loans	Bank liabilities with maturities <12 months	Usually unsecured
Investment loans	Long term bank loans	Bank liabilities with maturities >12 months	Usually unsecured
Bank loans (Credit lines + Investment loans)	Short + long term bank loans	Bank liabilities	Usually unsecured
Mortgages	Mortgages	Real estate collateralized bank liabilities	Residential and/or commercial real estate

Notes: Own illustration.

Obviously, the distinction between credit lines and investment loans is not always precise. Credit lines may be drawn with a longer maturity than 12 months, and investment loans may have fixed interest rates less than 12 months and use a rollover model, i.e., peg the interest rate every three months.

The available annual financial statements report all drawdowns of any type of bank loans and mortgages. However, neither the unused part of a credit line nor a distinct collateral information is available in the data. For example, a CHF 100,000 credit line may be drawn with CHF 80,000. The balance sheet would only report CHF 80,000 in short-term bank loans. Furthermore, it is not possible to distinguish between mortgages backed by residential real estate or commercial real estate. The balance sheet only reports a mortgage. However, on the asset side, the real estate properties are separated into commercial and noncommercial.

[3] Short term bank loans may include investment loans with maturities <12 months.

2.3.2 Financing Costs

Financing costs are the dependent variable in this research paper. This figure is directly derived from the financial statements using the following formula:

$$FinancingCosts\ (FC) = \frac{Financial\_Expenses}{Interest\_Bearing\_Debt(IBD)}$$

Interest bearing debt (IBD) consists of any financial debt where the lender charges a fee or interest for borrowing money to the borrower. Financial expenses are the annual incurred expenditure due to the IBD. Consequently, all interest payments and charges of bank loan transactions are subsumed in the profit and loss item “financial expenses”. However, this definition of financing costs includes all types of lenders that demand an interest rate or fee. Despite the risk awareness of nonbank lenders, they may differently assess credit risk compared to the bank. In particular, shareholder liabilities may account for lower or higher charges due to the existing equity-stake relationship to the SME. Based on the summary statistics (appendix A3), nonbank IBD, i.e., leasing liabilities with a mean of 0.1% with respect to total assets or shareholder liabilities (4% of total assets), represent only a small proportion of the financing structure of the SMEs. Bank loans (8%) and mortgages (21%) account for the largest part of the third-party financing in the balance sheets. However, to circumvent any bias in financing costs, firms with leasing and/or shareholder liabilities are excluded from the analyses (see data sample construction in sections 2.4.1 and 2.5.1). Using this restriction, I state the following approximation:

$$\sum_{i=1}^{n} BankloanRate_{i,j} \cdot \frac{1}{n}\ \approx\ FinancingCosts_j \mid \left(no\ leasing\ and\_or\ shareholder\ liablities_j\right)$$

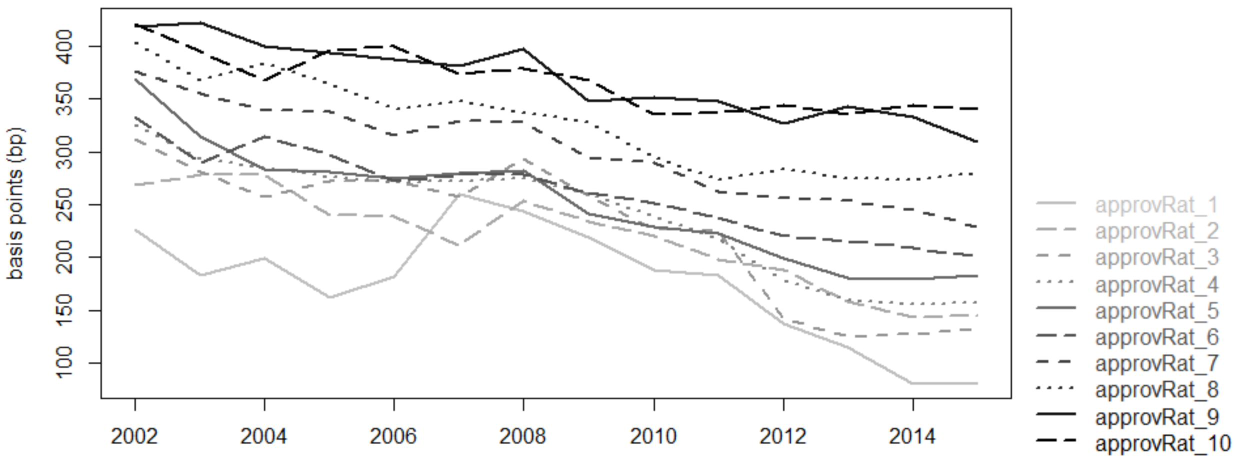
where j = SME

i= single bank loan agreement

n = all bank loan agreements of one firm j

This definition shall ensure that the financing costs are primarily determined by the bank loan pricing strategies. Based on the derived and elaborated hypothesis that credit risk is a main driver in the loan pricing equation, financing costs as defined above should be increasing with the approved ratings in the dataset. Using the entire dataset but excluding all firms with leasing and/or shareholder liabilities, figure 2.5 shows that financing costs are positively related to the approved rating classes {1-10}. This positive relation is persistent over time.

Figure 2.5: Financing Costs by Rating Class: All Bank Debt (n= 88,683)



Notes: The used sub-sample consists of all firms with bank debt, i.e. either mortgages, credit lines or investment loans, but without shareholder and/or leasing liabilities. *Source:* Proprietary Accounting Data.

Similar to the SNB data shown in section 2.2, figure 2.5 shows declining financing costs over time. This is driven by the decreasing market rates and thus lower funding costs for banks. Despite the positive relation between rating and financing costs, it is possible that better ratings show higher financing costs compared to worse ratings in certain time periods (i.e., rating2 vs rating1 in 2007). However, during the entire time period of 12 years, all firms with approved ratings lower than 7 report lower financing costs than firms with ratings larger than 7.

2.4 Initial Credit Risk Pricing

In this section, I analyze the influence of the bank's initial credit risk assessment on the SME's financing costs in the cross-section. The focus on these "first-time" borrowers shall minimize any influence from an existing credit relationship between the SME and bank. Furthermore, due to the first formal credit approval, this should be the most reliable point in time to measure to what extent banks pursue a risk-adjusted pricing strategy.

2.4.1 Data Sample

The data are restricted to firms that report new bank debt. Therefore, only firms and their first financial statement that enter the dataset during 2002 and 2015 are considered.

For banks that do only provide data for a part of the complete time period, new firms appearing in the same year as its bank first appears are excluded. To address the missing information (i.e., LGD) of the single loan transactions, the data are further split into two subsamples by loan type: a) firms reporting only unsecured bank loans (investment loans and/or credit lines) and b) firms reporting only mortgages and no other bank debt. Investment loans and credit lines are merged mainly because they use the same collateral, as well as the smooth transition between these two definitions.

Table 2.3 summarizes the subsample "new investment loans and/or credit lines". There are 3,791 firms that reported unsecured bank loans but neither mortgages nor leasing and/or shareholder liabilities. Only the first financial statement of the firms is considered.

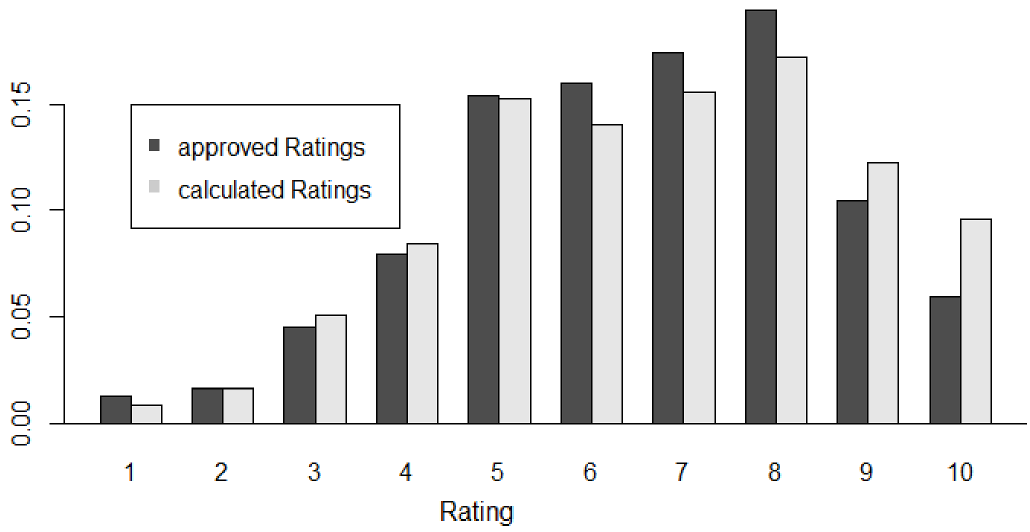
Table 2.3: Sample New Investment Loans and/or Credit Lines

Variables	mean	sd	q25	median	q75	n
Financing costs in bp	397.61	270.54	186.92	378.31	600.00	3'791
Calculated Rating	6.70	2.12	5.00	7.00	8.00	3'791
Applied Rating	6.66	2.11	5.00	7.00	8.00	3'791
Approved Rating	6.71	2.14	5.00	7.00	8.00	3'791
Property Plant Equipment (TA)	0.40	0.32	0.11	0.34	0.65	3'791
Residential Property (TA)	0.01	0.08	0.00	0.00	0.00	3'791
Accounts Payable (TA)	0.14	0.15	0.02	0.10	0.22	3'791
Credit lines (TA)	0.15	0.18	0.00	0.09	0.24	3'791
Investment loans (TA)	0.16	0.24	0.00	0.00	0.29	3'791
Bank loan (TA)	0.32	0.23	0.13	0.27	0.47	3'791
Longterm other Liabilities (TA)	0.06	0.14	0.00	0.00	0.02	3'791
Current Asset Ratio	0.59	0.32	0.34	0.65	0.88	3'791
Durable AssetRatio	0.41	0.32	0.12	0.35	0.66	3'791
Equity Ratio	0.32	0.22	0.15	0.29	0.46	3'791
Total Assets in Thousand CHF	4'532	13'297	291	682	2'317	3'791

Notes: The table depicts summary characteristics for the variables used in the analysis. "TA" indicates standardization to total assets. Bank loan (TA) represent the share of credit lines and investment loans to total assets. The used sub-sample consists of all firms reporting new credit lines and/or new investment loans, but without mortgages, shareholder and/or leasing liabilities.

Despite winsorizing the data, the subsample shows a median of total assets of CHF 682,000 but a mean of CHF 4.5 Mio. A relatively high equity ratio with a mean of 32% is common for SMEs. Bank loans account for 32% of total assets. Figure 2.6 shows the rating distribution of these SMEs. The difference between approved and calculated ratings shows that credit risk officers tend to move firms with best ratings (2-4) and worst ratings (9-10) to rating classes 5-8. Thus, rating classes 5 to 8 are even more pronounced for approved ratings than for calculated ratings.

Figure 2.6: Rating Distribution of new Investment Loans and/or Credit Lines (n= 3'791)



Rating	1	2	3	4	5	6	7	8	9	10
approved	49	61	170	301	585	607	660	736	396	226
calculated	31	62	194	320	580	532	589	653	466	364

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Firms	118	114	248	262	309	452	304	347	403	303	286	455	190

Notes: The used sub-sample consists of all firms reporting new credit lines and/or new investment loans, but without mortgages, shareholder and/or leasing liabilities. *Source:* Annual Accounting Data.

Table 2.4 summarizes the subsample "new mortgages". There are 4,025 firms that reported mortgages but neither unsecured bank loans nor leasing and/or shareholder liabilities. Again, only the first financial statement of the firms is considered.

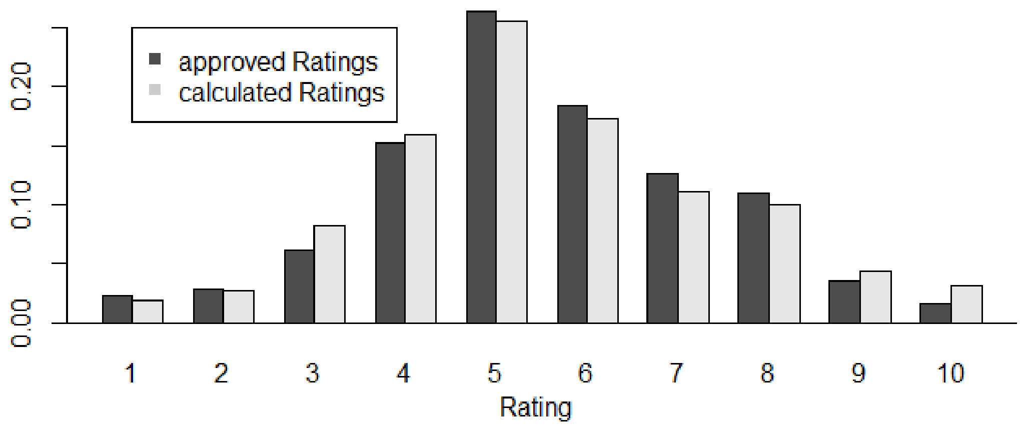
Table 2.4: Sample New Mortgages

variables	mean	sd	q25	median	q75	n
Financing Costs in bp	267.62	184.35	124.77	270.79	378.73	4'025
Calculated Rating	5.53	1.94	4.00	5.00	7.00	4'025
Applied Rating	5.59	1.95	4.00	5.00	7.00	4'025
Approved Rating	5.62	1.96	4.00	5.00	7.00	4'025
Property Plant Equipment (TA)	0.63	0.29	0.43	0.70	0.87	4'025
Residential Property (TA)	0.08	0.20	0.00	0.00	0.00	4'025
Accounts Payable (TA)	0.06	0.08	0.01	0.03	0.07	4'025
Mortgages (TA)	0.44	0.22	0.27	0.44	0.61	4'025
Longterm other Liabilities (TA)	0.05	0.11	0.00	0.00	0.04	4'025
Current Asset Ratio	0.30	0.23	0.10	0.23	0.46	4'025
Durable AssetRatio	0.70	0.23	0.54	0.77	0.90	4'025
Equity Ratio	0.34	0.21	0.18	0.32	0.48	4'025
Total Assets in Thousand CHF	4'879.80	10'239.41	908.00	1'745.50	4'271.50	4'025

Notes: The table depicts summary characteristics for the variables used in the analysis. "TA" indicates standardization to total assets. The used sub-sample consists of all firms reporting new mortgages, but without credit lines, investment loans, shareholder and/or leasing liabilities.

Compared to the unsecured loan sample, the firms' sizes are rather homogeneous in terms of a closer median to mean of total assets. With 44%, mortgages account for a larger part of total assets compared to bank loans or equity. Figure 2.7 shows the rating distribution of these SMEs. Firms holding only mortgages show a significantly better rating structure compared to firms holding only unsecured loans (figure 2.6). Rating class 5 is the most prominent rating class if the firms hold mortgages, whereas firms with unsecured loans predominantly receive a rating 8. One explanation might be that firms holding real estate are larger, older and financially more mature. Similar to the unsecured loans, credit officers tend to move firms with good ratings (3-4) and worst ratings (9-10) to rating classes 5-8.

Figure 2.7: Rating Distribution of new Mortgages (n = 4'025)



Rating	1	2	3	4	5	6	7	8	9	10
approved	95	114	249	614	1060	739	507	441	141	65
calculated	74	107	333	641	1026	694	448	402	177	123

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Firms	139	105	432	297	319	527	429	347	347	270	248	382	183

Notes: The used sub-sample consists of all firms reporting new mortgages, but without credit lines, investment loans, shareholder and/or leasing liabilities. *Source:* Annual Accounting Data.

2.4.2 Empirical Strategy

My aim is to quantify the relationship between the bank's initial credit risk assessment on the SME's financing costs. Based on the risk-adjusted pricing model, I follow the strategy to isolate the impact of the available credit ratings, reflecting the risk cost component, on the financing costs of the firm and control for the remaining RAP components using fixed effects (RAP see section 2.2.3). Each component and its control is explained below. If an SME receives new bank debt, its financial statement and rating appears in the dataset. The rating is based upon the financial statement of the same year. Therefore, a time lag of one year between rating and financing cost reporting ensures that the rating materializes in the interest paid by the firm. I use a multivariate regression model to analyze the respective relations by regressing the financing costs on the RAP components. Let *i* be an SME, *j* the bank and *t* time:

$$
\begin{aligned}
FC_{i,t} \quad = \quad & \beta_1 \cdot approvRAT_{i,t-1} + \gamma_1 \cdot shareCL_{i,t-1} + \gamma_2 \cdot owner_{i,t-1} \\
& + \theta_1 \cdot IND\_FE_i + \theta_2 \cdot bank\_FE_j + \theta_3 \cdot year\_FE_t + \varepsilon_{i,t}
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
FC_{i,t} \quad = \quad & \beta_2 \cdot calcRAT_{i,t-1} + \beta_3 \cdot bank\_discretion_{i,t-1} \\
& + \gamma_1 \cdot shareCL_{i,t-1} + \gamma_2 \cdot owner_{i,t-1} \\
& + \theta_1 \cdot IND\_FE_i + \theta_2 \cdot bank\_FE_j + \theta_3 \cdot year\_FE_t + \varepsilon_{i,t}
\end{aligned} \tag{2}
$$

where

$$bank\_discretion_{i,t-1} \coloneqq \left(approvRAT_{i,t-1} - calcRAT_{i,t-1}\right)$$

Equation (1) and (2) are used to estimate a linear dependence between credit risk $\left(approvRAT_{i,t-1};\ calcRAT_{i,t-1}\right)$ and pricing $\left(FC_{i,t}\right)$ for new bank loans. Financing costs $(FC_{i,t})$ are based on the definition introduced in section 2.3.2. There are two different ratings used in equations (1) and (2): $approvRAT_{i,t-1}$ reflects the final approved rating by the credit risk officer and $calcRAT_{i,t-1}$ the initial calculated quantitative rating. Both variables are vectors that each consists of ten dummy variables: i.e., $\left\{calcRAT1_{i,t-1};\ calcRAT2_{i,t-1}; \ldots.; calcRAT10_{i,t-1}\right\}$. The difference between these rating types is used to assess the bank's discretion. Both variables $approvRAT_{i,t-1}$ and $calcRAT_{i,t-1}$ are directly attributed to the risk component of the RAP model. The share of credit lines with respect to total bank debt $\left(shareCL_{i,t-1}\right)$ controls for differences between investment loans and credit lines. Regulatory and operational costs are mainly bank specific and are controlled by bank fixed effects $(bank\_FE_j)$. Funding costs depend on the year of origination as well as the loan duration chosen by the firm. Using year fixed effects $(year\_FE_t)$ addresses the former of these two issues. The duration of the bank debt is one of the main drawbacks in the available data, which cannot be fully controlled for. Typically, investment loans have a duration of less than 5 years. The difference in market rates (LIBOR) between one and five years lies between 3 and 110 basis points in 2002-2015. This difference is lower after 2009 compared to 2002-2009. Using the loan type as an additional explanatory variable shall address this issue in a robustness test (section 2.4.4).

Another issue is the information about the bank loan and mortgage collateral, which is missing from the underlying data. Due to the heterogeneity in terms of the LGD between bank loans and mortgage types, I use the introduced sample splits by loan types to overcome the missing LGD information. Credit lines and investment loans are usually unsecured and therefore merged in one sample. However, there are much more SMEs with both credit lines and investment loans than just one of these loan types. Mortgages are collateralized by commercial or residential real estate properties. To disentangle the impact of residential or commercial real estate collateral, I use an owner dummy whether the firm owns residential and/or commercial real estate $(owner_{i,t-1})$. This dummy is based on the available asset information from the financial statements. Despite the missing link, whether the property truly serves as collateral for the mortgage, this dummy is used as an indication for the collateral type.

Furthermore, industry (IND_FE_i) and time fixed effects $(year\_FE_t)$ control for systematic effects and business cycle effects (Demirgüç-Kunt & Huizinga, 1999). Changes in economic conditions (i.e., GDP, inflation) and other time variant unobserved variables are controlled with time fixed effects. Bank fixed effects $(bank\_FE_j)$ control for credit policies, administrative and capital costs. This should alleviate the concern that heterogeneity stemming from different credit strategies and internal cost structures of banks is responsible for the results. Different RAP strategies are also captured by bank fixed effects.

Based on this estimation strategy, coefficients of β_1 should capture if and how much the risk element of RAP influences the financing costs. In any given year, there are firms with different ratings. β_1 is identified by comparing the difference in financing costs between SMEs with different ratings. A positive β_1 shows that a poorer rating leads to higher financing costs. Equation (1) is linked to H1:

H1: Risk-Adjusted Pricing:	$H1_0$: $\beta_1 \leq 0$	Borrower's credit risk is not reflected in financing costs
	$H1_A$: $\beta_1 > 0$	Borrower's credit risk is reflected in financing costs

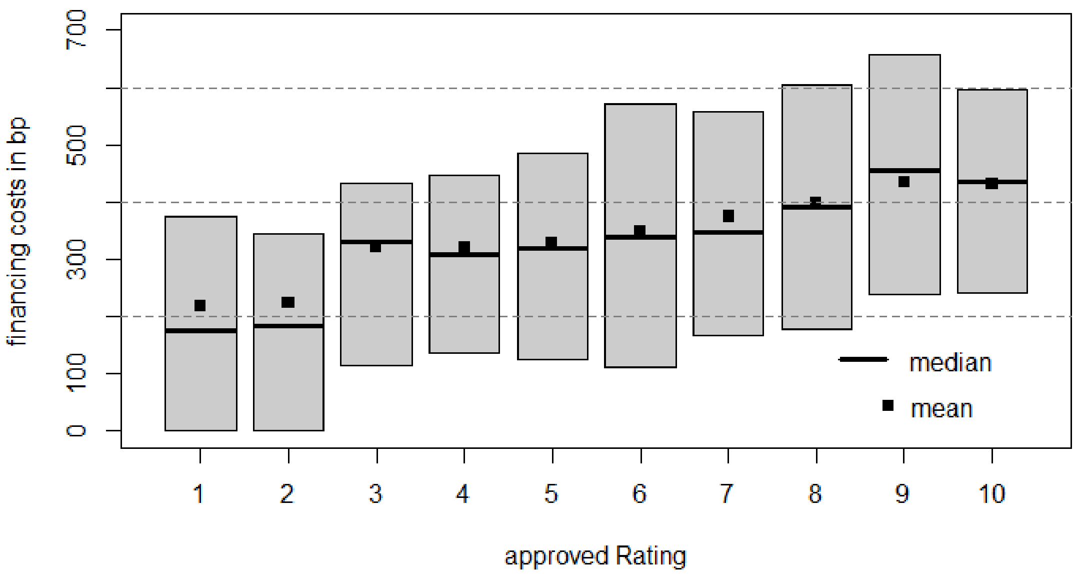
Equation (2) is used to estimate the impact of the RAP risk element as well as the credit risk officers' discretion on the financing costs. β_2 capture the quantitative risk element. Coefficients of β_3 should capture if and how much credit risk officers influence the financing costs. Therefore, equation (2) is linked to H2:

H2: Qual. Risk Assessment:	H2$_0$: $\beta_3 \leq 0$	Credit risk officer's rating discretion is not reflected in financing costs
	H2$_A$: $\beta_3 > 0$	Credit risk officer's rating discretion influences the financing costs

2.4.3 Results

Figure 2.8 shows univariate evidence that there is risk-adjusted pricing for investment loans and credit lines. Despite the varying dispersion in financing costs per rating class, mean and median values show increasing financing costs associated with increasing credit risk. The difference between the best and worst rating classes is 250 bp (median), resp. 210 bp (mean). This difference goes along with the lending rate statistics of the SNB for investment loans (SNB. 2015). The large dispersion in financing costs per rating class can be explained by the varying refinancing costs (market interest rates) between 2003 and 2015 as well as the difference in loan duration (1 month to ~5 years). However, the lower (higher) financing costs of firms with worse (better) ratings in the 25% and 75% quantiles may provide support for the influence of relationship banking.

Figure 2.8: Financing Costs and approved Rating Relation of new Investment Loans and/or Credit Lines (n= 3,791)



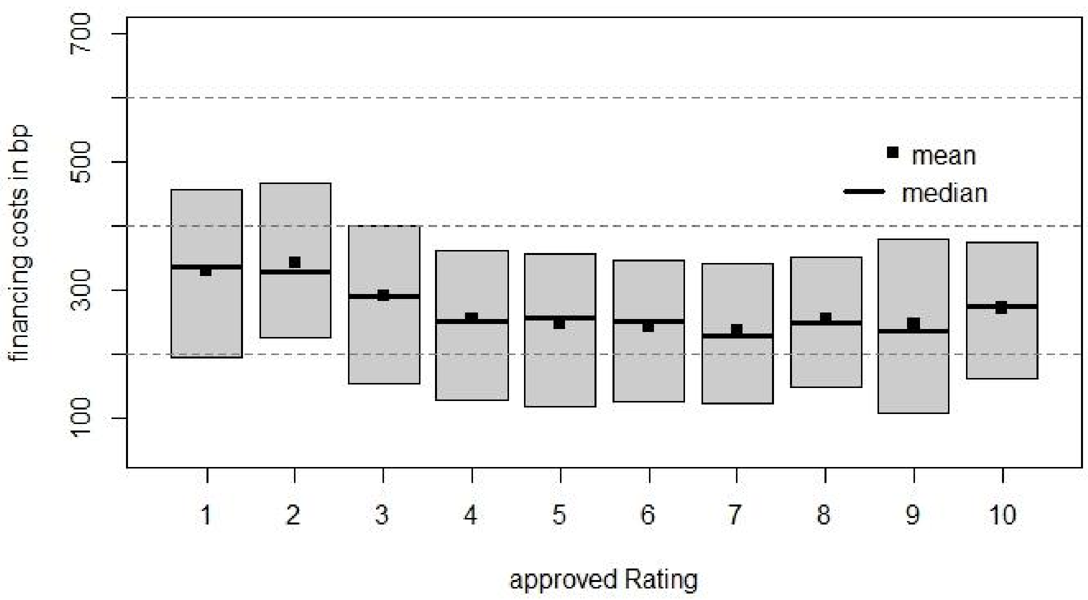
Notes: This graph plots financing costs in basispoints dependent on the approved rating classes. The used sub-sample consists of all firms reporting new credit lines and/or new investment loans, but no mortgages, shareholder and/or leasing liabilities. Number of firms equals number of financial statements. *Source:* Annual Accounting Data.

The positive relationship between credit risk and financing costs is stable between 2003 and 2015. However, the difference between high and low ratings has increased since 2003.

This is consistent with the distribution of the RAP concept starting after the Swiss real estate crisis in the nineties and the introduction of the rating models around 2000 (Appendix A8).

The distinct positive relation between approved ratings and financing costs for unsecured bank loans does not hold for firms reporting only mortgages. Figure 2.9 shows that the second sample, firms with only mortgages, has an almost uniform distribution for ratings four to nine. Furthermore, the firms with the best rating grades (one to three), i.e., firms with the lowest probability of default, report higher financing costs. Therefore, if mortgages are risk-adjusted priced, there must be systematic differences between the rating categories. One explanation might be the duration of the mortgage. However, assuming a normal distribution of mortgage duration per rating class leads to a positive relation between financing costs and rating. Thus, figure 2.9 should be similar to the unsecured loans (figure 2.8). It is likely that there is much more heterogeneity of mortgage duration per rating class. Firms with very good ratings may seek long maturities up to 10 years with higher refinancing costs, resulting in higher financing costs. Another explanation could be that banks use borrowers with top rating grades to subsidize debtors with lower ratings. On the other hand, ratings 1 and 2 may simply count as outliers due to the small number of firms with ratings 1 and 2. Lastly, there might be fundamental differences between the unsecured and mortgage loan markets.

Figure 2.9: Financing Costs and approved Rating Relation of new Mortgages (n= 4,025)



Notes: This graph plots financing costs in basispoints dependent on the approved rating classes. The used sub-sample consists of all firms reporting new mortgages, but without credit lines, investment loans, shareholder and/or leasing liabilities. Number of firms = financial statements. *Source:* Accounting Data.

The difference in the LGD between mortgages and unsecured bank loans is reflected in the level of financing costs. Firms with mortgages report substantially lower financing costs (median: 270 bp) compared to unsecured loans (median: 378 bp). LGD for real estate collateralized loans account for approx. 15-40%, whereas the unsecured loan LGD accounts for approx. 50-75% (BIS, 2006; Moody's, 2018). Because the analyzed data stem from banks that use the BIS standardized approach for credit risk, all these banks have to hold the same amount of capital for unsecured loans as to loans collateralized by commercial real estate.

Table 2.5 reports the estimates of β_1 in equation (1) and β_2 in equation (2) using the best approved or calculated rating class $\{approvRAT_{i,t-1} = 1;\ calcRAT_{i,t-1} = 1\}$ as the baseline dummy. The first two columns are run with the sample "new investment loans and/or credit lines". Running this equation with approved ratings (1.1) shows increasing estimates by rating class for the unsecured loans, which goes along with the univariate results and supports hypothesis H1. The estimates are highly statistically significant. A firm for which the banks internally approved a rating 6 pays 130 bp higher interest rates compared to a firm with rating 1. Supporting the results from the univariate box plot, there is not much difference between ratings 3 and 6. It seems that it only matters if a firm receives a top rating of 1 and 2 or the poorest ratings of 7 to 10. Using the same sample and equation but with calculated ratings (2.1) reports similar results. However, the difference between ratings 3 and 6 is more distinct. In regression (2.1) the variable $bank\_discretion_{i,t-1}$ is the difference between approved and calculated ratings and used to estimate the impact of the credit risk officers' discretion. The estimates for $bank\_discretion_{i,t-1}$ are positively related to the financing costs and significant from zero. This supports hypothesis H2. The credit officer's decision to override the calculated ratings results in financing costs that are 20 bp higher. Credit officers tend to apply a precautionary and conservative credit risk policy. The question arises to what extent credit officers follow a tendency to progressively increase poor ratings compared to good ratings. Calculating the Pearson correlation coefficient between $approvRAT_{i,t-1}$ and $bank\_discretion_{i,t-1}$ from the bank loan sample results in 0.18 (appendix A5). Despite the relatively low coefficient, this result supports H2 that credit officers tend to apply a precautionary approval practice. Appendix 5 shows the relation of $approvRAT_{i,t-1}$ and $bank\_discretion_{i,t-1}$ in box plot.

Table 2.5: Regression Results for New Investment Loans and/or Credit Lines

	Dependent variable: Financing Costs $(FC_{i,t})$			
2002-2015	*Sample:* New Investment Loans and/or Credit Lines		*Sample:* New Mortgages	
	(1.1)	(2.1)	(1.2)	(2.2)
	(Approved Ratings)	(Calculated Ratings)	(Approved Ratings)	(Calculated Ratings)
Rating2	-10.7 (54.0)	-19.0 (62.1)	23.8 (25.3)	9.1 (28.3)
Rating3	101.2** (45.1)	82.3 (53.5)	-1.8 (23.2)	-9.2 (24.9)
Rating4	110.5** (42.9)	99.4* (52.5)	-23.7 (21.9)	-6.9 (24.3)
Rating5	107.5*** (41.6)	107.6** (51.6)	-27.2 (21.7)	-14.5 (24.2)
Rating6	133.1*** (41.4)	132.9*** (51.5)	-30.3 (22.1)	-14.1 (24.5)
Rating7	160.1*** (41.6)	160.0*** (51.5)	-30.1 (22.7)	-27.8 (25.2)
Rating8	171.3*** (41.5)	175.9*** (51.6)	-25.2 (22.9)	-10.2 (25.5)
Rating9	212.1*** (43.1)	190.7*** (52.5)	-38.1 (27.2)	-37.9 (28.6)
Rating10	204.6*** (45.4)	209.6*** (53.5)	2.2 (33.4)	-16.3 (31.5)
Share_Creditlines_ TotalBankdebt	8.7 (12.3)	8.5 (12.4)		
Bank_discretion		20.0*** (5.1)		-2.2 (4.0)
RRE_Owner			-33.5*** (12.5)	-32.3*** (12.5)
CRE_RRE_Owner			-27.0*** (9.9)	-26.2*** (10.0)
Constant	173.0*** (63.9)	179.3** (70.7)	307.0*** (33.0)	293.7*** (34.7)
FixedEffects	bank; time; industry	bank; time; industry	bank; time; industry	bank; time; industry
Observations	2,747	2,747	2,962	2,962
R^2	0.1	0.1	0.1	0.1
Adjusted R^2	0.1	0.1	0.1	0.1
Residual Std. Error	257.1 (df = 2686)	257.3 (df = 2685)	163.4 (df = 2899)	163.5 (df = 2898)
F Statistic	4.4*** (df = 60; 2686)	4.3*** (df = 61; 2685)	7.5*** (df = 62; 2899)	7.3*** (df = 63; 2898)

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (1) and (2). Dependent variable is financing costs. The sample for regression results (1.1) and (2.1) consists of firms reporting first time borrowing investments loans or credit lines. The sample for regression (1.2) and (2.2.) consists of firms reporting first time borrowing mortgages. The variable Bank_discretion is defined as the difference of $(approvRAT_{i,t-1} - calcRAT_{i,t-1})$. The real estate ownership $(owner_{i,t-1})$ is represented with two dummies: RRE = Residential Real Estate Owner, CRE_RRE = Holding both Commercial and Residential Real Estate. Baseline dummy is CRE = Commercial Real Estate Owner. Standard errors are shown in parentheses. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

The third and fourth columns of table 2.5 represent the results for the sample "new mortgages". The results are not as coherent as those for unsecured bank loans. Similar to the univariate findings, table 2.5 reports neither a positive relation between financing costs and rating classes nor increasing financing costs per rating class. Accordingly, the coefficient of the rating dummies is not statistically significant. The best approved or calculated rating $\{approvRAT_{i,t-1} = 1;\ calcRAT_{i,t-1} = 1\}$ as baseline dummies for equation (1) and (2) result in negative estimates of β_1 and β_2 for the other rating classes –

with the exception of rating {2}. The mean financing costs for firms with rating {2} are highest. Furthermore, the differences between the magnitude of the estimates are very low. It seems that the individual bank's mortgage pricing policies, the year of origination and the industry explain some variations of the mortgage costs for firms.

However, the real estate owner variables *RRE_Owner* and *CRE_RRE_Owner* show significant relevance. In the regressions (1.2) and (2.2), firms holding commercial real estate are the baseline dummy (*CRE_Owner*) represented in the intercept. Thus, residential real estate owner pay approx. 30 bp less compared to commercial real estate owners. This positive effect of holding residential real estate is intuitive but lower than expected. In summary, it seems that the PD component, measured as the rating class of a client, is less important for pricing mortgages. Accordingly, the differentiation between calculated and internally approved ratings is negligible as well. The LGD component in terms of differentiation between commercial and residential real estate is more relevant.

2.4.4 Robustness

Despite the difficulty of separating credit lines and investment loans with the available balance sheet data, the available loan type information is used to address the shortcoming regarding the duration of the bank loan. Short-term bank loans are typically up to one year and long-term loans up to 5 years. To ensure that the previous results are not driven by the unobserved variable of chosen loan duration, I use only first-time borrowers with credit lines but without investment loans. This reduces the sample size significantly to 1,555 financial statements. Appendix A4 shows the estimated regressions for equation (1) and (2). All specifications show similar sizes of the estimated β compared with the existing results with equation (1). The coefficients for rating 2 to rating 5 are not statistically significantly different from zero. One reason might be the small sub-sample combined with the heterogeneity of the underlying banks. However, the magnitude of the estimated β and the significance for rating 6 to rating 10 support the previous results.

2.5 Rating Changes and Financing Costs

In this section, I analyze the impact of the bank's rating changes on the SME's financing costs using the panel structure within the data.

2.5.1 Data Sample

The available full dataset is restricted to firms with at least three consecutive years of data. Investment loans and mortgages usually contain fixed loan rates for a predetermined period. Unlike syndicated loans for large corporates, loan contracts of SMEs usually do not include covenants that trigger a loan rate change based on a rating change. Therefore, firms with investment loans and mortgages are excluded from the subsample. The final subsample for the panel analysis consists of firms reporting only credit lines and at least three consecutive years. Summary statistics are shown in table 2.6.

Table 2.6: Sample Panel

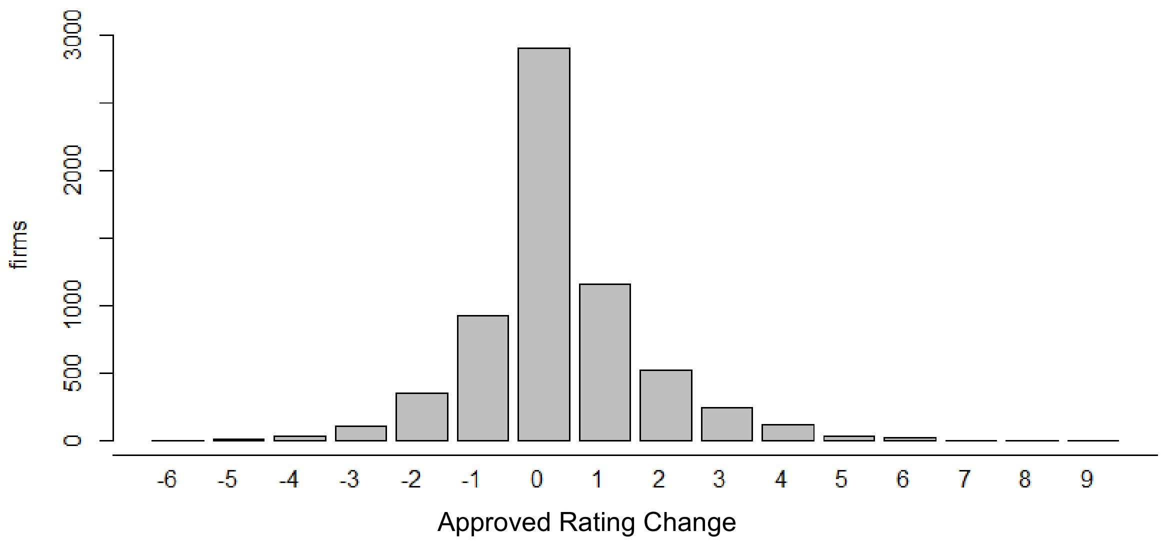
variables	mean	sd	q25	median	q75	n
Financing costs in bp	453.02	272.24	245.16	451.13	666.67	8'615
1year change in fin.costs (bp)	56.42	286.53	-93.09	19.31	199.40	6'464
Calculated Rating	7.15	1.88	6.00	7.00	9.00	8'615
Applied Rating	6.99	1.77	6.00	7.00	8.00	8'615
Approved Rating	7.02	1.76	6.00	7.00	8.00	8'615
Approved Rating Change	0.25	1.43	0.00	0.00	1.00	8'615
Property Plant Equipment (TA)	0.25	0.25	0.06	0.17	0.38	8'615
Residential Property (TA)	0.01	0.06	0.00	0.00	0.00	8'615
Accounts Payable (TA)	0.17	0.15	0.06	0.14	0.26	8'615
Credit lines (TA)	0.22	0.17	0.09	0.18	0.31	8'615
Longterm other Liabilities (TA)	0.05	0.13	0.00	0.00	0.02	8'615
Current Asset Ratio	0.74	0.25	0.61	0.83	0.93	8'615
Durable AssetRatio	0.26	0.25	0.07	0.17	0.39	8'615
Equity Ratio	0.36	0.21	0.19	0.34	0.50	8'615
Total Assets in Thousand CHF	3'321	10'622	306	661	1'793	8'615

Notes: The table depicts summary characteristics for the variables used in the analysis. "TA" indicates standardization to total assets. The used sub-sample consists of all firms reporting credit lines for three consecutive years, but without investment loans, mortgages, shareholder and/or leasing liabilities.

The panel shows slightly higher financing costs compared to the previous cross-sectional sample, including credit lines and investment loans (section 2.4.1). This may be due to distribution being different over time (reference rate variations between 2002 and 2015) or that credit lines are more costly due to the flexibility (i.e., liquidity cost component). The summary statistics already show a relation between approved rating change and one-year change in financing costs. A one-year change in financing costs in the 75% quantile is 180 bp above the median compared to the 25% quantile, which is 112 bp lower than the median. This left skewness is similar to the approved rating change. There is one rating class downgrade on the 75% quantile, whereas none for the 25% quantile.

Figure 2.10 shows the approved rating changes based on the chosen subsample. Approximately 45% of these firms remain in the rating classes of the previous year. Thus, banks changed more than 50% of all firms' ratings, 32% of which rated one rating class higher or lower compared to the previous year. This is a peculiarity for SMEs compared to large corporates. On the one hand, ratings of SMEs change much faster than they do for corporates due to rating agency policies to avoid many rating reversions. Second, financial statements of SME are inherently more unstable than those of large corporations.

Figure 2.10: Histogram Approved Rating Changes (n= 6,464)



Rating Change	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
Financial Stat.	1	13	38	105	352	932	2911	1163	527	244	115	33	24	2	2	2

Notes: This graph plots the histogram of approved rating changes between 2002 and 2015. The used sub-sample consists of all firms reporting credit lines for three consecutive years, but without investment loans, mortgages, shareholder and/or leasing liabilities.

2.5.2 Empirical Strategy

I isolate the risk pricing component from the other RAP components to show the relation between rating change and change in financing costs. The dependent variable is the change of financing costs $\Delta FC_{i,t+1}$. The estimation strategy is based on the assumption that if a bank calculates and approves a change in the SME rating, the bank will potentially change the loan rates and thus alter the financing costs of the SME. Obviously, there is a time lag of approximately one year until a rating change may materialize in the profit and loss statements. The observations in the financial statements have to be in consecutive years. Equation (3) summarizes the described regression model. Let *i* be an SME, *j* the bank and *t* time:

$$\begin{aligned} \Delta FC_{i,t+1} \quad = \quad & \beta_1 \cdot RATdown1_{i,t} + \beta_2 \cdot RATdown2_{i,t} + \beta_3 \cdot RATdown3_{i,t} \\ & + \zeta_1 \cdot RATup1_{i,t} + \zeta_2 \cdot RATup2_{i,t} + \zeta_3 \cdot RATup3_{i,t} + \\ & + \ \theta_1 \cdot bank\_FE_j + \ \theta_2 \cdot IND\_FE_i + \ \theta_3 \cdot year\_FE_t + \ \varepsilon_{i,t} \end{aligned} \tag{3}$$

The risk component of the RAP, the rating change is the main explanatory variable and consist of six dummy variables:

$$\{RATdown1_{i,t};\ RATdown2_{i,t}; RATdown3_{i,t}; RATup1_{i,t};\ RATup2_{i,t}; RATup3_{i,t}\}$$

where $RATdown1_{i,t}$ is a dummy variable for a rating downgrade by one rating class and $RATdown2_{i,t}$ for two rating classes and so forth.

A down- or upgrade of a firm in one single year may be insufficient to trigger a pricing change. A persistent rating change is more likely to result in pricing adjustments. Therefore, the previous rating change $\Delta RAT_{i,t-1}$ is considered in equation (3.2) to (3.5). This previous rating change is summarized in three categories: no rating change, upgrade and downgrade. The sample is split into these categories. Conditioning the regression on these categories ensures capturing the impact of a potential rating path.

Equation (3) is unconditioned (3.1)

and controlled for previous rating change (3.2)

Equation (3) is conditioned on:

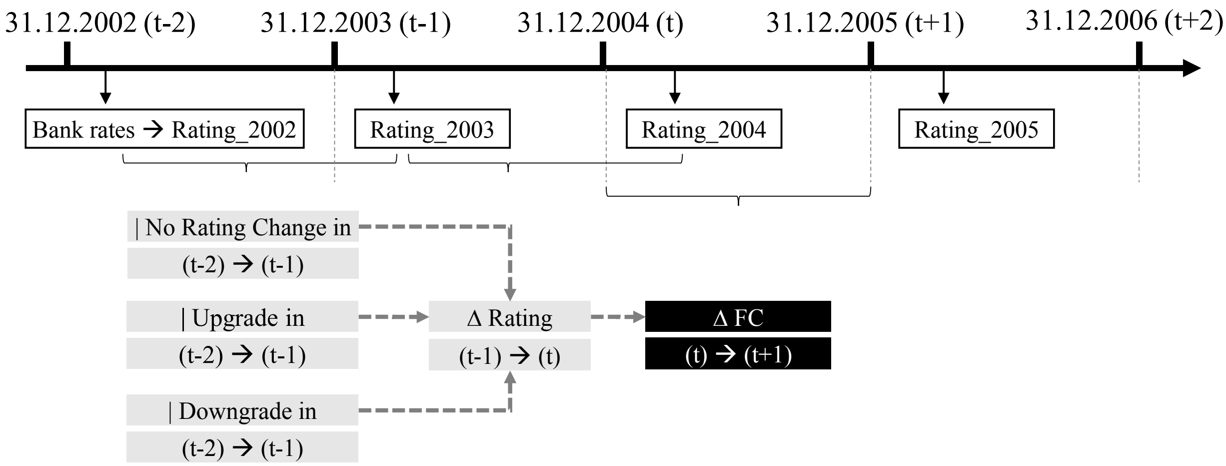
No Rating change in previous year *(t-1)* (3.3)

Rating upgrade in previous year *(t-1)* (3.4)

Rating downgrade in previous year *(t-1)* (3.5)

The dummy variables for the rating changes from equation (3) can be summarized by the variable $\Delta RAT_{i,t}$. Figure 2.11 illustrates the intended approach for equations (3) to (3.5).

Figure 2.11: Empirical Strategy for Panel Analysis



Notes: Own illustration.

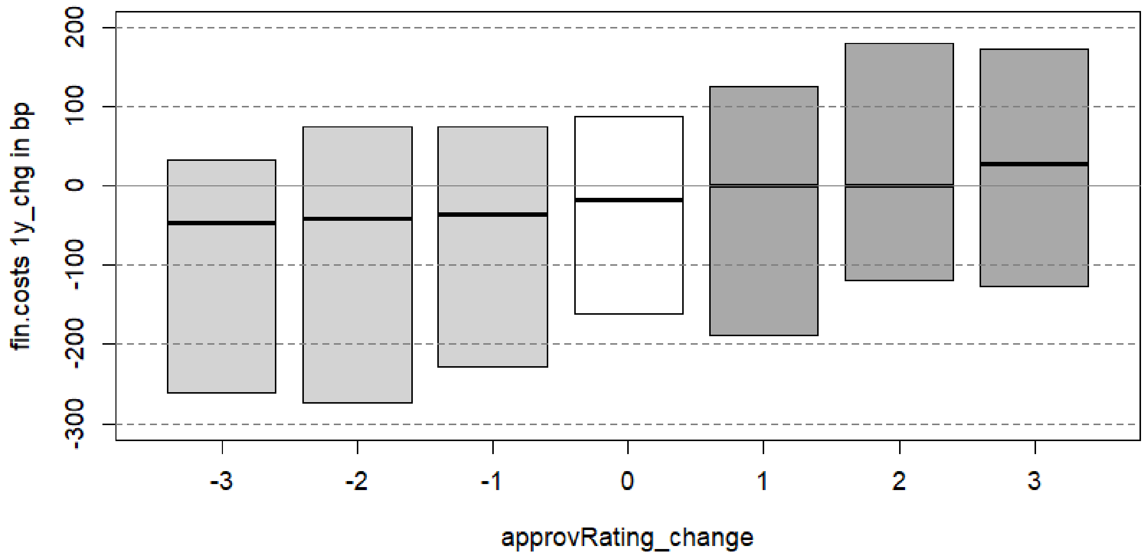
IND_FE_i, $bank\_FE_j$, and $year\_FE_t$ are industry, bank and year fixed effects. The dependent variable of interest is $\Delta FC_{i,t+1}$ in the time period subsequent to a rating change. The coefficient β should capture the relation between a rating down-/upgrade and a change in the financing costs. If the price setting follows a symmetrical approach, meaning that banks decrease interest rates in the case of an upgrade and increase rates if an SME was downgraded, both coefficients β and ζ are similar. According to the RAP, coefficients β have to be positive and ζ negative. A positive difference in the magnitude between β and ζ supports the asymmetric price setting strategy assumption. Equation (3) is directly linked to H3:

H3: "Rating Change Policy":	$H1_0$: $\lvert\beta\rvert \leq \lvert\zeta\rvert$	No evidence for asymmetric Pricing pricing behavior in favor of the bank.
	$H1_A$: $\lvert\beta\rvert > \lvert\zeta\rvert$	Asymmetric increase in financing costs for downgrades compared to upgrades.

2.5.3 Results

Figure 2.12 plots the relation between financing costs and rating changes, unconditional on rating changes in earlier years. Those firms that were downgraded report a positive change in their financing costs and *vice versa*.

Figure 2.12: Financing Costs Adjustments dependent on Rating Changes (n= 6,234)



Notes: This boxplot shows the relation between one year changes in financing costs in basispoints (bp) and approved rating changes. Bars report 25% - 75% quantiles. Single lines report median.

This plot gives support that overall the banks follow the risk-adjusted pricing strategy in both directions and not only if the firms receive a downgrade. However, the large dispersion per rating change category indicates that the price setting process does not exclusively depend on the rating. The comparatively small differences between the means per rating change also show that the rating has to change two classes or more to trigger a significant change in the loan rates. Furthermore, overall, the change in financing costs is more negative than positive. This can be attributed to the decreasing refinancing costs by the banks between 2002 and 2015. The 12-month LIBOR as well as the 5-year Swap decrease on average 23 bp per year and ~300 bp, respectively, over the entire time period.

Table 2.7 reports the estimates for β and ζ in equation (3). The first two columns use all financial statements with at least two consecutive financial statements. The relation between rating changes and changes in financing costs are highly significant. These results support H1, that banks follow the risk-adjusted pricing strategy consequently if there is a rating action. However, one must differentiate between the magnitude of rating change. The magnitude of change in financing costs due to an upgrade by two rating classes is slightly higher compared to that of a downgrade by two classes. On the other hand, a rating downgrade by one class does not trigger a statistically significant or substantial change in financing costs, whereas an upgrade by one class does.

Regression results in the second column (3.2) share these results and simultaneously control for any previous rating change – if available. The dummy variable “previous downgrade" is positive and the "previous upgrade" is negative, indicating a positive relationship between rating drift and financing costs. However, the coefficients are not statistically significant, and the magnitudes are low. To further analyze the rating path relevance, columns three (3.3) to five (3.5) report the estimates of β and ζ for the subsamples: (3.3) no previous rating change, (3.4) previous upgrade, (3.5) previous downgrade. Appendix A9 summaries the median and mean change in financing costs conditioned on the previous rating action.

Table 2.7: Regression Results for Panel Approved Ratings

Sample:	*Dependent variable:* Δ Financing Costs_1year $(\Delta FC_{i,t+1})$				
Credit Lines	(3.1)	(3.2)	(3.3)	(3.4)	(3.5)
2002-2015	Unconditional	Controlled for rating change (t-1)	Subsample: No change (t-1)	Subsample: Upgrade (t-1)	Subsample: Downgrade (t-1)
Rating_Downgrade1	8.52 (12.45)	9.03 (12.48)	12.28 (13.88)	33.41 (31.93)	17.29 (28.66)
Rating_Downgrade2	52.40*** (16.89)	53.60*** (16.97)	47.97** (19.32)	97.68*** (37.44)	81.89* (44.25)
Rating_Downgrade3	50.54*** (18.93)	52.09*** (19.04)	42.98** (21.46)	87.96** (42.59)	107.23** (52.34)
Rating_Upgrade1	-31.19** (13.54)	-31.80** (13.56)	-35.49** (15.07)	-42.63 (42.15)	-6.85 (27.30)
Rating_Upgrade2	-60.47*** (20.02)	-61.81*** (20.08)	-47.59** (23.10)	-189.58** (84.29)	-12.20 (36.68)
Rating_Upgrade3	-20.58 (28.60)	-21.65 (28.63)	-23.68 (31.80)	-30.97 (131.28)	60.04 (53.47)
previousRating_Downgrade		8.36 (11.83)			
previousRating_upgrade		-4.79 (12.87)			
Constant	29.31 (48.19)	26.79 (59.28)	10.65 (53.56)	-7.63 (128.05)	-103.18 (109.59)
FE	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry
Observations	4,376	4,376	2,781	661	818
R^2	0.02	0.02	0.03	0.07	0.07
Adjusted R^2	0.01	0.01	0.01	-0.01	0.01
Residual Std. Error	288.68 (df = 4319)	288.72 (df = 4317)	253.75 (df = 2724)	296.30 (df = 608)	271.00 (df = 765)
F Statistic	1.90*** (df = 56; 4319)	1.84*** (df = 58; 4317)	1.33* (df = 56; 2724)	0.90 (df = 52; 608)	1.10 (df = 52; 765)

Notes: The table reports the estimates of several linear regression models (OLS) based on equation (3). Dependent variable is the yearly change in financing costs. The sample for regression results (3.1) and (3.2) consists of firms reporting credit lines with at least two consecutive years. The sample for regression results (3.3), (3.4) and (3.5) consists of firms reporting credit lines with at least three consecutive years. This sample is split by conditioning on the previous rating change: (3.3) no change, (3.4) upgrade, (3.5) downgrade. Standard errors are shown in parentheses. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *** Significant at the 1 percent level / ** Significant at the 5 percent level / * Significant at the 10 percent level

There are two main findings regarding path dependency. First, a previous rating change results in a higher magnitude of change in financing costs compared to firms without a rating change in the year before. Second, there is a significant difference if the firms receive a subsequent rating change in the same direction versus the case of a rating reversal (up and down; down and up).

First, restricting the analysis to those firms that received an upgrade in the previous year (eq. 3.4), the regression results show that a rating action in the current year triggers higher changes in the financing costs compared to firms without a rating change in the year before. Furthermore, having a previous upgrade leads to an even higher magnitude of change in financing costs compared to firms with a prior downgrade. The current rating has to change at least two rating classes in either direction to trigger statistically significant changes in the financing costs. The result of equation (3.4) shows that a downgrade by two classes is followed by a change in financing costs of ~98 bp. On the other hand, a subsequent rating upgrade results in lower financing costs by ~190 bp. This indicates that the banks do not change the loan rates symmetrically, independent of the previous rating.

Similarly, the result of equation (3.5) reports a significant difference in financing costs between up- and downgrades in the current year for those firms that received a rating downgrade in the year before. While a downgrade of two rating classes results in a change in financing costs of ~80 bp, an upgrade by two rating classes translates to approximately 12 bp lower financing costs. Although the coefficient of the rating upgrade by two classes is not statistically significant, the change of financing costs in the subsample of previous upgrades is of higher magnitude than the firms that received a downgrade in the year before.

The second main finding relates to the difference between consecutive rating actions in the same direction as well as between rating change in the same direction and rating reversals. There is an asymmetry in magnitude between two consecutive rating upgrades compared to two consecutive downgrades. In both cases, the current rating change has to be at least two rating classes to trigger a change. Whereas the upgrade followed by an upgrade of two rating classes translates into a coefficient of lower financing costs of approximately 190 bp, a downgrade followed by a downgrade of two rating classes results in approximately 82 bp higher costs. These coefficients show that banks do not handle a persistent upgrade equally to a persistent downgrade. Thus, in contrast to H3, if the firm follows an upward drift, banks lower the loan rates more than in the case of a subsequent downgrade.

On the other hand, rating reversals reveals mixed results. A rating upgrade followed by a downgrade (~90 bp) results in the same magnitude as two consecutive rating downgrades (~80 bp). Therefore, in the case of a current downgrade, it does not matter whether the client already received a worse rating in the year before or not. In contrast, an upgrade in the current year triggers different sizes of changes in financing costs dependent on the previous rating actions. A downgrade followed by an upgrade only results in lower financing costs by ~12 bp compared to a persistent rating upgrade of ~200 bp. There is evidence that banks tend to smooth a persistent negative rating impact on financing costs but use a rating upgrade to offer better loan rates.

These findings regarding rating history dependency are contrary to IO expectations and provide support for relationship banking information production (Freixas & Rochet, 2008). It seems that banks use an asymmetric pricing policy in favor of the client's rating history. In addition to the explanation by the literature on relationship banking, there are other circumstances that influence loan rates. On the one hand, it is possible that there is more competition in the loan market. On the other hand, historically low interest rates may lead banks to lower credit margins even more.

2.5.4 Robustness

To test the robustness of the previous results, equation (3) is estimated again with subsamples conditioned on the previous rating change, but with different time windows. The observed time window is split into two data series of equal lengths: 2002-2008 and 2009-2015. Appendix A6 shows the results of both time windows. The magnitude and statistical significance of the estimated β between 2009 and 2015 are similar to the findings of the main analysis. There is less significance and a different magnitude for 2002-2008. However, both sets of estimation results show the expected relation between up- and downgrades on financing costs. One possible answer to the lower significance of 2002-2008 lies in the lower number of available observations compared to 2009-2015. Furthermore, the risk-adjusted pricing was relatively new in the first time period. Especially within the first years after implementation, there might be changes that are not systematically and hence do not reflect the pricing policies by banks.

2.6 Do Banks Subsidize SME's Financing Costs?

The previous results show that the relationship between the SME and banks plays a role in terms of the applied lending rates. The question arises as to what extent Swiss regional banks differ in their loan price setting compared to a pure risk-adjusted pricing model.

The relationship banking literature is able to explain why a bank may deviate from a pure risk-adjusted pricing model (i.e. Lehmann & Neuberger, 1998; Kirschenmann & Nordon, 2012; Degryse et al., 2009). A recent meta-study by Kysucky & Norden (2015) showed that long-lasting, exclusive and synergy-creating bank relationships are associated with lower loan rates. According to the meta-study, the bank market structure itself is also important in determining whether these benefits prevail or not. Borrowers benefit in countries with high bank competition (i.e., US, Argentina, Taiwan). Despite the high bank competition in Switzerland, there is an oligopolistic market structure in SME lending (section 2.2.1), which is why banks should not extensively deviate from risk-adjusted pricing. To keep risk-adjusted returns stable across time (Ryan et al., 2014), banks may only deviate from risk-adjusted pricing if it is a long-lasting, exclusive or synergy-creating bank relationship (Kysucky & Norden, 2015). Therefore, a deviation from the risk-adjusted pricing of a loan or commercial mortgage in favor of an SME, which bears a much higher credit risk than a residential mortgage, must be compensated by other cross-products with the same customer (synergy-creating bank relationship) or other bank businesses:

Using the bank loan information from the financial statements combined with the SME's rating, I am able to calculate a loan rate based on a purely risk-adjusted pricing model. Multiplying this theoretical loan rate with the outstanding loan amount, I receive the "theoretical financing costs". Any difference between these theoretical and the observed empirical financing costs reveals different pricing patterns used by banks.

The applied risk-adjusted pricing model depends on the components introduced in section 2.2.3. The source for each component is shown in table 2.8. I calculate two different theoretical loan rates. Approach (A) is based on fixed funding over the entire time period. Approach (B) uses variable funding costs that depend on the market interest rates. Approach (A) should reflect the sticky loan rate relation to market interest rates shown in the SNB statistics for investment loans in section 2.2.1.

Table 2.8: Theoretical Financing Costs Components

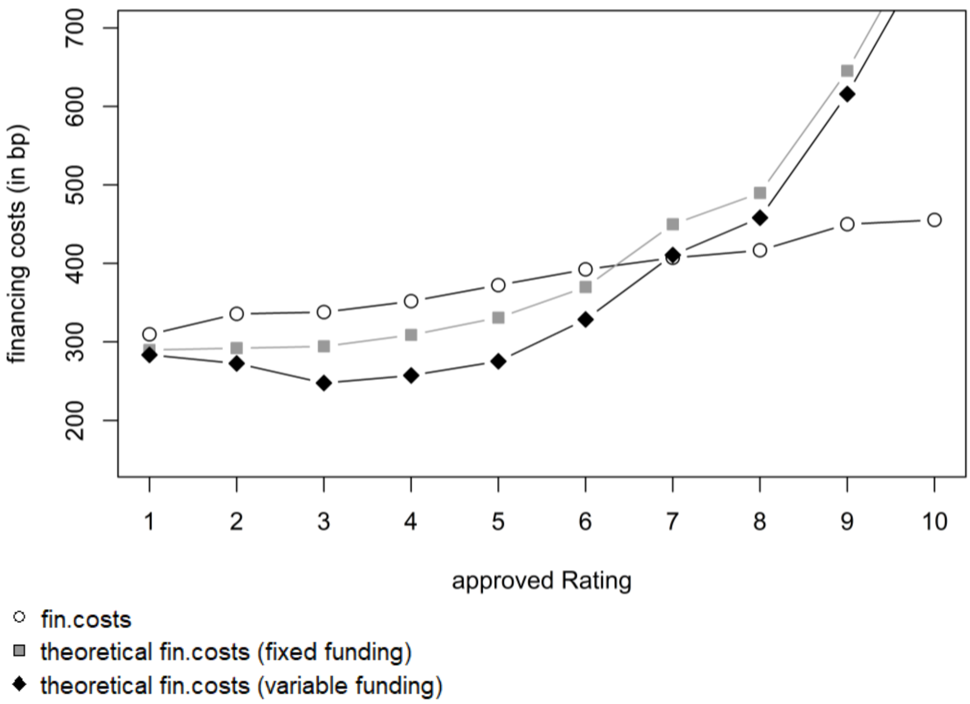
	(A) theoretical fin.costs with fixed funding	(B) theoretical fin.costs with variable funding
Funding costs - Fixed = over entire period same reference rate (SNB data suggests that banks use sticky opportunity costs as funding) - Variable = reference rate depend on time	Dependent on loan type: one rate per loan type 189 bp - 250 bp (Dietrich, 2012)	Dependent on time: Reference rate: 5 year government bond
Operating costs - dependent on loan amount - Source: Dietrich, 2012	18 - 83 bp	18 - 83 bp
Regulatory costs - BIS Standardized Approach Credit Risk - Assumption 1: no residential real estate collateral - Assumption 2: Retail loans (RWA = 75%) - Return goal: 3.5%	(8% * 75% * 3.5%) 21 bp (Dietrich, 2012: 13 bp)	(8% * 75% * 3.5%) 21 bp (Dietrich, 2012: 13 bp)
Creditrisk costs (Expected loss)	(PD * LGD) 15 - 825 bp	(PD * LGD) 15 - 825 bp
- LGD based on loan type (Moody's, 2018; internal bank data)	0.55 (unsecured) 0.15 (secured)	0.55 (unsecured) 0.15 (secured)
- PD based on rating (Moody's, 2018; internal bank data)	0.01% - 15%	0.01% - 15%
Total Lending rate	2.43% - 11.79%	1.54% - 12.07%

Notes: Own illustration.

Comparing the theoretical with the empirical financing costs not only shows differences in the pricing behavior of banks but is also a further robustness test on whether the definition of financing costs is a good proxy for bank lending rates (section 2.3.2).

To prevent any influence of lasting credit relationships, I use the subsamples introduced in section 2.4.1. Therefore, only "first-time borrowers" are considered. Figure 2.13 shows the mean of the empirical and theoretical financing costs of all investment loans and credit lines. Whereas the empirical costs are slightly higher for ratings 1 to 6, the theoretical financing costs for the worst rating grades 8, 9 and 10 are higher.

Figure 2.13: Mean Financing Costs of Investment Loans and Credit Lines (n= 3,791)



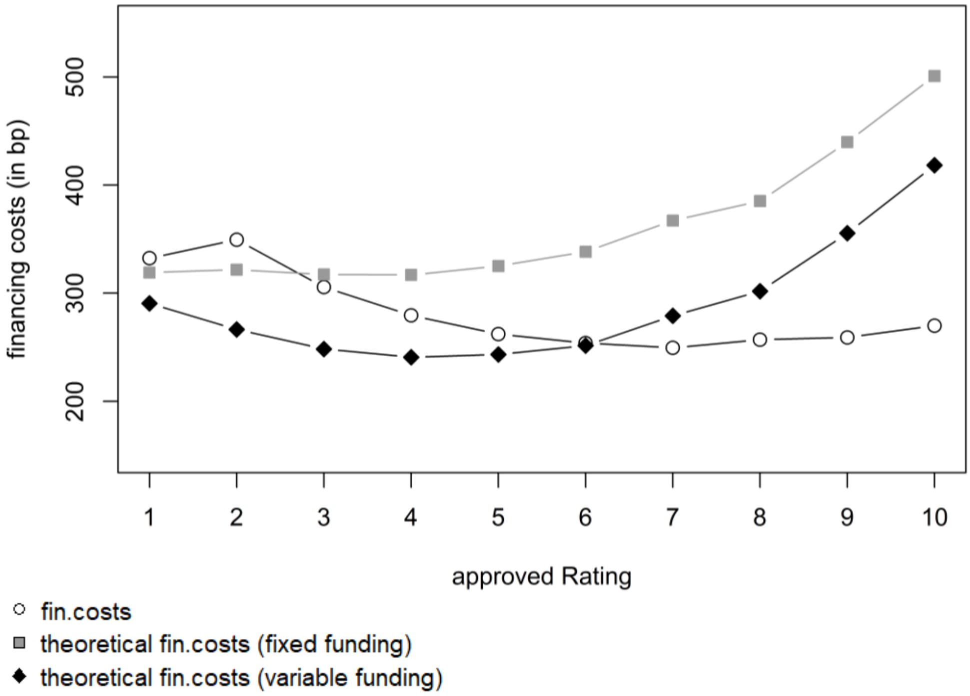
Notes: Own illustration.

The steep increase in theoretical financing costs for ratings 8 to 10 stem from the nonlinear relation between rating classes and probability of default. The graph above shows an inverse relation between rating and theoretical financing costs with variable funding for the best rating classes 1 to 3. This is because there are more observations with ratings of 1 and 2 in 2004 to 2006. The observed years for firms with rating classes 3 and higher are more equally weighted between 2003 and 2015. Therefore, the higher interest market rates in 2004-2006 compared with recent years increase the variable funding cost level for ratings 1 and 2.

It is not surprising that the theoretical cost model with fixed funding better explains the empirical costs. First, the SNB lending rate statistics (section 2.2.1) show sticky loan rates in relation to market interest rates. Second, investment loans have durations of several years, while the loan rate is mostly fixed. However, the fixed interest rate mortgages in the SNB statistics showed some decline in the loan rates over time, while investment loan rates are much more sticky (section 2.2.1).

Figure 2.14 plots the mean of the same variables for the subsample of new mortgages. Due to the much lower LGD component, the relation between theoretical costs and ratings is less pronounced. Empirically, firms with high probabilities of defaults report the lowest financing costs. This is in stark contrast to the calculated theoretical costs. Again, the worst rating classes should pay much higher financing costs in theory. Similar to the empirical observed costs, the relation of variable funded costs is inverse for the best rating classes. Although there are other firms in this sample as those of other bank loans, firms within the best rating classes are mostly represented in 2004 to 2006.

Figure 2.14: Mean Financing Costs of Mortgages (n= 4,025)



Notes: Own illustration.

The bank's pricing strategy, that firms with poor rating grades have to pay less than they would in a pure risk pricing model, is stable across the entire analyzed time period. A sample split by time (2002-2008 and 2009-2015) is shown in appendix A7. Therefore, the poorly rated firms are somehow subsidized by other businesses of the bank. Although the analyzed financing costs come from the "first-time" borrower, there might already exist a relationship between the entrepreneur of the firm and the bank. The entrepreneur might already have a mortgage on the privately held residential property. This relationship might have a positive impact on the loan application of his poor rated firm. Looking at the entire share of wallet of a customer may lead banks to support the firm's credit relationship with the private assets of the entrepreneur. Furthermore, the bank receives nonpublic information about the firm that may not fully be captured with a quantitative rating.

The existence of this effect shows that banks deviate systematically from a pure risk-adjusted pricing model (i.e., Cerquiro et al., 2011). This pricing behavior supports the theoretical models by Boot & Thakor (1994) and Petersen & Rajan (1995) and goes along with various empirical results related to the relationship banking literature (i.e., Bharath et al, 2011; Cenni et al, 2015).

In recent years, there has been a growing discussion on which bank loans will remain in the bank credit market and which ones will be superseded by crowd lending platforms (PwC, 2018). According to a study by Dietrich & Amrein (2014), half of the business loans raised in 2014 were in an interest rate range between 770 bp and 990 bp, while the lowest rate was 350 bp. On average, the loan rates by crowd lending were 890 bp in 2014. This is much higher than the mean of the financing costs of the subsample of investment loans and credit lines with 398 bp. It seems that the concluded crowd lending business loans bear a higher credit risk. This gives support for the argument that there are certain creditworthy companies that are not able to receive a loan using traditional bank financing channels (Dietrich & Amrein, 2018). Furthermore, a study by SECO (2017) showed that 27% of those SMEs that proclaimed to be in need of financing refrain from the application process for a bank loan. These are companies with relatively poor rating grades that expect a denial by the bank or unfavorable loan terms (i.e., high loan rates, additional collateral). (SECO, 2017, pp.49)

My results show that banks offer relatively comfortable conditions compared with crowd lending rates. At least partially, the deviance of the lending rates between banks and crowd lending platforms might stem from the relationship between the entire share of wallet of a bank customer and the bank.

2.7 Conclusion

In this paper, I examine to what extent bank credit risk assessment relates to the financing costs of SMEs. In my analysis, I look at this relation from different angles. First, I look at SMEs that report a new loan and estimate the initial effect of their rating on financing costs. Second, I analyze the impact of a rating change on financing costs. Third, I show the impact of the credit risk officer's discretion on the financing costs. Last, I draw a comparison between a theoretical purely risk-adjusted pricing model with the empirically observed financing costs.

In accordance with theory and existing literature, I find strong evidence that the financing costs of unsecured bank loans increase with the initial credit risk measured by the credit rating. However, the effect is only statistically and economically significant if a firm is in the top range of ratings {1-2} or in the lowest range of ratings {7-10}. Furthermore, there is evidence that the "discretion" of credit risk officer to amend the final rating has an impact on the final loan rate. In my panel analysis, I show that during the credit relationship, banks do not always follow a consequent risk-adjusted pricing strategy. I find strong evidence that the rating path plays an active role in the loan price setting of unsecured loans. In particular, persistent rating changes in the same direction, as well as rating reversals, trigger a larger change in financing costs than no previous rating change. However, not only is the rating path important to explaining deviations from the pure risk-adjusted pricing approach but also SMEs with high credit risk systematically report lower financing costs than a credit risk perspective would suggest.

There are substantial differences between collateralized and unsecured loans. There is evidence that the LGD component is relevant for mortgage pricing, but the rating (PD) is not. If an SME holds collateral, it is most likely commercial property. Using these real estate holdings as collateral leads to substantially lower financing costs (-108 bp) compared to those for unsecured loans. However, there is no statistical evidence that the SME's rating has a distinct relation to the mortgage loan rates.

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2.9 Appendix

A1: Dataset Construction

	#FS	#Firms
Original Sample	211'352	41'243
Dropping section:		
1) Consolidated financial statements	13'057	
2) Financial statements with other currency than CHF	844	
3) Financial statements with US GAAP, IFRS, others	878	
4) Financial statements with Total Assets CHF >300 Mio.	2'350	
5) Financial statements with Equity CHF <0	12'828	
6) Financial statements with more than 250 employees	2'946	
7) Financial statements with FY = 2016	759	
8) Financial statements with Equity > Total Assets	4	
9) Financial statements duplicate	2'970	
10) #FS with FC outlier (winsorized at 0.995)	17'112	
11) #FS with Total Assets outlier (winsorized at 0.995)	612	
12) #FS without calculated or approved rating	35'186	
13) #FS with negative interest bearing debt (IBD)	104	
Base Sample	121'702	30'033

A2: Variable Definition

Variables	Definition
BankLoan_TA	short and longterm bank loans, standardized to total assets
Mortgage_TA	Mortgages, standardized to total assets
PPE_TA	Property, plant and equipment, standardized to total assets
Longterm_otherLiabilities_TA	Not bank related interest bearing debt, standardized to total assets
LTotherLiab_TA	Longterm_otherLiabilities_TA
ResidentialProperty_TA	Non-commercial properties, standardized to total assets

A3: Summary Statistics of Full Data Set

This table presents summary statistics on SME' characteristics.

variables	mean	sd	q25	median	q75	n
Financing costs in bp	270.77	224.60	65.36	257.00	400.00	121,702
TotalAssets in Thousand CHF	5'665.73	11'854.05	777.00	1'849.00	4'994.00	121,702
PPE_TA	0.45	0.32	0.15	0.45	0.73	121,702
residProperty_TA	0.04	0.15	0.00	0.00	0.00	121,702
AccountsPayable_TA	0.11	0.12	0.02	0.06	0.14	121,702
Creditlines_TA	0.04	0.10	0.00	0.00	0.03	121,702
Investmentloans _TA	0.04	0.11	0.00	0.00	0.00	121,702
BankLoan_TA	0.08	0.15	0.00	0.00	0.09	121,702
mortgage_TA	0.21	0.25	0.00	0.08	0.41	121,702
ShareholderCredit_TA	0.04	0.11	0.00	0.00	0.00	121,702
LTleasing_TA	0.01	0.02	0.00	0.00	0.00	121,702
LTotherLiab_TA	0.08	0.15	0.00	0.00	0.11	121,702
currentAssetRatio	0.50	0.32	0.22	0.47	0.81	121,702
durableAssetRatio	0.50	0.32	0.19	0.53	0.78	121,702
EquityRatio	0.36	0.22	0.19	0.32	0.50	121,702
Calculated_Rating	5.96	2.06	4.00	6.00	7.00	121,702
Applied_Rating	6.03	2.01	5.00	6.00	7.00	121,702
Approved_Rating	6.08	2.02	5.00	6.00	7.00	121,702

Notes: The table depicts summary characteristics for the variables used in the analysis. “TA” indicates standardization to total assets.

A4: Robustness Initial Credit Risk Pricing: Unobserved Variable

Sample:	*Dependent variable:*	Financing Costs $\left(FC_{i,t+1}\right)$
New Credit Lines	(1.1)	(2.1)
2002-2015	(Approved Ratings)	(Calculated Ratings)
Rating2	1.6 (89.5)	-71.1 (106.0)
Rating3	93.4 (76.3)	75.9 (91.7)
Rating4	79.6 (73.1)	68.6 (90.0)
Rating5	111.6 (69.7)	102.7 (87.5)
Rating6	133.8* (68.5)	138.1* (84.8)
Rating7	190.8*** (69.0)	194.6** (86.8)
Rating8	193.7*** (68.6)	199.0** (86.8)
Rating9	223.4*** (70.5)	200.6** (87.9)
Rating10	257.9*** (73.3)	251.2*** (89.1)
bank_discretion		20.7** (8.8)
Constant	187.4* (102.6)	183.8 (116.1)
FE	bank;time;industry	bank;time;industry
Observations	1,555	1,555
R^2	0.1	0.1
Adjusted R^2	0.1	0.1
Residual Std. Error	284.7 (df = 1495)	284.3 (df = 1494)
F Statistic	2.6*** (df = 59; 1495)	2.6*** (df = 60; 1494)

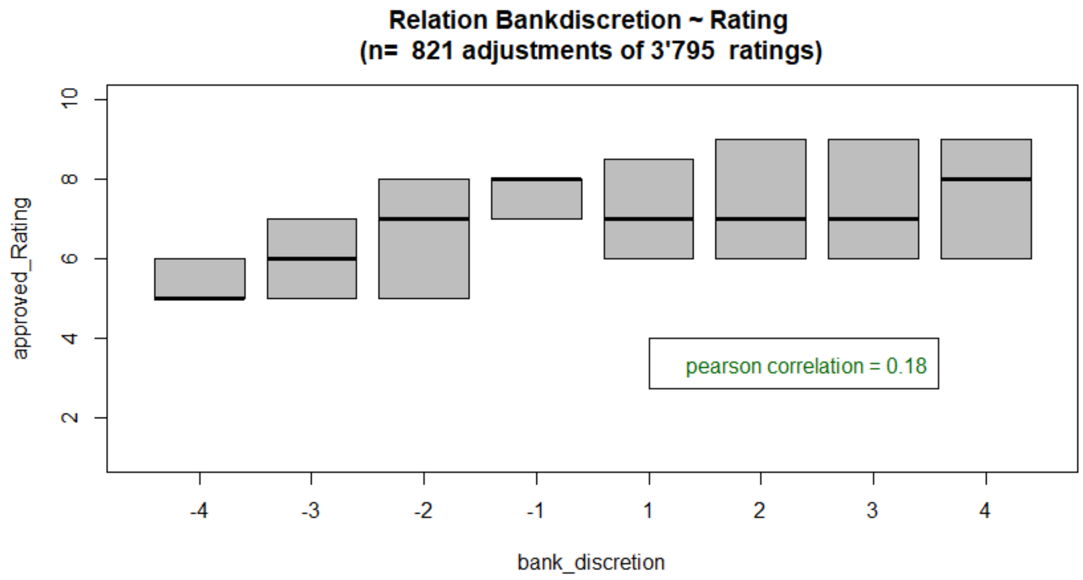
Notes: **p<0.1; **p<0.05; ***p<0.01*

Bank_discretion = (approved – calculated_Rating)

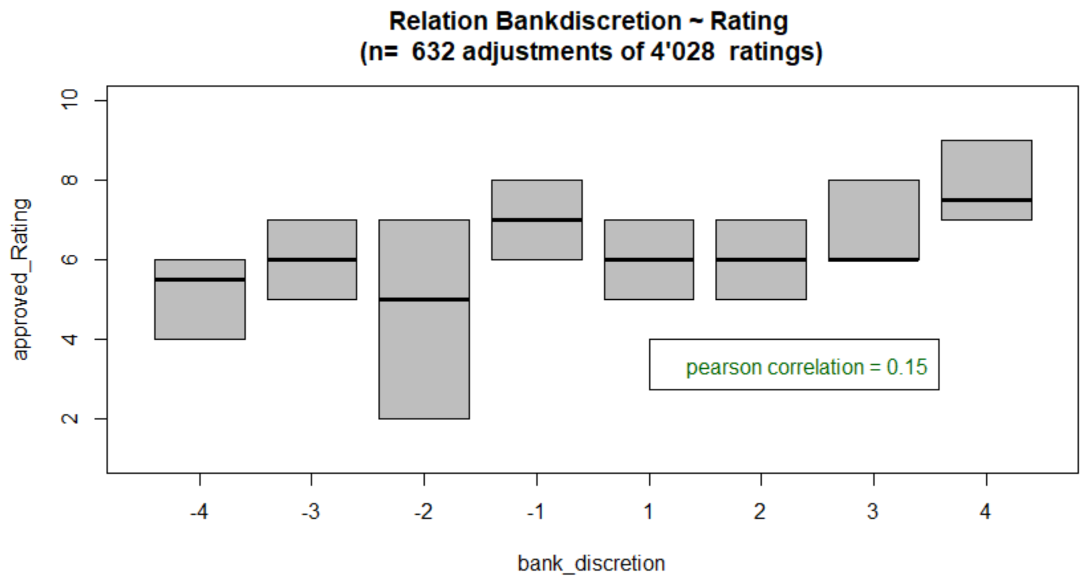
A5: Approved Ratings and Bank Discretion

The box plots show the relation between $approvRAT_{i,t-1}$ and $bank\_discretion_{i,t-1}$ using both cross-sectional sub-samples.

Sub-Sample: New Credit Lines and/or Investment Loans



Sub-Sample: New Mortgages



A6: Robustness Panel Analysis: Time Split

Regression Results Panel Approved Ratings 2009-2015

Sample:	*Dependent variable:* Δ Financing Costs_1year $(\Delta FC_{i,t+1})$					
Credit Lines with at least 3 consecutive years	(3.3)	(3.3)	(3.4)	(3.4)	(3.5)	(3.5)
2009-2015	No change	No change	Upgrade	Upgrade	Downgrade	Downgrade
ApprovedRating_Downgrade1	0.18 (16.68)	5.71 (16.98)	42.99 (32.80)	39.94 (34.66)	7.20 (30.07)	4.05 (30.82)
ApprovedRating_Downgrade2	61.82*** (23.22)	64.87*** (23.77)	91.68** (38.11)	94.88** (39.54)	79.93* (44.05)	91.40** (45.88)
ApprovedRating_Downgrade3	18.78 (24.40)	16.86 (25.06)	79.86** (39.94)	65.29 (44.12)	105.80** (50.73)	119.85** (53.17)
ApprovedRating_Upgrade1	-42.16** (18.30)	-35.06* (18.56)	-63.75 (43.35)	-75.78* (45.79)	-2.54 (28.70)	-4.11 (29.52)
ApprovedRating_Upgrade2	-54.67** (27.74)	-61.93** (28.04)	-167.84** (80.43)	-169.39* (86.39)	-47.74 (37.12)	-23.69 (38.97)
ApprovedRating_Upgrade3	-38.39 (38.43)	-47.79 (38.72)	-1.15 (120.56)	-17.96 (131.07)	46.33 (53.04)	91.36* (55.44)
Constant	-46.63*** (8.61)	-166.10*** (63.07)	-66.44*** (20.48)	133.88 (113.90)	-53.82*** (15.89)	-106.87 (90.91)
FE	no	bank;time;industry	no	bank;time;industry	no	bank;time;industry
Observations	2,195	2,169	563	559	709	703
R^2	0.01	0.04	0.04	0.09	0.02	0.08
Adjusted R^2	0.01	0.01	0.02	0.01	0.01	0.01
Residual Std. Error	277.78 (df = 2188)	275.72 (df = 2117)	291.02 (df = 556)	292.67 (df = 510)	272.51 (df = 702)	269.26 (df = 654)
F Statistic	3.45*** (df = 6; 2188)	1.63*** (df = 51; 2117)	3.40*** (df = 6; 556)	1.06 (df = 48; 510)	1.83* (df = 6; 702)	1.17 (df = 48; 654)

Notes: **p<0.1; **p<0.05; ***p<0.01*

Regression Results Panel Approved Ratings 2002-2008

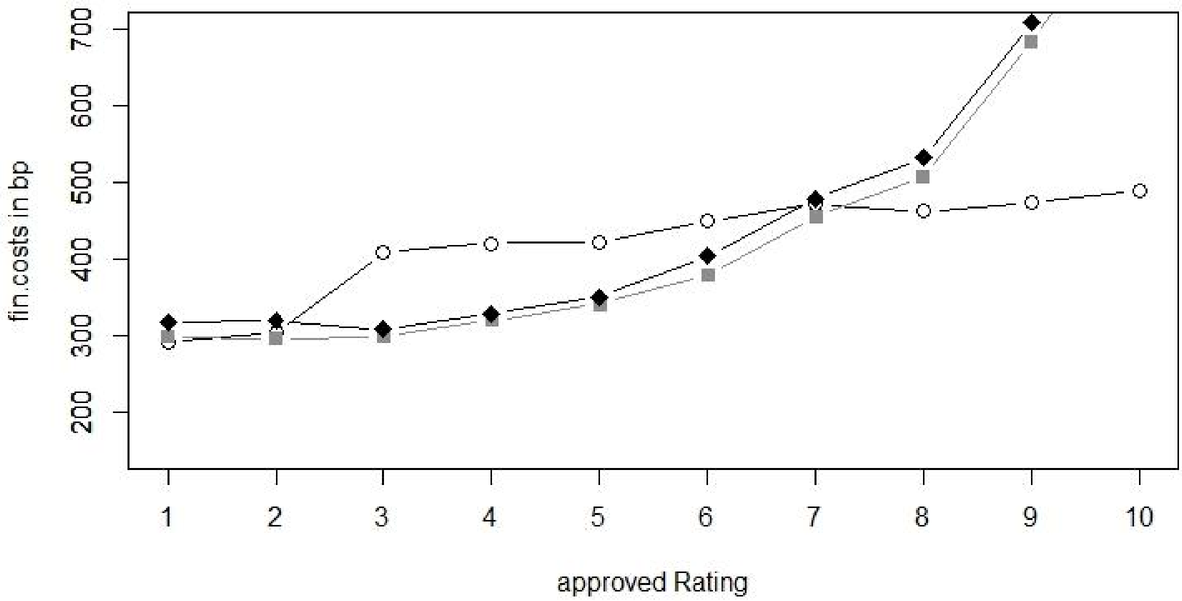
Sample:	*Dependent variable:* Δ Financing Costs_1year $(\Delta FC_{i,t+1})$					
Credit Lines with at least 3 consecutive years	(3.3)	(3.3)	(3.4)	(3.4)	(3.5)	(3.5)
2002-2008	No change	No change	Upgrade	Upgrade	Downgrade	Downgrade
ApprovedRating_Downgrade1	-16.06 (29.16)	-18.62 (29.90)	-39.59 (68.76)	-29.32 (78.70)	9.76 (58.48)	21.30 (63.87)
ApprovedRating_Downgrade2	7.10 (41.79)	21.92 (42.40)	91.28 (82.69)	95.22 (100.35)	-96.39 (115.82)	-79.87 (126.07)
ApprovedRating_Downgrade3	119.08** (57.91)	124.59** (59.28)	237.62* (131.47)	397.71** (157.34)	-208.19 (276.45)	-223.54 (292.69)
ApprovedRating_Upgrade1	-49.65 (31.70)	-51.04 (33.20)	114.63 (95.98)	154.83 (111.95)	-35.75 (57.03)	-46.55 (66.83)
ApprovedRating_Upgrade2	-137.81*** (47.94)	-149.07*** (49.66)	-280.00 (182.84)	184.01 (280.10)	-2.18 (87.67)	11.19 (97.92)
ApprovedRating_Upgrade3	-7.57 (70.80)	-19.15 (71.60)	39.49 (313.06)	-200.48 (368.06)	23.97 (126.23)	74.89 (138.69)
Constant	-49.11*** (13.71)	199.83 (165.25)	-57.35* (33.76)	-144.85 (243.00)	-84.35*** (28.51)	-62.36 (187.46)
FE	no	bank;time;industry	no	bank;time;industry	no	bank;time;industry
Observations	2,195	2,169	563	559	709	703
R^2	0.01	0.04	0.04	0.09	0.02	0.08
Adjusted R^2	0.01	0.01	0.02	0.01	0.01	0.01
Residual Std. Error	277.78 (df = 2188)	275.72 (df = 2117)	291.02 (df = 556)	292.67 (df = 510)	272.51 (df = 702)	269.26 (df = 654)
F Statistic	3.45*** (df = 6; 2188)	1.63*** (df = 51; 2117)	3.40*** (df = 6; 556)	1.06 (df = 48; 510)	1.83* (df = 6; 702)	1.17 (df = 48; 654)

Note: **p<0.1; **p<0.05; ***p<0.01*

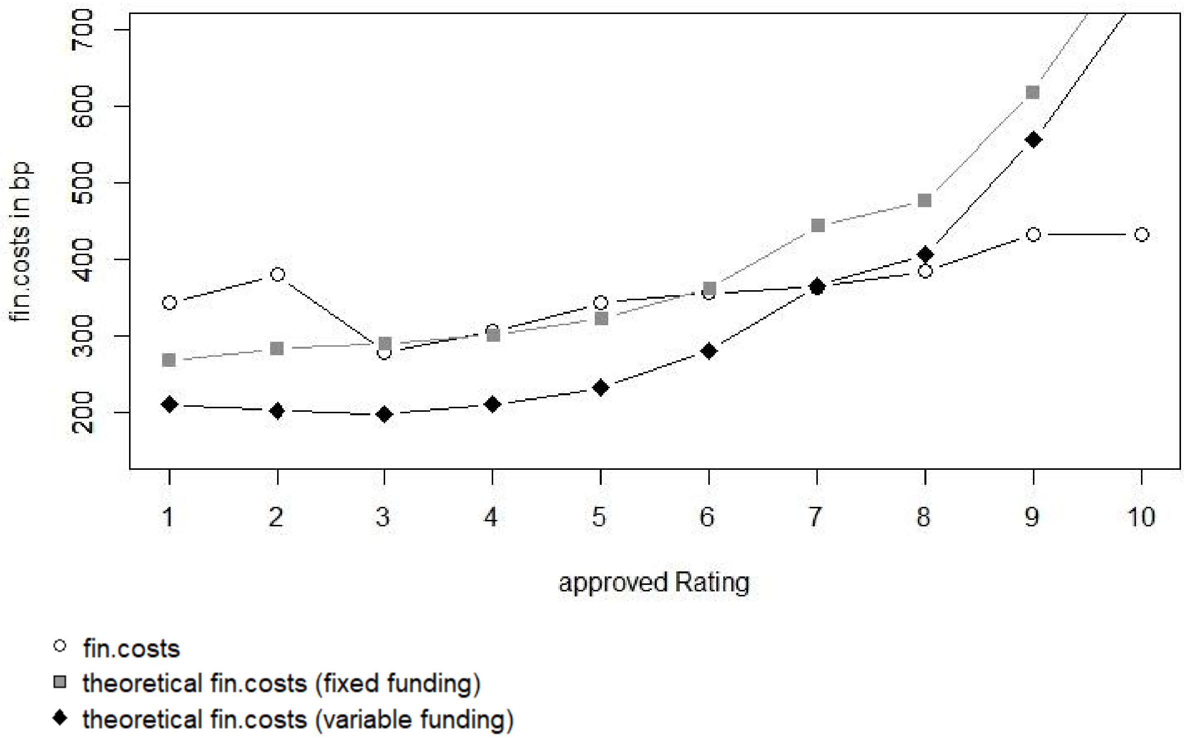
A7: Empirical vs Theoretical Financing Costs

A7.1: Time Split of Mean Financing Costs of Investment Loans and Credit Lines

Mean before 2009 [2003 - 2008]

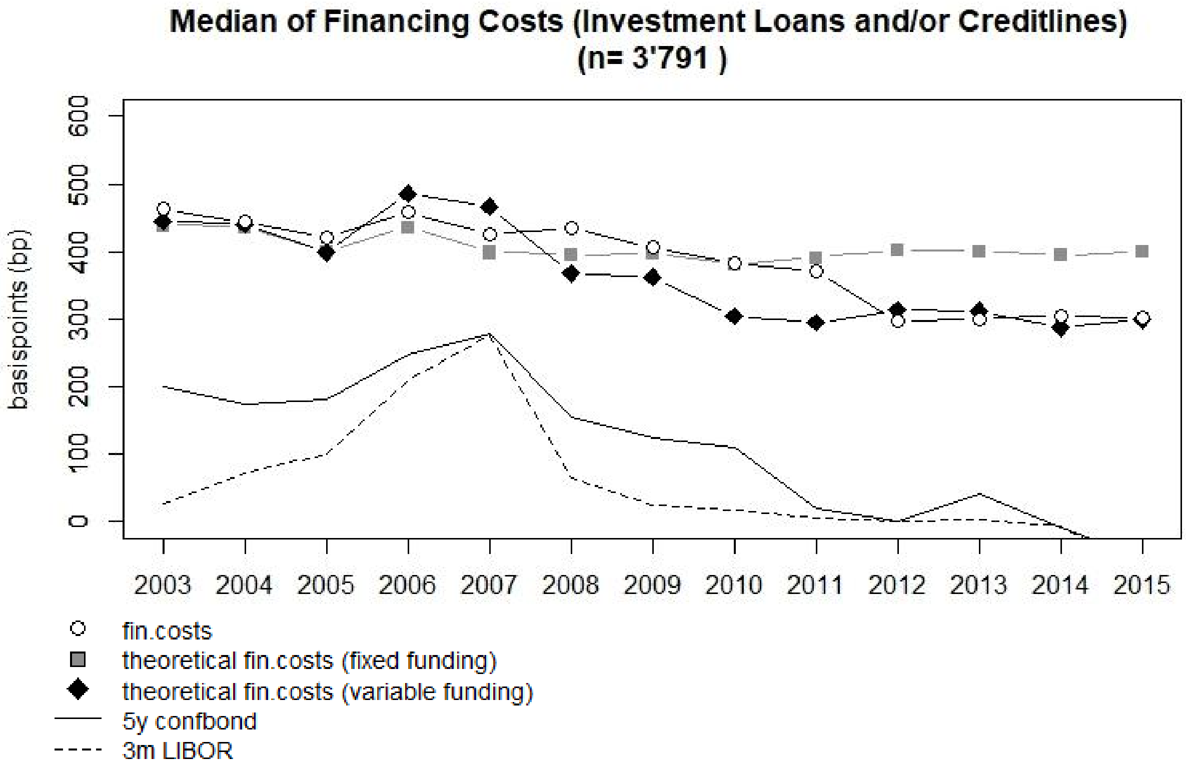


Mean after 2008 [2009 - 2015]



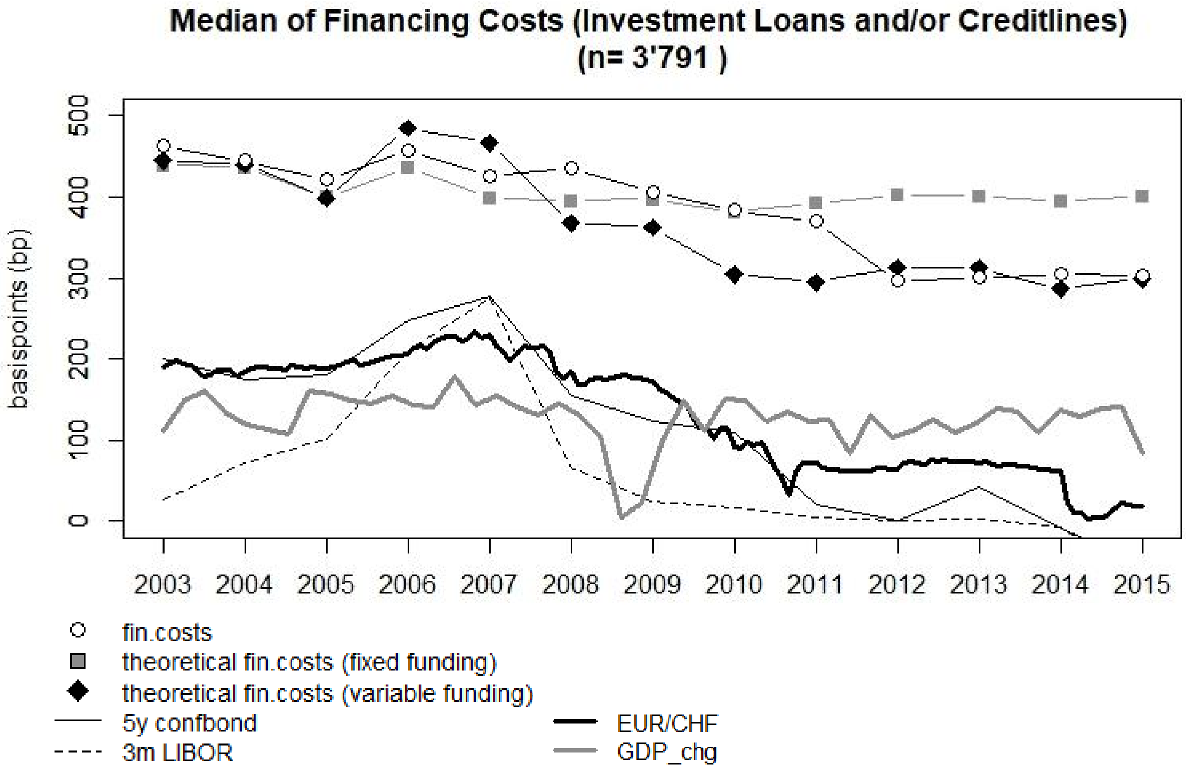
Notes: Own illustration. 2003-2008: n= 1’503; 2008-2015: n= 2’288

A7.2: Financing Costs of Investment Loans and Credit Lines over Time



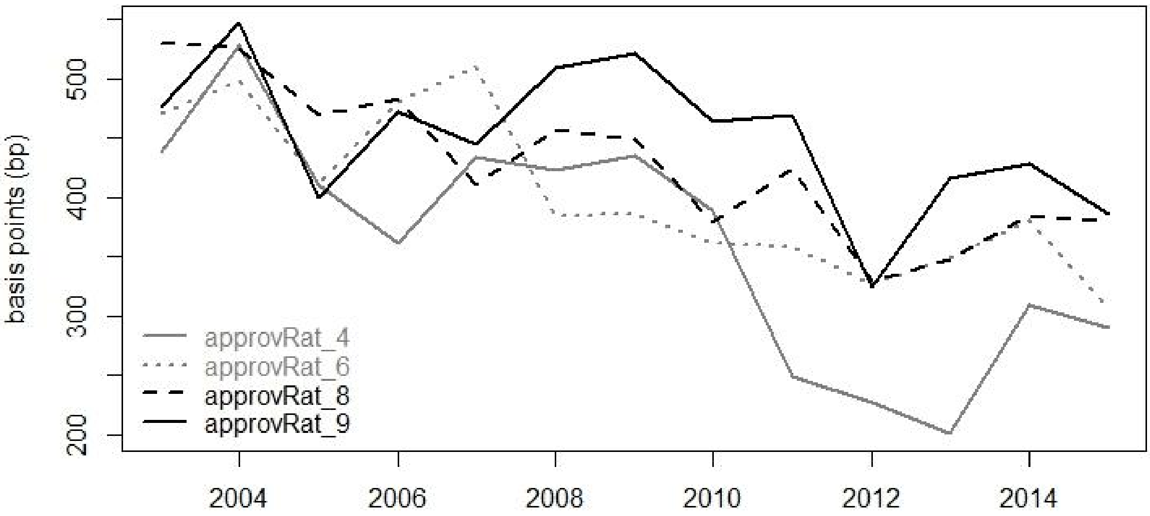
Notes: Own illustration

A7.3: Financing Costs and Macroeconomic Variables over Time



Notes: Own illustration

A8: Financing Costs and selected approved Rating over Time



Notes: This graph plots the mean of financing costs in basispoints dependent on four selected approved rating classes. Due to representation only rating classes with >300 financial statements. The used sub-sample consists of all firms reporting new credit lines and/or new investment loans, but without mortgages, shareholder and/or leasing liabilities. Number of firms equals number of financial statements. *Source:* Annual Accounting Data.

A9: Change in mean/median Financing Costs dependent on Rating Migration

Table below summarizes the change in financing costs (t+1) conditioned on the previous rating. If a client receives a consecutive rating upgrade the banks lower the loan rates more than in case of a subsequent downgrade. Those firms which received a downgrade in the previous year (t-1) show almost similar financing costs changes as those without any previous rating change in (t-1). Banks accept similar margins despite the higher credit risk. Furthermore, firms which were subsequently upgraded twice in a row show significant lower financing costs measured by the mean (-114 bp).

Rating Change (t-1)		Rating Change (t) Upgrade	Par	Downgrade	# financial statements
Upgrade	(# financial statements)	(145)	(383)	(478)	(1’006)
	Δ fin.costs (t+1) mean	-114 bp	-59 bp	-5 bp	
	Δ fin.costs (t+1) median	-24 bp	-24 bp	0 bp	
Par	(# financial statements)	(887)	(1’983)	(1’297)	(4’167)
	Δ fin.costs (t+1) mean	-94 bp	-45 bp	-28 bp	
	Δ fin.costs (t+1) median	-38 bp	-15 bp	0 bp	
Downgrade	(# financial statements)	(409)	(545)	(337)	(1’291)
	Δ fin.costs (t+1) mean	-60 bp	-55 bp	-25 bp	
	Δ fin.costs (t+1) median	-39 bp	-22 bp	0 bp	
	Δ market interest rates: 2002-2015		-300 bp		
	Δ market interest rates: mean per year		-23 bp		

Notes: The table depicts the mean and median change in financing costs (Δ financing costs) in basispoints (bp) conditioned on the previous rating change (t-1).

A10: List of abbreviations

EL	Expected Loss
FC	Financing Costs
FINMA	Swiss Financial Market Supervisory Authority
IBD	Interest Bearing Debt
LGD	Loss Given Default
PD	Probability of Default
PPE	Property plant and equipment
RAP	Risk-adjusted Pricing
RE	Real estate
RRE	Residential real estate
SA	Standardized Approach for Credit Risk
SME	Small and medium-sized enterprises
SNB	Swiss National Bank

Chapter 3
Rating Reversals in SME Lending

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Abstract

We document a significant path dependency in bank-internal credit ratings of small and medium-sized enterprises (SMEs): rating changes reverse over time. Our analysis is based on a sample of 39,651 credit ratings for 11,545 firms by 24 Swiss banks over the period of 2008 to 2016. All banks use the identical credit rating model. We show that 47% of companies that reported a downgrade from the previous year will be upgraded the following year. Vice versa, 43% of the firms that reported an upgrade were then downgraded. Furthermore, our results suggest that rating reversals persist across industry affiliation and that larger SMEs show slightly fewer reversals compared to the smallest firms. Our analysis also reports that rating reversals are equally prevalent if we consider pure quantitative ratings or approved ratings, which are influenced by loan or credit officer discretion.

Keywords: Rating Reversal, Rating Transition, Transition Matrices, Rating Migration, SME, Small Business Finance

JEL classification numbers: D22, G21, G24, L25

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3.1 Introduction

Recent changes in bank regulations and supervision call for a deeper understanding of credit risk assessment in bank lending. In particular, it is important to understand to what extent there are path dependencies in credit rating migration. The financial crisis of 2007-2009 highlighted that the loan loss provisioning method "*incurred loss*" resulted in delayed recognition of credit losses, which is why regulators called for an adjustment (Cohen & Edwards, 2017). Therefore, the International Accounting Standards Board (IASB) introduced in 2014 its "*IFRS 9 Financial Instruments*", and the US Financial Accounting Standards Board (FASB) in 2016 introduced its loan loss provisioning standard "*current expected credit losses (CECL)*". Both standards are based on a lifetime expected loss. This method incorporates the time to maturity of the credit risk (Zhang, 2018). Similarly, since the great financial crisis, scenario stress testing has emerged as an important instrument for banks and regulators alike to assess their financial stability (PwC, 2014; BCBS, 2018). Scenario stress testing over a certain period incorporates the credit risk over time as well. Therefore, loan loss provisioning and stress testing changes the risk perspective from a one-year risk measure to a forward-looking time-to-maturity risk measure. Since SME bears more volatile credit risk than large corporations (Chen, Hanson & Stein, 2017), and because of their relevance in an economy (Morgan & Pontines, 2018), it is important for banks and regulators to understand how SMEs migrate during time.

To calculate credit risk over a given time, rating transition matrices are necessary. As for the question of how a creditor's credit risk changes, it is inherently important to understand whether or not the credit rating depends on the previous rating(s). If downgrades are more likely to be followed by another downgrade, this is called *downward momentum* or *rating drift*. This effect is well documented for large corporations in the literature. A growing body of literature shows contrary rating behavior for small firms (Krüger et al., 2005; Mählmann, 2006; Liu, 2015). Small firms that reported a rating downgrade (upgrade) are more likely to be upgraded (downgraded). This is called a *rating reversal*.

In this paper, we study the credit rating migration of small and medium-sized enterprises (SMEs). We use SMEs' credit ratings from a proprietary dataset comprising 39,651 internal credit risk assessments by 24 Swiss regional banks. We analyze whether there is a relationship between the subsequent rating changes, if rating reversals prevail, and if this relation is stable across firm characteristics and different rating approach properties. Our empirical strategy is twofold. First, we aim to identify and quantify the magnitude of the relationship between the current and prior rating. We calculate transition matrices conditioned on the previous ratings similar to Bangia et al. (2002), and we use a linear and logit regression model. Second, we analyze the heterogeneity of the rating path relation with sample splits by industry sector and firm size.

Our results show a substantial reversal effect of SMEs' credit ratings. Rating transition matrices show that conditional on an upgrade in year *(t-1)*, the probability of a downgrade in the subsequent year *(t)* is $P(\text{down}|\text{up}) = 43.2\%$. This is much higher than the probability of an upgrade in *(t)* given that a client's rating improved in *(t-1)* which is $P(\text{up}|\text{up}) = 18.4\%$. Conversely, if a firm was downgraded in year *(t-1)*, it is most likely to move one or more rating classes up with $P(\text{up}|\text{down}) = 47.0\%$ in the subsequent assessment. The probability of moving further down, which is the downward momentum, is $P(\text{down}|\text{down}) = 17.8\%$, and the probability of staying in the same class $P(\text{par}|\text{down}) = 35.3\%$ is distinctly lower too. Similarly, our logit regression model shows that an upgrade in the previous year *(t-1)* of one rating class increases the probability of a downgrade in year *(t)* by 17 percentage points. Conversely, a downgrade by one rating class in the year *(t-1)* increases the probability of an upgrade in *(t)* by 19 percentage points.

This reversal effect persists relatively independently from firm characteristics and number of rating classes. Our results also show that qualitative risk assessment does not materially change the magnitude of reversals.

We contribute to the discussion of path dependency in rating changes. A standard specification to estimate rating transition probabilities is the first-order, time-homogeneous Markov model. However, different empirical studies show that non-Markovian behavior of the rating transitions is common. One of the most intensively analyzed behaviors is the rating drift or downward momentum (i.e., Altman & Kao, 1992; Lucas & Lonski, 1992; Carty & Fons, 1993, Bangia et al., 2002; Lando & Skødeberg, 2002; Güttler, 2006; Figlewski et al. 2006; Güttler & Raupach, 2008; Dang & Partington, 2014), which describes the empirical evidence showing that downgrades and defaults are more probable if the previous rating change was also a downgrade. What all of these studies have in common is that they use large corporations' rating changes. On the other hand, a few studies have analyzed the rating behavior of SMEs. Krüger et al. (2005), Mählmann (2006) and Liu (2015) use SME credit ratings and show that the probability of a reversal after one year is higher compared to rating drift in either direction. Using Swiss SME credit rating data, we confirm the findings of a rating reversal effect.

Furthermore, we analyze the heterogeneity of these rating reversions. It is important to understand if the effect is driven by certain SMEs or the rating approach properties. Only a homogenous effect allows to model SME's credit risk in a lifetime expected loss setting similarly. We show that rating reversals persist across industry affiliation and that larger SMEs show slightly fewer reversals compared to the smallest firms. Furthermore, we analyze the impact of qualitative credit risk assessments. We document that rating reversals are equally prevalent if we consider pure quantitative ratings or approved ratings which are influenced by loan or credit officer discretion. Last, we show that if we change the number of rating classes, then the probability of remaining in the rating class increases but the probability of a reversion dominates the drift.

The remainder of this paper is organized as follows. Section 3.2 develops the hypotheses. Section 3.3 provides an overview of the data. Section 3.4 shows the empirical strategy and the results of estimating the rating reversals. In the analysis of the heterogeneity of the reversal effect, section 3.5 shows whether the effect persists for different types of companies. Section 3.6 shows robustness tests and the impact of the rating approach and of the number of rating classes. Section 3.7 concludes the findings.

3.2 Development of Hypotheses

A standard approach to estimating rating transition probabilities is the first-order, time-homogeneous Markov model which is based on two assumptions: first, the probability of changing from one rating class to another does not depend on the rating history; second, the probability of changing from one rating class at time *(t)* to another rating class at time *(t+1)* depends only on the current rating class and not on the time (Güttler, 2006; Lando & Skødeberg, 2002; Kavvathas, 2000; Jarrow et al. 1997).

Existing empirical studies show that ratings follow a path which is contrary to the first-order Markov property. Research was mainly carried out on external rating data by rating agencies (i.e., Altman & Kao, 1992; Bangia et al., 2002; Lando & Skødeberg, 2002; Güttler, 2006; Figlewski et al. 2006; Güttler & Raupach, 2008; Dang & Partington, 2014). The data used consist of large corporations. For those ratings there is empirical evidence of a downward momentum (rating drift). On the other hand, few studies with SME credit ratings show a reversal behavior (Krüger et al., 2005; Mählmann, 2006; Liu, 2015). Our data set of bank ratings of Swiss SMEs is similar to these three studies. Therefore, we derive our first hypothesis from Krüger et al. (2005), Mählmann (2006) and Liu (2015) regarding path dependency:

H1: "Rating Reversal": SMEs are more likely to follow a rating reversal path than a first-order Markov process.

Further, we intend to analyze the heterogeneity of rating reversions. Sector affiliation might explain differences among firms in the rating reversal effect. Existing studies already incorporate the firm's sector affiliation in their analyses (i.e., Altman & Kao, 1992; Nickell et al. 2000; Bangia et al. 2002). However, potential differences in the rating reversal effect among sectors were not investigated. Certain industries show more volatile business development. This has an impact on the balance sheet and profit and loss statement.

H2: Industry affiliation: Industries with more volatile business development show higher levels of rating reversals.

In addition to sector affiliation, rating reversals might differ across various types of firms. Since large corporations' ratings show a rating drift (i.e., Lando & Skødeberg, 2002; Güttler, 2006; Dang & Partington, 2014), firm size might be an explanatory variable. Thus, the smallest SME should show more rating reversals than a larger SME.

H3: Firm Size: Larger firms revert to a lesser extent than smaller firms do.

3.3 Data

The dataset comprises 39,651 nonpublic available annual financial statements of 11,545 unique SMEs which were collected by 24 Swiss banks during the period 2008 to 2016. Each bank is a regionally focused commercial bank. Each observation includes the entire balance sheet (i.e., property plant and equipment (PPE), receivables, payables mortgages, equity, etc.), profit and loss (i.e., sales, EBITDA, depreciation, etc.) as well as some basic characteristics of the SME (i.e., number of employees, legal form and industry).

For each observation, the dataset shows two internal ratings used by the banks. The first rating reflects the PD of the SME, based on a mathematical-statistical model. Each rating class is associated with a PD. The second rating states the finally approved credit rating by credit risk officers, which additionally include a qualitative credit assessment by a credit risk specialist. Both rating types are expressed on an ordinal scale {1,2,3,4,5,6,7,8,9,10}, where {1} denotes the best, and {10} denotes the worst (close to default) rating.

All banks in the sample use the same software to enter the financial statements and the same rating model – the provider is an external firm specializing in credit risk solutions. This common rating approach is a mathematical-statistical model and its calculation is based on the financial statements of the SME (primary score) with an industry/sector comparison (secondary score). It is a hybrid PIT-TTC[1] model. The PD is estimated using ex-post default data. Thus, qualitative assessments by credit risk officers are reflected in the difference between the quantitative and approved rating.

[1] Point-in-time and through-the-cycle

The data used in the study are an unbalanced panel. Most SMEs do not report financial statements and credit ratings for all 8 years. There are various reasons for this, i.e., the SME became a new client during this time, or the SME went bankrupt or simply changed its bank relationship. In our analysis, we only use firms which report financial statements and credit ratings for at least three consecutive years. The dataset construction and the variable definitions are shown in Appendix A1. Table 3.1 summarizes the data.

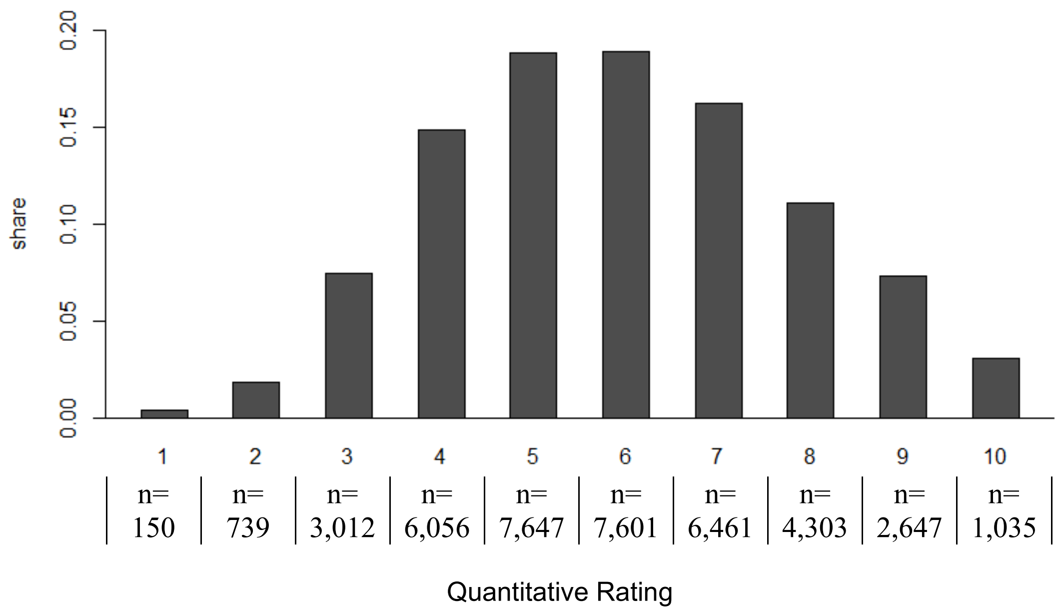
Table 3.1: Summary Statistics

Variables	mean	sd	min	median	max	n
Quantitative Rating	5.86	1.87	1.00	6.00	10.00	39,651
Approved Rating	5.88	1.79	1.00	6.00	10.00	39,651
Total Assets in Thousand CHF	5,795	12,277	11	1,897	145,234	39,651
Total Sales in Thousand CHF	7,140	23,868	94	2,259	1,177,680	39,651
Property Plant Equipment (TA)	0.42	0.31	-	0.39	0.99	39,651
Bank loan (TA)	0.07	0.13	-	-	0.99	39,651
Mortgage (TA)	0.18	0.23	-	-	0.98	39,651
Equity Ratio	0.39	0.22	-	0.36	1.00	39,651
Investments (TA)	0.09	0.62	-4.70	0.03	74.96	39,651
Number of Employees	19.64	3.13	1.00	8.00	249	39,651

Notes: The table depicts summary characteristics for the variables used in the analysis. “TA” indicates standardization to total assets. Bank loan (TA) represent the share of credit lines and investment loans to total assets. The sample consists of firms which report financial statements and credit ratings for at least three consecutive years.

Figure 3.1 shows the rating distribution of the SMEs where rating 1 is the best and rating 10 the worst. Rating classes 5 to 7 are the most used. To give an intuition of the rating classes 1 to 10, a map of the international rating agencies Moody’s and S&P is shown in Appendix A2.

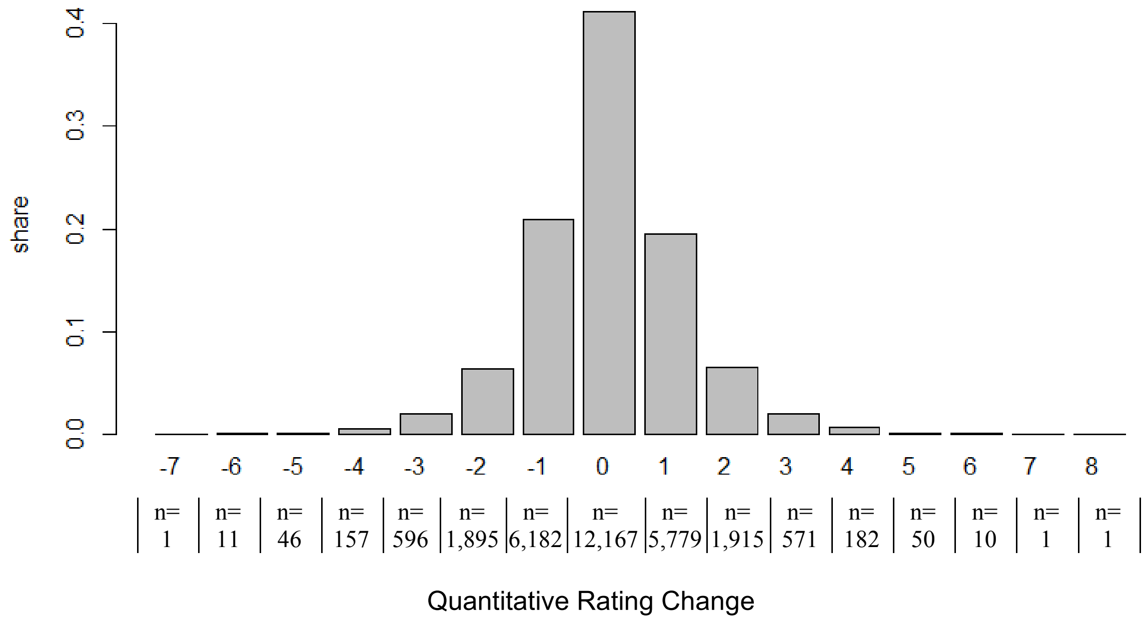
Figure 3.1: Rating Distribution (n= 39,651)



Notes: This graph plots the relative rating distribution by rating classes using the quantitative rating grades. The sample consists of firms which report financial statements and credit ratings with at least three consecutive years.

Figure 3.2 shows the rating changes. Approximately 42% of firms remain in the same rating class as they were in the previous year. Thus, banks changed more than 50% of all firms' ratings, and 40% of firms rated one rating class higher or lower compared to the previous year. This large share of migration is a peculiarity of SMEs compared to large corporations. On the one hand, ratings of SMEs change much faster than they do for corporations due to the rating agencies' policies to avoid numerous rating reversions. On the other hand, financial statements of SMEs are inherently unstable compared to those of large corporations.

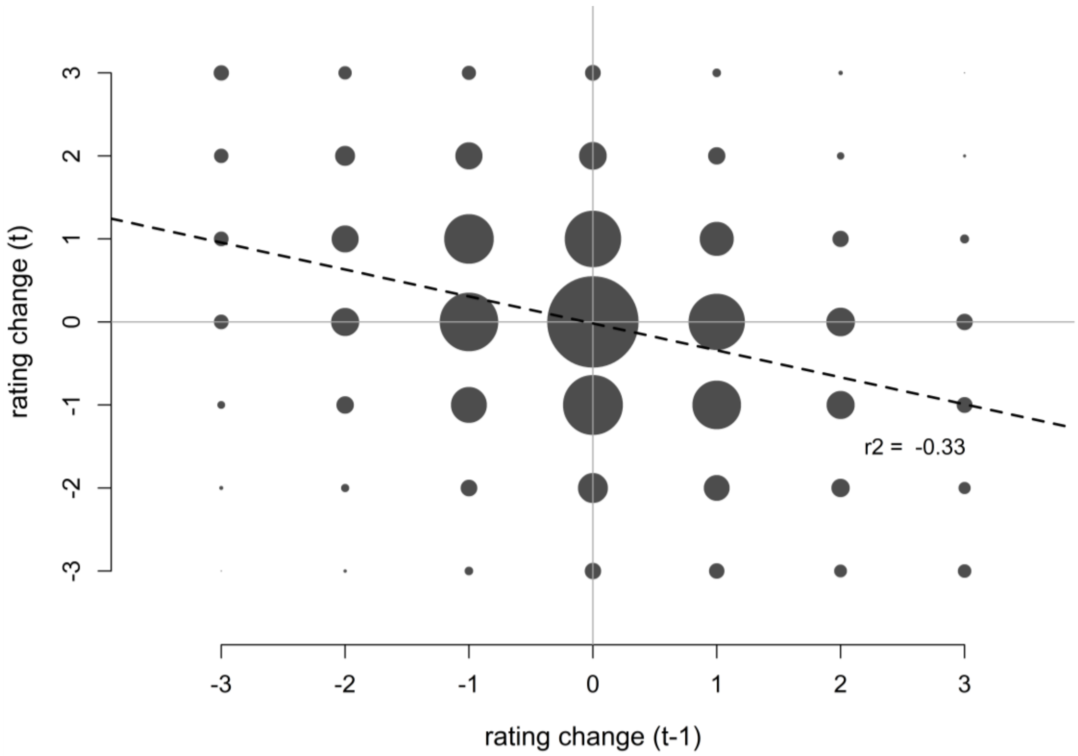
Figure 3.2: Histogram Quantitative Rating Changes (n= 29,564)



Notes: This graph plots the histogram of quantitative rating changes between 2008 and 2016. The sample consists of firms which report financial statements and credit ratings with at least three consecutive years.

Figure 3.3 shows the linear relation between rating changes in *(t)* and previous rating changes *(t-1)*. It is important to highlight that a downgrade is represented as a positive number and an upgrade is given by negative numbers. As the rating variable is ordinal scaled, the size of the bubbles represent the count of rating changes in the respective category. The bubble for a downgrade by one rating grade (+1) in *(t)* given a one rating grade upgrade (-1) in the previous year *(t-1)* is larger than for a downgrade (+1) in *(t)* given a downgrade (+1) in *(t-1)*. The same is true for upgrades given the previous rating change. There is a negative relationship between rating changes in *(t)* and previous rating changes *(t-1)*. The Pearson correlation coefficient is 0.33. This is the rating reversal effect.

Figure 3.3: Relation Rating Change in (t) ~ Rating Change in (t-1) (n= 18,223)



Notes: This graph plots the relationship between rating changes in *(t)* and previous rating changes *(t-1)* for the entire data sample from 2008-2016. Rating changes larger than 3 rating grades are subsumed in the rating change category "3". Conversely, rating changes with an upgrade larger than 3 are subsumed in the rating change category "-3".

3.4 Rating Reversals

We derive the rating transition matrices and quantify the reversal path-dependency of SMEs.

3.4.1 Transition Matrix Analysis

To analyze the first-order Markov property and the path dependency in SME ratings (hypothesis H1), we calculate four different transition matrices. This procedure was first introduced by Bangia et al. (2002) and followed in other studies (Krüger et al., 2005, Liu, 2015). Matrix M includes all rating transitions from one rating grade h at time *(t-1)* to rating grade j at time *(t)*. All SME ratings in matrix M are split into three subgroups, given the previous rating change *(t-1)*. These are defined as down-momentum matrix (given a downgrade the previous year), maintain-momentum matrix (given no change the previous year) and up-momentum matrix (given an upgrade the previous year):

$\{M(t)\}_{h,j}$ = unconditional transition probability from *(t-1)* to *(t)* from h to j

$\{M_{down}(t)\}_{h,j}$ = transition probability from *(t-1)* to *(t)* from h to j of obligors that have downgraded during the year *(t-2)* to *(t-1)*

$\{M_{par}(t)\}_{h,j}$ = transition probability from *(t-1)* to *(t)* from h to j of obligors that have no rating change during the year *(t-2)* to *(t-1)*

$\{M_{up}(t)\}_{h,j}$ = transition probability from *(t-1)* to *(t)* from h to j of obligors that have upgraded during the year *(t-2)* to *(t-1)*

By construction we obtain

$$M(t) = M_{down}(t) + M_{par}(t) + M_{up}(t)$$

Based on these transition matrices we calculate the overall probability of an upgrade or downgrade for each momentum-based migration matrix. Furthermore, following Krüger et al. (2005), for each rating grade in a momentum matrix, we calculate the sum of all elements to the right side of the diagonal as downgrade probability and all elements to the left side of the diagonal as upgrade probability. Comparing these up- and downgrade probabilities per rating class shows whether the firm's rating follows a drift or reverse.

There are two main methods used to calculate rating transition probabilities: the time-discrete cohort method and the time-continuous duration method. The main differences lie in the period between two observations of a firm as well as the transition variation over time. Based on the discrete time observation of the underlying rating data, the well-known cohort method is our first choice to calculate the rating matrices. However, we used both methods to calculate the transition matrices. Appendix A3 shows a short introduction and summary of the applied methods.

Table 3.2 shows the unconditional transition matrix $M(t)$ based on all transitions from 2008 to 2016 using the cohort method. The unconditional probability for a downgrade is 29% and is almost equal to the unconditional probability for an upgrade, which is 30%.

Table 3.2: Unconditional Transition Matrix Cohort Method

$\{M(t)\}_{h,j}$

		Rating(t)									
		1	2	3	4	5	6	7	8	9	10
Rating(t-1)	1	32.2%	33.0%	20.9%	5.2%	5.2%	2.6%	0.9%	0.0%	0.0%	0.0%
	2	7.6%	43.5%	29.1%	12.2%	3.6%	2.5%	1.1%	0.2%	0.0%	0.2%
	3	0.8%	7.4%	46.5%	27.5%	11.0%	4.2%	1.9%	0.6%	0.2%	0.0%
	4	0.3%	1.6%	14.9%	44.3%	24.2%	9.6%	3.4%	1.1%	0.4%	0.1%
	5	0.0%	0.5%	3.7%	21.1%	42.7%	20.7%	8.0%	2.4%	0.7%	0.1%
	6	0.0%	0.2%	1.8%	7.1%	23.1%	39.9%	19.0%	6.3%	1.9%	0.6%
	7	0.0%	0.1%	0.7%	3.1%	9.4%	24.7%	38.3%	17.5%	5.1%	1.2%
	8	0.0%	0.0%	0.4%	1.2%	4.0%	11.6%	25.8%	36.3%	17.0%	3.6%
	9	0.0%	0.0%	0.3%	0.8%	2.4%	5.4%	12.4%	25.2%	40.1%	13.4%
	10	0.0%	0.0%	0.1%	0.5%	1.0%	3.0%	6.6%	12.3%	31.6%	44.9%

P (down)	28.8%	n = 8,273
P (par)	41.1%	n = 11,826
P (up)	30.1%	n = 8,664

Notes: The matrix shows the rating transition probabilities based on 28,763 SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

Table 3.3 shows the down-momentum matrix, which includes the rating transitions in *(t-1)* to *(t)* restricted to firms which had a previous downgrade in *(t-2)* to *(t-1)*. With this restriction, the probability of an upgrade is 47%. A firm which received a downgrade is most likely to upgrade in the next financial year. This is the rating reversal effect, which is quite high.

Table 3.3: Downgrade Path Dependent Transition Matrices Cohort Method

$\{M_{down}(t)\}_{h,j}$

		Rating(t)									
		1	2	3	4	5	6	7	8	9	10
Rating(t-1)	1	na	na	na	na	na	na	na	na	na	na
	2	14.8%	44.4%	33.3%	7.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
	3	5.0%	20.7%	43.0%	21.5%	5.8%	0.8%	2.5%	0.8%	0.0%	0.0%
	4	1.3%	4.5%	27.1%	40.1%	17.5%	6.8%	2.3%	0.5%	0.0%	0.0%
	5	0.0%	1.2%	7.5%	29.7%	39.1%	14.8%	5.7%	1.4%	0.6%	0.0%
	6	0.0%	0.9%	3.3%	12.7%	28.2%	35.5%	13.9%	3.6%	1.5%	0.4%
	7	0.0%	0.1%	1.0%	5.8%	13.6%	30.7%	31.2%	14.0%	3.1%	0.6%
	8	0.0%	0.0%	1.1%	2.1%	6.4%	14.4%	26.4%	33.5%	14.0%	2.2%
	9	0.0%	0.0%	0.3%	1.0%	4.7%	6.6%	15.9%	28.8%	33.2%	9.5%
	10	0.0%	0.0%	0.3%	1.0%	1.7%	2.7%	7.6%	13.0%	36.5%	37.2%

P (down | down)	17.7%	n = 904
P (par | down)	35.3%	n = 1,800
P (up | down)	47.0%	n = 2,397

Notes: The matrix shows the rating transition probabilities based on 5,104 SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

Table 3.4 shows the rating transitions in *(t-1)* to *(t)* restricted to firms which had no rating migration in *(t-2)* to *(t-1)*.

Table 3.4: No Migration Path Dependent Transition Matrices Cohort Method

$\{M_{par}(t)\}_{h,j}$

Rating(t-1) \ Rating(t)	1	2	3	4	5	6	7	8	9	10
1	59.3%	29.6%	7.4%	0.0%	3.7%	0.0%	0.0%	0.0%	0.0%	0.0%
2	8.0%	50.7%	29.0%	8.0%	1.4%	2.2%	0.7%	0.0%	0.0%	0.0%
3	0.3%	7.7%	54.4%	25.6%	6.9%	3.3%	1.1%	0.5%	0.2%	0.0%
4	0.3%	1.3%	15.0%	52.5%	20.8%	7.2%	2.2%	0.5%	0.3%	0.0%
5	0.0%	0.4%	2.8%	20.4%	48.6%	20.2%	6.0%	1.3%	0.1%	0.2%
6	0.0%	0.0%	1.0%	5.9%	23.6%	44.8%	17.7%	4.9%	1.4%	0.6%
7	0.0%	0.1%	0.4%	1.5%	7.3%	24.8%	43.8%	16.8%	4.6%	0.6%
8	0.0%	0.0%	0.1%	0.3%	1.5%	8.0%	25.7%	44.6%	16.1%	3.6%
9	0.0%	0.0%	0.0%	0.6%	1.2%	3.2%	11.7%	21.1%	46.6%	15.6%
10	0.0%	0.0%	0.0%	0.4%	0.9%	3.0%	6.4%	10.6%	27.7%	51.1%

P (down | par)	25.5%	n = 1,817
P (par | par)	47.9%	n = 3,419
P (up | par)	26.6%	n = 1,901

Note: The matrix shows the rating transition probabilities based on 7,137 SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

The last rating matrix in Table 3.5 shows the up-momentum, which includes the rating transitions in *(t-1)* to *(t)* restricted to firms which had a previous upgrade in *(t-2)* to *(t-1)*. Firms which reported an upgrade in the previous year are most likely to downgrade with 43%. Once again, firms with rating reversals report the highest probability. On the other hand, the probability of a rating drift $P(\text{up}|\text{up})$ is relatively low at 18%.

Table 3.5: Upgrade Path Dependent Transition Matrices Cohort Method

$\{M_{up}(t)\}_{h,j}$

Rating(t-1) \ Rating(t)	1	2	3	4	5	6	7	8	9	10
1	17.4%	37.0%	19.6%	10.9%	6.5%	6.5%	2.2%	0.0%	0.0%	0.0%
2	8.7%	37.3%	29.8%	14.9%	5.6%	2.5%	1.2%	0.0%	0.0%	0.0%
3	0.3%	4.5%	38.1%	31.8%	16.4%	4.9%	2.9%	1.0%	0.2%	0.0%
4	0.1%	1.1%	9.7%	40.3%	29.4%	12.1%	4.9%	1.2%	0.9%	0.1%
5	0.0%	0.4%	2.6%	13.9%	40.0%	26.2%	11.3%	3.7%	1.7%	0.2%
6	0.0%	0.0%	1.0%	4.7%	18.6%	36.2%	25.5%	10.0%	3.2%	0.9%
7	0.0%	0.0%	0.0%	2.0%	6.8%	18.3%	39.2%	22.3%	9.1%	2.4%
8	0.0%	0.0%	0.0%	0.3%	1.5%	9.6%	18.9%	35.8%	27.0%	7.1%
9	0.0%	0.0%	0.6%	1.8%	1.2%	4.3%	10.4%	22.1%	38.7%	20.9%
10	na	na	na	na	na	na	na	na	na	na

P (down | up)	43.2%	n = 2,309
P (par | up)	38.4%	n = 2,048
P (up | up)	18.4%	n = 982

Notes: The matrix shows the rating transition probabilities based on 5,339 SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

All transition matrices are calculated using the duration method as well. The results are reported in Appendix A4. This method accounts for the time spent within a rating class. Therefore, it is not surprising that the probabilities of no change (par) increases for all conditioned subsamples. However, the probability of a rating reversal compared to a rating drift is still higher. The rating reversal effect, which is calculated using the duration method, is smaller compared to the cohort method but still significant.

Table 3.6 summarizes and compares the overall probabilities per momentum matrix with existing studies. To the best of our knowledge, there is only one study for large corporations which calculated these conditional matrices (Bangia et al. 2002). Other studies analyzing the rating drift (i.e., Altman & Kao, 1992; Lando & Skødeberg, 2002; Figlewski et al. 2006; Dang & Partington, 2014) mainly use regressions or probability models (i.e., Cox hazard model) and not conditional matrices. Table 3.6 shows the significant rating reversal effect in the SME data: P (up | down) of 47% and P (down | up) of 43%. Conversely, large corporations not only have less volatile ratings, but if they migrate, the probability of having rating downward drift is higher compared to the reversal path.

Table 3.6: Rating Transition of SME and Large Corporates

		SME		Large Corporates
Literature		this study	Liu, 2015	Bangia et al., 2002
Data		Swiss Banks & Financial Provider, 2008-2016, Switzerland	Canadian Financial Provider, 2006-2008, Canada	S&P, 1981-1998, mainly North America
$\boldsymbol{M_{down}}$	P (down | down)	18%	27%	13%
	P (par | down)	35%	38%	80%
	P (up | down)	**47%**	**35%**	**7%**
$\boldsymbol{M_{par}}$	P (down | par)	25%	29.2%	8%
	P (par | par)	48%	49.9%	88%
	P (up | par)	27%	21.0%	4%
$\boldsymbol{M_{up}}$	**P (down| up)**	**43%**	**35%**	**5%**
	P (par | up)	38%	50%	90%
	P (up | up)	19%	15%	5%

Notes: The table shows the rating transition probabilities split into the three transition matrices based on the SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

Following Krüger et al. (2005), Table 3.7 shows the probability of an upgrade and downgrade per rating class and for each momentum matrix. In line with the overall conditional probabilities, almost all rating classes in M_{down} show higher probabilities for a rating reversal $\mathrm{P}(\mathrm{down}|\mathrm{up})$ compared to a rating drift $\mathrm{P}(\mathrm{up}|\mathrm{up})$. The same is true for the downward-momentum matrix M_{up}. Only rating classes 2 and 3 show a higher probability of a rating drift. The probability of a rating 3 to downgrade being given a downgrade is 31%, which is higher than an upgrade being given a downgrade, with 26%.

Table 3.7: Up- and Downgrade Probabilities per Rating Class

Rating	M_{down}		M_{par}		M_{up}	
	P(down|down)	P(up|down)	P(down|par)	P(up|par)	P (down|up)	P(up|up)
1	100%	-	41%	-	83%	-
2	41%	15%	41%	8%	54%	9%
3	31%	26%	38%	8%	57%	5%
4	27%	33%	31%	17%	49%	11%
5	22%	38%	28%	23%	43%	17%
6	19%	45%	25%	31%	40%	24%
7	18%	51%	22%	34%	34%	27%
8	16%	50%	20%	36%	34%	30%
9	9%	57%	16%	38%	21%	40%
10	-	63%	-	49%	-	0%

Notes: The table shows the rating transition probabilities per rating class and wihtin the three transition matrices based on the SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

3.4.2 Regression Analysis

Despite the significant effect of reversals shown in the previous analysis, these results may be influenced by certain banks because of different credit policies. The conditions of the economy, along with the business cycle, and thus time itself, may further impact rating behavior. In addition, systematic effects within certain industries may have an influence. Therefore, we must control for differences across banks, time and industry affiliation. Next to the descriptive power of the calculated transition probabilities, we use a linear OLS and a logistic regression model to test whether transition intensities depend on previous rating changes. First, we estimate the impact of the previous rating change on the current rating change. Let *i* be an SME, *j* the bank and *t* time:

$$\Delta RAT_{i,t} = \alpha + \beta_1 \cdot \Delta RAT_{i,t-1} + \zeta_1 \cdot bank\_FE_j + \zeta_2 \cdot year\_FE_t + \zeta_3 \cdot IND\_FE_i \quad (1)$$

Second, we use dummy variables to estimate the rating dependency as follow:

$$RATdown\_dummy_{i,t} = \alpha + \gamma \cdot RATdown\_dummy_{i,t-1} + \beta_2 \cdot RATup\_dummy_{i,t-1} + \zeta_1 \cdot bank\_FE_j + \zeta_2 \cdot year\_FE_t + \zeta_3 \cdot IND\_FE_i \quad (2)$$

$$RATup\_dummy_{i,t} = \alpha + \beta_2 \cdot RATdown\_dummy_{i,t-1} + \gamma \cdot RATup\_dummy_{i,t-1} + \zeta_1 \cdot bank\_FE_j + \zeta_2 \cdot year\_FE_t + \zeta_3 \cdot IND\_FE_i \quad (3)$$

Equation (1) estimates a linear dependence between $\Delta RAT_{i,t}$, which defines the actual change of rating classes of a firm from *(t-1)* to *(t)* and $\Delta RAT_{i,t-1}$ and reflects the previous change in rating classes from *(t-2)* to *(t-1)*. $\Delta RAT_{i,t}$ is a variable with an ordinal scale from -10 to +10. The motivation behind this specification relies on the assumption that the probability of the rating change in time *(t)* strongly depends on the previous rating change in time *(t-1)*. If this path-dependency follows a rating drift, the coefficient of interest β_1 is positive. Conversely, if there is a rating reversion path, then the coefficient β_1 is negative. Support for the first-order Markov property would be a coefficient β_1 close to zero.

Equations (2) and (3) are similar to equation (1) but use dichotomous outcome variables to estimate the relationship between consecutive rating changes. Accordingly, we use dummy variables for an upgrade (up_dummy) or downgrade (down_dummy). Equation (2) estimates how a rating downgrade $(RATdown\_dummy_{i,t})$ from *(t-1)* to *(t)* is influenced by a previous rating down- $(RATdown\_dummy_{i,t-1})$ or upgrade $(RATup\_dummy_{i,t-1})$ from *(t-2)* to *(t-1)*. Equation (3) is the opposite, showing the impact on an actual downgrade $(RATup\_dummy_{i,t})$. The coefficients β_2 will show if a path dependency exists or not. Equations (1), (2) and (3) are directly linked to H1.

Industry (IND_FE_i) and time fixed effects $(year\_FE_t)$ control for systematic effects and business cycle effects. Changes in economic conditions (i.e., GDP, inflation) and other time variant unobserved variables are controlled using time fixed effects. Bank fixed effects $(bank\_FE_j)$ control for differences among banks regarding credit policies. This should alleviate the concern that heterogeneity stemming from different credit strategies of banks is responsible for the results.

Table 3.8 shows the results using equations (1), (2) and (3) to estimate the relationship between rating changes in *(t)* and rating changes in *(t-1)*.

Table 3.8: Regression Results

	Dependent variable:				
	$\Delta \mathrm{Rating}_{i,t}$	$\mathrm{Ratingdowngrade\ Dummy}_{i,t}$		$\mathrm{Ratingupgrade\ Dummy}_{i,t}$	
	(1)	(2)	(2)	(3)	(3)
	OLS	OLS	Logit (marginal effects)	OLS	Logit (marginal effects)
$\Delta \mathrm{Rating}_{i,t-1}$	-0.33*** (0.01)				
$\mathrm{RATdown\_dummy}_{i,t-1}$		-0.08*** (0.01)	-0.09*** (0.01)	0.20*** (0.01)	0.19*** (0.01)
$\mathrm{RATup\_dummy}_{i,t-1}$		0.18*** (0.01)	0.17*** (0.01)	-0.09*** (0.01)	-0.1*** (0.01)
Constant	1.04 (1.18)	0.22* (0.13)		0.23* (0.13)	
Fixed Effects	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry
Observations	18,223	18,223	18,223	18,223	18,223
R^2	0.12	0.06		0.07	
Adjusted R^2	0.11	0.05		0.06	
Residual Std. Error	1.18 (df = 17531)	0.44 (df = 18175)		0.44 (df = 18175)	
F Statistic	47.86*** (df = 48; 17531)	22.54*** (df = 47; 18175)		26.91*** (df = 47; 18175)	

Notes: The table reports the estimates of several linear regression models (OLS) and logistic regression models (logit) based on equation (1), (2) and (3). The sample consists of all firms with three consecutive ratings between 2008 and 2016. Standard errors are shown in parentheses and are clustered at the firm level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *p<0.1; **p<0.05; ***p<0.01

Regression (1) shows a statistically significant negative coefficient β_1. Since this is a linear dependence model, the current rating at time *(t)* decreases by 0.33 if the previous rating at time *(t-1)* increases by 1. This reverse relation also holds for equations (2) and (3). Using OLS to estimate equation (2) shows a positive coefficient β_2 for an upgrade in *(t-2)* increasing the downgrade in *(t)* by 0.18. The same is true for the relation and magnitude of β_2 in (3), which is positive and almost identical: a downgrade in *(t-2)* results in an upgrade in *(t)* by 0.20. These results support H1 “Rating Reversals”. Since equations (2) and (3) have dichotomous dependent variables, we use a logit model to estimate β_2. Appendix A5 shows the log odds. The marginal effects are shown in Table 3.8 next to the OLS results. The coefficient β_2 is almost of the same magnitude as the linear model. An upgrade in the previous year of one rating class increases the probability of a downgrade in the current year by 17 percentage points. Conversely, a downgrade by one rating class the year before increases the probability of an upgrade in *(t)* by 19 percentage points.

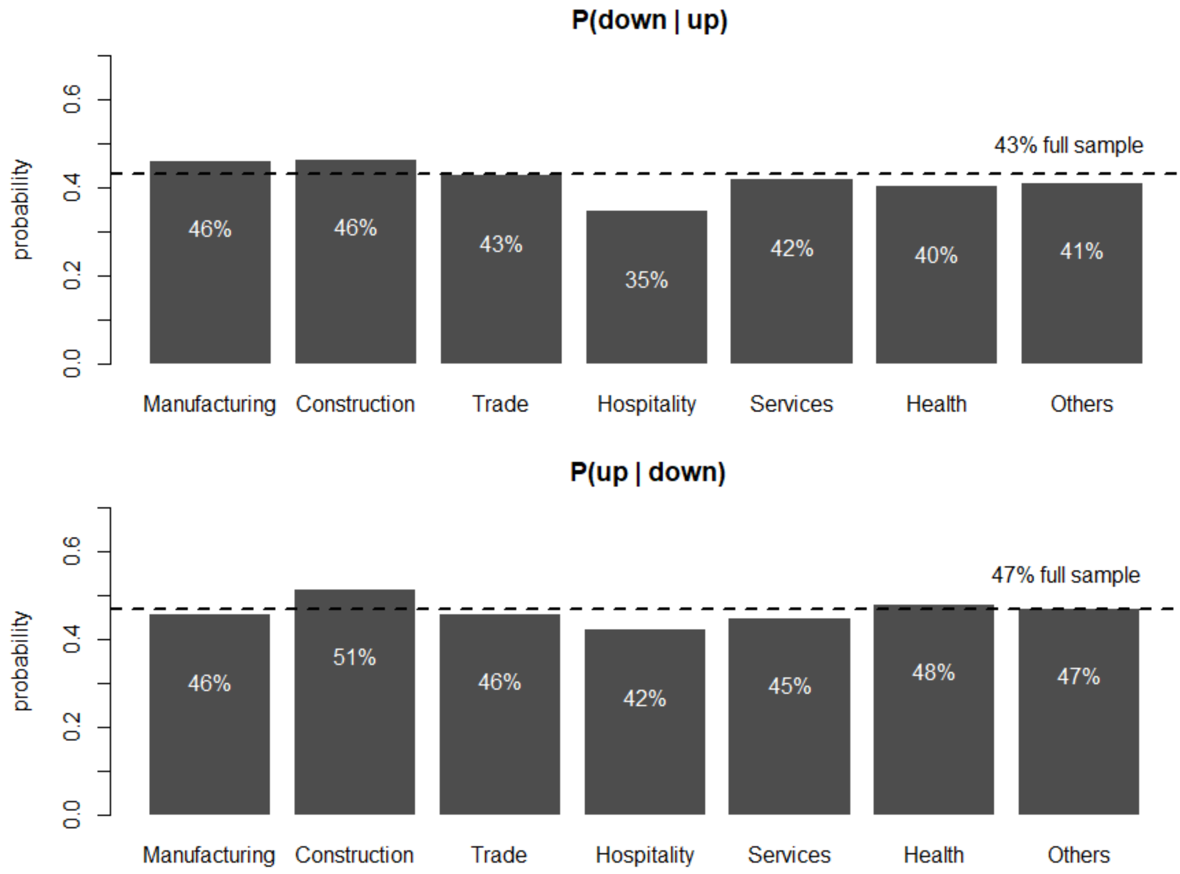
3.5 Role of Industry Sector and Firm Size

In this section, we analyze the heterogeneity of rating reversions. It is important to understand whether the effect is driven by certain types of firms. Only a persistent effect for SMEs allows the use of one transition matrix for all firms in an SME portfolio. We build different subsamples based on firm characteristics to assess whether the effect is different for certain types of firms or even cancels out. Subsamples based on financial figures may not contribute to a better understanding because these are mainly used to calculate the firm's rating and cause an endogeneity problem. We do not intend to back test the applied rating model.

To analyze the heterogeneity of the rating reversal effect, we use the industry affiliation as a first explanatory variable. Existing studies show that the rating development is indirectly dependent on the industry sector (Nickell et al., 2000). Since there is strong evidence that large corporations are different from SMEs in terms of rating behavior, firm size is our second explanatory variable. The literature suggests "Total Assets" as the key ratio for firm size. Despite the fact that "Total Assets" as a financial figure inherently influences the rating grade, we use this financial figure to test whether the smallest firms reverse more often compared to larger SMEs. However, to exclude the endogeneity problem using financial figures, we use the number of employees as a proxy for firm size as well.

Using the industry affiliation to split the data, Figure 3.4 shows the probabilities of a rating migration conditioned on a previous rating change in the opposite direction. Only firms in manufacturing and construction show slightly higher probabilities of a downgrade if they upgraded the previous year $P(\text{down}|\text{up})$. Construction shows a higher probability of a downgrade followed by an upgrade $P(\text{up}\,|\,\text{down})$. The fact that firms in the construction industry have a more volatile rating grade compared to other industries is interesting. In Switzerland the construction industry has reported a boom cycle during the last ten years. It seems that, despite this increasing demand for construction services, firms' credit quality varies.

Figure 3.4: Sample Split by Industry Sector



n= 8,664	n= 6,929	n= 8,514	n= 1,935	n= 5,365	n= 2,358	n= 7,149

Notes: The figure shows the probability of rating change in *(t)* conditioned on the previous year's rating change in *(t-1)* by seven industry sectors. Appendix A6 shows all conditional probabilities.

Furthermore, the results for the hospitality sector surprise as well. Figure 3.4 shows that the credit quality of restaurants, bars and hotels is less volatile compared to other branches. Using the linear dependence equation (1), we estimate β_1 based on the industry subsamples. Table 3.9 shows the regression results.

Table 3.9: Regression Results Sample Split by Industry Sector

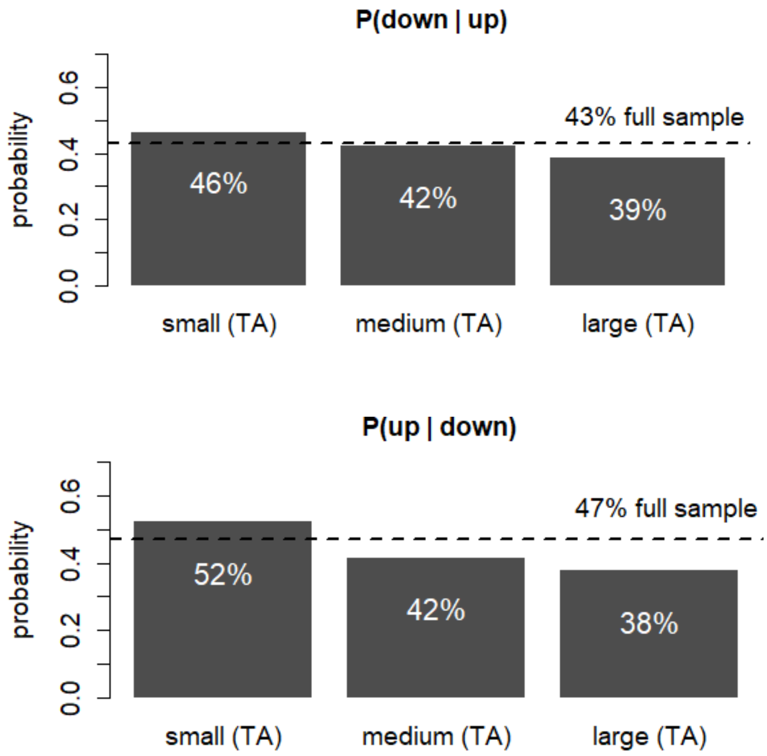
	Dependent variable: $\Delta \mathbf{Rating}_{i,t}$						
	Manufacturing	Construction	Trade	Hospitality	Services	Health	Others
	(1)	(1)	(1)	(1)	(1)	(1)	(1)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS
$\Delta \text{Rating}_{i,t-1}$	-0.34*** (0.02)	-0.37*** (0.02)	-0.34*** (0.02)	-0.24*** (0.03)	-0.31*** (0.02)	-0.35*** (0.03)	-0.33*** (0.02)
Constant	-0.27 (0.51)	0.92 (1.29)	-0.01 (0.57)	-0.31 (1.25)	-0.74 (1.13)	1.04 (1.10)	-1.4* (0.8)
Fixed Effects	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry	bank;time; industry
Observations	3,820	3,109	3,855	855	2,395	1,045	3,144
R^2	0.12	0.15	0.11	0.09	0.11	0.15	0.12
Adjusted R^2	0.11	0.14	0.11	0.07	0.1	0.13	0.11
Residual Std. Error	1.24 (df = 3792)	1.29 (df = 3081)	1.13 (df = 3828)	1.00 (df = 827)	1.13 (df = 2367)	1.09 (df = 1018)	1.13 (df = 3116)
F Statistic	18.91*** (df = 27; 3792)	19.78*** (df = 27; 3081)	18.60*** (df = 26; 3828)	3.21*** (df = 27; 827)	11.24*** (df = 27; 2367)	6.79*** (df = 26; 1018)	15.48*** (df = 27; 3116)

Notes: The table reports the estimates of the linear regression model (OLS) based on equation (1). The sample consists of all firms with three consecutive ratings between 2008 and 2016. Standard errors are shown in parentheses and are clustered at the firm level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The coefficient β_1 of all subsample regressions does not differ much from the estimate based on the full sample. Construction and health show a slightly higher β_1, meaning that these industries have a stronger path relation between first time lag rating changes. The opposite is true for firms in hospitality, which report a lower β_1. Therefore, restaurants and hotels have fewer reversals.

Our second variable of firm characteristics is firm size. Using “Total Assets” as a proxy for firm size, we split the full sample into three subsamples of equal length. Figure 3.5 shows the probabilities of rating reversals categorized by these three size types. Small firms measured by total assets seem to report more rating reversals compared to larger SMEs. This is true for the probability of a downgrade given an upgrade and vice-versa. This supports H3, that “large” SMEs’ credit ratings reverse less compared to their smaller counterparts.

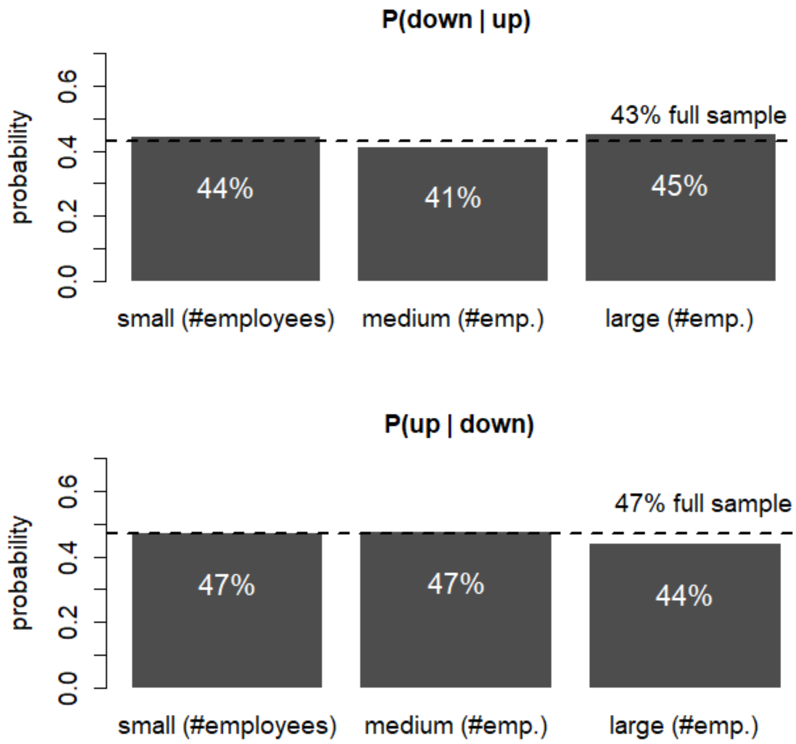
Figure 3.5: Sample split by Total Assets



Notes: The figure shows the probability of rating change in *(t)* conditioned on the previous year's rating change in *(t-1)*. The sample is split into three equal large subsamples by total assets (proxy for firm size).

Because total assets is an inherent part of the rating model itself, we also use employees as a proxy for firm size. We use the employee class definition introduced by the Swiss Federal Statistical Office (FSO): the smallest firms are defined as companies with less than 10 employees, the second size category of firms report 10-49 employees and the largest SME firms employ 50-249 employees. Given these three subsamples, Figure 3.6 shows the rating reversals for each firm size.

Figure 3.6: Sample split by Employees



Notes: The figure shows the probability of rating change in *(t)* conditioned on the previous year's rating change in *(t-1)*. The sample is split into three subsamples by number of employees (proxy for firm size) using the FSO definitions.

Contrary to the sample split by total assets, the firm size by number of employees does not or only marginally relates to the rating reversal behavior. However, the regression results shown in Table 3.10 report a slightly higher β_1 for small firms compared to large SMEs using both proxies for firm size: total assets and number of employees. Although the differences between small and large SMEs measured by β_1 is quite small, this supports H3: large SMEs' credit ratings reverse less compared to the smallest SME.

Table 3.10: Regression Results Sample Split by Total Assets and Employees

	Dependent variable: $\Delta\text{Rating}_{i,t}$			
	Total Assets: Small	**Total Assets: Large**	**Number of Employees: Small**	**Number of Employees: Large**
	(1)	(1)	(1)	(1)
	OLS	OLS	OLS	OLS
$\Delta\text{Rating}_{i,t-1}$	-0.37*** (0.01)	-0.32*** (0.01)	-0.36*** (0.01)	-0.32*** (0.02)
Constant	-0.07 (0.71)	0.11 (0.50)	0.54 (0.70)	1.26 (1.31)
Fixed Effects	bank; time; industry	bank; time; industry	bank; time; industry	bank; time; industry
Observations	5,860	6,222	5,830	2,052
R^2	0.15	0.1	0.13	0.11
Adjusted R^2	0.14	0.1	0.13	0.09
Residual Std. Error	1.22 (df = 5813)	1.18 (df = 6175)	1.21 (df = 5783)	1.25 (df = 2006)
F Statistic	22.29*** (df = 46; 5813)	15.51*** (df = 46; 6175)	19.26*** (df = 46; 5783)	5.74*** (df = 45; 2006)

Notes: The table reports the estimates of the linear regression model (OLS) based on equation (1). The sample consists of all firms with three consecutive ratings between 2008 and 2016 and is split into three subsamples by number of employees: small, medium and large. Standard errors are shown in parentheses and are clustered at the firm level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.6 Robustness

In our first robustness check we rule out that our results are driven by large outlier rating changes. Therefore, we exclude all rating changes higher than two rating classes in either direction (up- or downgrade). Appendix A7.1 shows all estimated regressions for equations (2) and (3) with the limitation on rating change size. The magnitude and relation of the estimated β_2 does not change.

As a second robustness check, we analyze the impact of time measured by the financial year. For this purpose, the dataset is split into sets containing three years each {2014-2016; 2013-2015; 2012-2014; 2011-2013; 2010-2012}. Again equations (2) and (3) are estimated using these subsamples. Appendix A7.2 shows that the rating reversals, which are estimated by β_2, persist. Only in 2011-2013, the probability of a rating downgrade in 2013 was higher if the firms reported a downgrade in 2012 compared to an upgrade in 2012. Furthermore, we calculate the conditional probabilities using these different time splits

{2014-2016; 2012-2014; 2010-2012}. Appendix A7.3 shows that the reversal effect prevails in all of these subsample splits.

3.6.1 Qualitative Risk Assessment

Rating agencies such as Moody's and S&P include soft factors (i.e., personal judgments) in the rating process. Krüger et al. (2005) mention that these personal credit assessments may explain the difference in rating path relationship between the observed rating reversal of nonpublic firms in their paper and the large corporation's rating drift observed by other studies. Rating reversals are most likely not in the interest of large creditors nor the agencies themselves (Löffler, 2005). Therefore, the qualitative risk assessment by rating agencies might induce effects such as a rating drift rather than a rating reversal.

In retail banking there is also a qualitative element of credit risk assessment. Credit risk or loan officers, which are separated from the bank's relationship managers, are used to assess loan applications. Several studies show that loan officers have discretion in the loan decision and the final rating grade that will be applied (Cerqueiro et al. 2011; Brown et al., 2012). Brown et al. (2012) show that credit risk officers tend to smooth rating changes. Since a subsequent combination of an up- and then a downward movement or vice versa is probably neither in the client's nor in the bank's interest, credit risk officers may smooth rating reversals more.

All banks in the data sample use a two-step rating approval approach. This involves a qualitative credit risk assessment performed by a credit risk specialist following the quantitative rating calculation. The underlying data includes the finally approved rating grade, which is a cross between a quantitative risk model and the qualitative personal judgment of a credit risk specialist.

We wish to examine whether the rating reversal effect changes significantly when we use this final rating grade, Therefore, we use the final approved rating grade and calculate the rating transition matrices introduced in section 3.4.1. Table 3.11 shows the probabilities of all first-year and unconditional second-year changes based on the quantitative rating model and the approved ratings by the loan officers. Including the loan officers' assessment, 46.4% of all SMEs remain in the previous rating class, which is 5.3% higher than the value based on the quantitatively calculated ratings alone.

Table 3.11: Rating Transition of Qualitative Risk Assessment: Unconditional Change

1st year change and unconditional 2nd year change			
	Quantitative Ratings	**Approved Ratings**	**+ / -**
P (down)	28.8%	26.2%	- 2.6pp
P (par)	41.1%	46.4%	+5.3pp
P (up)	30.1%	27.4%	-2.7pp

Notes: The table depicts the unconditional rating transition probabilities based on the SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

Table 3.12 shows the probabilities of rating changes conditioned on the previous year. The figures show that loan officers overall smooth rating changes. The probability P(par|.) increases for all conditioned subsamples. There is a marginally higher decrease of P(up|down) in the down-momentum matrix compared to P(down|down). Furthermore, in the up-momentum matrix the probability of a downgrade given an upgrade decreases much more than the rating drift P(up|up). However, the results do not suggest that credit risk officers specifically focus on rating reversals. The rating reversal effect persists independent from the qualitative risk assessment.

Table 3.12: Rating Transition of Qualitative Risk Assessment: Conditional Change

2nd year change				
		Quantitative Ratings	**Approved Ratings**	**+ / -**
$\boldsymbol{M_{down}}$	P (down | down)	17.7%	16.8%	-0.9pp
	P (par | down)	35.3%	38.4%	+3.1pp
	P (up | down)	**47.0%**	**44.7%**	-2.3pp
$\boldsymbol{M_{par}}$	P (down | par)	25.5%	22.6%	-2.9pp
	P (par | par)	47.9%	54.2%	+6.3pp
	P (up | par)	26.6%	23.2%	-3.4pp
$\boldsymbol{M_{up}}$	**P (down| up)**	**43.2%**	**39.6%**	-3.6pp
	P (par | up)	38.4%	42.1%	3.7pp
	P (up | up)	18.4%	18.2%	-0.2pp

Notes: The table illustrates the rating transition probabilities split into the three transition matrices based on the SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

3.6.2 Number of Rating Classes

According to the Basel Committee on Banking Supervision (BCBS), a bank should have a meaningful distribution of exposures across borrower rating classes. To meet this objective, a bank should have a minimum of seven borrower grades for nondefaulted borrowers (BCBS, 2006). If the number of rating classes is reduced, more SMEs remain in the same rating category. Conversely, the share of SMEs reporting a rating reversal is less likely.

Our SME data consist of ten rating grades. Using the quantitative rating score in our data, we change the width of rating classes to create new rating grades and new rating distributions. To show the impact on rating dependency, we change the number of rating classes to five and seven. Using these new rating classes, we recalculate the transition matrices introduced in section 3.4. Table 3.13 shows any one year's unconditional rating changes using three different rating distributions.

Table 3.13: Rating Transition by Number of Rating Classes: Unconditional Change

1st year change and unconditional 2nd year change			
	10 classes	**7 classes**	**5 classes**
P (down)	29%	22%	15%
P (par)	41%	55%	70%
P (up)	30%	23%	15%

Notes: The table depicts the unconditional rating transition probabilities based on the SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

Fewer rating classes reduce the proportion of rating changes. With seven borrower grades, which are required by the BCBS, only 45% credit ratings change. Table 3.14 shows the rating momentum matrices conditioned on the previous rating changes. At first glance it is interesting that the reversal effect retains its proportion and firms with a rating drift $P(up|up)$ and $P(down|down)$ decrease substantially.

Table 3.14: Rating Transition by Number of Rating Classes: Conditional Change

2nd year change					
		10 classes	**7 classes**	**5 classes**	
M_{down}	P (down | down)	18%	10%	4%	
	P (par | down)	35%	45%	53%	
	P (up | down)	**47%**	**45%**	**43%**	**Rating Reversal**
M_{par}	P (down | down)	25%	19%	11%	
	P (par | down)	48%	60%	76%	
	P (up | down)	27%	21%	13%	
M_{up}	**P (down | up)**	**43%**	**40%**	**39%**	**Rating Reversal**
	P (par | up)	38%	50%	57%	
	P (up| up)	18%	10%	4%	

Notes: The table depicts the rating transition probabilities split into the three transition matrices based on the SME ratings between 2008 and 2016. The calculation is based on the Cohort method.

However, using seven or five classes leads to a lower proportion of SMEs with a rating change, as Table 3.14 shows. SMEs with a subsequent change in the same direction (momentum) are rare because the border to the next rating grade is farther away if there are fewer rating classes. Therefore, the remaining SMEs which show a rating change tend to be reversals. This analysis shows that the rating reversal is relatively independent of the number of rating grades.

3.7 Discussion and Conclusion

In this paper, we examine to what extent changes in the credit ratings of Swiss SMEs depend on prior rating changes. We find a strong reversal relation between actual and prior rating changes. In light of the current implementation of the changes in loan loss provisioning under IFRS 9 and CECL and the growing relevance of stress testing, it is important for banks and regulators to understand how the credit risk of SMEs migrates in time.

We show that the rating reversals persist across industry affiliation. We also show the rating reversals are robust across firm size. Larger SMEs show only slightly fewer reversals compared with the smallest firms in the sample. Furthermore, our results suggest that a qualitative risk assessment by credit risk officers, similar to the rating approach of large rating agencies, does not specifically smooth out the rating reversal effect. These findings are important because only a homogenous effect allows us to model SMEs' credit risk in a lifetime expected loss setting similarly. In order to accurately reflect the credit risk of SMEs over time, the reversals should be considered in the rating transition matrices.

What are possible explanations for the pervasiveness of the rating reversal effect? A first possible explanation is that the underlying rating data might feature a mean reversion process. A mean reversion process suggest that borrowers have a "natural" or "true" rating that the rating model is trying to match. Shocks due to the business environment occur and temporarily drive the borrower's credit assessment away from the "true" rating, but a mean reversion process brings the borrower back toward the "true" rating. In this case, a pure through the cycle (TTC) rating model should be used to model the SME defaults, as it is superior to a PIT rating model.

A mean reversion process would suggests that large corporates have less noise in their rating assessments compared to SMEs. One reason for the difference of noise could be the business model itself. Large corporates are more diversified compared to small firms. Therefore, we would expect to see different degrees of reversals across different industry sectors, as they are differentially exposed to shocks in the business environment. Our results, however, show little variation of the magnitude of rating reversals by industry. Another reason for the mean reversion would be that large corporates are generally more resilient to economic shocks because of their size. This is somehow true, as we do not observe rating reversals for large corporates. For SMEs, however, our results show only little variation of the magnitude of rating reversals by firm size.

A second possible explanation is the absence of "window-dressing" among SMEs. While listed companies attach great importance to sustainable figures, small private companies do less. Large corporates are e.g. more likely to fund by the capital market and their ratings determine the bond's pricing. SMEs are unlikely to have access to the capital market and risk adjusted pricing for bank loans do not predominate. Therefore, large corporates have a greater intrinsic motivation to manage their accounting values than small firms to achieve sustainable figures and ratings. This should lead to unstable financial ratios for small private firms and more stable ratings for large listed corporates. Therefore, the relevance of sustainable financial figures could explain the difference between large listed companies and small private companies.

In terms of the relevance of accounting values, however, there are also differences between private firms. The larger the SME, the more likely it is that the company is working with budgets and using controllers to reach those figures. This is likely to be a question of available human resources, which depends on the size of the company. In addition, the size of SMEs itself may have an impact on the importance of sustainable financial results. If the intrinsic importance of accounting values causes rating reversals, then we would expect to see different degrees of reversals across firm size. Our results show only little variation of the magnitude of reversals by firm size. Therefore, neither mean reversion nor the relevance of accounting values (i.e., window dressing) can fully explain rating reversals.

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3.9 Appendix

A1: Dataset Construction

	#FS	#Firms
Original Sample	211'352	41'243
Dropping section:		
1) Consolidated financial statements	13'057	
2) Financial statements with other currency than CHF	844	
3) Financial statements with US GAAP, IFRS, others	878	
4) Financial statements with Total Assets = 0	28	
5) Financial statements with Total Assets CHF >300 Mio.	2'322	
6) Financial statements with Equity CHF <0	12'828	
7) Financial statements with more than 250 employees	2'946	
8) Financial statements with Equity > Total Assets	4	
9) Financial statements with more than 250 employee	2’946	
10) Financial statements duplicate	2'970	
11) Financial statements with old rating model	118’007	
12) Financial statements before 2008	32	
13) Financial statements of firms with less than 3 years	15’507	
14) Financial statements with Total Assets outlier (winsorized at 0.995)	288	
15) Financial statements without calculated or approved rating	20	
16) Financial statements with mismatch in quantitative and model rating	707	
17) Financial statements with defaulted ratings	1’263	
Base Sample	39’651	11’545

Variable Definition

Variables	
Quantitative Rating	Credit rating of a SME calculated with a statistical-mathematical model
Approved Rating	Finally approved credit rating of a SME based on the calculated rating and the personal assessment of a credit specialist (i.e., loan officer)
Total Assets in Thousand CHF	Total Assets (TA)
Total Sales in Thousand CHF	Total Sales
Property Plant Equipment (TA)	Property, plant and equipment, standardized to total assets (TA)
Bank loan (TA)	Used credit lines and investment loans granted by banks (without mortgages), standardized to total assets (TA)
Mortgage (TA)	Real estate collateralized bank loan, standardized o total assets (TA)
Equity Ratio	Equity / TA
Investments (TA)	Change in in PPE + depreciation on PPE

A2: Internal Rating Mapping on International Ratings

Internal Rating Grade	Moody's Rating	S&P Rating
1	Aaa, Aa	AAA, AA
2	A	A
3	Baa	BBB
4	Ba1	BB+
5	Ba2	BB
6	Ba3	BB-
7	B1	B+
8	B2	B
9	B3	B-
10	Caa	CCC

A3: Transition Matrices Methods

There are two main methods used to calculate rating transition probabilities: the time-discrete cohort method and the time-continuous duration method. The main differences lie in the period between two observations of a firm as well as the transition variation over time. Based on the discrete time observation of the underlying rating data, the well-known cohort method is our first choice to calculate the rating matrices. This is a nonparametric approach. It is an analytical method in which the transition probability of a constant group (cohort) of companies from the beginning of the year *t* to the end of the year t+1 is given by $P(t, t+1)$. Hence, the hj-element of this matrix describes the probability that a rated company starting in rating class h at date t moved to rating class j at date t+1 (Güttler, 2006; Lando & Skødeberg, 2002; Gavalas & Syriopoulos, 2014).

$$P(t, t+1) \quad = \quad \frac{\Delta N_{h,j}(t, t+1)}{Y_h(t)}$$

$\Delta N_{h,j}$ denotes the number of rating changes from rating class h at date *t* to rating class j at date t+1, and Y_h the number of rating observations in rating class h at date *t*. This leads to matrix $U(t)$, which includes the total number of transitions from one rating grade to another during t–1 to *t*. Each matrix element is divided by the number of firms that move from one state to another by the total number of companies in the initial rating category. This leads to matrix $M(t)$ where each element represents the probability of a specific rating transition.

The second main method, the duration method, offers an alternative approach to the discrete cohort method (Lando & Skodeberg, 2002). The duration method, often cited as hazard rate matrices, is a parametric method based on continuous time observation data. It is derived from a maximum likelihood estimator of the intensity matrix assuming time-homogeneity and first-order Markov property. Thus, it is based on survival analytic techniques (Skødeberg, 1998; Kavvathas, 2000; Liu, 2015; Mählmann, 2006). It relies on a continuously observed rating history, i.e., knowing the exact date within a year of a firm's rating change. This is a fundamental difference between ratings based on external agencies (i.e., Moody's and S&P) and internal bank ratings. Internal bank ratings of SMEs are not continuously monitored mainly because of the high cost of intense monitoring. This is in line with our underlying internal rating data, which contain neither continuous nor mixed discrete-continuous observations. They comprise yearly observed rating changes. Thus, the main difference between the duration and cohort method stems from the fact that firms remain longer than one year within a rating class. The time spent in a rating class is not accounted for in the cohort method. We follow McNeil et al. (2015), who introduced a continuous-time Markov chain to estimate the migration matrix. Let *(R_t)* denote a continuous-time stochastic process taking values in the set S which consists of the rating grades. Transition probabilities are summarized by a generator matrix $\Lambda = \left(\lambda_{hj}\right)$.

Let *P(t)* be the matrix of transition probabilities for the period [0, t]. Using the matrix exponential we obtain

$$P(t) = \exp(\Lambda t)$$

Following McNeil et al. (2015), a Markov chain with generator Λ can be constructed in the following way. An obligor remains in the rating state j for an exponentially distributed amount of time with parameter $\lambda = \sum_{k \neq j} \lambda_{hj}$. In case of a transition, the probability of moving from h to state j is given by λ_{hj}/λ.

Therefore, λ_{hj} is the instantaneous rate of migrating from j to k. The maximum likelihood estimator for the elements of the generator matrix is given by

$$\hat{\lambda}_{hj} = \frac{N_{hj}(T)}{\int_0^T Y_h(t)dt}$$

Therefore, $N_{hj}(T)$ is the total number of observed transitions from h to j over the time period [0,T] and $Y_h(t)$ is the number of obligors with rating h at time t.

A4: Transition Matrices Duration Method

Below four matrices shows the rating transition probabilities based on 11,545 SME ratings between 2008 and 2016. The calculation is based on the Duration Method.

$\{M(t)\}_{h,j}$ = Migration matrix, unconditional

Rating(t-1) \ Rating (t)	1	2	3	4	5	6	7	8	9	10
1	52.6%	19.8%	13.0%	6.8%	3.5%	2.7%	1.2%	0.3%	0.1%	0.0%
2	4.3%	58.8%	17.4%	9.8%	4.5%	2.8%	1.5%	0.6%	0.2%	0.2%
3	0.6%	4.7%	60.7%	17.1%	9.0%	4.3%	2.2%	0.9%	0.3%	0.1%
4	0.2%	1.4%	9.5%	60.4%	15.4%	7.6%	3.4%	1.4%	0.6%	0.2%
5	0.1%	0.6%	3.4%	13.3%	59.8%	13.0%	6.2%	2.4%	0.9%	0.2%
6	0.0%	0.3%	1.9%	6.1%	14.4%	58.2%	11.8%	4.8%	1.9%	0.6%
7	0.0%	0.1%	0.9%	3.2%	7.7%	15.2%	57.1%	10.5%	3.9%	1.2%
8	0.0%	0.1%	0.6%	1.8%	4.3%	9.0%	15.5%	55.7%	10.1%	2.8%
9	0.0%	0.0%	0.5%	1.2%	2.9%	5.4%	9.4%	15.0%	57.5%	7.9%
10	0.0%	0.0%	0.3%	0.8%	1.9%	3.5%	6.4%	9.6%	18.7%	58.8%

P (down)	20.1%	n = 5,769
P (par)	58.5%	n = 16,833
P (up)	21.4%	n = 6,163

$\{M_{down}(t)\}_{h,j}$ = Migration matrix, conditioned on downgrade in *(t-2)* to *(t-1)*

Rating(t-1) \ Rating (t)	1	2	3	4	5	6	7	8	9	10
1	100.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2	13.7%	62.5%	15.6%	6.4%	1.0%	0.3%	0.3%	0.1%	0.0%	0.0%
3	4.8%	13.4%	60.0%	12.3%	5.2%	1.5%	1.8%	0.7%	0.1%	0.0%
4	1.6%	4.6%	16.7%	58.5%	10.5%	4.7%	2.0%	0.9%	0.3%	0.2%
5	0.4%	1.9%	7.2%	18.0%	57.5%	9.0%	4.1%	1.2%	0.5%	0.1%
6	0.2%	1.2%	4.1%	10.1%	16.9%	55.3%	8.0%	2.6%	1.2%	0.3%
7	0.2%	0.5%	2.0%	5.8%	10.4%	17.4%	52.9%	7.9%	2.4%	0.5%
8	0.1%	0.3%	1.5%	3.2%	6.3%	10.6%	15.0%	53.6%	7.8%	1.6%
9	0.2%	0.2%	0.9%	2.3%	4.8%	6.6%	10.8%	15.9%	53.2%	5.1%
10	0.1%	0.1%	0.6%	1.7%	2.8%	3.8%	7.0%	10.0%	19.7%	54.2%

P (down | down)	13.7%	n = 698
P (par | down)	56.2%	n = 2,871
P (up | down)	30.1%	n = 1,535

$\{M_{par}(t)\}_{h,j}$ = Migration matrix, conditioned on no migration in *(t-2)* to *(t-1)*

Rating(t-1) \ Rating (t)	1	2	3	4	5	6	7	8	9	10
1	68.9%	20.2%	5.4%	1.6%	2.9%	0.5%	0.3%	0.1%	0.0%	0.0%
2	5.4%	63.3%	18.0%	7.5%	2.5%	1.8%	1.3%	0.2%	0.1%	0.0%
3	0.5%	5.1%	65.6%	16.5%	6.4%	3.6%	1.4%	0.6%	0.2%	0.0%
4	0.2%	1.3%	10.0%	64.7%	13.8%	6.3%	2.4%	0.9%	0.4%	0.1%
5	0.0%	0.4%	2.9%	13.7%	62.9%	12.9%	4.9%	1.5%	0.4%	0.2%
6	0.0%	0.1%	1.3%	5.4%	15.0%	60.7%	11.3%	4.1%	1.5%	0.6%
7	0.0%	0.1%	0.6%	2.2%	6.6%	15.6%	59.8%	10.5%	3.7%	0.9%
8	0.0%	0.0%	0.3%	0.9%	2.4%	7.1%	16.2%	60.0%	10.1%	3.0%
9	0.0%	0.0%	0.3%	0.8%	2.0%	3.9%	9.1%	13.4%	60.9%	9.6%
10	0.0%	0.0%	0.4%	0.7%	1.8%	3.2%	6.2%	8.4%	17.0%	62.4%

P (down | par)	18.3%	n = 1,308
P (par | par)	62.1%	n = 4,433
P (up | par)	19.6%	n = 1,396

$\{M_{up}(t)\}_{h,j}$ = Migration matrix, conditioned on upgrade in *(t-2)* to *(t-1)*

Rating(t-1) \ Rating (t)	1	2	3	4	5	6	7	8	9	10
1	45.4%	20.2%	11.7%	9.5%	4.4%	5.2%	2.5%	0.7%	0.3%	0.1%
2	4.4%	55.0%	16.6%	10.9%	6.2%	3.6%	2.0%	0.9%	0.3%	0.1%
3	0.3%	2.6%	55.3%	18.5%	12.2%	5.5%	3.4%	1.5%	0.6%	0.2%
4	0.1%	0.8%	5.9%	57.4%	17.6%	9.5%	5.0%	2.1%	1.2%	0.4%
5	0.0%	0.3%	2.0%	8.6%	58.0%	15.5%	8.9%	3.9%	2.0%	0.7%
6	0.0%	0.1%	1.0%	3.9%	11.3%	56.0%	15.3%	7.4%	3.5%	1.5%
7	0.0%	0.0%	0.3%	1.8%	5.5%	11.4%	57.4%	13.3%	6.9%	3.2%
8	0.0%	0.0%	0.2%	0.8%	2.6%	6.9%	11.7%	55.5%	15.1%	7.4%
9	0.0%	0.0%	0.4%	1.4%	1.6%	3.8%	7.4%	12.1%	56.5%	16.7%
10	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

P (down | up)	31.0%	n = 698
P (par | up)	56.7%	n = 3,025
P (up | up)	12.4%	n = 660

Notes: The above four matrices shows the rating transition probabilities based on 11'545 SME ratings between 2008 and 2016. The calculation is based on the Duration Method.

A5: Regression Results Logit

	Dependent variable:			
	Ratingdowngrade Dummy$_{i,t}$ (2)		**Ratingupgrade Dummy$_{i,t}$** (3)	
	Logit (log odds)	Logit (marginal effects)	Logit (log odds)	Logit (marginal effects)
RATdown_dummy$_{i,t-1}$	-0.47*** (0.04)	-0.09*** (0.01)	0.88*** (0.04)	0.19*** (0.01)
RATup_dummy$_{i,t-1}$	0.80*** (0.04)	0.17*** (0.01)	-0.49*** (0.04)	-0.1*** (0.01)
Constant	-1.29 (0.70)		-1.22 (0.69)	
Fixed Effects	bank;time;industry	bank; time; industry	bank;time;industry	bank; time; industry
Observations	18,223	18,223	18,223	18,223
Log Likelihood	-10,414.85		-10,535.06	
Akaike Inf. Crit.	20,925.71		21,166.12	

Notes: The table reports the estimates of the logistic regression models (logit) based on equation (2) and (3). The sample consists of all firms with three consecutive ratings between 2008 and 2016. Standard errors are shown in parentheses and are clustered at the firm level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *p<0.1; **p<0.05; ***p<0.01

A6: Subsample Analysis

Subsample “Industry Sectors”

	Full Sample	Manu-facturing	Con-struction	Trade	Hospitality	Services	Health	Others
P (down | down)	18%	21%	16%	16%	17%	18%	13%	18%
P (par | down)	35%	33%	33%	37%	40%	37%	39%	35%
P (up | down)	**47%**	**46%**	**51%**	**46%**	**42%**	**45%**	**48%**	**47%**
P (down | up)	**43%**	**46%**	**46%**	**43%**	**34%**	**42%**	**40%**	**41%**
P (par | up)	38%	35%	33%	40%	49%	41%	39%	43%
P (up | up)	18%	19%	21%	17%	17%	18%	21%	16%

Subsample “Total Assets”: Regression Results

	Total Assets: Small		**Total Assets: Large**	
	Dependent variable:			
	Ratingdowngrade Dummy$_{i,t}$	**Ratingupgrade Dummy$_{i,t}$**	**Ratingdowngrade Dummy$_{i,t}$**	**Ratingupgrade Dummy$_{i,t}$**
	(2)	(3)	(2)	(3)
	Logit (log odds)	Logit (log odds)	Logit (log odds)	Logit (log odds)
RATdown_dummy$_{i,t-1}$	-0.48*** (0.08)	0.94*** (0.07)	-0.52*** (0.08)	0.83*** (0.07)
RATup_dummy$_{i,t-1}$	0.92*** (0.07)	-0.53*** (0.08)	0.74*** (0.07)	-0.45*** (0.08)
Constant	-1.43 (1.26)	-1.18 (1.85)	-0.87 (0.93)	-2.2425
Fixed Effects	bank; time; industry	bank; time; industry	bank; time; industry	bank; time; industry
Observations	5,860	5,860	6,222	6,222
Log Likelihood	-3,325.95	-3,430.96	-3,583.97	-3,532.90
Akaike Inf. Crit.	6,747.90	6,957.92	7,263.93	7,161.80

Notes: The table reports the estimates of several logistic regression models (logit) based on equation (2) and (3). The sample consists of all firms with three consecutive ratings between 2008 and 2016 and is split into three equally length sub-samples by total assets. The above shows two sub-samples, representing the smallest and largest firms by total assets. Standard errors are shown in parentheses and are clustered at the firm level. If a coefficient is statistically significantly different from zero, it is shown with an asterisk: *p<0.1; **p<0.05; ***p<0.01

A7: Robustness

A7.1 Robustness Test "Large Changes / Outlier":

Only rating changes less than two rating classes in either direction (up- or downgrade)

	Dependent variable:	
	Ratingdowngrade $\text{Dummy}_{i,t}$	Ratingupgrade $\text{Dummy}_{i,t}$
	(2)	(3)
	Logit (log odds)	Logit (log odds)
$\text{RATdown\_dummy}_{i,t-1}$	-0.44*** (0.05)	0.85*** (0.04)
$\text{RATup\_dummy}_{i,t-1}$	0.77*** (0.04)	-0.47*** (0.04)
Constant	-1.29 (0.70)	-1.2* (0.69)
Fixed Effects	bank;time;industry	bank;time;industry
Observations	17,939	17,939
Log Likelihood	-10,223.83	-10,369.42
Akaike Inf. Crit.	20,543.67	20,834.84

Notes: *p<0.1; **p<0.05; ***p<0.01

A7.2 Robustness Test "Financial Year":

Rating changes per three-year splits: {2014-2016; 2013-2015; 2012-2014; 2011-2013; 2010-2012}

	Dependent variable:									
	Ratingdowngrade $\text{Dummy}_{i,t}$ (2)					Ratingupgrade $\text{Dummy}_{i,t}$ (3)				
	Logit 2014-2016	Logit 2013-2015	Logit 2012-2014	Logit 2011-2013	Logit 2010-2012	Logit 2014-2016	Logit 2013-2015	Logit 2012-2014	Logit 2011-2013	Logit 2010-2012
$\text{RATdown}_{i,t-1}$ (dummy)	-0.16 (0.23)	-0.50*** (0.06)	-0.44*** (0.08)	-0.67*** (0.17)	-0.92* (0.5)	0.95*** (0.22)	0.91*** (0.05)	0.84*** (0.06)	0.91*** (0.16)	1.41*** (0.40)
$\text{RATup}_{i,t-1}$ (dummy)	0.81*** (0.22)	0.75*** (0.05)	0.92*** (0.06)	0.61*** (0.15)	0.19 (0.45)	-0.35 (0.26)	-0.48*** (0.06)	-0.55*** (0.07)	-0.37** (0.18)	-0.37 (0.42)
Constant	-1.35* (0.76)	-1.20*** (0.14)	-1.26*** (0.17)	0.16 (0.41)	-18.96 (211.25)	-1.37* (0.72)	-0.99*** (0.14)	-0.83*** (0.16)	-1.03** (0.44)	1.13 (1.39)
Fixed Effects	bank; industry	bank; industry	bank; industry	bank; industry	bank; industry	bank; industry	bank; industry	bank; industry	bank; industry	bank; industry
Observations	655	9,497	6,644	1,150	226	655	9,497	6,644	1,150	226
Log Likelihood	-368.15	-5,353.2	-3,787.3	-681.1	-93.99	-343.9	-5,470.1	-3,846.9	-643.88	-119.82
Akaike Inf. Crit.	818.3	10,790	7,658.61	1,442.20	255.99	769.8	11,024.	7,777.98	1,367.77	307.64

Notes: *p<0.1; **p<0.05; ***p<0.01

A7.3 Robustness Test "Financial Year":

Rating change probabilities per year: {2014-2016; 2012-2014; 2010-2012}

	Full Sample	2014-2016	2012-2014	2010-2012
P (down | down)	18%	22%	18%	17%
P (par | down)	35%	36%	35%	29%
P (up | down)	**47%**	**42%**	**47%**	**54%**
P (down | up)	**43%**	**43%**	**45%**	**31%**
P (par | up)	38%	40%	37%	45%
P (up | up)	19%	17%	18%	24%

Curriculum Vitae

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Education

09/2013 – 02/2020	**Ph.D.** in Finance at University of St.Gallen (HSG), Switzerland
09/2009 – 05/2012	**Master of Arts** in Accounting and Finance at University of St.Gallen (HSG), Switzerland
10/2005 – 08/2008	**Bachelor of Science** in Business Administration at FHS St.Gallen University for Applied Science, Switzerland

Professional Experience

09/2019 – today	**Deputy Head Risk Office** at St.Galler Kantonalbank Ltd., (Switzerland)
07/2013 – 09/2019	**Risk Officer** at St.Galler Kantonalbank Ltd., (Switzerland)
08/2012 – 07/2013	**Consultant** Treasury and Financial Risk Management at PricewaterhouseCoopers Ltd., (Switzerland)
08/2008 – 08/2012	**Credit Risk Manager** at LGT Bank in Liechtenstein Ltd., (Liechtenstein)
07/2011 – 10/2011	**Corporate Lending Executive** at LGT Bank (Ireland) Ltd., (Ireland)
08/2003 – 10/2005	**Assistant Corporate Clients** at St.Galler Kantonalbank Ltd., (Switzerland)