Essays on Alternative Investments and Insurance

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The President:

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To my dear parents / Für meine geliebten Eltern
Christa & Naceur

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St. Gallen, July 2016

Semir Ben Ammar

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Executive Summary

This dissertation consists of four parts, focusing on alternative investments, catastrophe risk, and asset pricing in an insurance context. Several financial instruments (i.e., funds, options, and stocks) are analyzed with different perspectives on an insurer's balance sheet. The first part pertains infrastructure as an alternative investment and considers the asset side of life insurers, which are in need of stable, long-term cashflows in the current low-interest rate environment to match their liabilities. The second part analyzes equity returns of non-life insurers and the risk factors driving them. In a similar vein, the third part takes a look at the equity value of non-life insurers implied by option prices to analyze their catastrophe risk exposure. The fourth part considers the liability side of non-life insurers and how policyholder liabilities can be securitized to act as alternative investments through insurance-linked securities (ILS) funds.

The first part, "Common Risk Factors of Infrastructure Investments," deals with infrastructure as an alternative investment opportunity, which is driven by unique risk factors that cannot be well described by standard asset class factor models. Thus, a nine-factor model based on infrastructure-specific risk exposure is created. A large dataset of U.S. infrastructure stocks in different subsectors (utility, telecommunication, and transportation) and over a long period of time (1983 to 2011) is used to test the model. The new factor model is able to capture the variation of infrastructure returns better than the Fama/French three-factor, the Carhart four-factor or the extended Fung/Hsieh eight-factor models. The model helps to improve the evaluation of infrastructure funds and to better determine the cost of capital of infrastructure firms, which is increasingly relevant in light of the growing need for privately financed infrastructure projects.

The second part, "Insurance Asset Pricing is Different" examines stock returns of non-life insurers, due to their exposure towards natural and man-made disasters. A comprehensive asset pricing exercise is conducted using monthly data from 1988-2013. There is evidence that state-of-the-art models such as the Fama and French (2015) five-factor model cannot fully explain the abnormal returns of non-life insurance stocks. Hence, an insurance-specific five-factor asset pricing model is proposed, which is able to explain these return anomalies. Priced factors include the book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility, which are primarily tied to exogenous events affecting insurance supply and demand such as catastrophes.

In the third part, “Pricing of Catastrophe Risk and the Implied Volatility Smile,” the relation between catastrophe risk and the implied volatility smile of options written on non-life insurance stocks is analyzed. It can be shown that the slope is significantly steeper compared to non-financials and other financial institutions. There is also evidence that this effect has increased over time, suggesting a higher risk compensation for natural catastrophes. Furthermore, a link between the insurance-specific tail risk component derived from options and the risk spread from the catastrophe bond market can be established. The results thus provide an accurate, high-frequency calculation for catastrophe risk linking the traditional derivatives market with ILS.

In the fourth part, “Asset Pricing and Extreme Event Risk: Common Factors in ILS Funds,” the focus is on ILS as an alternative investment, which behaves unlike those of any other asset class. Therefore, traditional asset pricing models are not suitable for dedicated ILS funds. A unique and comprehensive database of ILS funds is set up and a detailed empirical analysis of these investment vehicles is provided. Furthermore, a factor model, which is able to explain both their time-series and cross-sectional return characteristics is derived. It can be shown that ILS funds have historically exhibited a superior risk-adjusted performance when traditional performance measures are considered. Using key return drivers, three new factors models are introduced. Despite a strong overall fit, significant positive alphas remain for one quarter of all funds in our sample. These are either attributable to manager skill, luck, or other unknown beta exposures.

Zusammenfassung

Die vorliegende Dissertation besteht aus vier Teilen, die sich mit den Themen Alternative Investments, Katastrophenrisiko und Asset Pricing im Versicherungskontext auseinandersetzen. Mithilfe verschiedener Finanzinstrumente (Aktien, Fonds und Optionen) wird die Bilanz eines Versicherungsunternehmens aus mehreren Blickwinkeln betrachtet. Der erste Teil der Dissertation untersucht Infrastruktur als eine alternative Investitionsmöglichkeit. Auf der Aktivseite eines Lebensversicherers stellen Infrastrukturinvestitionen im derzeitigen Niedrigzinsumfeld eine vielversprechende Möglichkeit für langfristig stabile Kapitalzuflüsse dar, um Verpflichtungen auf der Passivseite nachzukommen. Der zweite Teil analysiert die Aktienrendite der Nichtlebensversicherer und die Risikofaktoren, welche diese beeinflussen. Eng verbunden hiermit ist der dritte Teil, der das implizite Eigenkapital der Nichtlebensversicherer, ausgedrückt durch Optionspreise, betrachtet um das Katastrophenrisiko genauer zu untersuchen. Der vierte Teil schaut sich die Passivseite der Nichtlebensversicherer genauer an und welche Performance deren verbriefte Versicherungspolicen durch Insurance-Linked Securities (ILS)-Fonds als alternative Investitionsmöglichkeit bietet.

Der erste Teil, “Common Risk Factors of Infrastructure Investments,” beschäftigt sich mit Infrastruktur als alternative Investitionsmöglichkeit, welche durch besondere Risikofaktoren beeinflusst werden und sich nur schwer durch Standardmodelle erklären lassen. Aus diesem Grund wird ein Neun- Faktorenmodell, basierend auf infrastruktur-spezifischen Risikoeigenschaften, abgeleitet. Hierzu wird ein umfangreicher Datensatz an U.S. amerikanischen Infrastrukturaktien in verschiedenen Subsektoren (Versorgungsunternehmen, Telekommunikation und Transport) und über einen langen Zeitraum (1983 bis 2011) verwendet, um das Modell zu testen. Das neue Faktormodell ist in der Lage die Renditeänderungen der Infrastrukturaktien besser aufzufangen als das Fama/French Drei-Faktoren-, das Carhart Vier-Faktoren- oder das erweiterte Fung/Hsieh Acht-Faktoren-Modell. Das Modell eignet sich zur Bewertung von Infrastrukturfonds und zur besseren Bestimmung der Eigenkapitalkosten von Infrastrukturfirmen. Dies erscheint vor dem Hintergrund des wachsenden Bedarfs an privat finanzierten Infrastrukturprojekten besonders relevant.

Der zweite Teil, “Insurance Asset Pricing is Different,” untersucht die Aktienrenditen von Nichtlebensversicherern aufgrund ihrer Gefährdung durch Naturkatastrophen und von Menschen verursachten Unglücken. Hierzu wird eine Faktormodellanalyse auf Basis monatlicher Daten zwischen 1988 und 2013 durchgeführt. Offensichtlich sind moderne Faktormodelle, wie zum Beispiel das

Fama und French (2015) Fünf-Faktoren-Modell, nicht gänzlich in der Lage die abnormale Rendite der Nichtlebensversicherer zu erklären. Aus diesem Grund wird ein versicherungsspezifisches Fünf-Faktoren-Modell vorgeschlagen, welches in der Lage ist diese abnormalen Renditen zu erklären. Die gepreisten Faktoren setzen sich aus dem Buch-zu-Marktwert Verhältnis, der Short-Term Reversal, der Illiquidität und der Cashflow-Volatilität zusammen, die in erster Linie mit exogenen Ereignissen in Verbindung stehen und Nachfrage und Angebot nach Versicherungen beeinflussen.

Im dritten Teil, genannt "Pricing of Catastrophe Risk and the Implied Volatility Smile," wird die Beziehung zwischen Katastrophenrisiko und dem impliziten Volatilitäts-Smile von Optionen auf Nichtlebensversicherern untersucht. Es kann gezeigt werden, dass die Steigung des impliziten Volatilitäts-Smiles im Vergleich zu anderen Unternehmen signifikant steiler ist. Dieser Effekt scheint über die Zeit hinweg stärker geworden zu sein, was wiederum für eine höhere Risikokompensation von katastrophalen Ereignissen spricht. Des Weiteren lässt sich eine Verbindung zwischen dem versicherungsspezifischen Tail-Risiko aus Optionspreisen und dem Risiko-Spread aus Katastrophenanleihen herstellen. Die Ergebnisse bieten sich daher auch als Ansatzpunkt zur genauen Hochfrequenzberechnung von Katastrophenrisiko an und verbinden den traditionellen Derivatemarkt mit ILS Instrumenten.

Der vierte Teil,"Asset Pricing and Extreme Event Risk: Common Factors in ILS Funds," fokussiert sich auf ILS als eine alternative Investitionsmöglichkeit, die sich anders als traditionelle Anlageklassen verhält. Aus diesem Grund sind traditionelle Faktormodelle nicht für ILS-Fonds geeignet. Für diesen Teil wird eine umfangreiche Datenbank an ILS-Fonds angelegt und eine detaillierte empirische Analyse durchgeführt. Darüber hinaus, wird ein Faktormodell entwickelt, das in der Lage ist sowohl die Zeitreihe als auch den Querschnitt der Fondsrenditen zu erklären. Auf Basis traditioneller Risikomasse wird gezeigt, dass ILS-Fonds eine historisch betrachtet bessere risikoadjustierte Performance erzielten als andere Anlageklassen. Mithilfe theoretisch motivierter Renditetreiber werden drei neue Faktormodelle vorgestellt. Trotz des hohen Erklärungsgehaltes, ist ein Viertel aller Fonds in der Lage eine Outperformance zu erzielen. Diese Outperformance ist entweder der Managerfähigkeit, Glück, oder anderen unbekannten Beta-Faktoren geschuldet.

Synopsis

The first paper is titled "Common risk factors of infrastructure investments" and is co-authored with Martin Eling. It has been published in *Energy Economics*, Vol. 49, 2015, pp. 257–273.
Despite the economic importance of infrastructure, there is very little academic work on infrastructure investments and most of the studies that do exist use only infrastructure indices and a limited period of investigation. This paper contributes to the empirical literature on transport, telecommunication, and utility firms by developing an asset class factor model for infrastructure investments. Specifically, in this paper five factors are identified in addition to the market beta that are characteristic for infrastructure firms in terms of risk and return. We use these factors to develop a six-factor model and an augmented nine-factor model that is built on Carhart (1997). We empirically test the new models on a large dataset of U.S. infrastructure companies. The empirical focus on U.S. firms is advantageous for three reasons. First, most of the existing infrastructure papers consider markets outside the United States even though there is a great need for infrastructure investment in the United States. Second, a long time horizon can be investigated, which allows us to consider different subperiods. Third, analyzing individual shares of infrastructure firms instead of indices allows us to sort portfolios by size, book-to-market ratio, and other characteristics to control for stock anomalies and, thus, enhances the validity of the infrastructure models.

Abstract of "Common risk factors of infrastructure investments": The risk of infrastructure investments is driven by unique factors that cannot be well described by standard asset class factor models. We thus create a nine-factor model based on infrastructure-specific risk exposure, i.e., market risk, size, value, momentum, cash flow volatility, leverage, investment growth, term risk, and default risk. We empirically test our model on a large dataset of U.S. infrastructure stocks in different subsectors (utility, telecommunication, and transportation) and over a long period of time (1983 to 2011). The new factor model is able to capture the variation of infrastructure returns better than the Fama/French three-factor, the Carhart four-factor or the extended Fung/Hsieh

eight-factor models. Thus, our model helps to improve the evaluation of infrastructure funds and to better determine the cost of capital of infrastructure firms, something that is increasingly relevant in light of the growing need for privately financed infrastructure projects.

The second paper is titled "Insurance asset pricing is different" and is co-authored with Martin Eling and Andreas Milidonis. It is currently under review at the *Journal of Banking and Finance* and has been published as a working paper at the University of St.Gallen.
In spite of the risk-absorbing role for both p/l insurance stocks and insurance-linked securities, the underlying risk exposure has not been subject to a great deal of debate in the academic literature. For example, although the analysis of the cross-sectional risk exposure is the heart of modern asset pricing (see, e.g., Garlappi and Yan (2011); Brennan et al. (2012); Eisfeldt and Papanikolaou (2013)), there is very little literature addressing the insurance context. Our paper closes this gap by analyzing the cross-section of expected p/l insurance stock returns. We propose a new insurance-specific asset pricing model that takes into account the unique characteristics (anomalies) of the insurance industry. We compare its performance to the performance of six existing asset pricing models using the universe of the 127 U.S. p/l insurance stocks on a monthly basis over the time period from 1988 to 2013. We sort insurance stocks on 22 well-known and potential anomalies from the finance and insurance literature and test our model to the six competing models by running time-series regressions, Fama–MacBeth (1973) regressions, and testing the equality of the Hansen-Jagannathan distance (Kan and Robotti (2009)).

Abstract of "Insurance asset pricing is different": Property/liability insurers are important financial institutions exposed to natural and man-made disasters. We first conduct a comprehensive asset pricing exercise for the U.S. property/liability insurance universe using monthly data from 1988-2013. We find that state-of-the-art models such as the Fama and French (2015) five-factor model cannot fully explain the abnormal returns of property/liability insurance stocks. Hence, we propose an insurance-specific five-factor asset pricing model which is able to explain these return anomalies. Priced factors include the book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility, which are primarily tied to exogenous events affecting insurance supply and demand such as catastrophes.

The third paper is titled "Pricing of catastrophe risk and the implied volatility smile" and is a single authored paper. This paper received the 2016 Dorfman Award by the Western Risk and Insurance Association (WRIA) as the best PhD paper and is published as a working paper at the University of St.Gallen. Risk-averse households are interested in offloading catastrophe risk but face high insurance premiums given the expected losses (see Froot (2001) and Zanjani (2002)). Any insight into catastrophe risk can thus further enhance our understanding of risk-adequate compensation for this type of risk. The contribution of this paper is fourfold. First, we derive an option pricing model unique to P&C insurers which accounts for catastrophe risk and illustrates another financial source eligible for accurate pricing of catastrophe risk. Due to the limited understanding of catastrophe risk in combination with pricing, new methods to comprehend this risk in greater detail can reduce market imperfections. Second, fair pricing for catastrophe reinsurance can affect the capital requirements for catastrophe risk and thus reduce the cost of capital (Zanjani (2002)). Third, we further enhance the reasoning with regard to the implied volatility smile. That is, we address why there is an implied volatility smile and why it is shaped the way it is (Dennis and Mayhew (2002)). Fourth, we create a link between the traditional derivatives market and ILS. From an investor's perspective, this link might be an indicator for potential arbitrage opportunities if expectations on catastrophe risk in the two markets significantly diverge.

Abstract of "Pricing of catastrophe risk and the implied volatility smile": Property-casualty (P&C) insurers are exposed to rare but severe natural disasters. This paper analyzes the relation between catastrophe risk and the implied volatility smile of insurance stock options. We find that the slope is significantly steeper compared to non-financials and other financial institutions. We show that this effect has increased over time, suggesting a higher risk compensation

for natural catastrophes. We are also able to link the insurance-specific tail risk component derived from options with the risk spread from the catastrophe bond market, which specifically securitizes tail risk events. Our results thus provide an accurate, high-frequency calculation for catastrophe risk linking the traditional derivatives market with insurance-linked securities (ILS).

The fourth paper is titled "Asset Pricing and Extreme Event Risk: Common Factors in ILS Funds" and is co-authored with Alexander Braun and Martin Eling. It has been published as a working paper at the University of St.Gallen. Over the last two decades, a new asset class called insurance-linked securities (ILS) has emerged. Its dominant representative is the catastrophe (cat) bond, a financial instrument which pays regular coupons unless a disaster occurs during the contract term, leading to full or partial loss of principal. Cat bonds have been developed by (re)insurance companies as a hedge against extreme event exposure in their property risk portfolios. Regardless of the attractive historical performance and the substantial diversification potential offered by ILS, little is known about their return drivers to date. The paper at hand aims at filling this gap. Our contribution is threefold. First, we analyze the asset class' risk-return profile for the period from January 2002 to December 2015 relative to corporate bonds and hedge funds. For this purpose, we set up a dataset that almost covers the entire universe of existing and terminated ILS funds. Second, we demonstrate the inability of traditional factor models to explain both the time-series and cross-sectional return characteristics of ILS funds. Subsequently, we introduce three new factor models to address this issue: a single-index, a fixed-income-oriented four-factor, and a perils-based three-factor approach. Third, we draw on these factor models to determine whether certain funds were able to outperform their peers on a risk-adjusted basis in the past.

Abstract of "Asset Pricing and Extreme Event Risk: Common Factors in ILS Funds": The returns of funds that focus on catastrophe (cat) bonds and other insurance-linked securities (ILS) behave unlike those of any other asset class. Therefore, traditional asset pricing models, such as the five-factor approach of Fama and French (1993) and the seven-factor approach of Fung and Hsieh (2004), are not suitable for dedicated ILS funds. We set up a unique and comprehensive database of ILS funds, provide a detailed empirical analysis of these investment vehicles and derive a factor model, which is able to explain both their time-series and cross-sectional return characteristics. First of all, we show that ILS funds have historically exhibited a superior risk-adjusted performance when traditional performance measures are considered. Subsequently, we identify key return drivers and introduce three new factors models, relying on publicly-available indices. Despite a strong overall fit, we are left with significant positive alphas for one quarter of all funds in our sample. These are either attributable to manager skill, luck, or beta exposures associated with non-cat-bond ILS.

The different parts of this dissertation are linked in several different ways. The first connection consists of explaining the returns of financial instruments using common systematic risk exposures. As such, investors, managers, and policymakers are able to identify and focus on the main drivers of risk compensation and how to manage their risk based on a parsimonious number of factors. The second aspect connecting the different parts of this thesis is the overall perspective on a representative balance sheet of an insurer. Specifically, infrastructure can be an investment on the asset side of an insurer as a source of less volatile cash flows. ILS funds are extracting the liability side of an insurer which is then transferred to other risk takers and insurance stocks are the residual claims of investors on the equity side of an insurance company. The last aspect connecting this thesis is the investor's need for alternative investment opportunities in the current low-interest rate environment. On the one hand, infrastructure is an investment opportunity with theoretically stable cash flows, which is an interesting alternative for insurance companies themselves. On the other hand, funds, stocks, and options containing insurance risks can be a diversifying asset for mutual funds, pension funds, and other investors who do not have insurance risks on their liability side.

Overall this thesis is a helpful aide to several different parties. This includes policymakers and insurers who are given more insight on the pricing and financial effects of catastrophe risk. Investors benefit from this thesis by having a better understanding on the systematic risk components in ILS funds, insurance stocks, and infrastructure stocks. Thus, they can understand which funds / companies earn sufficiently high returns based on their risk assumption – and which do not.

References

Brennan, M. J., T. Chordia; A. Subrahmanyam; and Q. Tong. "Sell-Order Liquidity and the Cross-section of Expected Stock Returns." *Journal of Financial Economics*, Vol. 105, 2012, pp. 523–541.

Carhart, M. M., "On persistence in mutual fund performance." *Journal of Finance*, Vol. 52, 1997, pp. 57–82.

Dennis, P., and S. Mayhew. "Risk-neutral skewness: Evidence from stock options." *Journal of Financial and Quantitative Analysis*, Vol. 37, 2002, pp. 471–493.

Eisfeldt, A. L., and D. Papanikolaou. "Organization Capital and the Cross-section of Expected Returns." *Journal of Finance*, Vol. 68, 2013, pp. 1365–1406.

Fama, E. F. and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, Vol. 81, 1973, pp. 607–636.

Fama, E. F. and K. R. French. "Common risk factors in the returns on stocks and bonds." *Journal of Financial Economics*, Vol. 33, 1993, pp. 3–56.

Fama, E. F. and K. R. French. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics*, Vol. 116, 2015, pp. 1–22.

Froot, K. A. "The market for catastrophe risk: A clinical examination." *Journal of Financial Economics*, Vol. 60, 2001, pp. 529–571.

Fung, W. and D. A. Hsieh. “Hedge fund benchmarks: A risk-based approach.” *Financial Analysts Journal*, Vol. 60, 2004, pp. 65–80.

Garlappi, L. and H. Yan. “Financial Distress and the Cross-section of Equity Returns.” *Journal of Finance*, Vol. 66, 2011, pp. 789–822.

Kan, R. and C. Robotti. “Model Comparison Using the Hansen-Jagannathan Distance.” *Review of Financial Studies*, Vol. 22, 2009, pp. 3449–3490.

Zanjani, G. “Pricing and capital allocation in catastrophe insurance.” *Journal of Financial Economics*, Vol. 65, 2002, pp. 283–305.

Part I

Common Risk Factors of Infrastructure Investments

SEMIR BEN AMMAR and MARTIN ELING

Abstract

The risk of infrastructure investments is driven by unique factors that cannot be well described by standard asset class factor models. We thus create a nine-factor model based on infrastructure-specific risk exposure, i.e., market risk, size, value, momentum, cash flow volatility, leverage, investment growth, term risk, and default risk. We empirically test our model on a large dataset of U.S. infrastructure stocks in different subsectors (utility, telecommunication, and transportation) and over a long period of time (1983 to 2011). The new factor model is able to capture the variation of infrastructure returns better than the Fama/French three-factor, the Carhart four-factor or the extended Fung/Hsieh eight-factor models. Thus, our model helps to improve the evaluation of infrastructure funds and to better determine the cost of capital of infrastructure firms, something that is increasingly relevant in light of the growing need for privately financed infrastructure projects.

Keywords: Infrastructure · Asset class · Factor model · Leverage · Cashflow Volatility
JEL classification: G11 · G12 · G19 · L90 · O18

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1 Introduction

A well-developed infrastructure, whether energy, transport, or telecommunication, is often considered the foundation for economic growth (Esfahani and Ramirez (2003); Hashimzade and Myles (2010); Czernich et al. (2011); Andersen and Dalgaard (2013)). Due to renewal and extension, the need for infrastructure investment is continuously growing, and public finance by itself does not provide sufficient funds for such investments (OECD (2007)). This situation increases the relevance of privately financed projects for which financial markets can be a useful intermediary, for example, through infrastructure funds. The aim of this paper is, thus, to derive an asset class factor model for infrastructure investments that explains the specific characteristics of these investments. The study is motivated by the claims of investment advisors and many trade articles that infrastructure investments have a number of unique characteristics, such as uncorrelated returns with major asset classes, stable cash flows because of long-term contracts, and inflation protection (see Newell and Peng (2008); Finkenzeller, Dechant, and Schäfers (2010); Bird, Liem, and Thorp (2012)). For these reasons, institutional investors increasingly seek infrastructure investments as an alternative asset class promising sustainable returns at relatively low risk.

There is very little academic work on infrastructure investments and most of the studies that do exist use only infrastructure indices and a limited period of investigation. Newell and Peng (2008) analyze U.S. infrastructure indices with respect to risk-adjusted performance and portfolio diversification and show that listed infrastructure improved portfolio performance during the period 2003 to 2006, but strongly underperformed other asset classes during 2000 and 2003. Looking at Australian and U.S. infrastructure indices, Finkenzeller, Dechant, and Schäfers (2010) and Dechant and Finkenzeller (2012) document the asset allocation benefits of infrastructure both in a mean-variance and a mean-downside risk framework. Bitsch, Buchner, and Kaserer (2010) compare the infrastructure deals of private equity funds with non-infrastructure deals and find higher performance and lower default rates for infrastructure investments, but no evidence of more stable cash flows. To date, Bird, Liem, and Thorp (2012) is the only study to extent the traditional Fama/French three-factor for infrastructure investments. They show that infrastructure offers a partial inflation hedge, but they reject the hypothesis that infrastructure has defensive characteristics in the sense that infrastructure firms perform well during economic downturns.

This paper contributes to the empirical literature on transport, telecommunication, and utility firms by developing an asset class factor model for infrastructure investments.[1] This paper is linked to the ongoing discussion in energy economics about the risk and return characteristics of energy, transportation and telecommunication investments (see Boyer and Filion (2007); Ford (2007); Gasmi and Oviedo (2010); Elyasiani, Mansur, and Odusami (2011); Ramos and Veiga (2011); Aggarwal, Akhigbe, and Mohanty (2012); Sklavos, Dam, and Scholtens (2013); Bianconi and Yoshino (2014); or Lopatta and Kaspereit (2014)). Specifically, we identify five factors in addition to the market beta that are characteristic for infrastructure firms in terms of risk and return: cash flow volatility, leverage, an investment growth factor, a term premium and a default premium. We use these factors to develop a six-factor model and an augmented nine-factor model that is built on Carhart (1997). We empirically test the new models on a large dataset of U.S. infrastructure companies. The empirical focus on U.S. firms is advantageous for three reasons. (1) Most of the existing infrastructure papers consider markets outside the United States even though there is a great need for infrastructure investment in the United States.[2]

[1] Bird, Liem, and Thorp (2012) restrict their analysis to the inflation hedge and downside protection characteristics, thereby controlling for conditional heteroscedasticity (using GARCH models) and the impact of regulatory power through simulations of a covered call strategy. We expand their model by factors related to cash flow volatility, leverage effects, investment growth, default risk, term premium, and the consideration of a very long time horizon. Furthermore, we look at individual infrastructure returns; Bird, Liem, and Thorp (2012) consider indices.

[2] Although for several decades in the United States, capital has been allocated to alternative investments such as private equity or hedge funds, investors in the U.S. have only recently begun to pay attention to infrastructure as an investment opportunity. While other markets, such as the United Kingdom, Canada, and, especially, Australia, discovered infrastructure as an alternative field of investment in the early 1990s, the United States "do[es] not have a strong history of infrastructure privatization" (Newell and Peng (2008)). However, the current debt crisis in the United States implies a strict fiscal policy that will continue to affect public spending for infrastructure projects, while continuous urban development and growth in the country will demand intensive investment in infrastructure. Due to this increasing importance of infrastructure in the United States from both a governmental and investor's point of view, the empirical part of this study focuses on the U.S. infrastructure sector.

(2) A long time horizon can be investigated, which allows us to consider different subperiods. (3) Analyzing individual shares of infrastructure firms instead of indices allows us to sort portfolios by size, book-to-market ratio, and other characteristics to control for stock anomalies and, thus, enhances the validity of the infrastructure models.

This paper extends the findings of Bird, Liem, and Thorp (2012) by going beyond the aspects of inflation and downside protection and creates a detailed asset class factor model for infrastructure stocks that takes into account the relation between stock performance and cash flow volatility, large-scale up-front investments, high financial leverage and interest rate sensitivity. Our paper contributes to the emerging body of literature on the risk-return characteristics of infrastructure in several ways. First, we help explain the return variation in infrastructure stocks to improve the measurement of cost of capital and performance for such companies. We show that an infrastructure six-factor model based only on the infrastructure-specific characteristics is superior in explaining the cross-section of infrastructure returns compared to the Fama/French three-factor, the Carhart four-factor, or the Fung/Hsieh eight-factor models. Second, we shed some light on the mixed results in the literature as to whether infrastructure generates stable cash flows and tackle the heretofore unaddressed issue of infrastructure being sensitive to interest rate changes. Finally, we find that oligopolistic infrastructure industries earn on average 1.44% p.a. less than competitive infrastructure industries, while their Sharpe ratios are more than twice as high as those of industries with with more competitive market structures. Thus, infrastructure investments are most beneficial for investors in concentrated (i.e., oligopolistic) industries from a risk-return perspective.

Finding the common risk factors among infrastructure companies is important in understanding the pricing process of such firms. This is true for both investors and for public policymakers, who, in light of increasing privatization in the United States, need to know the fair rates of return so as to prevent monopolistic exploitation (Newbery (2002); Kessides (2004)). Our results allow better understanding of the risk and return drivers of infrastructure investments. We show that investors value cash flow stability with a premium and find that infrastructure firms are sensitive to interest rate changes with respect to the term and default premium. Furthermore, we show that only companies with low book-to-market ratios tend to invest in their asset base, which is positively valued with a risk premium.

The following section reviews the infrastructure literature and derives an asset class factor model for infrastructure stocks. Section 3 discusses the data and how the factors are constructed. Section 4 presents the empirical results, including robustness tests. Section 5 concludes.

2 Model development and hypotheses

Finkenzeller, Dechant, and Schäfers (2010) point out that infrastructure, despite having some characteristics in common with real estate, cannot be classified as such due to the monopolistic, less transparent structures, higher regulatory constraints, and higher investment necessary for the realization of infrastructure projects compared to real estate. Thus, the goal of this paper is to derive an asset class factor model for infrastructure based on the specific characteristics infrastructure companies are believed to have. More specifically, we want to determine which characteristics (i.e., mimicking portfolios) offer the highest explanatory power and the lowest pricing errors for the return variation of infrastructure firms.

One of the major challenges in constructing such a model is that – depending on the definition – "infrastructure" covers a wide array of activity. For example, companies operating pipelines might be affected by oil prices, but the returns of telecommunication businesses are not. Common to these companies are operational networks (Newbery (2002)) characterized by low risk, stable cash flows, high debt-to-equity ratios, a monopolistic structure, downside protection, and large-scale investments. We replicate these common characteristics to explain the cross-section of the return profiles. We also test whether the infrastructure sector is homogenous or heterogeneous by analyzing different subsectors (transport, telecommunication and utility firms) in our setting and analyze downside and inflation protection in more detail. Table 1 summarizes the infrastructure characteristics analyzed in previous studies.

Table 1: Characteristics of infrastructure investments and results from existing literature

Characteristic	Measured by	Result in existing literature
Low risk	RM-Rf	Rothballer and Kaserer (2012): market risk is lower compared to other equities.
Inflation hedge	Consumer Price Index (CPI), Treasury Inflation Protected Securities (TIPS)	Rödel and Rothballer (2012): hedge appears to be more wishful thinking than empirical fact; Bird, Liem, and Thorp (2012): support for utility sector to hedge against inflation but not infrastructure as a whole.
Stable cash flows	Volatility of cash flows	Bitsch (2012): infrastructure provides more stable cash flows than non-infrastructure investments, but investors' value cash flow volatility at a premium.
Uncorrelated returns	Comparison with returns of stocks, bonds, real estate	Finkenzeller, Dechant, and Schäfers (2010): low correlations with traditional asset classes in Australia.
Downside protection	Market timing (i.e., squared market factor)	Bird, Liem, and Thorp (2012): no downside protection of infrastructure investments. Dechant and Finkenzeller (2012): direct infrastructure investments reduce downside risk in portfolios.

Rothballer and Kaserer (2012) observe low market beta values and conclude that infrastructure is less risky than the overall market. Results about inflation are ambiguous, but it seems that no general inflation hedge is provided by infrastructure investments. Cash flow volatility is analyzed by Bitsch (2012), who finds more stable cash flow for unlisted infrastructure deals but cannot confirm a premium for such stability. Uncorrelated returns with traditional asset classes are confirmed for Australia by Finkenzeller, Dechant, and Schäfers (2010), a result that goes hand in hand with the low beta characteristic. Bird, Liem, and Thorp (2012) cannot confirm any downside protection from infrastructure investments. The interest rate sensitivity of infrastructure assets that might arise from the long-term horizon of future cash flows has not yet been analyzed.

The literature proposes two approaches for the construction of asset class factor models. The first is to consider macroeconomic factors; the second is to construct return portfolios based on firm-specific characteristics that reflect underlying risks (Campbell, Lo, and MacKinlay (1997)). Including both firm-specific and macroeconomic factors in the form of excess returns as in Fama and French (1993), we create dynamic portfolios that capture the infrastructure-specific relation between risk and return. Using mimicking portfolios measured as excess returns allow us to reveal pricing errors through a significant intercept in the time-series regression model, i.e., the alpha not being equal to zero for all test assets (Gibbons, Ross, and Shanken (1989)).

We consider a combination of common equity factors (i.e., Fama/French factors and momentum) and additional risk factors to explain the return variation of infrastructure stocks. We therefore augment the Carhart four-factor model with a cash flow volatility factor, an investment factor, a leverage factor, as well as with a term and default risk premium. For comparison, we also present the capital asset pricing model (CAPM), the Fama/French three-factor model, the Carhart four-factor model and the extended Fung/Hsieh eight-factor model. The CAPM (Sharpe (1964); Lintner (1965); Mossin (1966)) uses the market excess return ($R_{M,t} - R_{f,t}$) to explain stock returns:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{f,t}) + \epsilon_{i,t}. \tag{1}$$

However, the CAPM cannot explain anomalies such as the size effect or the performance differences between value and growth stocks. Fama and French (1992, 1993) developed a model to account for these empirical facts:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \epsilon_{i,t}. \tag{2}$$

The Fama/French three-factor model adds a zero investment portfolio to the pricing equation that goes long in stocks with small market capitalization and short in stocks with large market capitalization (SMB). The other factor is constructed as a zero investment portfolio going long in value stocks and short in growth stocks (HML).
Carhart (1997) extended this model by a momentum factor based on previous findings by Jegadeesh and Titman (1993) that past year winners outperform

past year losers:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t \\ + \beta_{i,MOM}MOM_t + \epsilon_{i,t}. \end{aligned} \tag{3}$$

We also test the well-known seven-factor model of Fung and Hsieh (2004), originally designed for hedge funds, in our setting given that infrastructure investment is often considered an alternative investment opportunity (Della Croce (2012)) and thus alternative investment risk factors should be considered as well. Moreover, it is common in the hedge fund literature to use many factors to explain these funds' returns. In addition to the Fung/Hsieh seven-factor model, we include a tradable liquidity factor resulting in an eight-factor model as proposed by Sadka (2010). The other factors of the eight-factor model are a market factor, a size factor, a term and credit spread factor, and three trend-following factors, i.e., PTFSBD regarding bonds, PTFSFX regarding currencies, and PTFSCOM regarding commodities. Following Sadka (2010) we use excess returns for all factors so as to test our hypotheses on the intercept. Formally, the extended Fung/Hsieh eight-factor model is:[3]

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,TERM}TERM_t \\ + \beta_{i,DEF}DEF_t + \beta_{i,PTFSBD}PTFSBD_t + \beta_{i,PTFSFX}PTFSFX_t \\ + \beta_{i,PTFSCOM}PTFSCOM_t + \beta_{i,LIQ}LIQ_t + \epsilon_{i,t}. \end{aligned} \tag{4}$$

Given that our analysis deals with a specific sector, we would expect that these models can capture some of the return variation of infrastructure firms. However, the additional characteristics relevant for the pricing of infrastructure stocks will require an augmented CAPM, Fama/French three-factor, or Carhart four-factor model as, e.g., suggested by Mohanty and Nandha (2011) for U.S. oil and gas stocks or by Sadorsky (2001) for Canadian oil and gas stocks.

[3] We use Pastor and Stambaugh's (2003) tradable liquidity factor from Robert F. Stambaugh's website `http://finance.wharton.upenn.edu/~stambaug/` and the trend-following factors from David A. Hsieh's website, `https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm`. Note that the trend-following factors are available only from January 1994 onward, which is why tests involving the Fung/Hsieh eight-factor model refer to a shorter time period compared to the other models.

Bird, Liem, and Thorp (2012) are the first to develop an augmented factor model for infrastructure investments. In fact, they propose two separate models. The first model augments the Fama/French three-factor model with the yield of Treasury Inflation Protected Securities (TIPS) minus the risk-free rate. The second model includes a market timing factor that accounts for the defensive characteristics of infrastructure investments. Motivated by Treynor and Mazuy (1966), Bird, Liem, and Thorp (2012) replicate market timing by the squared market excess return, assuming that the defensive investment characteristic of infrastructure is able reduce the decline in infrastructure asset prices during economic downturns. Both models are corrected for conditional heteroscedasticity and non-linearities in the error term using the GARCH approach. The model is empirically tested for sub-indices of the UBS Global Infrastructure and Utilities Index starting between 1990 and 1998 and ending in December 2011.

Extending the Fama/French three-factor or the Carhart four-factor model by additional factors when it comes to specific categories of equities is often proposed in the literature. Mohanty and Nandha (2011) augment the Carhart four-factor model by two additional factors when examining the cross-section of U.S. oil and gas stocks. The two factors are changes in oil prices and changes in the interest rate. Mohanty and Nandha (2011) find that the oil price has substantial influence on the oil and gas industry, whereas interest rates have no significant effect on the stocks of such companies. Moreover, their results show that companies classified as being in the pipeline subsector are neither sensitive to changes in oil price nor to changes in interest rates. Following that intuition, we first augment the Carhart four-factor model with the previously mentioned five factors, which should capture the special characteristics of infrastructure stock returns and, hence, explain the return variation of infrastructure investments in more detail. Formally, this infrastructure nine-factor model is described as:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i &+ \beta_{i,M}(R_{M,t} - R_{f,t}) + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t \\ &+ \beta_{i,MOM} MOM_t + \beta_{i,CFVOLA} CFVOLA_t + \beta_{i,LEV} LEV_t \\ &+ \beta_{i,INV} INV_t + \beta_{i,TERM} TERM_t + \beta_{i,DEF} DEF_t + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where the dependent variable is the excess return of infrastructure firms over the U.S. 1-month Treasury bill rate. In the following we discuss the rationale for including each factor in the six- and nine-factor model, respectively.[4] Table 2 provides an overview of the relationships we expect between the excess returns of infrastructure investments and all explanatory variables.

Furthermore, we specify an infrastructure six-factor model that is solely based on the infrastructure-specific characteristics and the market beta, arguing that these factors alone are superior in explaining infrastructure returns compared to the Fama/French three-factor or Carhart four-factor models. The infrastructure six-factor model is formally defined as:

$$\begin{aligned} R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{M,t} - R_{f,t}) + \beta_{i,CFVOLA} CFVOLA_t + \beta_{i,LEV} LEV_t \\ + \beta_{i,INV} INV_t + \beta_{i,TERM} TERM_t + \beta_{i,DEF} DEF_t + \epsilon_{i,t}. \end{aligned} \tag{6}$$

2.1 Cash flow volatility

Including cash flow volatility in our model is based on the assumption that infrastructure firms have stable cash flows because of "long-term sales contracts," low competition due to high entry barriers, and low research and development risk (Sawant (2010); Rothballer and Kaserer (2012)). Following the idea of the CAPM one might expect a positive link between cash flow volatility and returns. Huang (2009) has, however, documented that cash flow volatility is negatively correlated with future stock returns, thereby contradicting the traditional notion that volatility connotes risk.[5] We analyze ex post returns based on the past historical cash flow volatility and thus also expect to find a negative link.

The existing empirical literature on infrastructure shows mixed results. Bitsch, Buchner, and Kaserer (2010) analyze unlisted infrastructure deals worldwide and the difference in cash outflow volatility between infrastructure

[4]Note that all factors in our analysis are excess returns and hence the estimate of the factor risk premium corresponds to the sample mean of the factor (Cochrane (2005, p. 244)).

[5]These findings underline the results by Ang et al. (2006) for return volatility. Different explanations such as limits to arbitrage or overconfidence are discussed by Huang (2009), but a credible theoretical explanation for the phenomenon has not yet been developed.

Table 2: Hypotheses

Variable	Hypothesis	Rationale
RM-Rf	Positive relation between the market and infrastructure returns, but smaller than 1.	Infrastructure should co-move with the market but be less sensitive to the overall market given the constant demand for infrastructure services (Rothballer and Kaserer (2012)).
SMB	Negative relation between size effect and infrastructure returns.	Infrastructure can be considered as a large-cap industry on average; thus, a negative relation between SMB and infrastructure returns should be observed (Fama and French (1997)).
HML	Positive relation between value effect and infrastructure returns.	Since infrastructure firms do not offer many growth options, they can be considered as value stocks; thus, a positive relation between HML and returns should be observed. Bird, Liem, and Thorp (2012) refer to the "large asset base" resulting in a positive coefficient on HML.
Momentum (MOM)	Positive relation between past returns and infrastructure returns.	Constant (and sustainable) demand for infrastructure services should continuously generate positive returns.
Cash flow volatility (CFVOLA)	Negative relation between cash flow volatility and infrastructure returns.	Long-term concessions and inelastic demand for infrastructure services (e.g., electricity) should be valued at a premium by investors.
Leverage (LEV)	Positive relation between leverage and infrastructure returns.	High leverage allows initiating larger infrastructure projects, which promise higher returns, but also more risk, which needs to be compensated.
Investment growth (INV)	Positive relation between investment growth and infrastructure returns.	Infrastructure firms that invest in large-scale projects and renew their physical assets are able to generate excess returns in the long run.
Term premium (TERM)	Positive relation between term structure and infrastructure returns.	Term premium catches unexpected changes in interest rates. Infrastructure's long-term assets (investments) might be sensitive to interest rate changes.
Default premium (DEF)	Positive relation between default premium and infrastructure returns.	With increasing default probability, firms need to pay a risk premium, especially infrastructure firms with extensive use of debt.

and non-infrastructure deals. Their results show that there is no difference in volatility between the two categories. In contrast, Bitsch (2012) finds a difference in cash flow volatility between listed infrastructure and listed non-infrastructure funds. Infrastructure funds have lower cash flow volatility than non-infrastructure funds, and yet investors do not value this stability because cash flow volatility is positively correlated with the fund's value.

2.2 Leverage

According to the Modigliani-Miller theorem, capital structure should not influence expected returns. The infrastructure sector, however, is driven by high capital requirements to realize large-scale projects, resulting in very high leverage ratios. Bhandari (1988) shows that stock returns are positively correlated with leverage after controlling for market beta, size, and other factors. Under the assumption that leverage does not have the same meaning for different sectors, deviations within a specific sector could have an effect on stocks returns. As Bradley, Jarrell, and Han Kim (1984) show, telecommunication, transportation, and utility companies have by far the highest debt ratios. Bianconi and Yoshino (2014) show that leverage is significantly and robustly priced in oil and gas companies of the nonrenewable energy sector. Rothballer and Kaserer (2012) show that higher financial leverage also has a positive impact on return volatility of infrastructure stocks, meaning that higher leverage increases the risk profile of stocks. Fama and French (1992) argue that their HML factor accounts for differences in leverage, i.e., HML can be interpreted as an "involuntary leverage effect" that is able to capture the difference between market leverage and book leverage. However, the HML factor does not fully capture the impact of debt because it does not take into consideration the ratio between equity and the more relevant debt value but only the ratio between market and book equity. Higher leverage represents higher risk because there is a larger uncertainty for shareholders about whether payments will be made "due to the seniority of debt claims" (Rothballer and Kaserer (2012)). Hence, we believe that different levels of debt-to-equity ratios lead to substantial differences in the ability to generate cash flows. Leverage should thus be more relevant in explaining the variation of infrastructure returns than the book-to-market ratio, especially given the high significance of debt in infrastructure firms. We expect this relation to be positive because the borrowing of outside capital increases the return on equity.

2.3 Investment factor

There are two key assumptions behind our decision to include an investment factor in the pricing model. First, according to the investment-based asset pricing theory, investments "predict returns because high costs of capital imply low net present values of new capital and [hence] low investment. Low costs of capital, on the other hand, imply high net present values of new capital and thus high investment" (Ammann, Odoni, and Oesch (2012)). Second, infrastructure assets are not only characterized by high investment payments, especially at the beginning of their lifecycle; additionally, the very long time horizon of such infrastructure assets implies a high sensitivity toward investment payments. Also, renewing physical infrastructure is profitable only in the long run (Baur et al. (2006)). Thus, investments by infrastructure companies might be an important indicator of profit generation and, thereby, be a good predictor for the variation in equity returns. For a detailed description of the investment factor see Section 3.2.

2.4 Term structure and default premium

We include both a term premium (TERM) and a default premium (DEF), where the term premium indicates changes in the slope of the yield curve and the default premium indicates changes between corporate and government bonds (i.e., the credit risk). The term premium can be interpreted as an indicator for unexpected changes in the return of long-term government bonds; the default premium can be interpreted as shifts in the probability of default. Motivated by the high amount of debt, changes in the yield curve might affect the returns of infrastructure companies that are more leveraged than other companies. Also, the term premium compensates investors for "exposure to discount-rate shocks that affect all long-term securities" (Fama and French (1989)), which seems very relevant for long-term infrastructure assets.[6]

According to Ang, Bekaert, and Wei (2008), an "inflation risk premium that increases with maturity fully accounts for the generally upward sloping nominal term structure." Hence, changes in the term structure might also be the result of shocks in the inflation risk premium. Term structure might then be a good approximation for the hedging abilities of infrastructure toward an inflation effect or at least be highly correlated with inflation. The inflation aspect of infrastructure is examined by Rödel and Rothballer (2012), who, based on a set of global infrastructure stocks, find that infrastructure is not able to hedge against inflation. In contrast, Bird, Liem, and Thorp (2012) find some evidence that the utility industry is able to hedge inflation, while the telecommunication industry (represented by the UBS Infrastructure Index) cannot.

Furthermore, the default premium might shed some light on the return profile of infrastructure firms during distressed times. We expect that there is a positive link between the default premium and stock returns, since increasing default probability increases the risk for investors. This might be especially pronounced for infrastructure firms, which typically use a lot of debt and, hence, are more affected by credit risk.

3 Data and summary statistics

3.1 Data selection

Two of the major issues researchers face when analyzing infrastructure investments are the sparse data availability and the question of which infrastructure investment vehicle to analyze. We choose to analyze listed infrastructure because it has the most reliable dataset, which is crucial for our factor construction. Also, the long time frame allows us to show the risk and return profile of

[6]Sweeney and Warga (1986) regress the stock returns of 21 industry portfolios against the market and a series of simple changes in long-term interest rates. They find that it is only the stocks of electric utilities and the banking, finance, and real estate industry that are consistently sensitive to interest rates over the period 1960 to 1979. O'Neal (1998) confirms these results for electric utility firms.

infrastructure investments in the long run. Further, unlike equity infrastructure indices, we neither determine a specific liquidity level nor a certain market capitalization for our dataset. This means we are able to analyze the entire scope of infrastructure stocks without limitations.

Our definition of infrastructure follows that of Rothballer and Kaserer (2012) and thus comprises the utility, communication, and transportation industries.[7] Also in line with Rothballer and Kaserer (2012), we consider only companies that act as network operators and have either their own physical infrastructure or a concession to use physical infrastructure. Thus, contractors (e.g., construction firms) and other service providers (e.g., maintenance services) who depend on operators are excluded from this definition.

Our dataset includes all U.S. infrastructure stocks with SIC and GIC codes related to utilities, telecommunication, and transportation available on the CRSP and in the COMPUSTAT database.[8] Our analysis starts in January 1983 and ends in December 2011, yielding 348 monthly observations. The restrictive element in our dataset is the availability of large-scale quarterly data in COMPUSTAT, which we need for calculating a rolling standard deviation for the cash flow volatility factor.

To identify companies that own or operate physical infrastructure assets we apply a textual analysis of business descriptions from various sources (Thomson Worldscope (WC06092), SEC filings (10-K, 10-Q, S-1 filings), Bloomberg company overviews, and corporate websites). The actual company names are deleted in the textual analysis to avoid a precipitant assignment of companies that contain words such as “Energy” or “Utilities” in their trade name and which could occur in the same sentence as further textual conditions. As a result, this method is able to differentiate between companies (theoretically) generating stable cash flows through their physical assets and companies that are contractors or service providers. Furthermore, we include only those firms

[7] Although infrastructure can also comprise social infrastructure (e.g., schools, hospitals, and prisons), we do not include these types of “companies” in our dataset due to scarce data availability and the predominantly nonprofit focus of social infrastructure.

[8] Our selection of SIC and GIC codes is based on Rothballer and Kaserer (2012).

with ordinary common equity listed on the NYSE, AMEX, or NASDAQ. Hence, ADRs, REITs, and units of beneficial interest are excluded. We also exclude all stocks that do not have at least 24 months of consecutive return data and we do not consider firms with negative book values. All accounting data are retrieved from COMPUSTAT. The book common equity is calculated as the book value of stockholders' equity plus deferred taxes and investment tax credits subtracted from the book value of preferred stocks. After the complete screening process the initial dataset is reduced from 1040 stocks to 396 stocks.

3.2 Construction of explanatory variables

We construct a mimicking portfolio for cash flow volatility based on quarterly observations over a rolling three-year period. To be included in the calculation, a company must have at least eight non-missing values within that estimation window (Huang (2009)). We calculate the rolling standard deviation on standardized cash flow volatility and define cash flow as income before extraordinary items (COMPUSTAT item ibq) plus depreciation and amortization (item dpq) plus the quarterly change in working capital (item wcapq[*t*] - wcapq[*t-3 months*]).[9]

Using quarterly, as compared to annual, data enables us to increase the number of observations and improves the calculation of the standard deviation. To analyze ex post returns based on the past historical cash flow volatility and to make sure that accounting information from quarterly reports is known prior to stock market development, we match three-month lagged accounting data (i.e., the previous fiscal quarter) with stock returns. Hence, we assume that it takes about three months until quarterly accounting data are available to the public. This method is identical to that employed by Huang (2009). Having calculated the standard deviation of cash flows from t to *t-36 months* divided by sales in t we then rank each company according to the ratio of cash flow volatility and sales (CF/sales).[10] We create breakpoints for the bottom 30% (low

[9] Both deferred taxes and preferred taxes are largely missing in the quarterly dataset, which is why we do not include these items in the determination of cash flows (see Huang (2009)).

[10] Since we construct portfolios based on the ranking of cash flow volatility, we do not consider it necessary to winsorize cash flows.

CF/sales), middle 40% (medium CF/sales), and top 30% (high CF/sales) based on infrastructure firms listed on the NYSE, following Fama and French's (1993) approach to defining breakpoints.[11] In each month we assign all stocks to those three CF/sales groups based on the ranked values of CF/sales. Furthermore, we create six portfolios in each month based on the intersection between low CF/sales, middle CF/sales, and high CF/sales, as well as small and big market capitalization.[12] For each portfolio value-weighted returns are calculated. The mimicking portfolio is then the difference between the average return of the two high CF/sales portfolios and the average return of the two low CF/sales portfolios. Hence, our cash flow volatility factor indicates whether there is a premium being paid to investors if cash flows vary extensively over time.

The investment factor (INV) is calculated as the difference between a return portfolio of low investment growth and high investment growth. Investment growth (INVESTG) is defined as the absolute annual change in property, plant, and equipment (PPE) and inventory from the fiscal year ending in *t-2* to fiscal year ending in *t-1* divided by total assets of year *t-2*. Formally, investment growth is defined as:

$$INVESTG_t = \frac{(\text{PPE}_{t-1} + \text{inventory}_{t-1}) - (\text{PPE}_{t-2} + \text{inventory}_{t-2})}{\text{book value of total assets}_{t-2}}. \tag{7}$$

PPE is indicated as annual item PPEGT in COMPUSTAT, inventories as item INVT, and total assets as item AT. This investment factor is identical to the factor proposed by Chen, Novy-Marx, and Zhang (2011). Furthermore, we construct a high minus low leverage factor (LEV) based on the debt-to-equity ratio (DER) defined as (see Bhandari (1988)):

$$DER_t = \frac{\text{bookvalue of total assets}_{t-1} - \text{book value of common equity}_{t-1}}{\text{market value of common equity}_{t-1}}. \tag{8}$$

[11]Fama and French (1993) argue that the market value of NASDAQ and AMEX stocks is in general much smaller, which is why NYSE breakpoints guarantee a certain amount of market capitalization in each portfolio.

[12]We control for size in construction of the cash flow volatility factor because Minton and Schrand (1999) show that small firms tend to be more cash flow volatile.

In June of year t we sort all stocks according to their DER based on NYSE breakpoints. Stocks with low debt-to-equity ratios are in the bottom 30% and stocks with high debt-to-equity ratios in the top 30%. We also include two portfolios for small and large stocks. From the intersection of the DER and size portfolios we calculate value-weighted returns from July in year t to June of year $t+1$. We rebalance each portfolio in June of year $t+1$. The difference between the average return of the two high DER portfolios and the average return of the two low DER portfolios establishes our leverage factor LEV.

The definitions of the TERM and DEF factors are identical to those in Fama and French (1993). TERM is constructed as the monthly difference between long-term bond returns of the U.S. government and the one-month T-bill rate (retrieved from CRSP). The DEF factor is calculated as the spread between the return on a long-term corporate bond index (i.e., Barclays U.S. Aggregate Long-Term Corporate Bond Index BAA) and the return on the long-term government bond index.[13] Finally, we include RM-Rf, SMB, HML, and MOM (in line with Fama and French (1993) and Carhart (1997)). Data for these factors can be downloaded from Kenneth French's website (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`). The remaining data are taken from CRSP, COMPUSTAT, and Thomson Reuters Datastream.

3.3 Summary statistics

Panel A of Table 3 presents summary statistics for a value-weighted infrastructure (VWI) index in excess of the risk-free rate based on the entire sample and summary statistics for nine double-sorted excess return portfolios by size and book-to-market ratio. To account for the critique by Lewellen, Nagel, and

[13] In a similar vein, we constructed a regulatory risk factor as the return spread between a utility bond index and an overall industrial bond index. However, the use of a utility bond index is merely a weak approximation for infrastructure regulation in general. Furthermore, it can be questioned whether such an approximation sufficiently addresses regulatory risk. Regression results including such a factor in our model were insignificant and are available upon request.

Shanken (2010) on asset pricing tests in general,[14] we also include three market-beta portfolios (from low to high beta exposure based on a 36-month rolling window), three momentum portfolios (from low to high short-term momentum, based on a stock's past 12-month performance), and three industry portfolios, i.e., a value-weighted portfolio of transportation stocks, a value-weighted portfolio of telecommunication stocks, and a value-weighted portfolio of utility stocks. Panel B presents summary statistics for all 13 factors we use as explanatory variables in the different models.

Comparing the VWI index with the market return ($R_M - R_f$), reveals that infrastructure stocks on average offer a slightly lower return with a lower standard deviation. The portfolio returns of infrastructure stocks on average decrease with increasing market equity, while portfolio returns climb with increasing book-to-market equity. This is in line with previous findings showing higher returns for small and value stocks (see, e.g., Fama and French (1993); Bauman, Conover, and Miller (1998)). It is, however, also a first indication that large infrastructure firms do not necessarily exploit their monopolistic structure because large infrastructure firms do not outperform smaller ones.[15]

[14] A central point of criticism by Lewellen, Nagel, and Shanken (2010) is that asset pricing tests are limited to size and book-to-market portfolios whilst other portfolio sortings are ignored. They suggest to expand the set of test portfolios by including portfolios based on industry classification, beta or other characteristics which we rigorously follow (see Lewellen, Nagel, and Shanken (2010), p. 182).

[15] We also analyzed the correlation of independent factors. The correlation between HML and LEV is significant and positive (0.41), which is a meaningful finding since both ratios include the book value of equity in the nominator and the market value of equity in the denominator. However, the value of 0.41 also shows that there are substantial differences between the two factors so that HML will not absorb the explanatory power of LEV (multicollinearity is rejected). Moreover, we find a significant negative correlation (-0.53) between TERM and DEF that seems slightly higher than in previous studies. Peterson and Hsieh (1997), for example, find a correlation of -0.43 for the period 1976 – 1992. None of the correlations are extensive enough to cause multicollinearity issues.

Table 3: Summary statistics

PANEL A **Dependent variables**

Variable	*VWI*	*P 1/1*	*P 2/1*	*P 3/1*	*P 1/2*	*P 2/2*	*P 3/2*	*P 1/3*	*P 2/3*	*P 3/3*
Mean	0.48	0.58	0.47	0.40	0.81	0.70	0.63	0.91	0.90	0.65
Std. dev.	3.89	5.03	4.60	5.27	3.46	4.00	4.30	4.42	4.19	4.59
Min	-13.63	-25.49	-21.43	-18.12	-13.80	-14.22	-13.38	-20.02	-20.80	-26.50
Max	12.24	25.30	13.22	16.95	9.65	13.88	15.13	18.81	11.22	13.68
# of stocks (monthly average)	161.7	31.4	15.1	10.6	27.2	19.8	13.4	20.0	13.7	10.5

Variable	*P 1/4*	*P 2/4*	*P 3/4*	*P 1/5*	*P 2/5*	*P 3/5*	*P 1/6*	*P 2/6*	*P 3/6*
Mean	0.67	0.60	0.44	0.21	0.50	0.75	1.22	0.46	0.57
Std. dev.	3.63	4.07	6.05	5.45	3.72	4.27	6.68	6.12	3.99
Min	-12.70	-14.72	-24.32	-23.32	-12.83	-21.25	-26.01	-27.18	-12.66
Max	13.42	13.44	20.05	24.87	10.16	13.17	23.29	24.59	12.57
# of stocks (monthly average)	67.01	66.62	68.18	63.29	62.85	64.26	7.88	23.39	134.15

PANEL B **Independent variables**

Variable	*RM-Rf*	*SMB*	*HML*	*MOM*	*LEV*	*CFVOLA*	*INV*	*TERM*	*DEF*	*LIQ*
Mean	0.57	0.11	0.32	0.57	0.39	0.10	0.14	0.46	0.01	0.56
Std. dev.	4.58	3.19	3.11	4.71	2.92	2.29	2.29	3.60	2.21	3.81
Min	-23.14	-16.62	-12.87	-34.75	-11.38	-9.78	-6.73	-14.74	-11.12	-10.14
Max	12.43	22.06	13.88	18.40	12.08	9.61	8.61	17.33	10.17	21.00
T (months)	348	348	348	348	348	348	348	348	348	348

Variable	*PTFSBD*	*PTFSCOM*	*PTFSFX*
Mean	-1.24	-0.38	-0.18
Std. dev.	15.26	13.65	19.58
Min	-25.95	-23.04	-30.13
Max	68.86	64.75	90.27
T (months)	216	216	216

This table summarizes the dependent and independent variables for the regression analysis. Monthly excess returns and zero investment portfolios (mean) are reported in percentage points. VWI is a value-weighted infrastructure index. *P 1/1* to *P 3/3* are double-sorted size and book-to-market ratio portfolios, where the first figure denotes a small (1) to large (3) portfolio and the second figure denotes a low (1) to high (3) book-to-market ratio. Portfolios *P 1/4* to *P 3/4* are low to high beta portfolios, respectively. Portfolios *P 1/5* to *P 3/5* are low to high momentum portfolios, respectively. Portfolios *P 1/6* to *P 3/6* are three industry portfolios where *P 1/6* is a value-weighted index of transportation stocks, *P 2/6* is a value-weighted index of telecommunication stocks, and *P 3/6* is a value-weighted index of utility stocks. The time period spans January 1983 to December 2011. The time period for the trend-following factors is January 1994 to December 2011.

4 Empirical results

4.1 Main results from time series regressions

We now turn to a detailed analysis using 18 portfolios sorted by different characteristics in order to better understand the pricing errors in an infrastructure context and to account for the possibility that some characteristic portfolios are more difficult to price than others (Lewellen, Nagel, and Shanken (2010)). The majority of market betas in Table 4 are smaller than one except for the telecommunication industry and less surprisingly for high beta exposed infrastructure stocks, confirming the results of Rothballer and Kaserer (2012) that infrastructure overall poses low market risk.

Table 4: Standard CAPM factor loadings from time series regressions

Variables		Small	Med. Size	Big	Beta	Mom.	Indus.
β_M	Low	0.76***	0.71***	0.85***	0.18***	0.84***	0.99***
		(0.08)	(0.05)	(0.06)	(0.05)	(0.09)	(0.07)
	Mid	0.45***	0.47***	0.43***	0.50***	0.50***	1.10***
		(0.04)	(0.06)	(0.07)	(0.06)	(0.04)	(0.06)
	High	0.60***	0.55***	0.54***	1.17***	0.68***	0.48***
		(0.05)	(0.06)	(0.08)	(0.04)	(0.05)	(0.05)
α	Low	0.16	0.16	-0.01	0.57***	-0.27	0.66**
		(0.17)	(0.15)	(0.20)	(0.19)	(0.23)	(0.30)
	Mid	0.56***	0.40*	0.37*	0.31*	0.21	-0.17
		(0.15)	(0.21)	(0.21)	(0.19)	(0.17)	(0.22)
	High	0.53**	0.56***	0.29	-0.23	0.37**	0.29
		(0.22)	(0.19)	(0.25)	(0.17)	(0.15)	(0.19)
$Adj.R^2$	Low	46.9%	51.3%	55.1%	4.8%	49.9%	45.8%
	Mid	34.1%	28.0%	19.9%	31.7%	38.2%	67.5%
	High	37.5%	35.3%	27.9%	78.3%	52.8%	30.5%
GRS test statistic = 2.414* p(GRS) = 0.001**							

This table reports factor loadings on the market factor (RM-Rf) for 18 test portfolios. The intercepts (α) of each portfolio are reported in the middle of the table. The sample period is January 1983 to December 2011 (348 monthly observations). The GRS test statistics and the adjusted R^2 values from each time series are reported at the end of the table. Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation with lags of five. The test portfolios are nine double-sorted size and book-to-market ratio portfolios from small to big and from low to high, respectively (column 'Small' to 'Big'); three low to high market beta portfolios (column 'Beta'); three low to high momentum portfolios (column 'Mom.'), and three industry portfolios (column 'Indus.'), where the top portfolio is a value-weighted index of transportation stocks, the portfolio in the middle is a value-weighted index of telecommunication stocks, and the bottom portfolio is a value-weighted index of utility stocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The low R-square also suggests high idiosyncratic risk. The least well explained variations of returns occur at medium book-to-market ratio stocks and low beta stocks, where only 19.9% and 4.8%, respectively, of the variation in infrastructure stocks are explained. Most importantly, the GRS test statistic strongly rejects the null that the intercepts of the portfolios are jointly zero, which indicates that additional factors are necessary to price infrastructure firms.

For the Fama/French model (see Table 5) we see a strong increase in the explanatory power across all 18 portfolios, especially for the large, medium book-to-market ratio portfolio where the R-square almost doubles (from 19.9% to 39.5%), and the low beta portfolio where the R-square increases from 4.8% to 25.6%. However, 6 out 18 portfolios still show significant intercepts and formally the GRS test statistic rejects the null hypothesis that the intercepts are jointly zero. This suggests that the Fama/French model is not sufficiently able to price infrastructure investments.[16]

Regarding the infrastructure six-factor model, Table 6 reveals almost identical values in the adjusted R-square compared to the Fama/French model. Still, a parsimonious version of a six-factor is not able to explain the abnormal returns in some of the infrastructure portfolios. Formally, the GRS test statistic again rejects the null that the intercepts are jointly different from zero at a 5% significance level. Before we turn to the full version of the nine-factor infrastructure model, we first control for the extended Fung/Hsieh eight-factor model usually employed for hedge funds (see Table 7). The three characteristic hedge fund factors, i.e., the trend-following factors (PTFSBD, PTFSCOM, and PTFSFX) show no or very limited covariance with infrastructure returns. Also, liquidity covaries mildly with infrastructure returns. Overall, the eight-factor model by Fung and Hsieh (2004), and extended by Sadka (2010), is rejected by the GRS test statistic at the 10% significance level.

Looking at the infrastructure nine-factor model in Table 8, the inclusion of additional factors improves the explanatory power in excess of the Fama/French

[16]The Carhart four-factor model (i.e., adding the momentum factor to the Fama/French model) is also rejected by the GRS test statistic at the 10% level with a test statistic of 1.506 and a p-value of 0.08.

model up to 21.7 percentage points in case of the low beta portfolio (from 25.6% to 47.3%). Most importantly, however, is that the nine-factor infrastructure model is not rejected by the GRS test statistic, indicating that the model is well specified and able to explain abnormal returns in infrastructure returns. The additional power that the model is able to add in some portfolios emphasizes the need to consider additional factors in the case of infrastructure stocks so as to capture their specific characteristics. Regarding the individual factors, we find a significant and positive size premium for the smallest companies and a negative one for larger firms, showing that the SMB factor is a good proxy for size and confirming the size effect in infrastructure firms.

Moreover, we document a positive leverage exposure in all but the growth (i.e., low book-to-market) and low momentum portfolios. Given that infrastructure firms in the growth portfolios have a reduced risk of being distressed (Daniel and Titman (1997)), one might conclude that investors do not receive a leverage premium for such companies. We also find a negative relationship between returns and INV in the case of low book-to-market portfolios. This contradicts the results found by Chen, Novy-Marx, and Zhang (2011) and Ammann, Odoni, and Oesch (2012) with respect to overall stocks in the U.S. and European markets. First, their results indicate a positive relation between the investment factor and the variation of stock returns. Second, the investment factor should enhance the explanatory power of the return variation for all portfolios. One explanation for the negative factor loading in our model could be that infrastructure companies with low book-to-market ratios (i.e., infrastructure firms with more growth opportunities than other infrastructure firms) are considered as sustainable firms that are willing to invest and for which investors are willing to pay higher prices today.[17]

The factor loadings for the interest rate factors, TERM and DEF, remain positive and significant for the majority of portfolios, corroborating the idea that infrastructure firms are sensitive to changes in interest rates. Possibly this

[17] Note that the INV factor is constructed as low investments minus high investments. Thus a negative coefficient means that companies making investments receive a positive premium from investors.

Table 5: Fama/French factor loadings from time series regressions

Variables		Small	Med. Size	Big	Beta	Mom.	Indus.		Small	Med. Size	Big	Beta	Mom.	Indus.
β_M	Low	0.78***	0.77***	0.86***	0.31***	0.90***	1.06***	β_{SMB}	0.38***	0.01	-0.24***	-0.24***	-0.17**	0.07
		(0.05)	(0.03)	(0.06)	(0.05)	(0.08)	(0.06)		(0.07)	(0.09)	(0.07)	(0.07)	(0.07)	(0.11)
	Mid	0.52***	0.57***	0.57***	0.63***	0.59***	1.07***		0.11*	-0.03	-0.28***	-0.23***	-0.23***	-0.10
		(0.04)	(0.06)	(0.05)	(0.05)	(0.04)	(0.06)		(0.06)	(0.10)	(0.07)	(0.07)	(0.07)	(0.07)
	High	0.67***	0.68***	0.66***	1.18***	0.72***	0.60***		0.28***	-0.17***	-0.22***	-0.09	-0.07	-0.20***
		(0.04)	(0.04)	(0.07)	(0.04)	(0.05)	(0.05)		(0.07)	(0.06)	(0.08)	(0.06)	(0.07)	(0.07)
β_{HML}	Low	0.43***	0.31***	-0.12*	0.44***	0.13	0.38***	α	-0.03	0.03	0.04	0.38**	-0.33	0.49*
		(0.12)	(0.09)	(0.07)	(0.09)	(0.14)	(0.11)		(0.14)	(0.15)	(0.19)	(0.17)	(0.23)	(0.27)
	Mid	0.45***	0.46***	0.51***	0.42***	0.26***	-0.23**		0.36***	0.20	0.16	0.13	0.10	-0.07
		(0.08)	(0.09)	(0.11)	(0.09)	(0.07)	(0.09)		(0.13)	(0.18)	(0.17)	(0.16)	(0.15)	(0.22)
	High	0.57***	0.48***	0.44***	0.00	0.15	0.40***		0.28*	0.35**	0.10	-0.23	0.30**	0.12
		(0.08)	(0.08)	(0.09)	(0.06)	(0.12)	(0.10)		(0.16)	(0.16)	(0.22)	(0.17)	(0.14)	(0.17)
$Adj.R^2$	Low	55.6%	55.5%	56.8%	25.6%	51.5%	48.3%							
	Mid	47.2%	39.5%	39.5%	47.0%	48.1%	68.5%							
	High	51.1%	50.2%	40.0%	78.3%	54.3%	44.2%							
GRS test statistic = 1.94 p(GRS) = 0.012**														

This table reports factor loadings on the market factor (RM-Rf), the size factor (SMB), and the value factor (HML) for 18 test portfolios. The intercepts (α) of each portfolio are reported in the middle of the table. The sample period is January 1983 to December 2011 (348 monthly observations). The GRS test statistics and the adjusted R^2 values from each time series are reported at the end of the table. Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation with lags of five. The test portfolios are nine double-sorted size and book-to-market ratio portfolios from small to big and from low to high, respectively (column 'Small' to 'Big'); three low to high market beta portfolios (column 'Beta'); three low to high momentum portfolios (column 'Mom.'), and three industry portfolios (column 'Indus.'), where the top portfolio is a value-weighted index of transportation stocks, the portfolio in the middle is a value-weighted index of telecommunication stocks, and the bottom portfolio is a value-weighted index of utility stocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Parsimonious infrastructure asset class factor model from time series regressions

Variables		Small	Med. Size	Big	Beta	Mom.	Indus.		Small	Med. Size	Big	Beta	Mom.	Indus.
β_M	Low	0.70***	0.69***	0.87***	0.33***	0.80***	1.05***	β_{LEV}	0.06	0.11*	-0.01	0.62***	0.16	0.18*
		(0.04)	(0.03)	(0.07)	(0.04)	(0.08)	(0.08)		(0.12)	(0.06)	(0.10)	(0.07)	(0.17)	(0.10)
	Mid	0.52***	0.56***	0.55***	0.60***	0.56***	0.99***		0.39***	0.61***	0.54***	0.52***	0.32***	-0.40***
		(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)		(0.05)	(0.07)	(0.11)	(0.06)	(0.07)	(0.11)
	High	0.69***	0.66***	0.61***	1.09***	0.75***	0.60***		0.65***	0.58***	0.56***	-0.15**	0.21**	0.56***
		(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)		(0.07)	(0.08)	(0.09)	(0.07)	(0.09)	(0.07)
$\beta_{CFV.}$	Low	-0.06	-0.28**	-0.20*	-0.43***	-0.25*	-0.18	β_{INV}	-0.25**	-0.17***	-0.31***	0.07	-0.21*	-0.17
		(0.11)	(0.11)	(0.12)	(0.08)	(0.14)	(0.15)		(0.11)	(0.06)	(0.10)	(0.07)	(0.12)	(0.12)
	Mid	-0.22***	-0.31***	-0.47***	-0.32***	-0.22***	-0.06		-0.02	0.04	0.11	-0.12	0.08	0.10
		(0.07)	(0.09)	(0.10)	(0.08)	(0.08)	(0.09)		(0.05)	(0.06)	(0.10)	(0.08)	(0.08)	(0.09)
	High	-0.18**	-0.27***	-0.08	-0.18**	-0.26***	-0.42***		0.10	0.02	0.01	-0.09	-0.07	-0.12*
		(0.08)	(0.07)	(0.12)	(0.08)	(0.09)	(0.08)		(0.07)	(0.08)	(0.11)	(0.09)	(0.09)	(0.07)
β_{TERM}	Low	0.07	0.17**	0.04	0.20***	0.22**	-0.19*	β_{DEF}	0.37	0.38***	0.01	0.14	0.56***	-0.03
		(0.12)	(0.07)	(0.08)	(0.06)	(0.10)	(0.10)		(0.23)	(0.13)	(0.11)	(0.10)	(0.18)	(0.19)
	Mid	0.14**	0.24***	0.21***	0.19***	0.23***	0.12*		0.16	0.38***	0.24*	0.24**	0.20*	0.24
		(0.06)	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)		(0.11)	(0.11)	(0.13)	(0.11)	(0.11)	(0.17)
	High	0.07	0.21***	0.16*	0.04	0.09	0.19***		0.31***	0.20**	0.25	0.39***	0.04	0.22*
		(0.06)	(0.06)	(0.09)	(0.06)	(0.06)	(0.06)		(0.10)	(0.09)	(0.23)	(0.12)	(0.12)	(0.12)
α	Low	0.17	0.10	0.03	0.18	-0.36*	0.68**	$Adj.R^2$	49.3%	55.8%	57.3%	39.7%	54.7%	46.8%
		(0.16)	(0.16)	(0.19)	(0.15)	(0.20)	(0.30)							
	Mid	0.33**	0.03	0.03	0.02	-0.05	-0.02		47.3%	53.2%	40.3%	50.6%	50.3%	70.7%
		(0.13)	(0.14)	(0.17)	(0.15)	(0.15)	(0.21)							
	High	0.20	0.19	-0.04	-0.12	0.25	-0.02		55.2%	55.6%	40.7%	80.3%	56.9%	54.5%
		(0.19)	(0.15)	(0.23)	(0.16)	(0.15)	(0.14)							

GRS test statistic = 1.845 p(GRS) = 0.020**

This table reports factor loadings on the market factor (RM-Rf), the size factor (SMB), the value factor (HML), the momentum factor (MOM), the leverage factor (LEV), the cash flow volatility factor (CFVOLA), the investment factor (INV), and the two bond factors, i.e., the term structure factor (TERM) and the default factor (DEF), for 18 test portfolios. The intercepts (α), the adjusted R^2 values, and the GRS test statistic are reported at the end of the table. The sample period is January 1983 to December 2011 (348 monthly observations). Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation with lags of five. The test portfolios are nine double-sorted size and book-to-market ratio portfolios from small to big and from low to high, respectively (column 'Small' to 'Big'); three low to high market beta portfolios (column 'Beta'); three low to high momentum portfolios (column 'Mom.'), and three industry portfolios (column 'Indus.'), where the top portfolio is a value-weighted index of transportation stocks, the portfolio in the middle is a value-weighted index of telecommunication stocks, and the bottom portfolio is a value-weighted index of utility stocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Extended Fung/Hsieh eight-factor model from time series regressions

Variables		Small	Med. Size	Big	Beta	Mom.	Indus.		Small	Med. Size	Big	Beta	Mom.	Indus.
β_M	Low	0.65***	0.67***	0.87***	0.13*	0.83***	0.83***	β_{SMB}	0.24*	-0.09	-0.15**	-0.29***	-0.21*	-0.14
		(0.09)	(0.06)	(0.09)	(0.07)	(0.09)	(0.12)		(0.14)	(0.16)	(0.07)	(0.10)	(0.12)	(0.15)
	Mid	0.40***	0.40***	0.37***	0.49***	0.49***	1.16***		0.03	-0.08	-0.35***	-0.29***	-0.23***	0.01
		(0.06)	(0.08)	(0.10)	(0.07)	(0.05)	(0.06)		(0.11)	(0.08)	(0.11)	(0.11)	(0.06)	(0.10)
	High	0.55***	0.45***	0.44***	1.14***	0.65***	0.43***		0.15	-0.24**	-0.29***	-0.12*	-0.02	-0.26***
		(0.08)	(0.08)	(0.10)	(0.05)	(0.05)	(0.07)		(0.13)	(0.10)	(0.09)	(0.06)	(0.06)	(0.09)
β_{TERM}	Low	0.07	0.18**	0.07	0.26***	0.21**	-0.06	β_{DEF}	0.42	0.35***	0.04	0.26**	0.61***	0.05
		(0.13)	(0.08)	(0.09)	(0.08)	(0.10)	(0.11)		(0.26)	(0.13)	(0.11)	(0.12)	(0.21)	(0.21)
	Mid	0.17***	0.34***	0.26***	0.23***	0.24***	-0.02		0.15	0.39***	0.33**	0.32***	0.21*	0.11
		(0.06)	(0.08)	(0.08)	(0.06)	(0.06)	(0.08)		(0.12)	(0.14)	(0.14)	(0.11)	(0.11)	(0.17)
	High	0.14	0.29***	0.22**	0.05	0.16***	0.29***		0.26	0.37***	0.41*	0.41***	0.05	0.31***
		(0.10)	(0.09)	(0.10)	(0.07)	(0.05)	(0.07)		(0.16)	(0.12)	(0.22)	(0.12)	(0.12)	(0.12)
$\beta_{PTFSB.}$	Low	0.00	0.01	-0.01	-0.02	0.02	-0.07***	$\beta_{PTFSF.}$	0.02	0.01	-0.01	0.01	-0.01	0.01
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)		(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
	Mid	-0.02	-0.02	-0.02	-0.01	-0.02	0.01		0.00	0.00	-0.00	0.01	0.00	-0.04***
		(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	High	-0.01	-0.02	-0.03	-0.01	-0.02**	-0.02		0.01	0.01	-0.00	-0.02	-0.00	0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)		(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
$\beta_{PTFSC.}$	Low	0.01	-0.01	-0.01	-0.01	0.00	-0.00	β_{LIQ}	0.04	0.11	0.14**	0.06	0.02	0.12
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)		(0.07)	(0.07)	(0.05)	(0.07)	(0.08)	(0.12)
	Mid	-0.01	-0.01	-0.01	0.00	-0.00	0.03		0.03	0.10*	0.05	0.08	0.07	0.05
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.03)		(0.05)	(0.06)	(0.09)	(0.06)	(0.06)	(0.07)
	High	-0.01	0.01	-0.01	0.02	0.02*	-0.01		0.02	0.03	0.10	0.05	0.13**	0.11*
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)		(0.07)	(0.08)	(0.08)	(0.06)	(0.06)	(0.07)
α	Low	0.17	0.07	-0.25	0.48*	-0.53*	0.61	$Adj.R^2$	45.4%	50.6%	52.7%	10.7%	52.3%	42.9%
		(0.25)	(0.25)	(0.30)	(0.28)	(0.28)	(0.37)							
	Mid	0.33*	0.21	0.24	0.16	-0.11	-0.42		32.7%	31.7%	23.6%	38.5%	45.0%	69.1%
		(0.19)	(0.29)	(0.33)	(0.25)	(0.19)	(0.30)							
	High	0.30	0.45*	0.04	-0.37	0.23	0.08		37.5%	34.2%	28.2%	78.7%	49.9%	31.8%
		(0.29)	(0.25)	(0.34)	(0.23)	(0.20)	(0.27)							

GRS test statistic = 1.640* p(GRS) = 0.054

This table reports factor loadings on the market factor (RM-Rf), the size factor (SMB), the two bond factors, TERM and DEF, the three trend following factors, PTFSBD, PTFSFX, and PTFSCOM, and the tradable liquidity factor, LIQ, for 18 test portfolios. The intercepts (α), the adjusted R^2 values, and the GRS test statistic are reported at the end of the table. The sample period is January 1983 to December 2011 (348 monthly observations). Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation with lags of five. The test portfolios are nine double-sorted size and book-to-market ratio portfolios from small to big and from low to high, respectively (column 'Small' to 'Big'); three low to high market beta portfolios (column 'Beta'); three low to high momentum portfolios (column 'Mom.'), and three industry portfolios (column 'Indus.'), where the top portfolio is a value-weighted index of transportation stocks, the portfolio in the middle is a value-weighted index of telecommunication stocks, and the bottom portfolio is a value-weighted index of utility stocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

is a consequence of the high leverage in combination with the long duration of investments by infrastructure firms. However, there is no clear evidence of larger companies being more interest rate sensitive than smaller ones, as O'Neal (1998) found to be the case for electric utility companies. Finally, we observe that cash flow volatility has a negative and significant effect in 11 of the 18 portfolios. To some extent this corroborates the finding that infrastructure firms with stable cash flows are able to generate higher returns. Overall, our findings show that a nine-factor model is able to sufficiently explain the significant intercept values of infrastructure returns, and thus the abnormal returns of infrastructure investments. While the CAPM, the Fama/French three-factor, the Carhart four-factor, the infrastructure six-factor, and the Fung/Hsieh eight-factor models are rejected based on the joint significance of the intercepts, the nine-factor infrastructure model is able to explain these intercepts. On average, we can also subsume that utility stocks provide the lowest market exposure, whereas telecommunication stocks have medium and transport stocks the largest market exposure. Utility stocks also show the highest leverage, term structure, and default risk exposure. Telecommunication stocks are less exposed to book-to-market and leverage risk compared to the utility or telecommunication industry. Transportation stocks show on average the largest book-to-market risk exposure but the lowest term structure risk exposure. This indicates that, on average, the different infrastructure "sub-industries" share similar risk exposures but in many cases with different direction of signs.

4.2 Hansen-Jagannathan distance

Going beyond the question of whether an asset pricing model can reduce the pricing errors in *absolute* terms, Kan and Robotti (2009) point out that an important aspect of asset pricing is to compare the performance of competing models. In other words, is an asset pricing model able to significantly reduce the pricing errors *relative* to another asset pricing model? We thus implement the comparison test of the Hansen-Jagannathan (HJ) distance as suggested by Kan and Robotti (2009).[18] Technically, the HJ-distance is the distance between the true stochastic discount factor (SDF) and the implied SDF, but the HJ-distance can also be interpreted as the maximum pricing error of a portfolio of test assets that has a unit second moment (Hansen and Jagannathan (1997)). Thus, the HJ-distance is similar to our time-series analyses but from a different angle, that is, from an SDF approach, where pricing errors are based on sample moments and derived using GMM. While the HJ-distance allows testing whether or not an asset pricing model is rejected in absolute terms, Kan and Robotti's (2009) HJ-distance comparison allows testing whether two asset pricing models have the same HJ-distance and are thus equivalent or not. The model structure can be non-nested, nested, or overlapping. Since the market factor is an element in all models under consideration, the CAPM is a nested model for all other models. The Fama/French model is an overlapping model with the six-factor infrastructure model and the Fung/Hsieh eight-factor model. The nine-factor infrastructure model nests the CAPM, Fama/French, Carhart-model, and six-factor infrastructure models. Before we compare the HJ-distances, we analyze the HJ-distance for each model separately. Table 9 summarizes the HJ-distances and tests whether they are equal to zero.

[18] We would like to thank Raymond Kan for making the test code available to us.

Table 8: Extended infrastructure asset class factor model from time series regressions

Variables		Small	Med. Size	Big	Beta	Mom.	Indus.		Small	Med. Size	Big	Beta	Mom.	Indus.
β_M	Low	0.75***	0.73***	0.87***	0.39***	0.78***	1.09***	β_{SMB}	0.37***	0.04	-0.23***	-0.18***	-0.13*	0.07
		(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.07)		(0.07)	(0.09)	(0.08)	(0.07)	(0.07)	(0.10)
	Mid	0.57***	0.60***	0.62***	0.65***	0.60***	0.97***		0.15**	-0.00	-0.23***	-0.21***	-0.19***	-0.09
		(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	(0.06)		(0.06)	(0.08)	(0.08)	(0.08)	(0.06)	(0.08)
	High	0.73***	0.72****	0.67***	1.10***	0.80***	0.65***		0.29***	-0.14**	-0.26***	-0.12*	-0.08	-0.16**
		(0.04)	(0.04)	(0.06)	(0.04)	(0.03)	(0.04)		(0.07)	(0.07)	(0.08)	(0.06)	(0.05)	(0.08)
β_{HML}	Low	0.47***	0.26***	-0.13	0.28***	-0.09	0.37***	β_{MOM}	0.09	-0.02	0.06	0.10**	-0.34***	-0.02
		(0.12)	(0.09)	(0.09)	(0.07)	(0.11)	(0.11)		(0.08)	(0.06)	(0.06)	(0.05)	(0.08)	(0.07)
	Mid	0.39***	0.27***	0.37***	0.27***	0.17**	-0.17**		0.10***	0.09**	0.08	0.04	0.01	-0.08
		(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)		(0.04)	(0.04)	(0.07)	(0.05)	(0.04)	(0.07)
	High	0.37***	0.34***	0.30***	-0.01	0.20***	0.25***		0.03	0.08**	0.05	-0.03	0.36***	0.09*
		(0.06)	(0.07)	(0.09)	(0.06)	(0.06)	(0.07)		(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
β_{LEV}	Low	-0.10	0.02	0.02	0.50***	0.19	0.04*	$\beta_{CFV.}$	-0.07	-0.23**	-0.14	-0.28***	-0.25**	-0.11
		(0.08)	(0.06)	(0.12)	(0.06)	(0.12)	(0.10)		(0.08)	(0.10)	(0.13)	(0.08)	(0.12)	(0.14)
	Mid	0.25***	0.50***	0.38***	0.39***	0.24***	-0.34***		-0.17***	-0.23***	-0.28***	-0.17**	-0.11	-0.08
		(0.06)	(0.07)	(0.08)	(0.07)	(0.07)	(0.10)		(0.06)	(0.09)	(0.10)	(0.08)	(0.08)	(0.09)
	High	0.53***	0.44***	0.42***	-0.16**	0.11**	0.45***		-0.20***	-0.12	0.09	-0.14*	-0.15***	-0.29***
		(0.07)	(0.07)	(0.08)	(0.07)	(0.06)	(0.06)		(0.07)	(0.08)	(0.13)	(0.08)	(0.06)	(0.09)
β_{INV}	Low	-0.27***	-0.18***	-0.33***	0.04	-0.14	-0.18	β_{TERM}	0.08	0.17**	0.04	0.20***	0.20**	-0.19*
		(0.10)	(0.06)	(0.10)	(0.07)	(0.12)	(0.11)		(0.11)	(0.07)	(0.08)	(0.05)	(0.08)	(0.11)
	Mid	-0.05	0.01	0.07	-0.15**	0.07	0.12		0.14***	0.24***	0.20***	0.18***	0.22***	0.12*
		(0.06)	(0.06)	(0.10)	(0.07)	(0.08)	(0.09)		(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.07)
	High	0.09	-0.01	-0.03	-0.09	-0.15**	-0.16**		0.07	0.21***	0.15*	0.04	0.11**	0.18***
		(0.07)	(0.07)	(0.12)	(0.09)	(0.07)	(0.07)		(0.06)	(0.06)	(0.09)	(0.06)	(0.05)	(0.06)
β_{DEF}	Low	0.23	0.28*	0.13	0.16	0.40**	-0.15	α	-0.04	0.04	0.04	0.06	-0.12	0.59**
		(0.24)	(0.17)	(0.12)	(0.10)	(0.16)	(0.20)		(0.14)	(0.15)	(0.18)	(0.13)	(0.20)	(0.27)
	Mid	0.08	0.36***	0.23*	0.23**	0.19*	0.25		0.16	-0.10	-0.10	-0.06	-0.08	0.08
		(0.12)	(0.10)	(0.13)	(0.12)	(0.11)	(0.17)		(0.11)	(0.13)	(0.16)	(0.14)	(0.13)	(0.21)
	High	0.18*	0.18*	0.25	0.39***	0.22**	0.24*		0.06	0.07	-0.12	-0.09	-0.02	-0.13
		(0.10)	(0.11)	(0.23)	(0.12)	(0.09)	(0.13)		(0.15)	(0.13)	(0.22)	(0.16)	(0.12)	(0.13)
$Adj.R^2$	Low	57.3%	58.0%	58.8%	47.3%	63.0%	48.5%							
	Mid	55.8%	56.4%	49.2%	57.0%	54.7%	71.2%							
	High	61.3%	61.8%	47.0%	80.5%	70.8%	59.4%							
GRS test statistic = 1.394 p(GRS) = 0.132														

This table reports factor loadings on the market factor (RM-Rf), the size factor (SMB), the value factor (HML), the momentum factor (MOM), the leverage factor (LEV), the cash flow volatility factor (CFVOLA), the investment factor (INV), and the two bond factors, i.e., the term structure factor (TERM) and the default factor (DEF), for 18 test portfolios. The intercepts (α), the adjusted R^2 values, and the GRS test statistic are reported at the end of the table. The sample period is January 1983 to December 2011 (348 monthly observations). Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation with lags of five. The test portfolios are nine double-sorted size and book-to-market ratio portfolios from small to big and from low to high, respectively (column 'Small' to 'Big'); three low to high market beta portfolios (column 'Beta'); three low to high momentum portfolios (column 'Mom.'), and three industry portfolios (column 'Indus.'), where the top portfolio is a value-weighted index of transportation stocks, the portfolio in the middle is a value-weighted index of telecommunication stocks, and the bottom portfolio is a value-weighted index of utility stocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Summary of HJ-Distances

Model	(1) Null	(2) CAPM	(3) FF-3	(4) Carhart-4	(5) Infra-6	(6) Fung/Hsieh-8	(7) Infra-9
$\hat{\delta}$	0.382	0.359	0.312	**0.277**	**0.236**	0.345	**0.200**
p($\delta = 0$)	0.000	0.001	0.025	**0.107**	**0.518**	0.089	**0.506**
se($\hat{\delta}$)	0.057	0.056	0.057	0.057	0.072	0.106	0.067
2.5% CI(δ)	0.288	0.265	0.220	0.187	0.135	0.187	0.108
97.5% CI(δ)	0.517	0.486	0.447	0.411	0.424	0.584	0.379
J-test	44.70	35.30	30.12	23.18	**13.82**	17.23	**9.80**
p(J-test = 0)	0.000	0.006	0.011	0.057	**0.312**	0.069	**0.367**

This table presents the HJ-distances ($\hat{\delta}$) for each asset pricing model and their respective p-value ($p(\delta = 0)$). se($\hat{\delta}$) is the standard error of the HJ-distance. CI(δ) is the 95% confidence interval for δ. The J-test is the overidentifying test of Hansen (1982) and its respective p-value ($p(J - test = 0)$). The test assets are the 18 infrastructure portfolios. Bold test statistics and p-values indicate a test statistic above a p-value of 10%.

If a model correctly prices the test assets, the HJ-distance should not be rejected. As can be seen in Table 9 (bold figures), the HJ-distances for the six- and nine-factor infrastructure model are far from being rejected. The Carhart-model is not rejected either, based on the HJ-distance. However, Hansen's (1982) overidentification restrictions (i.e., the J-test) are valid only for the infrastructure models, suggesting that the two infrastructure models are doing a better job at reducing the pricing errors.

When we compare the equality of squared HJ-distance for each model (see Table 10), results for the six-factor infrastructure model corroborate its superior performance compared to all other models except the Fung/Hsieh model and the nine-factor infrastructure model. Since the six-factor model (which does not directly include a size or value risk factor) outperforms the Fama/French model, we can assume that the underlying (macroeconomic) risk drivers which are proxied by SMB and HML are also captured to some extent by the six-factor model. However, the fact that the six-factor infrastructure model does not outperform the Fung/Hsieh model can be largely attributed to its shorter sample period given that the Fung/Hsieh model is not outperforming the null model.[19] In contrast, the null of identical HJ-distances for the nine-factor infrastructure

[19] The null model only includes a constant, i.e., a vector of ones, but no time-varying factors as the other models.

model cannot be rejected except for the null model and the CAPM.

Table 10: Testing equality of squared HJ-Distances

Model	(1) CAPM	(2) FF-3	(3) Carhart-4	(4) Infra-6	(5) Fung/Hsieh-8	(6) Infra-9
Null	0.018**	0.049***	0.069***	0.090**	0.042	0.106**
	(0.029)	(0.008)	(0.006)	(0.039)	(0.999)	(0.044)
CAPM		0.031**	0.052***	0.073*	0.036	0.089*
		(0.016)	(0.009)	(0.053)	(0.999)	(0.059)
FF-3			0.020*	0.041*	0.003	0.057
			(0.055)	(0.059)	(0.948)	(0.166)
Carhart-4				0.021*	-0.024	0.037
				(0.059)	(0.622)	(0.272)
Infra-6					-0.026	0.016
					(0.576)	(0.410)
Fung/Hsieh-8						0.045
						(0.315)

This table compares the squared HJ-distances ($\hat{\delta}$) of the different factor models according to Kan and Robotti (2009). The test assets are the 18 infrastructure portfolios. We report the difference between the HJ-distances of the models in row i and column j, $\hat{\delta}_i - \hat{\delta}_j$, and the respective p-value in parentheses for the test $H_0 : \hat{\delta_i}^2 = \hat{\delta_j}^2$

This might be due to the few degrees of freedom for the nine-factor model in a test setting with 18 portfolios (see Choi, Kim, and Kim (2013)), especially given that the parsimonious six-factor model, without the other three factors (SMB, HML, and MOM) does exceptionally well compared to the other models.

4.3 Further tests

To investigate the role of infrastructure-specific risk factors and further validate the results from the time series regressions we conduct four other tests. These tests include subperiod analyses, the effect of industry concentration on infrastructure returns, the defensive characteristics (i.e., downside protection) of infrastructure investments and whether infrastructure serves as an inflation hedge. The last two aspects are not included in the main models, because previous studies (Bird, Liem, and Thorp (2012); Rödel and Rothballer (2012)) showed that infrastructure firms neither consistently hedges inflation nor offers defensive characteristics. Our extensive dataset and our infrastructure-specific factor models help to refine previous results and investigate the abilities of infrastructure investments in more detail.

4.3.1 Analysis of defensive characteristics

Based on our asset class factor model from Equation (5) and a squared market factor as in Treynor and Mazuy (1966), we also analyze the defensive characteristics of our nine size and book-to-market portfolios against market movements. The assumption is that certain portfolios with higher book-to-market ratios or larger market capitalization perform differently during economic downturns. Thus, our work goes beyond the previous analysis of Bird, Liem, and Thorp (2012), who analyze the U.S. and Australian markets, but cannot differentiate their indices by size or book-to-market characteristics. Figure 1 illustrates the predicted infrastructure returns from Equation (5), with the squared market excess return on the vertical axis and the market excess return on the horizontal axis. A convex relation (demonstrated by the solid red line) between predicted infrastructure returns and market excess returns would indicate that an increasingly severe market plunge has a decreasingly severe effect on the infrastructure firms.

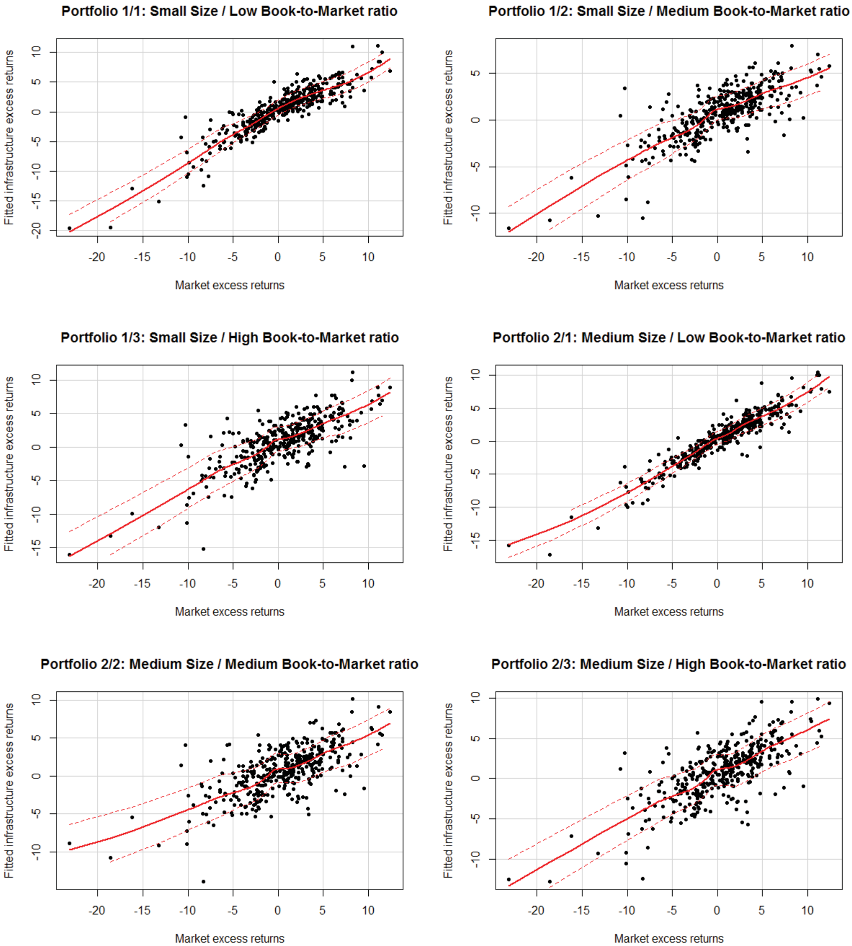
Figure 1 shows that all but one of the nine portfolios experience a concave, or (almost) linear relation between predicted infrastructure returns and the market excess return. Only portfolio 3/2 (i.e., the large market capitalization/medium book-to-market ratio portfolio) shows a significant convex relation between infrastructure and market returns. This result seems odd, given that all other large size portfolios have linear or concave relations, as do the medium book-to-market ratio portfolios. The low fit for portfolio 3/2 (an adjusted R-square of 50.5%) suggests that there are other and as yet unknown factors that, if they could be discovered and integrated into the model, might result in a more consistent picture of the defensive nature of infrastructure returns. Overall, our results confirm the findings of Bird, Liem, and Thorp (2012) that infrastructure firms do not behave defensively during economic downturns.[20]

[20] We also use a dummy variable for up and down markets (1 for up and 0 for down) to control for the defensive characteristics. Results are virtually identical and show no significant effects on the dummy variable.

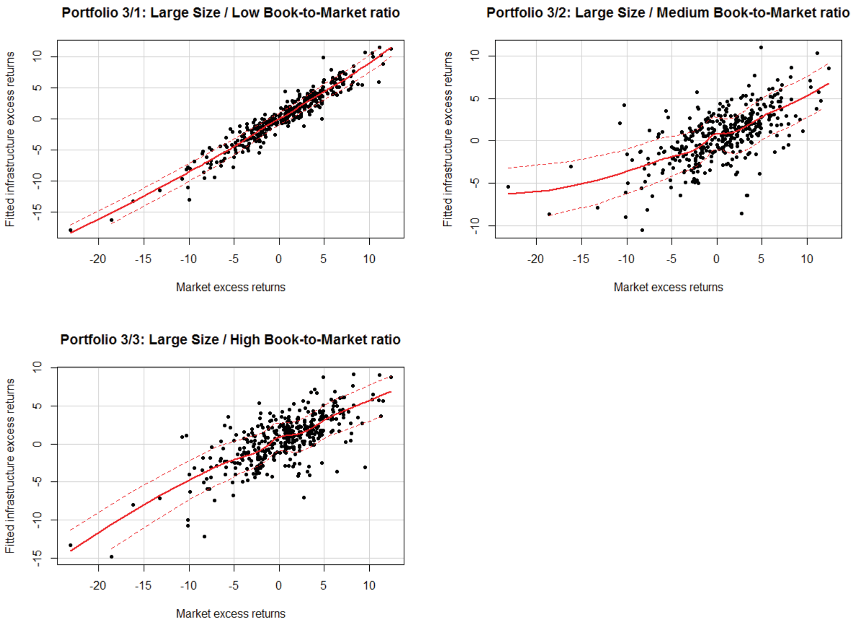
4.3.2 Analysis of inflation hedge

We further investigate the assumption that infrastructure is a potential hedge against inflation. This popular assumption among practitioners has been rejected by Rödel and Rothballer (2012) and is only weakly confirmed by Bird, Liem, and Thorp (2012) for utility stocks. To shed more light on these mixed results, we control for an inflation hedge ability of infrastructure firms in our model by including the total return of Treasury Inflation Protected Securities (TIPS) minus the risk-free rate. Our dataset allows us to differentiate both between industry sectors, size and book-to-market ratio, respectively. However, the TIPS return series only begins in February 1997 and hence covers less than half our entire sample period. We use the total return series of the Barclays US TIPS index, which aggregates all maturities to investigate the inflation hedging abilities of infrastructure returns. Subtracting the risk-free return from monthly TIPS series results in an excess return series for our inflation factor (INFL). In contrast to the Consumer Price Index (CPI), TIPS are tradable and, thus, represent investment returns, allowing us to directly determine the risk premium of inflation which is 0.35% per month. Given the close relation between inflation, term structure, default probability (i.e., they are all based on interest rates), we first note that the inflation factor, INFL, is highly correlated with the TERM factor ($\rho = 0.5$). As mentioned above (see section 2.4) this result is in line with Ang, Bekaert, and Wei (2008) who point out the relation between term structure and inflation. Regressing INFL on all other previously introduced dependent variables reveals that INFL is also highly dependent on the default factor, DEF, and to some extent on CFVOLA.

Figure 1: Evidence of defensive abilities by size and book-to-market portfolios



This figure illustrates the predicted infrastructure returns from Equation (5), with the squared market excess return on the vertical axis and the market excess return on the horizontal axis. A convex relation (demonstrated by the solid red line) between predicted infrastructure returns and market excess returns would indicate that an increasingly severe market plunge has a decreasingly severe effect on the infrastructure firms. Portfolio returns are sorted by market capitalization (size) and book-to-market ratio.



Equation (9) shows coefficient estimates with t-statistics in parentheses using Newey-West (1987) corrected standard errors with lags of three:

$$\begin{aligned} INFL = \underset{(1.54)}{0.18} - \underset{(-0.29)}{0.01}\,(RM\text{-}Rf) - \underset{(-1.19)}{0.03}\,SMB + \underset{(1.33)}{0.06}\,HML + \underset{(0.40)}{0.01}\,MOM - \underset{(-1.44)}{0.07}\,LEV + \\ \underset{(1.96)}{0.12}\,CFVOLA - \underset{(1.23)}{0.56}\,INV + \underset{(6.49)}{0.32}\,TERM + \underset{(2.01)}{0.21}\,DEF. \end{aligned} \tag{9}$$

The adjusted R-square of this regression is 35.9%. Based on this regression, we construct an orthogonalized inflation factor as the sum of the intercept and the residuals to eliminate multicollinearity issues. This factor can be interpreted as a zero-investment portfolio that is uncorrelated with all other factors. Table 11 shows the regression estimates for the inflation factor.

Table 11: Inflation hedge abilities of infrastructure firms

Panel A: Orthogonalized inflation factor and value-weighted infrastructure index

Variables	(1) CAPM	(2) FF-3	(3) Carhart-4	(4) Infra-6	(5) Fung/Hsieh-8	(6) Infra-9
$\beta_{INFL\perp}$	0.09	0.09	0.09	0.09	0.06	0.09
	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.10)
α	0.05	0.07	0.04	0.00	-0.06	0.01
	(0.20)	(0.19)	(0.19)	(0.18)	(0.18)	(0.18)
Monthly obs.	179	179	179	179	179	179
$Adj.R^2$	68.0%	68.9%	69.0%	73.6%	70.9%	74.1%

Panel B: Orthogonalized inflation factor and infrastructure returns

Variables		Small	Med. Size	Big	Beta	Mom.	Indus.
$\beta_{INFL\perp}$	Low	0.57**	-0.01	0.04	0.19	0.06	0.24
		(0.26)	(0.16)	(0.22)	(0.16)	(0.25)	(0.30)
	Mid	0.42**	0.21	0.17	0.01	0.06	-0.11
		(0.17)	(0.15)	(0.18)	(0.16)	(0.15)	(0.18)
	High	0.05	0.14	0.31	0.23	0.29**	0.32**
		(0.25)	(0.18)	(0.36)	(0.15)	(0.13)	(0.16)
$Adj.R^2$	Low	55.6%	55.6%	62.8%	43.5%	63.7%	49.4%
	Mid	59.3%	58.4%	56.6%	56.1%	49.6%	73.3%
	High	54.9%	43.6%	40.8%	79.7%	69.2%	53.9%

This table reports regression results for the inflation factor. The inflation factor (INFL) is the orthogonalized excess return of the TIPS return series over the 1-month T-bill rate. Panel A shows regression results for the value-weighted infrastructure index as dependent variable. Panel B shows factor loadings of INFL extracted from infrastructure nine-factor model regressions where the dependent variables are portfolio excess returns sorted by different characteristics explained above. Adjusted R^2s are also reported for these regressions. The sample period in Panel A and B is February 1997 to December 2011 (179 monthly observations). Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A of Table 11 runs different model specifications with the VWI index as dependent variable. Inflation is not significant in any of the model specifications, corroborating the results of Rödel and Rothballer (2012). Panel B demonstrates that infrastructure can hedge inflation in case of smaller growth firms, utility firms, and high momentum infrastructure firms. The majority of portfolios, however, does not hedge against inflation. A possible explanation why smaller growth firms are able to protect against inflation, at least to some extent, is their ability to adjust price changes faster than their larger and more complex competitors. Also their local focus could prevent them from confrontations with larger competitors in several areas at the same time, which would make them more vulnerable to pricing competitions despite the regulatory framework. Overall our results confirm the results of Rödel and Rothballer (2012) and Bird, Liem, and Thorp (2012) that infrastructure firms do not guarantee inflation protection. Only minor evidence suggests that utility firms and smaller growth firms are able to hedge inflation to some extent.

4.3.3 Analysis of subperiods

We divide the data into three equal subperiods of 116 months each. Table 12 reports the regression results for the three different subperiods between January 1983 and December 2011. The infrastructure six-factor model documents a significant improvement in explanatory power for all three periods compared to the Fama/French three-factor model. The biggest difference between the two models occurs in the most recent period where the infrastructure six-factor model explains 64.2 percentage points more in the time series variation of infrastructure returns than the Fama/French three-factor model. The smallest difference occurs during the time span of 1992 to 2002 where the adjusted R-square increases by 28.3 percentage points. The Fama/French factors, the momentum factor and the constructed infrastructure factors do not explain the variation during all time periods which suggests that infrastructure returns are not exposed to the same risk factors at all times, but are subject to time-varying risk components (e.g., the size factor is more relevant during distressed times than during economically stable times).

We also check for the model's performance during recession periods. This is especially important due to the fact that infrastructure investments should be resilient against strong market downturns during recessions. Thus, the following analysis can also be considered complementary to the analysis of defensive characteristics but with a stronger focus on severely negative market conditions.

For that purpose, we include three recession dummies for three recession periods between 1983 and 2011. The first recession dummy ($Dummy(Recession1)$) covers the period from July 1990 to March 1991. The second recession dummy ($Dummy(Recession2)$) covers the period from March 2001 to November 2001, and the third recession dummy ($Dummy(Recession3)$) covers the period from

Table 12: Robustness check for subperiods

	Infra. 9-factor model			Infra. 6-factor model			F/F 3-factor model			Infra. 9-factor model	Infra. 6-factor model	F/F 3-factor model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	1983/1-1992/8	1992/9-2002/4	2002/5-2011/12	1983/1-1992/8	1992/9-2002/4	2002/5-2011/12	1983/1-1992/8	1992/9-2002/4	2002/5-2011/12	1983/1-2011/12 excluding financial crisis (ex. 2008/09-2009/06)		
β_M	0.73***	0.80***	0.86***	0.66***	0.73***	0.82***	0.75***	0.81***	0.81***	0.75***	0.73***	0.76***
	(0.04)	(0.08)	(0.07)	(0.05)	(0.06)	(0.07)	(0.04)	(0.07)	(0.07)	(0.03)	(0.03)	(0.04)
β_{SMB}	-0.23**	0.00	-0.21***				-0.38***	-0.03	-0.21**	-0.11**		-0.14***
	(0.09)	(0.08)	(0.08)				(0.08)	(0.06)	(0.08)	(0.04)		(0.04)
β_{HML}	0.25**	0.16*	-0.12				0.27***	0.21**	0.11	0.07		0.16***
	(0.10)	(0.09)	(0.10)				(0.10)	(0.09)	(0.12)	(0.05)		(0.05)
β_{MOM}	0.14**	0.03	0.08							0.04		
	(0.05)	(0.05)	(0.06)							(0.04)		
β_{CFVOLA}	-0.17*	-0.29***	-0.14	-0.26**	-0.35***	-0.17*				-0.18***	-0.25***	
	(0.10)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)				(0.06)	(0.06)	
β_{LEV}	0.26***	-0.00	0.31***	0.34***	0.06	0.24***				0.16***	0.20***	
	(0.09)	(0.08)	(0.08)	(0.10)	(0.08)	(0.07)				(0.06)	(0.05)	
β_{INV}	-0.11	-0.00	0.01	-0.00	0.01	-0.03				-0.06	-0.04	
	(0.09)	(0.12)	(0.07)	(0.09)	(0.13)	(0.08)				(0.06)	(0.06)	
β_{TERM}	0.13	0.07	0.20***	0.14*	0.08	0.20***				0.17***	0.17***	
	(0.08)	(0.11)	(0.07)	(0.08)	(0.10)	(0.07)				(0.05)	(0.05)	
β_{DEF}	-0.07	0.06	0.20	-0.15	0.05	0.14				0.18*	0.15	
	(0.16)	(0.26)	(0.15)	(0.16)	(0.21)	(0.14)				(0.11)	(0.10)	
α	-0.06	-0.23	-0.00	0.13	-0.09	-0.01	0.08	-0.32	0.24	-0.05	-0.00	0.05
	(0.17)	(0.26)	(0.20)	(0.20)	(0.23)	(0.21)	(0.18)	(0.25)	(0.25)	(0.12)	(0.12)	(0.13)
Monthly obs.	116	116	116	116	116	116	116	116	116	348	348	348
$Adj.R^2$	79.9%	65.5%	78.3%	74.7%	38.0%	56.1%	24.4%	37.2%	14.1%	71.9%	70.9%	68.0%

This table reports regression results for three equal subperiods of 116 months each. The entire sample period starts in January 1983 and ends in December 2011. For each subperiod, the infrastructure nine-factor model (Columns 1–3), the infrastructure six-factor model (Columns 4–6), and the Fama/French three-factor model (Columns 7–9) are run. Columns 10–12 present regression results excluding the peak of the financial crisis (September 2008 to June 2009). The adjusted R^2 values from each time series are reported at the end of the table. Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

December 2007 to September 2009. Table 13 reports the results and shows that factor loadings are virtually identical to the loadings presented in Table 12. Interestingly, the coefficients on the first and last recession dummies are insignificant, suggesting that infrastructure returns might have some resilience during recession periods.

Table 13: Recession periods

Variables	(1) 1983/1-2011/12	(2) 1983/1-1992/8	(3) 1992/9-2002/4	(4) 2002/5-2011/12
β_{M}	0.73***	0.72***	0.78***	0.83***
	(0.03)	(0.04)	(0.07)	(0.05)
β_{SMB}	-0.14***	-0.23***	0.00	-0.24***
	(0.04)	(0.09)	(0.07)	(0.08)
β_{HML}	0.02	0.23**	0.15*	-0.15**
	(0.05)	(0.10)	(0.08)	(0.07)
β_{MOM}	0.05	0.14***	0.03	0.07*
	(0.03)	(0.05)	(0.05)	(0.04)
β_{LEV}	0.20***	0.27***	0.02	0.34***
	(0.06)	(0.09)	(0.08)	(0.07)
β_{CFVOLA}	-0.17***	-0.17*	-0.27**	-0.13
	(0.06)	(0.10)	(0.11)	(0.10)
β_{INV}	-0.05	-0.10	-0.01	-0.01
	(0.06)	(0.09)	(0.12)	(0.08)
β_{TERM}	0.17***	0.12	0.09	0.16***
	(0.04)	(0.08)	(0.10)	(0.05)
β_{DEF}	0.28***	-0.08	0.15	0.29***
	(0.08)	(0.17)	(0.23)	(0.08)
$Dummy(Recession1)$	-0.80	-0.74		
	(0.74)	(0.50)		
$Dummy(Recession2)$	-2.05**		-1.56**	
	(0.88)		(0.72)	
$Dummy(Recession3)$	-0.76			-0.73
	(0.54)			(0.58)
α	0.06	0.01	-0.10	0.09
	(0.11)	(0.18)	(0.25)	(0.19)
Monthly obs.	348	116	116	116
$Adj.R^2$	74.1%	80.1%	66.4%	81.7%

This table reports factor loadings from time series regressions for the infrastructure nine-factor model including dummy variables for three recession periods. The first recession dummy ($Dummy(Recession1)$) covers the period from July 1990 to March 1991. The second recession dummy ($Dummy(Recession2)$) covers the period from March 2001 to November 2001 and the third recession dummy ($Dummy(Recession3)$) covers the period from December 2007 to September 2009. The adjusted R^2 values from each time series are reported at the end of the table. Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3.4 Industry concentration and infrastructure returns

Another important aspect of infrastructure investments is their monopolistic behavior as a result of their market structure. How does industry concentration affect the returns of infrastructure stocks?[21] To measure industry concentration in our sample, we follow Hou and Robinson (2006) and calculate the Herfindahl-Hirschman Index (HHI) for each three-digit SIC code and sort each stock into quintiles based on their HHI value for each year.[22] HHI is defined as the sum of squared company sales in each industry. Following Hou and Robinson (2006), we average each HHI over a period of three years to avoid potential data errors in the industry classification. Hou and Robinson (2006) find that firms in more concentrated industries earn lower returns. They argue that high barriers to entry or those that engage in less innovation result in lower expected returns. The infrastructure sector, with its large upfront investments, can be considered as a sector of high barriers and, thus, we might expect lower returns the more concentrated the industry.

Table 14 confirms the results of Hou and Robinson (2006) for infrastructure stocks showing a monotonic pattern from high to low returns from quintile 1 (lowest concentration, i.e. most competitive) to quintile 5 (highest concentration, i.e. least competitive). In addition, we are able to take a closer look at the monopolistic behavior of infrastructure stocks. Infrastructure industries with more oligopolistic market structures earn on average 1.44% p.a. less than more competitive industries, while their Sharpe ratios are more than twice as high as those of industries with more competitive market structures. Thus, infrastructure investments are most beneficial for investors in concentrated industries from a risk-return perspective.

[21] We would like to thank an anonymous referee for this valuable comment.

[22] Note that Hou and Robinson (2006) exclude regulated industries from their sample which, in contrast, are the core industries of our sample. Our results thus complement the results of Hou and Robinson (2006).

Table 14: Infrastructure returns sorted by industry concentration

	1	2	3	4	5
Raw Return	1.03	1.01	1.00	0.94	0.91
Std. dev.	11.43	5.77	5.93	4.86	4.17
Min	-40.93	-18.25	-22.01	-17.63	-13.25
Max	46.30	21.51	18.34	17.02	14.52
Sharpe ratio (monthly)	0.06	0.11	0.11	0.12	0.13

This table summarizes average returns of infrastructure returns sorted by industry concentration (i.e. the Herfindahl-Hirschman Index). Portfolio 1 presents raw returns, standard deviation, minimum returns, maximum returns, and the monthly Sharpe ratio (based on excess returns) for the quintile of infrastructure stocks with the lowest industry concentration. Portfolio 5 presents the same statistics for the quintile of infrastructure stocks with the highest industry concentration.

To analyze this issue in greater detail, we run our nine-factor model on all five excess return quintiles sorted by HHI. Table 15 reports the results. First, we observe that none of the alphas are significantly different from zero. Second, we see that the nine factor model captures much of the time-series variation in the most concentrated infrastructure industries. It should be highlighted that the two most concentrated industries (quintiles 4 and 5) load significantly negative on the size factor SMB while the two least concentrated industries (quintiles 1 and 2) load significantly positive on SMB. This implies that the few companies in the most concentrated industries are also large infrastructure companies. Moreover, the most concentrated industries have the lowest market exposure and thus are most suitable for risk mitigation against market movements.

Table 15: Time series regressions and industry concentration

Variables	1	2	3	4	5
β_M	0.91***	0.87***	0.99***	0.76***	0.66***
	(0.16)	(0.06)	(0.06)	(0.05)	(0.05)
β_{SMB}	0.69***	0.20**	0.03	-0.20***	-0.14*
	(0.19)	(0.09)	(0.07)	(0.07)	(0.08)
β_{HML}	-0.98***	0.02	0.45***	-0.10	0.18**
	(0.20)	(0.11)	(0.14)	(0.08)	(0.07)
β_{MOM}	-0.38***	0.03	0.01	-0.00	0.08
	(0.15)	(0.05)	(0.06)	(0.07)	(0.05)
β_{LEV}	-0.15	0.01	-0.19**	0.02	0.48***
	(0.22)	(0.09)	(0.09)	(0.10)	(0.07)
β_{CFVOLA}	-0.44	-0.28**	-0.03	0.07	-0.37***
	(0.31)	(0.12)	(0.12)	(0.08)	(0.10)
β_{INV}	-0.52*	-0.14	-0.26*	-0.01	-0.17**
	(0.29)	(0.09)	(0.14)	(0.10)	(0.08)
β_{TERM}	0.05	0.00	-0.11*	0.15**	0.20***
	(0.18)	(0.08)	(0.06)	(0.07)	(0.06)
β_{DEF}	0.04	-0.05	-0.09	0.37**	0.18
	(0.33)	(0.16)	(0.15)	(0.16)	(0.14)
α	0.75	0.15	0.08	0.11	-0.13
	(0.50)	(0.24)	(0.20)	(0.18)	(0.15)
Monthly obs.	348	348	348	348	348
$Adj.R^2$	38.9%	45.4%	55.6%	62.5%	56.7%

This table reports factor loadings from time series regressions for the infrastructure nine-factor model. The dependent variable in each column is the excess return of infrastructure stocks sorted by industry concentration (i.e. the Herfindahl-Hirschman Index). Column 1 presents regression results for the quintile of infrastructure stocks with the lowest industry concentration. Column 5 presents regression results for the quintile of infrastructure stocks with the highest industry concentration. The adjusted R^2 values from each time series are reported at the end of the table. Standard errors are reported in parentheses and are computed using the Newey-West (1987) correction for heteroscedasticity and serial correlation. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5 Conclusion

This paper identifies the common risk factors that are priced in infrastructure companies and constructs an asset class factor model. Established pricing models are tested, i.e., the single-factor CAPM, the Fama/French three-factor model, the Carhart four-factor model, and the Fung/Hsieh eight-factor model. We create a six-factor model and a nine-factor model, both of which are superior in explaining the variation in infrastructure returns compared to the Fama/French three-factor model, the Carhart four-factor model or the Fung/Hsieh eight-factor model. The six-factor model consists of the market excess return and five additional factors: cash flow volatility, leverage, an investment factor, a term premium, and a default premium. The nine-factor model augments the Carhart four-factor model with the aforementioned five additional factors.

The infrastructure nine-factor model is the only model in the time-series analysis that explains all abnormal returns, i.e., the intercepts from time-series regressions are jointly different from zero. Furthermore, we show that the six-factor and nine-factor infrastructure models are the only ones not being rejected by the HJ-distances and Hansen's (1982) J-test. Finally, Kan and Robotti's (2009) HJ-distance comparison test suggests that the infrastructure six-factor model performs better than the CAPM, the Fama/French three-factor model, and the Carhart four-factor model.

Table 16 summarizes the results from all regressions and robustness tests for each factor. The findings for the market beta (RM-Rf) are in line with existing literature, thus confirming that low market betas are mostly attributable to utility stocks, whereas non-utility stocks within the infrastructure sector tend to be more affected by market movements (see Bird, Liem, and Thorp (2012); Rothballer and Kaserer (2012)). CFVOLA is also significant and loads negatively, which is in accordance with the results for stocks in general (see Huang (2009)) but in contrast to Bitsch (2012), who finds that investors value cash flow volatility at a premium. The findings with respect to MOM, LEV, INV, TERM, and DEF in terms of infrastructure investments have not yet been analyzed in the literature. Here we find that infrastructure firms are highly sensitive to interest rate changes regarding changes in the term structure. We also find an additional premium for high financial leverage that is economically significant. This emphasizes the need for infrastructure investments to consider leverage as an additional risk factor, since the HML factor alone is not sufficient to capture the return variation with respect to leverage.[23] Furthermore, we find that more oligopolistic infrastructure industries earn on average 1.44%

[23]Furthermore, we showed that infrastructure investments, in general, neither offer an inflation hedge nor are able to protect against downside risk, but have some resistance during recession periods. Only for utility firms an inflation hedge can be documented which confirms results for other countries and time periods (see Bird, Liem, and Thorp (2012); Rödel and Rothballer (2012)).

p.a. less than more competitive industries, while their Sharpe ratios are more than twice as high as those of industries with with more competitive market structures. Thus, infrastructure investments are most beneficial for investors in concentrated industries from a risk-return perspective.

Our results are useful for investors and policymakers interested in determining adequate costs of capital, measuring and evaluating infrastructure returns, and understanding the special characteristics of infrastructure investments such as diversification benefits and return volatility. Since factor loadings present the correlation structure between returns and the underlying risk factors, the factor exposures also indicate strategies for minimum variance hedging, for the replication of infrastructure returns, or, in general, for optimizing asset allocation.

On average, we can also subsume that utility stocks provide the lowest market exposure, whereas telecommunication stocks have medium and transport stocks have the largest market exposure. Utility stocks also show the highest leverage, term structure, and default risk exposure. Telecommunication stocks are less exposed to book-to-market and leverage risk compared to the utility or telecommunication industry. Transportation stocks show on average the largest book-to-market risk exposure but the lowest term structure risk exposure. Overall, this indicates that, on average, the different infrastructure "sub-industries" share similar risk exposures but with different direction of signs.

Future research might further investigate the risk exposure of unlisted infrastructure projects. Despite a vast set of significant risk factors in our model, unlisted infrastructure might react differently to our risk factors. Also, it could be very interesting to see how our infrastructure six- and nine-factor models perform in other countries, specifically with other regulatory regimes. The question of whether cash flow stability in less stable countries leads to expropriation, as indicated by Sawant (2010), is still unanswered. Similarly, political (i.e., corruption, expropriation) and regulatory risk factors and their effects on infrastructure returns could be further analyzed.

Table 16: Summary of results and comparison with existing literature

Variables	Hypothesis	Our results (on average)	Comparison with existing literature
RM-Rf	Positive relation between the market and infrastructure returns	Significantly positive and low (i.e., below 1)	In line with the result of Rothballer and Kaserer (2012). Utility stocks have low market betas whereas non-utility stocks within the infrastructure sector have higher betas.
SMB	Negative relation between size effect and infrastructure returns.	Significantly negative	Not in line with Bird, Liem, and Thorp (2012), who find no significant effect.
HML	Positive relation between value effect and infrastructure returns.	Significant	Not in line with Bird, Liem, and Thorp (2012), who find a significantly positive effect.
Momentum (MOM)	Positive relation between past returns and infrastructure returns.	Significantly positive	Not yet analyzed in an infrastructure context.
Cash flow volatility (CFVOLA)	Negative relation between cash flow volatility and infrastructure returns.	Significantly negative	In line with Huang (2009), but not in line with Bitsch (2012), who finds a positive relation between cash flow volatility and a fund's value.
Leverage (LEV)	Positive relation between leverage and infrastructure returns.	Significantly positive	Not yet analyzed in an infrastructure context.
Investment growth (INV)	Positive relation between investment growth and infrastructure returns.	Significantly negative relation between INV and returns of growth companies	Not in line with Chen, Novy-Marx, and Zhang (2011), who find a positive relation for stocks in general.
Term premium (TERM)	Positive relation between term structure and infrastructure returns.	Significantly positive	Not yet analyzed for infrastructure investments but in line with O'Neal (1998), who analyzes electric utility companies.
Default premium (DEF)	Positive relation between default premium and infrastructure returns.	Significantly positive	Not yet analyzed for infrastructure investments but in line with O'Neal (1998), who analyzes electric utility companies.

References

Aggarwal, R., Akhigbe, A. and Mohanty, S. K., 'Oil price shocks and transportation firm asset prices', *Energy Economics*, Vol. 34, 2012, pp. 1370–1379.

Ammann, M., Odoni, S. and Oesch, D., 'An alternative three-factor model for international markets: Evidence from the European monetary union', *Journal of Banking and Finance*, Vol. 36, 2012, pp. 1857–1864.

Andersen, T. B. and Dalgaard, C.-J., 'Power outages and economic growth in Africa', *Energy Economics*, Vol. 38, 2013, pp. 19–23.

Ang, A., Bekaert, G. and Wei, M. I. N., 'The term structure of real rates and expected inflation', *Journal of Finance*, Vol. 63, 2008, pp. 797–849.

Ang, A., Hodrick R. J., Xing Y. and Zhang X., 'The cross-section of volatility and expected returns', *Journal of Finance*, Vol. 61, 2006, pp. 259–299.

Bauman, W. S., Conover, C. M. and Miller, R. E., 'Growth versus value and large-cap versus small-cap stocks in international markets', *Financial Analysts Journal*, Vol. 54, 1998, pp. 75–89.

Baur, R., Hlavinek, P., Kukharchyk, T., Marsalek, J. and Mahrikova, I., 'Aging and renewal of urban water infrastructure', *Springer Netherlands*, 2006.

Bhandari, L. C., 'Debt/equity ratio and expected common stock returns: Empirical evidence', *Journal of Finance*, Vol. 43, 1988, pp. 507–528.

Bianconi, M. and Yoshino, J. A., 'Risk factors and value at risk in publicly traded companies of the nonrenewable energy sector', *Energy Economics*, Vol. 45, 2014, pp. 19–32.

Bird, R., Liem H. and Thorp, S., 'Infrastructure: Real assets and real returns', *European Financial Management*, Vol. 20, 2012, pp. 802–824.

Bitsch, F., 'Cash flow stability versus transparency: What do Investors Value about listed infrastructure funds?', *International Finance Review*, Vol. 13, 2012, pp. 199–229.

Bitsch, F., Buchner, A. and Kaserer, C., 'Risk, return and cash flow characteristics of infrastructure fund investments', *EIB papers*, Vol. 15, 2010, pp. 106–136.

Boyer, M. M. and Filion, D., 'Common and fundamental factors in stock returns of canadian oil and gas companies', *Energy Economics*, Vol. 29, 2007, pp. 428–453.

Bradley, M., Jarrell, G. A. and Han Kim, E., 'On the existence of an optimal capital structure: Theory and evidence', *Journal of Finance*, Vol. 39, 1984, pp. 857–878.

Campbell, J. Y., Lo, A.W. and MacKinlay, C., 'The econometrics of financial markets', *Princeton University Press*, New Jersey, 1997.

Carhart, M. M., 'On persistence in mutual fund performance', *Journal of Finance*, Vol. 52, 1997, pp. 57–82.

Chen, L., Novy-Marx, R. and Zhang, L., 'An alternative three-factor model', *Working Paper* (Washington University in St. Louis, 2011).

Choi, K.-J., Kim, D., and Kim, S.-H., 'Time-series and cross-sectional tests of asset pricing models', 2013, *Encyclopedia of finance*, pp. 745–753 .

Cochrane, J.H., 'Asset pricing', *Princeton University Press*, New Jersey, 2005.

Czernich, N., Falck, O., Kretschmer, T. and Woessmann L., 'Broadband infrastructure and economic growth', *The Economic Journal*, Vol. 121, 2011, pp. 505–532.

Daniel, K. and Titman S., 'Evidence on the characteristics of cross sectional variation in stock returns', *Journal of Finance*, Vol. 52, 1997, pp. 1–33.

Dechant, T. and Finkenzeller, K., 'The role of infrastructure investments in a multi-asset portfolio – Answers from dynamic asset allocation', *Working Paper* (University of Regensburg, 2012).

Della Croce, R., 'Trends in large pension fund investment in infrastructure', OECD Working Papers on Finance, Insurance and Private Pensions, Vol. 29, 2012, *OECD Publishing*.

Elyasiani, E., Mansur, I. and Odusami, B., 'Oil price shocks and industry stock returns', *Energy Economics*, Vol. 33, 2011, pp. 966–974.

Esfahani, H. S. and Ramirez, M. T., 'Institutions, infrastructure, and economic growth', *Journal of Development Economics*, Vol. 70, 2003, pp. 443–477.

Fama, E. F. and French, K. R., 'Business conditions and expected returns on stocks and bonds', *Journal of Financial Economics*, Vol. 25, 1989, pp. 23–49.

Fama, E. F. and French, K.R., 'The cross-section of expected stock returns', *Journal of Finance*, Vol. 47, 1992, pp. 427–465.

Fama, E. F. and French, K. R., 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics*, Vol. 33, 1993, pp. 3–56.

Fama, E. F. and French, K. R., 'Industry costs of equity', *Journal of Financial Economics*, Vol. 43, 1997, pp. 153–193.

Finkenzeller, K., Dechant, T. and Schäfers, W., 'Infrastructure: A new dimension of real estate? An asset allocation analysis', *Journal of Property Investment and Finance*, Vol. 28, 2010, pp. 263–274.

Ford, G. S., 'Does a municipal electric's supply of communications crowd out private communications investment? An empirical study', *Energy Economics*, Vol. 29, 2007, pp. 467–478.

Fung, W. and Hsieh, D. A., 'Hedge fund benchmarks: A risk-based approach', *Financial Analysts Journal*, Vol. 60, 2004, pp. 65–80.

Gasmi, F. and Oviedo, J. D., 'Investment in transport infrastructure, regulation, and gas-gas competition', *Energy Economics*, Vol. 32, 2010, pp. 726–736.

Gibbons, M. R., Ross, S. A. and Shanken, J., 'A test of the efficiency of a given portfolio',*Econometrica*, Vol. 57, 1989, pp. 1121–1152.

Hansen, L. P., 'Large sample properties of generalized method of moments estimators', *Econometrica*, 1982, pp. 1029–1054.

Hansen, L. P. and Jagannathan, R., 'Assessing specification errors in stochastic discount factor models', *Journal of Finance*, Vol. 52, 1997, pp. 557–590.

Hashimzade, N. and Myles, G. D., 'Growth and public infrastructure', *Macroeconomic Dynamics*, Vol. 14, 2010, pp. 258–274.

Hou, K. and Robinson, D.T., 'Industry concentration and average stock returns', *Journal of Finance*, Vol. 61, 2006, pp. 1927–1956.

Huang, A. G., 'The cross section of cashflow volatility and expected stock returns', *Journal of Empirical Finance*, Vol. 16, 2009, pp. 409–429.

Jegadeesh, N. and Titman, S., 'Returns to buying winners and selling losers: Implications for stock market efficiency', *Journal of Finance*, Vol. 48, 1993, pp. 65–91.

Kan, R. and Robotti, C., 'Model comparison using the Hansen-Jagannathan distance', *Review of Financial Studies*, Vol. 22, 2009, pp. 3449–3490.

Kessides, I. N., 'Reforming infrastructure: Privatization, regulation, and competition', *World Bank*, 2004.

Lewellen, J., Nagel S. and Shanken J., 'A skeptical appraisal of asset pricing tests', *Journal of Financial Economics*, Vol. 96, 2010, pp. 175–194.

Lintner, J., 'The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets', *Review of Economics and Statistics*, Vol. 47, 1965, pp. 13–37.

Lopatta, K., and Kaspereit, T., 'The cross-section of returns, benchmark model parameters, and idiosyncratic volatility of nuclear energy firms after Fukushima Daiichi', *Energy Economics*, Vol. 41, 2014, pp. 125–136.

Minton, B. A. and Schrand, C., 'The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing', *Journal of Financial Economics*, Vol. 54, 1999, pp. 423–460.

Mohanty, S. K. and Nandha, M., 'Oil risk exposure: The case of the US oil and gas sector', *Financial Review*, Vol. 46, 2011, pp. 165–191.

Mossin, J., 'Equilibrium in a capital asset market', *Econometrica*, Vol. 34, 1966, pp. 768–783.

Newbery, D. M., 'Privatization, restructuring, and regulation of network utilities', *MIT Press*, 2002.

Newell, G. and Peng, H., 'The role of U.S. Infrastructure in investment portfolios', *Journal of Real Estate Portfolio Management*, Vol. 14, 2008, pp. 21–34.

Newey, W. K. and West, K. D., 'A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix', *Econometrica*, Vol. 55, 1987, pp. 703–708.

O'Neal, E. S., 'Why electric utility stocks are sensitive to interest rates', *Financial Review*, Vol. 33, 1998, pp. 147–162.

OECD, 'Infrastructure to 2030: Mapping policy for electricity, water and transport', Vol.2, 2007, *OECD publications*, Paris.

Pastor, L. and Stambaugh, R.F., 'Liquidity risk and expected stock returns', *Journal of Political Economy*, Vol. 111, 2003, pp. 642–685.

Peterson, J. D. and Hsieh, C. H., 'Do common risk factors in the returns on stocks and bonds explain returns on REITS?', *Real Estate Economics*, Vol. 25, 1997, pp. 321–345.

Ramos, S. B. and Veiga, H., 'Risk factors in oil and gas industry returns: International evidence', *Energy Economics*, Vol. 33, 2011, pp. 525–542.

Rödel, M. and Rothballer, C., ‘Infrastructure as hedge against inflation – Fact or fantasy?’, *Journal of Alternative Investments*, Vol. 15, 2012, pp. 110–123.

Rothballer, C. and Kaserer, C., ‘The risk profile of infrastructure investments: Challenging conventional wisdom’, *Journal of Structured Finance*, Vol. 18, 2012, pp. 95–109.

Sadka, R., ‘Liquidity risk and the cross-section of hedge-fund returns’, *Journal of Financial Economics*, Vol. 98, 2010, pp. 54–71.

Sadorsky, P., ‘Risk factors in stock returns of Canadian oil and gas companies’, *Energy Economics*, Vol. 23, 2001, pp. 17–28.

Sawant, R. J., ‘The economics of large-scale infrastructure FDI: The case of project finance’, *Journal of International Business Studies*, Vol. 41, 2010, pp. 1036–1055.

Sharpe, W. F., ‘Capital asset prices: A theory of market equilibrium under conditions of risk’, *Journal of Finance*, Vol. 19, 1964, pp. 425–442.

Sklavos, K., Dam, L., and Scholtens, B., ‘The liquidity of energy stocks’, *Energy Economics*, Vol. 38, 2013, pp. 168–175.

Sweeney, R. J. and Warga, A. D., ‘The pricing of interest-rate risk: Evidence from the stock market’, *Journal of Finance*, Vol. 41, 1986, pp. 393–410.

Treynor, J. and Mazuy, K., ‘Can mutual funds outguess the market’, *Harvard Business Review*, Vol. 44, 1966, pp. 131–136.

Part II

Insurance Asset Pricing is Different

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Abstract

Property/liability insurers are important financial institutions exposed to natural and man-made disasters. We first conduct a comprehensive asset pricing exercise for the U.S. property/liability insurance universe using monthly data from 1988-2013. We find that state-of-the-art models such as the Fama and French (2015) five-factor model cannot fully explain the abnormal returns of property/liability insurance stocks. Hence, we propose an insurance-specific five-factor asset pricing model which is able to explain these return anomalies. Priced factors include the book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility, which are primarily tied to exogenous events affecting insurance supply and demand such as catastrophes.

Keywords: Asset Pricing · Insurance Stocks · Factor Model · Anomalies · Cross-Section · Risk Factors
JEL classification: G12 · G22

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1 Introduction

Asset pricing models are expected to explain cross-sectional variation in stock returns. However, most asset pricing papers exclude insurance companies, banks, and other financial institutions from cross-sectional asset pricing tests (see, e.g., Brennan, Chordia, and Subrahmanyam (1998); Fama and French (2008); Hou, Xue, Zhang (2015)).[1] The exclusion of financial sector stock returns has typically gone largely unnoticed in the asset pricing literature; however, economically significant benefits could be associated with studying and investing in such stocks. Investors looking for portfolio diversification opportunities might benefit from investing in insurance stocks if their returns are exposed to distinct risks and thus are not perfectly correlated with the rest of the economy.

In this paper we argue that the insurance sector is different in terms of such risk characteristics and deserves an asset pricing model of its own. The motivation to study the insurance industry in isolation is threefold. First, even though state-of-the-art asset pricing models such as the Fama and French (2015) five-factor model or the Hou, Xue, Zhang (2015) four-factor model perform very well in a portfolio setting for the entire universe of stocks (often excluding financial firms), it is unclear how far this holds for the insurance sector. Second, by definition the insurance sector is different than other sectors (including banks) because of a few reasons: (a) it is exposed to risks largely uncorrelated with financial risk, such as catastrophe risk; (b) much of its business is based on reputational capital and (reimbursement) promises (see e.g. Milidonis (2013)) and (c) it faces a rather unique but homogeneous regulatory oversight. These reasons justify testing the hypothesis of whether known return anomalies that apply to non-insurance stocks would also apply on the insurance sector. The third motivating aspect results from the prior two: can we propose an insurance-specific asset pricing model that addresses the uniqueness of the publicly-traded insurance sector, which provides a lower correlation with the rest of the market (Ibragimov, Jaffee, and Walden (2009))?

[1] The reason for excluding financial firms is their high leverage, their "accounting treatment of revenues and profits [which] is significantly different than that in other sectors" (Opler and Titman (1994)), and the regulated nature of financial firms (Fama and French (2000)).

The focus of our analysis is the U.S. property/liability (p/l) insurance sector which contributes more than 3% to the U.S. GDP.[2] Moreover, it provides a risk pooling and risk management mechanism for individuals and institutions which cannot otherwise offload their risks and thus enables other economic activity. The insurers' investment portfolio, which includes collected insurance premiums on outstanding insurance contracts, offers an important source of capital to the economy. Recently, insurance risks have also been securitized (e.g. via cat bonds), thus providing a new market of financial instruments called insurance-linked securities.

In spite of the important economic role for both p/l insurance stocks and insurance-linked securities, the underlying risk exposure has not been subject to a great deal of debate in the academic literature. For example, although the analysis of the cross-sectional risk exposure is the heart of modern asset pricing (see, e.g., Garlappi and Yan (2011); Brennan et al. (2012); Eisfeldt and Papanikolaou (2013)), there is very little literature addressing the insurance context.[3]

Our paper closes this gap by analyzing the cross-section of expected p/l insurance stock returns. We propose a new insurance-specific asset pricing model that takes into account the unique characteristics (anomalies) of the insurance industry. We compare its performance to the performance of six existing asset pricing models using the universe of the 127 U.S. p/l insurance stocks on a monthly basis over the time period from 1988 to 2013. We sort insurance stocks on 22 well-known and potential anomalies from the finance and insurance literature and test our model to the six competing models by running time-series regressions, Fama–MacBeth (1973) regressions, and testing the equality of the Hansen-Jagannathan distance (Kan and Robotti (2009)).

We also contribute to the discussion on interest rate exposure, leverage, size, and other firm characteristics discussed in the literature, which so far

[2] https://research.stlouisfed.org/fred2/series/DDDI10USA156NWDB

[3] An exception is Barber and Lyon (1997), who sort portfolios of financial firms, to some extent analyzing the cross-section of insurance stocks, although no formal tests are conducted in their paper.

has focused on the time-series relation (see, e.g., Brewer et al. (2007); Carson, Elyasiani, and Mansur (2008)). Moreover, this study can be considered as an out-of-sample test on the accuracy of asset pricing models in general. One central critique in asset pricing is the data snooping bias (Lo and MacKinlay (1990)) through portfolio formation, which is why Lewellen, Nagel, and Shanken (2010) emphasize the use of different test assets. All assets should be priced by one stochastic discount factor and insurance stocks might be one of the most challenging test assets, since their risk exposure is theoretically different from other stocks due to the above mentioned reasons.[4]

The central findings of this paper are that the existing asset pricing models fall short of explaining a large proportion of the cross-sectional variation of insurance stock returns, while the proposed insurance-specific asset pricing model significantly improves the explanation of the insurance-specific cross-sectional variation. Our results on insurance companies thus complement those of Viale, Kolari, and Fraser (2009) on banks. Specifically, the most significant pricing factors for p/l insurance stocks are the book-to-market (B/M) ratio, short-term reversal, illiquidity, and cashflow volatility. The book-to-market effect is related to the default likelihood (Vassalou and Xing (2004)) and illiquidity is attributable to small insurance stocks with low trading volume and high bid–ask spreads. The short-term reversal anomaly holds against a battery of robustness tests and earns up to 25% p.a., corroborating the findings of Hameed and Mian (2015) for intra-industry reversals. The cashflow volatility anomaly is related to the reinsurance cycle: insurers with high cashflow volatility in the past, experience a higher deterioration of their returns than low cashflow volatility insurers during catastrophic events. However, high cashflow volatility insurers quickly recover after the event, possibly due to an overreaction during the catastrophic event, or a potential increase in insurance demand in the immediate aftermath of a high-impact event such as a natural disaster.

The remainder of this paper is organized as follows. Section 2 gives a brief

[4] Thus, to some extent, our study is also similar in nature to Ang, Shtauber, and Tetlock (2013), who investigate the pricing of OTC traded stocks as a special case of test assets. In contrast to the listed market, they find that the OTC liquidity premium is significantly larger, whereas the momentum premium is significantly lower.

literature review. Section 3 describes the anomalies and highlights the benchmark model. Section 4 provides a description of the data and the methodology. Section 5 shows the empirical results. Section 6 looks at stock returns and catastrophe risk. Section 7 checks for robustness, and Section 8 concludes.

2 Literature review

Cummins and Harrington (1988) test the CAPM on p/l insurance stocks and find that it is correctly specified during the period 1980–1983, but inconsistent in earlier periods. Barber and Lyon (1997) analyze the cross-section of financial firms for the time period July 1973 to December 1994 and find that size and B/M patterns also exist in financial firms. Although their study sorts all insurance stocks by size and book-to-market ratio, they do not explicitly discuss insurance stocks and do not provide further statistics or asset pricing tests to analyze the cross-sectional relationship.

More recent related research on insurance analyzes cost of equity estimation (Cummins and Phillips (2005); Wen et al. (2008)) and the time series characteristics of insurance stocks (Brewer et al. (2007); Carson, Elyasiani, and Mansur (2008)).[5] Cummins and Phillips (2005) investigate the cost of equity for p/l insurers using the CAPM and the Fama–French (1993) three-factor model. They find that the cost of capital estimates of Fama and French's (1993) three-factor model are significantly higher than those of the CAPM. The authors explicitly note that they do not intend to "study asset pricing anomalies or to develop and test a multi-factor asset pricing model," but rather to estimate "divisional costs of capital by line for property-liability insurers" (Cummins and Phillips (2005), p. 449).

Wen et al. (2008) evaluate a model by Rubinstein (1976) and Leland

[5]Note that significant coefficients in a time-series regression can only be an initial indicator of risk. For example, the market factor is highly correlated with stock returns and yet does not capture risk in the sense that a higher exposure leads to higher returns. Rather, the market factor can be seen as a level factor capturing the grand mean. Including the market factor thus makes sense even if it does not capture the cross-section of stock returns (Ferson, Sarkissian, and Simin (1999)).

(1999), which captures the skewness and kurtosis in the market beta. They run panel regressions of the absolute difference between basic CAPM betas and Rubinstein–Leland (1976, 1999) model betas (as dependent variable) against firm-level characteristics. They find that the absolute difference is significantly influenced by firm size, degree of leverage, and skewness. Although their paper does not employ traditional asset pricing tests, it is a good starting point for asset pricing in the insurance industry as they report abnormal returns using single-sorted portfolios based on size, skewness, degree of normality, and subperiods.[6]

More literature exists on the time-series correlation between factors and insurance stock returns. Brewer et al. (2007) address the interest rate sensitivity of life insurers and find that their returns are negatively correlated with changes in interest rates. Carson, Elyasiani, and Mansur (2008) investigate the market risk, interest rate risk, and interdependencies across insurance industries within a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) time-series framework and find greater market exposure in life and health insurers compared to p/l insurers. They also find that interest rate sensitivity is negative and greatest for life insurers, while interdependencies in returns are strongest between p/l and health insurers.[7]

Regarding the bank literature, Viale, Kolari, and Fraser (2009) analyze the cross-section of bank stocks in general. Using size and B/M sorted portfolios as test assets, they find that the market excess return and shocks to the slope of the yield curve explain the cross-section of expected bank stock returns. In contrast to the portfolio sorting results of Barber and Lyon (1997), they find no evidence of SMB or HML being priced in bank stock returns. Gandhi and Lustig (2015) specifically analyze commercial banks and show that the size anomaly in U.S. commercial bank stocks differs from the overall equity market,

[6] Cummins and Lamm-Tennant (1994) derive a factor model that accounts for both financial and insurance leverage. They stress contradictory results on insurance leverage, referring to Fairley (1979) and Cummins and Harrington (1985), and show that the two leverage factors have a significant positive impact on the insurers' equity CAPM betas.

[7] Interestingly, none of them or any other study analyzed liquidity risk or momentum patterns, two topics that have received wide attention in the finance literature over the last years.

since large banks are "too big to fail," and thus such banks earn significantly lower returns than smaller banks.

3 Benchmark model and potential anomalies

Our main benchmark model in the empirical part is the Fama–French (2015) five-factor model, which performs well in capturing stock return anomalies and has the same number of factors as our insurance-specific five-factor model. We decide to use Fama and French's (2015) five-factor model as they include financial firms in their factor construction, while on the other hand the competing model of Hou, Xue, and Zhang (2015) explicitly excludes financial firms. The central hypothesis (H_0) throughout the paper is thus that the Fama and French (2015) model is the correctly specified model to explain the cross-section of insurance stock returns.

Furthermore, we hypothesize that the most popular anomalies in the (non-financial, U.S.) equity market are either not present in insurance stocks or different in magnitude and/or direction compared to other industries for the following reasons. First, financial institutions tend to be excluded from asset pricing tests. Second, p/l insurers are exposed to large losses through catastrophes that can exceed their capital sources (Cummins, Doherty, and Lo (2002)). These losses from natural disasters (which do not need to be large in magnitude) expose insurance stock returns to risks that the rest of the market does not experience, or if they do, they typically transfer this risk exposure to the insurance sector (Ibragimov, Jaffee, and Walden (2009)).

Due to these aspects, we argue that insurers are different than the rest of the equity market, either because some risk factors are not priced at all in the insurance sector, or these risk factors are priced at a different magnitude, or because the insurance sector is priced by a different set of factors than the general equity market. Specifically, we consider 22 well-known and potential anomalies from the finance and insurance literature (see e.g. Hou, Xue, and Zhang (2015) or Cummins and Lamm-Tennant (1994)) which might exist in insurance stocks and which can be summarized in the following 12 broad categories[8]:

1. Market risk: We expect that the market beta itself is not priced as a risk factor identical to the findings of broad-based studies (Fama and French (1992)) and previous findings by Cummins and Harrington (1988) on p/l insurers for earlier periods but downside and upside beta might be important in the cross-section of insurance stock returns (Ang, Chen, and Xing (2006)).

2. B/M ratio: Insurers with high B/M ratios might earn higher returns. However, under the premise of the B/M ratio approximating some type of distress risk (Chen and Zhang (1998)) and given that p/l insurers are exposed to non-market-related externalities (catastrophes), the B/M ratio of insurers might have a different time-series pattern.

3. Size (market capitalization): Larger insurers might earn lower returns as they might have a more diversified insurance portfolio and thus a lower risk exposure. Possibly, larger insurers are considered "too big to fail" and thus earn lower returns as a result of this guarantee (see Gandhi and Lustig (2015)).

4. Past returns (momentum, prior month return, reversal): Past "winning" insurers should outperform past "losing" insurers (Jegadeesh and Titman (1993)). We also test whether previous-month returns (i.e., short-term reversal) predict the cross-sectional behavior (Jegadeesh (1990); Hameed and Mian (2015)) and whether a long-term reversal (De Bondt and Thaler (1987)) exists when insurers are sorted by their returns over the past 36 months.

5. Liquidity (market-wide liquidity): The 2008 financial crisis has illustrated the importance of liquidity for financial institutions (Brunnermeier and Pedersen (2009)). We thus test whether liquidity as defined by Pàstor and Stambaugh (2003) has a cross-sectional impact on insurers' stock returns. Specifically, we hypothesize that a stronger exposure to the market illiquidity of insurance stocks requires a risk premium and thus higher returns.

[8] For a detailed description of the anomalies and the portfolio formation, see Appendix B.

6. Leverage (total, insurance, financial, broker/dealer): Total, insurance, and financial leverage relate to default risk (Bhandari (1988); Cummins and Lamm-Tennant (1994)). Broker/dealer leverage relates to the fact that insurers might be exposed to the leverage adjustments of sophisticated market participants (i.e., broker/dealers) whose leverage "is a good empirical proxy for the marginal value of wealth" (Adrian, Etula, and Muir (2014)).

7. Interest rates (term structure and default risk): Large investments in bonds suggest that changes in interest rates have an impact on the cross-section of insurance stocks. An asset allocation towards long-term bonds and corporate bonds (instead of government bonds) should result in higher returns (Carson, Elyasiani, and Mansur (2008)).

8. Volatility (cashflow volatility, idiosyncratic risk): Both cashflow volatility (Huang (2009)) and idiosyncratic risk (with respect to the Fama–French (1993) three-factor model, Ang et al. (2006)) result in lower returns the larger the respective exposure. The volatility measures relate to the fact that information uncertainty creates negative future returns. With insurance stocks being exposed to uncertainty about claims payments to policyholders, the relationship between information uncertainty and cross-sectional patterns might be of great interest.

9. Distribution (co-skewness, co-kurtosis, downside risk, upside risk): Distribution-linked variables could be related to the heavy tails of insurance claims and thus have predictive power on returns. We consider co-skewness (Harvey and Siddique (2000)), co-kurtosis (Fang and Lai (1997); Dittmar (2002)), and downside (upside) movements with the market (Ang, Chen, and Xing (2006)).

10. Investments: Similar to the interest rate exposure, we argue that historically higher investment income should lead to higher future investment income (Badrinath and Wahal (2002)) and relate the investment cashflow to the cross-sectional return behavior.

11. Asset growth: Stocks with previously high asset growth show on average lower returns compared to low asset growth firms (Cooper, Gulen, and

Schill (2008)). One explanation is that investors overextrapolate past gains to growth. We test whether a similar negative relation between asset growth and expected returns exists for insurance stocks. Asset growth is also used by both Fama and French (2015) and Hou, Xue, and Zhang (2015) as a proxy for investment activity.

12. Profitability: Both Fama and French (2015) and Hou, Xue, and Zhang (2015) consider profitability as a key variable to define the discount rate meaning that a firm with higher expected profitability given a certain asset base should earn higher returns than a low profitability firm.

4 Data and methodology

Two approaches are commonly used in the asset pricing literature to analyze the cross-section of returns. The first is to examine portfolios of returns sorted by different characteristics in order to identify monotonic return patterns that cannot be explained by standard asset pricing models. The second approach is to run Fama–MacBeth (1973) regressions of portfolios or individual stocks within different model frameworks. After sorting insurance stocks in portfolios to identify return patterns, we also run Fama–MacBeth (1973) regressions on both individual stocks and single-sorted portfolios.

4.1 Asset pricing models

Asset pricing models impose a linear relationship between expected returns and beta, which is why asset pricing models are in general known as beta-pricing models.[9] To test this relationship, we run the Fama–MacBeth (1973) two-pass regression methodology. The general setting of the first-pass time-series regression for each stock $i = 1,..,N$, with K factors is defined as:

$$R_{i,t}-R_{f,t}=\alpha_i+\sum_{k=1}^{K}\beta_{i,k}f_{k,t}+\epsilon_{i,t}, \tag{1}$$

[9] Depending on the number of factors (K), this is also known as a K-factor beta-pricing model (see Kan, Robotti, and Shanken (2013)).

where $R_{i,t}-R_{f,t}$ is the excess return of stock i over the risk-free rate, $\beta_{i,k}$ is the sensitivity of stock i to factor k, and $f_{k,t}$ is the realization of factor k at time t. The idiosyncratic return of stock i at time t is denoted by $\epsilon_{i,t}$.

The second-pass cross-sectional regressions of the Fama–Macbeth (1973) method use the beta estimates from time-series regressions as independent variables and estimates at each time period t in the following regression:

$$R_{i,t}-R_{f,t} = z_t + \sum_{k=1}^{K} \lambda_{k,t}\hat{\beta}_{k,i,t} + \alpha_{i.t}, \tag{2}$$

where z is the zero-beta rate with expected mean of zero, λ_k is the risk premium of factor k, $\hat{\beta}_{k,i}$ is the beta estimate from a time-series regression, and α_i are the residuals (i.e., pricing errors) of each stock i in the cross-section.

We test six models from the finance literature and later derive an empirically driven model for insurance stocks, which is the seventh model to be tested. The first model we test is the CAPM, which is the only model tested in the insurance literature so far (Cummins and Harrington (1988)). The cross-sectional specification for the CAPM is:

$$\mathrm{E}\left(R^e\right) = z + \lambda_{MKT}\beta_{i,MKT}, \tag{3}$$

where $\mathrm{E}\left(R^e\right)$ is the expected excess return of insurance stock i and MKT refers to the excess return of the stock market index.

The second model is the empirically motivated Fama–French (1993) three-factor model and extends the CAPM by a size (SMB) and a value (HML) factor, with the cross-sectional model being:

$$\mathrm{E}\left(R^e\right) = z + \lambda_{MKT}\beta_{i,MKT} + \lambda_{SMB}\beta_{i,SMB} + \lambda_{HML}\beta_{i,HML}, \tag{4}$$

where SMB is a zero-investment portfolio between stocks of small and large market capitalizations, and HML is a zero-investment portfolio between stocks with high and low B/M ratios.

The third model extends the Fama–French (1993) three-factor model with a momentum factor following Carhart (1997):

$$\mathrm{E}\left(R^{e}\right)=z+\lambda_{MKT}\beta_{i,MKT}+\lambda_{SMB}\beta_{i,SMB}+\lambda_{HML}\beta_{i,HML}+\lambda_{MOM}\beta_{i,MOM}, \quad (5)$$

where *MOM* is a zero-investment portfolio that is calculated as the spread between returns of stocks with positive returns and those with negative returns over the months *t–12* to *t–2*.

The fourth model is the five-factor model by Petkova (2006), which is set in an ICAPM framework. Petkova (2006) uses innovations in the term spread, the default spread, the aggregate dividend yield of the S&P 500, and the 1-month T-Bill rate. The cross-sectional relation is:

$$\begin{aligned} \mathrm{E}\left(R^{e}\right) &= z+\lambda_{MKT}\beta_{i,MKT}+\lambda_{\hat{u}^{div}}\beta_{i,\hat{u}^{div}}+\lambda_{\hat{u}^{TERM}}\beta_{i,\hat{u}^{TERM}} \\ &+ \lambda_{\hat{u}^{DEF}}\beta_{i,\hat{u}^{DEF}}+\lambda_{\hat{u}^{RF}}\beta_{i,\hat{u}^{RF}}, \end{aligned} \quad (6)$$

where $\hat{u}^{div}$ refers to innovations in the dividend yield of the stock market, $\hat{u}^{TERM}$ are innovations in *TERM*, where *TERM* is identical to the previous definition, $\hat{u}^{DEF}$ are innovations in *DEF*, and $\hat{u}^{RF}$ are innovations in the 1-month T-Bill (*RF*). Identical to Petkova (2006) and Kan, Robotti, and Shanken (2013), we extract innovations from a first-order vector autoregressive (VAR(1)) system comprising seven state variables, which are *MKT, SMB*, *HML*, *TERM*, *DEF*, *DIV*, and *RF.* We follow Petkova (2006) and first demean the state variables in the VAR(1) system and then orthogonalize the innovations of the state variables to the excess market factor for interpretational reasons.

In a fifth model we look at the Hou, Xue, and Zhang (2015) four-factor model which includes the market excess return, the SMB factor, an investment factor (IA), and a profitability factor (ROE). The investment factor is a long portfolio in low investment stocks and a short portfolio in high investment stocks. Investment is defined as the annual change in total assets divided by one-year-lagged total assets. The profitability factor is defined as a long portfolio in stocks with high profitability (i.e., high return on equity) and a short portfolio in stocks with low profitability (i.e., low return on equity). Profitability is defined as net income before extraordinary items divided by book equity:

$$\mathrm{E}\left(R^{e}\right)=z+\lambda_{MKT}\beta_{i,MKT}+\lambda_{SMB}\beta_{i,SMB}+\lambda_{IA}\beta_{i,IA}+\lambda_{ROE}\beta_{i,ROE}. \quad (7)$$

The sixth model is the Fama and French's (2015) five-factor model, is very similar to Hou, Xue, and Zhang's (2015) four-factor model except for keeping the HML factor and a slightly different factor construction. It extends the Fama and French (1993) three-factor model by an RMW and a CMA factor. The RMW factor is defined as the difference between a strong and a weak profitability return portfolio and CMA is defined as the difference between stocks of low and high investment activity in terms of total assets:

$$\begin{aligned}\mathrm{E}\left(R^{e}\right) &= z+\lambda_{MKT}\beta_{i,MKT}+\lambda_{SMB}\beta_{i,SMB}+\lambda_{HML}\beta_{i,HML} \quad (8)\\ &+ \lambda_{RMW}\beta_{i,RMW}+\lambda_{CMA}\beta_{i,CMA}.\end{aligned}$$

The insurance-specific model that we propose, takes into account the unique features of insurance stocks, which stem primarily from their exposure to extraordinary risks that are uncorrelated with returns from the rest of the market, such as catastrophe risk. Henceforth we refer to this model as the insurance five-factor (INS-5) model. The INS-5 model's five factors are: (a) the excess market return (MKTRF); (b) a zero-investment portfolio sorted by B/M ratio (BMF); (c) a zero-investment portfolio sorted by prior month return; (d) a zero-investment portfolio sorted by liquidity exposure (LQF); and (e) a zero-investment portfolio sorted by cashflow volatility (CFVF). Formally, the cross-sectional relation of this insurance-specific five factor model (INS-5) is described as:

$$\begin{aligned}\mathrm{E}\left(R^{e}\right) &= z+\lambda_{MKT}\beta_{i,MKT}+\lambda_{BMF}\beta_{i,BMF}+\lambda_{PRETF}\beta_{i,PRETF} \quad (9)\\ &+ \lambda_{LQF}\beta_{i,LQF}+\lambda_{CFVF}\beta_{i,CFVF}.\end{aligned}$$

More details on the derivation and economic interpretation of the factors are discussed below.

4.2 Data

Our sample consists of all traded U.S. p/l insurers with SIC code 6331.[10] We only include U.S. common stocks (excluding ADR and units of beneficiary interest) and exclude stocks with negative book values. We further delete stocks with unreported book equity in year *t-1.* To be included in our dataset, stocks must also have at least 36 months of consecutive return data. Our data spans a period of more than 25 years (July 1988 to December 2013).[11] Appendix A reports the number of stocks per year in our sample.

Stock return data and accounting information are retrieved from CRSP and COMPUSTAT, respectively. The Fama–French (2015) factors, the 1-month T-Bill yield, and the momentum factor are downloaded from Kenneth French's website. Data on Hou, Xue, and Zhang's (2015) factors are available from the authors of the paper.[12] The dividend yield on the S&P 500 is downloaded from Robert Shiller's website (`http://aida.wss.yale.edu/~shiller/data.htm`). Data on the broker/dealer leverage factor comes from Tyler Muir's website (`http://faculty.som.yale.edu/tylermuir/data.html`). The liquidity factor from innovations is retrieved from Robert Stambaugh's website (`http://finance.wharton.upenn.edu/~stambaugh/liq_data_1962_2012.txt`) The term spread, its changes, and innovations are constructed from the spread between 10-year Treasury and 1-year Treasury constant maturity rates. The default spread, its changes, and innovations are constructed from Moody's seasoned Baa corporate bond yield and the 10-year Treasury rate. All interest yields are retrieved from the FRED® database of the Federal Reserve Bank of St. Louis.

[10] We use the SIC code classification based on COMPUSTAT, as this classification is more accurate to the actual industry classification (Kahle and Walkling (1996)).

[11] Asset pricing studies should span at least 20 years (see Cochrane (2005), p. 287) to draw any conclusions. Also, insurance stocks before 1987 drastically reduce both in absolute numbers (i.e., while there are 61 p/l insurers in 1987, there are only 41 in 1986 and the number continues to decrease further back in time) and in the availability of accounting data.

[12] We would like to thank Lu Zhang for providing us the data.

5 Empirical evidence

We first present results of single-sorted portfolios (Section 5.1), followed by time series and cross-sectional regression analyses of insurance stocks (Sections 5.2 to 5.6). We also provide economic interpretations of our results (Section 5.7).

5.1 Stock return anomalies

Following the finance literature that analyzes the cross-section of stock returns (e.g., Vassalou and Xing (2004); Cooper, Gulen, and Schill (2008)) we first sort portfolios by characteristics of insurance stocks to evaluate their return pattern. This allows us also to compare their pattern with the non-financial sector and to evaluate insurance-specific characteristics.[13] We sort insurance stocks based on 22 characteristics introduced in Section 3 (see also Appendix B for a detailed description of the variables and the portfolio formation).[14]

We follow Barber and Lyon (1997) in using equally weighted portfolios to avoid giving too much weight to a few large insurers in our small sample, which would thus bias the actual return pattern (illustrating idiosyncratic instead of systemic risk). Between 1988 and 2013 AIG and Travelers together constituted on average more than 38 percent of the entire p/l market capitalization in our sample. Furthermore, equally weighted returns are more in line with Fama–MacBeth (1973) regressions, which equally weight each stock. Table 1 presents average monthly returns of characteristic-sorted portfolios for p/l insurers.

Following Fama and French (1993) in their factor construction and Fama and French (2008) in focusing on the most extreme return portfolios, we break insurance stocks into three groups based on the breakpoints for the bottom

[13] Sorting portfolios and analyzing the mean returns of these portfolios give an idea of inherent return premiums, which is why the spread between portfolios sorted by high and low exposures to a characteristic are often considered as risk factors. Another advantage of the portfolio formation is that they do not require linearity assumptions in contrast to regression analyses. However, the disadvantage of portfolio sorting "are that confounding effects can obfuscate return premiums based on univariate sorts" (Ang, Shtauber, and Tetlock (2013)) leading to ambiguous inferences.

[14] All portfolio returns are sorted by their past characteristics to avoid a look-ahead bias. All information is known at the date of portfolio formation and thus the portfolios are tradable.

20% (low), middle 60% (mid), and top 20% (high) of the ranked values of each characteristic.[15] The CAPM alphas, FF-3 alphas, the HXZ-4 alphas, and the FF-5 alphas in Panel A of Table 1 are the abnormal returns from a spread portfolio between the high and low sorted return portfolios. A significant spread indicates that the return difference cannot be explained by the respective factor model. Panel B of Table 1 reports the alpha values of the FF-5 factor model and shows which insurance stock portfolio is most difficult to price for the model.

First, we see that against the theoretical prediction of the CAPM, p/l insurance stocks sorted by CAPM beta do not result in higher returns the higher the beta exposure. This is not surprising, as the CAPM has also been rejected for p/l insurers and non-financial firms in the past (Cummins and Harrington (1988); Fama and French (1992)). Furthermore, we do not find a significant size effect, although the monotonic pattern of higher returns for small insurers and low returns for large insurers is identical to non-financial firms (Fama and French (1993)).[16] Only the HXZ-4 model suggests a size anomaly as it is not able to capture this effect. Possibly the investment and profitability factors exaggerate the size anomaly resulting in a significant intercept. This result does not hold in other model specifications including the Fama and French (2015) five-factor model. We do, however, find a significant effect in all model specifications for the B/M ratio. The monthly return spread between low B/M and high B/M returns is 0.83%.

The fact that the CAPM (Table 1, Panel A) cannot explain the return difference between low and high B/M portfolios is not surprising; it is why Fama and French (1993) developed the HML factor to explain this return variation. But interestingly, the FF-3 and the FF-5 factor models, which explicitly include this B/M-related factor, are not able to capture the return difference in B/M portfolios. Especially, those insurers with high B/M ratio are a challenge to the FF-5 factor model (Table 1, Panel B). This suggests that the B/M ratio for p/l stocks has a different pricing cycle or simply a different meaning than the B/M ratio in non-insurance stocks.

[15] In later robustness tests (Section 7), we also look at ten return portfolios.

[16] We also used total assets instead of market capitalization and did not find a significant size effect either.

Table 1: Sorted portfolios

Panel A: Average monthly returns of characteristic-sorted portfolios and spreads from p/l insurers (in % per month, July 1988–December 2013)

Quantile	β_{CAPM}	β^{+}	β^{-}	Size	B/M	MOM	RET$_{t-1}$	β_{LIQ}	REV	ID-VOLA	CF-VOLA	CO-SKEW	CO-KURT	Asset Growth	OP	$\beta_{\Delta TERM}$	$\beta_{\Delta DEF}$	$\beta_{B/D\ LEV}$	INVEST	INS LEV	FIN LEV	Total LEV
1 (low)	1.28	1.14	1.24	1.30	0.83	1.03	2.23	0.94	1.53	1.05	1.20	1.27	1.34	1.38	1.14	0.87	1.36	1.15	1.09	0.70	1.08	0.74
2 (mid)	0.95	1.03	1.04	1.04	1.01	1.09	1.04	1.07	0.97	1.09	1.20	1.04	1.01	1.03	1.05	1.11	1.08	0.85	1.03	1.16	0.99	1.12
3 (high)	1.33	1.26	1.10	1.02	1.66	1.16	0.09	1.40	1.07	1.24	0.34	1.09	1.09	1.10	1.14	1.33	0.90	1.40	1.37	1.29	1.33	1.37
Spread (3-1)	0.06 [0.21]	0.11 [0.36]	-0.13 [-0.48]	-0.28 [-0.87]	0.83*** [2.82]	0.13 [0.37]	-2.14*** [-7.31]	0.46* [1.84]	-0.46 [-1.53]	0.19 [0.57]	-0.84** [-2.47]	-0.17 [-0.69]	-0.25 [-1.03]	-0.28 [-1.11]	0.00 [0.00]	0.46 [1.50]	-0.46 [-1.56]	0.26 [0.95]	0.28 [1.23]	0.58* [1.68]	0.25 [0.94]	0.63* [1.82]
CAPM Alpha (Spread)	-0.00 [-0.04]	0.04 [0.11]	-0.31 [-1.18]	-0.24 [-0.68]	0.65** [2.23]	0.37 [1.22]	-2.04*** [-7.10]	0.30 [1.31]	-0.29 [-0.97]	-0.18 [-0.64]	-1.08*** [-3.38]	-0.11 [-0.41]	-0.20 [-0.86]	-0.20 [-0.83]	0.15 [0.56]	0.29 [1.02]	-0.24 [-0.86]	0.31 [1.12]	0.26 [1.10]	0.37 [1.18]	0.09 [0.39]	0.44 [1.36]
FF-3 Alpha (Spread)	-0.22 [-0.88]	-0.13 [-0.42]	-0.25* [-1.67]	-0.45 [-1.51]	0.64** [2.26]	0.43 [1.50]	-2.01*** [-6.84]	0.22 [0.96]	-0.21 [-0.72]	-0.23 [-0.80]	-1.15*** [-3.56]	-0.13 [-0.48]	-0.18 [-0.75]	-0.14 [-0.58]	0.14 [0.49]	0.22 [0.76]	-0.18 [-0.66]	0.30 [1.14]	0.25 [1.01]	1.34 [0.50]	-0.08 [-0.38]	0.18 [0.65]
HXZ-4 Alpha (Spread)	-0.56* [-1.94]	-0.39 [-1.02]	-0.59* [-1.83]	-0.71** [-2.28]	0.75** [2.47]	-0.17 [-0.49]	-1.97*** [-5.87]	0.39 [1.56]	-0.44 [-1.51]	0.19 [0.71]	-0.76** [-2.52]	-0.30 [-1.00]	-0.31 [-1.15]	-0.51* [-1.95]	-0.18 [-0.63]	-0.16 [0.55]	-0.21 [-0.79]	0.16 [0.48]	0.51** [2.16]	-0.05 [-0.14]	-0.28 [-1.08]	-0.05 [-0.15]
FF-5 Alpha (Spread)	-0.25 [-0.83]	-0.12 [-0.34]	-0.30 [-0.94]	-0.27 [-0.77]	0.84*** [2.76]	0.26 [0.73]	-2.03*** [-6.09]	0.33 [1.29]	-0.36 [-1.25]	-0.03 [-0.09]	-0.96*** [-2.70]	-0.28 [-1.00]	-0.18 [-0.75]	-0.33 [-1.26]	0.08 [0.24]	0.24 [0.77]	-0.10 [-0.37]	0.13 [0.52]	0.31 [1.23]	0.25 [0.75]	-0.06 [-0.23]	0.26 [0.72]
# of obs.	306	306	306	306	306	306	306	306	306	306	306	306	306	306	306	306	306	258	306	306	306	306

Panel B: Alphas from Fama and French (2015) five-factor model regressions (in % per month, July 1988–December 2013)

Quantile	β_{CAPM}	β^{+}	β^{-}	Size	B/M	MOM	RET$_{t-1}$	β_{LIQ}	REV	ID-VOLA	CF-VOLA	CO-SKEW	CO-KURT	Asset Growth	OP	$\beta_{\Delta TERM}$	$\beta_{\Delta DEF}$	$\beta_{B/D\ LEV}$	INVEST	INS LEV	FIN LEV	Total LEV
1 (low)	0.34* [1.80]	0.17 [0.73]	0.23 [1.29]	0.14 [0.60]	-0.16 [-0.68]	-0.15 [-0.60]	1.06*** [4.67]	-0.11 [-0.52]	0.35 [1.65]	0.11 [0.65]	0.23 [1.21]	0.24 [1.08]	0.23 [1.05]	0.31 [1.51]	-0.06 [-0.24]	-0.13 [0.52]	0.04 [0.22]	0.20 [0.42]	0.03 [0.12]	-0.29* [-1.68]	0.17 [1.01]	-0.24 [-1.33]
2 (mid)	-0.04 [-0.25]	0.03 [0.22]	0.04 [0.30]	0.07 [0.45]	-0.05 [-0.32]	0.11 [0.75]	0.05 [0.37]	0.06 [0.46]	-0.04 [-0.27]	0.05 [0.32]	0.17 [1.09]	0.04 [0.25]	0.01 [0.06]	0.04 [0.25]	0.08 [0.48]	0.10 [0.68]	0.09 [0.61]	-0.19 [-1.12]	-0.02 [-0.12]	0.20 [1.14]	-0.03 [-0.16]	0.16 [0.96]
3 (high)	0.08 [0.35]	0.04 [0.17]	-0.07 [-0.26]	-0.13 [-0.57]	0.68*** [2.64]	0.11 [0.50]	-0.97*** [-3.88]	0.22 [0.93]	-0.01 [-0.04]	0.08 [0.33]	-0.74** [-2.42]	-0.04 [-0.23]	0.04 [0.20]	-0.02 [-0.09]	0.02 [0.10]	0.11 [0.47]	-0.05 [-0.25]	0.23 [1.13]	0.34 [1.49]	-0.04 [-0.13]	0.10 [0.45]	0.02 [0.06]

All data are monthly returns (in %). T-statistics are presented in brackets and calculated from Newey-West standard errors with lags of five. The sample period is July 1988 to December 2013. Panel A reports raw returns from low to high exposure for each variable presented in the first row. Panel A also reports the return spread between high minus low exposure, the intercept from time-series regressions of the CAPM (i.e., CAPM Alpha (Spread)), the Fama and French (1993) factor model (i.e., FF-3 Alpha (Spread)), the Hou, Xue, Zhang (2015) four factor model (i.e., HXZ-4 Alpha (Spread)), and the Fama and French (2015) five-factor model (i.e., FF-5 Alpha (Spread)). Panel B reports the intercepts from time-series regressions of the FF-5 factor model for each portfolio from low to high exposure for each variable presented in the first row of Panel B. Portfolios in Panel B are excess returns over the 1-month T-Bill rate for the low to high exposures. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We also find that the past month return is a strong predictor for the following month return. Specifically, a positive return in the previous month results in a negative return in the following month and vice versa. The spread is significant, with an average return of 2.14% per month. Direction and size of the variable are similar to Jegadeesh (1990), who reports a monthly return of 2.49%. In further robustness tests we confirm that this effect is not attributable to small insurers, market microstructure, or specific time periods. One explanation for this effect pertains to liquidity provisions by market makers and institutional investors who are forced to sell their shares during volatile times (Hameed and Mian (2015)). Note also that momentum-sorted portfolios do not create a significant spread, which is distinct from the finance literature. Moreover, we observe a strong return pattern based on past cashflow volatility. The monthly return spread is 0.84%. The result that lower cashflow volatility leads to higher returns is in line with Huang (2009), who also finds a negative relation between returns and cashflow volatility. Another important aspect is that low and medium portfolios share the same return, but it is the portfolio with the highest cashflow volatility that drops significantly in its risk compensation and leads to a significant spread. The abnormal return spread from cashflow volatility can be explained neither by the FF-5 nor the HXZ-4 model. Portfolios sorted by insurance leverage, total leverage, and liquidity result in a monotonic pattern and a significant return spread. However, this spread difference can be explained by the CAPM.

5.2 Fama–Macbeth (1973) regression with individual stock returns

Having analyzed univariate portfolio sorts, we now turn to the cross-sectional regressions to validate these results and to see whether other model specifications can explain them. We first run univariate Fama–Macbeth (1973) regressions on the insurance stock returns for each independent variable. Table 2 shows the results and confirms that B/M, prior month return, and cashflow volatility are significantly priced. We also find that liquidity is priced in the cross-section (but not insurance or total leverage). In contrast to our portfolio sorting, we now also find that beta exposure from changes in the term structure and beta exposure from changes in the default premium are priced cross-sectionally.

Following univariate Fama–MacBeth (1973) regressions, we further investigate the different pricing components in a multivariate framework to analyze the variables' unique pricing ability. Table 3 shows the results from Fama–Macbeth (1973) regressions with several robustness tests of all significant variables from univariate regressions.

These results are robust to variations in the sample's market capitalization, trading volume, and relative bid–ask spread, except for liquidity, which becomes insignificant if we exclude the fifth percentile of smallest stocks (in terms of market capitalization), followed by the exclusion of the fifth percentile of least traded insurance stocks (in terms of dollar trading volume), and stocks above the 95^{th} percentile with the highest relative bid–ask spread. We again confirm that B/M, prior month return, cashflow volatility, and liquidity remain significant in a multivariate framework, corroborating the fact that these variables are indeed priced in the cross-section of insurance stocks. It should be noted that liquidity becomes insignificant in our last and most demanding robustness test where we exclude 15% percent of our total sample size (Table 3, Model V), suggesting that the liquidity anomaly is attributable to small, less frequently traded insurance stocks with high bid–ask spreads.

Table 2: Fama–MacBeth (1973) regressions with individual stock returns (univariate)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)
Independent variable	β	β^+	β^-	**Size**	**B/M**	**MOM**	**RET**$_{t-1}$	β_{LIQ}	**REV**	**ID-VOLA**	**CF-VOLA**
Coefficient	0.24 [0.93]	0.04 [0.20]	-0.04 [-0.18]	-0.07 [-1.18]	0.49** [2.16]	0.08 [0.16]	-9.51*** [-7.16]	0.75* [1.77]	-0.41 [-1.35]	4.41 [0.43]	-3.19** [-2.57]
Const. (z)	0.73*** [2.56]	0.84*** [3.11]	0.80*** [2.98]	1.70** [2.29]	0.34 [1.17]	0.59** [2.40]	0.96*** [3.17]	0.75*** [2.88]	0.93*** [3.46]	0.67** [2.40]	0.94*** [3.53]
Avg. R^2	0.05	0.05	0.04	0.05	0.04	0.02	0.04	0.03	0.04	0.05	0.05

	(XII)	(XIII)	(XIV)	(XV)	(XVI)	(XVII)	(XVIII)	(XIX)	(XX)	(XXI)	(XXII)
Independent variable	**CO-SKEW**	**CO-KURT**	**Asset Growth**	**OP**	$\beta_{\Delta TERM}$	$\beta_{\Delta DEF}$	$\beta_{B/DLEV}$	**INVEST**	**INS/LEV**	**FIN/LEV**	**Total LEV**
Coefficient	-0.01 [-0.78]	-0.00 [-1.64]	-0.13 [-0.25]	0.06 [0.07]	5.17** [2.02]	-4.42* [1.92]	0.99 [0.94]	0.51 [1.20]	0.00 [0.06]	0.00 [0.13]	0.00 [0.23]
Const. (z)	0.85*** [3.25]	0.78*** [2.98]	0.82*** [3.08]	0.73** [2.29]	0.67** [2.54]	0.67** [2.56]	0.01 [1.25]	0.94*** [3.17]	0.79*** [3.27]	0.80*** [3.27]	0.79*** [3.24]
Avg. R^2	0.04	0.03	0.03	0.04	0.04	0.04	0.05	0.03	0.03	0.03	0.03

This table shows Fama–MacBeth (1973) regressions of individual insurance stock returns in excess of the risk-free rate. The independent variables are those described in Section 3 and are winsorized at the 1^{st} and 99^{th} percentile. The sample period is July 1988 to December 2013. T-statistics are in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Fama–MacBeth (1973) regressions with individual stock returns (multivariate)

	(I)	(II)	(III)	(IV)	(V)
B/M	0.48**	0.51**	0.61***	0.42*	0.54**
	[2.16]	[2.12]	[2.65]	[1.71]	[2.23]
RET_{t-1}	-8.37***	-8.21***	-8.36***	-7.63***	-8.18***
	[-5.48]	[-5.39]	[-5.34]	[-5.08]	[-5.32]
β_{LIQ}	0.81*	0.78*	0.88*	0.80*	0.66
	[1.91]	[1.71]	[1.97]	[1.93]	[1.62]
CF-VOLA	-3.83**	-3.73**	-3.72**	-3.57**	-3.44**
	[-2.35]	[-2.37]	[-2.20]	[-2.27]	[-2.27]
$\beta_{\Delta TERM}$	-2.10	-1.70	-1.15	-0.84	1.83
	[-0.44]	[-0.34]	[-0.24]	[-0.17]	[0.39]
$\beta_{\Delta DEF}$	-6.17	-6.56	-4.69	-4.56	-1.62
	[-1.41]	[-1.44]	[-1.10]	[-1.04]	[-0.40]
Const. (z)	0.37	0.39	0.34	0.50	0.52
	[1.12]	[1.15]	[1.03]	[1.50]	[1.56]
Obs.	15,365	14,871	14,793	14,861	13,832
Avg. R^2	0.23	0.22	0.23	0.22	0.22
Sample excludes:		$<5^{th}$ pctile. market cap.	$<5^{th}$ pctile. trading vol.	$>95^{th}$ pctile. rel. bid–ask spread	$<5^{th}$ pctile. market cap. /$<5^{th}$ pctile. trading vol./$>95^{th}$ pctile. rel. bid–ask spread

Model (I) includes all significant variables from univariate sorts and regressions. Model (II) excludes all firm months with market capitalization below the sample's 5^{th} percentile. Model (III) excludes all firm months with trading volume below the sample's 5^{th} percentile. Model (IV) excludes all firm months with relative bid–ask spreads above the sample's 95^{th} percentile. Model (V) sequentially excludes all firm months with market capitalization below the sample's 5^{th} percentile, all firm months with trading volume below the sample's 5^{th} percentile, and all firm months with relative bid–ask spreads above the sample's 95^{th} percentile. Dependent variables are winsorized at the 1^{st} and 99^{th} percentile. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.3 Principal component analysis and risk factors

Our results imply that the B/M ratio, prior month return, cashflow volatility, and liquidity are priced in insurance stock returns. We now investigate whether these four characteristics represent systematic risk and can therefore be matched by covariances with risk factors (see Vassalou and Xing (2004); Gandhi and Lustig (2015)). In general, a linear factor model predicts average returns on a cross-section of returns related to risk premiums that are exposed to risk factors.

According to Ross (1976) and his arbitrage pricing theory (APT), these factors should capture the common variation in asset returns. To follow this intuition, we sort each insurance stock into five quintiles according to each significant characteristic found above. We then run four principal component analyses (for each of the four characteristics) on each of the five return portfolios, following Lustig, Roussanov, and Verdelhan (2011) and Gandhi and Lustig (2015).

Table 4 shows the loadings of the first and second principal components on our characteristic-sorted portfolios. The first principal component explains between 68.59% and 71.52% of the return variance in insurance stocks. Since the loadings on the first principal components are all of similar size and direction, an interpretation as level factor, such as the market factor, is comprehensible. The second principal components, in contrast, load from negative to positive (and vice versa) on the different characteristics and explain between 8.77% and 13.40% of the return variance. Thus, the second principal components on each characteristic-sorted portfolio can be interpreted as slope factors because of their increase (decrease) in loadings. We follow Lustig, Roussanov, and Verdelhan (2011) in interpreting the first component as level factor and the second component as slope factor. Since no other principal components exhibit a similar increasing (decreasing) pattern to the second principal components, they are most likely to explain the cross-section of insurance stock returns as candidate risk factor. Motivated by the principal component analyses and following Lustig, Roussanov, and Verdelhan (2011) as well as Gandhi and Lustig (2015), we construct four risk factors from returns of the second principal component.

Table 4: Principal components

Panel A: First principal component

Portfolio	B/M	RET_{t-1}	β_{LIQ}	CFVOLA
1 (Low)	0.45	0.41	0.44	0.47
2	0.47	0.45	0.46	0.47
3	0.47	0.46	0.45	0.47
4	0.45	0.47	0.46	0.46
5 (High)	0.40	0.44	0.43	0.35
% Variance	68.59	71.52	71.62	69.00

Panel B: Second principal component

Portfolio	B/M	RET_{t-1}	β_{LIQ}	CFVOLA
1 (Low)	-0.46	0.88	-0.06	-0.31
2	-0.29	-0.11	-0.37	-0.24
3	0.15	-0.06	-0.28	-0.10
4	-0.13	-0.23	-0.11	-0.03
5 (High)	0.82	-0.40	0.88	0.91
% Variance	11.68	9.61	8.77	13.40

This table reports the principal component coefficients of the relevant characteristic-sorted portfolios on B/M ratio (B/M), prior month return (RET_{t-1}), Liquidity (β_{LIQ}), and cashflow volatility (CFVOLA). In the last row of each panel the share of the total variance explained by each principal component in percent is reported. The sample period is July 1988 to December 2013.

To emphasize the most extreme portfolios, we go three quarters long in the portfolio with the highest characteristic (i.e., portfolio 5) and one quarter long in the portfolio with the second highest characteristic (i.e., portfolio 4). To have a zero-investment portfolio we also go three quarters short in the portfolio with the lowest characteristic (i.e., portfolio 1) and one quarter short in the portfolio with the second lowest characteristic (i.e., portfolio 4).[17] Formally,

[17] The results are robust in the construction of the factors as long as the top and bottom portfolios outweigh the portfolios in the middle. Results are available upon request from the authors. Lustig, Roussanov, and Verdelhan (2011) only use the most extreme portfolios to construct their portfolios. In contrast, our approach of combining the sorted portfolios is more in line with that of Fama and French (1993), who combine four out of six portfolios to construct their HML factor and six out of six to construct their SMB factor.

each excess-return portfolio is constructed as:

$$F_{i,t} = \frac{3}{4} * \left(portfolio5_{i,t} - portfolio1_{i,t}\right) + \frac{1}{4} * \left(portfolio4_{i,t} - portfolio2_{i,t}\right). \tag{10}$$

That is, for each characteristic-sorted portfolio (i.e., B/M, RET_{t-1}, CFVOLA, β_{LIQ}) a risk factor (denoted with i) is constructed. We denominate the factors BMF, PRETF, CFVF, and LQF.

On the one hand, the first principal component (PC1), which is a level factor, suggests that it follows the market. The correlation of the excess market return with each of the first principal components shows a correlation factor of 0.63 and 0.64 (see Appendix C). On the other hand, our constructed risk factors based on the four characteristics show a significant correlation with the second principal components (PC2) between 0.75 and 0.97.[18] We also want to highlight that the risk factor constructed from the B/M ratio (BMF) should be theoretically related to Fama and French's (1993) HML factor to some extent. However, HML and the B/M ratio appear to have different meanings. Both factors are uncorrelated with a correlation coefficient of 0.02.

5.4 Fama–Macbeth (1973) regression with portfolios using risk factors

Having constructed the insurance-specific risk factors, we now turn to cross-sectional regressions following Fama and MacBeth (1973) to analyze whether there is a linear relationship between the covariance of our factors and the average insurance stock returns. On the left-hand side, we use the excess returns on the 20 portfolios sorted by B/M, RET_{t-1}, CFVOLA, and β_{LIQ} (four characteristics times five portfolios), as these portfolios provide the most variation in average returns. On the right-hand side we use the different asset pricing models described in Section 4.1 including the insurance-specific INS-5 model with the excess market return (MKTRF), a zero-investment portfolio sorted by B/M ratio (BMF), a zero-investment portfolio sorted by prior month return, a zero-investment portfolio sorted by liquidity exposure (LQF), and a

[18] Lustig, Roussanov, and Verdelhan (2011) show a similar correlation for their currency risk factor and the second principal component of 0.94.

zero-investment portfolio sorted by cashflow volatility (CFVF). Table 5 reports the Fama–MacBeth (1973) regressions for all seven models.

Table 5: Fama–Macbeth (1973) regression with portfolios and risk factors

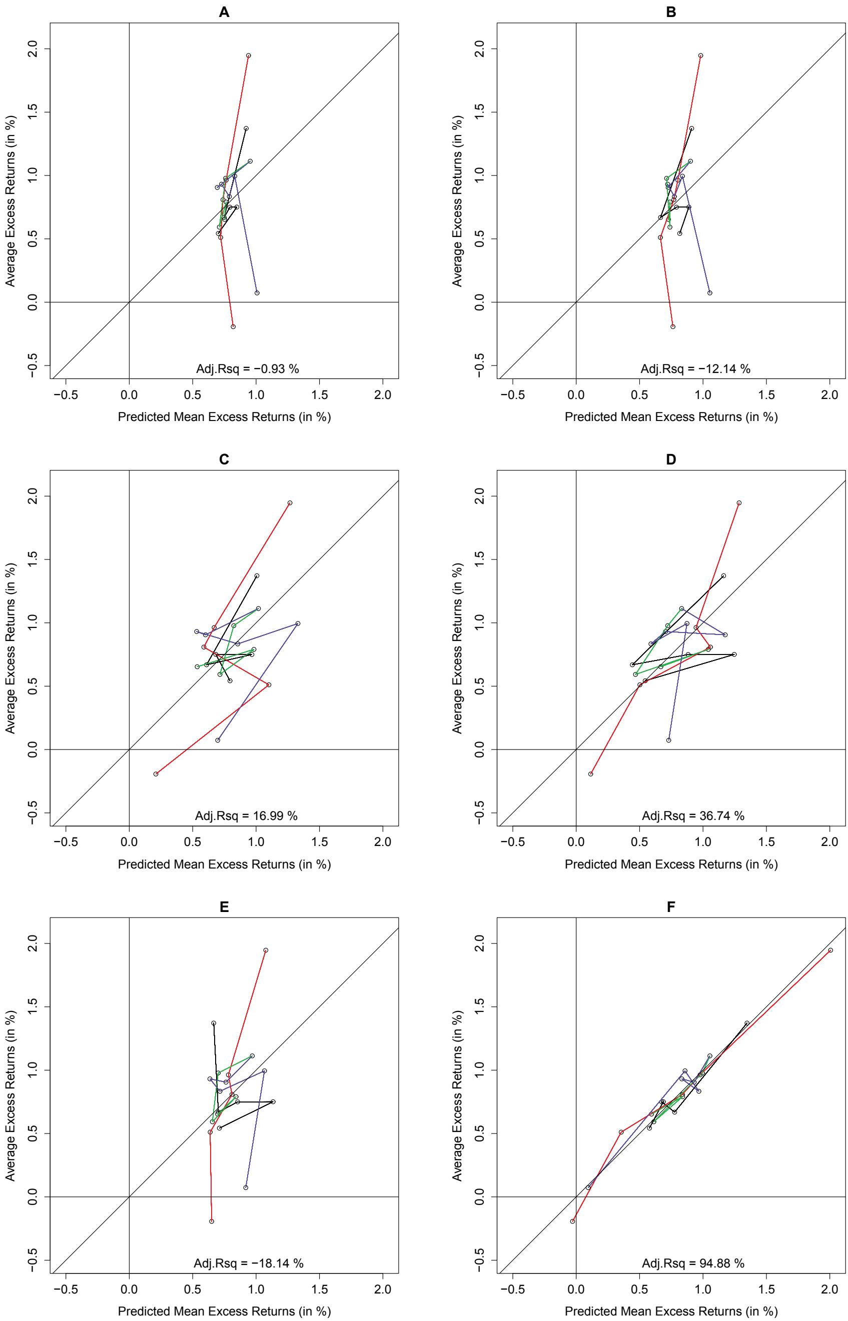
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**
	CAPM	FF-3	Carhart-4	Petkova-5	HXZ-4	FF-5	INS-5
β_{MKTRF}	1.02	1.65*	2.43**	1.46*	4.35	2.30	2.76***
	[1.18]	[1.66]	[2.29]	[1.80]	[5.06]	[2.53]	[2.82]
β_{BMF}							0.60**
							[2.36]
β_{PRETF}							-1.68***
							[-7.15]
β_{LQF}							0.38*
							[1.80]
β_{CFVF}							-0.62**
							[-2.08]
β_{SMB}		0.33	0.71		2.52***	0.95**	
		[0.63]	[1.28]		[4.81]	[1.98]	
β_{HML}		-0.90	0.88			-0.75	
		[-1.30]	[1.24]			[-1.06]	
β_{MOM}			3.24***				
			[3.85]				
β_{RMW}						0.57	
						[0.90]	
β_{CMA}						-0.65	
						[-1.41]	
β_{IA}					-1.00**		
					[-2.37]		
β_{ROE}					1.81***		
					[3.69]		
$\beta\hat{\mathbf{u}}^{\mathbf{T}ERM}$				0.37***			
				[4.58]			
$\beta\hat{\mathbf{u}}^{\mathbf{D}EF}$				-0.28***			
				[-4.14]			
$\beta\hat{\mathbf{u}}^{\mathbf{d}iv}$				0.02			
				[1.02]			
$\beta\hat{\mathbf{u}}^{\mathbf{R}F}$				0.03***			
				[2.84]			
Const. (z)	0.30	0.23	-1.42	0.24	-2.38	-0.49	-0.52
	[0.69]	[0.46]	[-0.88]	[0.02]	[-1.37]	[-0.67]	[-0.89]
Avg. $\mathbf{R}^2$	0.46	0.48	0.50	0.52	0.53	0.53	0.58

Column (I) describes the CAPM, column (II) the Fama–French (1993) three-factor model, column (III) the Carhart (1997) four-factor model, column (IV) the Petkova (2006) five-factor model, column (V) the Hou, Xue, Zhang (2015) four-factor model, column (VI) the Fama and French (2015) five-factor model, and column (VII) the INS-5 model. Standard errors are Shanken (1992) corrected.

We see that the market factor is insignificant in the CAPM, but becomes significant and positive in most of the other specifications, suggesting that the CAPM requires some type of conditioning, which then results in a significant pricing of the market factor. Interestingly, HML is insignificant and does not imply a linear relationship with our test assets. We do, however, find a significant relationship between Fama and French's (1993) size factor, Carhart's (1997) momentum factor and our test assets. Similarly, the Petkova (2006) five-factor model indicates four significant factors. How differently the models perform in the cross-section is visually illustrated in Figure 1. The y-axis shows the historical average excess return of each of the 20 portfolios, while the x-axis provides the predicted excess return from each model on the 20 portfolios. Graphs A, B, C, D, E, and F show the actual excess returns and the predicted return by the CAPM, Fama and French's (1993) three-factor model, Petkova's (2006) five-factor model, Hou, Xue, and Zhang's (2015) four factor model, Fama and French's (2015) five-factor model and the insurance-specific 5-factor model, respectively. Each graph also provides the adjusted R-square from a single cross-sectional regression.[19] Neither the CAPM nor the Fama and French (1993) three-factor models nor the Fama and French (2015) five factor model is doing well in predicting the portfolio return. The Petkova (2006) five-factor model, however, is doing better compared to the Fama and French (1993) three-factor model with a cross-sectional, adjusted R-square of 16.99%. From the comprehensive factor models, the Hou, Xue, and Zhang (2015) is doing much better than Fama and French's (2015) five-factor model with a cross-sectional R-square of 36.74%. However, the INS-5 model is doing an excellent job in capturing the cross-sectional variation with an adjusted R-square of 94.88%, supporting the fact that the INS-5 model is well specified. Note that we also compute the Hansen-Jagannathan distance to compare the different models later on in this paper.

[19]The R-square values in the Fama–MacBeth (1973) regressions are average R-squares from 306 monthly cross-sectional regressions. As noted by Kan, Robotti, and Shanken (2013), a single cross-sectional R-square as presented in Figure 1 is preferable to compare different models.

Figure 1: Actual vs. predicted returns



5.5 Time-series regressions with portfolios using risk factors

The following time-series regressions give further insight into the covariances and pricing errors from different asset pricing models. Table 6 shows factor loadings, intercept values, and the GRS-test statistic from time-series regressions on the Fama and French (2015) factors with 4x5 characteristic-sorted excess portfolios. Although SMB, HML, and RMW load significantly on the different portfolios, the loadings do not show a monotonic pattern, which would indicate a higher beta exposure followed by higher average returns. The fact that the Fama and French (2015) five-factor model cannot capture the cross-sectional return variation of the test assets is also reflected in the intercept, with 4 out of 20 intercepts being highly significant. This is formally confirmed by the GRS-test statistic, which is rejected at the 1% significance level.

In contrast, the INS-5 model is formally not rejected by the GRS-test statistic, although seven out of the twenty portfolios have weakly significant intercepts (Table 7). More importantly, the factor loadings on the different portfolios show in all cases a monotonic increase/decrease for each portfolio, which should capture the cross-sectional variation. For example, the BMF factor loads significantly negatively (i.e., -0.54) on the lowest B/M portfolios and then continuously increases in factor loadings up to a significant 0.66 in the highest B/M portfolio. Because of this pattern in covariances, cross-sectional patterns in returns can be captured.[20] Here, the Fama and French (2015) five-factor model would do much better if the short-term reversal (RET_{t-1}) anomaly in insurance stocks was not as dominant as it is.

[20] The factor loadings, intercept values, and GRS-test statistic for the CAPM and the Carhart (1997) model are also rejected. We do not report time-series regressions on the Petkova (2006) model because the factors are not returns and thus no interpretation of the intercepts is possible.

Table 6: Time series regression – FF-5 factor model

	Low	2	Medium	3	High	
MKTRF	0.67***	0.82***	0.63***	0.60***	0.69***	Book-to-market portfolios
	[8.43]	[8.58]	[9.29]	[9.53]	[8.51]	
	0.86***	0.64***	0.64***	0.60***	0.69***	RET_{t-1} portfolios
	[11.81]	[10.09]	[8.78]	[8.43]	[8.66]	
	0.65***	0.63***	0.61***	0.71***	0.84***	Liquidity portfolios
	[9.64]	[8.82]	[8.39]	[9.59]	[13.02]	
	0.61***	0.66***	0.67***	0.65***	0.85***	Cashflow volatility portfolios
	[7.58]	[8.00]	[9.33]	[10.50]	[10.33]	
SMB	-0.38***	-0.26***	-0.03	-0.05	-0.04	Book-to-market portfolios
	[-4.07]	[-3.19]	[-0.31]	[-0.57]	[-0.31]	
	-0.25**	-0.15*	-0.15*	-0.13*	-0.13	RET_{t-1} portfolios
	[-2.54]	[-1.77]	[-1.83]	[-1.96]	[-1.30]	
	-0.15*	-0.07	-0.23**	-0.27***	-0.14*	Liquidity portfolios
	[-1.70]	[-1.05]	[-2.18]	[-3.10]	[-1.92]	
	-0.21***	-0.25***	-0.18**	0.08	-0.20	Cashflow volatility portfolios
	[-2.60]	[-2.75]	[-2.39]	[0.93]	[-1.46]	
HML	0.13	0.38**	0.34***	0.39***	0.46***	Book-to-market portfolios
	[1.10]	[2.32]	[3.43]	[4.63]	[2.71]	
	0.50***	0.27***	0.19**	0.37***	0.37***	RET_{t-1} portfolios
	[3.70]	[2.61]	[2.23]	[4.07]	[2.63]	
	0.23**	0.32***	0.32***	0.36***	0.59***	Liquidity portfolios
	[2.00]	[3.09]	[3.26]	[3.89]	[3.72]	
	0.24**	0.22**	0.43***	0.28***	0.60***	Cashflow volatility portfolios
	[2.44]	[1.99]	[4.68]	[2.87]	[2.60]	
RMW	0.38***	0.49***	0.31**	0.31***	-0.01	Book-to-market portfolios
	[4.13]	[4.55]	[2.46]	[2.70]	[-0.06]	
	0.30*	0.31***	0.39***	0.31***	0.19	RET_{t-1} portfolios
	[1.82]	[3.19]	[4.05]	[2.96]	[1.39]	
	0.32***	0.38***	0.30**	0.35***	0.23	Liquidity portfolios
	[2.96]	[3.89]	[2.38]	[2.99]	[1.53]	
	0.42***	0.32***	0.25**	0.40***	0.05	Cashflow volatility portfolios
	[4.11]	[2.96]	[2.40]	[3.67]	[0.23]	
CMA	0.15	0.01	-0.01	0.05	0.09	Book-to-market portfolios
	[0.77]	[0.08]	[-0.06]	[0.37]	[0.41]	
	-0.04	0.05	0.15	0.04	0.24	RET_{t-1} portfolios
	[-0.20]	[0.41]	[1.40]	[0.28]	[1.22]	
	0.28**	0.05	-0.07	0.19	0.04	Liquidity portfolios
	[2.00]	[0.36]	[-0.41]	[1.32]	[0.23]	
	0.02	0.27	-0.03	0.04	-0.08	Cashflow volatility portfolios
	[0.17]	[1.49]	[-0.20]	[0.26]	[-0.38]	
α	-0.16	-0.15	0.05	-0.04	0.68***	Book-to-market portfolios
	[-0.68]	[-0.77]	[0.28]	[-0.21]	[2.64]	
	1.06***	0.27	0.07	-0.17	-0.97***	RET_{t-1} portfolios
	[4.67]	[1.38]	[0.42]	[-0.89]	[-3.88]	
	-0.11	0.05	-0.03	0.17	0.22	Liquidity portfolios
	[-0.52]	[0.27]	[-0.19]	[0.95]	[0.93]	
	0.22	0.17	0.13	0.23	-0.73**	Cashflow volatility portfolios
	[1.17]	[0.88]	[0.64]	[1.09]	[-2.27]	

GRS-test statistic = 3.95*, p-value=0.00**

This table presents time-series regressions on excess returns of insurance stocks sorted by B/M, prior month return, liquidity, and cashflow volatility The sample period is July 1988 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of five. The GRS-test statistic tests the null that all intercepts are jointly zero. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Time series regression – INS-5 model

	Low	2	Medium	3	High	
MKTRF	0.46***	0.57***	0.50***	0.44***	0.51***	Book-to-market portfolios
	[7.02]	[6.18]	[7.98]	[7.00]	[6.84]	
	0.53***	0.49***	0.47***	0.44***	0.55***	RET_{t-1} portfolios
	[7.14]	[7.12]	[7.07]	[6.06]	[7.74]	
	0.50***	0.51***	0.42***	0.47***	0.52***	Liquidity portfolios
	[7.13]	[7.28]	[5.46]	[6.32]	[7.46]	
	0.47***	0.48***	0.51***	0.53***	0.46***	Cashflow volatility portfolios
	[6.74]	[6.98]	[6.50]	[7.83]	[6.38]	
BMF	-0.54***	-0.42***	-0.02	-0.02	0.66***	Book-to-market portfolios
	[-6.62]	[-3.47]	[-0.41]	[-0.38]	[7.40]	
	-0.09	-0.12	-0.04	-0.13*	-0.09	RET_{t-1} portfolios
	[-1.00]	[-1.36]	[-0.61]	[-1.82]	[-0.99]	
	-0.10	-0.10	-0.09	-0.04	-0.12	Liquidity portfolios
	[-1.00]	[-1.63]	[-1.22]	[-0.48]	[-1.28]	
	-0.13*	-0.16*	-0.03	-0.01	-0.18**	Cashflow volatility portfolios
	[-1.94]	[-1.93]	[-0.36]	[-0.18]	[-2.27]	
PRETF	-0.07	0.04	0.10	-0.04	-0.04	Book-to-market portfolios
	[-0.74]	[0.46]	[1.18]	[-0.59]	[-0.42]	
	-0.68***	-0.11	-0.01	0.16*	0.56***	RET_{t-1} portfolios
	[-7.66]	[-1.29]	[-0.07]	[1.92]	[6.60]	
	-0.03	-0.02	-0.00	-0.05	-0.02	Liquidity portfolios
	[-0.34]	[-0.34]	[-0.01]	[-0.58]	[-0.23]	
	-0.02	-0.00	-0.02	0.04	-0.03	Cashflow volatility portfolios
	[-0.23]	[-0.03]	[-0.19]	[0.61]	[-0.34]	
LQF	0.02	0.05	-0.03	0.03	0.03	Book-to-market portfolios
	[0.27]	[0.54]	[-0.37]	[0.30]	[0.34]	
	0.07	-0.05	0.02	0.03	0.04	RET_{t-1} portfolios
	[0.81]	[-0.60]	[0.30]	[0.32]	[0.53]	
	-0.51***	-0.19**	0.04	0.19*	0.70***	Liquidity portfolios
	[-5.02]	[-2.43]	[0.53]	[1.92]	[7.27]	
	0.03	0.03	0.04	-0.02	0.05	Cashflow volatility portfolios
	[0.38]	[0.34]	[0.54]	[-0.28]	[0.51]	
CFVF	-0.01	0.10	0.01	-0.01	0.03	Book-to-market portfolios
	[-0.20]	[1.03]	[0.07]	[-0.11]	[0.39]	
	0.13	-0.08	-0.12**	0.02	0.09	RET_{t-1} portfolios
	[1.53]	[-1.41]	[-2.25]	[0.36]	[1.28]	
	0.12*	-0.05	-0.02	-0.15**	0.15**	Liquidity portfolios
	[1.75]	[-0.81]	[-0.22]	[-2.23]	[2.27]	
	-0.28***	-0.16***	-0.10	0.02	1.00***	Cashflow volatility portfolios
	[-3.92]	[-2.67]	[-1.59]	[0.35]	[12.78]	
a	0.35	0.66*	0.54*	0.23	0.49	Book-to-market portfolios
	[1.16]	[1.90]	[1.70]	[0.87]	[1.56]	
	0.43	0.42	0.36	0.50*	0.41	RET_{t-1} portfolios
	[1.55]	[1.43]	[1.27]	[1.69]	[1.53]	
	0.52*	0.43	0.28	0.37	0.54*	Liquidity portfolios
	[1.92]	[1.39]	[0.89]	[1.17]	[1.96]	
	0.38	0.52*	0.33	0.65**	0.34	Cashflow volatility portfolios
	[1.37]	[1.77]	[0.99]	[2.26]	[1.16]	

GRS-test statistic = 0.677, p-value=0.848

This table presents time-series regressions on excess returns of insurance stocks sorted by B/M, prior month return, liquidity, and cashflow volatility. The sample period is July 1988 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of five. The GRS test statistic tests the null that all intercepts are jointly zero. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.6 Comparing Hansen-Jagannathan distances

Based on the time-series and cross-sectional evidence, we are interested in whether the INS-5 factor model is also statistically outperforming the other models. First, we report the Hansen-Jagannathan (HJ) distance for each model and whether it is statistically different from zero (Table 8). All but the INS-5 model are rejected.

Table 8: Hansen-Jagannathan distance

	Null	CAPM	FF3	PETK-5	HXZ-4	FF-5	INS-5
$\hat{\delta}$	0.606	0.559	0.558	0.507	0.472	0.538	0.173
p($\delta = 0$)	0.000	0.000	0.000	0.001	0.014	0.000	0.972
Std. Err.	0.059	0.059	0.061	0.075	0.071	0.066	0.069
2.5% CI(δ)	0.503	0.457	0.454	0.383	0.352	0.424	0.085
97.5% CI(δ)	0.737	0.693	0.696	0.681	0.631	0.685	0.356
Max. Error	12.2	11.2	11.2	10.2	9.5	10.8	3.5
J-test	82.57	76.80	63.98	45.96	35.70	35.53	6.47
p(J-test)	0.000	0.000	0.000	0.000	0.003	0.002	0.971

This table shows the HJ distance for the Null (i.e., a constant), the CAPM, the Fama–French (FF-3) model, the Petkova model (PETK-5), the famand the p/l insurance model. The models are estimated using excess returns on the 20 portfolios sorted by B/M ratio, prior month return, liquidity, cashflow volatility, and the gross return on the 1-month T-bill return. $\hat{d}$ is the HJ distance. p($d = 0$) is the p-value for the test H_0: $d = 0$. CI(d) is the 95% confidence interval for d. J-test is the Hansen optimal GMM specification test statistic and p(J-test) its associated p-value of Hansen's J-test.

To compare the different models statistically, we follow Kan and Robotti (2009) and analyze the difference in the squared HJ distance. From the conventional models from the finance literature, Petkova's (2006) five-factor model is again outperforming the Fama–French (1993) three-factor model, as we could already see in the graphs in Section 5.4. Again, though, we also see that the INS-5 model is significantly outperforming all other models at the 1% level (Table 9). Furthermore, we confirm our observation from the single cross-sectional regression where the Hou, Xue, and Zhang (2015) four-factor model outperforms the Fama and French (2015) five-factor model.

Table 9: Tests of equality of squared Hansen-Jagannathan distances

	CAPM	FF3	PETK5	HXZ	FF-5	INS-5
Null	0.055***	0.056***	0.110***	0.144***	0.078***	0.337***
	(0.002)	(0.007)	(0.008)	(0.003)	(0.010)	(0.000)
CAPM		0.001	0.056*	0.089**	0.023	0.283***
		(0.897)	(0.079)	(0.017)	(0.278)	(0.000)
FF3			0.055***	0.089***	0.022*	0.282***
			(0.002)	(0.000)	(0.087)	(0.000)
PETK-5				0.034	-0.033*	0.227***
				(0.346)	(0.0078)	(0.000)
HXZ-4					-0.066***	0.193***
					(0.000)	(0.0002)
FF-5						0.259***
						(0.000)

This table compares the squared HJ distances ($\hat{d}$) of the different factor models according to Kan and Robotti (2009). The test assets are the 20 excess return portfolios sorted by B/M ratio, prior month return, liquidity, and cashflow volatility. We report the difference between the HJ distances of the models in row i and column j, $\hat{d}_i - \hat{d}_j$, and the respective p-value in parentheses for the test $\mathrm{H}_0 : \hat{d}_i^2 = \hat{d}_j^2$.

5.7 Interpretation of results

A central question is what the four factors are proxying for. Table 3 already showed that – in line with the general finance literature – liquidity is directly linked to trading volume, size, and bid–ask spreads, since liquidity is becoming insignificant if the most extreme observations related to these three conditions are excluded. In the next three sections we show that 1) high and low exposures to cashflow volatility are directly linked to the Rate-on-Line index and the reinsurance cycle; 2) short-term reversals are linked to liquidity provisions by market makers due to market volatility; and 3) the book-to-market ratio is a proxy for default risk.

Cashflow volatility and the reinsurance cycle Doherty and Kang (1988) and Cummins and Weiss (2009) emphasize that the (re-)insurance business is subject to periods of "soft" and "hard" markets. During soft markets, insurers can obtain sufficient reinsurance coverage while paying low premiums. During hard markets, however, insurers have to pay higher premiums and coverage supply is limited (Cummins and Weiss (2009)). Cummins and Weiss (2009) also note that reinsurance prices "tend to spike following large loss events." The theoretical literature on the reinsurance cycle highlights that this pattern is the result of risk aversion and capital depletion following large losses. The risk aversion of the insurer (i.e., the investors and policyholders of the insurer) is a function of its capital structure (Froot and Stein (1998)). The more capital is held by the insurer, the lower the insurance price, due to the inverse relationship between capital and risk aversion. Also insurers are even more risk averse if insurance risk can affect the company's solvency (Froot (2007)). Within this model framework, Froot (2007) predicts that (re)insurance prices increase due to large loss shocks that reduce the company's capital. We hypothesize that the reinsurance cycle is related to cashflow volatility. Insurers with higher cashflow volatility in the past experience a stronger decrease in returns (compared to insurers with low cashflow volatility) if insurance prices increase after catastrophic events. That is, investors withdraw capital from high cashflow volatility insurers when insolvency might become an issue, as noted by Froot (2007).

To help us interpret the meaning of p/l insurance companies being exposed to high and low cashflow volatility in the past, we employ quarterly changes in the Lane Financial LLC synthetic Rate-on-Line index as a measure for catastrophe insurance pricing. The index is a proxy for the reinsurance cycle because it measures how reinsurance prices change over time in relation to the coverage they provide.[21] The index uses secondary market quotes for all outstanding insurance-linked security (ILS) and industry loss warranty (ILW) premiums and is published by the Thomson Reuters ILS Community. Specifically, the index represents the ratio of the ILS and ILW premiums divided by the reinsurance limit that each instrument covers. We run quarterly time-series regressions with the return spread between insurers exposed to low and high cashflow volatility as the dependent variable (Columns 1 and 2), and the separate excess return of low (Columns 3 and 4) and high cashflow volatility insurers (Columns 5 and

[21]See Braun (2015) for using the index as a proxy for the reinsurance cycle. We would like to thank Alexander Braun for making the data available to us. For further details about the index, see Braun (2015).

6).[22] Control variables are the five factors of Fama and French (1993). Results in Table 10 indicate that the spread is indeed highly correlated with the Rate-on-Line index. A closer look at the cashflow-volatility return series in Columns 5 and 6 reveals that this effect is mostly attributable to the returns of the high cashflow volatility insurers. This corroborates the idea that price increases as a result of catastrophic events lead to decreasing returns in insurance stocks that have experienced strong variations in their cashflows in the past. Insurers with low cashflow volatility in the past are, however, not affected by catastrophic turbulence.

Table 10: Cashflow volatility and Rate-on-Line index

	(1)	(2)	(3)	(4)	(5)	(6)
	CFVOLA 1-5 (Spread)	CFVOLA 1-5 (Spread)	CFVOLA 1 (Low)	CFVOLA 1 (Low)	CFVOLA 5 (High)	CFVOLA 5 (High)
ΔRate-on-Line	0.24***	0.21**	-0.04	0.05	-0.28*	-0.15**
	[2.92]	[2.36]	[-0.38]	[0.85]	[-1.93]	[-2.30]
MKTRF		-0.03		0.59***		0.62**
		[-0.09]		[3.27]		[2.56]
SMB		0.30		-0.10		-0.40
		[0.60]		[-0.43]		[-0.90]
HML		-0.51		0.19		0.70**
		[-1.43]		[1.23]		[2.37]
RMW		0.82*		0.37		-0.45
		[1.80]		[1.46]		[-0.90]
CMA		0.03		0.24		0.20
		[0.09]		[1.45]		[0.61]
a	1.66	1.11	2.42**	0.11	0.76	-1.00
	[0.99]	[0.79]	[2.43]	[0.13]	[0.38]	[-0.77]
Adj. R^2	0.03	0.07	-0.01	0.47	0.03	0.37
Obs.	66	66	66	66	66	66

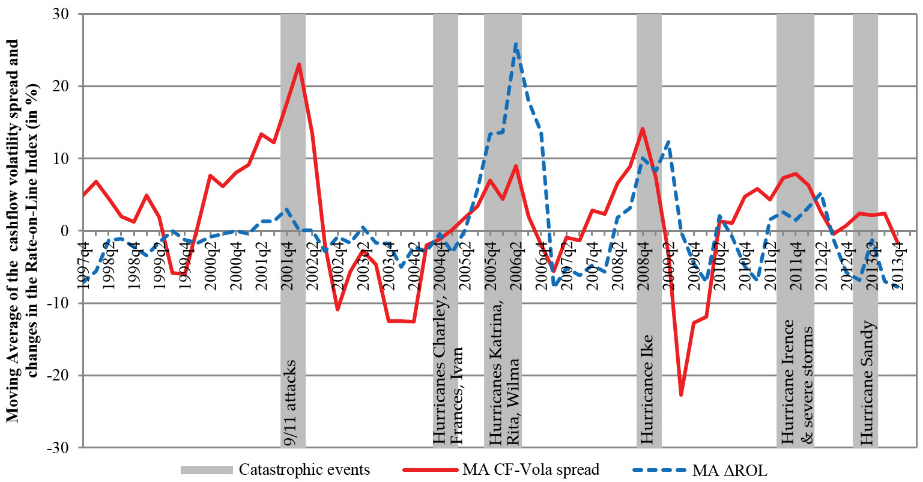
This table presents time-series regressions on return spreads of insurance stocks sorted by historical cashflow volatility in Columns 1 and 2 (low minus high cashflow volatility) and excess returns on insurance stocks with low historical cashflow volatility (Columns 3 and 4) and high cashflow volatility (Columns 5 and 6). The sample period is April 1997 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of four. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 2 illustrates the low minus high cashflow volatility return spread (solid line), the changes in the Rate-on-Line index (dashed line) and the twelve highest insured losses in the U.S. during the period 1997 to 2013 (shaded

[22] Because changes to the synthetic Rate-on-Line index are first available in April 1997, the time-series regression starts in the second quarter of 1997.

areas). We see that spikes in the cashflow volatility spread coincide with the Rate-on-Line index and catastrophic events, including the 9/11 attacks and Hurricane Katrina. This graphically demonstrates the empirical results of Table 10. Furthermore, following each catastrophic event it appears that the cashflow volatility (low minus high) spread sharply drops during the event period. One interpretation is that high cashflow volatility insurers receive new capital from equity investors, driving up equity prices of these insurers as soon as estimates for a catastrophic event can be better assessed. This would imply that investors in general overreact to catastrophic news and sell their investment until new information about the losses of high cashflow volatile insurers is available.

Figure 2: Cashflow volatility and reinsurance cycle



The solid line (MA CF-Vola spread) in this figure illustrates the three quarter moving average of the time series of the low (20th percentile) minus high (20th percentile) characteristic-sorted stock returns. The dashed line (MA ΔROL) illustrates the three quarter moving average of the time series of the changes in the Rate-on-Line index. Moving averages are in percent. The gray-shaded bars represent severe man-made and natural catastrophes based on insured losses.

One development that might suggest that the spread in cashflow volatility is not necessarily disentangled from the overall economy can be seen during the financial crisis. Investors seem to have withdrawn a significant amount from high cashflow volatility insurers, not only because of Hurricane Ike making landfall on September 7, 2008 and being recorded as the fourth largest catastrophe in the U.S. (in terms of insured losses), but possibly also because of the financial crisis with the bankruptcy of Lehman Brothers on September 15, 2008 during the same period, resulting in a significant spike during 2008 and exceeding the cashflow changes during Hurricanes Katrina, Rita, and Wilma.

Short-term reversal and liquidity provisions To interpret the short-term reversal effect, we first control for several aspects mentioned in the literature with regard to unconditional short-term reversal. First, Cheng et al. (2014) find that the one month reversal strategy in the overall stock market becomes insignificant in the post-2000 period. Second, several papers mention a strong January effect in the reversal strategy due to tax loss selling (see George and Hwang (2004); Hameed and Mian (2015)). Third, we control for stocks below a price of $5 due to the effects of market microstructure (see Hameed and Mian (2015)). Table 11 shows the results for the different settings with the return spread between high minus low prior-month return insurers as dependent variable and the Fama and French (2015) factors as controls. Since all control variables are excess returns, we can interpret the constant as the abnormal return from the high minus low return spread. In all cases the constant remains highly significant, a result which is in line with the results for intra-industry reversal by Hameed and Mian (2015). However, we acknowledge that there is a minor decrease in the reversal strategy for the post-2000 period and also a minor decrease compared to the results for stock prices above $5 (see Table 1, Panel A, Column RET_{t-1}). The largest decrease in the return strategy is due to the January effect, corroborating the results of George and Hwang (2004).[23]

[23] The combination of excluding stocks below a price of $5, the months of January, and dates before the year 2000 still results in a significant spread of -1.86% per month and a t-statistic of -4.15.

Table 11: Pre- and post-2000 period, January effect, and market microstructure

	07/1988–12/1999		*01/2000–12/2013*		*Excluding January effect*		*Excluding stocks below $5*	
	High minus low prior-month return reversal portfolio (**RET**$_{t-1}$)		High minus low prior-month return reversal portfolio (**RET**$_{t-1}$)		High minus low prior-month return reversal portfolio (**RET**$_{t-1}$)		High minus low prior-month return reversal portfolio (**RET**$_{t-1}$)	
MKTRF		-0.34***		-0.14		-0.11		-0.24***
		[-3.99]		[-0.90]		[-1.11]		[-3.36]
SMB		0.18		0.10		0.08		0.10
		[1.00]		[0.52]		[0.63]		[0.81]
HML		-0.00		-0.12		-0.19		-0.17
		[-0.00]		[-0.44]		[-0.96]		[-1.05]
RMW		0.36		-0.22		-0.12		-0.32*
		[1.36]		[-0.60]		[-0.58]		[-1.82]
CMA		-0.12		0.37		0.40		0.20
		[-0.39]		[1.21]		[1.51]		[1.32]
α	-2.36***	-2.13***	-1.96***	-1.91***	-1.75***	-1.72***	-2.01***	-1.73***
	[-5.90]	[-5.41]	[-4.80]	[-3.84]	[-5.61]	[-5.02]	[-6.88]	[-5.96]
Adj. R^2	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.06
Obs.	138	138	168	168	281	281	306	306

This table presents time-series regressions on return spreads of insurance stocks sorted by prior-month returns (high minus low prior-month return). The sample period is July 1988 to December 2013 (306 observations). Columns 1 and 2 separate the dataset into periods before (138 observations) and after (168 observations) the year 2000. Column 3 excludes the months of January (281 observations), and Column 4 excludes stocks with prices below $5. T-statistics in brackets are Newey–West (1987) corrected with lags of five. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Hameed and Mian (2015) also find that short-term reversal is pervasive within industries and attribute this fact to order imbalances and non-information shocks. Similar to Nagel (2012), they also find that the reversals are more intense after market declines and periods of high volatility as a result of funding constraints. The argument is that market makers can pledge securities as collateral in return for funding. Market declines and increasing volatility reduce the value of the collateral and require higher margins. Consequently, liquidity providers are more risk averse to making markets during financial distress. Such distress then increases the expected return for liquidity suppliers (Brunnermeier and Pedersen (2009)).

To control for the effect of funding constraints, we follow Hameed and Mian

(2015) and include the historical volatility (measured as the sum of squared five-minute returns within the month), a dummy variable for market declines (DOWN, taking the value of one if the past three-month return on the CRSP equal-weighted market return is negative and zero otherwise). We also include the difference between the implied and realized volatilities (VIX-VOL) being interpreted as a risk aversion index (Bollerslev, Gibson, and Zhou (2011)).[24] Moreover, we include a catastrophe risk premium derived from catastrophe bonds under the assumption that liquidity providers are not only concerned by margin calls due to market volatility, but also by reduced market values of insurance stocks due to larger losses from catastrophic events.[25] Identical to Hameed and Mian (2015), we lag these variables by two months to ensure that market conditions are known one month prior to the formation period of the reversal strategy. As control variables ($controls_t$) we include the January effect, defined as a dummy variable taking the value of one in January and zero otherwise, a dummy variable for the pre-decimalization period when the tick size changed to decimals in April 2001. As in Hameed and Mian (2015) we include the Fama–French (1993) three factors (MKTRF, SMB, and HML) and Pàstor–Stambaugh (2003) traded liquidity factor (PS_LIQ) as additional control variables (F_t):

$$\begin{aligned} R_t^{Loser-Winner} &= \alpha + \beta_{VOL} VOLA_{t-2} + \beta_{DOWN} DOWN_{t-2} \\ &+ \beta_{(VIX-VOLA)}(VIX_{t-2} - VOLA_{t-2}) \\ &+ \beta_{CATRisk} CATRisk_{t-2} + c' controls_t + \beta' F_t + \epsilon_t. \end{aligned} \tag{11}$$

Results are presented in Table 12 and show that historical volatility is a significant driver of short-term reversal returns, although the economic impact for p/l insurance stocks appears to be smaller than for intra-industry reversals in general (see Hameed and Mian (2015)). The catastrophe risk premium is insignificant, suggesting that short-term reversals are not driven by overreac-

[24] We would like to thank Hao Zhou for making the historical volatility and the volatility risk premium available on his website at https://sites.google.com/site/haozhoupersonalhomepage/.

[25] We thank Alexander Braun for making the quarterly catastrophe bond index available. Since the focus here is on the volatility variables (available on a monthly basis), we interpolate the quarterly catastrophe bond index to have monthly risk premiums.

tions of market participants (i.e., market makers, institutional investors) with respect to (uncorrelated) catastrophes, but only by liquidity provisions in the market. Again, both the pre-decimalization period and the January effect have a significant impact on short-term reversals.

Book-to-market ratio and default probability To interpret the book-to-market ratio, we show that some of the information in the book-to-market ratio is default related. Vassalou and Xing (2004) show that the size and book-to-market effect are related using default likelihood indicators (DLI) from equity returns based on Merton's (1974) option pricing model.[26] We sort p/l insurance stocks by high and low exposure to DLI (calculated from the balance sheet information of each insurer) to proxy for the default risk in insurance stocks on an aggregate level. The spread is denoted as HL-DLI. As another control variable that might have an effect on the book-to-market ratio we include the return spread from high and low loss ratios in insurance stocks. The loss ratio is defined as incurred losses to written premiums during a fiscal year.[27] Additional controls are the Fama–French (2015) factors. We run time-series regressions to link default probability with the book-to-market ratio. Table 13 shows that HL-DLI is significant at the 5% level in all model settings as is RMW. Apparently there is negative relation between high profitability and high book-to-market ratios. In line with Vassalou and Xing (2004), SMB as another driver of default risk is also weakly significant. The loss ratio, however, does not contribute as an indicator of default risk in this context.

[26] For a detailed description of the construction of DLI, see Vassalou and Xing (2004).

[27] We sort each stock in July of year t based on loss ratio ending in the fiscal year t-1, similar to the construction of the HML factor. We include this variable since high losses ratios could result in an increased default risk.

Table 12: Short-term reversal and market conditions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VOLA		0.02***						0.02***	0.03***	0.02***	0.02***
		[3.80]						[2.83]	[3.57]	[3.32]	[3.00]
DOWN					-0.86	-1.53**	-1.50**		-1.53**	-1.50**	-2.03***
					[-1.64]	[-2.42]	[-2.37]		[-2.50]	[-2.45]	[-2.61]
PreDecimal				1.39**	1.02*	1.39**	1.32**	1.60**	1.61***	1.55**	2.78**
				[2.21]	[1.75]	[2.32]	[2.18]	[2.56]	[2.72]	[2.59]	[2.45]
January				4.92***	4.94***	4.75***	4.44***	4.95***	4.77***	4.38***	3.74***
				[5.25]	[5.29]	[4.93]	[4.68]	[5.16]	[4.85]	[4.56]	[3.05]
MKTRF							0.13			0.16**	0.16*
							[1.46]			[2.02]	[1.75]
SMB							-0.17			-0.21*	-0.23
							[-1.39]			[-1.88]	[-1.64]
HML							0.02			0.02	-0.01
							[0.19]			[0.13]	[-0.05]
PS_LIQ							-0.04			-0.05	-0.07
							[-0.53]			[-0.73]	[-0.81]
VIX	0.05		0.09*	0.06		0.09**	0.09**				
	[1.32]		[1.92]	[1.48]		[2.15]	[1.99]				
CATRisk			-0.14								-0.08
			[-0.68]								[-0.35]
VIX-VOLA								-0.02	-0.01	-0.02	-0.03*
								[-1.31]	[-0.78]	[-1.36]	[-1.67]
α	1.13	1.84***	0.99	-0.01	1.54***	-0.19	-0.12	1.05**	1.29**	1.41***	2.27*
	[1.36]	[5.69]	[0.75]	[-0.01]	[3.58]	[-0.22]	[-0.13]	[2.07]	[2.49]	[2.61]	[1.79]
Adj. R^2	0.0	0.01	0.01	0.08	0.07	0.09	0.09	0.09	0.11	0.11	0.11
Obs.	286	286	197	286	304	286	286	286	286	286	197

This table presents time-series regressions on return spreads of insurance stocks sorted by prior-month return (high prior-month return minus low prior-month return). The sample period is January 1990 (July 1997) to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of five. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13: Book-to-market ratio and distance-to-default

	(1)	(2)	(3)	(4)
HL-DLI	-0.11**	-0.10**	-0.10**	-0.10**
	[-2.22]	[-2.31]	[-2.24]	[-2.23]
MKTRF		0.05	0.05	0.04
		[0.56]	[0.50]	[0.45]
SMB		0.29*	0.30*	0.31*
		[1.78]	[1.80]	[1.83]
HML		0.28	0.30	0.28
		[1.27]	[1.29]	[1.18]
RMW		-0.40**	-0.40**	-0.39**
		[-2.28]	[-2.21]	[-2.14]
CMA		0.00	-0.01	-0.00
		[0.02]	[-0.02]	[-0.01]
LossRatio			0.01	0.01
			[0.13]	[0.15]
Financial Crisis				-1.67
				[-1.53]
α	0.76**	0.76**	0.79**	0.86**
	[2.55]	[2.48]	[2.40]	[2.51]
Adj. R^2	0.03	0.10	0.10	0.10
Obs.	297	297	273	273

This table presents time-series regressions on return spreads of insurance stocks sorted by their default likelihood indicators (high minus low default likelihood indicator). The sample period is July 1990 to March 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of five. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6 Insurance stock returns and catastrophe risk

Ben Ammar (2016) shows that catastrophe risk is inherent in option prices of p/l insurance stocks. Specifically, he detects catastrophe risk in the steepness of the implied volatility smile of put options written on p/l insurance stocks in comparison to non-financials. If catastrophe risk is not only observable in option prices but also priced in stock returns, sorting stocks based on catastrophe risk should result in higher returns for p/l stocks with higher exposure.[28]

[28] We would like to thank Manuel Ammann for this helpful comment.

Three limitations need to be highlighted with regard to the sample and measuring catastrophe risk. First, option prices from OptionMetrics start in January 1996. Thus, our sample is eight years shorter than the previous analyses. Second, not all p/l insurers with listed stock returns have options written on their stocks. Thus, our sample is also reduced in the number of cross-sectional observations. The total number of stocks having options is 53, which is below the sample size of 67 stocks in Ben Ammar (2016). The reason for that is the more stringent data selection described in Section 4.2. such as stocks having 36 months of consecutive return data. Third, without a control group and controls for firm specific factors such as leverage, the implied volatility smile is rather a measure of tail risk in general (Kelly and Jiang (2014)), than insurance-specific catastrophe risk. To overcome the last shortcoming we use the aggregate catastrophe risk measure (i.e., the coefficient from cross-sectional Fama-MacBeth (1973) regressions) over time, identified and provided by Ben Ammar (2016), and run rolling regression over the past 36 months on the excess returns of p/l insurance stocks. Furthermore, we match all p/l insurance stocks with their corresponding average monthly implied volatility smiles. We define the beta exposure on the aggregate measure as catastrophe risk, whereas the "pure" steepness of the implied volatility is defined as tail risk.

As Ben Ammar (2016) we define the steepness of the implied volatility smile as the difference between the implied volatility of a put option with a delta of -0.2 and a delta of -0.8. All options have a constant maturity of 30 days. Regarding tail risk, each stock is then sorted into quintiles based on the past month's steepness of the implied volatility smile. Regarding catastrophe risk, each stock is sorted into quintiles based on the beta exposure on aggregate catastrophe risk over the past 36 months. We report the returns for the 20% (low), middle 60% (mid), and top 20% (high) breakpoints of the ranked values. Table 14 presents the sorting results.

Table 14: Sorted portfolios on catastrophe risk and tail risk

	Catastrophe risk	Tail risk
Low	1.29	1.15
Mid	0.92	0.97
High	0.58	0.50
Spread (3-1)	-0.71	-0.65*
	[-1.60]	[-1.67]
Obs.	180	215

This table presents sorted return portfolios based on catastrophe risk and tail risk. The spread is the return difference between the portfolio with the highest and the lowest exposure on catastrophe and tail risk. The sample period for catastrophe risk-sorted portfolios is February 1996 to December 2013. The sample period for tail risk-sorted portfolios is January 1999 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of four. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We see that both measures create the same monotonic pattern with almost identical spread sizes. However, only the tail risk spread is subject to a weakly statistically significant difference at the 10%-level. In contrast to what we expect, though, stocks with steeper implied volatility smiles earn lower returns than stocks with a flatter implied volatility smiles. A possible explanation could be that investors are not charging a sufficient risk premium for tail risk which should reflect both economic downturns and catastrophic events. This result is again different from the overall finance literature which shows that tail risk earns a positive premium (Kelly and Jiang (2014)). The question that remains to be answered is whether the factor models can explain the weakly significant spread caused by tail risk. We thus run the INS-5 model, the FF-5 model, and the HXZ-4 model on the return spread. Table 15 presents the results.

Table 15: Time-series regressions on tail risk-sorted portfolios

	(1)	(2)	(3)
MKTRF	0.26**	0.21	0.33**
	[2.45]	[1.24]	[2.20]
BMF	-0.23*		
	[-1.77]		
PRETF	-0.00		
	[-0.02]		
LQF	-0.14		
	[-1.11]		
CFVF	-0.04		
	[-0.42]		
SMB		-0.13	-0.05
		[-0.91]	[-0.35]
IA		-0.05	
		[-0.28]	
ROE		-0.04	
		[-0.22]	
HML			-0.25
			[-1.29]
RMW			0.45**
			[2.05]
CMA			0.12
			[0.50]
α	-0.69	-0.75	-1.07**
	[-1.59]	[-1.64]	[-2.40]
Adj. R^2	0.08	0.03	0.05
Obs.	215	215	215

This table presents coefficients from time series regressions based on the INS-5 model, the HXZ-4 model, and the FF-5 model, respectively. The dependent variable is the return spread between stocks with high and low tail risk exposure. The sample period for tail risk-sorted portfolios is February 1996 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of four. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

First, we observe that the intercept of the INS-5 model is insignificant and smaller than the intercepts calculated by the HXZ-4 and the FF-5 model. In fact, the FF-5 model is again overestimating the intercept and showing a significant t-statistic at the 5%-level. The second observation is that, aside from the market factor, the weakly significant BMF factor is responsible for capturing some of the tail risk exposure. This would be partly in line with the theoretical relationship between tail risk, distressed firms, and the book-to-market ratio (Vassalou and Xing (2004)). Overall, evidence for priced tail risk and catastrophe risk in p/l stock returns is weak to non-existent. In addition, the weakly statistical evidence appears to be captured by the INS-5 model.

7 Robustness

In the following robustness tests we run Fama–MacBeth (1973) regressions, and time-series regressions using size- and B/M-sorted portfolios.

7.1 Size and B/M portfolios

A potential point of critique to our approach so far is that most asset pricing tests intend to explain the cross-section of size and B/M-sorted portfolios (Fama and French (1993)). Although there is a B/M ratio anomaly in insurance stock returns (that is not related to the B/M anomaly of the rest of the economy), we did not find a size anomaly when we compared insurance stock returns in the lowest 20th and in the highest 80th percentiles. Three explanations could be possible. First, there is indeed no size anomaly in insurance stocks and never has been. Second, there was a size anomaly that has disappeared, which is also suggested by some studies for equities in the non-financial sector (Hirshleifer (2001); Schwert (2003)). Third, the size anomaly is "hidden" in the most extreme-sorted stocks in the insurance sector. The last explanation is for us difficult to test, since the low number of insurance stocks in our sample increases the measurement error in each portfolio the fewer insurance stocks it contains. Nevertheless, a natural question to ask is thus how the Fama–French (2015) five-factor model copes with insurance stocks sorted on these two characteristics, and how the INS-5 model deals with size and B/M portfolios. At the cost of estimation precision, we create ten size and ten B/M portfolios. This means that on the one hand betas from time-series regressions are estimated with larger errors. On the other hand, a larger cross-section is available, which enhances the estimation in each monthly cross-section.

When we simply sort insurance stocks into ten size portfolios (Panel A of Table 16), we find indeed that the smallest stocks provide a large and statistically significant increase in return, from 0.71% in the second smallest to 1.87% in the smallest portfolio. This supports the idea that only the smallest stocks in the insurance sector are exposed to a size anomaly.

Similarly, the B/M anomaly is driven by the most extreme portfolios when sorted by B/M (Panel B of Table 16). However, the changes between the extreme and next to extreme portfolios are not as severe as in the size anomaly. To further investigate the size and B/M characteristics, we run time-series and cross-sectional regressions on all portfolios in the following sections.

7.2 Fama–MacBeth (1973) regressions with B/M and size portfolios

We first run Fama–MacBeth (1973) regressions, as in Section 5.4. However, this time the dependent variables are ten size- and ten B/M-sorted insurance stock portfolios. Here, we indeed find a weakly significant coefficient on the SMB factor as can be seen in Table 17, supporting the idea that there is some size exposure in the most extreme portfolios.

When we visually compare the ten size- and ten B/M-sorted portfolios (Figure 3), we also see that the overall fit using the INS-5 model is superior to the Fama–French (2015) five-factor model. The Fama–French (2015) five-factor model has an adjusted R-square of 20.41% (Graph E) versus an adjusted R-square of 43.92% in the INS-5 model (Graph F). The Hou, Xue, and Zhang (2015) four-factor model (Graph D) is doing again surprisingly good in explaining the cross-section of size and B/M sorted insurance stock returns with an adjusted R-square of 42.09% and thus almost as good as the INS-5 model.

Table 16: Size-sorted and B/M-sorted portfolios

Panel A: Ten size-sorted portfolios

	Small (1)	2	3	4	5	6	7	8	9	Large (10)	10-1	9-2	8-3
SIZE avg. return	1.87	0.71	0.89	0.98	1.01	1.35	1.01	1.02	1.10	0.94	-0.93** [-2.19]	0.39 [1.09]	0.14 [0.52]
Avg. # of stocks	6.67	6.09	6.19	6.26	6.16	6.31	6.34	6.24	6.42	5.89			

Panel B: Ten B/M-sorted portfolios

	Low (1)	2	3	4	5	6	7	8	9	High (10)	10-1	9-2	8-3
B/M avg. return	0.72	0.91	1.17	0.90	1.03	1.05	1.03	0.84	1.41	1.87	1.15** [2.46]	0.50 [1.29]	-0.33 [-1.05]
Avg. # of stocks	6.27	5.55	5.82	5.69	5.56	5.79	5.90	5.56	5.42	4.75			

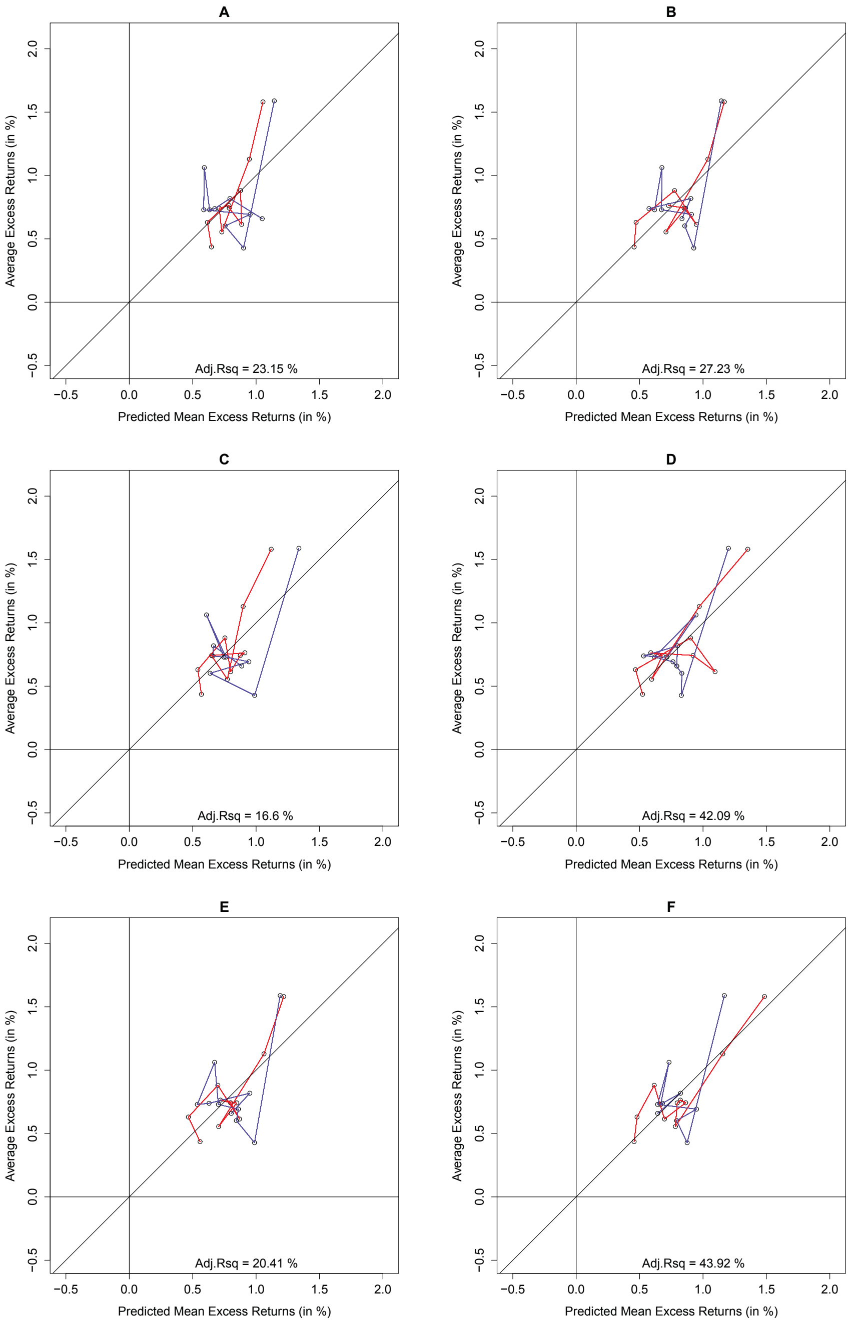
Panel A reports ten size-sorted portfolios (based on market capitalization), including the average number of stocks for each portfolio and the return difference between small and large portfolios. Panel B reports ten B/M-sorted portfolios, including the average number of stocks for each portfolio and the return difference between high and low B/M-sorted portfolios.

Table 17: Fama–Macbeth (1973) regression with portfolios and risk factors

	(I) CAPM	(II) FF-3	(III) Carhart-4	(IV) Petkova-5	(V) HXZ-4	(VI) FF-5	(VII) INS-5
β_{MKTRF}	1.75*	1.63*	1.78*	2.20**	2.66**	1.38	1.01
	[1.85]	[1.66]	[1.76]	[2.05]	[2.38]	[1.43]	[1.00]
β_{BM}							0.66**
							[2.55]
β_{PRET}							-0.00
							[-0.00]
β_{LIQ}							0.17
							[0.26]
β_{CFVOLA}							0.06
							[0.11]
β_{SMB}		0.87*	0.85*		1.42**	0.70	
		[1.70]	[1.67]		[2.52]	[1.53]	
β_{HML}		0.48	0.45			0.45	
		[0.82]	[0.78]			[0.81]	
β_{MOM}			0.70				
			[0.80]				
β_{RMW}						-0.59	
						[-1.07]	
B_{CMA}						0.46	
						[1.06]	
β_{IA}					0.047		
					[0.11]		
β_{ROE}					-0.016		
					[-0.04]		
$\hat{\mathbf{u}}^{\mathbf{T}ERM}$				0.07			
				[0.65]			
$\hat{\mathbf{u}}^{\mathbf{D}EF}$				0.02			
				[0.19]			
$\hat{\mathbf{u}}^{\mathbf{d}iv}$				0.01			
				[0.62]			
$\hat{\mathbf{u}}^{\mathbf{R}F}$				-0.03			
				[-1.31]			
Const. (z)	-0.063	-0.24	-0.470	-0.20	-1.00	-0.04	0.35
	[-0.13]	[-0.48]	[-0.75]	[-0.02]	[-1.30]	[-0.06]	[0.68]
Avg. $\mathbf{R}^2$	0.33	0.37	0.39	0.38	0.40	0.43	0.45

Column (I) describes the CAPM, column (II) the Fama–French (1993) three-factor model, column (III) describes the Carhart (1997) four-factor model, column (IV) the Petkova (2006) five-factor model, column (V) Hou, Xue, Zhang (2015) four-factor model, column (VI) the Fama and French 5-factor model and column (VII) the insurance-specific 5-factor model. Standard errors are Shanken (1992) corrected.

Figure 3: Actual vs. predicted returns



7.3 Time-series regressions

When we run time-series regressions on the ten size-sorted portfolios, we find that the difference between the most extreme portfolios is still not explained by the Fama–French (2015) five-factor model, despite the inclusion of the SMB factor due to the significant intercept value (Panel A of Table 18). The reason behind that is an insignificant SMB loading in the smallest insurance stocks, which should load significantly positive to capture the variation. In contrast, the SMB factor is able to capture the variation in the largest stocks, as can be seen in the increasing factor loadings from portfolio 8 to portfolio "large" in Panel A of Table 18.

When we run the INS-5 five-factor model (which does not have an explicit size factor such as SMB), we see that the intercept is only weakly significant (Panel B of Table 18), which still suggests that even the INS-5 factor model is challenged by the smallest insurers. It appears, though, that BMF captures most of the size anomaly by loading significantly positive on the smallest insurance stocks with a coefficient of 0.40 (suggesting that they also have high B/M ratios) and then continues to load significantly negative on the largest insurance stocks with a coefficient of -0.63 (suggesting that they also have low B/M ratios).

For the ten B/M-sorted portfolios, the results corroborate that the Fama–French (2015) five-factor model is not able to capture even the variation in portfolios for which it was in part designed, leaving a significant intercept between the most extreme B/M-sorted portfolios (Panel A of Table 19). In contrast, the INS-5 model captures the significant intercept between the most extreme portfolios (Panel B of Table 19).

8 Conclusion

The insurance industry is different compared to the non-financial sector primarily because it is exposed to a set of risks that are typically less correlated with financial risk. Hence insurance stock returns offer opportunities for investors aiming to diversify their portfolios. To properly price insurance stocks, we

Table 18: Ten size-sorted portfolios

Panel A: Fama-French (2015) five-factor model on ten size-sorted portfolios

	Small (1)	2	3	4	5	6	7	8	9	Large (10)	10-1	9-2	8-3
MKTRF	0.86***	0.67***	0.55***	0.57***	0.51***	0.56***	0.57***	0.69***	0.81***	1.15***	0.29**	0.15	0.14*
	[7.13]	[7.80]	[6.72]	[7.69]	[6.40]	[5.87]	[7.37]	[9.91]	[7.61]	[8.08]	[2.10]	[1.41]	[1.87]
SMB	-0.00	0.05	0.19*	0.14	0.13	-0.00	-0.05	-0.43***	-0.58***	-1.07***	-1.07***	-0.63***	-0.62***
	[-0.02]	[0.47]	[1.87]	[1.17]	[1.17]	[-0.03]	[-0.58]	[-4.91]	[-5.13]	[-8.54]	[-4.86]	[-4.07]	[-5.10]
HML	0.09	0.18	0.30**	0.33***	0.19*	0.30**	0.35***	0.31***	0.75***	0.56**	0.47	0.58*	0.01
	[0.50]	[1.16]	[2.00]	[2.90]	[1.71]	[2.02]	[3.05]	[2.64]	[2.74]	[1.98]	[1.22]	[1.79]	[0.07]
RMW	0.36	0.26	0.35**	0.08	0.47***	0.48***	0.45***	0.25**	0.09	0.28*	-0.08	-0.17	-0.10
	[1.15]	[1.47]	[2.51]	[0.61]	[3.72]	[3.55]	[4.76]	[2.53]	[0.35]	[1.83]	[-0.24]	[-0.59]	[-0.62]
CMA	0.48	0.32	0.14	-0.21	0.31*	0.18	-0.14	0.06	-0.04	-0.17	-0.65	-0.36	-0.08
	[1.42]	[1.40]	[0.72]	[-1.35]	[1.73]	[0.71]	[-0.79]	[0.32]	[-0.17]	[-0.51]	[-1.21]	[-1.21]	[-0.34]
α	0.58*	-0.36	-0.12	0.16	-0.02	0.30	0.07	0.06	0.04	-0.30	-0.88**	0.40	0.17
	[1.81]	[-1.37]	[-0.49]	[0.66]	[-0.09]	[1.18]	[0.34]	[0.27]	[0.14]	[-1.01]	[-2.17]	[0.96]	[0.58]
Adj. R^2	0.27	0.26	0.29	0.37	0.26	0.26	0.33	0.42	0.36	0.51	0.14	0.10	0.10

Panel B: INS-5 model on ten size-sorted portfolios

	Small (1)	2	3	4	5	6	7	8	9	Large (10)	10-1	9-2	8-3
MKTRF	0.55***	0.49***	0.49***	0.59***	0.41***	0.45***	0.46***	0.47***	0.44***	0.65***	0.10	-0.05	-0.02
	[6.05]	[5.80]	[6.00]	[10.94]	[5.72]	[5.39]	[6.30]	[8.38]	[3.59]	[4.61]	[0.91]	[-0.42]	[-0.38]
BMF	0.40***	0.04	-0.05	0.01	-0.18**	-0.08	-0.23***	-0.22**	-0.05	-0.63***	-1.03***	-0.09	-0.17
	[3.54]	[0.47]	[-0.73]	[0.12]	[-2.16]	[-0.83]	[-2.68]	[-2.34]	[-0.23]	[-2.86]	[-4.80]	[-0.42]	[-1.53]
PRETF	0.01	0.01	-0.12	-0.05	-0.07	-0.01	0.05	0.03	-0.12	-0.04	-0.06	-0.12	0.15
	[0.12]	[0.05]	[-1.27]	[-0.61]	[-0.81]	[-0.05]	[0.57]	[0.28]	[-0.73]	[-0.32]	[-0.36]	[-0.82]	[1.22]
LQF	-0.20	-0.08	-0.11	-0.01	0.00	-0.05	0.07	0.04	0.37	0.25*	0.45**	0.45	0.14
	[-1.22]	[-0.64]	[-1.15]	[-0.12]	[0.00]	[-0.44]	[0.94]	[0.39]	[1.35]	[1.71]	[2.02]	[1.39]	[1.30]
CFVF	0.45***	0.28*	-0.05	-0.06	-0.08	-0.24***	-0.13**	-0.09	-0.03	0.11	-0.34*	-0.31	-0.04
	[3.81]	[1.87]	[-0.63]	[-0.89]	[-1.16]	[-2.89]	[-2.04]	[-1.50]	[-0.21]	[0.65]	[-1.73]	[-1.34]	[-0.41]
α	1.28***	0.21	0.03	0.08	0.33	0.61	0.46	0.47	0.12	0.40	-0.87*	-0.09	0.43
	[3.24]	[0.53]	[0.10]	[0.29]	[0.97]	[1.63]	[1.57]	[1.44]	[0.32]	[0.87]	[-1.96]	[-0.22]	[1.43]
Adj. R^2	0.41	0.26	0.23	0.33	0.19	0.21	0.29	0.30	0.18	0.33	0.36	0.07	0.03

This table presents time-series regressions on excess returns of insurance stocks sorted by market capitalization (i.e., size) into ten deciles. Panel A reports time-series regressions for the Fama–French (2015) five-factor model. Panel B reports time-series regressions for the INS-5 model. The last three columns in each panel show time-series regressions on the spreads between the highest (second highest, and third highest, respectively) and the lowest (second lowest, and third lowest, respectively) portfolios. The sample period is July 1988 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of five. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 19: Ten B/M-sorted portfolios

Panel A: Fama-French (2015) five-factor model on ten B/M-sorted portfolios

	Low (1)	2	3	4	5	6	7	8	9	High (10)	10-1	9-2	8-3
MKTRF	0.72***	0.62***	0.90***	0.75***	0.55***	0.71***	0.61***	0.60***	0.71***	0.65***	-0.07	0.09	-0.30**
	[8.55]	[6.03]	[7.15]	[9.50]	[8.28]	[8.47]	[6.81]	[8.31]	[9.20]	[4.68]	[-0.42]	[0.92]	[-2.20]
SMB	-0.51***	-0.24**	-0.49***	-0.07	0.15	-0.25**	-0.00	-0.09	0.04	-0.07	0.44	0.28	0.41**
	[-4.38]	[-2.30]	[-3.76]	[-0.79]	[1.19]	[-2.56]	[-0.01]	[-0.68]	[0.28]	[-0.32]	[1.56]	[1.54]	[2.22]
HML	0.10	0.14	0.36*	0.39**	0.37***	0.31***	0.48***	0.30***	0.31*	0.70**	0.60	0.17	-0.06
	[0.71]	[1.12]	[1.87]	[2.14]	[3.03]	[2.88]	[3.76]	[2.93]	[1.94]	[2.08]	[1.43]	[0.82]	[-0.28]
RMW	0.32***	0.45***	0.53***	0.48***	0.28	0.33***	0.34***	0.29*	0.28	-0.30	-0.62*	-0.17	-0.24
	[2.93]	[3.51]	[3.65]	[4.09]	[1.59]	[2.60]	[2.63]	[1.69]	[1.41]	[-0.94]	[-1.83]	[-0.72]	[-1.20]
CMA	0.24	0.04	-0.02	0.05	-0.07	0.03	0.08	0.01	0.26	-0.19	-0.44	0.22	0.03
	[1.14]	[0.20]	[-0.10]	[0.26]	[-0.30]	[0.13]	[0.36]	[0.08]	[1.14]	[-0.38]	[-0.71]	[0.86]	[0.13]
α	-0.29	-0.05	-0.06	-0.27	0.10	0.02	-0.02	-0.11	0.28	1.07***	1.36***	0.33	-0.05
	[-1.30]	[-0.16]	[-0.22]	[-1.18]	[0.48]	[0.07]	[-0.07]	[-0.41]	[0.94]	[2.68]	[3.04]	[0.83]	[-0.16]
Adj. R^2	0.31	0.23	0.40	0.42	0.30	0.36	0.35	0.30	0.33	0.21	0.07	0.05	0.06

Panel B: INS-5 model on ten B/M-sorted portfolios

	Low (1)	2	3	4	5	6	7	8	9	High (1)	10-1	9-2	8-3
MKTRF	0.47***	0.46***	0.56***	0.58***	0.51***	0.50***	0.46***	0.43***	0.51***	0.49***	0.02	0.05	-0.13
	[7.01]	[5.49]	[5.08]	[6.70]	[7.74]	[6.91]	[5.94]	[6.89]	[5.83]	[4.91]	[0.22]	[0.71]	[-1.46]
BMF	-0.57***	-0.50***	-0.50***	-0.36***	0.01	-0.04	-0.04	-0.00	0.41***	0.97***	1.54***	0.91***	0.49***
	[-6.45]	[-5.07]	[-3.02]	[-3.87]	[0.10]	[-0.53]	[-0.62]	[-0.01]	[5.21]	[5.70]	[11.91]	[8.28]	[3.01]
PRETF	-0.02	-0.13	0.06	0.03	0.10	0.10	-0.03	-0.05	0.12	-0.25	-0.23*	0.25***	-0.11
	[-0.21]	[-1.22]	[0.49]	[0.29]	[0.80]	[1.39]	[-0.38]	[-0.57]	[1.52]	[-1.44]	[-1.87]	[2.79]	[-0.88]
LQF	0.03	0.01	0.11	-0.00	0.01	-0.07	0.10	-0.05	0.11	-0.02	-0.04	0.10	-0.16
	[0.26]	[0.13]	[0.88]	[-0.04]	[0.06]	[-0.72]	[1.08]	[-0.55]	[1.43]	[-0.10]	[-0.41]	[1.08]	[-1.11]
CFVF	0.02	-0.06	0.13	0.07	-0.04	0.04	-0.12	0.10	0.04	-0.02	-0.04	0.10	-0.03
	[0.36]	[-0.75]	[0.97]	[0.95]	[-0.50]	[0.32]	[-1.26]	[1.37]	[0.64]	[-0.17]	[-0.47]	[1.03]	[-0.20]
α	0.36	0.30	0.86**	0.45	0.47	0.59*	0.22	0.20	0.65*	0.16	-0.20	0.36	-0.66
	[1.18]	[0.81]	[2.04]	[1.29]	[1.23]	[1.83]	[0.62]	[0.68]	[1.69]	[0.31]	[-0.49]	[1.04]	[-1.47]
Adj. R^2	0.37	0.32	0.30	0.35	0.23	0.25	0.22	0.23	0.37	0.41	0.60	0.44	0.11

This table presents time-series regressions on excess returns of insurance stocks sorted by book-to-market ratio into ten deciles. Panel A reports time-series regressions for the Fama–French (2015) five-factor model. Panel B reports time-series regressions for the INS-5 model. The last three columns in each panel show time-series regressions on the spreads between the highest (second highest, and third highest, respectively) and the lowest (second lowest, and third lowest, respectively) portfolios. The sample period is July 1988 to December 2013. T-statistics in brackets are Newey–West (1987) corrected with lags of five. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

conduct an asset pricing exercise using the state-of-the art asset pricing models (such as the Fama and French (2015) or Hou, Xue, and Zhang (2015)). We find that these models fall short of explaining a large part of the cross-sectional variation in p/l insurance stock returns. This is an important finding, because it indicates that insurance practitioners who use CAPM and the FamaFrench (1993) three-factor model as industry standards (e.g., to price insurance policies) are not taking all necessary risk factors into account.

To address this deficiency in the literature, we propose the insurance-specific five-factor (INS-5) model which uses the book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility factors in addition to the excess market return. We find that these factors offer a significant marginal explanation of the cross-section variation in p/l insurance stocks. The INS-5 model provides more accurate cost-of-capital estimates than existing asset pricing models. We provide an economic interpretation for each risk factor which are default likelihood, liquidity provisions by market makers, size, market microstructure (i.e., trading volume and bid-ask spreads) and the reinsurance cycle. The risk factors thus represent a combination of general risk factors and insurance-specific factors. Our discussion provides new insights into the ongoing discussion on the pricing determinants of insurance products and on the correct determination of costs of capital in the insurance sector.[29] The results also reflect anecdotal evidence on underwriting cycles often discussed in the p/l insurance sector and provide a robust empirical foundation for these stylized facts.

Our paper also provides an avenue for future research in the insurance sector. For example, a comparison of cost-of-capital estimates from our model with existing industry practices might yield useful insights as to which p/l insurance products are underpriced or overpriced. Also our findings are limited

[29]A correct asset pricing model and thus accurate cost of equity is crucial for fairly priced insurance products. Capital costs are of great importance in the insurance industry in some capital-intensive lines of insurance business, where capital costs can constitute the bulk of the premium (Zanjani (2002)). Standard asset pricing ignores the fact that policyholders, unlike in any other industry, depend on the solvability of the insurer if claims have to be paid (Doherty and Tinic (1981); Zanjani (2002)). Thus, it is very likely that the cost of capital and therefore the return for shareholders deviates from what standard asset pricing models would predict.

to the U.S. sector, so that their generalizability to other countries needs to be tested. Another useful extension might be an analysis of the life and health insurance sector. Although this paper emphasizes the high relevance of cross-sectional relationships, which – in contrast to the overall finance literature – are underrepresented in the insurance literature, further research also might analyze the variations of insurance stocks and factors in a time-series context, for instance for the purpose of risk management.

References

Adrian, T.; T. Muir; and E. Etula. "Financial Intermediaries and the Cross-section of Asset Returns." *Journal of Finance*, 69 (2014), 2557–2596.

Ang, A.; J. Chen; and Y. Xing. "Downside Risk." *Review of Financial Studies*, 19 (2006), 1191–1239.

Ang, A.; R. J. Hodrick; Y. Xing; and X. Zhang. "The Cross−section of Volatility and Expected Returns." *Journal of Finance*, 61 (2006), 259–299.

Ang, A.; A. A. Shtauber; and P. C. Tetlock. "Asset Pricing in the Dark: The Cross-section of OTC Stocks." *Review of Financial Studies*, 26 (2013), 2985–3028.

Badrinath, S. G., and S. Wahal. "Momentum Trading by Institutions." *Journal of Finance*, 57 (2002), 2449–2478.

Barber, B. M., and J. D. Lyon. "Firm Size, B/M Ratio, and Security Returns: A Holdout Sample of Financial Firms." *Journal of Finance*, 52 (1997), 875–883.

Ben Ammar, S., "Pricing of Catastrophe Risk and the Implied Volatility Smile." *Working Paper*, University of St.Gallen (2016).

Bhandari, L. C. "Debt/Equity Ratio and Expected Common Stock Returns: Empirical Evidence." *Journal of Finance*, 43 (1988), 507–528.

Bollerslev, T.; M. Gibson; and H. Zhou. "Dynamic Estimation of Volatility Risk Premia and Investor Risk Aversion from Option-Implied and Realized Volatilities." *Journal of Econometrics*, 160 (2011), 235–245.

Braun, A. "Pricing in the Primary Market for Cat Bonds: New Empirical Evidence." *Journal of Risk and Insurance* (2015), doi: 10.1111/jori.12067.

Brennan, M. J.; T. Chordia; and A. Subrahmanyam. "Alternative Factor Specifications, Security Characteristics, and the Cross-section of Expected Stock Returns." *Journal of Financial Economics*, 49 (1998), 345–373.

Brennan, M. J.; T. Chordia; A. Subrahmanyam; and Q. Tong. "Sell-Order Liquidity and the Cross-section of Expected Stock Returns." *Journal of Financial Economics*, 105 (2012), 523–541.

Brewer, E.; J. M. Carson; E. Elyasiani; I. Mansur; and W. L. Scott. "Interest Rate Risk and Equity Values of Life Insurance Companies: A GARCH–M Model." *Journal of Risk and Insurance*, 74 (2007), 401–423.

Brunnermeier, M. K.; and L. H. Pedersen. "Market Liquidity and Funding Liquidity." *Review of Financial Studies*, 22 (2009), 2201–2238.

Carhart, M. M. "On Persistence in Mutual Fund Performance." *Journal of Finance*, 52 (1997), 57–82.

Carson, J, M.; E. Elyasiani; and I. Mansur. "Market Risk, Interest Rate Risk, and Interdependencies in Insurer Stock Returns: A System−GARCH Model." *Journal of Risk and Insurance*, 75 (2008), 873–891.

Chen, N.; and F. Zhang. "Risk and Return of Value Stocks." *Journal of Business*, 71 (1998), 501–535.

Cheng, S.; A. Hameed; A. Subrahmanyam; and S. Titman. "Short-Term Reversals: The Effects of Institutional Exits and Past Returns." Working Paper. (2014).

Cochrane, J. H. *Asset Pricing.* Princeton, NJ: Princeton University Press (2005).

Cooper, M. J.; H. Gulen; and M. J. Schill. "Asset Growth and the Cross−section of Stock Returns." *Journal of Finance*, 63 (2008), 1609–1651.

Cummins, J. D., and S. Harrington. "Property-Liability Insurance Rate Regulation: Estimation of Underwriting Betas Using Quarterly Profit Data." *Journal of Risk and Insurance*, 52 (1985), 16–43.

Cummins, J. D., and S. E. Harrington. "The Relationship between Risk and Return: Evidence for Property-Liability Insurance Stocks." *Journal of Risk and Insurance*, 55 (1988), 15–31.

Cummins, J. D., and J. Lamm-Tennant. “Capital Structure and the Cost of Equity Capital in the Property-Liability Insurance Industry.” *Insurance: Mathematics and Economics*, 15 (1994), 187–201.

Cummins, J. D., and J. F. Outreville. “An International Analysis of Underwriting Cycles in Property-Liability Insurance.” *Journal of Risk and Insurance*, 54 (1987), 246–262.

Cummins, J. D., and R. D. Phillips. “Estimating the Cost of Equity Capital for Property-Liability Insurers.” *Journal of Risk and Insurance*, 72 (2005), 441–478.

Cummins, J. D., and M. A. Weiss. “Convergence of Insurance and Financial Markets: Hybrid and Securitized Risk−Transfer Solutions.” *Journal of Risk and Insurance*, 76 (2009), 493–545.

Cummins, J. D.; N. Doherty; and A. Lo. “Can Insurers Pay for the Big One? Measuring the Capacity of the Insurance Market to Respond to Catastrophic Losses.” *Journal of Banking and Finance*, 26 (2002), 557–583.

Daniel, K., and S. Titman. “Evidence on the Characteristics of Cross Sectional Variation in Stock Returns.” *Journal of Finance*, 52 (1997), 1–33.

De Bondt, W. F. M., and R. H. Thaler. “Further Evidence on Investor Overreaction and Stock Market Seasonality.” *Journal of Finance*, 42 (1987), 557–581.

Dittmar, R. F. “Nonlinear Pricing Kernels, Kurtosis Preference, and Evidence from the Cross Section of Equity Returns.” *Journal of Finance*, 57 (2002), 369–403.

Doherty, N. A., and H. B. Kang. “Interest Rates and Insurance Price Cycles.” *Journal of Banking and Finance*, 12 (1988), 199–214.

Doherty, N. A., and S. M. Tinic. “Reinsurance under Conditions of Capital Market Equilibrium: A Note.” *Journal of Finance*, 36 (1981), 949–953.

Eisfeldt, A. L., and D. Papanikolaou. "Organization Capital and the Cross−section of Expected Returns." *Journal of Finance*, 68 (2013), 1365–1406.

Fairley, W. B. "Investment Income and Profit Margins in Property-Liability Insurance: Theory and Empirical Results." *Bell Journal of Economics*, (1979) 192–210.

Fama, E. F., and K. R. French. "The Cross-section of Expected Stock Returns." *Journal of Finance*, 47 (1992), 427–465.

Fama, E. F., and K. R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, 33 (1993), 3–56.

Fama, E. F., and K. R. French. "Forecasting Profitability and Earnings." *Journal of Business*, 73 (2000), 161–175.

Fama, E. F., and K. R. French. "Dissecting Anomalies." *Journal of Finance*, 63 (2008), 1653–1678.

Fama, E. F., and K. R. French. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics*, 116 (2015), 1–22.

Fama, E. F., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy*, 81 (1973), 607–636.

Fang, H., and T.−Y. Lai. "Co−kurtosis and Capital Asset Pricing." *Financial Review*, 32 (1997), 293–307.

Ferson, W. E.; S. Sarkissian; and T. Simin. "The Alpha Factor Asset Pricing Model: A Parable." *Journal of Financial Markets*, 2 (1999), 49–68.

Froot, K. A. "Risk Management, Capital Budgeting, and Capital Structure Policy for Insurers and Reinsurers." *Journal of Risk and Insurance*, 74 (2007), 273–299.

Froot, K. A., and J. C. Stein. "Risk Management, Capital Budgeting, and Capital Structure Policy for Financial Institutions: An Integrated Approach." *Journal of Financial Economics*, 47 (1998), 55–82.

Gandhi, P., and H. Lustig. “Size Anomalies in U.S. Bank Stock Returns.” *Journal of Finance*, 70 (2015), 733–768.

Garlappi, L., and H. Yan. “Financial Distress and the Cross−section of Equity Returns.” *Journal of Finance*, 66 (2011), 789–822.

George, T. J., and C.-Y. Hwang. “The 52-Week High and Momentum Investing.” *Journal of Finance*, 59 (2004), 2145–2176.

Hameed, A. and G. M. Mian. “Industries and Stock Return Reversals.” *Journal of Financial and Quantitative Analysis*, 50 (2015), 89–117.

Harvey, C. R., and A. Siddique. “Conditional Skewness in Asset Pricing Tests.” *Journal of Finance*, 55 (2000), 1263–1295.

Hirshleifer, D. “Investor Psychology and Asset Pricing.” *Journal of Finance*, 56 (2001), 1533–1597.

Hou, K., C. Xue, and L. Zhang. ”Digesting anomalies: An investment approach.” *Review of Financial Studies*, 28 (2015), 650-705.

Huang, A. G. “The Cross Section of Cashflow Volatility and Expected Stock Returns.” *Journal of Empirical Finance*, 16 (2009), 409–429.

Ibragimov, R.; D. Jaffee; and J. Walden. “Nondiversification Traps in Catastrophe Insurance Markets.” *Review of Financial Studies*, 22 (2009), 959–993.

Jegadeesh, N. “Evidence of Predictable Behavior of Security Returns.” *Journal of Finance*, 45 (1990), 881–898.

Jegadeesh, N., and S. Titman. “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.” *Journal of Finance*, 48 (1993), 65–91.

Kahle, K. M., and Walkling, R. A. “The Impact of Industry Classifications on Financial Research.” *Journal of Financial and Quantitative Analysis*, 31 (1996), 309–335.

Kan, R., and C. Robotti. “Model Comparison Using the Hansen-Jagannathan Distance.” *Review of Financial Studies*, 22 (2009), 3449–3490.

Kan, R.; C. Robotti; and J. Shanken. “Pricing Model Performance and the Two−Pass Cross−sectional Regression Methodology.” *Journal of Finance*, 68 (2013), 2617–2649.

Kelly, B., and H. Jiang. “Tail risk and asset prices.” *Review of Financial Studies*, 27 (2014), 2841–2871.

Leland, H. E. “Beyond Mean-Variance: Performance Measurement in a Non-symmetrical World.” *Financial Analysts Journal*, (1999), 27–36.

Lewellen, J.; S. Nagel; and J. Shanken. “A Skeptical Appraisal of Asset Pricing Tests.” *Journal of Financial Economics*, 96 (2010), 175–194.

Lo, A. W., and A. C. MacKinlay. “An Econometric Analysis of Nonsynchronous Trading.” *Journal of Econometrics*, 45 (1990), 181–211.

Lustig, H.; N. Roussanov; and A. Verdelhan. “Common Risk Factors in Currency Markets.” *Review of Financial Studies*, 24 (2011), 3731–3777.

Merton, R. C. “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates.” *Journal of Finance*, 29 (1974), 449–470.

Milidonis, A. “Compensation Incentives of Credit Rating Agencies and Predictability of Changes in Bond Ratings and Financial Strength Ratings.” *Journal of Banking and Finance*, 37 (2013), 3716–3732.

Nagel, S. “Evaporating Liquidity.” *Review of Financial Studies*, 25 (2012), 2005–2039.

Newey, W. K., and K. D. West. “A Simple Positive-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix.” *Econometrica*, 55 (1987), 703–708.

Opler, T. C., and S. Titman. “Financial Distress and Corporate Performance.” *Journal of Finance*, 49 (1994), 1015–1040.

Pstor, L., and R. F. Stambaugh. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, 111 (2003), 642–685.

Petkova, R. "Do the Fama–French Factors Proxy for Innovations in Predictive Variables?" *Journal of Finance*, 61 (2006), 581–612.

Ross, S. A. "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory*, 13 (1976), 341–360.

Rubinstein, M. "The Valuation of Uncertain Income Streams and the Pricing of Options." *Bell Journal of Economics*, 7 (1976), 407–425.

Schwert, G. W. "Anomalies and Market Efficiency." In *Handbook of the Economics of Finance*. G. M. Constantinides, M. Harris, and R. M. Stulz, eds. Amsterdam: North Holland (2003).

Shanken, J. "On the Estimation of Beta-Pricing Models." *Review of Financial Studies*, 5 (1992), 1–55.

Thomann, C. "The Impact of Catastrophes on Insurer Stock Volatility." *Journal of Risk and Insurance*, 80 (2013), 65–94.

Vassalou, M., and Y. Xing. "Default Risk in Equity Returns." *Journal of Finance*, 59 (2004), 831–868.

Viale, A. M.; J. W. Kolari; and D. R. Fraser. "Common Risk Factors in Bank Stocks." *Journal of Banking and Finance*, 33 (2009), 464–472.

Wen, M.-M.; A. D. Martin; G. Lai; and T. J. O'Brien. "Estimating the Cost of Equity for Property-Liability Insurance Companies." *Journal of Risk and Insurance*, 75 (2008), 101–124.

Zanjani, G. "Pricing and Capital Allocation in Catastrophe Insurance." *Journal of Financial Economics*, 65 (2002), 283–305.

A Firm data

Table A: Firm data

Year	Property/Casualty (SIC code 6331)	Year	Property/Casualty (SIC code 6331)
1987	61	**2001**	55
1988	66	**2002**	54
1989	67	**2003**	56
1990	71	**2004**	58
1991	77	**2005**	61
1992	81	**2006**	64
1993	94	**2007**	59
1994	90	**2008**	54
1995	89	**2009**	53
1996	89	**2010**	48
1997	78	**2011**	47
1998	74	**2012**	44
1999	65	**2013**	43
2000	61		

This table shows the number of companies in the p/l insurance sector. Columns 1 and 3 report the year for which insurer information is available. Columns 2 and 4 report the number of p/l insurers (SIC code 6331) per year.

B Stock characteristics

Table B: Analyzed characteristics

β / $\beta^{-/}$ β^{+}	Regular CAPM / downside / upside betas are measured as the co-movement of daily excess returns with the market excess return over the past 250 trading days. At the end of each month *t* stock returns are sorted based on the beta value measured over past 250 trading days until the end of month *t-1*. Portfolios are rebalanced monthly.
Size	Size is measured as the market capitalization of a stock. Market capitalization is measured at the end of June of year *t* and defined as price times shares outstanding. Based on the market capitalization measured in June of year *t* equal-weighted portfolios are created from July of year *t* until June of year *t+1*. Portfolios are rebalanced yearly.
B/M	Book-to-market equity is the ratio of the book value of equity to the market value of equity, both being measured in December of year *t-1*. Book equity is book equity per share plus investment tax credit if available. Market equity is defined as price times shares outstanding. In July of year *t* we sort stocks based on the book-to-market ratio measured in December of year *t-1*. Equal weighted return portfolios are then calculated from July of year *t* until June of year *t+1*. Portfolios are yearly rebalanced.
MOM	Momentum is the cumulative monthly stock return from month *t-12* to *t-2*. The t-*1* month return is skipped to avoid the previous month return anomaly. Based on the prior 11-month return from t-12 to t-2 equal weighted return portfolios are created. Portfolios are rebalanced monthly.
RET$_{t-1}$	Short-term reversal is defined as the stock's raw return in month *t-1*. As in Jegadeesh (1990) we sort stocks in month *t* based on the previous month return and calculate equal-weighted portfolios. Portfolios are rebalanced monthly.
β_{LIQ}	Liquidity beta is measured as the co-movement with Pstor and Stambaugh's (2003) innovations in market-wide liquidity. The liquidity beta is measured as post-ranking beta using monthly data in a rolling window from *t-36* to *t-1*. Portfolio returns are then calculated in *t* based on the beta exposure over the previous 36-months from *t-36* to *t-1*. Portfolios are rebalanced monthly.
REV	Long-term reversal is defined as the cumulative monthly stock return from month*t-36* to *t-13*. Based on the prior 24-month return from *t-36* to *t-13* equal weighted return portfolios are created. Portfolios are rebalanced monthly.
ID-VOLA	As in Ang et al. (2006) we calculate the standard deviation of the residuals from time-series regressions of the excess stock return on the Fama and French (1993) three factors. We use daily returns to run the time-series rergession in each month and require at least 15 daily returns per month. Equal-weighted portfolios in month *t* are then sorted based on the idiosyncratic volatility in month *t-1*. Portfolios are rebalanced each month.
CF-VOLA	Cashflow volatility is defined as the standard deviation over the previous eight quarterly cashflow figures and cashflow itself is defined as the sum of income before extraordinary items, depreciation, and amortization. Cashflows are additionally standardized by quarterly sales figures (Huang 2009). Following Huang (2009) stocks are then sorted in month *t* based on the calculated cashflow volatility lagged by three months. Portfolios are quarterly rebalanced.
CO-SKEW	Co-skewness is defined as the coefficient on the squared market factor from a time-series regression of daily excess returns on the market factor and the squared market factor over the past 250 trading days. At the end of each month *t* stock returns are sorted based on the coefficient measured over past 250 trading days until the end of month *t-1*. Portfolios are rebalanced monthly.

CO-KURT	Co-kurtosis is defined as the coefficient on the cubic market factor from a time-series regression of daily excess returns on the market factor, the squared market factor, and the cubic market factor over the past 250 trading days. At the end of each month *t* stock returns are sorted based on the coefficient measured over past 250 trading days until the end of month *t-1*. Portfolios are rebalanced monthly.
OP	Following Fama and French (2015) we measure (operating) profitability at the end of year *t-1* as annual revenues minus cost of goods sold, interest expense, and selling, general, and administrative expenses. All items are then divided by the book equity at the end of year *t-1*. Based on the profitability figure in year *t-1* equal weighted return portfolios are then calculated from July of year *t* until June of year *t+1*. Portfolios are yearly rebalanced.
Asset Growth	Asset growth is defined as the change in total assets from December in calendar year *t-2* to December in calendar year *t-1*divided by total assets in year *t-2* (Cooper, Gulen, and Schill 2008). Based on the asset growth figure in year *t-1* equal weighted return portfolios are then calculated from July of year *t* until June of year *t+1*. Portfolios are yearly rebalanced.
$\beta_{\Delta TERM}$	$\beta_{\Delta TERM}$ is defined as the beta exposure over the past 36 months. ΔTERM is the change in yields between the 10-year constant maturity yield and 1-year constant maturity yield downloaded from the Federal Reserve Economic Data (FRED). $\beta_{\Delta TERM}$ is measured as the co-movement of excess returns with ΔTERM . $\beta_{\Delta TERM}$ is measured as post-ranking beta using monthly data in a rolling window from *t-36* to *t-1*. Portfolio returns are then calculated in *t* based on the beta exposure over the previous 36-months from *t-36* to *t-1*. Portfolios are rebalanced monthly.
$\beta_{\Delta DEF}$	$\beta_{\Delta DEF}$ is defined as the beta exposure over the past 36 months. ΔDEF is the change in yields between the 10-year constant maturity yield and 1-year constant maturity yield downloaded from the Federal Reserve Economic Data (FRED). $\beta_{\Delta DEF}$ is measured as the co-movement of excess returns with ΔDEF. $\beta_{\Delta DEF}$ is measured as post-ranking beta using monthly data in a rolling window from *t-36* to *t-1*. Portfolio returns are then calculated in *t* based on the beta exposure over the previous 36-month from *t-36* to *t-1*. Portfolios are rebalanced monthly.
INVEST	Investment performance is defined as the cashflows from investment activity (COMPUSTAT item: IVNCF) standardized by total insurance premiums (COMPUSTAT item: IPTI).
$\beta_{B/DLEV}$	$\beta_{B/DLEV}$ is defined as the beta exposure over the past 36 months (i.e., 12 quarters). B/D LEV is the broker/dealer leverage factor downloaded from Tyler Muir's website. $\beta_{B/DLEV}$ is measured as the co-movement of excess returns with B/D LEV . $\beta_{B/DLEV}$ is measured as post-ranking beta using quarterly data in a rolling window from month *t-36* to *t-1*. Portfolio returns are then calculated in *t* based on the beta exposure over the previous 36-months from *t-36* to *t-1*. Portfolios are quarterly rebalanced.
INS/LEV	Insurance leverage is defined as other liabilities (COMPUSTAT item: LO) divided by market equity, both being measured in December of year *t-1*. In July of year *t* we sort stocks based on insurance leverage from *t-1*. Equal weighted return portfolios are then calculated from July of year *t* until June of year *t+1*. Portfolios are yearly rebalanced.
FIN/LEV	Financial leverage is defined as the sum of current debt (COMPUSTAT item: DLC) and non-current debt (COMPUSTAT item: DLTT) divided by market equity, both being measured in December of year *t-1*. In July of year *t* we sort stocks based on financial leverage from *t-1*. Equal weighted return portfolios are then calculated from July of year *t* until June of year *t+1*. Portfolios are yearly rebalanced.
Total LEV	Total leverage is defined as the difference between total assets and book equity, all divided by market equity and measured in December of year *t-1*. In July of year *t* we sort stocks based on total leverage from *t-1*. Equal weighted return portfolios are then calculated from July of year *t* until June of year *t+1*. Portfolios are yearly rebalanced.

C Principal components

Table C: Correlation of principal components with common factors

Panel A: Correlation of excess market return with first principal components (level factor)

	PC1 (B/M)	PC1 (RET_{t-1})	PC1 (LIQ)	PC1 (CFVOLA)
MKTRF	0.64			
MKTRF		0.64		
MKTRF			0.63	
MKTRF				0.63

Panel B: Correlation of risk factors with second principal components (slope factor)

	PC2 (B/M)	PC2 (RET_{t-1})	PC2 (LIQ)	PC2 (CFVOLA)
BMF	0.95			
PRETF		-0.93		
LQF			0.75	
CFVF				0.97

Panel A of this table shows the correlation between the excess market return and the first principal components, where each first principal component is derived from five characteristic-sorted portfolios (i.e., B/M, RET_{t-1}, LIQ, and CFVOLA). Panel B reports the correlation of each constructed factor according to equation (8) and their second principal components, respectively.

Part III

Pricing of Catastrophe Risk and the Implied Volatility Smile

SEMIR BEN AMMAR

Abstract

Property-casualty (P&C) insurers are exposed to rare but severe natural disasters. This paper analyzes the relation between catastrophe risk and the implied volatility smile of insurance stock options. We find that the slope is significantly steeper compared to non-financials and other financial institutions. We show that this effect has increased over time, suggesting a higher risk compensation for natural catastrophes. We are also able to link the insurance-specific tail risk component derived from options with the risk spread from the catastrophe bond market, which specifically securitizes tail risk events. Our results thus provide an accurate, high-frequency calculation for catastrophe risk linking the traditional derivatives market with insurance-linked securities (ILS).

Keywords: Implied volatility · Options · Catastrophe risk · Tail risk · Natural disasters
JEL Classification: G12 · G13 · G14 · G22

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"The hurricane does not know the rate that was charged for the hurricane policy, so it's not going to respond to how much you charge. And if you charge an inadequate premium, you will get creamed over time."

-Warren Buffett-
June 9th 2014, Las Vegas

1 Introduction

Options allow us to evaluate the expectation of market participants regarding extreme events (Backus, Chernov, and Martin (2011)). Since property-casualty (P&C) insurance companies are exposed to natural and man-made catastrophes, options written on P&C insurance stocks should exhibit a catastrophe risk premium in the tail of their density function. This risk premium should be in excess of the tail risk in stock prices induced by market events, given that P&C insurance companies are also exposed to the overall economic development and thus the same market events. This paper analyzes the slope of the implied volatility, i.e., the absolute difference between out-of-the-money (OTM) and in-the-money (ITM) put options, as a measure of tail risk to identify a catastrophe risk premium. The idea behind this approach is that OTM options provide more effective protection against rare events than ITM options (Kelly, Pástor, and Veronesi (2015)).

There are at least three motivating aspects in analyzing tail risk specifically using options on P&C insurance stocks to identify inherent catastrophe risk.[1] First of all, catastrophes can cause great damage to specific regions. Risk-averse households are interested in offloading such risks but face high insurance premiums for this type of risk (see Froot (2001) and Zanjani (2002)). Any insight into catastrophe risk can thus further enhance our understanding of risk-adequate compensation for this type of risk. Second, some market participants specifically

[1] We define catastrophe risk as a specific and independent component of the overall tail risk to which companies are exposed. Thus, catastrophe risk is one of many potential sources of distress to a firm (here the P&C insurer). We follow Froot's (2001) definition of catastrophe risk itself, which relates to all events linked to natural hazard (e.g., hurricanes, earthquakes, wind and ice storms, floods, etc.) causing financial losses.

securitize part of their tail risk (i.e., catastrophe risk) in financial markets by means of insurance-linked securities (ILS).[2] This allows us to verify our results for catastrophe risk in another market and establish a link between the two. Third, P&C insurers use risk mitigation techniques to reduce tail risk exposure, especially excess-of-loss reinsurance. This provides an opportunity to test whether the implied volatility slope reflects differences in the amount of risk mitigation.

No previous studies on options written on insurance stocks exist. However, the finance literature focuses on two aspects closely related to ours. First, the determinants of the implied volatility smile are important to explain the anomaly of the implied volatility smile itself (Dennis and Mayhew (2002); Bollen and Whaley (2004)). Second, the relation between the implied volatility smile and tail risk has recently gained much attention with regard to financial guarantees (Kelly, Lustig, and Nieuwerburgh (2015)) and political uncertainty (Kelly, Pástor, and Veronesi (2015)). Our paper adds an important perspective to the discussion between tail risk and the implied volatility smile by linking catastrophe risk with the steepness of the implied volatility smile.

The contribution of this paper is fourfold. First, we derive an option pricing model unique to P&C insurers which accounts for catastrophe risk and uses the derivatives market for accurate pricing of catastrophe risk. Due to the limited understanding of catastrophe risk in combination with pricing, new methods to comprehend this risk in greater detail can reduce market imperfections. Second, fair pricing for catastrophe reinsurance can affect the capital requirements for catastrophe risk and thus reduce the cost of capital (Zanjani (2002)). Third, we further enhance the reasoning with regard to the implied volatility smile. That is, we address why there is an implied volatility smile and

[2] The banking sector has also begun to apply a similar technique using contingent convertible (coco) bonds in the wake of the financial crisis. However, catastrophe bonds have already attracted investors at the end of the 1990s and, more importantly, catastrophe risk is (in general) uncorrelated with the market (Froot et al. (1995) and Zanjani (2002)), whereas coco bonds are most likely to be triggered when the rest of the economy suffers a simultaneous downturn. Thus, from an investor's perspective, the identification of catastrophe risk can be interesting for diversification purposes. In our research design, this means we have an independent component of tail risk.

why it is shaped the way it is (Dennis and Mayhew (2002)). Fourth, we create a link between the traditional derivatives market and ILS. From an investor's perspective, this link might be an indicator for potential arbitrage opportunities if expectations on catastrophe risk in the two markets significantly diverge.

The first finding of this paper is the identification of a catastrophe risk premium in the implied volatility smile. The implied volatility of OTM put options written on P&C insurers is 120 basis points higher than OTM put options on matched non-financials with identical historical volatility. The second finding is a strong correlation between the extracted catastrophe risk premium from option markets and the risk spreads from catastrophe bonds with expected loss and default risk being significant drivers of this result. The third finding is that catastrophe risk in derivatives has increased over time, that is, the implied volatility smile became steeper over time in comparison to options written on the rest of the market. The fourth finding is a steepening implied volatility smile around hurricane events on the day of the landfall and the days following. This suggests that market participants are more likely to protect themselves against natural catastrophes the more information about such an event arrives.

The remainder of this paper is organized as follows. Section 2 gives a brief literature review. Section 3 derives the option pricing model for P&C insurers and the corresponding hypotheses. Section 4 provides a description of the methodology and Section 5 a description of the data. Section 6 shows the empirical results. Section 7 checks for robustness and Section 8 concludes.

2 Literature

No previous studies on insurance options exist, yet there are two strands of literature relevant to this paper. The first one deals with the general findings from the finance literature regarding the determinants of the implied volatility smile and its relation to tail risk. The second strand of literature refers to the findings on insurance-specific catastrophe risk.[3]

Regarding the determinants of the implied volatility slope, Dennis and Mayhew (2002) identify several factors including beta, size, trading volume, the slope of the market index, and the volatility environment. Effects regarding the leverage effect are ambiguous, however. While Toft and Prucyk (1997) find that highly leveraged firms have steeper slopes than less leveraged firms, Dennis and Mayhew (2002) find no robust effect regarding leverage. As highlighted by Dennis and Mayhew (2002), leverage is unlikely to be a driving factor of the implied volatility smile, because currency options that cannot be subject to the leverage hypothesis also display an implied volatility smile. Also, Bakshi, Kapadia, and Madan (2003) find that index volatility smiles have a steeper slope than individual stock option smiles. Again, they empirically show that the volatility smile is not the result of the leverage effect, as assumed by Toft and Prucyk (1997). Bollen and Whaley (2004) find that the volatility smile is the result of demand pressure from public order flow. That is, the more investors ask for OTM put options on indices and OTM call options on individual stocks, the more expensive they get. Furthermore, Kelly, Lustig, and Nieuwerburgh (2015) identify cheaper prices for OTM put options on a financial sector index during the financial crisis than the sum of its individual constituents. This means that the financial sector received a government guarantee against the tail risk of plummeting stock prices and default. Another study by Kelly, Pástor, and Veronesi (2015) indicates that options in weak economies or politically uncertain countries are more valuable and contain a risk premium to protect against the tail risk of political events. Table 1 summarizes the determinants and other special risk characteristics affecting the slope of the implied volatility and classifies this paper in the literature.

[3]From a broader perspective, this paper is also related to the real effects of risk management on financial instruments, most notably Pérez-González and Yun (2013) who analyze weather derivatives as a risk mitigation instrument for energy companies.

Table 1: Factors affecting the implied volatility smile

Factors	*Effect on implied volatility smile*	*Source*
All options		
Beta	Steeper for stocks with larger betas.	Dennis and Mayhew (2002)
Size (market cap)	Steeper for large firms.	Dennis and Mayhew (2002)
Volume	More positive for stocks with higher trading volume.	Dennis and Mayhew (2002)
Net Buying Pressure	Steeper for options which have a higher demand in contrast to those with lower demand.	Bollen and Whaley (2004)
Leverage	Ambiguous results: Toft and Prucyk (1997) find that highly leveraged firms have steeper slopes than less leveraged firms. Dennis and Mayhew (2002) find no robust effect regarding leverage.	Toft and Prucyk (1997); Dennis and Mayhew (2002)
Market Index	Steeper for individual options when market index options have steeper slope.	Dennis and Mayhew (2002)
Volatility Environment	Steeper during times of high volatility.	Dennis and Mayhew (2002)
Structure (Index vs. individual stock options)	Index volatility smiles have steeper slope than individual stock option smiles.	Bakshi, Kapadia, and Madan (2003)
Specific options		
Financial Guarantees	OTM put options on a financial sector index were cheaper during the financial crisis than the sum of its individual constituents, demonstrating an implicit insurance in the financial sector against default.	Kelly, Lustig, Nieuwerburgh (2015)
Political Risk	Options in weak economies and politically uncertain countries are more valuable, including protection against tail risk.	Kelly, Pástor, and Veronesi (2015)
Catastrophe Risk	**OTM put options of property-casualty insurers contain a risk premium for catastrophic events in excess of the market-wide tail risk.**	**This paper**

Regarding the second strand of literature (insurance-specific catastrophe findings), Thomann (2013) analyzes the relation between natural catastrophes, the 9/11 terrorist attacks, and the volatility of insurance stocks. He finds that natural catastrophes increase the volatility of insurance stocks but reduce the correlation of insurance stocks with the market. Blau, Ness, and Wade (2008); Ewing, Hein, and Kruse (2006); and Lamb (1995, 1998) find that insurer stock prices start declining in the week before landfall of a potential catastrophe in the cases of Hurricanes Katrina, Floyd, and Andrew. Interestingly, Blau, Ness, and Wade (2008) do not find significant short-selling activity prior to Katrina's landfall but during three trading days after the landfall. From a general perspective, researchers observe that investors are crash-averse and thus receive a premium in returns or insure themselves through OTM index options (see Jackwerth and Rubinstein (1996), Ait-Sahalia and Lo (2000), and Garleanu, Pedersen, and Poteshman (2009)).

Froot (2001) investigates the importance of fair pricing of catastrophe risk and the reduction of market imperfections and shows that high catastrophe risk premiums can be attributed to supply restrictions, capital market imperfections, and the market power exerted by traditional reinsurers. Furthermore, Zanjani (2002) shows that capital costs have a significant effect on catastrophe insurance markets because of high marginal capital requirements. Depending on the pricing of catastrophe insurance, these capital costs can be reduced if catastrophe risk is priced accurately.

3 Model framework and hypotheses

The main idea explored throughout this paper is that catastrophe risk is priced in OTM stock options. Catastrophe risk has to be compensated in addition to the tail risk of the overall economy and can occur either as man-made catastrophes or natural catastrophes. A candidate to investigate the relationship between catastrophe risk and the implied volatility function are options written on P&C insurance stocks, which insure the economy against large losses as a result of natural or man-made catastrophes. To answer the question about catastrophe risk being priced in stock options, we approach the issue from three different angles.

First, if catastrophe risk is an additional pricing component in deep OTM options of P&C insurers, then their slope should be steeper than for options on all other stocks. We thus compare the implied volatility function of options written on P&C insurers with the implied volatility function of options written on non-financial stocks.[4] Second, if investors and market makers anticipate catastrophes during the development of hurricanes and tropical storms and want to be insured against large losses after landfall, the difference between the slope of P&C insurance options and non-financials options should increase. Hence, we expect tail risk to increase at the arrival of new information on catastrophes. Third, if options on insurance stocks indeed capture the risk of natural disasters, their slope should be highly correlated with the catastrophe risk premium, which can be observed in catastrophe bonds. Thus, options of P&C stocks can be a high frequency, risk-neutral proxy for catastrophe risk.[5]

To formalize our assumptions and to provide us with more insight about the effects of catastrophe risk, we derive an option pricing model which accounts for an independent catastrophe risk component. For that purpose we adapt the jump-diffusion model by Martzoukos and Trigeorgis (2002). In contrast

[4]We exclude all financial stocks from the control group for several reasons. One reason is the potential ties between the banking and insurance sector, such as bancassurance, which diffuse catastrophe risk throughout the financial system. Another reason, and closely related to the previous one, is the spillover effects identified between financial institutions, especially during volatile times (Adams, Füss, and Gropp (2014)). The last point involves effects on options written on financial institutions. Kelly, Lustig, and Nieuwerburgh (2015) document a government guarantee in OTM index options written on large financial institutions which could bias our results. Note, however, that if this government guarantee exists in individual options in a similar fashion, it would in fact decrease the implied volatility in OTM options and result in even larger discrepancies in the implied volatility slope between P&C insurers and all other stocks. In robustness tests we also include all other financial institutions to account for such potential effects (see Section 7.1).

[5]Since, in general, catastrophe bonds exclude man-made disasters (i.e., terrorism attacks or oil spills) but insurance companies write insurance for such occasions, the correlation between the slope from options on insurance stocks and the premium inherent in catastrophe bonds should not fully coincide. Furthermore, the recent entrance of large institutional investors (i.e. pension funds) in the catastrophe bond market resulted in decreasing yields for such instruments. Thus, a question that remains to be asked is whether catastrophe bonds still adequately compensate for the risk investors are bearing. Our approach might therefore be a method to indicate prices of catastrophe bonds in the absence of man-made disasters.

to Martzoukos and Trigeorgis (2002), we extend the model for financial and catastrophic shocks, provide economic intuition on the model, and further investigate the model's reaction along moneyness.[6] For the non-financials stock and its single exposure to economic jump events, the model collapses to the jump-diffusion model by Merton (1976). We start with a stock, V, from the non-financial sector, which follows the continuous-time stochastic process:

$$\frac{\mathrm{d}V}{V} = \mu \mathrm{d}t + \sigma \mathrm{d}W^{(V)} + k_{econ}\mathrm{d}q_{econ}, \tag{1}$$

where μ is the drift of the underlying and σ is the volatility. $\mathrm{d}W^{(V)}$ is an increment to a standard Brownian motion, and k_{econ} is the jump size caused by an economic shock, i.e., an exogenous shock, affecting the entire economy. $\mathrm{d}q_{econ}$ counts the number of economically related jumps with intensity λ_{econ} of a Poisson process.

Another stock, S, from the P&C insurance industry follows the continuous-time stochastic process:

$$\frac{\mathrm{d}S}{S} = \mu \mathrm{d}t + \sigma \mathrm{d}W^{(S)} + k_{econ}\mathrm{d}q_{econ} + k_{cat}\mathrm{d}q_{cat} \tag{2}$$

We assume that the P&C insurance stock follows the same process as the non-financials stock with identical drift and volatility except for an independent Brownian motion, $\mathrm{d}W^{(S)}$, and an additional jump component, $k_{cat}\mathrm{d}q_{cat}$. Specifically, the P&C stock is both affected by economic shocks such as the non-financials stock and additionally exposed to jumps caused by catastrophic events with jump size k_{cat} and the jump counter $\mathrm{d}q_{cat}$ with intensity λ_{cat} of a Poisson process. Note that the two Poisson processes related to economic events and catastrophic events are independent from each other. Furthermore, the risk neutral drift is defined as $r - \delta^*$, where r is the riskless rate and δ^* is

[6] From a theoretical perspective, the model we propose, applies to all catastrophic events – both man-made and natural. Within the category of natural catastrophes, the model is both suitable for events that "announce" themselves, such as hurricanes, and for sudden events, such as earthquakes. The reason for the suitability is the instantaneous adaptability of all parameters at the arrival of new information. From an empirical perspective, however, the model (more precisely, the difference between models) might be challenged by the fact that both P&C insurance stocks and all other stocks react evenhandedly to man-made disasters (i.e., terrorist attacks). Also empirically difficult to prove is the model's prediction for earthquakes, as there has not been a substantial earthquake in the U.S. during the sample period.

defined, in the case of a P&C stock, as:

$$\delta^* \equiv \delta + \lambda_{econ}\bar{k}_{econ} + \lambda_{cat}\bar{k}_{cat}. \tag{3}$$

As such, δ^* accounts for the dividend yield, δ, and the jump effects, $\lambda_{econ}\bar{k}_{econ}$ and $\lambda_{cat}\bar{k}_{cat}$, caused by economic and catastrophic events. For the non-financials stock, the risk-neutral drift obviously excludes the jump component related to catastrophic events. In integral form, the P&C insurance stock is thus defined as:

$$\begin{aligned}\ln[S(T)] - \ln[S(0)] = \int_0^T \left[r - \delta^* - 0.5\sigma^2\right] \mathrm{d}t + \int_0^T \sigma \mathrm{d}W^{(S)}(t) + \\ \sum_{q=1}^{n_{econ}} \ln(1 + k_{econ,q}) + \sum_{q=1}^{n_{cat}} \ln(1 + k_{cat,q}),\end{aligned} \tag{4}$$

with n_{econ} indicating the number of economic jump events and n_{cat} indicating the number of catastrophic jump events. Again, the model assumes that the term $\sum_{q=1}^{n_{cat}} \ln(1 + k_{cat,q})$ is only present in P&C insurance stocks but not in non-financials stocks. We also assume that the jump size of an economic shock, $1 + k_{econ}$, and a catastrophic event, $1 + k_{cat}$, are log-normally distributed with:

$$\ln(1 + k_{econ}) \sim \mathbf{N}(\gamma_{econ} - 0.5\sigma^2_{econ}, \sigma^2_{econ}) \tag{5}$$

and

$$\ln(1 + k_{cat}) \sim \mathbf{N}(\gamma_{cat} - 0.5\sigma^2_{cat}, \sigma^2_{cat}) \tag{6}$$

where $\mathbf{N}(.,.)$ denotes the normal density function with mean $\gamma_{econ} - 0.5\sigma^2_{econ}$ for economically related events and $\gamma_{cat} - 0.5\sigma^2_{cat}$ for catastrophically related events. The variance of the jump size is defined as σ^2_{econ} and σ^2_{cat}, respectively. The expected value of the economic jump size is

$$E[k_{econ}] \equiv \bar{k}_{econ} = exp(\gamma_{econ}) - 1, \tag{7}$$

and the expected value of the catastrophic jump size is

$$E[k_{cat}] \equiv \bar{k}_{cat} = exp(\gamma_{cat}) - 1. \tag{8}$$

For the model development, it is important to highlight the difference between the jump size means of economic and catastrophic events. While economic shocks can be positive or negative with potentially equal probability (e.g., higher or lower than expected economic growth, central bank interventions, new technologies, economic crises, bailouts, etc.), catastrophic events are *on average* negative, with either a negative impact (i.e., catastrophe occurs) or no impact (i.e., catastrophe does not occur) but theoretically not a positive impact. In other words, a P&C insurer has already collected all premiums at the beginning of the year. These funds can only decrease in value through the occurrence of catastrophic events. Hence, there is no upside but only a downside to the earnings.[7] Under this assumption, the expected jump size of catastrophic shocks should be more negative than the expected jump size of economic shocks (i.e., $\gamma_{cat} < \gamma_{econ}$). We can then define the value of a European put option on a P&C insurance stock as:

$$F_{Put}(S, X, T, \sigma, \delta, r, \lambda_i, \gamma_i, \sigma_i) = e^{-rT} \sum_{n_{econ}=0}^{\infty} \sum_{n_{cat}=0}^{\infty} \{P(n_{econ}, n_{cat}) \times E[(X - S_T)^+ | (n_{econ}, n_{cat}) jumps]\} \tag{9}$$

where X is the strike price of the put option and $P(n_{econ}, n_{cat})$ describes the joint probabilities of economic and catastrophic shocks on a P&C insurer. Because the probabilities for catastrophic and economic jumps are assumed to be independent, this term is defined as:

$$P = (n_{econ}, n_{cat}) = \frac{e^{(-\lambda_{econ} - \lambda_{cat})T} (\lambda_{econ} T)^{n_{econ}} (\lambda_{cat} T)^{n_{cat}}}{n_{econ}! n_{cat}!} \tag{10}$$

Based on Martzoukos and Trigeorgis (2002) and the Black-Scholes model, we can derive the risk-neutral expectation $E[(X - S_T)^+ | (n_{econ}, n_{cat}) jumps]$ of a put option written on a P&C insurance stock which is subject to jumps

[7] We acknowledge that this is a simplified perspective, given that other factors play an important role, too, such as reinsurance cover or the safety loadings in insurance prices. However, on average, this assumption should hold if insurance prices are fair.

caused by the overall economy and by catastrophic events, as follows:

$$E[(X - S_T)^+ | (n_{econ}, n_{cat}) jumps] = XN(-d_{2n}) - Se^{[(r-\delta^*)T + (n_{econ}\gamma_{econ}) + (n_{cat}\gamma_{cat})]} N(-d_{1n}) \tag{11}$$

where d_{1n} is defined as:

$$d_{1n} \equiv \frac{\ln(S/X) + (r - \delta^*)T + (n_{econ}\gamma_{econ}) + (n_{cat}\gamma_{cat}) + 0.5\sigma^2 T + 0.5 n_{econ}\sigma^2_{econ} + 0.5 n_{cat}\sigma^2_{cat}}{\sqrt{\sigma^2 T + n_{econ}\sigma^2_{econ} + n_{cat}\sigma^2_{cat}}}, \tag{12}$$

and d_{2n} is defined as:

$$d_{2n} \equiv d_{1n} - \sqrt{\sigma^2 T + n_{econ}\sigma^2_{econ} + n_{cat}\sigma^2_{cat}} \tag{13}$$

Having defined the model, we can calibrate it and use it to guide the empirical analyses. Because no previous empirical analysis on options written on insurance stocks exists, we do not have a strong prior on the effect of catastrophes on these instruments. However, as mentioned before, we reckon that the mean jump size for catastrophes is more negative than for economic shocks. Aside from reasonable values for the non-financials stock which follows the calibration by Martzoukos and Trigeorgis (2002), our only condition is that $\gamma_{cat} < \gamma_{econ}$. For simplicity, we assume identical standard deviations of the jumps, i.e. $(\sigma_{cat} = \sigma_{econ})$. The following Table 2 summarizes our calibration values.

Table 2: Option model calibration

P&C insurance stock		Non-financials stock	
$S =$	100	$V =$	100
$\sigma =$	0.20	$\sigma =$	0.20
$r =$	0.02	$r =$	0.02
$\delta =$	0.03	$\delta =$	0.03
$T =$	0.083	$T =$	0.083
$\gamma_{econ} =$	-0.02	$\gamma_{econ} =$	-0.02
$\sigma_{econ} =$	0.50	$\sigma_{econ} =$	0.50
$\lambda_{econ} =$	1.00	$\lambda_{econ} =$	1.00
$\gamma_{cat} =$	-0.10		
$\sigma_{cat} =$	0.50		
$\lambda_{cat} =$	1.00		

This table presents the parameters used to calibrate the model for a representative option written on a P&C insurance stock and a representative option written on a stock from the non-financial sector. Both instruments share the same parameters and values, except for the additional catastrophe-related parameters used in the P&C insurance stock.

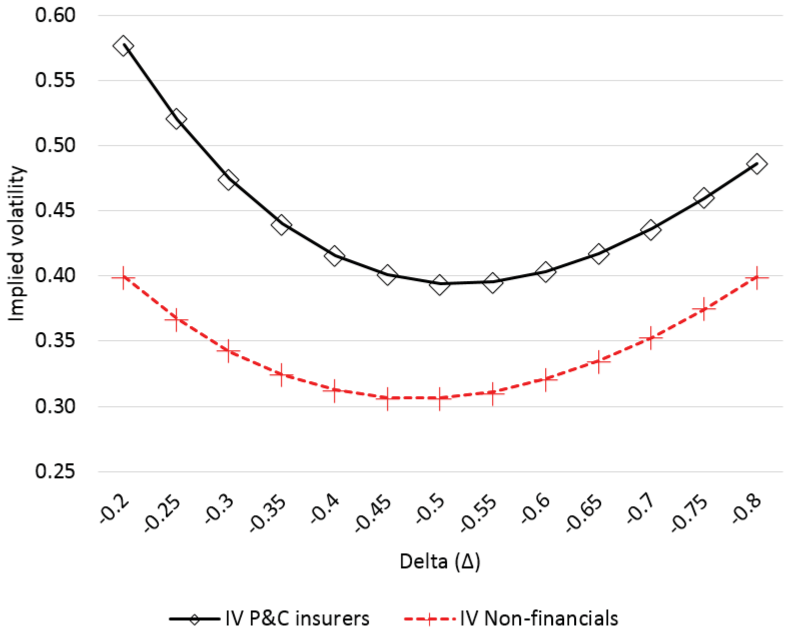
As OptionMetrics reports implied volatilities on a grid of delta (Δ) values between -0.2 and -0.8, we report the model results on exactly the same grid to facilitate comparisons.[8] We compute put option prices based on the model and accordingly extract Black-Scholes implied volatilities and delta values.[9] Figure 1 shows the results from our model calibration.[10]

[8] As noted by Kelly, Pástor, and Veronesi (2015), delta is also a better measure for moneyness, as it reflects the probability of an option contract to expire in the money by considering maturity, volatility, and the risk-free rate.

[9] We use a cubic function to fit the implied volatilities on the delta grid between -0.2 and -0.8.

[10] Appendix A also illustrates model sensitivities for other calibrations of the catastrophe-related parameters.

Figure 1: Modeled implied volatility smiles (P&C insurers vs. non-financial firms)



This figure illustrates the modeled implied volatilities (IV) of one-month-to-expiration put options written on P&C insurance stocks (black line marked by squares) and non-financials stocks (red dotted line marked by crosses) along moneyness. Moneyness is expressed in delta values on the x-axis. The P&C insurance stock is calibrated with S = 100, σ = 0.20, r = 0.02, δ = 0.03, T = 0.083, γ_{econ} = -0.02, σ_{econ} = 0.50, λ_{econ} = 1.00, γ_{cat} = -0.10, σ_{cat} = 0.50, and λ_{cat} = 1.00. The non-financials stock is calibrated with V = 100, σ = 0.20, r = 0.02, δ = 0.03, T = 0.083, γ_{econ} = -0.02, σ_{econ} = 0.50, and λ_{econ} = 1.00.

Our first observation is that insurance put options are more expensive at all moneyness categories (delta values). Our second observation, which addresses the main idea of this paper, is the steeper slope of insurance put options compared to non-financials put options as a result of the additional negative catastrophe jump probability. The third observation we make in our model is that a negative increase in the mean jump size increases the steepness of the slope. This effect is more pronounced the less uncertainty about the jump prevails, σ_{cat}, and the more negative the jump size is. Motivated by the model's response to catastrophic events, we formulate our hypotheses.

Hypothesis 1: The implied volatility slope of put options written on P&C insurers is on average steeper than the slope of put options written on non-financials.

Because it is unknown when and where a catastrophe will occur, an additional tail risk component related to catastrophe risk should result in a steeper implied volatility smile, which is the result of higher implied volatilities of OTM put options and lower ITM implied volatilities with the jump size, γ_{cat}, and the jump uncertainty, σ_{cat}, driving this effect.

Hypothesis 2: The implied volatility slope of put options written on P&C insurers is related to the risk premium from the catastrophe bond market.

If the tail risk component is indeed related to losses caused by catastrophes, the steepness of the implied volatility smile should follow the price development of the catastrophe bond market because this market provides a price orientation for actively traded catastrophe risk. If the no-arbitrage condition holds, both markets should share a common time-series variation.

Hypothesis 3: In comparison to the slope of put options written on non-financials, the implied volatility slope of put options written on P&C insurers is steeper after a catastrophic event compared to before the event.

Because uncertainty about the jump, σ_{cat}, reduces in terms of whether and where an event occurs, and estimations about the jump size, γ_{cat}, increase in the case of realized catastrophes, the slope of the implied volatility should become even steeper after an event.

4 Methodology

We analyze the difference between OTM and ITM put options. That is, our main focus is the difference in levels of the implied volatility smile. As mentioned above, the main idea is that OTM options provide a more effective protection against rare events than ITM options (Kelly, Pástor, and Veronesi, 2015). Our slope measure follows Kelly, Pástor, and Veronesi (2015) where the slope of the implied volatility function of firm i at time t is the difference in implied volatilities between OTM puts, $IVola_{i,t}^{OTMP}$, and ITM puts, $IVola_{i,t}^{ITMP}$. Formally, the slope is defined as:

$$SLOPE_{i,t} = IVola_{i,t}^{OTMP} - IVola_{i,t}^{ITMP} \tag{14}$$

where $IVola_{i,t}^{OTMP}$ corresponds to the implied volatility of an OTM put option with a fixed delta of -0.20 and a constant time to maturity of 30 days. $IVola_{i,t}^{ITMP}$ corresponds to the implied volatility of an ITM put option with a fixed delta of -0.80 and a constant time to maturity of 30 days.[11] As noted by Bollerslev and Todorov (2011), short-maturity OTM options are worthless unless a big jump occurs before expiration, making them particularly interesting in the context of catastrophe risk. In univariate tests, we first analyze whether the slope of the implied volatility of options on insurance stocks is in fact steeper than the rest of the market, as we hypothesize. We do so by comparing the implied volatility slope of P&C insurers and non-financial firms at the end of each month.

Identical to Yan (2011), we start out using end-of-month observations in the implied volatilities to guarantee homogeneity between all options while finding a matching historical volatility in the control group (i.e., options on non-financials).[12] We then turn to weekly cross-sectional Fama-MacBeth (1973) regression as in Dennis and Mayhew (2002) to control for other variables that might influence a steeper slope in insurance stocks. Formally, the cross-sectional Fama-MacBeth (1973) regression is defined as:

[11] We use these parameters because the implied volatility grid provided by OptionMetrics is bounded by delta values between -0.20 and -0.80. Thus, we use the most extreme delta values available to approximate the most efficient and the least efficient way to protect against rare events.

[12] For further details, see Section 6.1.

$$\begin{aligned} SLOPE_{i,t} = \alpha_{i,t} &+ INSURANCE_{i,t} + IVATM_{i,t} + LEVERAGE_{i,t} + SIZE_{i,t} \\ &+ BETA_{i,t} + VOLUME_{i,t} + CALLPUTOI_{i,t} \\ &+ SLOPE_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

where $INSURANCE_{i,t}$ is the variable of interest and defined as a dummy variable taking the value of one if the slope refers to a P&C insurer and zero if it refers to a non-financials stock. If P&C insurers indeed bear a risk premium for natural catastrophes (and man-made disasters) compared to the rest of the market, this variable should be significantly positive, meaning that the difference between OTM and ITM put options is larger for P&C insurers.

Following Dennis and Mayhew (2002), the first control variable is $IVATM_{i,t}$ which is the contemporaneous weekly average of at-the-money (ATM) implied volatilities of company i at week t. We use a delta of -0.50 for an option to be ATM. If the overall level influences the slope in the cross-section, it is necessary to control for an effect which could limit the upper bound of OTM options. We also include $LEVERAGE_{i,t}$ as a control variable. We divide the book value of total assets by the market value of equity and take the natural logarithm of the ratio to define $LEVERAGE_{i,t}$ (Kelly, Lustig, and Nieuwerburgh (2015)). We use total assets from the last fiscal year lagged by four months and contemporaneous market equity at time t. This variable might be particularly important, because P&C insurers are characterized by high leverage values. Black (1976) and Toft and Prucyk (1997) argue that leverage mechanically results in higher volatilities because, as the equity value of a levered company decreases, the leverage ratio has to increase, and thus the volatility of that company has to increase. However, results about leverage in the implied volatility context are ambiguous. For example, there are significantly steep slopes for unlevered firms and also currency options that are not exposed to leverage ratios (Dennis and Mayhew (2002)).

The third control variable is $SIZE_{i,t}$, measured as the contemporaneous natural logarithm of market equity of stock i at time t. It could be the case that smaller companies tend to be more risky (Banz (1981)) and might be more susceptible to default risk (Vassalou and Xing (2004)). Furthermore, we check for the systematic risk, $BETA_{i,t}$, of each stock, assuming that higher risk exposure should result in steeper slopes. The rolling market beta is calculated by regressing daily excess returns of stock i against CRSP's value-weighted market return in excess of the risk-free rate over the past 200 days. Another control variable is $VOLUME_{i,t}$ which is defined as the logarithm of average daily trading volume over week t. We include this variable as a proxy for liquidity (Dennis and Mayhew (2002)). More trading activity in the underlying stock implies a higher demand for options including hedges against downside movements in stock prices. The control variable $CALLPUTOI_{i,t}$ captures the trading pressure between calls and puts which could explain higher prices due to higher demand for either one of them (Dennis and Mayhew (2002); Bollen and Whaley (2004)). We determine the total open interest over the entire week for calls and puts and then divide this number by the difference between total open interest in calls and total open interest in puts over the entire week. This measure is bound between -1 and +1. A negative value indicates larger interest for put options, and a positive value indicates larger interest for call options. To capture any persistence and residual explanatory power in the implied volatility slope, we include the implied volatility slope lagged by one week, $SLOPE_{i,t-1}$.

In addition to the cross-sectional Fama-MacBeth (1973) regressions, we run pooled time-series cross-sectional regressions with clustered standard errors by firm and week to account for market-wide factors, the unbalanced panel, and the firm and time dependency (Petersen (2009)). It is well-known that volatility appears in clusters, with certain time periods being more volatile than others (Maheu and McCurdy (2004)). Thus, if some stocks are more prone to changes in volatility clustering or changes in overall market volatility than others, the slope of implied volatility could also be affected. The pooled time-series cross-sectional regression can therefore capture the time series variation in the slope of the implied volatilities and is formally defined as:

$$
\begin{aligned}
SLOPE_{i,t} = \alpha_{i,t} &+ INSURANCE_{i,t} + IVATM_{i,t} + LEVERAGE_{i,t} \\
&+ SIZE_{i,t} + BETA_{i,t} + VOLUME_{i,t} + CALLPUTOI_{i,t} \\
&+ SLOPE500_{i,t} + IVATM500_{i,t} + SLOPE_{i,t-1} + \varepsilon_{i,t}.
\end{aligned} \tag{16}
$$

To capture the market-wide effects, we include both the slope of the S&P500 Index ($SLOPE500_{i,t}$) and the overall level of the market volatility proxied by the implied volatility of ATM options of the S&P500 Index ($IVATM500_{i,t}$).

5 Data

We retrieve daily data on all put options from the standardized volatility surface provided by OptionMetrics between January 1996 and December 2013. The complete sample consists of 67 U.S. P&C insurers and 5596 companies from the non-financial sector.[13] OptionMetrics' volatility surface calculates an interpolated implied volatility surface using a kernel smoothing algorithm for puts and calls with different strikes and maturities. The resulting standardized grid includes delta values in steps of 0.05 from -0.20 (i.e. OTM put option) to -0.80 (i.e. ITM put options). Binomial trees are used to first compute the underlying implied volatilities, allowing for early exercise and considering expected dividends to be paid until the maturity of the options. Note that a standardized option is only documented in OptionMetrics' volatility surface if there are sufficient underlying option data on each day to accurately determine an interpolated implied volatility. The advantage of using the standardized volatility surface is that we do not have to proceed with ranges of diverging maturity or strike prices, which could ultimately introduce a measurement bias.

To analyze catastrophe risk, we differentiate between P&C insurers with SIC code 6331 and all other options that are not financial stocks (i.e. excluding options with SIC codes between 6000 and 6999).[14] Using short-dated options

[13] A complete list of all 67 P&C insurers can be found in Appendix B.

[14] We focus on P&C insurers identified by the SIC code to avoid any selection bias and also because investors might not be able to differentiate how much exposure the underlying insurer has towards catastrophe risk. This argument is based on the opacity of insurance markets and the well-protected underwriting exposure (Cummins and Weiss (2009)).

with 30 days to maturity has two advantages. First, they are the most liquidly traded ones in contrast to options with longer maturities (Driessen, Maenhout, and Vilkov (2009)). Second, a natural disaster is temporarily restricted. That is, an earthquake takes only a few minutes, and a hurricane in general takes no more than two to three weeks from initial development until landfall. Thus, the actual cost after a disaster can be roughly estimated after such an event. Consequently, investors would want to be insured for the time period in which actual costs are estimated to avoid the greatest uncertainty about claim payments.[15]

We only use individual equity options and exclude index options (i.e., the OptionMetrics index flag equals 0). Accounting data to calculate leverage figures are retrieved from COMPUSTAT. Daily trading information regarding volume, size, and returns are from CRSP. Data on open interest and the implied volatility of the S&P500 are gathered from OptionMetrics. Another analysis in this paper refers to the link between the implied volatility slope and catastrophe risk. Since there is in fact a market for catastrophe risk in the form of catastrophe bonds, we can actually relate the slope of the implied volatility to actual catastrophe risk. For that purpose, we use the quarterly data of cat bond spreads from Braun (2016).[16] If both measures are related to each other, they should be highly correlated. This would not only provide evidence of what the slope is in fact measuring but also establish accurate pricing for catastrophe risk.

Table 3 summarizes the dependent and independent variables in terms of mean, standard deviation, and the number of firm-week observations. Panel A reports these variables for the treatment group of P&C insurers and Panel B for the control group of stocks in the non-financials sector. Panel C reports market-wide explanatory variables based on the S&P500.

[15]Overall, this intuition is contrary to a financial crisis, which includes contagion effects and risks that can take several months or even years to be discovered.

[16]The term “spread” relates to the yield from primary markets at initial issuance of the catastrophe bond in excess of the risk free rate. We would like to thank Alexander Braun for making the data available to us.

Table 3: Descriptive statistics

	Panel A: P&C insurers			*Panel B: Non-Financials*		
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
$SLOPE_{i,t}$	0.058	0.116	28,290	0.034	0.111	1,947,873
$IVATM_{i,t}$	0.338	0.179	28,290	0.518	0.268	1,947,873
$LEVERAGE_{i,t}$	1.355	0.742	27,887	-0.141	1.197	1,760,953
$SIZE_{i,t}$	9.538	1.527	27,868	7.673	1.653	1,760,307
$BETA_{i,t}$	0.872	0.331	27,829	1.160	0.592	1,837,527
$VOLUME_{i,t}$	1,273,109	6,435,054	28,290	1,472,984	4,421,952	1,894,309
$CALLPUTOI_{i,t}$	0.242	0.419	28,290	0.279	0.361	1,947,873
	Panel C: Market (S&P 500)					
Variable	Mean	Std. Dev.	Obs.			
$SLOPE500_t$	0.065	0.032	936			
$IVATM500_t$	0.195	0.076	936			

This table presents the mean, standard deviation (Std. Dev.), and the number of firm-week observations of the dependent variable ($SLOPE_{i,t}$) and the explanatory variables. Panel A reports these variables for property-casualty insurers. Panel B reports these variables for the control group of stocks in the non-financials sector. Panel C reports market-wide explanatory variables based on the S&P500. The sample period starts in the first week of January 1996 and ends in the last week of December 2013.

6 Empirical analysis

The empirical analysis starts with univariate tests (Section 6.1), followed by Fama-MacBeth (1973) regressions (Section 6.2) and panel (pooled cross-sectional time-series) regressions (Section 6.3) and then establishes the link between the implied volatility slope and the catastrophe risk market (Section 6.4). The last analysis addresses the reaction of the implied volatility around catastrophic events (Section 6.5).

6.1 Implied volatility of P&C insurers and non-financials

To adequately compare the implied volatility of P&C insurers with the rest of the market in univariate tests we use a matching procedure based on the realized volatility of a stock. This procedure guarantees both a fair comparison of the slope and of the levels of the implied volatility *at each value of delta*.[17]

Specifically, the implied volatility measures the future volatility market participants expect for a stock. Assuming there are two stocks with the same realized volatility in time t, one could expect that their future volatility is identical, too, unless market participants expect the future volatility of one stock to be higher than the rest of the market due to additional risk components. Here, we expect that investors add an additional risk component in (deep) OTM put options of P&C insurers due to catastrophe risk, a risk component which should not appear in non-financials with identical realized volatility. Using data on realized volatility over the past 365 days from OptionMetrics, we match the implied volatility of insurance stocks with the implied volatility of non-financials stocks.[18] At the end of each month, we match each P&C insurance stock with a portfolio of all available non-financial stocks of identical realized volatility.[19]

Panel A of Table 4 shows the mean of the implied volatilities (and the standard deviation) of puts on P&C insurers stocks at different values of delta. Panel B shows the mean of the implied volatilities (and the standard deviation) of puts on non-financials stocks at different values of delta.[20] Table 5 tests the equality of the implied volatilities between P&C insurers and non-financials. As expected, the deep OTM insurance stock options are significantly higher (i.e., an implied volatility of 0.407) than those of deep OTM non-financials options. The matching procedure appears to be well specified as ATM options at a delta value of -0.50 for both categories are virtually identical (0.337 vs. 0.337 with a

[17]Note that the matching procedure is not necessary for our key analysis regarding the slope that we propose, which is overall steeper for P&C insurers compared to non-financial firms. However, the overall level of OTM, ATM, and ITM implied volatilities of non-financials is higher. In the following regression analysis, we are only interested in the slope and do not compare implied volatilities at different delta values. Thus, we include all P&C insurers and non-financial firms without any matching procedure in the regression analysis. Similar matching procedures in the context of stock splits are used by Shaik (1989).

[18]We use 365-days historic volatility to avoid seasonal effects that might affect shorter volatility measures.

[19]Since there are more non-financial stocks than P&C insurer stocks, we average the implied volatility from non-financials options to avoid any selection bias.

[20]Note that six realized volatility observations from P&C insurers could not be matched with identical realized volatility from non-financials. For the sake of completeness, we report all implied volatilities of P&C insurers. If we exclude the six observations, results are virtually unchanged. Furthermore, the following regression analysis uses the entire universe of P&C insurers and non-financials.

Table 4: Implied volatilities for options from P&C insurers and non-financials

Panel A	*Puts on property-casualty insurance stocks*												
Δ	**-0.20**	**-0.25**	**-0.30**	**-0.35**	**-0.40**	**-0.45**	**-0.50**	**-0.55**	**-0.60**	**-0.65**	**-0.70**	**-0.75**	**-0.80**
Mean	0.407	0.384	0.368	0.357	0.348	0.342	0.337	0.333	0.331	0.33	0.333	0.339	0.348
Std. dev.	0.228	0.220	0.213	0.207	0.204	0.201	0.200	0.197	0.194	0.195	0.197	0.200	0.203
Obs.	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552
Panel B	*Puts on non-financials stocks*												
Δ	**-0.20**	**-0.25**	**-0.30**	**-0.35**	**-0.40**	**-0.45**	**-0.50**	**-0.55**	**-0.60**	**-0.65**	**-0.70**	**-0.75**	**-0.80**
Mean	0.396	0.376	0.363	0.353	0.346	0.341	0.337	0.334	0.333	0.335	0.339	0.346	0.358
Std. dev.	0.165	0.164	0.163	0.162	0.162	0.161	0.160	0.160	0.160	0.160	0.161	0.163	0.166
Obs.	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546

This table presents the mean and standard deviation of implied volatilities of individual equity options with one month (30 days) to expiration and fixed deltas at the end of each month during the sample period. Panel A shows the implied volatilities of all P&C insurers with SIC code 6331. Panel B shows the matched implied volatilities of non-financial firms with identical historical volatility over the past 365 days. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013.

t-statistic for the difference of -0.10).

In contrast, deep ITM put options for non-financials have significantly higher implied volatilities than P&C insurers. This suggests that investors and market makers are indeed more worried about severe declines in P&C stock prices for which they want to be insured against but not about smaller movement where deep ITM options can be useful.[21] This relation between delta and implied volatilities is also illustrated in Figure 2.

We can see that the shape of the implied volatility smile of P&C insurers from actual data follows closely the shape described by the option pricing model and also exhibits a steeper slope than non-financials.[22] However, the shape and level of the implied volatility smile of non-financials is much closer and steeper to the P&C insurers. An explanation for such a pattern is that non-financials are exposed to other tail risk components which are, however, not as extreme as catastrophes for P&C insurers.[23] This would explain the similar level in implied volatilities of put options written on P&C insurers and non-financials and at the same time account for the steeper slope of non-financials.

With the discovery of a significantly positive difference between P&C insurers and non-financials in OTM put options but none between ATM put options and a significantly negative one between ITM put options, the question remains whether this difference also results in a statistically significant slope difference between the two groups. We compute the slope as defined in Section 4 for both P&C insurers and non-financials. Table 6 shows that the parametric and the non-parametric difference between both slopes is highly significant, meaning

[21] We also run non-parametric tests presented in Table 5 using the Wilcoxon–Mann–Whitney rank-sum test. In this setting, median implied volatilities of P&C insurers are not higher than the implied volatilities of non-financials. However, the median difference becomes smaller the more out-of-the-money the option gets. There might be several reasons for that including stronger effects in the post-Katrina period and peak events (i.e., hurricanes) which further increase the slope during specific time periods. These reasons explain to some extent the discrepancy between the mean and the median difference in implied volatilities.

[22] Although we are interested in the shape of the implied volatility, it should be mentioned that the levels are overestimated by the model which is mainly attributable to an extensive λ_{cat} and σ_{cat}, and thus represent a calibration issue.

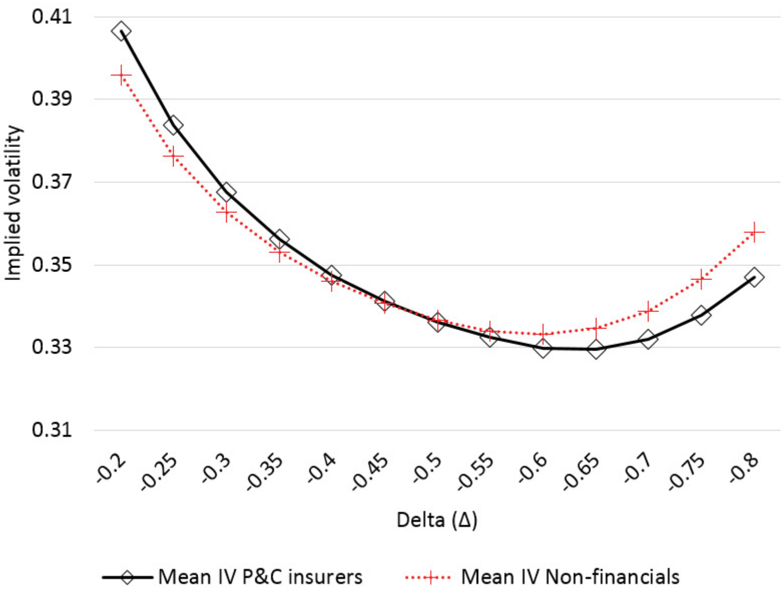
[23] Each company could be exposed to an industry-specific tail risk component. For example, a pharmaceutical could be sued for a flawed drug, or an automotive company could be forced to recall their vehicles because of defective brakes.

Table 5: Testing equality of implied volatilities

	Puts												
Δ	**-0.20**	**-0.25**	**-0.30**	**-0.35**	**-0.40**	**-0.45**	**-0.50**	**-0.55**	**-0.60**	**-0.65**	**-0.70**	**-0.75**	**-0.80**
Mean P&C	0.407	0.384	0.368	0.356	0.348	0.341	0.336	0.333	0.330	0.329	0.332	0.338	0.347
Mean non-financials	0.396	0.376	0.363	0.353	0.346	0.341	0.337	0.334	0.333	0.335	0.339	0.346	0.358
Difference (Mean)	0.011***	0.007**	0.005	0.003	0.002	0.000	0.000	-0.002	-0.004	-0.005*	-0.007**	-0.009***	-0.011***
t-statistic	[3.11]	[2.21]	[1.49]	[0.99]	[0.49]	[0.14]	[-0.10]	[-0.48]	[-1.14]	[-1.68]	[-2.15]	[-2.69]	[-3.37]
Difference (Median)	-0.004***	-0.004***	-0.002***	-0.004***	-0.003***	-0.005***	-0.005***	-0.006***	-0.007***	-0.009***	-0.012***	-0.014***	-0.019***
Wilcoxon-z	[-3.68]	[-3.90]	[-3.97]	[-3.98]	[-4.02]	[-4.26]	[-4.61]	[-4.89]	[-5.57]	[-6.57]	[-7.57]	[-8.74]	[-10.01]
Hist. volatility							0.323						
Obs.							6546						

This table reports the means of implied volatilities of options written on property-casualty insurers and non-financial firms. Time to expiration of the individual equity options is one month (30 days). Each implied volatility corresponds to a fixed delta value (Δ). Implied volatilities of the non-financial control group are matched with implied volatilities of P&C insurers based on identical historical volatility over the past 365 days. The table also reports the difference of the means (Difference (Mean)) for each delta category with T-statistics reported in brackets below the mean values. The difference in medians (Difference (Median)) is shown below with z-statistics of the Wilcoxon–Mann–Whitney rank-sum test in brackets. The average realized volatility for all stocks over the entire sample is 0.323. Six non-matched implied volatilities from the P&C sample are excluded. Each sample thus consists of 6,546 observations. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 2: Implied volatility smiles of traded put options (property-casualty insurers vs. non-financial firms)



This figure illustrates the implied volatilities of one-month-to-expiration put options of property-casualty insurance stocks (black line marked by squares) and non-financials stocks (red dotted line marked by crosses) derived from traded put options along moneyness. Moneyness is expressed in delta values on the x-axis. The matched sample consists of non-financial stocks and property-casualty insurance stocks based on 365-day realized volatility. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013.

Table 6: Univariate comparison of the slope of the implied volatilities (property-casualty insurers vs. non-financial firms)

	P&C insurers	Non-financials	*Unpaired two-sided t-test* Mean	*Wilcoxon test* Median
$IVOLA_{i,t}^{OTMP}$	0.407	0.396		
$IVOLA_{i,t}^{ITMP}$	0.347	0.358		
$SLOPE_{i,t}$	0.060	0.038	0.022***	0.004***
			[9.50]	[7.11]
Obs.	6546	6546		

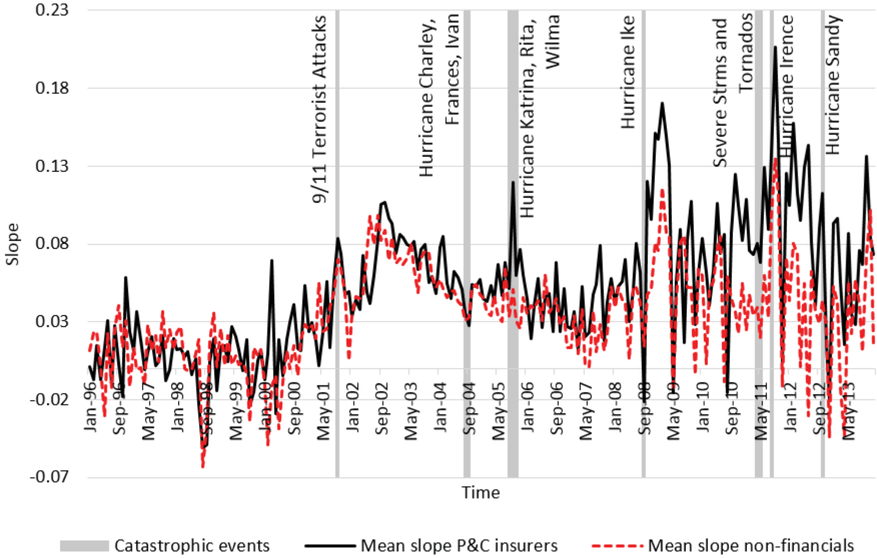
This table reports the mean of implied volatilities of out-of-the-money (OTM) and in-the-money (ITM) put options written on property-casualty insurers and non-financial firms. The slope of property-casualty insurers and non-financials is defined as the difference between OTM (delta = -0.20) and ITM (delta = -0.80) put options. The table also compares the means between the slopes of property-casualty insurers and non-financials using an unpaired two-sided t-test as well as their medians based on the Wilcoxon–Mann–Whitney rank-sum test. Time to expiration of the individual equity options is one month. Implied volatilities of the non-financial comparison group are matched with implied volatilities of property-casualty insurers based on 365 days of realized volatility. The average realized volatility for all stocks over the entire sample is 0.323. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013. T-statistics and z-statistics are reported in brackets, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

that investors expect a higher probability of tail risk for P&C insurers, although historical volatility would not imply such a difference.

Beyond the time-series averages of the implied-volatilities for P&C insurers and non-financials, it might be of interest how the two groups develop over time. We thus graph the slope of the implied volatility for both categories separately in Figure 3. An interesting observation we make here is that the slope of P&C insurers was identical and even slightly below the slope of non-financials during the time until Hurricane Katrina in 2005.

Since Hurricane Katrina, however, it appears that P&C insurers were mostly above the slope of non-financials, suggesting that a change in perception among market participants occurred regarding large losses insurers are exposed to.

Figure 3: Slope of the implied volatility smile of P&C insurers and non-financials over time



This figure illustrates the slope of the implied volatility smile from options written on property-casualty insurers (black solid line) and non-financials (red dotted line) over time, with identical 365-days historical volatility. The sample period is January 1996 to December 2013.

6.2 Fama-Macbeth (1973) regressions

We now turn to the multivariate analysis of the slope, including all equity options on P&C insurers and non-financials. Table 7 reports the results of the cross-sectional regression analysis with the slope (as defined in Section 4) as the dependent variable. When we only include the dummy variable $INSURANCE_{i,t}$ in our regression (Column I), we find similar results for the difference in slopes as in Table 6, both in terms of economic and statistical significance. Note that the dependent variable includes all slopes of P&C insurers and non-financials. Column II includes the control variables presented in Section 4. The economic and statistical difference of $INSURANCE_{i,t}$ remains highly significant at the 1%-level. We also include the previous week implied volatility slope (Column III) to capture any omitted factors. The implied volatility slope of the previous week is highly significant, which suggests that the slope is very persistent and thus predicable over time (see An et al. (2014)). The variable $INSURANCE_{i,t}$, though, remains statistically and economically significant at the 1%-level.

Overall, the results show that fundamental and option-related data cannot explain the steeper slope of options written on P&C insurers. Rather, they are specifically exposed to extreme catastrophe events which investors and market markers acknowledge with higher OTM put option prices (and lower ITM put option prices) compared to options on non-financials.

6.3 Panel regression

While the Fama-MacBeth (1973) regressions indicate significant relationships between the slope insurance-specific catastrophe risk, they do not allow us to check time-dependent effects. Specifically, volatility in general is found to cluster. That is, some periods in time show stronger volatility patterns, while other periods are less volatile. If some options are more prone to changes in volatility clustering or changes in overall market volatility compared to others, the slope of implied volatility could also be affected. The pooled time-series cross-sectional regression can therefore capture the time series variation in the slope of the implied volatilities. Table 8 shows the results of the panel regression. Again, $INSURANCE_{i,t}$ is highly significant in all settings. Indeed, the level

Table 7: Fama-MacBeth (1973) regressions

	(I)	(II)	(III)
$INSURANCE_{i,t}$	0.016***	0.015***	0.005***
	[7.47]	[6.59]	[6.37]
$IVATM_{i,t}$		-0.043***	-0.031**
		[-10.03]	[-2.44]
$LEVERAGE_{i,t}$		-0.003***	-0.004
		[-2.95]	[-1.25]
$SIZE_{i,t}$		-0.001	-0.002
		[-0.99]	[-1.35]
$BETA_{i,t}$		0.007***	0.002**
		[6.68]	[2.04]
$VOLUME_{i,t}$		-0.000	0.000
		[-1.10]	[0.97]
$CALLPUTOI_{i,t}$		-0.001	0.000
		[-0.64]	[0.45]
$SLOPE_{i,t-1}$			0.649***
			[50.03]
Intercept	0.032***	0.053***	0.037**
	[15.11]	[6.48]	[2.29]
Avg. R^2	0.00	0.04	0.46
Weeks	936	928	928
Obs.	1,976,163	1,736,945	1,733,939

This table reports Fama-MacBeth (1973) regressions with the slope of the implied volatility smile as dependent variable. The sample period is January 1996 to December 2013. T-statistics are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. Avg. R^2 is the time-series average R-square from each weekly cross-sectional regression. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

of the market volatility proxied by the implied volatility of ATM S&P500 Index put option captures some of the time-series variation of the slope of the implied volatility. The slope of S&P500 Index put options, however, is insignificant and appears to have no impact on the slope of individual equity options as soon as the past slope of the individual stock is included in the regression setting.

6.4 Linking catastrophe risk with the implied volatility slope

As a result of an active primary market for catastrophe risk and ex-post figures for insured (and uninsured) losses caused by catastrophic events, we can further investigate how the implied volatility slope of P&C insurers is related to the catastrophe market after controlling for all firm-specific parameters. For that purpose, we extract the slope coefficient on $INSURANCE_{i,t}$ from cross-sectional Fama-MacBeth (1973) regressions. Because insurance losses are only available on a yearly basis, we calculate in a first run the 12-month rolling mean of the extracted slope coefficient on $INSURANCE_{i,t}$.

When we illustrate the data on total losses, available from Swiss Re, against the rolling coefficient we observe a matching effect between the two time series (Figure 4). Several observations must be highlighted. First, the graph not only shows insured but also uninsured losses, which might suggest that market participants anticipate the full losses correctly but cannot predict how much of the losses are indeed insured.[24] Second, the data shows worldwide losses. Given the strong interconnectedness between insurers - especially reinsurers - around the globe, it is not far-fetched to assume that market participants react to catastrophic news from the entire world, such as the Tohoku earthquake in Japan in 2011 (which caused the Fukushima incident). The third point we want to highlight is that the slope coefficient does not react to man-made disasters, specifically the 9/11 Terrorist Attacks. Because such an event has an impact on the entire economy, P&C insurers do not react in isolation despite an increase

[24] Anecdotal evidence supports this idea. During Hurricane Sandy, cat bonds issued by Chubb Corporation were oversold under the impression that these cat bonds would be triggered given the strong underwriting of Chubb in flood insurance. However, these predictions were not met, and prices heavily recovered (http://www.artemis.bm/blog/2012/11/12/catastrophe-bond-prices-recover-some-sandy-losses-last-week/).

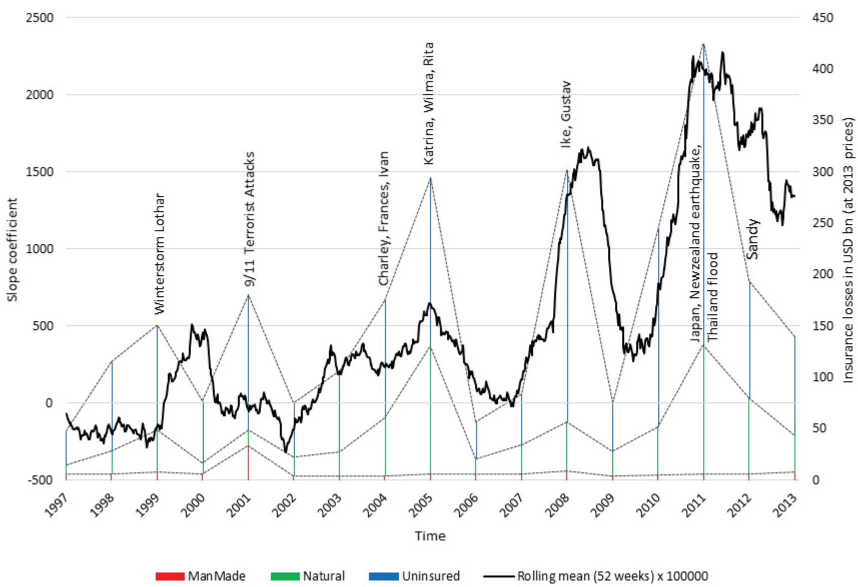
Table 8: Panel regression with cross-sectional and time-series clustered standard errors

	(I)	(II)	(III)	(IV)
$INSURANCE_{i,t}$	0.024***	0.023***	0.023***	0.008***
	[5.56]	[5.05]	[5.13]	[4.98]
$IVATM_{i,t}$		-0.026***	-0.046***	-0.016***
		[-6.25]	[-11.18]	[-9.16]
$LEVERAGE_{i,t}$		-0.000	-0.001	-0.000*
		[-0.32]	[-1.60]	[-1.88]
$SIZE_{i,t}$		-0.001	-0.002***	-0.001***
		[-1.46]	[-4.04]	[-3.05]
$BETA_{i,t}$		0.009***	0.012***	0.004***
		[10.01]	[13.94]	[10.62]
$VOLUME_{i,t}$		-0.000	-0.000	-0.000
		[-0.40]	[-0.12]	[-1.52]
$CALLPUTOI_{i,t}$		-0.008***	-0.007***	-0.002***
		[-6.00]	[-5.86]	[-4.52]
$SLOPE500_{i,t}$			-0.197***	-0.032
			[-4.73]	[-1.21]
$IVATM500_{i,t}$			0.179***	0.051***
			[9.77]	[4.31]
$SLOPE_{i,t-1}$				0.664***
				[122.02]
Intercept	0.034***	0.045***	0.038***	0.012***
	[38.23]	[8.91]	[7.39]	[4.91]
R^2	0.00	0.01	0.01	0.45
Weeks	936	928	928	928
Firms	5,609	4,912	4,912	4,908
Obs.	1,976,163	1,736,945	1,736,945	1,733,939

This table reports panel regressions with clustered standard errors by firm and week (Petersen (2009)) with the slope of implied volatility as the dependent variable. The sample period is January 1996 to December 2013. T-statistics are reported in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

in the implied volatility slope during that time. The last point to address is the discrepancy between the coefficient and the insurance losses in the year 2000. One explanation is that winterstorm Lothar occurred between December 25 and December 27, 1999, and thus total losses were assigned to that year. If these losses were more appropriately assigned to year 2000, both figures would align much better.

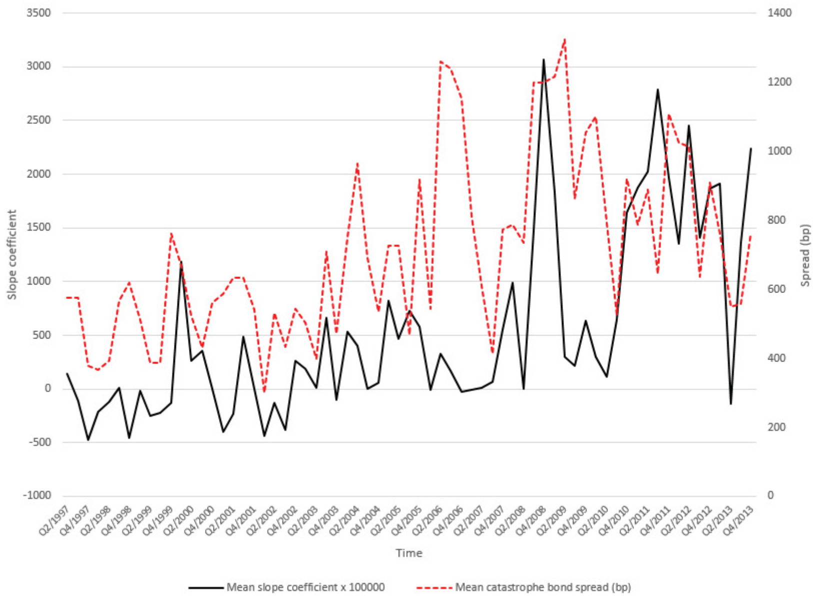
Figure 4: Total losses and the slope coefficient



This figure illustrates the 12-month rolling mean of the slope coefficient on $INSURANCE_{i,t}$ (black solid line) extracted from weekly cross-sectional regressions (i.e., Fama-MacBeth (1973) regression) with all control variables described under Formula (24). At the end of each year, global total losses from man-made (red bar), natural (green bar), and uninsured (blue bar) catastrophes are indicated. The graph also highlights the most severe catastrophes during that year. Data on insured and uninsured losses are retrieved from the *sigma* world insurance database provided by Swiss Re Economic Research & Consulting.

Despite this first indication of the implied volatility smile being connected to catastrophe risk, hard evidence is still missing. We thus turn to the catastrophe bond market. Data for catastrophe bond spreads is available on a quarterly basis. This time we start by showing the quarterly means of the slope coefficient on $INSURANCE_{i,t}$ against the quarterly mean spread of catastrophe bonds at issuance. Figure 5 illustrates the time series.

Figure 5: Catastrophe bond spreads and the slope coefficient



This figure illustrates the quarterly means of the slope coefficient on $INSURANCE_{i,t}$ (black solid line) against the quarterly mean spread of catastrophe bonds at issuance over the risk free rate (red dotted line). The spread is expressed in basis points. To compare both time-series, the slope coefficient is multiplied by 100,000.

We find a 49.4% correlation between catastrophe bond spreads and our mean coefficient. Despite this high correlation, it is not a perfect correlation. Two main possible reasons for this come to mind. First, our implied volatility measure does not contain pricing components which, in contrast, can be observed in the cat bond market. This is particularly pronounced in the graph for the period after Hurricane Katrina in which the implied volatility smile reacts to Katrina itself, but only marginally to increasing prices during the 2006 period with record-high prices. A second reason could be that the securitization of catastrophe risk is not representative for the entire U.S. P&C insurance industry.

To address the first point, we run time-series regressions in a multivariate setting. We start with an univariate regression in which the quarterly mean spread of catastrophe bonds at issuance, CAT_t, is the dependent variable. Braun (2016) identified the pricing components of cat bonds in the primary market (i.e., the yields at issuance) and thus we can decompose CAT_t in its individual risk drivers. Three parameters are important for our aggregate catastrophe risk measure. First, the expected loss, EL_t, which refers to the losses predicted by models for a specific tranche of cat bonds and, second, the default spread from bond markets. Specifically, we use the Bank of America Merrill Lynch U.S. High Yield BB Option-Adjusted Spread, $BBSPR_t$, which is defined as the yield index for the BB-rated bonds over the Treasury rate. The third parameter is the rate-on-line index, $ROLX_t$, which addresses the price dynamics of reinsurance contracts. This price dynamic is known as the reinsurance cycle and a well-known phenomenon for increasing reinsurance prices after catastrophes to make up for the incurred losses. This pricing component is in fact not directly related to immediate tail risk and thus should be the least relevant pricing component with respect to the implied volatility smile. Table 9 presents the results.

Table 9: Implied volatility slope and ILS

	(I)	(II)	(III)
CAT_t	1.636***	1.476***	
	[3.18]	[3.01]	
EL_t			3.131***
			[3.17]
$BBSPR_t$			1.514***
			[2.92]
$ROLX_t$			3.287
			[0.54]
$orthCAT_t$			0.521
			[0.77]
$SLOPE500_t$		7.943	
		[1.61]	
Intercept	-619.091**	-1,033.053***	-820.772
	[-2.05]	[-3.29]	[-1.47]
Adj. R^2	0.23	0.29	0.29
Obs.	67	67	67

This table reports time series regressions of quarterly means of the slope coefficient on $Insurance_{i,t}$ as dependent variable and cat bond related variables as explanatory variables. As an additional control, the slope of the S&P500 is also included ($SLOPE500_t$). CAT_t is the quarterly mean yield spread of catastrophe bonds at issuance over the risk free rate. EL_t is the average expected loss of all catastrophe bond tranches. $BBSPR_t$ is the yield of the BofA Merrill Lynch US High Yield BB Option-Adjusted Spread. $ROLX_t$ is the Lane Financial LLC Synthetic Rate on Line Index. $orthCAT_t$ is the orthogonalized catastrophe bond yield spread on EL_t, $BBSPR_t$, and $ROLX_t$. T-statistics are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 3. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Column (I) corroborates the high correlation result and what we have already seen in Figure 5 - that the spread of catastrophe bonds at issuance, CAT_t, is significantly related to the slope coefficient on $INSURANCE_{i,t}$ and thus the implied volatility smile. Column (II) runs a control regression with the implied volatility slope of the S&P500 as independent variable, $SLOPE500_t$, to ensure that the results are not driven by other market factors. Column (III) then decomposes CAT_t in its individual risk factors, EL_t, $BBSPR_t$, and $ROLX_t$. All remaining pricing components are included in the orthogonalized cat bond spread, $orthCAT_t$, on the three risk factors. As expected, EL_t is the most important driver of the implied volatility smile of P&C insurers, showing clear evidence that the implied volatility slope is indeed related to natural catastrophe risk. Furthermore, we see that price dynamics, i.e., the reinsurance cycle, $ROLX_t$, have no impact on the implied volatility smile. This is what we expected, given a missing urgency of potential default due to price dynamics. The most challenging result, though, is the highly significant BB Option-Adjusted Spread, $BBSPR_t$. Up to this point, we assumed that our difference-in-difference approach (i.e., P&C insurers vs. non-financials) would extract the financial distress component if both groups react identically to economic stress. The fact that the spread is significant, though, shows that the implied volatility of P&C insurers has a remaining reaction towards economic shocks and that our approach did not fully disentangle catastrophe risk from economic distress. Overall, our results show that the implied volatility slope is indeed related to catastrophe risk.

6.5 Event study

Having analyzed catastrophe risk in a multivariate framework, we now conduct an event study to control for the reaction of the implied volatility slope around 12 natural catastrophes in the United States between January 1996 and December 2013.[25] For that purpose, we identify the costliest natural catastrophes related to hurricanes and storms in the United States during that period.[26] Specifically, we investigate 11 hurricanes and one tropical storm listed in Appendix C, sorted by first appearance and differentiated by peril, first appearance, landfall, end date, geographic region, type of event, insured loss as documented, and the

[25]We choose these 12 events based on Swiss Re's 2014 Sigma Report which identifies 40 of the costliest catastrophic events between 1970 and 2013 (`http://media.swissre.com/documents/sigma1_2014_en.pdf`). Over our sample period 12 natural catastrophes occurred in the U.S. (excluding Hurricane Ike).

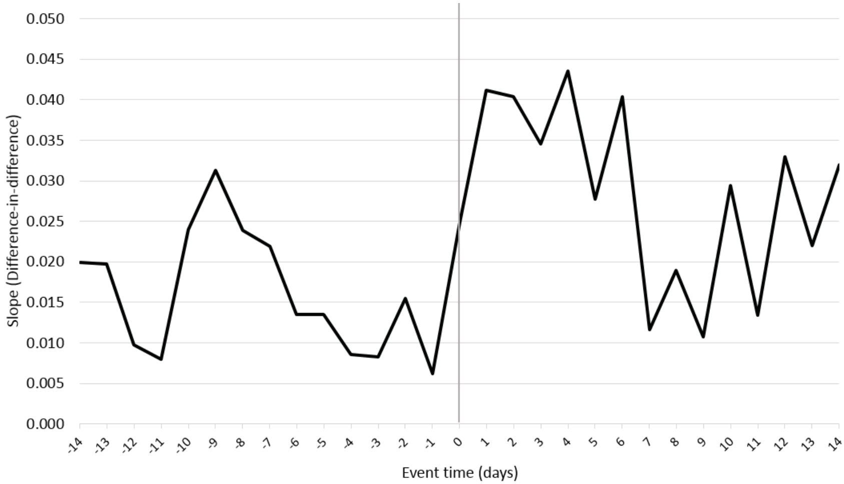
[26]Note that the analysis based on the largest catastrophes in the U.S. ex-post needs to be interpreted cautiously, because a look-ahead bias is introduced by considering catastrophes of which the final costs to insurance companies is known sometime after the event.

ranking of the loss.[27] The question is whether the steeper slope of insurers is simply higher (due to other unknown factors) or whether the slope shows some reaction around the peak event of a catastrophe. If investors anticipate catastrophes or expect losses to insurance companies after the peak of the event to be extremely high, the implied volatility slope might be significantly larger for P&C insurers than options on non-financials.

Although it can take several months or even years until claims by policyholders are settled, first rough estimates of the damages are reported within the first two weeks after the event. We calculate the daily difference in slopes between P&C insurers and non-financials (difference-in-differences) around a natural catastrophic event. The time frame is 14 business days before and 14 days after landfall, where landfall is defined as day zero. In case of multiple landfalls, the first landfall is assigned as day zero. If landfall occurs on a weekend or a holiday, we use the following trading day as the day of landfall. Results on the difference-in-differences between the implied volatility smile of P&C insurers and non-financials are visualized for each day in Figure 6. We see that the slope difference is constantly above zero during the event period, but we also see that the slope difference peaks the first time nine business days before landfall. This is somewhat surprising, as it is well in advance before the average first appearance in our sample (ca. 5 days; see Appendix C). An explanation could be the hurricane seasons of 2004 and 2005, during which 7 out of 12 hurricanes occurred in close sequence. Thus, effects from the previous hurricane are possibly confounding the period before the next hurricane.

[27] There were no earthquakes in the U.S. during our sample period, and we exclude Hurricane Ike from our event study, because it occurred at around the same time as the peak of the financial crisis and the collapse of Lehman brothers. We include the only tropical storm Allison because of the large insured losses it incurred. We also exclude the 9/11 terrorist attacks as they not only financially affected insurers but also the entire economy.

Figure 6: Event study



This figure shows the difference in slopes between P&C insurers and non-financials (difference-in-difference) around a natural catastrophic event. The time frame is 14 business days before and 14 business days after landfall. Landfall occurs on day zero. In case of multiple landfalls, the first landfall is used as day zero. If multiple events occur during a short period of time and the slope difference would be categorized both as pre- and post event, we only account for it once in the pre-event period but not again in the post-event period.

We then ask the question whether the post-event slope is higher than the pre-event slope. As we already accounted for the slope of the control group, we conduct a parametric t-test and non-parametric Wilcoxon rank-sum test between the two slopes. Table 11 reports the test results and the slope difference before and after the event. Both the parametric and non-parametric test show a significantly steeper slope after the event, again, emphasizing the fact that the slope reacts to natural catastrophes.[28]

[28] Note that the average pre- and post-slopes in the graph do not fully align with the numbers in Table 11, because there are events with more observations (i.e., options) than others and consequently have more weight, whereas the graph averages all observations on a specific day.

Table 10: Pre- and post-event comparison of the difference-in-differences slope

	Pre-Slope	Post-Slope	*Unpaired two-sided t-test*	*Wilcoxon test*
$SLOPE_{i,t}$	0.017	0.032	0.015***	0.003***
			[3.76]	[3.00]
Obs.	4097	3422		

This table compares the time period in the difference in slopes between P&C insurers and non-financials (difference-in-differences) 14 business days before and 14 business days after a hurricane landfall. All hurricanes in the United States between 1996 and 2013 are considered (Hurricane Ike is excluded, as it occurs around the same time as the Lehman collapse). An unpaired two-sided t-test is used to test the means before and after the event period. The median difference is reported and the non-parametric Wilcoxon–Mann–Whitney rank-sum test is applied. T-statistics and z-statistics are reported in brackets, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

7 Robustness tests

This section runs several robustness tests with respect to the sample and time period. The first robustness test refers to controlling for other financial institutions as a test group. The second test separates between primary insurers, reinsurers, and the use of reinsurance coverage. The third test addresses the seasonality of catastrophes (i.e. hurricane season vs. non-hurricane season) whether the effect is constant over time and whether the financial crisis had an impact on the slope effect.

7.1 Other financial institutions and systemic relevance

In the previous sections we focused on options written on stocks from the non-financial sector as a control group. We argued that options written on stocks from the financial sector might create some confounding effects, such as systemic risk exposure, which become prevalent in extreme scenarios, or government guarantees or a diffusion of catastrophe risk through stakes in P&C insurers (e.g., bancassurance).

In this section, we want to address this issue by including other financial companies and comparing them with P&C insurers. For that purpose we select all put options in OptionMetrics with SIC codes between 6000 and 6999, except, of course P&C insurers (SIC code 6331), which comprise our experimental group. We run the same regressions as before. Note that our sample size is strongly reduced when running regressions with $LEVERAGE_{i,t}$ and $SIZE_{i,t}$ due to the lower availability of accounting information for financial institutions in COMPUSTAT. We thus run our regressions both with and without these two variables. Results for the variable of interest $INSURANCE_{i,t}$, however, remain robust in all specifications. Furthermore, we include a dummy variable being one for all systemically important financial institutions (SIFI) except for AIG.[29] AIG is the only company which is both a SIFI and a P&C insurer. It might be that our results are driven by AIG and that the slope of AIG is steeper than for the rest of the P&C insurers. We thus look at AIG separately and include a dummy variable, $AIG_{i,t}$, being one if the company is AIG and zero otherwise. The $SIFI_{i,t}$ dummy variable ought to capture any effect in their implied volatility smile. On the one hand, government guarantees could reduce the steepness of the slope, which is what Kelly, Lustig, and Nieuwerburgh (2015) observe in index options. Since we are looking at individual options of financial institutions, this effect might also exist in a reduced form, but it could also be that the connectivity of the financial sector and associated spillover effects translate in steeper slopes of the implied volatility. Results are reported in Table 11.

We see that the economic size of the coefficient on $INSURANCE_{i,t}$ has decreased by approximately half compared to the previous regressions with non-financials as the control group, suggesting that some of our concerns regarding other financial institutions might be true. To our surprise though, AIG is not a driving force of our results at all. Quite the contrary, $AIG_{i,t}$ shows a highly significant negative coefficient, meaning that AIG's implied volalitity smile is much flatter than the implied volatility smile of other P&C insurers. SIFIs, in general, also do not confound our results. Although not being statistically significant under all specifications the overall direction of the $SIFI_{i,t}$ dummy

[29] A complete list of SIFIs can be found in Appendix D. Information on systemically important banks and insurers is retrieved from the Financial Stability Board (`www.fsb.org/wp-content/uploads/r_141106b.pdf` and `www.fsb.org/wp-content/uploads/FSB-communication-G-SIIs-Final-version.pdf`). Our selection of SIFIs refers to those identified by November 2014.

Table 11: Financial institutions

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$INSURANCE_t$	0.010***	0.006***	0.002***	0.004***	0.014***	0.013***	0.012***	0.004***	0.006***
	[4.70]	[3.74]	[3.50]	[4.54]	[3.11]	[3.03]	[2.71]	[2.62]	[4.03]
$SIFI_t$	0.006*	-0.003*	-0.001*	-0.002**	0.005	-0.007	-0.006	-0.002	-0.003***
	[1.85]	[-1.81]	[-1.76]	[-2.44]	[1.17]	[-1.28]	[-1.13]	[-1.21]	[-2.70]
AIG_t	-0.030***	-0.030***	-0.011***	-0.015***	-0.040***	-0.042***	-0.039***	-0.013***	-0.016***
	[-3.60]	[-4.73]	[-4.33]	[-5.25]	[-9.00]	[-7.75]	[-7.34]	[-7.08]	[-11.33]
$IVATM_t$		-0.038***	-0.016***	-0.013***		0.038***	0.016	0.006	-0.005
		[-3.62]	[-3.73]	[-4.53]		[3.36]	[1.18]	[1.01]	[-1.32]
$LEVERAGE_t$		0.004***	0.001***			0.003**	0.003**	0.001**	
		[4.05]	[3.71]			[2.21]	[2.46]	[2.14]	
$SIZE_t$		-0.003***	-0.001***			-0.001	-0.002*	-0.000	
		[-2.88]	[-2.95]			[-1.01]	[-1.72]	[-1.15]	
$BETA_t$		0.009***	0.003***	0.008***		0.007**	0.010***	0.003**	0.012***
		[4.59]	[4.27]	[12.13]		[2.47]	[3.02]	[2.37]	[13.48]
$VOLUME_t$		0.000**	0.000	0.000		0.000	0.000	0.000	-0.000*
		[2.29]	[1.14]	[1.36]		[0.16]	[0.18]	[0.07]	[-1.90]
$CALLPUTOI_t$		-0.000	-0.000	0.000		-0.010***	-0.009***	-0.003***	-0.001
		[-0.04]	[-0.56]	[0.50]		[-3.11]	[-3.06]	[-2.88]	[-1.53]
$SLOPE500_t$							0.048	0.055	0.030
							[0.72]	[1.48]	[1.01]
$IVATM500_t$							0.094**	0.016	0.033**
							[2.55]	[0.91]	[2.55]
$SLOPE_{t-1}$			0.684***	0.708***				0.677***	0.695***
			[91.38]	[115.76]				[78.86]	[90.81]
$Intercept$	0.039***	0.072***	0.024***	0.008***	0.045***	0.036***	0.027**	0.008*	-0.005***
	[16.54]	[6.83]	[6.56]	[8.15]	[26.92]	[3.17]	[2.35]	[1.71]	[-2.94]
Avg. R^2	0.01	0.10	0.52	0.54					
R^2					0.00	0.01	0.01	0.47	0.52
Weeks (cluster)	936	928	928	935	936	928	928	928	935
Firms (cluster)					1699	874	874	873	1566
Obs.	477,025	290,056	289,089	435,522	477,025	290,056	290,056	289,089	435,522
Regression type	*FMB*	*FMB*	*FMB*	*FMB*	*Pooled*	*Pooled*	*Pooled*	*Pooled*	*Pooled*

This table reports Fama-MacBeth (1973) regressions and pooled regressions with clustered standard errors by firm and week (Petersen (2009)) with the slope of implied volatility as dependent variable. The control group ($INSURANCE_t = 0$) consists of all financial institutions with SIC codes between 6000 and 6999 (excluding P&C insurers with SIC code 6331). $SIFI_t$ is a dummy variable taking the value of one if the financial institutions is considered systemically relevant (excluding AIG) and zero otherwise. AIG is a dummy variable taking the value one for American International Group and zero otherwise. All other controls are as previously defined. The sample period is January 1996 to December 2013. T-statistics for Fama-MacBeth regressions are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

variable is negative, meaning a flatter slope as well. Overall, results are robust against this additional control group.

7.2 Reinsurers, insurance losses, and tail risk mitigation

One of the typical features of insurers is assuming risk, not only from policyholders but also from other insurers which is termed reinsurance.[30] The question is then, whether insurers ceding more of their (tail) risk to reinsurers have a less steep implied volatility slope than those which purchase less reinsurance. In addition, those considered as reinsurers might have a steeper implied volatility slope because they sell reinsurance. Technically, excess-of-loss reinsurance, a non-proportional reinsurance type, is the reinsurance type we are interested in, as it caps the losses in the tail of the loss distribution. However, the datasource (ORBIS) we use to determine the reinsurance coverage does not differentiate between the two reinsurance types which is a limitation of this investigation.

The following sample only consists of reinsurers and primary insurers but does not employ a control group as in the previous sections (i.e., non-financials).[31] The dummy variable $REINSURER_{i,t}$ takes on the value of one if the insurer at hand is a reinsurer and zero if it is a primary insurer. Following Cummins and Phillips (2005), our definition of a reinsurer is based on the North American Industry Classification System (NAICS) code 524130 for property/casualty reinsurance. Because of tax reasons, and higher investment flexibility, most of the reinsurers in our sample are headquartered on the Bermudas. Our sample consists of 10 Bermuda-based, 2 U.S.-based, 1 Swiss-based, 1 Luxembourg-based, and 1 Cayman Islands-based reinsurers (P&C insurers marked by (R) in Appendix B). These 15 reinsurers are a subsample of the 67 P&C insurers.

To further investigate tail risk mitigation techniques, we retrieve data on

[30] There are two main categories of reinsurance: proportional and non-proportional. Proportional means that both the primary insurer and the reinsurer share a predefined ratio of the incurred losses. In contrast, non-proportional requires the primary insurer to cover all losses up to a predefined threshold. When that threshold is exceeded, the reinsurer jumps in and covers the following losses up to a maximum.

[31] Because non-financials do not purchase reinsurance coverage and we do not know whether, how much, and what type of primary insurance policies they buy.

reinsurance coverage for each insurer at each year from the ORBIS database. Reinsurance coverage ($REINSCOVER_{i,t}$) is defined as $(1 - \frac{net\ premiums}{premiums\ written})$. The difference between gross premiums and net premiums is the absolute amount of reinsurance which an insurer purchases. We then run the same regressions described in Section 4 with the implied volatility slope on the left-hand side, but in a reduced sample of primary insurers and reinsurers. In addition, we include an interaction term between being a reinsurer and the value of reinsurance coverage. As before, we control for all other firm- and market-specific variables. We run both Fama-MacBeth (1973) regressions and panel regressions with clustered standard errors by firm and week (Petersen (2009)). Table 12 presents the results.

Results regarding the reinsurer and primary insurer sample are not as distinct as the ones we observe for P&C insurers against non-financials and other financial institutions in previous sections. The Fama-MacBeth (1973) regressions in Column (I), (II), and (III) show that the implied volatility slope is less steep for reinsurers compared to primary insurers and that reinsurance coverage increases the steepness of the slope. Both results appear counterintuitive at first unless investors believe that buying reinsurance is a signal for being more at risk and thus in need for more protection. In contrast, a reinsurer only bears losses up to a certain limit which could be an explanation why investors believe catastrophe risk is limited, too.

Although these results are statistically significant based on Fama-MacBeth (1973) regressions, they cannot be confirmed using pooled regressions with clustered standard errors by firm and week. As Petersen (2009) shows, standard errors under Fama-MacBeth (1973) regressions are biased downwards if there is a firm effect present. Because we are now analyzing the same industry (i.e., P&C insurers) the presence of a common firm effect is comprehensible. Overall, this suggests that investors do not or are not able to distinguish between the risk profile of reinsurers and primary insurers and the respective reinsurance coverage they purchase.

Table 12: Reinsurers and reinsurance cover

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$REINSURER_{i,t}$	-0.005*	-0.009***	-0.004***	0.002	-0.006	-0.006	-0.002
	[-1.70]	[-2.58]	[-2.72]	[0.14]	[-0.47]	[-0.47]	[-0.50]
$REINSCOVER_{i,t}$	0.038***	0.022**	0.011**	0.031	-0.013	-0.009	-0.004
	[3.66]	[2.12]	[2.04]	[1.10]	[-0.45]	[-0.34]	[-0.38]
$REINSURER_{i,t} \times REINSCOVER_{i,t}$	0.012	0.040**	0.014	0.067	0.133	0.125	0.042
	[0.73]	[2.13]	[1.63]	[0.73]	[1.52]	[1.40]	[1.35]
$IVATM_{i,t}$		0.049**	0.022*		0.093***	0.076*	0.036*
		[2.13]	[1.68]		[2.88]	[1.68]	[1.82]
$LEVERAGE_{i,t}$		0.003	0.003*		0.002	0.003	0.000
		[1.60]	[1.93]		[0.34]	[0.41]	[0.15]
$SIZE_{i,t}$		-0.004**	-0.002*		-0.009***	-0.009***	-0.002**
		[-2.24]	[-1.82]		[-3.29]	[-3.32]	[-2.46]
$BETA_{i,t}$		0.001	-0.001		0.017*	0.017*	0.005
		[0.26]	[-0.18]		[1.84]	[1.93]	[1.44]
$VOLUME_{i,t}$		0.000	0.000		-0.000	-0.000	-0.000**
		[0.69]	[0.42]		[-1.03]	[-0.77]	[-2.21]
$CALLPUTOI_{i,t}$		-0.000	-0.001		-0.011	-0.010	-0.004*
		[-0.11]	[-0.56]		[-1.63]	[-1.48]	[-1.74]
$SLOPE500_{i,t}$						0.169	0.099*
						[1.27]	[1.80]
$IVATM500_{i,t}$						0.013	-0.018
						[0.15]	[-0.49]
$SLOPE_{i,t-1}$			0.632***				0.654***
			[40.79]				[30.16]
Intercept	0.044***	0.060***	0.025***	0.051***	0.093***	0.083***	0.024**
	[12.11]	[3.62]	[3.04]	[9.34]	[2.97]	[2.94]	[2.45]
Avg. R^2	0.11	0.44	0.68				
R^2				0.01	0.05	0.05	0.45
Weeks (cluster)	935	923	923	935	923	923	923
Firms (cluster)				65	65	65	65
Obs.	27,511	27,085	27,063	27,511	27,085	27,085	27,063
Regression type	*FMB*	*FMB*	*FMB*	*Pooled*	*Pooled*	*Pooled*	*Pooled*

This table reports Fama-MacBeth (1973) regressions and pooled regressions with clustered standard errors by firm and week. The dependent variable is the slope of implied volatility. The sample period is January 1996 to December 2013. T-statistics for Fama-MacBeth regressions are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

7.3 Seasonality, subperiods, and the financial crisis

In the event study, we have seen that the implied volatility slope is affected by hurricanes and significantly larger after the event with an additional reaction approximately ten days before the event. This might suggest that the implied volatility slope is steeper during the hurricane season and lower during the non-hurricane season. However, assuming that insurers are constantly exposed to catastrophes which are difficult to predict and not even seasonal, e.g., an earthquake, a man-made disaster, or an off-season hurricane / natural event, then the slope should be larger throughout the year. According to the National Hurricane Center, the U.S. hurricane season in the Atlantic starts June 1st and ends November 30th, whereas the Eastern Pacific hurricane season already starts May 15th but also ends November 30th. To control for potential seasonal effects in implied volatilities of P&C insurers due to hurricanes, we create a dummy variable, $HURSEASON_{i,t}$, being one during the overlapping Eastern Pacific and Atlantic hurricance months of May to November and zero during the months of December to April. The interaction term between $INSURANCE_{i,t}$ and $HURSEASON_{i,t}$ should then be significant and positive if there is indeed a seasonal effect in P&C options. Table 13 reports the multivariate results.[32]

[32] We only report pooled regressions because $HURSEASON_{i,t}$ is a time dummy.

Table 13: Seasonality

	(I)	(II)	(III)	(IV)
$INSURANCE_{i,t}$	0.024***	0.022***	0.023***	0.007***
	[4.93]	[4.48]	[4.55]	[4.17]
$HURSEASON_{i,t}$	-0.001	-0.001	-0.002	-0.001
	[-0.34]	[-0.51]	[-1.12]	[-0.99]
$INSURANCE_{i,t} \times HURSEASON_{i,t}$	0.001	0.001	0.001	0.001
	[0.50]	[0.44]	[0.43]	[0.95]
Controls	NO	YES	YES	YES
R^2	0.00	0.01	0.01	0.45
Weeks	936	928	928	928
Firms	5,609	4,912	4,912	4,908
Obs.	1,976,163	1,736,945	1,736,945	1,733,939

This table reports panel regressions with clustered standard errors by firm and week (Petersen (2009)). $HURSEASON_{i,t}$ is a dummy variable taking the value of one for the Atlantic hurricane season June to November and zero for the months December to May. $INSURANCE_{i,t} \times HURSEASON_{i,t}$ is an interaction term between the dummy variable $INSURANCE_{i,t}$ and $HURSEASON_{i,t}$. The sample period is January 1996 to December 2013. T-statistics are reported in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Column (I) does not include any control variables. The interaction term $INSURANCE_{i,t} \times HURSEASON_{i,t}$ shows no significance. When controlling for the same variables as in Section 6.3, this result remains robust. Overall we do not find a seasonal effect in implied volatilities. That is, the implied volatility is not steeper during the hurricance season, which suggests that derivatives on P&C insurers are constantly more expensive than their non-financials counterparts throughout the year.

Having addressed the seasonal aspect within the years, we now address changes in the implied volatility over the sample period. With Hurricane Katrina being the costliest and most devastating hurricane in U.S. history, we separate our sample in two equally long subperiods of nine years, where 1996 until 2004 is the pre-Katrina subperiod and 2005 until 2013 is the post-Katrina subperiod. Possibly the attitude towards natural catastrophes changed after that among investors, speculators, and market makers. We run Fama-MacBeth (1973) regressions and pooled regressions as in the previous sections on the two subsamples. Results are shown in Table 14 and show that the slope of P&C

insurers indeed changed compared to non-financials in the post-Katrina period. Specifically in univariate pooled and Fama-MacBeth (1973) regressions, the slope is both statistically and economically much smaller compared to the post-Katrina period. When we control for the firm and market-specific variables we even observe an insignificant effect on the variable of interest, $INSURANCE_{i,t}$. One explanation could be that, similar to the market crash of 1987 introducing the implied volatility smile, Hurricane Katrina could have had a similar effect in creating an additional risk awareness (or "additional" smile) on top of the implied volatility smile. A second explanation might be the overall increase of natural disasters in the post 2005 years and thus a steeper slope.

The last potential reason we can think of is related to the financial crisis of 2008, which simply might be driving the result of a steeper slope. To control for this effect, we include a dummy variable for the financial crisis, $FinCrisis_{i,t}$, which takes on the value of one for the time between February 2008 and July 2009, which is the time frame of the financial crisis according to the National Bureau of Economic Research (NBER) based Recession Indicators for the United States and zero else. Moreover, we include an interaction term between $INSURANCE_{i,t}$ and $FinCrisis_{i,t}$ to check for a higher steepness of P&C insurers during the financial crisis. We run the regression only on the post-Katrina period (2005-2013) to ensure that our results apply to the "steep" period.[33] Results on the regressions are presented in Table 15. We find that the interaction term is insignificant in both specifications. This suggests that the steeper slope of P&C insurers is not driven by the financial crisis.

[33] Again, because the dummy variable for the financial crisis is a time dummy we only report pooled regressions with clustered standard errors by firm and week.

Table 14: Subperiods

	Pre-Katrina (2005)				Post-Katrina (2005)			
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**	**(VIII)**
$INSURANCE_t$	0.003**	0.000	0.005*	-0.000	0.030***	0.010***	0.034***	0.012***
	[2.58]	[0.51]	[1.94]	[-0.40]	[8.59]	[8.15]	[5.79]	[5.86]
$IVATM_t$		-0.046*		-0.019***		-0.016***		-0.013***
		[-1.81]		[-11.38]		[-6.32]		[-4.44]
$LEVERAGE_t$		-0.009		-0.001***		0.000		0.000
		[-1.30]		[-6.30]		[1.41]		[0.93]
$SIZE_t$		-0.003		0.000		-0.001***		-0.001***
		[-0.91]		[1.24]		[-3.68]		[-4.30]
$BETA_t$		0.001		0.005***		0.003***		0.002***
		[0.57]		[12.11]		[4.11]		[3.70]
$VOLUME_t$		0.000		0.000***		-0.000***		-0.000***
		[1.06]		[3.80]		[-5.86]		[-2.73]
$CALLPUTOI_t$		0.001		-0.004***		-0.000		0.000
		[0.73]		[-8.18]		[-0.62]		[0.19]
$SLOPE500_t$				-0.109***				0.028
				[-5.15]				[0.56]
$IVATM500_t$				0.081***				0.029
				[6.69]				[1.53]
$SLOPE_{t-1}$		0.644***		0.690***		0.654***		0.652***
		[25.19]		[103.02]		[116.23]		[94.05]
Intercept	0.027***	0.046	0.028***	0.003	0.038***	0.028***	0.038***	0.020***
	[7.05]	[1.41]	[19.11]	[1.24]	[22.01]	[8.62]	[35.98]	[5.42]
Avg. R^2	0.00	0.47			0.00	0.44		
R^2			0.00	0.50			0.00	0.43
Weeks (cluster)	468	460	468	460	468	468	468	468
Firms (cluster)			3522	2991			4434	3994
Obs.	837,594	692,521	837,594	692,521	1,138,569	1,041,418	1,138,569	1,041,418
Regression type	FMB	FMB	Pooled	Pooled	FMB	FMB	Pooled	Pooled

This table reports Fama-MacBeth (1973) regressions and pooled regressions with clustered standard errors by firm and week (Petersen (2009)), with the slope of implied volatility as dependent variable. The sample is split into two equally long time periods of nine years. The first time period is considered the pre-Katrina period (1996 - 2004), and the second period is considered the post-Katrina period (2005 - 2013). T-statistics for Fama-MacBeth regressions are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15: Panel regression (Post Katrina) controlling for financial crisis

	(I)	(II)	(III)	(IV)
$INSURANCE_t$	0.033***	0.031***	0.012***	0.011***
	[5.77]	[4.39]	[5.87]	[4.50]
$FinCrisis_t$	0.010***	0.010***	0.003	0.003
	[3.46]	[3.40]	[1.10]	[1.07]
$INSURANCE_t \times FinCrisis_t$		0.013		0.004
		[1.22]		[0.99]
$Intercept$	0.036***	0.036***	0.020***	0.020***
	[32.4]	[32.75]	[5.44]	[5.45]
Controls	NO	NO	YES	YES
R^2	0.00	0.00	0.43	0.43
Weeks	468	468	468	468
Firms	4,434	4,434	3,994	3,994
Obs.	1,138,569	1,138,569	1,041,418	1,041,418

This table reports panel regressions with clustered standard errors by firms and week (Petersen (2009)) with the slope of implied volatility as dependent variable. The sample period covers the post-Katrina period (2005 - 2013). $FinCrisis_t$ is a dummy variable taking the one for the months between February 2008 and July 2009. $INSURANCE_t \times FinCrisis_t$ is an interaction term between the two dummy variables. T-statistics are reported in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

8 Conclusion

This paper analyzes the implied volatility slope of P&C insurers. With P&C insurers being exposed to natural and man-made disasters and OTM put options protecting against tail risk, we argue that the exposure towards catastrophe risk should be identifiable in the implied volatility smile. P&C insurers are particularly convenient for analyzing the relation between tail risk and option prices, because of their specific exposure to extreme events (i.e., natural disasters), their use of risk mitigation techniques against tail risk (i.e., reinsurance), and the securitization of catastrophe risk.

Our findings support this idea, both with financials and non-financials as control groups. We also confirm that the implied volatility slope of P&C insurers is related to risk premiums from the cat bond market with a correlation of 49.4%. The main drivers in the tail risk of the implied volatility slope are expected losses from natural catastrophes and the default spread (i.e., BB-rated option-adjusted yield over the treasury yield). Pricing dynamics such as the reinsurance cycle, however, do not affect the implied volatility smile. Furthermore, we find that the slope is in fact steeper on the day and after the days following a hurricane event supporting the idea that the slope reacts to potentially large losses of natural catastrophes. Lastly, we show that the effect of a steeper slope has increased over time, possibly because of an increasing number of natural disasters in recent times.

Further insights into catastrophe risk can have real effects on the pricing of catastrophe-related insurance prices. Among other things, the slope can be used as a guidance tool for the primary market how market participants evaluate the probability and compensation for catastrophe risk on average. A specific advantage of our method is the daily (high-frequency) determination of catastrophe risk using traditional option markets.

Future research might analyze how catastrophe risk deploys in other tail risk-oriented financial instruments, such as Credit Default Spreads (CDS). We established a link between put options and catastrophe bonds, but it might be of interest to emphasize how the different tail-risk-oriented instruments, i.e., put options, CDS, and catastrophe bonds interact with each other and whether arbitrage opportunities exist between them. In general, it can be asked how catastrophe risk can be financially exploited. The replication of (zero-beta) investments using put options on P&C insurers could be an efficient way for investors to earn uncorrelated returns with the market by being exposed towards catastrophe risk. The essence of this investment opportunity would be similar to a catastrophe bond but unlike catastrophe bonds which are only available to qualified investors, put options can be accessed by a wider public. The question here would be, though, whether transaction costs can be overcome. Going beyond the natural catastrophe risk aspect in option prices, it would be interesting to investigate the implied volatility smile of life insurers and their potential tail risk due to pandemics, longevity risk, or mortality risk. Lastly, future research might investigate the assumption of independence between natural catastrophes and economic downturns. Both our model and our empirical research design throughout the paper assume a clear separation between the two factors, allowing us to identify a difference-in-differences effect caused by catastrophes. However, if catastrophes exceed a critical mass, the effect between natural catastrophes and economic downturns might become indistinguishable because the natural catastrophe affects the real economy. A model which accounts for this downside correlation might thus be more appropriate.

References

Adams, Zeno, Roland Füss, and Reint Gropp, 2014, Spillover effects among financial institutions: A state-dependent sensitivity value-at-risk approach, *Journal of Financial and Quantitative Analysis*, Vol. 49, 575–598.

Ait-Sahalia, Yacine, and Andrew W. Lo, 2000, Nonparametric risk management and implied risk aversion, *Journal of Econometrics*, Vol. 94, 9–51.

An, Byeong-Je, Andrew Ang, Turan G. Bali, and Nusret Cakici, 2014, The joint cross section of stocks and options, *The Journal of Finance*, Vol. 69, 2279–2337.

Backus, David, Mikhail Chernov, and Ian Martin, 2011, Disasters implied by equity index options, *The Journal of Finance*, Vol. 66, 1969–2012.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock return characteristics, skew laws, and the differential pricing of individual equity options, *Review of Financial Studies*, Vol. 16, 101–143.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics*, Vol. 9, 3–18.

Black, Fischer, 1976, Studies of stock price volatility changes, American Statistical Association Proceedings of the 1976 meetings of the business and economics statistics section, 177-181.

Blau, Benjamin M., Robert A. Van Ness, and Chip Wade, 2008, Capitalizing on catastrophe: Short selling insurance stocks around hurricanes Katrina and rita, *Journal of Risk and Insurance*, Vol. 75, 967–996.

Bollen, Nicolas P. B., and Robert E. Whaley, 2004, Does net buying pressure affect the shape of implied volatility functions?, *The Journal of Finance*, Vol. 59, 711–753.

Bollerslev, Tim, and Viktor Todorov, 2011, Tails, fears, and risk premia, *The Journal of Finance*, Vol. 66, 2165–2211.

Braun, Alexander, 2016, Pricing in the primary market for cat bonds: New empirical evidence, *Journal of Risk and Insurance*, forthcoming.

Cummins, J. David, and Mary A. Weiss, 2009, Convergence of insurance and financial markets: Hybrid and securitized risk-transfer solutions, *Journal of Risk and Insurance*, Vol. 76, 493–545.

Dennis, Patrick, and Stewart Mayhew, 2002, Risk-neutral skewness: Evidence from stock options, *Journal of Financial and Quantitative Analysis*, Vol. 37, 471–493.

Driessen, Joost, Pascal J. Maenhout, and Grigory Vilkov, 2009, The price of correlation risk: Evidence from equity options, *The Journal of Finance*, Vol. 64, 1377–1406.

Ewing, Bradley T., Scott E. Hein, and Jamie B. Kruse, 2006, The response of insurer stock prices to natural hazards, *Weather and Forecasting*, Vol. 21, 395–407.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *The Journal of Political Economy*, 607–636.

Froot, Kenneth A., Brian S. Murphy, Aaron B. Stern, and Stephen E. Usher, 1995, The emerging asset class: Insurance risk, *Special report*, Guy Carpenter and Company, New York.

Froot, Kenneth A., 2001, The market for catastrophe risk: A clinical examination, *Journal of Financial Economics*, Vol. 60, 529–571.

Garleanu, Nicolae, Lasse Heje Pedersen, and Allen M. Poteshman, 2009, Demand-based option pricing, *Review of Financial Studies*, Vol. 22, 4259–4299.

Hagendorff, Bjoern, Jens Hagendorff, Kevin Keasey, and Angelica Gonzalez, 2014, The risk implications of insurance securitization: The case of catastrophe bonds, *Journal of Corporate Finance*, Vol. 25, 387–402.

Jackwerth, Jens Carsten, and Mark Rubinstein, 1996, Recovering probability distributions from option prices, *The Journal of Finance*, 1611–1631.

Kelly, Bryan, and Hao Jiang, 2014, Tail risk and asset prices, *Review of Financial Studies*, forthcoming.

Kelly, Bryan T., Hanno Lustig, and Stijn Van Nieuwerburgh, 2015, Too-systemic-to-fail: What option markets imply about sector-wide government guarantees, *American Economic Review*, (forthcoming).

Kelly, Bryan, Lubos Pástor, and Pietro Veronesi, 2015, The price of political uncertainty: Theory and evidence from the option market, *The Journal of Finance*, (forthcoming).

Lamb, Reinhold P., 1995, An exposure-based analysis of property-liability insurer stock values around hurricane Andrew, *Journal of Risk and Insurance*, Vol. 62, 111–123.

Lamb, Reinhold P., 1998, An examination of market efficiency around hurricanes, *Financial Review*, Vol. 33, 163–172.

Maheu, John M., and Thomas H. McCurdy, 2004, News arrival, jump dynamics, and volatility components for individual stock returns, *The Journal of Finance*, Vol. 59, 755–793.

Martzoukos, Spiros H., and Lenos Trigeorgis, 2002, Real (investment) options with multiple sources of rare events, *European Journal of Operational Research*, Vol. 136, 696–706

Merton, Robert C., 1976, Option pricing when underlying stock returns are discontinuous, *Journal of Financial Economics*, Vol. 3, 125–144.

Newey, Whitney K., and Kenneth D. West, 1987, A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, Vol. 55, 703-708.

Pérez-González, Francisco, and Hayong Yun, 2013, Risk management and firm value: Evidence from weather derivatives, *The Journal of Finance*, Vol. 68, 2143–2176.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, *Review of Financial Studies*, Vol. 22, 435–480.

Sheikh, Aamir M., 1989, Stock splits, volatility increases, and implied volatilities, *The Journal of Finance*, Vol. 44, 1361–1372.

Thomann, Christian, 2013, The impact of catastrophes on insurer stock volatility, *Journal of Risk and Insurance*, Vol. 80, 65–94.

Toft, Klaus Bjerre, and Brian Prucyk, 1997, Options on leveraged equity: Theory and empirical tests, *The Journal of Finance*, Vol. 52, 1151–1180.

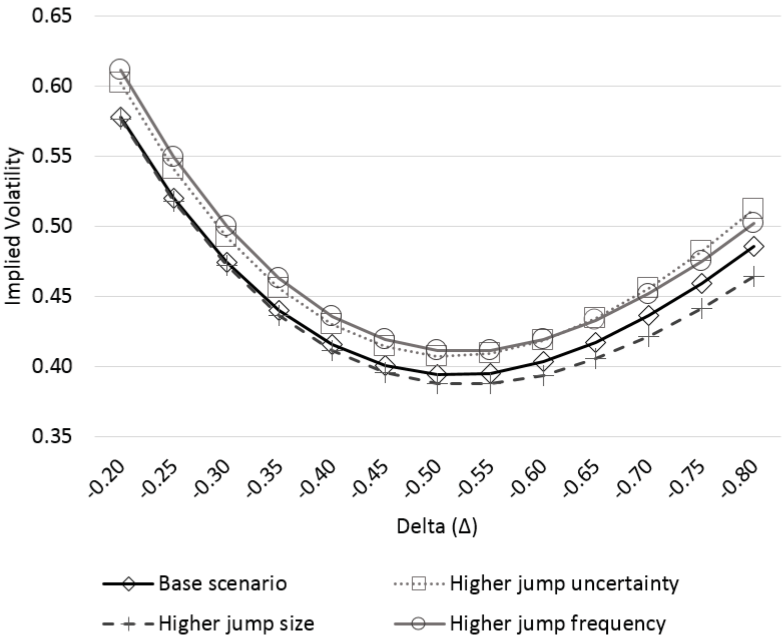
Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *The Journal of Finance*, Vol. 59, 831–868.

Yan, Shu, 2011, Jump risk, stock returns, and slope of implied volatility smile, *Journal of Financial Economics*, Vol. 99, 216–233.

Zanjani, George, 2002, Pricing and capital allocation in catastrophe insurance, *Journal of Financial Economics*, Vol. 65, 283–305.

A Model sensitivity

Figure A: Modeled implied volatility smiles (P&C insurers)



This figure illustrates the modeled implied volatilities of one-month-to-expiration put options written on P&C insurance stocks for different catastrophe-related parameters. The "Base scenario" is identical to the main calibration for a P&C insurance stock in Section 3 (black line marked by downward pointing squares). The second scenario "Higher jump uncertainty" changes, ceteris paribus, the value of σ_{cat} to 0.55. The third scenario "Higher jump size" changes, ceteris paribus, the value of γ_{cat} to -0.12. The fourth scenario "Higher jump frequency" changes, ceteris paribus, the value of λ_{cat} to 1.20.

B Property/casualty insurers with options

Table B: P&C insurers

Company name	CUSIP	Company name	CUSIP
20TH CENTURY INDUSTRIES	90130N10	KEMPER CORP DE	48840110
ACE LTD **(R)**	H0023R10	LOEWS CORP	54042410
ALLEGHANY CORP DE	01717510	MAIDEN HOLDNGS LTD **(R)**	G5753U11
ALLIED WORLD ASSUR CO HLDGS AG	H0153110	MARKEL CORP	57053510
ALLSTATE CORP	02000210	MEADOWBROOK INSURANCE GROUP INC	58319P10
ALTERRA CAPITAL HOLDINGS LTD	G0229R10	MERCURY GENERAL CORP NEW	58940010
AMERICAN FINANCIAL GROUP INC NEW	02593210	MONTPELIER RES HOLDINGS LTD **(R)**	G6218510
AMERICAN INTERNATIONAL GROUP INC	02687478	MUTUAL RISK MANAGEMENT LTD	62835110
AMERISAFE INC	03071H10	NAVIGATORS GROUP INC	63890410
AMTRUST FINANCIAL SERVICES INC	03235930	ODYSSEY RE HOLDINGS CORP	67612W10
ARCH CAPITAL GROUP LTD NEW **(R)**	G0450A10	OHIO CASUALTY CORP	67724010
ASPEN INSURANCE HOLDINGS LTD **(R)**	G0538410	ONEBEACON INSURANCE GROUP LTD	G6774210
ASSURANT INC **(R)**	04621X10	PHILADELPHIA CONSOLIDATED HLG CO	71752810
AXIS CAPITAL HOLDINGS LTD **(R)**	G0692U10	PLATINUM UNDERWRITERS HLDGS LTD **(R)**	G7127P10
BERKLEY W R CORP	08442310	PROASSURANCE CORP	74267C10
BERKSHIRE HATHAWAY INC DEL	08467070	PROGRESSIVE CORP OH	74331510
C N A FINANCIAL CORP	12611710	R L I CORP	74960710
CHUBB CORP	17123210	RELIANCE GROUP HOLDINGS INC	75946410
CINCINNATI FINANCIAL CORP	17206210	RENAISSANCERE HOLDINGS LTD **(R)**	G7496G10
COMMERCE GROUP INC MASS	20064110	SAFECO CORP	78642910
EMPLOYERS HOLDINGS INC	29221810	SAFETY INSURANCE GROUP INC	78648T10
ENDURANCE SPECIALTY HOLDINGS LTD **(R)**	G3039710	SEABRIGHT HOLDINGS INC	81165610
EVEREST RE GROUP LTD **(R)**	G3223R10	SELECTIVE INSURANCE GROUP INC	81630010
FIRST MERCURY FINANCIAL CORP	32084110	STATE AUTO FINANCIAL CORP	85570710
FLAGSTONE REINSURANCE HLDGS SA **(R)**	L3466T10	TOWER GROUP INTERNATIONAL LTD	G8988C10
FRONTIER INSURANCE GROUP INC	35908110	TRANSATLANTIC HOLDINGS INC **(R)**	89352110
GLOBAL INDEMNITY PLC	G3931910	TRAVELERS COMPANIES INC	89417E10
GREENLIGHT CAPITAL RE LTD **(R)**	G4095J10	TRAVELERS PPTY CASUALTY CORP NEW	89420G10
H C C INSURANCE HOLDINGS INC	40413210	TRAVELERS PPTY CASUALTY CORP NEW	89420G40
HANOVER INSURANCE GROUP INC	41086710	UNITED FIRE GROUP INC	91034010
HARTFORD FINANCIAL SVCS GRP INC	41651510	UNIVERSAL INSURANCE HOLDINGS INC	91359V10
HILLTOP HOLDINGS INC	43274810	VALIDUS HOLDINGS LTD **(R)**	G9319H10
HORACE MANN EDUCATORS CORP NEW	44032710	ZENITH NATIONAL INSURANCE CORP	98939010
INFINITY PROPERTY & CASUALTY COR	45665Q10		

Property/casualty insurers marked by **(R)** are also reinsurers according to the North American Industry Classification System.

C Natural catastrophes in the U.S. (1996–2013)

Table C: Catastrophic events in the U.S. (1996–2013)

Peril	First appearance (start date)	Landfall / Peak	End date	Geographic region of catastrophe	Event	Insured loss (indexed to 2013 in $M)	Rank (loss)
Hurricane Georges	9/15/1998	9/21/1998	9/29/1998	LA, MS, AL, FL	Floods	5,240	14
Hurricane Floyd	9/7/1999	9/14/1999	9/16/1999	NC, SC, VA, MD, PA, NY, NJ, DE, RI, CT, MA, NH, VT	Heavy rain, floods	4,100	18
Tropical storm Allison	6/5/2001	6/5/2001	6/17/2001	TX, LA, MS, FL, VA, PA	Floods	4,925	15
Hurricane Charley	8/9/2004	8/13/2004	8/14/2004	FL, SC, NC	Storm surge	10,313	9
Hurricane Frances	8/25/2004	9/2/2004	9/9/2004	FL, SC, NC	Storm surge, floods	6,593	12
Hurricane Ivan	9/2/2004	9/16/2004	9/21/2004	AL, FL, GA, MS, LA, SC, NC, VA, WV, MD, TN, KY, OH, DE, NJ, PA, NY	Damage to oil rigs, storm surge, floods	17,218	5
Hurricane Jeanne	9/13/2004	9/14/2004	9/29/2004	FL, GA, SC, NC, VA, MD, DE, NJ, PA, NY	Floods, landslides	4,872	16
Hurricane Katrina	8/23/2005	8/25/2005	8/30/2005	FL, LA, MS, AL, TN, KY, IN, OH, GA.	Storm surge, levee failure, damage to oil rigs	80,373	1
Hurricane Rita	9/18/2005	9/24/2005	9/26/2005	FL, AL, MS, LA, AR, TX	Floods, damage to oil rigs	12,510	7
Hurricane Wilma	10/15/2005	10/21/2005	10/26/2005	FL	Floods	15,570	6
Hurricane Ike	9/1/2008	9/7/2008	9/15/2008	TX, LA, AR, TN, IL, IN, KY, MO, OH, MI, PA.	Floods, offshore damage	22,751	4
Hurricane Irene	8/21/2011	8/22/2011	8/30/2011	NC, VA, MD, NJ, NY, CT, RI, MA, VT	Extensive flooding	6 274	13
Hurricane Sandy	10/21/2012	10/24/2012	10/31/2012	MD, DE, NJ, NY, CT, MA, RI	Storm surge	36,890	2

Notes: Data on the events is retrieved from Swiss Re's 2014 Sigma Report. Events are presented in chronological order. Hurricane Ike is written in Italics and is not included in the event study due to the close proximity to the financial crisis. Data about appearance, landfall, and end date are from the National Hurricane Center (NHC) using the HURDAT2 dataset.

D Systemically important financial institutions (SIFI)

Table D: Systemically important financial institutions (SIFI)

	Company name	CUSIP
Banks		
	BANCO SANTANDER S A	05964H10
	BANK OF AMERICA CORP	06050510
	BANK OF NEW YORK MELLON CORP	06405810
	BARCLAYS PLC	06738E20
	CITIGROUP INC	17296742
	CREDIT SUISSE GROUP	22540110
	GOLDMAN SACHS GROUP INC	38141G10
	H S B C HOLDINGS PLC	40428040
	I N G GROEP N V	45683710
	JPMORGAN CHASE & CO	46625H10
	LLOYDS BANKING GROUP PLC	53943910
	MITSUBISHI UFJ FINANCIAL GP INC	60682210
	MIZUHO FINANCIAL GROUP INC	60687Y10
	MORGAN STANLEY DEAN WITTER & CO	61744644
	ROYAL BANK SCOTLAND GROUP PLC	78009768
	STATE STREET CORP	85747710
	SUMITOMO MITSUI FINANCIAL GP INC	86562M20
	WELLS FARGO & CO NEW	94974610
	DEUTSCHE BANK A G	D1819089
	U B S AG	H8923133
Life insurers		
	AEGON N V	00792410
	METLIFE INC	59156R10
	PRUDENTIAL FINANCIAL INC	74432010
	PRUDENTIAL PLC	74435K20
P&C insurers		
	AMERICAN INTERNATIONAL GROUP INC	02687478

Part IV

Asset Pricing and Extreme Event Risk: Common Factors in ILS Funds

SEMIR BEN AMMAR, ALEXANDER BRAUN, and MARTIN ELING

Abstract

Often classified as hedge funds, the returns of collective investment vehicles that focus on catastrophe (cat) bonds and other insurance-linked securities (ILS) behave unlike those of any other asset class. Therefore, traditional asset pricing models, such as the five-factor approach of Fama and French (1993) and the seven-factor approach of Fung and Hsieh (2004), are not suitable for these funds. We set up a comprehensive database, run an empirical performance analysis, and introduce three new factor models based on publicly-available indices, which decently explain the time-series and cross-sectional return characteristics of ILS funds. Our results indicate that the latter have historically exhibited a superior risk-adjusted performance. Despite a strong overall fit of the factor models, we are left with significant positive alphas for about one quarter of the funds in our sample. Those are either attributable to manager skill, luck, or beta exposures associated with non-cat-bond ILS.

Key words: Insurance-Linked Securities · Investment Funds · Factor Model · Catastophe Bonds

JEL Classification: G12 · G22 · G23

This paper has been presented at the 2016 meeting of the Western Risk and Insurance Association.

1 Introduction

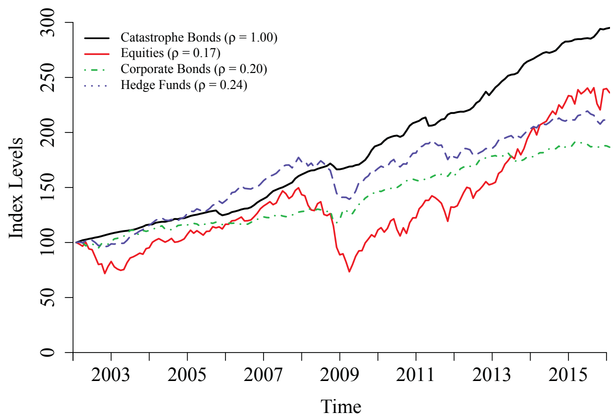
Over the last two decades, a new asset class called insurance-linked securities (ILS) has emerged. Its dominant representative is the catastrophe (cat) bond, a financial instrument which pays regular coupons unless a disaster occurs during the contract term, leading to full or partial loss of principal. Cat bonds have been developed by (re)insurance companies as a hedge against extreme event exposure in their property risk portfolios. They typically cover natural perils such as windstorms and earthquakes in different regions around the world and may be triggered either through insurance losses or physical parameter measurements in excess of a threshold.[1] The market for cat bonds has witnessed substantial growth rates in the recent past. Its popularity among investors is based on attractive rates of return that are largely uncorrelated with other asset classes (see Figure 1). However, direct investments in cat bonds and other ILS requires a lot of specific expertise (see, e.g., Braun et al., 2013). An alternative way to gain exposure is given by open-end funds. Although the latter are sometimes still lumped together with mutual funds or hedge funds in the fixed income space, their returns exhibit a unique behavior.[2]

Consequently, traditional factor models are not suitable to analyze the behavior of dedicated ILS funds. Existing empirical research, however, mainly focuses on explaining the risk spread of the underlying cat bonds themselves (see, e.g., Galeotti et al., 2013; Braun, 2016; Gürtler et al., 2016) as well as their risk implications (see Hagendorff et al., 2013, 2014). A specific factor model for the returns of diversified ILS portfolios has not been suggested yet. Given the abundance of the asset pricing literature, this is quite astonishing. In the wake of the pioneering work of Sharpe (1964, 1992) and Fama and French (1992, 1993), several authors began to employ factor models for style analysis and performance measurement purposes. Blake et al. (1993), e.g., apply the idea of an asset class factor model as coined by Sharpe (1992) to bond mutual funds.

[1] A detailed explanation of the structural features of cat bonds can be found in Braun (2016).

[2] A distinct characteristic of hedge funds is their ability to employ sophisticated strategies (e.g., short selling, leverage, and derivatives). Yet, the majority of hedge funds trades in traditional asset classes such as equities and fixed income. ILS funds, in contrast, distinguish themselves by focusing on the entirely new market of investable insurance risk.

Figure 1: Catastrophe bonds and other asset classes



This figure illustrates the development of catastrophe bonds and other asset classes from January 2002 to December 2015. The figures have been estimated based on the following indices: Swiss Re Global Cat Bond Performance Index (cat bonds), S&P 500 Performance Index (equities), Barclays' Investment Grade Total Return Corporate Bond Index (corporate bonds), HFRI Fund Weighted Total Return Composite Index (hedge funds). Behind each asset class, we have included the return correlations (ρ) with the Swiss Re Global Cat Bond Performance Index.

Furthermore, Fung and Hsieh (1997) extend the original setup to account for dynamic trading strategies of hedge fund managers. Carhart (1997) adds a momentum factor to the classical three-factor model of Fama and French (1992) and analyzes the persistence of equity mutual fund returns. Based on their earlier insights, Fung and Hsieh (2004) develop a comprehensive risk-factor approach to explain the returns of diversified hedge fund portfolios. More recently, Sadka (2010) added a liquidity risk factor for hedge funds, Chen et al. (2010) control for several sources of nonlinearity in bond mutual fund returns to evaluate managers' timing ability, and Ammann et al. (2010) develop a model that accounts for the particularities of convertible bond funds.

Regardless of the attractive historical performance and the substantial diversification potential offered by ILS funds, little is known about their return drivers to date. The paper at hand aims at filling this gap. Our contribution is threefold. First, we analyze the asset class' risk-return profile for the period from January 2002 to December 2015 relative to corporate bonds and hedge funds. For this purpose, we set up a dataset that almost covers the entire universe of existing and terminated ILS funds. Second, we demonstrate the inability of traditional factor models to explain both the time-series and cross-sectional return characteristics of ILS funds. Subsequently, we introduce three new factor models to address this issue: a single-index, a fixed-income-oriented four-factor, and a perils-based three-factor approach. Third, we draw on these factor models to determine whether certain funds were able to outperform their peers on a risk-adjusted basis in the past.

Our findings indicate that ILS funds exhibited a superior historical performance based on the Sharpe Ratio, the Sortino Ratio, the Excess Return on VaR, and the Calmar Ratio. In addition, they delivered positive returns in approximately 90% of all analyzed months compared to 66% during the same period for hedge funds and 70% for corporate bonds. The three and four-factor models which we propose are found to explain the time series of ILS fund returns with adjusted R-squareds of around 70% which can be further increased to 80% when controlling for a single extreme outlier caused by the impact of Hurricane Katrina on the relatively small fund market in August 2005. Finally, despite the good fit of the factor models, we are left with significant positive alphas for one quarter of all funds in the cross-section. These are either attributable to manager skill, luck, or exotic beta exposures originating from ILS other than cat bonds. Owing to the rapidly increasing size of the ILS market, the aforementioned empirical evidence should provide valuable insights for style analysis, risk management, performance measurement, and portfolio optimization.

The remainder of this paper is organized as follows. In Section 2, we describe the (classical and new) factor models that form the center of our analysis. A description of our data both for the ILS funds and the risk factors is provided in Section 3. The empirical results are presented in Section 4, including the historical performance of ILS funds, time-series regressions, and an assessment of the models' ability to explain the cross-section of expected returns. In Section 5, we test the robustness of our results for various subperiods and alternative ILS portfolios. Our conclusions are presented in Section 6.

2 Factor models

2.1 Traditional factor models

First of all, we run a simple asset class factor model in the spirit of Sharpe (1992). As indicated by their name, such models can be employed to reveal a fund's passive exposure to various asset classes. We include an equity market index, a treasury bond index, a municipal bond index, a corporate bond index, a mortgage-backed securities index, a convertible bond index, a real estate index, a hedge fund index, and a commodities index. To avoid collinearity issues that may arise due to the correlations of the fixed income indices, we test the full model as well as three submodels with different factor combinations. Subsequently, we run the Carhart (1997) four-factor model, which adds an equity momentum factor (MOM) to the classical setup of Fama and French (1993). Finally, we focus on specific fixed income and hedge fund factor models that have been proposed in the literature, since ILS funds are often classified into either one of these two asset categories. Fama and French (1993) as well as Blake et al. (1993) include bond-specific factors. The former extend their three-factor equity model by a government bond index (TERM) and a corporate bond index (DEF), while the latter rely on TERM as well as a high yield bond index (*HYield*) and a mortgage-backed securities index (*Mortgage*). From the hedge fund literature, we adopt the seven-factor approach of Fung and Hsieh (2004). This model comprises four of the five factors suggested by Fama and French (1993) plus three trend-following factors for bonds (PTFSBD), exchange rates (PTFSFX), and commodities (PTFSCOM). In contrast to Fung and Hsieh (2004), we measure TERM and DEF in excess returns instead of yields.[3] All factors are measured as monthly returns in excess of the one-month T-Bill rate.

[3] This has been suggested by Sadka (2010) and ensures that alpha can be interpreted as an excess return as well.

2.2 New ILS-specific factor models

We begin with a single-factor approach in the spirit of the capital asset pricing model (CAPM), which will be termed the *CAT-CAPM*. The only factor in this model is an index of all outstanding USD and EUR-denominated catastrophe bonds, independent of ratings, reference perils, and trigger types. If ILS funds exclusively pursue a by-and-hold strategy in a diversified cat bond portfolio, this model should be well-suited to explain their excess returns over time. Formally, the *CAT-CAPM* is defined as:

$$R^e_{p,t} = \alpha + \beta_{p,1} CATMKT_t + \epsilon_t, \tag{1}$$

where $CATMKT_t$ and $R^e_{p,t}$ denote the returns on the cat bond market factor and the ILS fund, respectively, both in excess of the 1-Month T-Bill rate.

In addition, we propose a *ratings model*, which is constructed as follows:

$$R^e_{p,t} = \alpha + \beta_{p,1} CATMKO_t + \beta_{p,2} BBCAT_t + \epsilon_t. \tag{2}$$

with $BBCAT_t$ being the return on an index of BB-rated cat bonds in excess of the 1-Month T-Bill rate and $CATMKO_t$ representing the excess return of the market factor $CATMKT_t$, orthogonalized on $BBCAT_t$. In orthogonalizing the market factor, we follow Fama and French (1993), who suggest this proceeding if the additional factor shares a large degree of variance with the market factor. This is particularly relevant in the case of cat bonds, because the vast majority of them is issued with a BB rating (see, e.g., Braun, 2016). The rotated market factor thus captures the return variation of all outstanding cat bonds that exhibit a non-BB rating.

$BBCAT_t$ can be further unfolded into different fixed income risk drivers. More specifically, $BBCAT_t$ should include a term component (i.e., a treasury index minus the risk free rate), a default risk component (i.e., a BB-rated corporate bond index minus a treasury index), as well as a potential insurance risk component (i.e., a BB-rated catastrophe bond index minus a BB-rated corporate bond index). Formally, this *spread model* can be expressed as:

$$R^e_{p,t} = \alpha + \beta_{p,1}CATMKO1_t + \beta_{p,2}TERM3Y_t + \beta_{p,3}DEFCOR_t \\ + \beta_{p,4}DEFCAT_t + \epsilon_t, \tag{3}$$

where $CATMKO1_t$ is the excess return of the market factor orthogonalized on $TERM3Y_t$, $DEFCOR_t$, and $DEFCAT_t$. The maturity of cat bonds typically ranges between one and three years (see, e.g., Braun, 2016). Accordingly, $TERM3Y_t$ is the return on treasury bonds with a maturity between one and three years in excess of the risk-free rate. $DEFCOR_t$ is the return on corporate bonds with a maturity of one to three years in excess of the return on treasuries with a maturity between one and three years. Finally, $DEFCAT_t$ is the return on cat bonds in excess of the return on corporate bonds with maturity between one and three years. This factor is particularly interesting, since the existence of a return premium above comparably-rated corporate debt has regularly been conjectured among industry practitioners (see, e.g., RMS, 2012). Anecdotal evidence for this notion dates back to the early days of the ILS market when it was termed the novelty or esoteric risk premium (see, e.g., Bantwal and Kunreuther, 2000). More recently, however, empirical research showed that the yield spreads of cat bonds did not exceed those of corporate bonds at all times (see, e.g., Partner Re, 2015; Braun, 2016). This is in line with theoretical reasoning: in the absence of arbitrage, instruments with the same rating and maturity should not offer different returns. Hence, by testing whether the factor $DEFCAT_t$ is priced, it is possible to shed light on the question whether a premium for the esoteric nature of catastrophe risk (still) exists.
Finally, we introduce a three-factor *perils model* of the form

$$R^e_{p,t} = \alpha + \beta_{p,1}CATMKO2_t + \beta_{p,2}USHU_t + \beta_{p,3}USEQ_t + \epsilon_t, \tag{4}$$

where $CATMKO2_t$ is the excess return of the market factor orthogonalized on $USHU_t$ and $USEQ_t$. $USHU_t$ is a single-peril U.S. hurricane bond index in excess of the 1-Month T-Bill rate and $USEQ_t$ is a single-peril U.S. earthquake bond index in excess of the 1-Month T-Bill rate. Orthogonalizing the market factor on these two factors yields a new variable, which captures variation in the market returns that relates to all remaining cat bonds, i.e. U.S. and non-U.S. multi-peril as well as non-U.S. single-peril bonds.[4] This model should be suitable for style analysis, i.e., it can reveal in which specific types of cat bonds an ILS fund invests.

3 Data

3.1 ILS funds

Our first contribution is a comprehensive dataset, which we composed by identifying all live and terminated ILS funds reported on Bloomberg, industry websites, such as the Artemis Deal Directory or www.insurancelinked.com, press releases, and the Morningstar CISDM database. For each fund, we retrieved monthly net-of-fee total return data from Bloomberg. In addition, we collected information about the current assets under management (AuM), expense ratios, front and back loadings, performance fees, top ten holdings, and cash holdings. In case this information was unavailable on Bloomberg, we searched for it through various internet sources. As several funds do not report return data to Bloomberg, we also obtained return data under confidentiality agreements directly from the funds.[5] We controlled for any duplicate funds listed under a different name and, whenever available, used the institutional share class quoted in U.S. Dollars. We were able to identify a total of 55 funds with return data starting in January 2001 and ending in December 2015.

Table 1 shows the funds' characteristics on an aggregate level ("All Funds") as well as separately for the Bloomberg categories "Alternative" and "Fixed Income." ILS funds in the categories "Equity", "Mixed Allocation", "Specialty",

[4]It would certainly be insightful to add a U.S. multi-peril cat bond index to the model. In this case, the cat risk in a fund's portfolio could be identified even more precisely and the orthogonalized market factor would simply capture all non-U.S. perils. Unfortunately, however, data for such an index is not publicly available.

[5]It should be noted that Fermat Capital, which has USD 4.7 bn of AuM and is thus one of the largest dedicated ILS funds in existence, refrained from providing return information. Furthermore, there are no fund of funds in our sample.

as well as those without any classification have been subsumed under "Other".[6] A special category for ILS does not exist. Hence, a fund being classified as "Fixed Income" and being invested in government bonds would be in the same category as an ILS fund being classified as "Fixed Income." Although this is a very broad categorization, it allows for a certain aggregation and enables us to check, whether the categorization has an actual effect on the risk-return profile of the funds. However, as stressed by Fung and Hsieh (1997), what the funds say they do is not necessarily what they actually do. Hence, the true investment style can only be assessed by means of factor models that explain the fund returns. Interestingly, the super-ordinate category by Bloomberg and the CISDM database for several ILS funds is hedge funds. The largest part of ILS funds, however, falls within the super-ordinate category of "open-ended mutual fund". Thus, we decided to use Bloomberg's mutual fund categorization in the following.

In addition, we report fund characteristics for surviving funds and acquired or dissolved funds (i.e., "Live" or "Dead"). Based on the latest reported AuM of surviving funds, the total size of the ILS fund market is USD 21.80 billion, which compares to an outstanding catastrophe-bond market volume of USD 25.96 billion at the end of 2015 as reported by the Artemis Deal Directory. Under the assumption that ILS funds only invest in catastrophe bonds, this would imply that our sample covers approximately 83.98% of the total market volume for catastrophe bonds. Swiss Re (2013) estimated that 61% of the outstanding cat bond volume is held by dedicated funds. Hence, in combination with 22.98% of assets under management in other ILS instruments our sample of funds should convey a relatively complete picture of the market. Table 1 shows that dead funds on average exhibited slightly higher expense ratios and load fees than surviving funds.[7] However, surviving funds charged a higher variable compensation (i.e., a higher performance fee of 7.33 % p.a. for surviving funds compared to 5.45 % p.a. for dead funds) suggesting that they tend to rely on a better performance to earn the bulk of their fees. However, the only

[6] The classification "Equity" could be chosen by a fund because there are not only bonds but also equity shares in certain ILS instruments (e.g., in so-called sidecars), which are accessed first in case of a trigger event.

[7] Note that fees could have decreased over time such that they now appear different for dead than for live funds.

Table 1: Fund characteristics

Category	Time Period	# of Funds	Avg. AuM (USD millions)	Avg. Exp. Ratio (% p.a.)	Avg. Max. Load (Front and Back, % p.a.)	Avg. Performance Fee (% p.a.)	Avg. Fund Age (years)	Avg. Top 10 Holdings (% of AuM)	Avg. Cash holdings (% of AuM)
All Funds	01/2001 - 12/2015	57	428.99	1.69	1.42	6.92	5.45	39.50	13.33
By Fund Category									
Alternative	07/2002 - 12/2015	20	311.29	1.64	0.65	7.65	5.05	38.21	6.75
Fixed Income	06/2001 - 12/2015	15	543.39	1.79	2.53	2.86	5.89	43.60	11.42
Other	01/2001 - 12/2015	22	460.89	1.61	1.41	9.41	5.52	33.93	20.22
By Current Status									
Live Funds	01/2001 - 12/2015	45	506.85	1.69	1.12	7.33	5.97	39.99	11.33
Dead Funds	07/2002 - 10/2013	12	149.98	1.76	2.34	5.45	3.51	33.67	22.23

This table summarizes the characteristics of 57 ILS funds both aggregated ("All funds") and separated by Bloomberg category ("Alternative", "Fixed Income", or "Other") as well as status (i.e., "Live" or "Dead"). We report the time period, the number of funds in each category, the average assets under management (AuM) in U.S. Dollars, the average expense ratio, the average maximum loading based on the sum of back and front loadings if charged, the average performance fee if charged, the average fund age in years, the average top ten holdings as a share of total AuM, and the average cash holdings as a share of total AuM. Note that nine of the funds classified as "Other" did neither exhibit a Bloomberg category nor offer additional information. All figures are based on the latest available date. The overall sample starts in January 2001 and ends in December 2015.

statistically significant difference between live and dead funds can be found in their maximum load fees. On average, an ILS fund is approximately six years old, illustrating that this fast-growing part of the investment industry is still in its early phase.[8] Dead funds, in contrast, tend to discontinue their business after 3 $\frac{1}{2}$ years. Furthermore, surviving funds seem to exhibit a larger concentration on their top ten holdings securities (i.e., 39.99% vs. 33.67%) and hold a lower amount of cash.

3.2 Potential biases in ILS funds data

When working with mutual and hedge fund data, one needs to be aware of several reporting biases, which we cannot fully exclude for ILS funds as well. These include survivorship bias, backfilling bias, self-selection bias, and managed returns (see, e.g., Carhart et al., 2002; Fung and Hsieh, 2000). As Bloomberg does not delete the returns of defunct or acquired returns, survivorship bias in the return statistics is less of an issue for us. Because new (and defunct) funds receive quite some attention within the ILS community, news reports are useful in keeping track of all funds. Given the manageable ILS market size we are convinced to have covered almost the entire universe of live and dead funds. Nevertheless, we cannot rule out the possibility that some minor funds, which failed and never reported their returns to any data provider, are not included in our sample.

Backfilling bias occurs, when funds join a database after an incubation period. Those with a good track record may decide to disclose their past returns, whereas bad performing funds have an incentive to refrain from backfilling information. As a consequence, performance figures may be upward biased. Because we know the vast majority of ILS funds and were able to obtain returns for all of them but one, we are convinced that backfilling bias is not a major issue in our empirical analysis.

Furthermore, self-selection bias might cause an upward bias in our performance analysis. When we identified the funds, we checked various sources to determine whether a major exposure to ILS exists (see Section 3.1). However,

[8] The average age of high yield bond funds between 1991 and 2010 was about 15 years (see Fang et al., 2014).

if a fund never states the intention to invest in ILS, yet does so, it would not be included in our sample. Apart from that, ILS funds in less-regulated domiciles may decide to refrain from disclosing return data to the public. Two aspects mitigate this kind of bias. First, it will only be large if non-reporting funds substantially underperform their reporting counterparts. Second, a fund which does not state to invest in ILS, will find it difficult to attract ILS investors. Thus, self selection bias should be negligible.

Another source of bias are managed returns. Because of a hedge-fund like fee structure and the relative illiquidity of the underlying assets, some ILS funds might be inclined to inflate or smooth their returns (see Getmansky et al., 2004; Agarwal et al., 2011). Yet, many ILS funds pursue a buy-and-hold rather than an active management approach. Comparing the return history of ILS funds and cat bonds, we see that the latter have a higher mean percentage of positive returns (93.23% for cat bonds and 89.29% for ILS funds). In addition, we observe only one large drawdown in the returns after Hurricane Katrina. Finally, we do not find the characteristic December spike generated by hedge fund managers to boost fees (see Agarwal et al., 2011). Accordingly, it is safe to state that managed returns are currently not major concern for ILS funds.

3.3 Factors and indices

The catastrophe bond market factor is the Swiss Re Global Catastrophe Bond Index [Bloomberg ticker: SRGLTRR], which tracks the aggregate performance of all USD and EUR denominated catastrophe bonds capturing all ratings, perils, and triggers. For the *perils model*, we also include the Swiss Re U.S. Wind Catastrophe Bond Index [Bloomberg ticker: SRUSWTRR], tracking the total return on all single-peril U.S. wind catastrophe bonds and the Aon Benfield Securities U.S. Earthquake Catastrophe Bond Index [Bloomberg ticker: AONCUSEQ], tracking the total return on all single-peril U.S. earthquake catastrophe bonds. For the *ratings model*, we use the Swiss Re BB-rated Catastrophe Bond Index [Bloomberg ticker: SRBBTRR], which tracks the total return on all outstanding cat bonds with a BB rating by S&P or Fitch (or the Moody's equivalent Ba). As described above, for the *spread model*, we further unfold the BB cat bond index into three separate components. First, for TERM3Y, we calculate the difference between Barclays 1-3 years U.S. Treasury Total Return Index [Datastream mnemonic: LHG13US] and the 1-Month T-Bill rate. Second, DEFCOR is calculated as the difference between Barclays 1-3 years U.S. High Yield (Moody's BA) Total Return Index [Datastream mnemonic: LHHY13B] and the Barclays 1-3 years U.S. Treasury Total Return Index. Third, DEFCAT is the difference between the Swiss Re BB-rated Catastrophe Bond Index [Bloomberg ticker: SRBBTRR] and the Barclays 1-3 years U.S. High Yield (Moody's BA) Total Return Index. Table 2 summarizes the statistical properties of the factors for the time period between January 2002 and December 2015.

The average monthly return of DEFCAT (0.05) is not significantly different from zero. Therefore, an additional return premium for the nontraditional nature of the insurance risk does not seem to be present. Nevertheless, DEFCAT exhibits certain peaks over time, implying that it may have been priced in the past. All other factors exhibit statistically significant positive means. Comparing TERM3Y and DEFCOR, we notice that the default risk premium (0.30) is three times as large as the term premium (0.10). The *ratings model* summarizes all three elements (TERM3Y, DEFCOR, and DEFCAT) in the average monthly return of BBCAT (0.45). The remaining contribution in the *spread model* equals 0.18 and comes from CATMKO1, which captures general market volatility as well as any other risk drivers. Turning to the *perils model*, we notice that both U.S. hurricane and U.S. earthquake exposures are associated with much higher risk premiums than other perils (CATMKO2). This is consistent with earlier empirical evidence for an excess spread on transactions that cover so-called peak territories such as the U.S., which are abundant in the cat bond market (see, e.g., Braun, 2016).[9] Table 3 shows the correlation for the new factors and highlights the need to orthogonalize the catastrophe bond market factor (CATMKT) not only for interpretative reasons but also for statistical reasons due to the relatively high correlations between CATMKT, USHU, and BBCAT. It also shows that multicollinearity is not an issue for the suggested factor model specifications.

[9] Transactions for nonpeak territories, in contrast, are a relatively rare and sought-after means for the diversification of ILS portfolios. Accordingly, they pay significantly lower spreads (see, e.g., Braun, 2016).

Table 2: New factors

	Avg. Return (% per month)	Volatility (per month)	t-stat.	Median	Min.	Max.	Skewness	Kurtosis	Obs.
CATMKT	0.54	0.75	7.11***	0.50	–3.57	2.73	–1.32	10.08	168
BBCAT	0.45	0.88	4.93***	0.42	–4.90	2.99	–2.37	15.61	168
CATMKO1	0.18	0.21	8.81***	0.14	–0.65	0.96	0.26	5.55	168
TERM3Y	0.10	0.39	2.81***	0.08	–1.09	1.53	0.40	5.04	168
DEFCOR	0.30	1.84	1.71*	0.45	–11.31	7.59	–2.27	19.13	168
DEFCAT	0.05	1.73	0.30	0.09	–6.98	11.16	1.21	15.67	168
CATMKO2	0.17	0.48	2.88***	0.17	–3.52	1.14	–3.97	27.04	168
USHU	0.63	0.94	6.66***	0.39	–2.17	4.45	0.86	5.90	168
USEQ	0.40	0.56	7.81***	0.40	–5.83	1.46	–8.18	91.58	168

This table summarizes the new factors used for the ILS fund market. All factors are excess returns. The table reports monthly average return, volatility based on monthly returns, the median, the minimum, the maximum, the skewness, and the kurtosis of the excess return of the factors. The table also reports t-statistics of factors being significantly different from zero using Newey and West (1987) robust standard errors with lags of four. The last column reports the number of time-series observations. The factors start in January 2002 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) CATMKT	1.00								
(2) BBCAT	0.96	1.00							
(3) CATMKO1	0.28	0.00	1.00						
(4) TERM3Y	0.04	0.08	0.00	1.00					
(5) DEFCOR	0.23	0.19	0.00	–0.44	1.00				
(6) DEFCAT	0.24	0.29	0.00	0.28	–0.86	1.00			
(7) CATMKO2	0.64	0.65	0.09	0.08	0.08	0.22	1.00		
(8) USHU	0.76	0.69	0.32	0.00	0.19	0.15	0.00	1.00	
(9) USEQ	0.38	0.39	–0.01	–0.05	0.28	–0.09	0.00	0.34	1.00

This table shows the correlation of the new factors for ILS funds. All factors are excess returns. The time period of the data is from January 2002 to December 2015.

The Fama and French (1993) factors SMB, HML, and the Carhart (1997) momentum factor (MOM) have been downloaded from Kenneth French's data library. The excess market index MKTRF is the total return of the MSCI WORLD minus the risk free rate. Furthermore, we obtained the hedge fund factors PTFSBD, PTFSFX, and PTFSCOM from the website of David Hsieh. *Convertible* is the total return of Merrill Lynch's All Convertible Index [Datastream mnemonic: MLCVXA0]. The Fama and French (1993) TERM and DEF factors are calculated as the difference between the total return of the Barclays U.S. Long-Term Government Bond Index [Datastream mnemonic: LHGOVLG] and the risk-free rate as well as the difference between the total return of the Barclays U.S. Long-Term Corporate Bond Index [Datastream mnemonic: LHCCRLG] and the Long-Term Government Bond Index, respectively. *Municipal* is the total return of the Barclays Municipal Bond Index [Datastream mnemonic: LHMUNIC] minus the risk-free rate. *Mortgage* is the total return of the Barclays U.S. Mortgage-Backed Securities Index [Datastream mnemonic: LHMNBCK] minus the risk-free rate. *Treasury* is the total return of the Barclays U.S. Treasuries Index [Datastream mnemonic: LHUSTRY] minus the risk-free rate. *HYield* is the total return of the Barclays Global High Yield Index [Datastream mnemonic: LHMGHYD] minus the risk-free rate. *Corporate* is the total return of the Barclays U.S. Corporate Bond Index [Datastream mnemonic: LHCCORP] minus the risk-free rate. *Real estate* is the total return of the S&P Case/Shiller Composite-20 Home Price Index [Bloomberg ticker:

SPCS20 Index] minus the risk-free rate. *Hedge fund* is the total return of the HFRI Fund Weighted Composite Index [Bloomberg ticker: HFRIFWI Index] minus the risk-free rate. *Commodity* is the return of the S&P Goldman Sachs Commodities Index [Bloomberg ticker: SPGSCITR Index] minus the risk-free rate.

4 Empirical results

In a first step, we present the risk and return characteristics of the ILS funds in our sample and compare them to hedge funds and corporate bonds. Subsequently, we run time-series regressions to estimate the traditional factor pricing models and the new ILS models. Finally, we address the ability of the new approaches to explain the cross section of ILS fund returns.

4.1 Performance attribution of ILS funds

To measure the performance of ILS funds on an aggregate level, we construct equally weighted indices for all funds, live and dead funds, as well as for each Bloomberg category. Table 4, which summarizes the return characteristics of these indices, also includes the corresponding figures for a hedge fund and a corporate bond benchmark. Note that to obtain a more comprehensive picture of the risk-return characteristics, it is common to consider the maximum available time period for each fund (see, e.g., Chen et al., 2010). Over the last 15 years, ILS funds have earned an average annual return of 5.64% and exhibited a p.a. volatility of 2.26%. The lowest return (–3.46%) occurred in the aftermath of the Tohoku earthquake off the coast of Japan in March 2011. In addition, we observe a slightly lower return earned by dead ILS funds as well as by those Bloomberg categories that are perceived as less risky, such as "Fixed Income." The return difference between live and dead funds is significant at the 10%-level. The corporate bond index yielded an average annual return of 7.51% p.a., but its volatility of 8.20% p.a. was more than three times as high as for ILS funds. It also exhibits a considerably more negative minimum return of –15.13%. Finally, hedge funds, as which some ILS funds are classified, achieved a similar average annual return of 5.41%. However, they did so at the expense of a much higher volatility (5.98%) and a more negative minimum return (–6.84%).

Table 5 displays additional risk characteristics of the equally-weighted ILS fund indices as well as the hedge fund and corporate bond benchmarks. We show these measures because ILS and particularly cat bonds may exhibit rare but very severe negative returns. Hence, the classical volatility is less suited for this asset class. Examining the semi-standard deviation (1.49%) and the 99.5 percent value-at-risk (1.05%), however, we again observe a much lower result compared to corporate bonds or hedge funds. Even the maximum drawdown from peak to trough merely amounts to 6.98%. Consequently, common financial performance measures such as the Sharpe Ratio, the Sortino Ratio, the Excess Return on VaR, and the Calmar Ratio, look much more favorable for ILS funds than for other asset classes. Clearly, these results raise suspicion. The reason for such an odd risk profile is an empirical rather than a theoretical one. Cat bonds securitize extreme-event insurance risk, i.e., natural disasters with reccurrence periods of 100, 200, 500 or even 1000 years (see, e.g., Smolka, 2006). Against this background, even a performance history of 15 years, which covers the entire period during which the ILS market existed, is very short. In fact, the substantial drawdowns that are to be expected following a real mega event are much larger than anything that has been observed to date. This is a crucial aspect when analyzing the performance of ILS and a major reason for the fact that many industry professionals construct their portfolios based on forward-looking risk analyses by specialized modelling firms such as RMS, AIR, and EQECAT. Hence, historical performance figures as shown in this section should generally be interpreted with utmost caution.

4.2 Time-series regressions

Traditional factor models

Table 6 shows the coefficients for four asset class factor models in the sense of Sharpe (1992). To account for the high correlation between the different fixed income indices, we ran a full model as well as three variations with different factor combinations. The dependent variable is the aggregated ILS fund index in excess of the one-month T-Bill rate. All factors are excess returns as well.

Table 4: Return characteristics

Classification	Time Period	Obs.	Avg. Return (% p.a.)	Median (% p.a.)	Min. (% monthly return)	Max. (% monthly return)	Volatility (p.a.)	Skewness	Kurtosis
All funds	01/2001 - 12/2015	180	5.64	6.40	-3.46	2.12	2.26	-2.61	14.97
By Fund Category									
Alternative	07/2002 - 12/2015	162	5.97	6.37	-4.07	1.89	2.42	-2.41	15.47
Fixed Income	06/2001 - 12/2015	175	4.52	4.63	-4.28	1.54	1.95	-3.98	30.66
Other	01/2001 - 12/2015	180	6.08	7.12	-5.30	2.86	3.29	-2.95	17.34
By Current Status									
Live Funds	01/2001 - 12/2015	180	5.83	6.51	-3.53	2.23	2.45	-2.75	15.20
Dead Funds	07/2002 - 10/2013	136	4.89	5.76	-2.99	1.86	2.23	-2.01	10.29
Comparison Indices									
ILS Fund Index	01/2006 - 12/2015	120	6.31	6.60	-3.94	1.60	2.07	-3.51	27.44
Hedge Fund Index	01/2001 - 12/2015	180	5.41	7.71	-6.84	5.15	5.98	-0.83	4.95
Corporate Bond Index	01/2001 - 12/2015	180	7.51	11.32	-15.13	7.59	8.20	-1.90	14.64

This table summarizes the return characteristics of 57 ILS funds both aggregated ("All funds") and separated by Bloomberg category ("Alternative", "Fixed Income", or "Other") as well as status (i.e., "Live" or "Dead"). We report the time period, the number of time-series observations, the annualized average return, annualized median return, the monthly minimum return, the monthly maximum return, the annualized volatility, the skewness, and the kurtosis. The table also shows benchmark indices for corporate bonds (Merrill Lynch BB corporate bond performance index) and hedge funds (HFRI Fund Weighted Composite Index) as a basis for comparisons. In addition, we included the EurekaHedge ILS Advisers Index, which was available for the time period January 2006 until December 2015. The overall sample starts in January 2001 and ends in December 2015.

Table 5: Risk characteristics

Classification	Time Period	Downside-Volatility (p.a.)	VaR (% per month)	Max. Draw-down (in %)	Sharpe Ratio (p.a.)	Sortino Ratio (p.a.)	Excess return on VaR	Calmar Ratio (p.a.)	% of positive months
All funds	01/2001 - 12/2015	1.49	1.05	6.98	1.86	2.81	0.33	0.60	88.89
By Fund Category									
Alternative	07/2002 - 12/2015	1.51	1.13	4.07	1.94	3.12	0.35	1.16	88.89
Fixed Income	06/2001 - 12/2015	1.39	0.93	4.28	1.63	2.28	0.28	0.74	92.00
Other	01/2001 - 12/2015	2.40	1.71	15.28	1.41	1.93	0.23	0.30	92.22
By Current Status									
Live Funds	01/2001 - 12/2015	1.67	1.17	8.79	1.79	2.62	0.31	0.50	90.56
Dead Funds	07/2002 - 10/2013	1.42	1.09	2.99	1.52	2.39	0.26	1.13	84.56
Comparison Indices									
ILS Fund Index	01/2006 - 12/2015	1.32	0.87	3.94	2.51	3.95	0.50	1.32	93.33
Hedge Fund Index	01/2001 - 12/2015	3.88	3.57	21.42	0.66	1.02	0.09	0.19	65.56
Corporate Bond Index	01/2001 - 12/2015	5.78	4.89	25.13	0.74	1.05	0.10	0.24	71.11

This table summarizes risk and performance characteristics of 57 ILS funds both aggregated ("All funds") and separated by Bloomberg category ("Alternative", "Fixed Income", or "Other") as well as status (i.e., "Live" or "Dead"). We report the time period, the annualized semi-standard deviation, the 99.5 percent value-at-risk (VaR) of the monthly series, the maximum drawdown, the annualized Sharpe ratio, the annualized Sortino ratio, the Excess Return on Value-at-Risk, the annualized Calmar ratio, and the percentage of positive monthly returns over the sample period. The table also shows benchmark indices for corporate bonds (Merrill Lynch BB corporate bond performance index) and hedge funds (HFRI Fund Weighted Composite Index) as a basis for comparisons. In addition, we included the EurekaHedge ILS Advisers Index, which was available for the time period January 2006 until December 2015. The overall sample starts in January 2001 and ends in December 2015.

Our first observation is the extremely low adjusted R-squared of not more than 2%. Furthermore, we notice alpha of at least 0.30% per month. The full model does not result in any significant coefficients, whereas the three variations show some weak exposure towards the equity market (MKTRF), hedge funds, and convertible bonds. Table 7 shows the results for the traditional risk factor models of Fama and French (1993), Blake et al. (1993), Carhart (1997), and Fung and Hsieh (1997). Once more, we find some mostly weak statistical significances, although the adjusted R-squared does not exceed 3% and alpha remains at the same level as in the case of the asset class models in Table 6.

Table 6: Asset class factor models

	(1)	(2)	(3)	(4)
MSCI	-0.01	0.01		
	(0.01)	(0.01)		
TREASURY	-0.01	-0.00		0.03
	(0.05)	(0.03)		(0.04)
MUNICIPAL	0.04	0.06		0.05
	(0.03)	(0.04)		(0.03)
CORPORATE	-0.00	0.04	0.03	0.01
	(0.04)	(0.04)	(0.03)	(0.04)
MORTGAGE	0.11		0.09	
	(0.10)		(0.07)	
CONVERTIBLE	0.04			0.03**
	(0.03)			(0.02)
REAL ESTATE	0.01	-0.00	0.01	0.00
	(0.05)	(0.05)	(0.05)	(0.05)
HEDGE FUND	0.02		0.06*	
	(0.06)		(0.03)	
COMMODITY	-0.00	-0.00	-0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Constant (alpha)	0.30***	0.32***	0.30***	0.32***
	(0.08)	(0.08)	(0.08)	(0.08)
Adj. R^2	0.01	0.02	0.02	0.02
Obs.	168	168	168	168

This table shows the coefficients of asset class factors on the excess return of the ILS fund index over the one-month T-Bill rate. The asset class factors are all monthly excess returns. Standard errors in parentheses are Newey-West (1987) corrected with lags of four. The analysis starts in January 2002 and ends in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Risk factor models

	(1)	(2)	(3)	(4)
MKTRF	0.01		0.02*	0.01
	(0.01)		(0.01)	(0.01)
SMB	-0.00		-0.00	0.00
	(0.02)		(0.02)	(0.02)
HML	0.01		0.01	
	(0.02)		(0.02)	
TERM	0.03*	-0.00		0.03*
	(0.02)	(0.02)		(0.02)
DEF	0.03**			0.03*
	(0.02)			(0.02)
HYIELD		0.04***		
		(0.01)		
MORTGAGE		0.12		
		(0.10)		
MOM			-0.01	
			(0.01)	
PTFSBD				0.00
				(0.00)
PTFSFX				-0.00
				(0.00)
PTFSCOM				0.00
				(0.00)
Constant (alpha)	0.34***	0.31***	0.35***	0.34***
	(0.08)	(0.08)	(0.07)	(0.07)
Adj. R^2	0.01	0.03	0.00	0.00
Obs.	168	168	168	168

This table shows the coefficients of risk factors from established factor models on the excess return of the ILS fund index over the one-month T-Bill rate. The risk factors are all monthly excess returns. Standard errors in parentheses are Newey-West (1987) corrected with lags of four. The analysis starts in January 2002 and ends in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

To control for statistical artifacts, we test the significant factors from Tables 6 and 7 in combination with the cat bond market factor CATMKT. The results of this analysis are shown in Table 8. Now the adjusted R-squared jumps to 67% and, apart from CATMKT, the coefficients of all independent variables, including the constant (alpha), become insignificant. We may thus conclude that traditional factor models are not suited to explain the time series of ILS fund returns.[10]

Table 8: Control regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CATMKT	0.69***	0.70***	0.70***	0.70***	0.70***	0.71***	0.71***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
MKTRF		-0.00					
		(0.01)					
TERM			-0.00				
			(0.01)				
DEF				-0.01			
				(0.01)			
HYIELD					-0.01		
					(0.01)		
CONVERTIBLE						-0.01	
						(0.01)	
Hedge Fund							-0.02
							(0.02)
Constant (alpha)	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Adj. R^2	0.67	0.67	0.67	0.67	0.67	0.67	0.67
Obs.	168	168	168	168	168	168	168

This table shows the coefficients of asset class factors and risk factors from established factor models on the excess return of the ILS fund index over the one-month T-Bill rate. The asset class factors and risk factors are all monthly excess returns. Standard errors in parentheses are Newey-West (1987) corrected with lags of four. The analysis starts in January 2002 and ends in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

New ILS-specific factor models

Having demonstrated the failure of the traditional approaches, we now test our new ILS-specific factor models. Column (1) in Table 9 shows the *CAT-CAPM*. We observe a highly significant coefficient for CATMKT (market beta), an insignificant intercept, and an adjusted R-squared of 0.67. One reason for

[10] We again address the issue of a potential exposure towards other asset classes on an individual fund basis in Section 4.4.

the market beta of 0.69 is that the diversified basket of cat bonds held by the funds in our equally-weighted index may differ from the market portfolio. In addition, the funds may also invest in ILS other than cat bonds, such as collateralized reinsurance, industry loss warranties (ILWs), or extreme-mortality securitizations.[11] Column (2) contains the results for the *spread model*. We find significant coefficients for all four factors, paired with an insignificant intercept and an R-squared of 0.69. Particularly TERM3Y, DEFCOR, and DEFCAT seem to have a impact on the time series. Therefore, ILS fund returns seem to be mainly driven by the variation of fixed-income risk premiums. Moreover, the results for the *perils model* are displayed in Column (3). This model is associated with an adjusted R-squared of 69%. The high coefficient for CATMKO2 indicates that multi-peril cat bonds explain the lion's share of the return time series, whereas single-peril U.S. hurricane and particularly earthquake bonds are associated with weaker effects. This is in line with Braun (2016), who finds that the majority of historical primary market issuances were multi-peril cat bonds. Finally, it should be noted that a combination of the *perils model* and the *spread model* does not improve the fit to the time series, since their respective factors are largely buried in CATMKT and thus simply provide a different breakdown of the same variance.

The residuals of the aforementioned regressions in Figure 2 reveal an interesting fact. Overall, the models capture the time-series variation quite well. The only exception is the August 2005 return, which was heavily influenced by Hurricane Katrina. For some reason, neither the single-peril U.S. hurricane factor (USHU) nor the orthogonalized cat bond market (CATMKO2) seem to capture this effect. Hence, we need to take a closer look at the underlying data. According to information from AON Benfield, a total of 67 transactions were outstanding in August 2005. One of them, the indemnity-triggerd multi-peril bond KAMP Re covering U.S. hurricanes and earthquakes, was the first cat bond that ever defaulted due to a natural disaster (see Artemis Deal Directory). KAMP Re generated a return of –5% in August 2005. Due to its multi-peril status, however, this was not reflected by USHU. Similarly, the overall market index did

[11] On the individual fund level (see next section) we will observe many funds with *CAT-CAPM* betas equal to one, suggesting that their portfolio composition closely resembles the cat bond market portfolio.

not react, because the bond's portfolio weight amounted to no more than 13%. Nevertheless, we observe a clear reaction of our ILS fund index. This is due to the fact that the latter comprises merely 14 constituents in August 2005, five of which exhibit a negative return of at least 3.8%. Evidently, these funds must have exhibited a much higher exposure to KAMP Re than the market portfolio.[12]

Table 9: New ILS-specific factor models

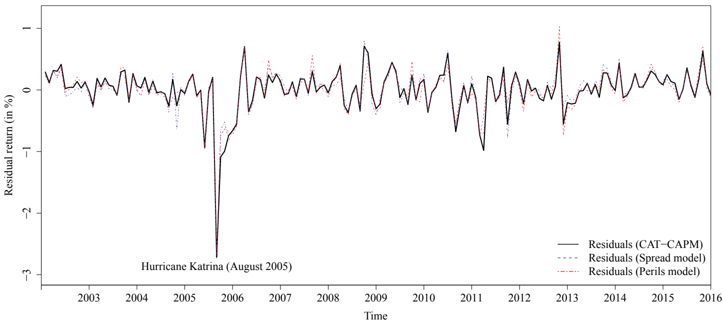
	(1)	(2)	(3)	(4)	(5)	(6)
CATMKT	0.69***			0.68***		
	(0.09)			(0.09)		
CATMKO1		0.28*			0.27	
		(0.15)			(0.16)	
TERM3Y		0.64***			0.66***	
		(0.07)			(0.08)	
DEFCOR		0.59***			0.58***	
		(0.07)			(0.06)	
DEFCAT		0.59***			0.58***	
		(0.07)			(0.06)	
CATMKO2			0.87***			0.85***
			(0.13)			(0.12)
USHU			0.33***			0.33***
			(0.03)			(0.03)
USEQ			0.07**			0.07**
			(0.03)			(0.03)
KATRINA				-2.74***	-2.76***	-2.70***
				(0.06)	(0.05)	(0.06)
Constant (alpha)	-0.02	0.04	0.02	0.01	0.06	0.04
	(0.08)	(0.05)	(0.05)	(0.07)	(0.04)	(0.04)
Adj. R^2	0.67	0.69	0.69	0.78	0.80	0.80
Obs.	168	168	168	168	168	168

This table shows the coefficients of the new risk factors on the excess return of the ILS fund index over the one-month T-Bill rate. The asset class factors and risk factors are all monthly excess returns. Standard errors in parentheses are Newey and West (1987) corrected with lags of four. The analysis starts in January 2002 and ends in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[12] According to AON Benfield, KAMP Re suffered from an extreme negative return (-78%) in September 2005. Despite its low weight in the market portfolio, this effect is large enough to be captured by CATMKT, CATMKO1, and CATMKO2. Consequently, the corresponding residual in Figure 2 is much smaller.

To account for this issue, we augment the three models by the dummy variable *Katrina*, which equals one in August 2005 and zero otherwise. In doing so, we are able to increase the adjusted R-squareds for the time series by more than 10 percentage points. The coefficient for *Katrina* is highly significant and implies an extraordinary negative return of approximately 2.7% in August 2005.

Figure 2: Residuals



This figure illustrates residuals of *CAT-CAPM*, the *spread model*, and the *perils model* on the excess return of the ILS fund index over the one-month T-Bill rate. The downward spike in the residuals occurs in August 2005. The analysis starts in January 2002 and ends in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels,

4.3 The cross section of expected excess returns

We now draw on our new factor models to explain differences in the cross section of expected excess returns generated by ILS funds. Before addressing each fund individually, we examine the Bloomberg categories using the (augmented) *perils model* as a benchmark. Table 10 shows the respective results. We estimate a negative and significant abnormal return (alpha) for the "Fixed Income" ILS funds, implying that the constituents of this category have underperformed the benchmark during the time period under consideration. In contrast to that, insignificant alphas can be documented for the categories "Alternative" and "Other." The category "Other" additionally exhibits a lower adjusted R-squared. This hints at the possibility that funds in this category might also invest in other asset classes apart from ILS. To test this hypothesis, one would need to run a style analysis on the individual funds, using the full asset class factor model shown in Table 6. Another explanation could be holdings in non-cat-bond ILS such as extreme mortality bonds, which cannot be captured by our risk factors and for which there are no return indices. In contrast to that, the significantly negative alphas for defunct funds reported in the last column of Table 10 suggest underperformance to be the main reason due to which they dropped out of the market.

Next, we turn to the fund level. In the following, the dummy variable *Katrina* will no longer be included in the models, since it merely captures a single outlier in the time series and is therefore irrelevant for the cross section of expected excess returns. We follow Fung and Hsieh (2004) as well as Chen et al. (2010) and only include funds that have at least 24 months of consecutive return data. As a consequence, our sample reduces from 57 to 50 funds.[13]

Table 11 contains the percentage of positive significant (+), negative significant (–), and insignificant (0) alphas estimated by the *CAT-CAPM*. The model is not able to explain the positive abnormal returns of 30.00% of the ILS funds in the sample. At the same time, only 6.00% of all ILS funds underperformed the *CAT-CAPM* benchmark. The corresponding figures for the *spread model* are shown in Table 12. Surprisingly, it results in a higher percentage of significantly positive alphas (34.00%) and a lower fraction of negative alphas (2.00%) than the *CAT-CAPM*. Despite its better fit to the time series, it is thus a much less challenging benchmark for ILS funds.

[13] Using funds with at least 36 months of consecutive return data would substantially reduce our sample to 38 funds but the key findings remain unchanged. In contrast, using funds with at least 12 months of consecutive return data increases the number of funds to 56 at the cost of estimation precision, yet, the cross-sectional findings are almost identical.

Table 10: Subindices

	(1)	(2)	(3)	(4)	(5)	(6)
		Fund category			Current status	
	All Funds	Alternative	Fixed Income	Other	Live	Dead
CATMKO2	0.85***	0.90***	0.73***	0.91***	0.91***	0.71***
	(0.12)	(0.11)	(0.17)	(0.32)	(0.15)	(0.07)
USHU	0.33***	0.31***	0.28***	0.39***	0.33***	0.29***
	(0.03)	(0.03)	(0.02)	(0.06)	(0.03)	(0.03)
USEQ	0.07**	0.19***	0.26***	-0.23***	0.02	0.21***
	(0.03)	(0.03)	(0.02)	(0.06)	(0.04)	(0.03)
KATRINA	-2.70***	-1.18***	-0.96***	-5.64***	-3.42***	-1.38***
	(0.06)	(0.05)	(0.07)	(0.15)	(0.07)	(0.04)
Constant (alpha)	0.04	0.03	-0.09**	0.17	0.08	-0.07**
	(0.04)	(0.04)	(0.05)	(0.11)	(0.05)	(0.04)
Adj. R^2	0.80	0.67	0.80	0.56	0.77	0.68
Obs.	168	162	168	168	168	136

This table shows the coefficients of the *perils model* augmented by the hurricane dummy variable. The dependent variable in column (1) is the excess return of the ILS fund index over the one-month T-Bill rate. The dependent variables in column (2) - (4) are excess returns of ILS funds distinguished by their respective fund category. The dependent variables in column (5) and (6) are excess returns for ILS funds distinguished by their current status (i.e, dead or live). The time period for the different excess return indices ranges between January 2002 and December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Time series regressions of individual funds on *CAT-CAPM*

	(1)	(2)	(3)	(4)	(5)	(6)
		Fund category			Current status	
	All Funds	Alternative	Fixed Income	Other	Live	Dead
Alpha distr.						
+	30.00%	35.29%	7.69%	40.00%	37.50%	0.00%
0	64.00%	58.82%	76.92%	60.00%	56.50%	90.00%
−	6.00%	5.88%	15.38%	0.00%	5.00%	10.00%
No. of funds	50	17	13	20	40	10

This table shows the distribution of alphas (i.e., the constant) coefficients of the *CAT-CAPM* on excess returns of individual ILS funds. To be included in the individual fund regression a fund must have at least 24 months of consecutive return data. Alphas are considered significantly positive (+) or negative (−) if they are significant at the 10%-level. Alphas are considered insignificant (0) if they are significant above the 10%-level. The number of funds in each category is reported in the last row of the table. The time period for each individual fund ranges between January 2002 and December 2015.

Table 12: Time series regressions of individual funds on *spread model*

	(1)	(2)	(3)	(4)	(5)	(6)
		Fund category			Current status	
	All Funds	Alternative	Fixed Income	Other	Live	Dead
Alpha distr.						
+	34.00%	29.41%	7.69%	55.00%	40.00%	10.00%
0	64.00%	70.59%	84.62%	45.00%	57.50%	90.00%
−	2.00%	0.00%	7.69%	0.00%	2.50%	0.00%
No. of funds	50	17	13	20	40	10

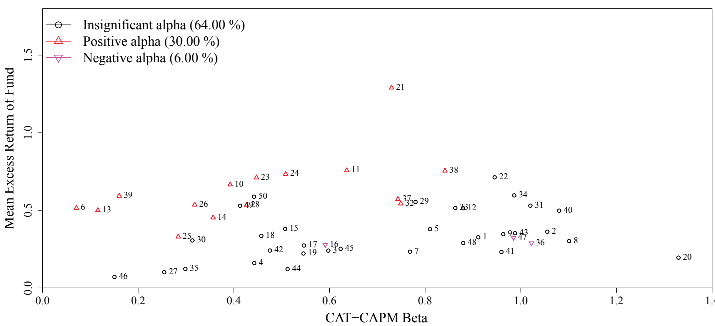
This table shows the distribution of alphas (i.e., the constant) coefficients of the *spread model* on excess returns of individual ILS funds. To be included in the individual fund regression a fund must have at least 24 months of consecutive return data. Alphas are considered significantly positive (+) or negative (−) if they are significant at the 10%-level. Alphas are considered insignificant (0) if they are significant above the 10%-level. The number of funds in each category is reported in the last row of the table. The time period for each individual fund ranges between January 2002 and December 2015.

Table 13: Time series regressions of individual funds on *perils model*

	(1)	(2)	(3)	(4)	(5)	(6)
		Fund category			Current status	
	All Funds	Alternative	Fixed Income	Other	Live	Dead
Alpha distr.						
+	28.00%	29.41%	7.69%	25.00%	35.00%	0.00%
0	46.00%	41.18%	30.77%	75.00%	45.00%	50.00%
−	26.00%	29.41%	61.54%	0.00%	20.00%	50.00%
No. of funds	50	17	13	20	40	10

This table shows the distribution of alphas (i.e., the constant) coefficients of the *perils model* on excess returns of individual ILS funds. To be included in the individual fund regression a fund must have at least 24 months of consecutive return data. Alphas are considered significantly positive (+) or negative (−) if they are significant at the 10%-level. Alphas are considered insignificant (0) if they are significant above the 10%-level. The number of funds in each category is reported in the last row of the table. The time period for each individual fund ranges between January 2002 and December 2015.

Figure 3: CAT-CAPM beta representation



This figure illustrates the actual mean excess returns of 50 ILS funds against their beta estimated by the *CAT-CAPM*. Black circles indicate insignificant alpha values. Red upward pointing triangles indicate significant positive alphas at the 10%-level. Magenta downward pointing triangles indicate significant negative alphas at the 10%-level. The percentage of insignificant, significantly positive, and significantly negative alphas are documented in the legend.

Finally, we focus on the results for the *perils model* as reported in Table 13. Now, the number of funds with significantly negative intercepts rises substantially to 26.00%, implying that a lot more of the managers than suggested by

Tables 11 and 12 were in fact unable to earn back their fees. Another 46.00% of the funds exhibit an insignificant alpha. Hence, the *perils model* seems to be the most strict benchmark of the three. Nevertheless, it still leaves the positive expected excess returns of 28.00% of the ILS funds unexplained. This raises the question whether approximately one quarter of all funds were indeed able to outperform the market for cat bonds or whether their alphas stem from other (traditional or exotic) risk exposures that are not captured by our ILS-specific factor models. We will further deal with this question in the next section.

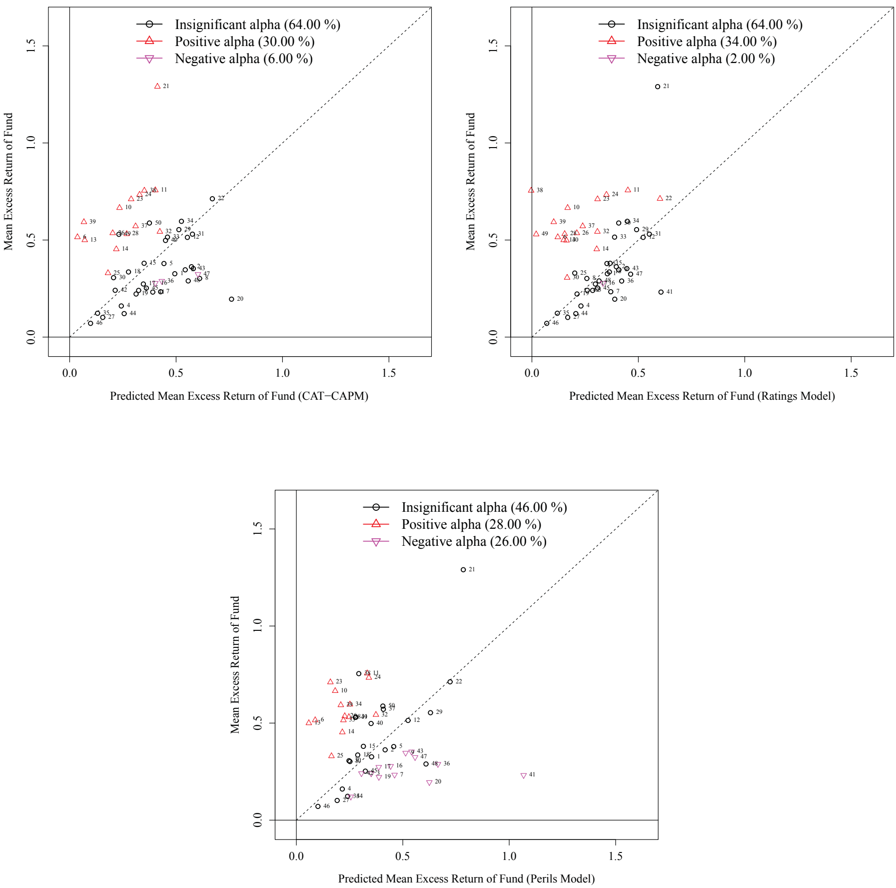
For the time being, however, we continue with a visual inspection of the cross-sectional results. In Figure 3, we have plotted the actual mean excess returns of the ILS funds against their cat bond market betas estimated by means of the *CAT-CAPM*. This graph tells us that if ILS funds only invest in a diversified basket of cat bonds, their returns should increase with beta, that is, there should be a linear relationship between fund beta and return.[14] Most of the funds have a beta between 0.10 and 1.00 meaning that ca. 10% to 100% of their assets are invested in cat bonds. Six funds, however, have a beta larger than 1.00 meaning that there are funds who use leverage to increase their exposure towards cat bonds or overweigh lower, i.e. riskier, cat bond layers relative to the market portfolio. Interestingly though, their returns are not larger than those of their peers with lower betas. Moreover, all funds with significantly positive alphas (based on the *CAT-CAPM*) have a beta exposure below 0.85. Again, this is an indication for manager skill, luck, or additional holdings of non-cat-bond ILS or other asset classes.

Figure 4 illustrates the cross-sectional results by plotting the actual mean excess returns against the mean excess return predicted by each of the three ILS-specific factor models. In the absence of significant abnormal excess returns, all funds should concentrate along the dotted 45-degree line. Yet, both for the *CAT-CAPM* and the *spread model*, several funds that lie substantially below the 45-degree line exhibit insignificant alphas. Only the *perils model* seems to be sufficiently well-suited to identify both significantly positive or negative

[14] The fact that not all funds in our sample operate(d) during the same time period can impair the linear relationship.

alphas of ILS funds. Overall, we conclude that about one quarter of all ILS funds exhibits expected excess returns that cannot be explained by any of the three factor models.

Figure 4: Predicting the cross-section of ILS funds



This figure illustrates the actual mean excess returns of 50 ILS funds and their predicted mean excess returns by the *CAT-CAPM* (upper left), the *spread model* (upper right), and the *perils model* (bottom), respectively. Black circles indicate insignificant alpha values. Red upward pointing triangles indicate significant positive alphas at the 10%-level. Magenta downward pointing triangles indicate significant negative alphas at the 10%-level. The legend on top of each graph highlights the percentage of insignificant, significantly positive, and significantly negative alphas predicted by the respective model.

4.4 Alpha explanations

In this section, we want to further investigate whether the 28% of ILS funds that outperformed our *perils model* are in fact skilled fund managers. If a handful of funds invest in traditional asset classes, we would measure an outperformance, since the *perils model* does not control for such an exposure. In Tables 6 and 7, we found some weak exposure to the equity market and bond markets. Thus, we integrate the high yield bond index $HYIELD_t$ into the *perils model*. Because the latter exhibits a relatively high correlation to stock markets, we orthogonalize $MKTRF_t$ on $HYIELD_t$ and label the resulting rotated equity market factor as RMO_t. The augmented *perils model* is then defined as:

$$\begin{aligned} R^e_{p,t} = \alpha \ &+ \beta_{p,1} CATMKO2_t + \beta_{p,2} USHU_t + \beta_{p,3} USEQ_t + \beta_{p,4} RMO_t \\ &+ \beta_{p,5} HYIELD_t + \epsilon_t, \end{aligned} \tag{5}$$

As shown in Table 14, the positive abnormal returns for 13 of the 14 funds identified in the previous section remain statistically significant. Consequently, beta exposures to traditional asset classes are not the source of alpha that the *perils model* revealed in ILS funds.

Table 14: Perils model, equities, corporate bonds and ILS funds with positive alpha

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	0.46***	0.40**	0.44**	0.43***	0.25***	0.52***	0.37***
	(0.07)	(0.16)	(0.20)	(0.08)	(0.05)	(0.09)	(0.05)
Adj. R^2	0.34	0.34	0.00	0.04	0.44	0.40	0.66
# of obs.	121	115	94	92	91	55	55

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Alpha	0.15**	0.30***	0.26***	0.10	0.38***	0.34**	0.41***
	(0.06)	(0.03)	(0.05)	(0.09)	(0.13)	(0.14)	(0.10)
Adj. R^2	0.24	0.63	0.66	0.71	0.83	0.77	0.07
# of obs.	54	52	48	36	34	34	24

This table shows the intercept (i.e., alpha) of 14 funds from running time-series regressions of excess fund returns against the augmented *perils model* in equation (5). The 14 funds were identified based on having positive abnormal returns under the *perils model*. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Another explanation could be certain fund characteristics. On the one hand, larger funds might have more resources to make informed investment decisions and earn higher returns. On the other hand, they might suffer from diseconomies of scale and thus earn lower returns. Data on this question, however, is very limited. Because we only have access to two variables which are measured for almost all funds, we are left with fund size, measured as the natural logarithm of assets under management (AuM), and fund age, measured as the natural logarithm of years that the fund is (was) active, as regressors.[15] We run a single cross-sectional regression of each fund's alpha (based on the *perils model*) against its fund size and fund age. The respective results can be found in Table 15.

Table 15: Alpha, fund size, and fund age

	(1)	(2)	(3)
ln(AuM)	0.07***		0.08***
	(0.03)		(0.03)
ln(Age)		-0.01	-0.10
		(0.07)	(0.06)
Constant	-0.33**	0.05	-0.22
	(0.14)	(0.12)	(0.15)
Obs.	48	50	48
Adj. R^2	0.15	0.01	0.20

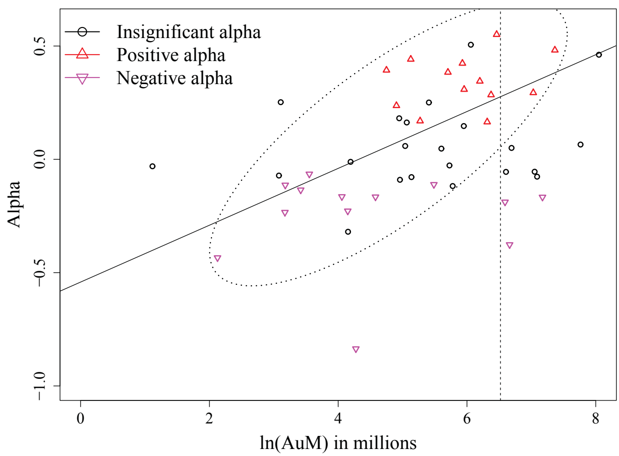
This table shows the coefficients on the natural logarithm of assets under management, ln(AuM), and the natural logarithm of fund age measured in years, ln(Age), from a single cross-sectional regression against each fund's alpha. Two out 50 funds do not have any AuM information. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In contrast to Chen et al. (2004), who show that fund size erodes the performance of mutual funds, we find a significant and positive relationship between fund size and abnormal returns. The positive relationship between fund size and performance is also in contrast to the evidence found in hedge funds (see, e.g., Ammann and Moerth, 2005). However, it is important to highlight that our analysis is limited to a single cross-sectional regression based on the

[15] Two out 50 funds do not have any AuM information and are thus excluded from regressions involving fund size.

latest available data. Nevertheless, one relevant take-away upholds. Small funds and funds which have performed badly – and thus became smaller – are correctly identified as "underperformers" by our *perils model*. Subsequently, these underperformers might not be able to attract new fund inflows from investors. Figure 5, in which we have plotted alphas against fund size, reveals another important aspect. Funds exceeding USD 680 million in AuM are not necessarily outperformers on average. Rather, the positive relationship between fund size and returns is much more blurred and is not as clear as below that size frontier. This suggests that there might be an optimal size for ILS funds, which balances economies of scale and the supply of ILS investment opportunities.

Figure 5: Alpha and fund size



This figure illustrates the abnormal returns (alpha) from the *perils model* of 48 ILS funds against their respective fund size (two funds do not have AuM information). Fund size on the x-axis is the natural logarithm of assets under management (AuM) in USD millions. Black circles indicate insignificant alpha values. The solid black line shows the estimation slope of alpha against fund size based on funds not exceeding USD 680mn in AuM. The dotted black line indicates a break in the functional relationship between alpha and fund size at USD 680mn. Red upward pointing triangles indicate significant positive alphas at the 10%-level. Magenta downward pointing triangles indicate significant negative alphas at the 10%-level.

5 Robustness

5.1 Subperiods

To assess the robustness of our results over time, we separate the overall sample (January 2002 until December 2015) into four equally long subperiods and run the *perils model* against the excess return of the aggregate ILS fund index. We also include the Katrina dummy variable during the period July 2005 until December 2008. Table 16 shows the respective results.

Table 16: Subperiods

	(1) 01/2002–06/2005	(2) 07/2005–12/2008	(3) 01/2009–06/2012	(4) 07/2012–12/2015
CATMKO2	0.88***	0.97***	0.91***	0.24***
	(0.11)	(0.16)	(0.03)	(0.06)
USHU	0.41***	0.37***	0.27***	0.40***
	(0.06)	(0.08)	(0.05)	(0.03)
USEQ	0.10	0.05	0.25***	-0.00
	(0.17)	(0.03)	(0.08)	(0.09)
KATRINA		-2.63***		
		(0.08)		
Constant	0.00	-0.02	-0.06	0.18***
	(0.10)	(0.07)	(0.07)	(0.03)
Adj. R^2	0.50	0.83	0.89	0.83
Obs.	42	42	42	42

This table shows the coefficients of the *perils model* over different time periods. The dependent variable is the excess return of the ILS fund index over the one-month T-Bill rate. Column (1) - (4) show the results for time periods January 2002 until June 2005, July 2005 until December 2008, January 2009 until June 2012, and July 2012 until December 2015, respectively. We model is augmented by the Katrina dummy during the period July 2005 until December 2008. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Our first finding is that the *perils model* performs very well over the last three subperiods with adjusted R-squareds between 83% and 89%. The orthogonalized cat bond market factor (CATMKO2) as well as the single-peril hurricane factor (USHU) are highly significant at all times, meaning that the majority of funds is constantly invested in multi-peril risks and single-peril U.S. hurricane risk.

However, the single-peril earthquake factor (USEQ) is only significant in the time period January 2009 to June 2012. This could be due to the fact that many funds gain earthquake risk exposure through multiperil bonds. The second finding is a much lower explanatory power of 50% in the first subperiod. A likely reason is that only few ILS funds existed in those early days of the industry. Hence, portfolio compositions that differ from the market indices have a stronger impact. The last finding is the significant alpha in the most recent subperiod with an unexplained monthly return of 0.18%. This subperiod is characterized by the largest number of funds. A potential explanation for the significant abnormal return might be found in the advent of several non-cat-bond segments of the ILS market.

5.2 Out-of-sample tests

To avoid in-sample overfitting, we are now interested how well our augmented *perils model* and *spread model* perform on the excess returns (over the one-month T-Bill rate) of other indices related to the securitization of natural catastrophes. The first index is the Eurekahedge index which also tracks the aggregate performance of ILS funds. Hence, we expect that our model should perform as good as on our proprietary aggregate ILS fund index. The second index is the Mercury investible Catastrophe Risk Index, also known as MiCRIX, which tracks the performance of a diversified portfolio of peak peril industry loss warranties (ILWs). Both indices start in January 2006. In contrast to cat bonds, ILWs are uncollateralized and unfunded double-trigger contracts, whose main trigger relies on an insurance industry loss index.[16] The results reported in Table 17 indicate that, as expected, the Eurekahedge index can be well described by either model with adjusted R-squareds of 77% for the *perils model* and 75% for the *spread model*. In contrast, ILWs represented by the MiCRIX can be less explained by the ILS fund models with adjusted R-squareds of 58% and 57%, respectively. This suggests that the pricing of cat bonds has some effect on ILWs, yet other effects are at play. One explanation could be that insurance companies focus on other regions or have a lower exposure than cat bonds.

[16] For a detailed discussion of ILWs and catastrophe swaps, refer to Braun (2011).

Table 17: Out-of-sample indices

	(1)	(2)	(3)	(4)
	Eurekahedge	Eurekahedge	MiCRIX	MiCRIX
CATMKO1		0.32		0.55
		(0.24)		(1.13)
TERM3Y		0.62***		1.92***
		(0.12)		(0.51)
DEFCOR		0.54***		1.65***
		(0.10)		(0.40)
DEFCAT		0.55***		1.91***
		(0.11)		(0.44)
CATMKO2	0.81***		3.01***	
	(0.18)		(0.78)	
USHU	0.27***		0.89***	
	(0.03)		(0.17)	
USEQ	0.18***		-0.02	
	(0.02)		(0.23)	
Constant	0.05	0.08	-0.31	-0.24
	(0.05)	(0.06)	(0.27)	(0.38)
Adj. R^2	0.77	0.75	0.58	0.57
Obs.	120	120	120	120

This table shows the coefficients of the *perils model* augmented by the hurricane option factor and the *spread model* augmented by the hurricane option factor. The dependent variable in Column (1) and (2) is the excess return of the Eurekahedge catastrophe bond fund index over the one-month T-Bill rate. The dependent variable in Column (3) and (4) is the excess return of the Mercury investible Catastrophe Risk Index (MiCRIX) over the one-month T-Bill rate. Standard errors in parentheses are Newey-West (1987) corrected with lags of four. The indices start in January 2006 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6 Conclusion

A better understanding of catastrophe funds is crucial for investors to make sophisticated investment decisions. This can be proven to be difficult due to the limited information by some of the ILS funds. Using the first comprehensive dataset on ILS funds, this paper tried to understand the performance features of cat bonds funds in comparison to other asset classes and to understand the key performance drivers of this innovative asset class.

We show that ILS funds are the highest performing asset class based on a battery of risk measures including the Sharpe Ratio, the Sortino Ratio, the Excess Return on VaR, or the Calmar Ratio. ILS funds are also consistently delivering positive returns on an aggregate basis in ca. 90% of all analyzed months compared to 67% during the same period for hedge funds. We also show that single-peril hurricane, single-peril earthquake and multi-peril risks are driving the performance for ca. three quarters of all ILS funds. Vice versa, one quarter of all ILS funds is able to consistently generate significant alphas, even under the new model setting. Our findings may help to promote a better understanding of the main return drivers of ILS funds. Hence, they should be relevant to fund managers and investors alike. We hope to contribute to the transparency of cat bond funds in order to support the further growth of this segment in the capital market.

Despite the empirical findings of outperformance, several limitations with regard to ILS funds need to be highlighted. Although, we rigorously combed through the entire fund universe to identify live and dead ILS funds, reporting biases such as survivorship, backfilling, managed returns, and self-selection cannot be fully excluded. We believe, however, that by the construction of our database these biases have no big magnitude, if any.

Beyond the data limitation, limitations on the ILS investment opportunity need to be addressed. First and foremost, the fact that ILS funds invest in (the non-occurence of) extreme events means that such events can result in large losses in cat bonds and subsequently in ILS funds. If a fund is not optimally diversified the risk of total loss must be considered as a reality. Second, despite having seen large extreme events such as Hurricane Katrina and the Tohoku earthquake, it remains an open question how an extreme catastrophic event looks like, how large the losses by such an event would be, and what the final effect on ILS funds would be.

The most challenging aspect for future research would be to identify ILS other than cat bonds and how such instruments drive the performance of ILS funds. Furthermore, more research is needed to better understand whether fund managers with superior risk-adjusted performance are simply lucky or actually skilled in making investment decisions.

References

Agarwal, V., Daniel, N. D., and Naik, N. Y. (2011). Do Hedge Funds Manage Their Reported Returns? *Review of Financial Studies*, 24(10):3281–3320.

Ammann, M., Kind, A., and Seiz, R. (2010). What Drives the Performance of Convertible-Bond Funds? *Journal of Banking and Finance*, 34(11):2600–2613.

Ammann, M. and Moerth, P. (2005). Impact of Fund Size on Hedge Fund Performance. *Journal of Asset Management*, 6(3):219–238.

Bantwal, V. J. and Kunreuther, H. C. (2000). A Cat Bond Premium Puzzle? *Journal of Psychology and Financial Markets*, 1(1):76–91.

Blake, C., Elton, E. J., and Gruber, M. J. (1993). The Performance of Bond Mutual Funds. *Journal of Business*, 66(3):371–403.

Braun, A. (2011). Pricing Catastrophe Swaps: A Contingent Claims Approach. *Insurance Mathematics and Economics*, 49(3):520–536.

Braun, A. (2016). Pricing in the Primary Market for Cat Bonds: New Empirical Evidence. *Journal of Risk and Insurance*, (forthcoming).

Braun, A., Müller, K., and Schmeiser, H. (2013). What Drives Insurers Demand for Cat Bond Investments? Evidence from a Pan-European Survey. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 38(July):580–611.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1):57–82.

Carhart, M. M., Carpenter, J. N., Lynch, A. W., and Musto, D. K. (2002). Mutual Fund Survivorship. *The Review of Financial Studies*, 15(5):1439–1463.

Chen, J., Hong, H., Huang, M., Kubik, J. D., American, T., Review, E., and Dec, N. (2004). Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *American Economic Review*, 94(5):1276–1302.

Chen, Y., Ferson, W., and Peters, H. (2010). Measuring the Timing Ability and Performance of Bond Mutual Funds. *Journal of Financial Economics*, 98(1):72–89.

Fama, E. F. and French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56.

Fang, J., Kempf, A., and Trapp, M. (2014). Fund Manager Allocation. *Journal of Financial Economics*, 111(3):661–674.

Fung, W. and Hsieh, D. A. (1997). Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies*, 10(2):275–302.

Fung, W. and Hsieh, D. A. (2000). Performance Characteristics of Hedge Funds and Commodity Funds. *Journal of Financial and Quantitative Analysis*, 35(3):291–307.

Fung, W. and Hsieh, D. A. (2004). Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal*, 60(5):65–80.

Galeotti, M., Gürtler, M., and Winkelvos, C. (2013). Accuracy of Premium Calculation Models for CAT Bonds - An Empirical Analysis. *Journal of Risk and Insurance*, 80(2):401–421.

Getmansky, M., Lo, A. W., and Makarov, I. (2004). An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. *Journal of Financial Economics*, 74(3):529–609.

Gürtler, M., Hibbeln, M., and Winkelvos, C. (2016). The Impact of the Financial Crisis and Natural Catastrophes on CAT Bonds. *Journal of Risk and Insurance*, (forthcoming).

Hagendorff, B., Hagendorff, J., and Keasey, K. (2013). The Shareholder Wealth Effects of Insurance Securitization: Preliminary Evidence from the Catastrophe Bond Market. *Journal of Financial Services Research*, 44(3):281–301.

Hagendorff, B., Hagendorff, J., Keasey, K., and Gonzalez, A. (2014). The Risk Implications of Insurance Securitization: The Case of Catastrophe Bonds. *Journal of Corporate Finance*, 25:387–402.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica (1986-1998)*, 55(3):703–708.

Partner Re (2015). The Drivers of Catastrophe Bond Pricing. *Partner Reviews*, (October).

RMS (2012). Cat Bonds Demystified: RMS Guide to the Asset Class.

Sadka, R. (2010). Liquidity Risk and the Cross-Section of Hedge-Fund Returns. *Journal of Financial Economics*, 98(1):54–71.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance*, 19(3):425–442.

Sharpe, W. F. (1992). Asset Allocation: Management Style and Performance Measurement. *The Journal of Portfolio Management*, 18(2):7–19.

Smolka, A. (2006). Natural Disasters and the Challenge of Extreme Events: Risk Management from an Insurance Perspective. *Philosophical Transactions of the Royal Society A*, 364(1845):2147–2165.

Swiss Re (2013). Insurance-Linked Securities Market Update.

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