Asset Pricing of Financial Institutions: The Cross-Section of Expected Stock Returns in the Property/Liability Insurance Industry

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Abstract

Insurance companies are important financial institutions exposed to natural and man-made disasters. We conduct a comprehensive examination of existing asset pricing models in the US insurance universe (1988-2013) and propose an insurance-specific asset pricing model. We find that extant asset pricing models fail to explain the cross-section of insurance stock returns. Instead, we provide evidence that the factors of the insurance-specific model (book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility) are priced in the cross-section of property/liability insurance stocks. Our model takes into account both insurance-specific anomalies primarily related to the insurance business cycle and externalities imposed by catastrophe risk.

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I. Introduction

Extant asset pricing models are expected to explain cross-sectional variation in asset 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)).[1] The exclusion of financial sector stock returns has typically gone 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 could benefit from investing in insurance stocks as their returns are typically less correlated with general market trends.

In this paper we analyze the cross-section of 127 U.S. property/liability (p/l) insurance stocks in the time period 1988 to 2013. The motivation to do this is threefold. First, state-of-the-art asset pricing models such as the Fama and French (1993) three-factor model or Petkova (2006) five-factor model perform extremely well in a portfolio setting for the entire universe of stocks (excluding financial firms), but how far this holds for the insurance sector is unclear. Second, and in close connection with pricing models in general, it is unclear whether known anomalies from the finance literature also exist in insurance stocks and whether specific characteristics of insurance stocks result in a return pattern (i.e., a potential anomaly). Hence, we propose an insurance-specific asset pricing model that addresses the uniqueness of insurance stocks, which stem primarily from their exposure to extraordinary risks – such as catastrophe risk – that are uncorrelated with returns from the rest of the market (Ibragimov, Jaffee, and Walden (2009)).

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

The p/l insurance sector has important economic functions as shock absorber and risk bearer for individuals and institutions. Insurers provide services such as underwriting, pricing, claim management, and consultancy. Moreover, their large investment portfolios provide an important source of capital to the economy. Recently, the risks inherent in p/l insurers have also been securitized (e.g., cat bonds), forming a complete new market of financial instruments called insurance-linked securities, which are also increasingly important in terms of market volume.

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 almost no literature on this in the insurance context.[2] Next, from the general arguments for the exclusion of financial firms from asset pricing tests, another reason for the non-existence of such literature is the scarcity of insurance stocks.

Our paper closes this gap by analyzing the cross-section of expected insurance stock returns. We employ four existing asset pricing models,[3] and propose an insurance-specific asset pricing model that takes into account the unique characteristics (anomalies) of the insurance industry. We test these models by running time-series and Fama–MacBeth (1973) regressions on

[2] 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.

[3] The four models are the CAPM, Fama and French’s (1993) three-factor model (FF-3), FF-3 with momentum (Carhart (1997)), and an ICAPM with innovations in state variables (Petkova (2006)). In additional tests available on request, we also test Fama and French’s (2015) recent five-factor model (FF-5).

portfolios and individual stock returns and sort insurance stocks on 21 characteristics that could contribute to the explanation of risk and return in the insurance industry.[4]

We also contribute to the discussion on interest rate exposure, leverage, size, and other firm characteristics discussed in the insurance literature, which so far 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 very different from other stocks due to the above mentioned reasons.

The central findings of this paper are that the existing asset pricing models fail to explain the cross-section of insurance stock returns, while the insurance-specific asset pricing model offers a better alternative in addressing this cross-sectional variation.[5] 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

[4] The 21 characteristics are CAPM beta, downside beta, upside beta, size, B/M ratio, illiquidity, momentum, short-term reversal (i.e., prior-month return), long-term reversal, idiosyncratic volatility, cashflow volatility, co-skewness, co-kurtosis, asset growth, investment performance, term spread, default spread, broker-dealer leverage, insurance leverage, financial leverage, and total leverage.

[5] For example, the size anomaly identified in the finance literature is only present in the smallest decile of insurance stocks. The Fama–French (1993) three-factor model can neither explain the size nor the B/M anomaly in the insurance stocks. A five-factor model built on the insurance-specific anomalies explains the cross-sectional variation. Our results complete those of Fama and French (1992, 1993) on non-financial firms and Viale, Kolari, and Fraser (2009) on banks.

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 catastrophe.

The remainder of this paper is organized as follows. Section II gives a brief literature review. Section III describes our hypotheses. Section IV provides a description of the data and the methodology. Section V shows the empirical results. Section VI checks for robustness, and Section VII concludes.

II. Literature review

Only one paper, by Cummins and Harrington (1988), analyzes the cross-section of p/l insurance stocks, finding that the CAPM is correctly specified during the period 1980–1983, but inconsistent in earlier periods. Since then, to the best of our knowledge, there has not been any research to directly analyze the cross-section of p/l insurance returns.[6]

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

[6] 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 covers both bank and insurance, they do not explicitly discuss insurance stocks, only sort portfolios, and do not provide further asset pricing tests to analyze the cross-sectional relationship.

et al. (2007); Carson, Elyasiani, and Mansur (2008)).[7] 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 (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.[8]

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

[7] 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)).

[8] 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.

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.[9]

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, since large banks are "too big to fail," and thus such banks earn significantly lower returns than smaller banks. Table A1 in the Appendix summarizes the existing literature and outlines our contribution.[10]

III. Benchmark model and potential anomalies

Our main benchmark model in the empirical part is the Fama–French (1993) three-factor model, which has shown superior performance in the U.S. equity market (see Cooper, Gulen, and Schill (2008), among others) and which also represents the state of the art in the insurance literature

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9 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.

10 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.

(see Cummins and Phillips (2005); Wen et al. (2008)). The central hypothesis (H_0) throughout the paper is thus that the Fama–French model is the correctly specified model to explain the cross-section of insurance stock returns.

Furthermore, we hypothesize that known 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. We attribute this hypothesis to three aspects. First, financial institutions are generally excluded from asset pricing tests (Barber and Lyon (1997)); Gandhi and Lustig (2015)) due to their high leverage, thus giving leverage ratios a different meaning than for non-financial firms (Fama and French (1993)) and, due to the regulatory aspect of financial institutions, binding them to keep certain solvency ratios or follow other regulatory constraints. Second, p/l insurers are threatened by large losses through catastrophes that can exceed their capital sources (Cummins, Doherty, and Lo (2002)). The third reason is related to the previous one, as losses from natural disasters (which do not need to be large in magnitude) result in uncorrelated returns from the rest of the market (Ibragimov, Jaffee, and Walden (2009)).

Due to these three aspects, we argue that insurers are unlike the general equity market, where either risk factors are priced differently in magnitude or not at all, or where other risk factors are priced that do not appear in the general equity market. Specifically, we consider 21 potential stock anomalies, which can be summarized in the following 11 broad categories[11]:

(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.

[11] For a detailed description of the characteristics and the portfolio formation, see Appendix D.

(2) B/M ratio: Insurers with high B/M ratios should 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 should earn lower returns as they might have a more diversified insurance portfolio and thus a lower risk exposure.

(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.

(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.

IV. 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.

A. 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.[12] 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:

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + \varepsilon_{i,t}, \quad (1)$$

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 $\varepsilon_{i,t}$.

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:

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

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 four models from the finance literature and later derive an empirically driven model for insurance stocks, which is the fifth 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:

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

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

where $\mathrm{E}(R^e)$ 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:

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

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):

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

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:

(6) $$\mathrm{E}(R^e) = z + \lambda_{MKT}\beta_{i,MKT} + \lambda_{\hat{u}^{div}}\beta_{i,\hat{u}^{div}} + \lambda_{\hat{u}^{TERM}}\beta_{i,\hat{u}^{TERM}} + \lambda_{\hat{u}^{DEF}}\beta_{i,\hat{u}^{DEF}} + \lambda_{\hat{u}^{RF}}\beta_{i,\hat{u}^{RF}},$$

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.

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. Next to 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 zero-investment portfolio sorted by cashflow volatility (CFVF) is considered. Formally, the cross-sectional relation of this insurance-specific five factor model (INS5) is described as:

$$\text{(7)} \qquad \mathrm{E}(R^e) = z + \lambda_{MKT}\beta_{i,MKT} + \lambda_{BMF}\beta_{i,BMF} + \lambda_{PRETF}\beta_{i,PRETF} + \lambda_{LQF}\beta_{i,LQF} + \lambda_{CFVF}\beta_{i,CFVF}$$

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

B. Data

Our sample consists of all traded U.S. p/l insurers with SIC code 6311.[13] 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).[14] Table A2 in the Appendix reports the number of stocks per year in our sample.

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

[14] 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,

Stock return data and accounting information are retrieved from CRSP and COMPUSTAT, respectively. The Fama–French (1993) factors, the 1-month T-Bill yield, and the momentum factor are downloaded from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). 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. Table A3 in the Appendix summarizes the used accounting information and factor variables.

V. Empirical evidence

We first present results of single-sorted portfolios (Section V.A), followed by time series and cross-sectional regression analyses of insurance stocks (Sections V.B to V.F). We also provide economic interpretations of our results (Section V.G).

A. 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

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there are only 41 in 1986 and the number continues to decrease further back in time) and, more importantly, in the availability of accounting data.

the non-financial sector and to evaluate insurance-specific characteristics.[15] We sort insurance stocks based on 21 characteristics introduced in Section III (see also Table A4 in the Appendix for a detailed description).[16] Table 1 presents average monthly returns of characteristic-sorted portfolios for p/l insurers. Following Fama and French (1993) in their factor construction and given the sample size, we break insurance stocks into three groups based on the breakpoints for the bottom 20% (low), middle 60% (mid), and top 20% (high) of the ranked values of each characteristic.[17] The CAPM alphas and Fama–French (1993) three-factor alphas in 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 CAPM in Panel A or the Fama–French (1993) three-factor model in Panel B of Table 1.[18]

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[15] 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.

[16] 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. 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. Between 1999 and 2005 AIG and Citigroup constituted more than 20 percent of the entire p/l market capitalization (Thomann (2013)). Furthermore, equally weighted returns are more in line with the approach of Fama–MacBeth (1973) regressions, which equally weight each independent variable.

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

[18] We also ran the newly developed Fama–French (2015) five-factor model, including a profitability and an investment factor. The main results remain virtually identical. In case of the spread between high and low book-to-market ratio insurance stocks, the Fama–French (2015) five-factor model even increases the spread difference in terms of significance.

Table 1

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

Quantile	β_{CAPM}	β^{+}	β^{-}	**Size (MC)**	**B/M**	**MOM**	**RET_{t-1}**	**LIQ**	**REV**	**ID-VOLA**	**CF-VOLA**	**CO-SKEW**	**CO-KURT**	**Asset Growth**	$\beta_{\Delta TERM}$	$\beta_{\Delta DEF}$	**INVEST**	$\beta_{B/D\ LEV}$	**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	0.87	1.36	1.09	1.15	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	1.12	1.08	1.03	0.85	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	1.33	0.90	1.37	1.40	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]	0.46 [1.50]	-0.46 [-1.56]	0.28 [1.23]	0.26 [0.95]	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]	0.29 [1.02]	-0.24 [-0.86]	0.26 [1.10]	0.31 [1.12]	0.37 [1.18]	0.09 [0.39]	0.44 [1.36]
# of observations (*T*)	306	306	306	306	306	306	306	306	306	306	306	306	306	306	306	306	306	258	306	306	306

Panel B: Alphas from Fama–French 3-factor model regressions (in % per month, July 1988–December 2013)

Quantile	**β**	**β^{+}**	**β^{-}**	**Size (MC)**	**B/M**	**MOM**	**RET_{t-1}**	**LIQ**	**REV**	**ID-VOLA**	**CF-VOLA**	**CO-SKEW**	**CO-KURT**	**Asset Growth**	**ΔTERM**	**ΔDEF**	**INVEST**	**B/D LEV**	**INS/ LEV**	**FIN/ LEV**	**Total LEV**
1 (low)	0.44** [2.38]	0.31 [1.45]	0.46** [2.42]	0.38 [1.63]	0.06 [0.26]	-0.12 [-0.55]	1.20*** [6.05]	0.12 [0.54]	0.47** [2.17]	0.31* [1.80]	0.44** [2.29]	0.34 [1.55]	0.40** [2.23]	0.44** [2.39]	0.07 [0.31]	0.32 [1.34]	0.16 [0.67]	0.14 [0.60]	-0.09 [-0.53]	0.32 [2.05]	-0.03 [-0.16]
2 (mid)	0.16 [0.97]	0.22 [1.35]	0.22 [1.43]	0.26 [1.54]	0.15 [0.92]	0.32** [2.07]	0.24 [1.47]	0.24* [1.65]	0.14 [0.83]	0.27 [1.54]	0.36** [2.16]	0.20 [1.27]	0.17 [1.05]	0.17 [1.08]	0.27* [1.70]	0.23 [1.48]	0.67 [1.15]	0.01 [0.07]	0.40** [2.16]	0.16 [0.90]	0.34* [1.96]
3 (high)	0.22 [0.98]	0.18 [0.79]	0.01 [0.06]	-0.07 [-0.37]	0.70*** [3.00]	0.31 [1.45]	-0.81*** [-3.49]	0.34 [1.54]	0.27 [1.24]	0.08 [0.36]	-0.71** [-2.50]	0.20 [1.05]	0.23 [1.10]	0.29 [1.16]	0.29 [1.33]	0.14 [0.66]	0.41* [1.88]	0.43* [1.93]	0.04 [0.17]	0.25 [1.32]	0.15 [0.62]
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]	0.22 [0.76]	-0.18 [-0.66]	0.25 [1.01]	0.30 [1.14]	1.34 [0.50]	-0.08 [-0.38]	0.18 [0.65]

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 with the market factor as independent variable (i.e., CAPM Alpha (Spread)), and the number of monthly observations. Panel B reports the intercepts from time-series regressions with the market factor, SMB, and HML as independent variables (i.e., FF-3 Alpha) 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. The last row indicates the FF-3 alpha from time-series regressions on the spread between high minus low exposure (i.e., FF-3 Alpha (Spread)). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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)).[19] We do, however, find a significant effect 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 Fama–French three-factor model, which explicitly includes this B/M-related factor, is not able to capture the return difference in B/M portfolios (Table 1, Panel B). This suggests that the B/M ratio for p/l stocks has a different pricing cycle and a different meaning than the B/M ratio in non-insurance stocks.[20]

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

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

[20] One explanation could be that the (insurance-specific) B/M ratio reflects some type of distress, as Chen and Zhang (1998) observe for global equity markets. If that is the case, insurance stocks might experience this distress during market downturns, but also during natural catastrophes, which do not necessarily have an effect on non-insurance firms. A related reason for the different cycle could be the so-called underwriting cycle, which results in higher insurance prices during "hard markets" and low prices during "soft markets" (Cummins and Outreville 1987).

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 leading to a significant spread. The abnormal return spread from cashflow volatility can be explained neither by the CAPM nor the Fama–French (1993) three-factor 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; that is, the CAPM-alpha from time series regression is insignificant.

As noted by Daniel and Titman (1997), differences in average returns may not be the result of different risk exposure, but rather the result of the (size and B/M ratio) characteristics themselves. For that purpose, we also look at the beta exposure on SMB and HML-sorted portfolios from three-year rolling regressions and yearly rebalancing. Table A5 in the Appendix (Panel A) reports the average returns from low to high exposure, the spread, and the CAPM alpha of that spread. Results show that insurance stocks with low SMB exposure earn higher returns. This contradicts the idea that higher SMB exposure leads to higher returns. For the HML exposure we also observe a reverse relation from what we would have expected. A high beta exposure to the HML factor results in lower returns, however, the spread is insignificant.

B. 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.[21]

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^-**	**Ln(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)**
Independent variable	**CO-SKEW**	**CO-KURT**	**Asset Growth**	**$\beta_{\Delta TERM}$**	**$\beta_{\Delta DEF}$**	**INVEST**	**B/D LEV**	**INS/ LEV**	**FIN/ LEV**	**Total LEV**
Coefficient	-0.01 [-0.78]	-0.00 [-1.64]	-0.13 [-0.25]	5.17** [2.02]	-4.42* [1.92]	0.51 [1.20]	0.99 [0.94]	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]	0.67** [2.54]	0.67** [2.56]	0.94*** [3.17]	0.01 [1.25]	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	0.03	0.05	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 III. 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.

Following univariate Fama–MacBeth (1973) regressions, we further investigate the different pricing components in a multivariate framework to analyze the variables' unique pricing ability.

[21] We also report the cross-sectional regressions on the beta exposure of SMB and HML in Table A6 in the Appendix. Again, results from cross-sectional regressions confirm the results from portfolio sorts, with SMB being negatively priced in the cross-section and thus contradicting the idea that SMB exposure is positively priced.

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 95th 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 3: Fama–MacBeth (1973) regressions with individual stock returns (multivariate)

	(I)	(II)	(III)	(IV)	(V)
B/M	0.49**	0.51**	0.61***	0.46*	0.58**
	[2.15]	[2.07]	[2.62]	[1.87]	[2.38]
RET_{t-1}	-7.72***	-7.58***	-7.60***	-6.90***	-7.47***
	[-4.78]	[-4.72]	[-4.54]	[-4.36]	[-4.67]
β_{LIQ}	0.85**	0.81*	0.94**	0.84**	0.61
	[2.07]	[1.86]	[2.17]	[2.08]	[1.55]
CF-VOLA	-3.43**	-3.44**	-3.26**	-3.25**	-3.32**
	[-2.25]	[-2.36]	[-2.11]	[-2.23]	[-2.29]
$\beta_{\Delta TERM}$	-2.05	-1.69	-1.19	-0.59	1.52
	[-0.44]	[-0.34]	[-0.25]	[-0.12]	[0.30]
$\beta_{\Delta DEF}$	-5.21	-6.03	-3.87	-3.77	-1.39
	[-1.24]	[-1.34]	[-0.93]	[-0.88]	[-0.33]
β_{SMB}	-0.10	-0.03	-0.09	-0.07	0.07
	[-0.56]	[-0.17]	[-0.51]	[-0.37]	[0.40]
Const. (z)	0.34	0.35	0.28	0.44	0.40
	[1.06]	[1.06]	[0.90]	[1.35]	[1.21]
Obs.	15,365	14,871	14,793	14,861	13,832
Avg. R^2	0.26	0.25	0.27	0.26	0.26
Sample excludes observations:		<5th pctile. market cap.	<5th pctile. trading vol.	>95th pctile. rel. bid–ask spread	<5th pctile. market cap. / <5th pctile. trading vol./ >95th 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 5th percentile. Model (III) excludes all firm months with trading volume below the sample's 5th percentile. Model (IV) excludes all firm months with relative bid–ask spreads above the sample's 95th percentile. Model (V) sequentially excludes all firm months with market capitalization below the sample's 5th percentile, all firm months with trading volume below the sample's 5th percentile, and all firm months with relative bid–ask spreads above the sample's 95th percentile. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C. 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 monotonic 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}	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}	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 (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).[22] Formally, each excess-return portfolio is constructed as:

$$F_{i,t} = \frac{3}{4} * \left(portfolio\_5_{i,t} - portfolio\_1_{i,t}\right) + \frac{1}{4} * \left(portfolio\_4_{i,t} - portfolio\_2_{i,t}\right). \quad (8)$$

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

[22] The following 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 on 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.

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 Table A7 in the Appendix). On the other hand, our constructed risk factors based on the four characteristics show a significant correlation with the second principal components (PC2) of between 0.75 and 0.97.[23]

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. However, as we have already seen in β_{HML}-sorted portfolios and the respective alpha values (Table A5 in the Appendix), HML and the B/M ratio have different meanings. This is also validated by the correlation of Fama and French's (1993) HML factor with our B/M sorted factor, BMF. Both factors are uncorrelated with a correlation coefficient of 0.02.

D. 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 LIQ (four risk factors x 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 IV.A 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 zero-investment portfolio

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

sorted by cashflow volatility (CFVF). Table 5 reports the Fama–MacBeth (1973) regressions for all five models and two control regressions.

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

	(I) CAPM	**(II)** FF-3	**(III)** Carhart-4	**(IV)** Petkova-5	**(V)** Insurance-5	**(VI)** Control-1	**(VII)** Control-2
β_{MKTRF}	1.017	1.65*	2.43**	1.46*	2.11**	2.80**	2.64***
	[1.18]	[1.66]	[2.29]	[1.80]	[2.15]	[2.50]	[2.67]
β_{BMF}					0.77**	0.60**	0.58**
					[2.38]	[2.36]	[2.29]
β_{PRETF}					-2.09***	-1.68***	-1.68***
					[-6.96]	[-7.16]	[-7.19]
β_{LQF}					0.44*	0.39*	0.39*
					[1.65]	[1.80]	[1.84]
β_{CFVF}					-0.87**	-0.62**	-0.58*
					[-2.30]	[-2.08]	[-1.96]
β_{SMB}		0.33	0.71				
		[0.63]	[1.28]				
β_{HML}		-0.90	0.88				
		[-1.30]	[1.24]				
β_{MOM}			3.24***			-0.48	
			[3.85]			[-0.49]	
$\hat{u}^{TERM}$				0.37***			0.06
				[4.58]			[0.76]
$\hat{u}^{DEF}$				-0.28***			-0.03
				[-4.14]			[-0.39]
$\hat{u}^{div}$				0.02			
				[1.02]			
$\hat{u}^{RF}$				0.03***			0.01
				[2.84]			[0.96]
Const. (z)	0.30	0.23	-1.42	0.24	-0.21	-0.54	-0.43
	[0.69]	[0.46]	[-0.88]	[0.02]	[-0.35]	[-0.81]	[-0.01]
Avg. R^2	0.46	0.48	0.50	0.52	0.59	0.60	0.60

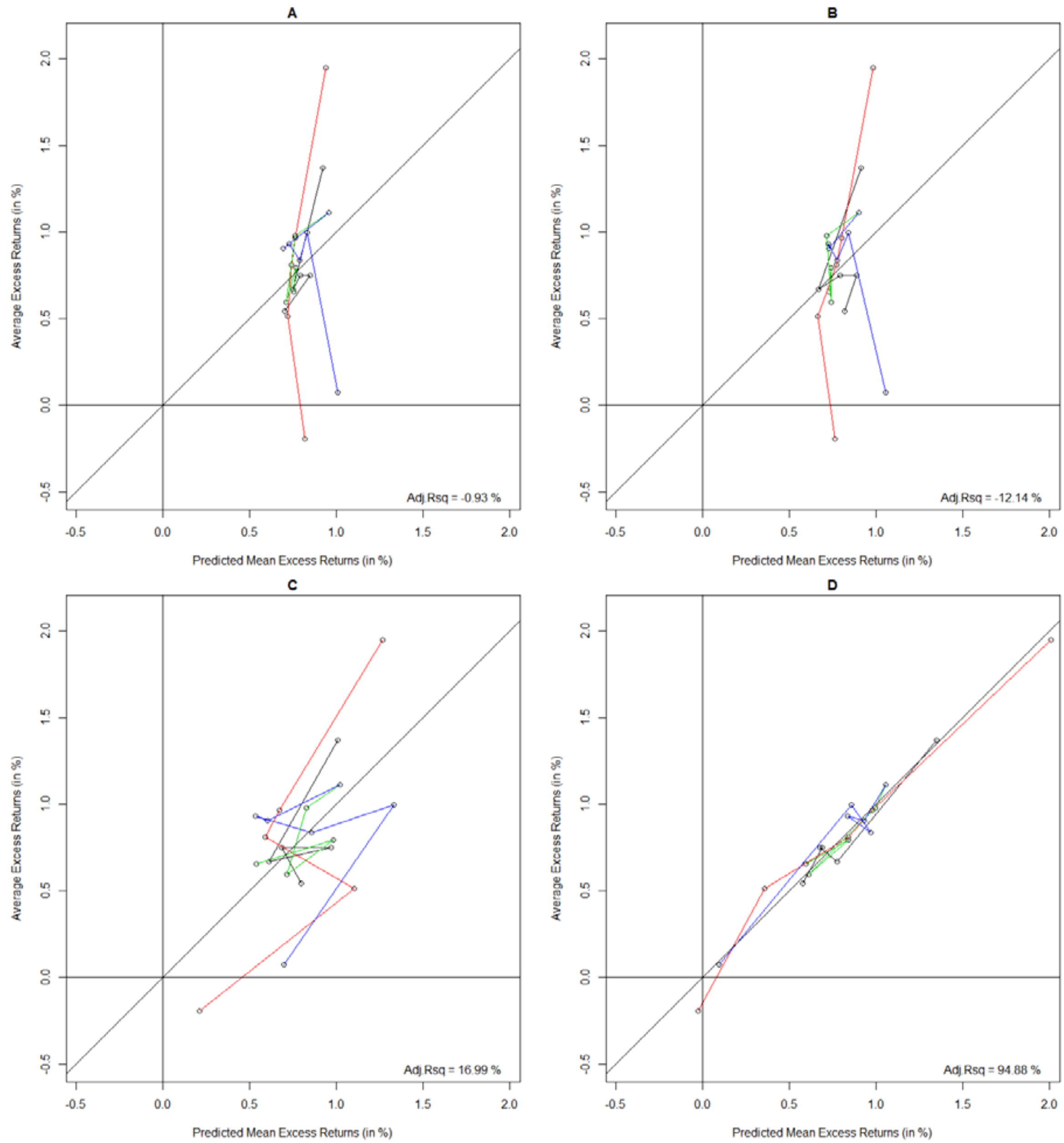
Column (I) describes the CAPM, column (II) the Fama–French (1993) three-factor model, column (III) the Carhart (1997) four-factor model, column (IV) the Petkova (2006) five-factor model, and column (V) the INS5 model. Standard errors are Shanken (1992) corrected.

We see that the market factor is insignificant in the CAPM, but becomes significant and positive in all other specifications, suggesting that the CAPM needs some type of conditioning, which then results in a significant pricing of the market factor. Interestingly, SMB and HML are insignificant and do not imply a linear relationship between their covariances and our test assets. We do, however, find a significant relationship between Carhart's (1997) momentum factor, MOM, and our test assets. This relationship, though, is not robust if we include MOM in our INS5 model (column VI). Similarly, the Petkova (2006) five-factor model indicates four significant factors that lose their significance in our control regressions (column VII), except for the market factor.

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, and D show the actual excess returns and the predicted return by the CAPM, Fama–French (1993) three-factor model, Petkova (2006) five-factor model, and INS5 model, respectively. Each graph also provides the adjusted R-square from a single cross-sectional regression.[24] Neither the CAPM nor the Fama–French (1993) three-factor models is doing well in predicting the portfolio return. The Petkova (2006) five-factor model, however, is doing better compared to the Fama–French (1993) three-factor model with a cross-sectional, adjusted R-square of 16.99%. However, the INS5 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 INS5 model is well specified. Note that we also compute the Hansen-Jagannathan distance to compare the different models later on in this paper.

[24] The R-square values in the Fama–MacBeth (1973) regressions are average R-squares from 306 monthly cross-sectional regressions.

Figure 1: Actual vs. predicted returns



Graphs A, B, C, and D show the actual excess returns and the predicted return by the CAPM, the FF-3 model, the Petkova (2006) five-factor model, and the insurance-5 model. In the bottom right the adj. R-square from a single cross-sectional regression is reported. The portfolios are 20 excess return portfolios sorted by B/M ratio, prior month return, liquidity, and cashflow volatility (4 characteristics x 5 portfolios). The black line connects all B/M-sorted portfolios. The red line connects the prior month return portfolios. The green line connects the liquidity sorted portfolios, and the blue line connects the cashflow volatility sorted portfolios.

E. 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 (1993) factors with 4x5 characteristic-sorted excess portfolios. Although SMB and HML 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–French (1993) three-factor model cannot capture the cross-sectional return variation of the test assets is also reflected in the intercept, with 10 out of 20 intercepts being significantly different from zero. This is formally confirmed by the GRS-test statistic, which is rejected at the 1% significance level.

In contrast, the INS5 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.[25]

[25] Note that we only report factor loadings for the portfolios for which the factor is intended to explain the cross-sectional variation in returns. 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 – FF3 factor model

	Low	2	Medium	3	High
			Book-to-market portfolios		
MKTRF	0.59***	0.74***	0.58***	0.55***	0.69***
	[7.19]	[6.91]	[8.79]	[9.93]	[9.08]
			RET_{t-1} portfolios		
	0.82***	0.58***	0.56***	0.55***	0.63***
	[11.97]	[9.07]	[7.44]	[8.27]	[8.55]
			Liquidity portfolios		
	0.57***	0.57***	0.56***	0.63***	0.80***
	[9.06]	[8.06]	[7.17]	[8.94]	[12.42]
			Cashflow volatility portfolios		
	0.54***	0.58***	0.63***	0.58***	0.85***
	[6.89]	[6.97]	[9.47]	[9.73]	[9.04]
			Book-to-market portfolios		
SMB	-0.45***	-0.37***	-0.10	-0.11	-0.02
	[-3.64]	[-3.65]	[-1.25]	[-1.12]	[-0.20]
			RET_{t-1} portfolios		
	-0.32***	-0.21**	-0.22**	-0.20***	-0.13
	[-2.95]	[-2.50]	[-2.07]	[-2.77]	[-1.55]
			Liquidity portfolios		
	-0.18**	-0.15*	-0.31***	-0.32***	-0.19***
	[-2.09]	[-1.88]	[-2.60]	[-2.77]	[-2.93]
			Cashflow volatility portfolios		
	-0.30***	-0.28***	-0.24***	-0.01	-0.23*
	[-2.69]	[-2.60]	[-3.33]	[-0.06]	[-1.88]
			Book-to-market portfolios		
HML	0.28***	0.49***	0.40***	0.48***	0.50***
	[2.66]	[3.66]	[5.12]	[6.99]	[4.75]
			RET_{t-1} portfolios		
	0.55***	0.35***	0.34***	0.45***	0.51***
	[6.67]	[3.84]	[4.20]	[5.83]	[4.84]
			Liquidity portfolios		
	0.42***	0.42***	0.36***	0.51***	0.65***
	[4.48]	[5.67]	[3.69]	[5.89]	[6.69]
			Cashflow volatility portfolios		
	0.33***	0.41***	0.47***	0.39***	0.57***
	[3.82]	[4.49]	[6.48]	[4.37]	[4.14]
			Book-to-market portfolios		
α	0.06	0.09	0.20	0.13	0.70***
	[0.26]	[0.43]	[1.00]	[0.74]	[3.00]
			RET_{t-1} portfolios		
	1.20***	0.44**	0.31*	-0.01	-0.81***
	[6.05]	[2.08]	[1.66]	[-0.05]	[-3.49]
			Liquidity portfolios		
	0.12	0.25	0.09	0.39**	0.34
	[0.54]	[1.25]	[0.58]	[2.13]	[1.54]
			Cashflow volatility portfolios		
	0.43**	0.41**	0.24	0.43*	-0.72**
	[2.25]	[2.01]	[1.24]	[1.92]	[-2.49]

GRS-test statistic = 4.62***, 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 – INS5 model

	Low	2	Medium	3	High
			Book-to-market portfolios		
MKTRF	0.46***	0.57***	0.50***	0.44***	0.51***
	[7.02]	[6.18]	[7.98]	[7.00]	[6.84]
			RET_{t-1} portfolios		
	0.53***	0.49***	0.47***	0.44***	0.55***
	[7.14]	[7.12]	[7.07]	[6.06]	[7.74]
			Liquidity portfolios		
	0.50***	0.51***	0.42***	0.47***	0.52***
	[7.13]	[7.28]	[5.46]	[6.32]	[7.46]
			Cashflow volatility portfolios		
	0.47***	0.48***	0.51***	0.53***	0.46***
	[6.74]	[6.98]	[6.50]	[7.83]	[6.38]
			Book-to-market portfolios		
BMF	-0.54***	-0.42***	-0.02	-0.02	0.66***
	[-6.62]	[-3.47]	[-0.41]	[-0.38]	[7.40]
			RET_{t-1} portfolios		
PRETF	-0.68***	-0.11	-0.01	0.16*	0.56***
	[-7.66]	[-1.29]	[-0.07]	[1.92]	[6.60]
			Liquidity portfolios		
LQF	-0.51***	-0.19**	0.04	0.19*	0.70***
	[-5.02]	[-2.43]	[0.53]	[1.92]	[7.27]
			Cashflow volatility portfolios		
CFVF	-0.28***	-0.16***	-0.10	0.02	1.00***
	[-3.92]	[-2.67]	[-1.59]	[0.35]	[12.78]
			Book-to-market portfolios		
α	0.35	0.66*	0.54*	0.23	0.49
	[1.16]	[1.90]	[1.70]	[0.87]	[1.56]
			RET_{t-1} portfolios		
	0.43	0.42	0.36	0.50*	0.41
	[1.55]	[1.43]	[1.27]	[1.69]	[1.53]
			Liquidity portfolios		
	0.52*	0.43	0.28	0.37	0.54*
	[1.92]	[1.39]	[0.89]	[1.17]	[1.96]
			Cashflow volatility portfolios		
	0.38	0.52*	0.33	0.65**	0.34
	[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.

F. Comparing Hansen-Jagannathan distances

Based on the time-series and cross-sectional evidence, we are interested in whether the INS5 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 INS5 model are rejected.

Table 8: Hansen-Jagannathan distance

	Null	CAPM	FF3	PETK5	INS5
$\hat{\delta}$	0.606	0.559	0.558	0.507	0.173
p($\delta = 0$)	0.000	0.000	0.000	0.001	0.972
Std. Err.	0.059	0.059	0.061	0.075	0.069
2.5% CI(δ)	0.503	0.457	0.454	0.383	0.085
97.5% CI(δ)	0.737	0.693	0.696	0.681	0.356
Max. Error	12.2	11.2	11.2	10.2	3.5
J-test	82.57	76.80	63.98	45.96	6.47
p(*J*-test)	0.000	0.000	0.000	0.000	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 (PETK5), and 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. $\hat{\delta}$ is the HJ distance. p($\delta = 0$) is the p-value for the test H_0: $\delta = 0$. CI(δ) is the 95% confidence interval for δ. *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 V.D. Again, though, we also see that the INS5 model is significantly outperforming all other models at the 1% level (Table 9).

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

	CAPM	FF3	PETK5	INS5
Null	0.055***	0.056***	0.110***	0.337***
	(0.002)	(0.007)	(0.008)	(0.000)
CAPM		0.001	0.056*	0.283***
		(0.897)	(0.079)	(0.000)
FF3			0.055***	0.282***
			(0.002)	(0.000)
PETK5				0.227***
				(0.000)

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 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*, $\hat{\delta}_i - \hat{\delta}_j$, and the respective p-value in parentheses for the test $H_0 : \hat{\delta}_i^2 = \hat{\delta}_j^2$.

G. 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.

a. 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.[26] 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.[27] 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

[26] See Braun (2015) for using the index as a proxy for the reinsurance cycle.

[27] We would like to thank Alexander Braun for making the data available to us. For further details about the index, see Braun (2015).

(Columns 3 and 4) and high cashflow volatility insurers (Columns 5 and 6).[28] Control variables are the Fama–French (1993) three factors and the Pàstor–Stambaugh (2003) traded liquidity factor. 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) CF volatility spread	(2) CF volatility spread	(3) CFVOLA 1 (Low)	(4) CFVOLA 1 (Low)	(5) CFVOLA 5 (High)	(6) CFVOLA 5 (High)
ΔRate-on-Line	0.24***	0.21***	-0.04	0.03	-0.28*	-0.17**
	[2.92]	[2.68]	[-0.38]	[0.52]	[-1.93]	[-2.49]
MKTRF		-0.31		0.47***		0.77***
		[-1.37]		[3.79]		[4.33]
SMB		0.36		-0.02		-0.38
		[0.79]		[-0.10]		[-0.89]
HML		-0.17		0.45***		0.62***
		[-0.75]		[4.31]		[2.85]
PS_LIQ		0.16		-0.18		-0.33
		[0.56]		[-1.22]		[-1.20]
α	1.66	1.99	2.42**	1.14	0.76	-0.85
	[0.99]	[1.49]	[2.43]	[1.46]	[0.38]	[-0.77]
Adj. R^2 (%)	2.9	3.4	-1.3	47.2	3.1	39.7
Obs.	66	66	66	66	66	66

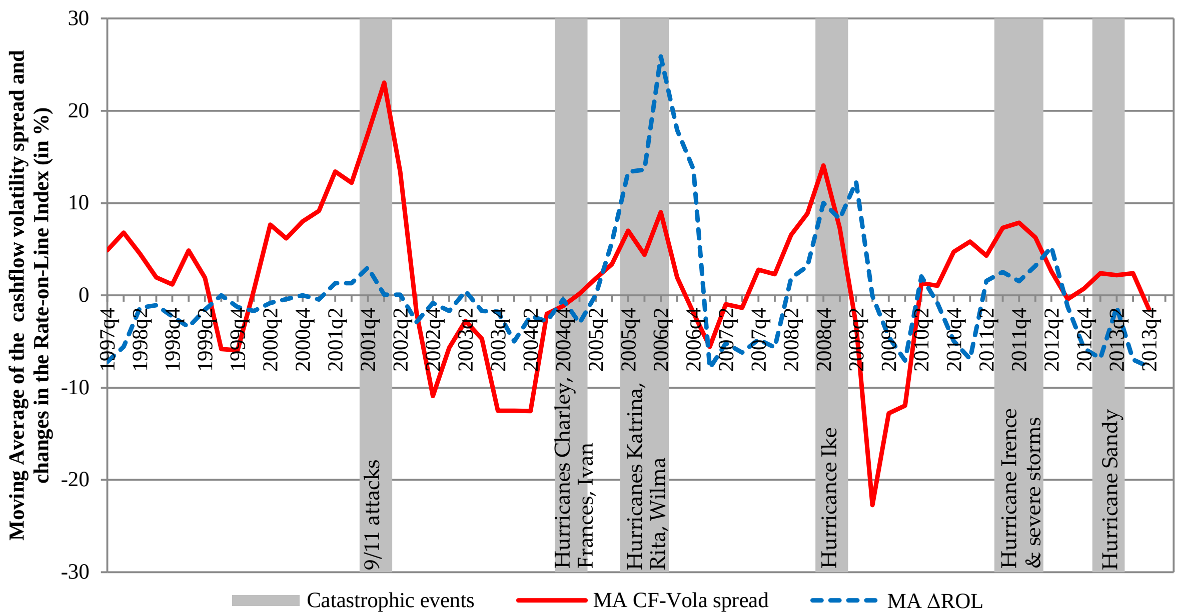
This table presents time-series regressions on return spreads of insurance stocks sorted by historical cashflow volatility in Columns 1 and 2 (low minus high cashflow volatility) and excess returns on insurance stocks with low historical cashflow volatility (Columns 3 and 4) and high cashflow volatility (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 five. *, **, 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

[28] 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.

the period 1997 to 2013 (shaded areas).[29] 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 (see Table A8 in the Appendix).

29 See Appendix C for more details about each event. We also add one quarter of shading to each event in Figure 2, because it can take several weeks to months until accurate estimates of the claims are available in the market.

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.

b. 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–French (1993) factors and Pàstor–Stambaugh (2003) traded liquidity factor 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).[30]

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***		-0.13		-0.13		-0.21***
		[-4.00]		[-1.01]		[-1.51]		[-2.81]
SMB		0.11		0.22		0.18		0.20
		[0.66]		[1.32]		[1.40]		[1.35]
HML		-0.08		-0.04		-0.03		-0.14
		[-0.60]		[-0.19]		[-0.25]		[-1.35]
PS_LIQ		-0.02		0.05		0.08		-0.02
		[-0.21]		[0.42]		[0.90]		[-0.23]
α	-2.36***	-2.07***	-1.96***	-1.96***	-1.75***	-1.72***	-2.01***	-1.82***
	[-5.90]	[-5.29]	[-4.80]	[-4.51]	[-5.61]	[-5.48]	[-6.88]	[-6.47]
Adj. R^2 (%)	0.0	5.9	0.0	-0.0	0.0	0.0	0.0	3.7
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)).

[30] 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.

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 (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)).[31] 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.[32] 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. We again include the Fama–French (1993) three factors and Pàstor–Stambaugh (2003) traded liquidity factor as additional control variables (F_t):

$$(9)\qquad R_t^{Loser-Winner} = \alpha + \beta_{VOL}VOLA_{t-2} + \beta_{DOWN}DOWN_{t-2} + \beta_{(VIX-VOLA)}(VIX_{t-2} - VOLA_{t-2}) + \beta_{CATRisk}CATRisk_{t-2} + c'controls_t + \beta' F_t + \varepsilon_t.$$

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

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[31] 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/haozhouspersonalhomepage/.

[32] 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 (in contrast to Section V.G.a where we work with quarterly data).

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 overreactions 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.

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	1.2	0.7	7.7	7.4	9.0	8.9	9.2	10.5	11.2	11.2
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.

c. 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.[33] 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

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

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.[34] Additional controls are the Fama–French (1993) factors and Pàstor–Stambaugh (2003) traded liquidity factor. 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. 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.

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

	(1)	(3)	(4)	(5)
HL-DLI	-0.11**	-0.10**	-0.10**	-0.10**
	[-2.22]	[-2.16]	[-2.12]	[-2.10]
MKTRF		0.12	0.12	0.11
		[1.20]	[1.19]	[1.13]
SMB		0.38*	0.38*	0.39*
		[1.93]	[1.93]	[1.97]
HML		0.20	0.20	0.18
		[1.47]	[1.45]	[1.31]
PS_LIQ		-0.02	-0.04	-0.05
		[-0.18]	[-0.33]	[-0.36]
Loss Ratio			0.02	0.02
			[0.22]	[0.23]
Financial Crisis				-0.02
				[-1.58]
α	0.01**	0.01*	0.01*	0.01**
	[2.55]	[1.93]	[1.85]	[2.04]
Adj. R^2 (%)	2.7	9.9	9.9	10.0
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.

[34] 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.

VI. Robustness

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

A. Size and B/M portfolios

A potential point of critique to our approach so far is that the Fama–French (1993) three-factor model was constructed to explain size and B/M-sorted portfolios in the cross-section of stock returns (and so far we only look at B/M-sorted portfolios). 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 (1993) three-factor model copes with insurance stocks sorted on these two characteristics, and how the INS5 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 14), 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 (t-value for the differences between 2 and 1 is 3.01). This supports the idea that only the smallest stocks in the insurance sector are exposed to a size anomaly.

Table 14: 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.

Similarly, the B/M anomaly is driven by the most extreme portfolios when sorted by B/M (Panel B of Table 14). 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.

B. Fama–MacBeth (1973) regressions with portfolios sorted by B/M and size

We first run Fama–MacBeth (1973) regressions, as in Section V.D. 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, supporting the idea that there is some size exposure in the most extreme portfolios. Still, BMF from the INS5 model seems also to capture this weakly significant anomaly, leaving the SMB coefficient insignificant if we include BMF in the regression (Column IV of Table 15).

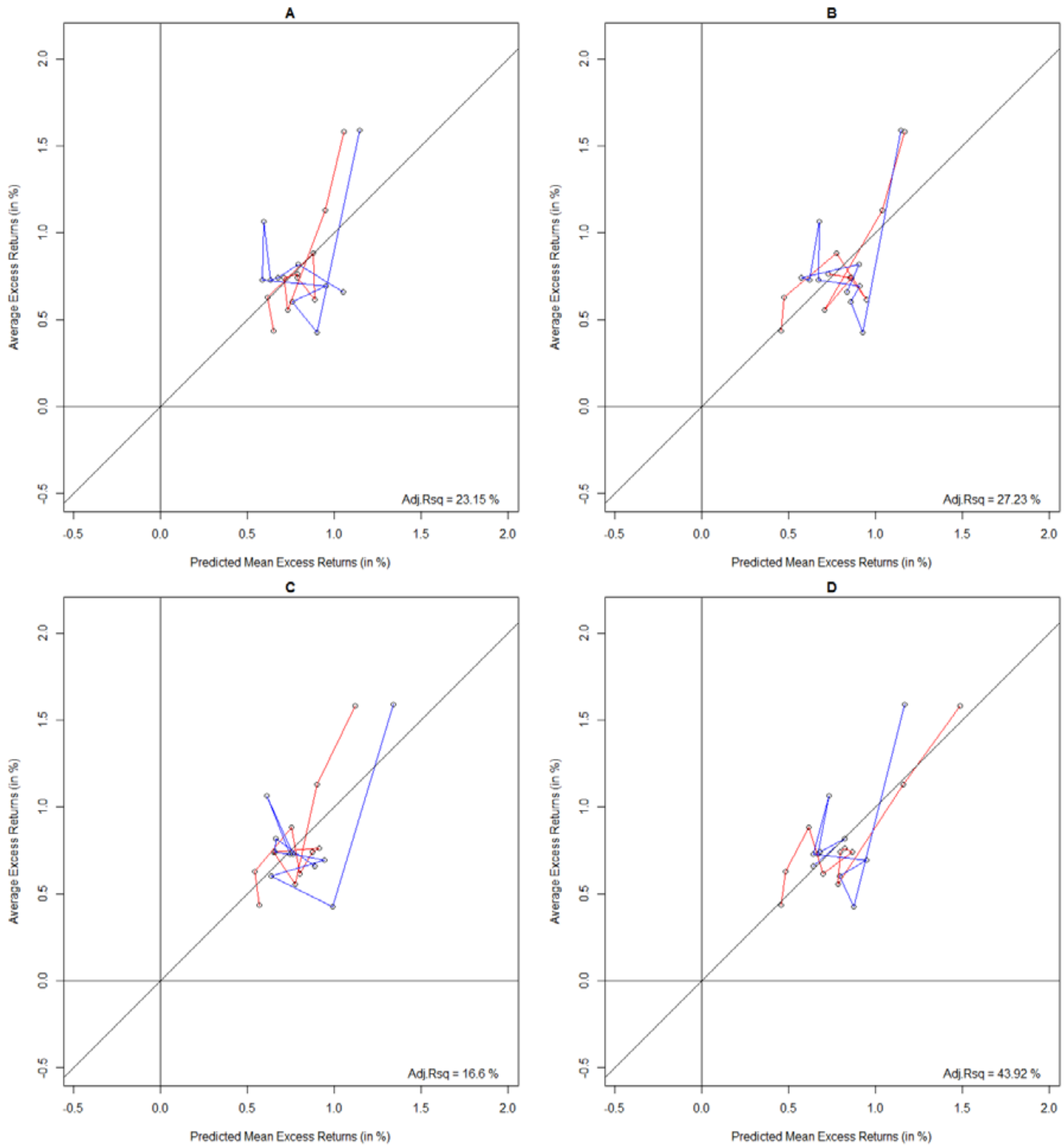
Table 15: Fama–Macbeth (1973) regression with portfolios and risk factors

	(I) FF-3	**(II)** Petkova-5	**(III)** INS5	**(IV)** Control-1
β_{MKTRF}	1.63*	2.20**	1.013	-0.070
	[1.66]	[2.05]	[1.00]	[-0.07]
β_{BM}			0.664**	0.623**
			[2.55]	[2.33]
β_{PRET}			-0.003	
			[-0.00]	
β_{LIQ}			0.167	
			[0.26]	
β_{CFVOLA}			0.061	
			[0.11]	
β_{SMB}	0.87*			-0.164
	[1.70]			[-0.32]
β_{HML}	0.48			0.166
	[0.82]			[0.28]
$\hat{u}^{TERM}$		0.07		
		[0.65]		
$\hat{u}^{DEF}$		0.02		
		[0.19]		
$\hat{u}^{div}$		0.01		
		[0.62]		
$\hat{u}^{RF}$		-0.03		
		[-1.31]		
Const. (z)	-0.24	-0.20	0.348	0.782
	[-0.48]	[-0.02]	[0.68]	[1.47]
Avg. R^2(%)	0.37	0.38	0.45	0.43

Column (I) describes the Fama–French (1993) three-factor model. Column (II) describes the Carhart (1997) four-factor model. Column (III) describes the Petkova (2006) five-factor model. Column (IV) describes the five-factor insurance model. Standard errors are Shanken (1992) corrected.

When we visually compare the ten size- and ten B/M-sorted portfolios (Figure 3), we also see that the overall fit using the INS5 model is superior to the Fama–French (1993) three-factor model. The Fama–French (1993) three-factor model has an adjusted R-square of 27.23% (Graph B) versus an adjusted R-square of 43.92% in the INS5 model (Graph D).

Figure 3: Actual vs. predicted returns



Graph A shows the actual excess returns and the predicted return by the CAPM. Graph B shows the actual excess returns and the predicted returns by the FF-3 model. Graph C shows the actual excess returns and the predicted return by the Petkova (2006) five-factor model. Graph D shows the actual excess returns and the predicted return by the INS5 model. In the bottom right the adj. R-square from a single cross-sectional regression is reported. The portfolios are 20 excess return portfolios sorted by B/M ratio and size. The red line connects the B/M sorted portfolios, and the blue line connects the size sorted portfolios.

C. 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 (1993) three-factor model, despite the inclusion of the SMB factor due to the significant intercept value (Panel A of Table 16). 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 16.

Table 16: Ten size-sorted portfolios

Panel A: Fama-French (1993) three-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	0.74***	0.59***	0.48***	0.58***	0.40***	0.47***	0.51***	0.64***	0.80***	1.12***	0.38**	0.22*	0.17**
	[7.13]	[6.66]	[5.84]	[7.55]	[5.23]	[5.03]	[5.93]	[10.01]	[7.25]	[7.12]	[2.47]	[1.96]	[2.50]
SMB	-0.01	0.04	0.13	0.09	0.07	-0.08	-0.18	-0.48***	-0.60***	-1.16***	-1.15***	-0.64***	-0.61***
	[-0.06]	[0.37]	[1.40]	[0.83]	[0.56]	[-0.63]	[-1.49]	[-4.63]	[-5.13]	[-8.84]	[-5.63]	[-4.96]	[-5.11]
HML	0.38**	0.38***	0.43***	0.26**	0.42***	0.48***	0.38***	0.39***	0.76***	0.54***	0.16	0.38*	-0.04
	[2.54]	[3.18]	[4.17]	[2.30]	[3.77]	[3.95]	[3.86]	[4.53]	[3.91]	[2.84]	[0.60]	[1.70]	[-0.44]
α	0.89**	-0.15	0.09	0.14	0.29	0.58**	0.25	0.20	0.07	-0.21	-1.10***	0.22	0.10
	[2.56]	[-0.58]	[0.36]	[0.60]	[1.17]	[2.31]	[1.11]	[0.99]	[0.33]	[-0.79]	[-2.74]	[0.67]	[0.39]
Adj. R^2	24.8%	24.6%	26.9%	35.4%	21.8%	22.5%	28.5%	40.1%	35.2%	49.3%	12.2%	8.3%	8.9%

Panel B: INS5 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	41.4%	26.1%	22.6%	33.4%	19.4%	20.7%	29.1%	29.7%	18.0%	32.9%	35.6%	6.5%	3.4%

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 (1993) three-factor model. Panel B reports time-series regressions for the INS5 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.

When we run the INS5 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 16). This seems to be mostly attributed to the BMF factor, which already showed in the Fama–MacBeth (1973) regressions in Section VI.B that it remains significant even if SMB was included (Table 15). Here, in the time-series regressions BMF loads 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 (1993) three-factor model is not able to capture even the variation in portfolios for which it was designed, leaving a significant intercept between the most extreme B/M-sorted portfolios (Panel A of Table 17). In contrast, the INS5 model captures all significant intercepts between the most extreme portfolios (Panel B of Table 17).

Table 17: Ten B/M-sorted portfolios

Panel A: Fama-French (1993) three-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	0.64***	0.54***	0.82***	0.67***	0.51***	0.65***	0.54***	0.56***	0.64***	0.72***	0.08	0.10	-0.26*
	[7.68]	[5.33]	[5.96]	[7.52]	[7.19]	[8.32]	[6.84]	[7.87]	[8.36]	[6.32]	[0.62]	[0.95]	[-1.67]
SMB	-0.54***	-0.33**	-0.62***	-0.17*	0.08	-0.32***	-0.07	-0.15	0.02	-0.03	0.51**	0.35*	0.47***
	[-3.93]	[-2.59]	[-4.02]	[-1.95]	[0.68]	[-3.93]	[-0.48]	[-1.30]	[0.12]	[-0.19]	[2.06]	[1.76]	[2.80]
HML	0.28***	0.26**	0.46***	0.51***	0.40***	0.39***	0.59***	0.37***	0.49***	0.55***	0.27	0.23	-0.09
	[2.59]	[2.17]	[2.89]	[3.93]	[3.85]	[4.49]	[6.46]	[4.12]	[3.96]	[2.96]	[1.21]	[1.39]	[-0.50]
α.	-0.07	0.18	0.20	-0.03	0.22	0.19	0.17	0.04	0.49	0.87**	0.93**	0.31	-0.16
	[-0.29]	[0.59]	[0.76]	[-0.12]	[1.03]	[0.75]	[0.75]	[0.15]	[1.59]	[2.35]	[2.17]	[0.82]	[-0.53]
Adj. R^2	28.7%	20.1%	36.2%	38.4%	27.7%	34.2%	32.8%	28.4%	31.9%	19.4%	3.8%	3.8%	4.4%

Panel B: INS5 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	0.47***	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	36.5%	32.3%	30.2%	34.9%	23.0%	24.7%	21.7%	22.7%	36.8%	41.3%	60.4%	43.9%	11.2%

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 (1993) three-factor model. Panel B reports time-series regressions for the INS5 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.

VII. Conclusion

Extant asset pricing models (such as CAPM, Fama–French (1993) or Petkova (2006)) fail to explain the cross-sectional return behavior of stocks in the p/l industry. This is an important finding, because it indicates that insurance practitioners – which use CAPM and the Fama–French (1993) three-factor model as industry standards (e.g., to price insurance policies) – are not taking all necessary risk factors into account.

A second main result of the paper is that the book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility are priced in the cross-section of p/l insurance stocks. We use those four factors plus the market factor to develop an insurance-specific five-factor (INS5) model that provides more accurate cost-of-capital estimates than existing 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.[35] The results also reflect anecdotal evidence 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 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.

Future research might also analyze the relevance and potential spill-over effects of our risk factors outside the insurance context, for example for other sectors exposed to catastrophic risk

[35] 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.

like the construction industry or the energy and utility sector. Because insurers act as shock absorbers there could also be a link between economic growth and our risk factors if the overall exposure to these risk factors increases and insurers pursue a more conservative underwriting strategy.

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.

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.

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.

Leland, H. E. "Beyond Mean-Variance: Performance Measurement in a Nonsymmetrical 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.

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.

Pástor, 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.

Online Appendix A: Literature overview and contribution of this paper

Table A1: Literature overview and contribution of this paper

Field of Research	Financial firms (focus on banks)			Property / liability insurers					
Paper / **Criteria**	Barber and Lyon (1997)	Viale, Kolari, and Fraser (2009)	Gandhi and Lustig (2015)	Cummins and Harrington (1988)	Cummins and Lamm-Tennant (1994)	Cummins and Phillips (2005)	Carson, Elyasiani, and Mansur (2008)	Wen et al. (2008)	**This paper**
Industry	Financial firms (banking and insurance)	Banks	Commercial banks	p/l	p/l	p/l	p/l, Accident & Health, Life	p/l	p/l
Portfolios or Stocks	Portfolios	Portfolios	Portfolios	Stocks	Stocks	Portfolios	Portfolios	Stocks and portfolios	Stocks and portfolios
Time period	1973–1994 (22 years)	1986–2003 (18 years)	1970 (1980) – 2013 (43 and 33 years, resp.)	1970–1983 (14 years)	1980–1989 (9 years)	1997–2000 (4 years)	1991–2001 (11 years)	1970–2001 (31 years)	1988–2013 (26 years)
Theoretical or empirical	Empirical / descriptive (sorting portfolios)	Empirical	Theoretical and empirical	Empirical	Theoretical and empirical	Empirical	Empirical	Empirical	Empirical
Framework / Model	No model (portfolio sorting only)	Petkova (2006) 5-factor model	Fama–French (1993) 3-factor model and bond factors	CAPM with skewness and idiosyncratic risk	ICAPM	CAPM and Fama–French (1993) 3-factor model	Extended CAPM with System-GARCH	CAPM and Rubinstein–Leland (1976, 1999)	CAPM, ICAPM, Fama–French (1993) 3-factor model, insurance-specific 5-factor model (INS5)
Asset pricing test (i.e., testing pricing errors)	No	Yes	Not applicable (focus on largest commercial banks)	Partially (i.e., testing significance of risk premium)	No	No	No	No	Yes (i.e., cross-sectional pricing of traded factors, HJ distance, time-series regressions including tests on intercepts)
Approach	Sorting stocks by characteristics into equally weighted portfolios	Time-series and cross-sectional regressions	Time-series regressions	Run cross-sectional regressions with average insurance stocks returns	Run factors against CAPM beta in pooled regression	Compare cost of capital estimates	Time-series regression	Compare risk estimates (i.e., betas) of CAPM and RL	Sort stocks by characteristics; run Fama–MacBeth (1973) regressions, time-series regressions; Hansen-Jagannathan (HJ) distance comparison
Key findings	Size and B/M anomalies are also present in financial firms	Term structure and default spread are sufficient in pricing the cross-section of bank stocks	Size anomaly different for commercial banks: lower returns for largest banks compared to other banks due to government guarantees	Idiosyncratic risk is correlated with returns	Insurance leverage and financial leverage affect market beta	CoC for insurers using Fama–French model significantly higher than CAPM estimates	Market risk is greatest for accident & health insurers. Interest rate sensitivity greatest for life insurers	Small insurers (with asymmetric returns) should use RL model rather than CAPM to estimate cost of capital	Book-to-market ratio; prior-month return; illiquidity; cashflow volatility are priced. Size anomaly only in the smallest decile

Online Appendix B: Firm data

Table A2: Firm data

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.

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		

Online Appendix C: Summary statistics

Panel A of Table A3 summarizes the monthly individual stock returns of the p/l insurance industry and the independent variables relevant for cross-sectional regressions.[36] These independent variables are firm specific and differ among all insurers. Beta values in Panel A are computed from rolling time-series regressions on each firm. The independent variables are also the 21 characteristics on which we sort insurance stocks and which were introduced in Section III. Panel B of Table A3 reports the factor variables employed by the different asset pricing models presented in Section IV.A. These variables are used both in cross-sectional and time-series regressions and are common to all insurers. The market excess return is the excess return of CRSP's equally weighted market return index. The fact that the p/l insurance sector differs from the overall market is indicated through a correlation of only 0.65 between the market and an equally weighted return index of p/l insurers.

[36] The maximum raw return in Table A3 dates back to American International Corp. (AIG) in August 2009; the minimum return also belongs to AIG and dates back to September 2008.

Table A3: Summary statistics

Panel A: Characteristic values of insurers

	Mean	Std. Dev.	Min.	Max.
Dependent variables				
Raw return	0.011	0.104	-0.835	2.45
Independent variables				
β_{CAPM}	0.588	0.444	-0.407	1.820
β_{Downside}	0.633	0.533	-0.996	2.229
β_{Upside}	0.547	0.651	-1.383	2.224
Ln(Market Cap)	12.953	2.074	8.343	17.386
Book-to-market	0.934	0.503	0.246	3.772
Momentum	0.066	0.297	-0.909	0.817
Previous month return	0.007	0.088	-0.282	0.276
β_{LIQ}	0.048	0.415	-1.292	1.433
REV	0.149	0.447	-1.273	1.246
ID-VOLA	0.020	0.016	0.003	0.093
CF-VOLA	0.082	0.159	0.004	1.230
$\beta_{\text{CO-SKEW}}$	-2.367	16.162	-67.120	51.368
$\beta_{\text{CO-KURT}}$	-24.283	1351.874	-6197.054	5079.027
Asset growth	0.109	0.187	-0.308	1.161
$\beta_{\Delta\text{TERM}}$	0.017	0.047	-0.087	0.170
$\beta_{\Delta\text{DEF}}$	-0.023	0.051	-0.195	0.095
INVEST	-0.187	0.271	-1.091	0.628
$\beta_{\text{B/D LEV}}$	0.001	0.006	-0.018	0.024
INS LEV	231.266	584.050	0	3636.551
FIN LEV	17.552	46.174	0	300.144
Total LEV	266.194	650.513	0.243	3899.635
β_{SMB}	0.435	0.588	-0.964	2.296
β_{HML}	0.401	0.623	-1.524	2.329

Panel B: Factor variables

	$\boldsymbol{R_{MKTRF}}$	$\boldsymbol{SMB}$	$\boldsymbol{HML}$	$\hat{\boldsymbol{u}}^{\boldsymbol{TERM}}$	$\hat{\boldsymbol{u}}^{\boldsymbol{DEF}}$	$\hat{\boldsymbol{u}}^{\boldsymbol{div}}$	$\hat{\boldsymbol{u}}^{\boldsymbol{RF}}$
Mean	0.008	0.002	0.002	0.000	0.000	0.000	0.000
Std. dev.	0.053	0.032	0.031	0.003	0.003	0.001	0.000
Min.	-0.206	-0.164	-0.127	-0.008	-0.010	-0.002	-0.001
Max.	0.220	0.220	0.139	0.010	0.021	0.003	0.001
Obs.	306	306	306	306	306	306	306

This table reports summary statistics for the dependent and independent variables. Panel A shows the realized raw return of p/l insurers. Panel B reports the independent variables, which are winsorized at the 1st and 99th percentiles and used in cross-sectional regression tests.

Online Appendix D: Analyzed characteristics

Data are retrieved from the Center for Research in Security Prices (CRSP), Compustat, and personal webpages of academics. All variables used in this study are measured once a year or once a month depending on the variable. We use only information known to investors at the date of calculation and thus do not introduce a look-ahead bias.

Table A4: Analyzed characteristics

β / β^- / β^+	Regular CAPM / downside / upside betas are measured as post-ranking betas using daily data in a rolling window of one year and in step sizes of one month.
Ln(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. The natural logarithm is applied in individual stocks regressions.
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 (Compustat data item "bkvlps") plus investment tax credit (Compustat data item "txditc") if available. Market equity is defined as price times shares outstanding.
MOM	Momentum is the cumulative monthly stock return from month $j-12$ to $j-2$. The *j-1* month return is skipped to avoid the previous month return anomaly. The Momentum variable is measured each month.
RET_{t-1}	The previous month return is defined as CRSP's raw return from month *j-1*.
β_{LIQ}	The liquidity beta is measured as the co-movement with Pàstor 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 of three years and step sizes of one month.
REV	Reversal is defined as the cumulative monthly stock return from month $j-37$ to $j-13$.
ID-VOLA	Idiosyncratic volatility.
CF-VOLA	Cashflow volatility is defined as the standard deviation over the previous eight quarterly cashflow figures. Cashflow is defined as the sum of income before extraordinary items, depreciation, and amortization. Cashflows are additionally standardized by quarterly sales figures (Huang 2009).
CO-SKEW	Co-skewness is defined as the coefficient on a squared market factor from rolling regressions on daily excess returns over the past year.
CO-KURT	Co-kurtosis is defined as the coefficient on a cubic market factor from rolling regressions on daily excess returns over the past year.
Asset Growth	Asset growth is defined as the percentage change in total assets from the fiscal year ending in calendar year $t-2$ to fiscal year ending in calendar year $t-1$ (Cooper, Gulen, and Schill 2008).
$\beta_{\Delta TERM}$	$\beta_{\Delta TERM}$ 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 FRED.
$\beta_{\Delta DEF}$	$\beta_{\Delta DEF}$ is defined as the beta exposure over the past 36 months. ΔDEF is the change in yields between Moody's Baa corporate bond and the 10-year Treasury yield downloaded from FRED.
INVEST	Investment performance is defined as the cashflows from investment activity (COMPUSTAT item: IVNCF) standardized by total insurance premiums (COMPUSTAT item: IPTI).
$\beta_{B/D\ LEV}$	$\beta_{B/D\ LEV}$ is defined as the exposure of the broker/dealer leverage factor over the past 36 months (12 quarters). The broker/dealer leverage factor is downloaded from Tyler Muir's website.
INS/LEV	Insurance leverage is defined as other liabilities (COMPUSTAT item: LO) divided by market equity.
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.
Total LEV	Total leverage is defined as the difference between total assets and book equity divided by market equity.

Online Appendix E: β_{SMB} and β_{HML}-sorted portfolios

In Table A5 we find that there is a weakly significant size effect that is not explained by the CAPM. The direction of this effect is surprising, with low SMB exposure earning higher returns; that is, low exposure to the small company effect results in higher returns. This somewhat contradicts the idea that higher SMB exposure leads to higher returns, but rather suggests that a large SMB exposure is not compensated by higher returns. A larger insurance company earns lower returns (i.e., stocks sorted by market capitalization), but a low SMB exposure results in higher returns. This effect in SMB exposure, however, can be explained by the Fama–French (1993) three-factor model itself.

The HML (beta exposure) sorting follows the same logic as the SMB (beta exposure) sorting. Here again, we observe a reverse relation from what we would have expected. A high beta exposure to the HML factor results in lower returns, although we would expect that a high exposure – that is, a strong effect on the B/M anomaly – leads to larger returns. Note, however, that the spread is not significant (Panel A of Table A5 in the Appendix), but the Fama–French (1993) three-factor alpha becomes significant, suggesting that the Fama–French (1993) three-factor model is falsely specified for the insurance sector to capture its unique B/M effect. Specifically, it explains why the Fama–French (1993) three-factor model is not able to capture the B/M anomaly in insurance stocks shown in Table 1.

Table A5: β_{SMB} and β_{HML}-sorted portfolios

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

Quantile	β_{SMB}-sorted	β_{HML}-sorted
1 (low)	1.28	1.20
2 (mid)	1.15	1.08
3 (high)	0.72	1.03
Spread (3-1)	-0.56* [-1.78]	-0.17 [-0.61]
CAPM Alpha (Spread)	-0.53* [-1.66]	-0.27 [-1.04]
# of observations (*T*)	306	306

Panel B Alphas from Fama–French 3-factor model regressions (in % per month, July 1988–December 2013)

	β_{SMB}-sorted	β_{HML}-sorted
1 (low)	0.26 [1.33]	0.37 [1.64]
2 (mid)	0.33** [2.08]	0.28* [1.81]
3 (high)	-0.12 [-0.53]	-0.09 [-0.46]
FF-3 Alpha (Spread)	-0.38 [-1.39]	-0.46* [-1.84]

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 beta exposure on SMB and HML. Panel A also reports the return spread between high minus low exposure, the intercept from time-series regressions with the market factor as independent variable (i.e., CAPM Alpha(Spread), and the number of monthly observations. Panel B reports the intercepts from time-series regressions with the market factor, SMB, and HML as independent variables (i.e., FF-3 Alpha) 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. The last row indicates the FF-3 alpha from time-series regressions on the spread between high minus low exposure (i.e., FF-3 Alpha (Spread).

Online Appendix F: Fama–MacBeth (1973) regressions with individual stock returns

Table A6: Fama–MacBeth (1973) regressions with individual stock returns (univariate)

	(I)	**(II)**
β_{SMB}	-0.35* [-1.77]	
β_{HML}		-0.08 [-0.34]
Const.	0.92*** [3.15]	0.86*** [3.46]
Avg. R^2	0.03	0.04

Online Appendix G: Correlation of principal components with common factors

Table A7: 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.

Online Appendix H: Catastrophic events in the U.S.

Table A8: Catastrophic events in the U.S. by insured loss (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)
9/11 Terrorist attacks	9/11/2001	9/11/2001	9/11/2001	NY, DC	Terror attack on WTC, Pentagon, and other buildings	25,664	3
Hurricane Charley	08/09/2004	08/13/2004	08/14/2004	FL, SC, NC	Storm surge	10,313	8
Hurricane Frances	08/25/2004	09/02/2004	09/09/2004	FL, SC, NC	Storm surge, floods	6,593	11
Hurricane Ivan	09/02/2004	09/16/2004	09/21/2004	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 Katrina	08/23/2005	08/25/2005	08/30/2005	FL, LA, MS, AL, TN, KY, IN, OH, GA	Storm surge, levee failure, damage to oil rigs	80,373	1
Hurricane Rita	09/18/2005	09/24/2005	09/26/2005	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	09/01/2008	09/07/2008	09/15/2008	TX, LA, AR, TN, IL, IN, KY, MO, OH, MI, PA	Floods, offshore damage	22,751	4
Severe storms and tornadoes	04/22/2011	04/25/2011	04/25/2011	AL, AR, LA, MS, GA, TN, VA, KY, IL, MO, OH, TX, OK	Storms and tornadoes	7,856	9
Severe storms and tornadoes	05/20/2011	05/22/2011	05/27/2011	MO, TX, OK, KS, AR, GA, TN, VA, KY, IN, IL, OH, WI, MN, PA	Storms and tornadoes	7 587	10
Hurricane Irene	08/21/2011	08/22/2011	08/30/2011	NC, VA, MD, NJ, NY, CT, RI, MA, VT	Extensive flooding	6 274	12
Hurricane Sandy	10/21/2012	10/24/2012	10/31/2012	MD, DE, NJ, NY, CT, MA, RI	Storm surge	36,890	2