Asset Pricing of Financial Institutions:
The Cross-Section of Expected Insurance Stock Returns

Semir Ben Ammar[a,*], Martin Eling[a] and Andreas Milidonis[b]

This version: 2015/01/12

Abstract
Two unsolved empirical questions are whether existing asset pricing models are able to explain the cross-section of insurance stock returns and whether there are other insurance specific return anomalies. We analyze the cross-section of 127 U.S. property/liability insurance stocks in the time period 1988 to 2013 to answer these two questions. We find that the book-to-market ratio, prior month return, illiquidity, and cashflow-volatility are priced in the cross-section of property/liability insurance stocks. Existing asset pricing models (e.g., Fama and French, 1993; Petkova, 2006) are not able to explain the cross-section of insurance stock returns. We develop a five factor model build upon the insurance-specific anomalies which explains the cross-sectional variation. Our results complete those of Fama and French (1992, 1993) on non-financial firms and Viale et al. (2009) on banks and shed new light on the pricing determinants of insurance products.

EFM classification: 310, 350, 740

Keywords: Asset pricing; Insurance Stocks; Multifactor Models; Anomalies; Cross-Section; Risk Factors

---

**Corresponding author:* Tel.: +41 71 224 79 94.

E-mail addresses: semir.benammar@unisg.ch, martin.eling@unisg.ch, amilidonis@ntu.edu.sg

[a] *Institute of Insurance Economics, University of St. Gallen, Kirchlistrasse 2, 9010 St. Gallen, Switzerland*

[b] *Insurance Risk and Finance Research Centre, Nanyang Business School, Singapore and University of Cyprus.*

1 Introduction

The finance literature in general excludes 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 main prediction of an asset pricing model, though, is that the expected return on *any* risky asset is linear in beta. Put in other words, the cross-sectional difference between the mean return of two assets is entirely predicted by their beta exposure. Since asset pricing models ought to capture cross-sectional discrepancies across all assets, it is an economically relevant question whether these models are able to price also insurance stocks.

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).[2] Third, 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.[3]

---

[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.

[2] The p/l insurance sector is exposed to unique risks from catastrophes resulting in barrier option-like return characteristic and returns which are uncorrelated with returns from the rest of the market. Two unsolved empirical questions are thus whether existing asset pricing models are able to explain the cross-section of expected insurance stock returns and whether there are other insurance specific return anomalies.

[3] 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 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 thus the return for shareholders deviates from what standard asset pricing models would predict.

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), or Eisfeldt and Papanikolaou (2013)), there is almost no literature on this in the insurance context.[4] Next from the general arguments for the exclusion of financial firms from asset pricing tests, another main reason for the almost non-existence of such literature for insurance is the scarce amount of insurance stocks.

Our paper closes this gap in the literature by analyzing the cross-section of expected insurance stock returns. We consider five asset pricing models[5], four of them are well known in the finance literature, the fifth one is constructed from our empirical findings and based on relevant hypotheses for each empirical finding. We test these models by running time-series regressions and Fama-MacBeth (1973) regressions on portfolios and individual stock returns. Moreover, we analyze well-known and potentially insurance-specific stock return anomalies which should be explained by asset-pricing models. For that purpose, we sort insurance stocks according to 21 characteristics.[6] Finally, we contribute to the discussion on interest rate exposure, leverage, size and other firm characteristics discussed in the insurance literature, which so far focused on the time-series relation (see e.g., Brewer et al. (2007) or Carson, Elyasiani, and Mansur (2008)).[7]

The central findings of this paper are that the book-to-market (B/M) ratio, prior month return, illiquidity, and cashflow-volatility are priced in the cross-section of p/l insurance stocks. The size anomaly is only present in smallest decile of insurance stocks. The Fama/French model can neither explain the size nor the B/M anomaly in the insurance stocks. A five factor model build

---

4 The only two exceptions are Harrington (1983) and Cummins and Harrington (1988). Barber und Lyon (1997) sort portfolios for financial firms and thus implicitly also analyze cross-section of insurance stocks although no formal tests are conducted in their paper.

5 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)).

6 The 21 characteristics are CAPM beta, downside beta, upside beta, size, B/M ratio, illiquidity, momentum, 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.

7 This study can also be considered as an out-of-sample test on the accuracy of asset pricing models in general. One central critique in asset pricing is the data snooping bias (Lo and MacKinlay (1990)) through portfolio formation, which is why Lewellen, Nagel, and Shanken (2010) emphasize the use of different test assets. All assets should be priced by one stochastic discount factor and insurance stocks might be one of the most challenging test assets, since their risk exposure is theoretically very different from other stocks.

upon 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 et al. (2009) on banks.

The remainder of this paper is organized as follows. Section 2 gives a brief literature review. Section 3 describes our hypotheses. Section 4 provides a description of the data and the methodology. Section 5 shows the empirical results. Section 6 checks for robustness, and Section 7 concludes.

2 Literature review

There are only two relatively old papers that analyze the cross-section of insurance stocks. Harrington (1983) investigates life insurers, finding some evidence of a significant relationship between mean returns and systematic risk (i.e. the CAPM-beta), but also a significant relationship between mean returns and measures of nonsystematic risk. The second one by Cummins and Harrington (1988) addressing p/l insurers finds that the CAPM is correctly specified during the period 1980 – 1983, but inconsistent in earlier periods. Since then, no researcher has directly analyzed the cross-section of insurance return.[8]

More recent related research on insurance analyzes cost of equity estimation (Cummins and Phillips (2005); Wen et al. (2008)) and the time series characteristics of insurance stocks (Brewer et al. (2007); Carson, Elyasiani, and Mansur (2008)).[9] Cummins and Phillips (2005) investigate the cost of equity for p/l insurers using the CAPM and the FF-3 model. They find that the costs of capital estimates of FF-3 model are significantly higher than those of the CAPM. The authors

---

[8] 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. More recently, Viale, Kolari, and Fraser (2009) analyze the cross-section of bank stocks. 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, they find no evidence of SMB or HML being priced in bank stock returns.

[9] Note that significant coefficients in a time-series regressions can only be a first indicator about risk. For example, the market factor is highly correlated with stock returns and yet is not capturing 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 makes thus sense even if it is not capturing the cross-section of stocks returns (Ferson, Sarkissian, and Simin (1999)).

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 applied by 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 RL-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 this paper only covers property/liability insurers and 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.[10]

More insurance literature exists on the time-series correlation between factors and insurance stock returns. Brewer et al. (2007) address the interest rate sensitivity of life insurers and find that their returns are negatively correlated with changes in interest rates. Carson, Elyasiani, and Mansur (2008) investigate the market risk, interest rate risk, and interdependencies across insurance industries within a GARCH time-series framework and find greater market exposure in life and health insurers compared to property/liability insurers. They also find that interest rate sensitivity is negative and greatest for life insurers while interdependencies in returns are strongest between property/liability and health insurers.[11] Table 1 summarizes the existing insurance literature and outlines the contribution of this paper.[12/13]

---

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

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

[12] It should be noted that there are numerous papers which apply asset pricing-pricing models in an insurance context. Especially, asset pricing models that account not only for shareholder but also policyholder interests go beyond the scope of this paper. See, e.g., Doherty (1991), Froot and Stein (1998), Froot and O'Connell (1997), Zanjani (2002), and Froot (2007), where risk management issues are integrated in standard asset pricing. Eckles, Halek, and Zhang (2013) apply the CAPM to analyze the impact of accruals quality.

Regarding the financial sector, i.e. commercial banks, Gandhi and Lustig (2014) show that the size anomaly in U.S. 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 1: Literature overview and contribution of this paper

Criteria \ **Paper**	Harrington (1983)	Cummins and Harrington (1988)	Cummins and Lamm-Tennant (1994)	Barber and Lyon (1997)	Cummins and Phillips (2005)	Brewer et al. (2007)	Carson, Elyasiani, and Mansur (2008)	Wen et al. (2008)	**This Paper**
Industry	Life	p/l	p/l	Financial firms (banking and insurance)	p/l	Life	p/l, A&H, Life	p/l	p/l
Portfolios or Stocks	Stocks and Portfolios	Stocks	Stocks	Portfolios	Portfolios	Portfolios	Portfolios	Stocks and Portfolios	Stocks and portfolios
Time period	1961-1976 (16 years)	1970 – 1983 (14 years)	1980 – 1989 (9 years)	1973 – 1994 (22 years)	1997 – 2000 (4 years)	1975 – 2000 (26 years)	1991 – 2001 (11 years)	1970 – 2001 (31 years)	1988 – 2013 (25.5 years)
Theoretical or empirical	Empirical	Empirical	Theoretical and Empirical	Empirical / descriptive (sorting portfolios)	Empirical	Empirical	Empirical	Empirical	Empirical
Actual estimation of cost of capital	No	No	No	No	Yes	No	No	No	No
Framework / Model	CAPM	CAPM with skewness and idiosyncratic risk	ICAPM	No model (portfolio sorting only)	CAPM and Fama-French 3-Factor model (1993)	Extended CAPM with GARCH-M	Extended CAPM with System-GARCH	CAPM and Rubinstein-Leland (1976, 1999)	CAPM, ICAPM, APT (5 models)
Asset pricing test (i.e. testing pricing errors)	Partially (i.e. testing significance of risk premium)	Partially (i.e. testing significance of risk premium)	No	No	No	No	No	No	Yes (i.e. cross-sectional pricing of traded factors, HJ distance, time-series regressions including tests on intercepts)
Approach	Run cross-sectional regressions with average insurance stocks returns	Run cross-sectional regressions with average insurance stocks returns	Run factors against CAPM beta in pooled regression	Sorting stocks by characteristics into equally-weighted portfolios	Compare CoC estimates.	Time-Series regression	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; HJ-Distance comparison
Key findings	Idiosyncratic risk is correlated with returns	Idiosyncratic risk is correlated with returns	Insurance leverage and financial leverage affect market beta.	Size and B/M anomalies are also present in financial firms.	CoC for insurers using Fama-French model significantly higher than CAPM estimates.	Stock returns of life insurers are negatively related to changes in interest rates.	Market risk is greatest for A&H insurers. Interest rate sensitivity greatest for life insurers.	Small insurers (with asymmetric returns) should use RL model rather than CAPM to estimate CoC.	Book-to-market ratio; prior-month return; illiquidity; cashflow volatility. Size anomaly only in the smallest decile.

[13] From a more holistic point of view, 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.

3 Hypotheses

Our main benchmark model in the empirical part is the Fama-French model which has shown superior performance in the U.S. equity market (see Cooper, Gulen, and Schill (2008) amongst others) and which also represents the state of the art in the insurance literature (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 in general excluded from asset pricing tests (Barber and Lyon (1997)), Ghandi and Lustig (2014)) due to their high leverage, thus giving leverage ratios a different meaning than for non-financial firms (Fama and French (1993)) and due 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 which give p/l insurers a barrier option-like characteristic introducing high downside risk.[14] The third reason is somewhat related to the previous one as losses from natural disasters (which do not need to be large in magnitude in contrast to the previous barrier option-like characteristic) result in uncorrelated returns from the rest of the market (Ibragimov, Jaffee, and Walden (2009)).[15]

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

[14] A barrier option pays a certain amount at expiration as long as a specific barrier is not hit. In case of an insurer this barrier can be interpreted as the solvency capital level. If a catastrophe is large enough to strike the barrier an insurer becomes immediately insolvent and would be unable to recover.

[15] The fact that natural disasters are (to some extent) uncorrelated with the rest of the market also led to a new financial instrument in the early nineties, so-called insurance-linked securities (ILS).

(1) Market risk: We expect that the market beta itself is not priced as risk factor identical to the findings on broad based studies (Fama and French (1992)) and previous findings by Cummins and Harrington (1988) on p/c insurers for earlier periods.

(2) B/M ratio: Insurers with high B/M ratios should earn higher returns. However, with p/c insurers being exposed to non-market related natural disasters and under the premise of the B/M ratio approximating some type of distress risk (Chen and Zhang (1998)) we expect a different meaning of the B/M ratio of insurers.

(3) Size (market capitalization): Larger insurers earn lower returns compared to smaller insurers as they might have a more diversified insurance portfolio and thus a lower risk exposure on their liability side.

(4) Past returns (momentum, prior month return, reversal): As for the finance literature in general, we expect similar results from past returns including a momentum effect based on the returns over the past twelve months (excluding the previous month before ranking the stocks). That is, past "winning" insurers outperform past "losing" insurers (Jegadeesh and Titman (1993)). We also expect that previous month returns, despite the transaction intensity, predict the cross-sectional behavior of insurance stocks as a result of overreaction to information. Last, we expect a return reversal when insurers are sorted by their returns over the past 36 months (excluding the previous 12 before ranking the stocks).

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

(6) Leverage (total, insurance, financial, Broker / Dealer): We also look at four different measures addressing leverage exposure. Total leverage, insurance leverage and financial

leverage relate to a lower solvency level and thus a higher risk of default (Bhandari (1988); Cummins and Lamm-Tennant (1994)). The 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 and treasuries made by insurers suggest that changes in interest rates, i.e. in the term structure and the ratings of interest-bearing securities have an impact on the cross-section of insurance stocks depending on the asset allocation of the insurer. An asset allocation towards long-term bonds and corporate bonds (instead of government bonds) should result in higher income and thus higher returns.

(8) Volatility (cashflow volatility, idiosyncratic risk): Both cashflow volatility (Huang (2009)) and idiosyncratic risk (with respect to the FF-3 model, Ang et al. (2006)) result in lower returns the larger the respective exposure. The two 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 from insurance contracts, the relationship between information uncertainty and cross-sectional patterns might be of great interest.

(9) Distribution (coskewness, cokurtosis, downside risk, upside risk): The distribution of past returns for the cross-sectional behavior of stocks is analyzed by Harvey and Siddique (2000) for co-skeweness, Fang and Lai (1997) and Dittmar (2002) for co-kurtosis, Ang, Chen, and Xing for downside (upside) movements with the market. All of these distribution-linked variables could also be related to the heavy-tails of insurance claims and thus have predictive power on returns.

(10) Investments: We directly relate the investment cashflow to the insurer cross-sectional return behavior. Similar to the interest rate exposure, we argue that historically higher investment income by an insurer should lead to higher investment income in the future.

(11) Asset growth: Asset contractions are followed by abnormally high returns, that is, 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 also expect a similar negative relation between asset growth and expected returns for insurers.

4 Data and Methodology

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

4.1 Asset pricing models

Asset pricing models impose a linear relationship between expected returns and beta exposures, which is why asset pricing models are in general known as beta-pricing models.[16] To test this relationship we run 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:

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

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

where $R_{i,t} - R_{f,t}$ is the excess return of stock *i* over the risk-free rate, $\beta_{i,k}$ is the sensitivity of the 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 uses the beta estimates from time-series regressions as independent variables and estimates at each time period *t* the following regression:

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

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 tested model in the insurance literature so far (Harrington (1983); Cummins and Harrington (1988)). The cross-sectional specification for the CAPM is:

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

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 FF-3 model and extends the CAPM by a size (SMB) and a value (HML) factor with the cross-sectional model being,

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

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

The third model extends the FF-3 model with a momentum factor following Carhart (1997):

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

where *MOM* is a zero investment portfolios 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 dividend yield and the 1-Month T-Bill rate. The cross-sectional relation is:

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

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

4.2 Data

Our data sample consists of all traded U.S. property/liability insurers with SIC code 6311.[17] We only include U.S. common stocks (excluding ADR and units of beneficiary interest) and exclude

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

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).[18] Table A1 in the Appendix reports the number of stocks per year in our sample.

Stock return data and accounting information is retrieved from CRSP and COMPUSTAT, respectively. The FF-3 factors, the 1-month T-Bill yield, and the momentum factor are downloaded from Kenneth French's website.[19] The dividend yield on the S&P 500 is downloaded from Robert Shiller's website.[20] Data on the broker/dealer leverage factor comes from Tyler Muir's website.[21] The liquidity factor from innovations is retrieved from Robert Stambaugh's website.[22] 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.

Panel A of Table 2 summarizes the monthly individual stocks returns of the property/liability insurance industry and the independent variables relevant for cross-sectional regressions.[23] 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 3. Panel B of Table 2 reports the factor variables employed by the different asset pricing models presented in Section 4.1. These variables are used both in cross-sectional and time-series

---

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

19 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

20 http://aida.wss.yale.edu/~shiller/data.htm.

21 http://faculty.som.yale.edu/tylermuir/data.html.

22 http://finance.wharton.upenn.edu/~stambaugh/liq_data_1962_2012.txt.

23 The maximum return for Non-Life dates back to American International Corp (Ticker: AIG) in August 2009; the minimum return also belongs to AIG and dates back to September 2008.

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 p/l insurance sector differs from the overall market is indicated through a correlation of merely 0.65 between the market and an equally-weighted return index of p/l insurers.

Table 2: Summary Statistics

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 1th and 99th percentile and used in cross-sectional regression tests.

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

	$\boldsymbol{R_{MKTRF}}$	$\boldsymbol{SMB}$	$\boldsymbol{HML}$	$\hat{u}^{TERM}$	$\hat{u}^{DEF}$	$\hat{u}^{div}$	$\hat{u}^{RF}$
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

5 Empirical evidence

We first present results of single-sorted portfolios in section 5.1 followed by time series and cross-sectional regression analyses of insurance stocks in section 5.2 to 5.6.

5.1 Stock return anomalies

Following the finance literature that analyzes the cross-section of stock returns (e.g., Vassalou and Xing (2004); Cooper, Gulen, and Schill (2008)) we sort portfolios by characteristics of insurance stocks to evaluate their return pattern. This allows us also to compare their pattern with the non-financial sector and to evaluate insurance-specific characteristics. Sorting portfolios and analyzing the mean returns of these portfolios give an idea about inherent return premiums which is why the spread between portfolios sorted by high and low exposures towards 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, Tetlock (2013)) leading to ambiguous inferences.

We sort insurance stocks based on 21 characteristics. These characteristics are the market, downside, and upside beta exposure, size (market capitalization), B/M ratio, momentum, pervious-month returns, liquidity, long-term reversal, idiosyncratic volatility, cashflow volatility, co-skewness, co-kurtosis, asset growth, changes in the term and default spread, investment performance, broker-dealer leverage, insurance leverage, financial leverage, and total leverage.[24] 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.[25] Table 3 presents average monthly returns of characteristics-sorted portfolios for p/l insurers (in %

[24] For a detailed description of the characteristics and the portfolio formation see the Appendix.

[25] We follow Barber and Lyon (1997) 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 weights each independent variable.

p.a.). Given the sample size we construct three return portfolios. The CAPM alphas and FF-3 alphas in Table 3 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 Table 3 Panel A or the FF-3 model in Table 3 Panel B.

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 non-financial firms and p/l insurers in the past (Cummins and Harrington (1988), and 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)).[26] We do, however, find a significant effect between portfolios sorted by B/M ratio (B/M). The monthly return spread between low B/M and high B/M insurer returns is a statistically and economically significant 0.83% (or 9.96% p.a.). Less surprising is the fact that the CAPM cannot explain the return difference between low and high B/M portfolios which is why Fama and French (1993) developed the HML factor to explain this return variation. However, it is more surprising that 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 either (Table 3, Panel B). This suggests that the B/M ratio in the p/l insurance sector has a different pricing cycle and a different meaning than the B/M ratio in non-insurance stocks.[27] One explanation could be that the (insurance-specific) B/M ratio reflects some type of distress as Chen and Zhang (1998) for global equity markets. If that is the case, insurance stocks will most likely experience this distress during market downturns but also during natural catastrophes which do not necessarily have an effect on non-insurance firms.

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

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

[27] A 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 Weiss (2009)).

month and vice versa. The spread is economically and statistically significant with an average return of 2.14% per month (or 25.68% p.a.). Both direction and economic size of the variable is similar to the findings of Jegadeesh (1990) who reports a monthly return of 2.49%. Note that p/l insurance stocks are not characterized by being microcaps or being thinly traded and thus this pattern cannot be associated with this behavior. Rather another explanation in this context could be brought forward and links overreaction by investors and the negative autocorrelation in stocks returns. Note also the fact 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% (or 10.08% p.a.). 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 which drops significantly in its risk compensation and leading to a significant spread. The abnormal return spread from cashflow volatility can be neither explained by the CAPM nor the FF-3 model.

Last but not least, portfolios sorted by insurance leverage, total leverage, and liquidity result in monotonic pattern and a significant return spread. However, this spread difference can be explained by the CAPM, i.e., the CAPM-alpha from time series regression is insignificant.

Table 3

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

Decile	**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)

Decile	**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 three. 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)).

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. Panel A of Table 4 reports the average returns from low to high exposure, the spread, and the CAPM alpha of that spread. We find that here is a weakly significant size effect which is not explained by the CAPM. The direction of this effect is surprising with low SMB exposure earning higher returns, that is, low exposure towards 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 FF-3 model.

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 towards 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 4) but the FF-3 alpha becomes significant, suggesting that the FF-3 model is falsely specified for the insurance sector to capture its unique B/M effect. Specifically, it explains why the FF-3 factor is not able to capture the B/M anomaly in insurance stocks shown in Table 3.

Table 4

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

Decile	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 three. 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)).

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

Having analyzed univariate portfolio sorts, we now turn to the cross-sectional regressions to validate these results and to see whether other model specification can explain them. We first run univariate Fama-Macbeth (1973) regressions on the insurance stocks returns for each independent variable. Table 5 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.

Table 5: Fama-MacBeth (1973) regressions with individual stock returns (univariate)

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)	(XI)	(XII)	(XIII)	(XIV)	(XV)	(XVI)	(XVII)	(XVIII)	(XIX)	(XX)	(XXI)
β	0.24 [0.93]																				
$β^+$		0.04 [0.20]																			
$β^-$			-0.04 [-0.18]																		
Ln(size)				-0.07 [-1.18]																	
B/M					0.49** [2.16]																
MOM						0.08 [0.16]															
RET_{t-1}							-9.51*** [-7.16]														
$β_{LIQ}$								0.75* [1.77]													
REV									-0.41 [-1.35]												
ID- VOLA										4.41 [0.43]											
CF-VOLA											-3.19** [-2.57]										
CO-SKEW												-0.01 [-0.78]									
CO-KURT													-0.00 [-1.64]								
Asset Gtrh.														-0.13 [-0.25]							
$β_{ΔTERM}$															5.17** [2.02]						
$β_{ΔDEF}$																-4.42* [1.92]					
INVEST																	0.51 [1.20]				
B/D LEV																		0.99 [0.94]			
INS/ LEV																			0.00 [0.06]		
FIN/ LEV																				0.00 [0.13]	
Total LEV																					0.00 [0.23]
Const.	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]	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	0.05	0.05	0.04	0.05	0.04	0.02	0.04	0.03	0.04	0.05	0.05	0.04	0.03	0.03	0.04	0.04	0.03	0.05	0.03	0.03	0.03

In accordance with Table 4, we also report the cross-sectional regressions on the beta exposure of SMB and HML in Table 6. 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 6: 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

Following univariate Fama-MacBeth (1973) regressions, we further investigate the different pricing components in a multivariate framework to analyze the variables' unique pricing ability. Table 7 shows the results from Fama-Macbeth (1973) regressions with several robustness tests of all significant variables from univariate regressions.

Table 7: 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.	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:		<5^{th} pctile. market cap.	<5^{th} pctile. trading vol.	>95^{th} pctile. rel. bid-ask spread	<5^{th} pctile. market cap. / <5^{th} pctile. trading vol./ >95^{th} pctile. rel. bid-ask spread

Model (I) includes all significant variables from univariate sorts and regressions. Model (II) excludes all firm months with market capitalization below the samples 5^{th} percentile. Model (III) excludes all firm months with trading volume below the samples 5^{th} percentile. Model (IV) excludes all firm months with relative bid-ask spreads above the samples 95^{th} percentile. Model (V) sequentially excludes all firm months with market capitalization below the samples 5^{th} percentile, all firm months with trading volume below the samples 5^{th} percentile, and all firm months with relative bid-ask spreads above the samples 95^{th} percentile.

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 the 95^{th} percentile of stocks 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 7, Model V), suggesting that the liquidity anomaly is attributable to small, less frequently traded insurance stocks with high bid-ask spreads.

5.3 Principal component analysis and risk factors

So far our results imply that the B/M ratio, prior month return, cashflow volatility, and liquidity are priced in insurance stocks returns. The question, we have to ask at this point is if these characteristics are systematic risk components in insurance stocks and therefore can be matched by covariances with risk factors (see Vassalou and Xing (2004); Ghandi and Lust (2014)).

In general, a linear factor model predicts average returns on a cross-section of returns related to risk premiums which are exposed to risk factors. According to Ross (1976) in 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 on each of the five return portfolios following Lustig, Roussanov, and Verdelhan (2011) and Ghandi and Lustig (2014). Table 8 shows the loadings of the first (Panel A) and second (Panel B) principal components on our characteristic-sorted portfolios. The first principal component explains between 68.59% and 71.52% of the return variation 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 variation. Thus, the second principal components on each characteristic-sorted portfolio can be interpreted as slope factors because of their monotonic increase (decrease) in loadings. Since no other principal components exhibit a similar increasing (decreasing) pattern as 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 Ghandi and Lustig (2014), we construct risk factors from returns for each of the second principal components.

Table 8: 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
% Var	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
% Var	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}). The last row each panel reports the share of the total variance explained by each principal component in percent. 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 to highest characteristic (i.e. portfolio 4). To have a zero-investment portfolio we also go three quarters short in the portfolio with lowest characteristic (i.e. portfolio 1) and one quarter short in the portfolio with the second to lowest characteristic (i.e. portfolio 4).[28] Formally, each excess-return portfolio is constructed as:

$$F_{i,t} = \frac{3}{4} * (portfolio\_5 - portfolio\_1) + \frac{1}{4} * (portfolio\_4 - porfolio\_2)$$

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

On the one hand the first principal component (PC1), which is a level factor, suggests that it follows the market as indicated in Panel A of Table 9. The correlation of the excess market

[28] The following results are robust to the construction of the factors as long as the top and bottom portfolios outweigh the portfolios in the middle. Results are available upon request from the authors.

return with each of the first principal components shows a high correlation factor of 0.63 and 0.64. On the other hand, our constructed risk factors based on the four characteristics show a high correlation with the second principal components (PC2) between 0.75 and 0.97 suggesting that our constructed factors adequately replicate the second principal components.

Table 9: 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 (B/M)	0.64			
MKTRF (RET_{t-1})		0.64		
MKTRF (LIQ)			0.63	
MKTRF (CFVOLA)				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

Here, we also want to highlight the fact that the risk factor constructed from the B/M ratio (i.e., 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 4), 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.

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

Having constructed the insurance-specific risk factors we now turn to cross-sectional regressions following Fama and MacBeth (1973) to analyze if there is a linear relationship between the covariance of our factors and the average insurance stocks 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 as these portfolios provide the most variation in average returns. On the right hand side we use the different asset pricing models described in Section 4.1. and the insurance-specific model including 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). Formally, the model is described as:

$$R_{i,t} - R_{f,t} = \alpha + \beta_{i,MKTRF} MKTRF_t + \beta_{i,BMF} BMF_t + \beta_{i,PRETF} PRETF_t + \beta_{i,LQF} LQF_t + \beta_{i,CFVF} CFVF_t$$

Table 10 reports the Fama-MacBeth (1973) regressions for all five models and two control regressions.

Table 10: Fama Macbeth (1973) regression with portfolios and risk factors

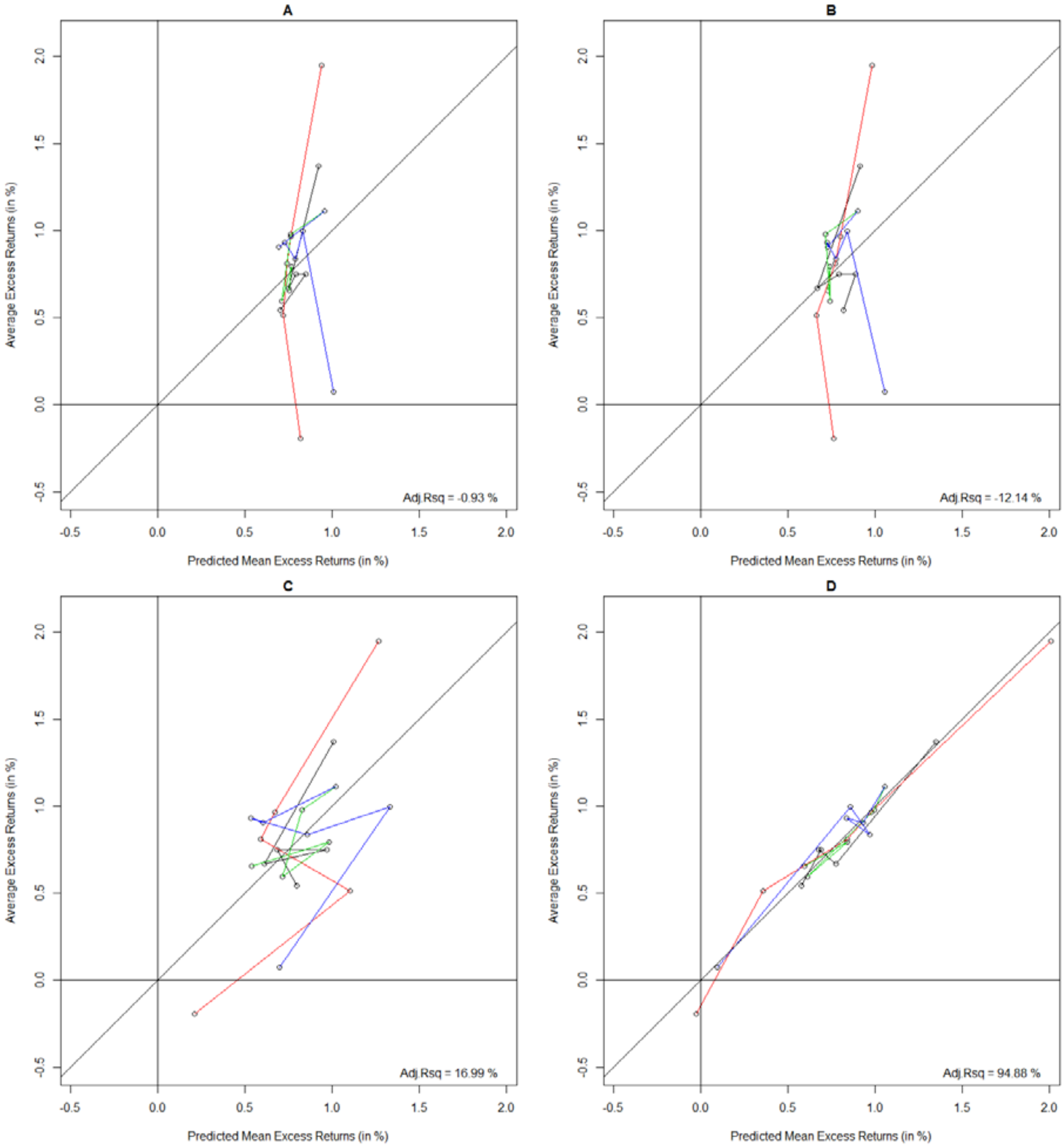
	(I) CAPM	**(II)** FF-3	**(III)** Carhart-4	**(IV)** Petkova-5	**(V)** Insurance-5	**(VI)** Control-1	**(VII)** Control-2
β_{MKTRF}	1.017	1.65*	2.43**	1.46*	2.11**	2.80**	2.64***
	[1.18]	[1.66]	[2.29]	[1.80]	[2.15]	[2.50]	[2.67]
β_{BMF}					0.77**	0.60**	0.58**
					[2.38]	[2.36]	[2.29]
β_{PRETF}					-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. (α)	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	46.0	0.48	0.50	0.52	0.59	0.60	0.60

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

First of all we see that the market factor is insignificant in the CAPM but becomes significant and positive in all other specifications suggesting that 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 insurance-specific five-factor model (see Regression VI). Similarly, the Petkova-5 model indicates four significant factors which lose their significance in our control regressions (see Regression VII) except for the market factor.

How different the models perform in the cross-section is visually compared 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 form each model on the 20 portfolios.

Figure 1: 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 model. Graph D shows the actual excess returns and the predicted return by 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.

Graph A in Figure 1 shows the actual excess returns and the predicted return by the CAPM. Graph B shows the predicted returns by the FF-3 model. Graph C is the Petkova (2006) model and Graph D is our insurance-5 model. Each graph also provides the adjusted R-square from a single cross-sectional regression.[29] Neither the CAPM nor the FF-3 models are doing well in predicting the portfolio return. The Petkova model, however, is doing surprisingly well compared to the FF-3 model with a cross-sectional, adjusted R-square of 16.99%. However, the insurance-5 model is doing an excellent job in capturing the cross-sectional variation with an adjusted R-square of 94.88% supporting the fact that insurance five-factor model is well specified.

5.5 Time-series regressions with portfolios using risk factors

The following time-series regressions give further insight into the covariances and pricing errors from different asset pricing models. Table 11 shows factor loadings, intercept values, and the GRS-test statistic from time-series regressions on the Fama and French (1993) factors with 4x5 characteristics 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 FF-3 model cannot capture the cross-sectional return variation of the test assets is also reflected the intercept with 10 out of 20 intercepts being significantly different form zero. This is formally confirmed by the GRS-test statistic which is rejected at the 1%-significance level.

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

Table 11: Time series regression – FF3 factor model

	Low	2	Medium	3	High
			Book-to-market portfolios		
β_{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		
β_{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		
β_{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. Standard errors in parentheses are Newey-West (1987)-corrected with lags of four. 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.

In contrast the insurance-specific five-factor model is formally not rejected by GRS-test statistic although seven out of the twenty portfolios have weakly significant intercepts (Table 12). More importantly the factor loadings on the different portfolios show in all cases a monotonic increase / decrease for each portfolio it should capture the cross-sectional variation.[30] For example, the BMF factor loads significantly negative (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. We not report time-series regressions on the Petkova model because the factors are not returns and thus no interpretation about the intercepts is possible.

[30] Note that we only report factor loadings for the portfolios the factor is intended to explain the cross-sectional variation in returns.

Table 12: Time series regression - Insurance 5-factor model

	Low	2	Medium	3	High
			Book-to-market portfolios		
β_{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		
β_{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		
β_{PRETF}	-0.68***	-0.11	-0.01	0.16*	0.56***
	[-7.66]	[-1.29]	[-0.07]	[1.92]	[6.60]
			Liquidity portfolios		
β_{LQF}	-0.51***	-0.19**	0.04	0.19*	0.70***
	[-5.02]	[-2.43]	[0.53]	[1.92]	[7.27]
			Cashflow volatility portfolios		
β_{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. Standard errors in parentheses are Newey-West (1987)-corrected with lags of four. The GRS test statistic tests the null that all intercepts are jointly zero. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.6 Comparing Hansen-Jagannathan distances

Based on the time-series and cross-sectional evidence we are interested whether the insurance-specific 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 13). All but the insurance-specific model are rejected suggesting that it is the only model not being rejected.

Table 13: 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 Fama-French (FF-3) model 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 one-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 statistically compare the different models 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 five-factor model is again outperforming the FF-3 model as we could already see in the Graphs in Section 5.4. Again, though, we also see that the insurance five-factor model is significantly outperforming all other models at the 1%-level (Table 14).

Table 14: 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 : $\hat{\delta}_i^2 = \hat{\delta}_j^2$.

6 Robustness

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

6.1 Size and B/M portfolios

A potential point of critique is that the FF-3 model was designed constructed to explain size and B/M-sorted portfolios in the cross-section of stock returns. 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 compare 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 which 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 difficult to answer since the low number of insurance stocks in our sample increases the measurement error in each portfolio the less insurance stocks it contains. Nevertheless, a natural question to ask is thus, how does the Fama-French model cope with insurance stocks sorted on these two characteristics and how does the Insurance five-factor model deal with size and B/M portfolios? At the cost of estimation precision we create 10 size and 10 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 10 size portfolios (Panel A of Table 15), we find indeed that the smallest stocks provide a large increase in return from 0.71% (or 8.52% p.a.) in the second to smallest to 1.87% (or 22.24% p.a.) in the smallest portfolio. This supports the idea that only the smallest stocks in the insurance sector are exposed to a size anomaly.

Table 15: Size-sorted and B/M-sorted portfolios

Panel A: Ten size-sorted portfolios

	Small	2	3	4	5	6	7	8	9	Large	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			

This table reports 10 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: Ten B/M-sorted portfolios

	Low	2	3	4	5	6	7	8	9	High	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			

This table reports 10 B/M-sorted portfolios including the average number of stocks for each portfolio and the return difference between high and low B/M portfolios.

Similarly, the B/M anomaly is driven by the most extreme portfolios when sorted by B/M (Panel B of Table 15). 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 characteristic, we run time-series and cross-sectional regressions on all portfolios in the following sections.

6.2 Fama-MacBeth (1973) regressions with portfolios sorted by B/M and size

We first run Fama-MacBeth (1973) regressions as in Section 5.4. However, this time, the dependent variables are 10 size and 10 B/M sorted insurance stock portfolios. Here, we find indeed a weakly significant coefficient on the SMB factor supporting the idea that there some size-exposure in the most extreme portfolios. Still, BMF from the insurance-specific five-factor model seems to capture also this weakly significant anomaly leaving the SMB coefficient insignificant if we include BMF in the regression (Column IV of Table 16).

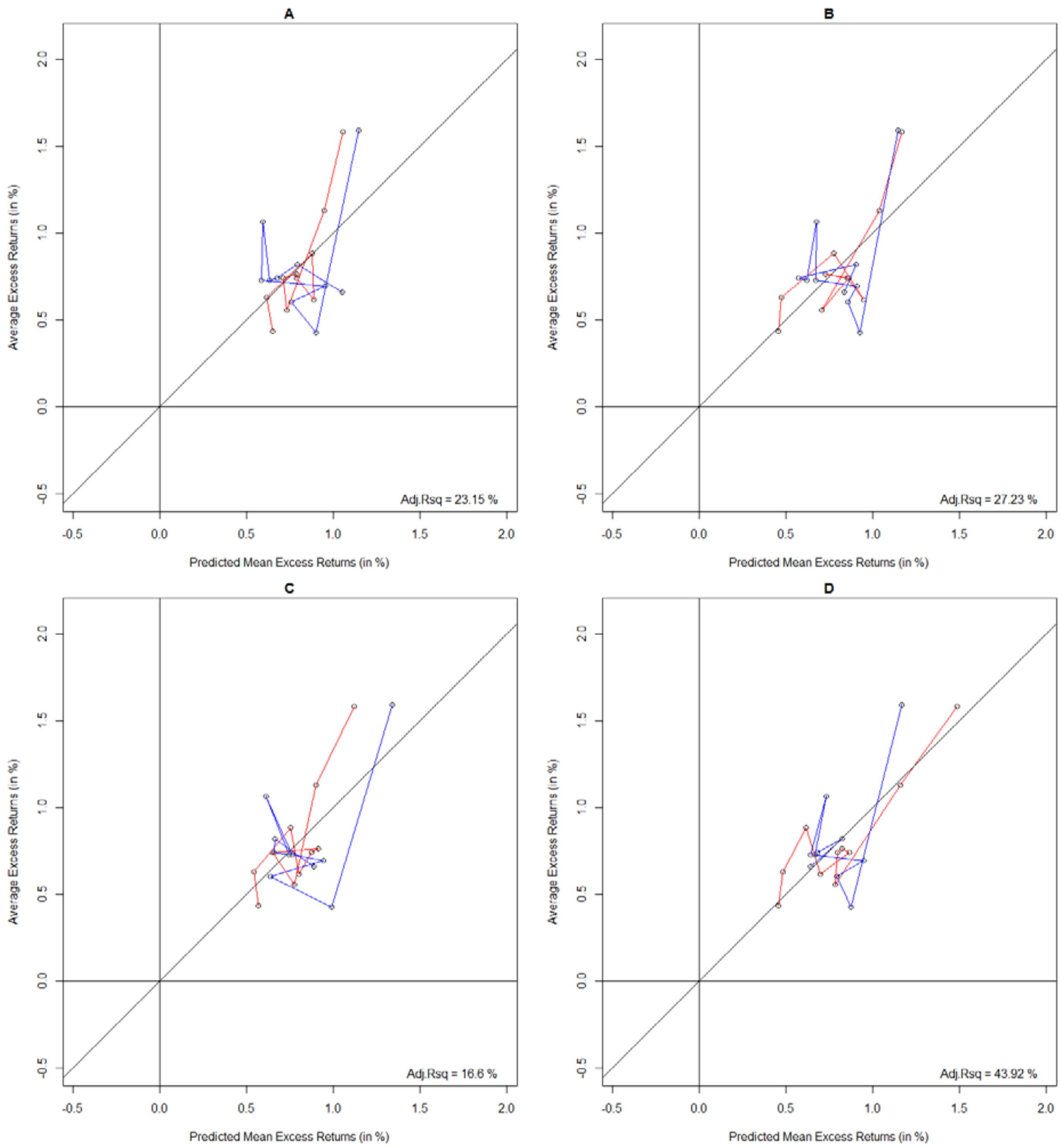
Table 16: Fama Macbeth (1973) regression with portfolios and risk factors

	(I) FF-3	(II) Petkova-5	(III) Insurance-5	(IV) Control-1
β_{EMKT}	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. (α)	-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 10 size and 10 B/M sorted portfolios, we also see that the overall fit using the insurance five-factor model is superior to the FF-3 model. The FF-3 model has an adjusted R-square of 27.23% (Graph B) versus an adjusted R-square of 43.92% in the insurance five-factor model (Graph D).

Figure 2: 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 model. Graph D shows the actual excess returns and the predicted return by 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, and size.

6.3 Time-series regressions

When we run time series regressions on the 10 size-sorted portfolios we find that the difference between the most extreme portfolios is still not explained by the FF-3 factor model despite the inclusion of the SMB factor due to the significant intercept value (Panel A of

Table 17). 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 17.

Table 17: Ten size-sorted portfolios

Panel A: Fama-French Model on ten size-sorted portfolios

	Small	2	3	4	5	6	7	8	9	Large	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]
Const.	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													

Panel B: Insurance 5-factor model on ten size-sorted portfolios

	Small	2	3	4	5	6	7	8	9	Large	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]
Const	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													

When we run the insurance-specific 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 17). This seems to be mostly attributed to the BMF factor, which already showed in the Fama-MacBeth (1973) regressions in Section 6.2 that it remains significant even if SMB was included (Table 16). 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 10 B/M sorted portfolios, results are corroborated that the FF-3 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 18). In contrast the insurance-5 model captures all significant intercepts between the most extreme portfolios (Panel B of Table 18).

Table 18: Ten B/M-sorted portfolios

Panel A: Fama-French Model on ten B/M-sorted portfolios

	Low	2	3	4	5	6	7	8	9	High	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]
Const.	-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													

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

	Low	2	3	4	5	6	7	8	9	High	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]
Const	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													

7 Conclusion

This paper is the first to analyze traditional and state of the art models from the asset pricing literature in an insurance context. We show which risk factors are priced in insurance stocks through cross-sectional regressions on beta coefficients.

We analyze return anomalies in property/liability (p/l) insurance stocks returns. Natural disasters, exclusion in previous asset pricing test, regulation in the insurance sector, and high leverage, require a separate analysis of insurance stocks whether return anomalies persist and whether existing asset pricing models are able to explain the cross-section of expected insurance stock returns. Analyzing insurance stocks between 1988 and 2013, we find that the B/M ratio, prior month return, illiquidity, and cashflow-volatility are priced in the cross-section of (p/l) insurance stocks. The size anomaly is only present in smallest decile of insurance stocks. The Fama/French model from the overall equity market can neither explain the size nor the B/M anomaly in the insurance stocks. A five factor model build upon 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 et al. (2009) on banks. Our findings also shed new light on the pricing determinants of insurance products and provide accurate cost of capital estimates.

Although this paper emphasizes the high relevance of cross-sectional relationships, which seems to be underrepresented (especially in contrast to the overall finance literature), this does not prevent further research to analyze the variations of insurance stocks and factors in a time-series context for the purpose of risk management, i.e. hedging.

Appendix

Table A1: Firm Data

This table shows the number of companies in the property/liability insurance sector. Column 1 and 3 report the year insurer information is available. Column 2 and 4 report the number of property/liability 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		

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 being known to investors at the date of calculation and thus do not introduce a look-ahead bias.

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 on 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 comovement with Pastor and Stambaugh's (2001) 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
CFVOLA	Cashflow-volatility is defined as the standard deviation over the previous eight quarterly cashflows 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.

Literature

Adrian, Tobias, Tyler Muir, and Erkko Etula, 2013, Financial intermediaries and the cross-section of asset returns, *Journal of Finance 69*, 2557-2596.

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies 19*, 1191-1239.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, T*he Journal of Finance 61*, 259-299.

Ang, Andrew, Assaf A. Shtauber, and Paul C. Tetlock, 2013, Asset pricing in the dark: The cross-section of OTC stocks, *Review of Financial Studies 26*, 2985-3028.

Barber, Bead M., and John D. Lyon, 1997, Firm size, B/M ratio, and security returns: A holdout sample of financial firms, *The Journal of Finance 52*, 875-883.

Bhandari, Laxmi Chand, 1988, Debt/equity ratio and expected common stock returns: Empirical evidence, *The Journal of Finance 43*, 507-528.

Brennan, Michael J., Tarun Chordia, and Avanidhar Subrahmanyam, 1998, Alternative factor specifications, security characteristics, and the cross-section of expected stock returns, *Journal of Financial Economics 49*, 345-373.

Brennan, Michael J., Tarun Chordia, Avanidhar Subrahmanyam, and Qing Tong, 2012, Sell-order liquidity and the cross-section of expected stock returns, *Journal of Financial Economics 105*, 523-541.

Brewer, Elijah, James M. Carson, Elyas Elyasiani, Iqbal Mansur, and William L. Scott, 2007, Interest rate risk and equity values of life insurance companies: A GARCH–M model, *Journal of Risk and Insurance 74*, 401-423.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies 22*, 2201-2238.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *The Journal of Finance 52*, 57-82.

Carson, James M., Elyas Elyasiani, and Iqbal Mansur, 2008, Market risk, interest rate risk, and interdependencies in insurer stock returns: A system-GARCH model, *Journal of Risk and Insurance 75*, 873-891.

Chen, Nai-fu, and Feng Zhang, 1998, Risk and return of value stocks, *The Journal of Business 71*, 501-535.

Cochrane, John H., 2005, Asset Pricing, *Princeton University Press*.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *The Journal of Finance 63*, 1609-1651.

Cummins, J. David, Georges Dionne, James B. McDonald, and B. Michael Pritchett, 1990, Applications of the GB2 family of distributions in modeling insurance loss processes, *Insurance: Mathematics and Economics 9*, 257-272.

Cummins, J. David, and Joan Lamm-Tennant, 1994, Capital structure and the cost of equity capital in the property-liability insurance industry, *Insurance: Mathematics and Economics 15*, 187-201.

Cummins, J. David, and Richard D. Phillips, 2005, Estimating the cost of equity capital for property-liability insurers, *Journal of Risk and Insurance 72*, 441-478.

Cummins, J. David, and Scott E. Harrington, 1988, The relationship between risk and return: Evidence for property-liability insurance stocks, *Journal of Risk and Insurance 55*, 15-31.

Cummins, J. David, and Scott Harrington, 1985, Property-liability insurance rate regulation: Estimation of underwriting betas using quarterly profit data, *Journal of Risk and Insurance 52*, 16-43.

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

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *The Journal of Finance 52*, 1-33.

Dittmar, Robert F., 2002, Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns, *The Journal of Finance 57*, 369-403.

Doherty, Neil A., 1991, The design of insurance contracts when liability rules are unstable, *Journal of Risk and Insurance 58*, 227-246.

Doherty, Neil A., and Seha M. Tinic, 1981, Reinsurance under conditions of capital market equilibrium: A note, *The Journal of Finance 36*, 949-953.

Eckles, David L., Martin Halek, and Rongrong Zhang, 2013, Information risk and the cost of capital, *Journal of Risk and Insurance 81*, 861-882.

Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2013, Organization capital and the cross-section of expected returns, *The Journal of Finance 68,* 1365-1406.

Fairley, William B., 1979, Investment income and profit margins in property-liability insurance: Theory and empirical results, *The Bell Journal of Economics,* 192-210.

Fang, Hsing, and Tsong-Yue Lai, 1997, Co-kurtosis and capital asset pricing, Financial Review 32, 293-307.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *The Journal of Political Economy 81*,607-636.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *The Journal of Finance 47*, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics 33*, 3-56.

Fama, Eugene F., and Kenneth R. French, 2000, Forecasting profitability and earnings, *The Journal of Business 73*, 161-175.

Fama, Eugene F., and Kenneth R. French, 2008, Dissecting anomalies, *The Journal of Finance 63*, 1653-1678.

Ferson, Wayne E., Sergei Sarkissian, and Timothy Simin, 1999, The alpha factor asset pricing model: A parable, *Journal of Financial Markets 2*, 49-68.

Froot, Kenneth A., 2007, Risk management, capital budgeting, and capital structure policy for insurers and reinsurers, *Journal of Risk and Insurance 74*, 273-299.

Froot, Kenneth A., and Jeremy C. Stein, 1998, Risk management, capital budgeting, and capital structure policy for financial institutions: An integrated approach, *Journal of Financial Economics 47*, 55-82.

Froot, Kenneth A., and Paul G. J. O'Connell, 1997, On the pricing of intermediated risks: Theory and application to catastrophe reinsurance, (*National Bureau of Economic Research*).

Gandhi, Priyank, and Hanno Lustig, 2013, Size anomalies in U.S. Bank stock returns, *The Journal of Finance*.

Garlappi, Lorenzo, and Hong Yan, 2011, Financial distress and the cross-section of equity returns, *The Journal of Finance 66*, 789-822.

Harrington, Scott E., 1983, The relationship between risk and return: Evidence for life insurance stocks, *Journal of Risk and Insurance* 587-610.

Harvey, Campbell R., and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *The Journal of Finance 55*, 1263-1295.

Hirshleifer, D., 2001. Investor psychology and asset pricing. *The Journal of Finance 56*, 1533–1597

Huang, Alan Guoming, 2009, The cross section of cashflow volatility and expected stock returns, *Journal of Empirical Finance 16*, 409-429.

Ibragimov, Rustam, Dwight Jaffee, and Johan Walden, 2009, Nondiversification traps in catastrophe insurance markets, *Review of Financial Studies 22*, 959-993.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *The Journal of Finance 45*, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, The Journal of Finance 48, 65-91.

Kahle, K.M., Walkling, R.A., 1996, The impact of industry classifications on financial research, *Journal of Financial and Quantitative Analysis 31*, 309–335.

Kan, Raymond, and Cesare Robotti, 2009, Model comparison using the Hansen-Jagannathan distance, *Review of Financial Studies 22*, 3449-3490.

Kan, Raymond, Cesare Robotti, and Jay Shanken, 2013, Pricing model performance and the two-pass cross-sectional regression methodology, *The Journal of Finance*.

Leland, Hayne E., 1999, Beyond mean-variance: Performance measurement in a nonsymmetrical world, *Financial Analysts Journal* 27-36.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics 96*, 175-194.

Lo, Andrew W., and A. Craig MacKinlay, 1990, An econometric analysis of nonsynchronous trading, *Journal of Econometrics 45*, 181-211.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2011, Common risk factors in currency markets, *Review of Financial Studies 24*, 3731-3777.

Newey, Whitney K., and Kenneth D. West, 1987, A simple positive-definite heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica 55*, 703–708.
Opler, Tim C., and Sheridan Titman, 1994, Financial distress and corporate performance, *The Journal of Finance 49*, 1015-1040.
Pástor, Luboš, and Robert F. Stambaugh, Liquidity risk and expected stock returns, *Journal of Political Economy 111*, 642-685.
Petkova, Ralitsa, 2006, Do the fama–french factors proxy for innovations in predictive variables?, *The Journal of Finance 61*, 581-612.
Ross, Stephen A., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory 13*, 341-360.
Rubinstein, Mark, 1976, The valuation of uncertain income streams and the pricing of options, *The Bell Journal of Economics 7*, 407-425.
Schwert, G.W., 2003. Anomalies and market efficiency. In: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of the Economics of Finance. Amsterdam, North Holland.
Shanken, Jay, 1992, On the estimation of beta-pricing models, *Review of Financial Studies 5*, 1-55.
Thomann, Christian, 2013, The impact of catastrophes on insurer stock volatility, *Journal of Risk and Insurance 80*, 65-94.
Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *The Journal of Finance 59*, 831-868.
Viale, Ariel M., James W. Kolari, and Donald R. Fraser, 2009, Common risk factors in bank stocks, *Journal of Banking & Finance 33*, 464-472.
Wen, Min-Ming, Anna D. Martin, Gene Lai, and Thomas J. O'Brien, 2008, Estimating the cost of equity for property-liability insurance companies, *Journal of Risk and Insurance 75*, 101-124.
Zanjani, George, 2002, Pricing and capital allocation in catastrophe insurance, *Journal of Financial Economics 65*, 283-305.