The Journal of Risk and Insurance

. Vol. 87, No. 1, 213–245 (2020).
DOI: 10.1111/jori.12267

Estimating the Cost of Equity Capital for Insurance Firms With Multiperiod Asset Pricing Models

Alexander Barinov
Jianren Xu
Steven W. Pottier

Abstract

Previous research on insurer cost of equity (COE) focuses on single-period asset pricing models. In reality, however, investment and consumption decisions are made over multiple periods, exposing firms to time-varying risks related to economic cycles and market volatility. We extend the literature by examining two multiperiod models—the conditional capital asset pricing model (CCAPM) and the intertemporal CAPM (ICAPM). Using 29 years of data, we find that macroeconomic factors significantly influence and explain insurer stock returns. Insurers have countercyclical beta, implying that their market risk increases during recessions. Further, insurers are sensitive to volatility risk (the risk of losses when volatility goes up), but not to insurance-specific risks, financial industry risks, liquidity risk, or coskewness after controlling for other economy-wide factors.

Introduction

Prior studies on insurer cost of equity (COE) focus on single-period asset pricing models, such as the capital asset pricing model (CAPM) and the Fama and French (1993) three-factor model (FF3). Merton's (1973) seminal article on multi-period asset pricing demonstrates that when investment decisions are made at more than one date, additional factors are required to construct a multi-period model because of uncertain changes in future investment opportunities. Moreover, firms are exposed to business and economic cycles. Multi-period models account for the time-varying risks (factors) that reflect these cycles.

Alexander Barinov is at the Department of Finance, School of Business, University of California Riverside, 900 University Ave., Riverside, CA 92521. Barinov can be contacted via e-mail: alexander.barinov@ucr.edu. Jianren Xu (corresponding author) is at the Department of Finance, Insurance, Real Estate and Law, G. Brint Ryan College of Business, University of North Texas, 1155 Union Circle #305339, Denton, TX 76203-5017. Xu can be contacted via email: jianren.xu@unt.edu. Steven W. Pottier is at the Department of Insurance, Legal Studies, and Real Estate, Terry College of Business, University of Georgia, 610 South Lumpkin Street, Athens, GA 30602. Pottier can be contacted via e-mail: spottier@uga.edu. Steven Pottier gratefully acknowledges the support of a Terry-Sanford Research Grant.

In this study, we extend the insurance literature by examining two multi-period models—the conditional CAPM (CCAPM) and the intertemporal CAPM (ICAPM). These two models are examined along with the single-period models studied in the prior literature—the CAPM and FF3, as well as newer single-period models like the Fama and French (2015) five-factor (FF5) model and the Adrian, Friedman, and Muir (2016) (AFM) model with financial industry risk factors.[1,2] Our empirical analysis consists of three major parts. First, we evaluate the four asset pricing models mentioned earlier (CAPM, FF5, CCAPM, and ICAPM) and consider their applicability to insurance firms by examining the relation between realized (actual) returns on portfolios of insurer stocks and the risk factors associated with each model. We show that insurance firms are exposed to volatility risk and have countercyclical betas. More specifically, insurance portfolio values drop when current consumption has to be cut in response to surprise increases in expected market volatility, and its market beta increases in recessions when bearing risk is more costly. Therefore, insurers are riskier and thus should have higher cost of capital than what the CAPM/FF5 estimates.

FF3/FF5 are also often regarded as ICAPM-type models with *SMB*, *HML*, and recently *RMW* and *CMA* acting as "placeholders" for yet unidentified risk.[3] While a number of articles have tried to identify the risks behind these factors (Liew and Vassalou, 2000; Petkova and Zhang, 2005; Petkova, 2006; Campbell, Polk, and Vuolteenaho, 2010), the consensus as to which business cycle variables are behind the factors still has not emerged. Even more, a number of articles have contested the claim that *SMB* and *HML* are driven by risk and argued that they represent mispricing and market sentiment swings (Daniel and Titman, 1997; Baker and Wurgler, 2006).

Company stakeholders might want to know not only the COE of their firm or projects, but also the reasons behind a certain rate, namely, what risks result in a high or low COE. Without risk-based explanations, stakeholders might feel uncomfortable accepting a COE estimate. The additional alternative that the factors can be picking up market-wide mispricing makes the decision even more complicated. For example, the "Model Performance and Applicability and Insurer Risk Sensitivities" section reveals that insurers tend to be value (positive *HML* beta) firms. If we believe that *HML* picks up high returns of value firms as their underpricing is corrected, should we benchmark insurers' COE against other value firms, thus asking them to deliver a higher return than their risk warrants and abandoning some positive NPV projects?

[1]In the "Asset Pricing Models and Literature" section, we review the related literature on insurer cost of equity capital and argue that since the models used are single-period models, they do not account for the time-varying risks that insurers face.

[2]As discussed in the "Asset Pricing Models and Literature" section, while reestimating beta(s) in CAPM/FF5 allows for the COE to vary over time, these approaches do not incorporate the covariance of factor beta(s) with economic conditions. In COE estimation, the CAPM and FF5 implicitly assume, by using long-term averages of the factor risk premiums, that the amount of risk in the economy is constant. Thus, in the CAPM and FF5, there is no possible covariance between the betas and the business cycle "by construction."

[3]For example, this is the view Fama and French took in their original article, Fama and French (1993), as well in subsequent articles like Fama and French (1995) and Fama and French (1996).

(This is what using FF5 in COE estimation suggests.) Alternatively, should we exercise all positive NPV projects, effectively ignoring the positive *HML* beta if we think *HML* is mispricing?

Theory-based multiperiod models, such as the CCAPM and ICAPM, considered in our article, are immune to both problems. First, they identify the risks they are talking about ("insurance companies lose more than average when market volatility increases," "the market beta of insurance companies increases when deflation occurs"). Second, they are only picking up risk-based effects in expected returns/COE, and one does not have to worry about mispricing.

In the second major part of our empirical analysis, we also consider for potential inclusion in the CCAPM and ICAPM the underwriting cycle variables, in addition to the standard business cycle variables from the finance literature. Further, we add the insurance factors and financial industry factors (the AFM factors) to FF5. While changes to underwriting cycle variables and insurance/financial industry factors clearly affect the value of insurers, it is not clear *a priori* that they will be related to expected returns because all their effects can be on the cash-flow side.

The finance theory suggests (e.g., Cochrane, 2007) that only the variables that are related to expected market risk premium and thus to marginal utility of consumption should be included in any asset pricing models (either CCAPM or ICAPM in this study). We check the existence of such a relation between several underwriting cycle variables (including average combined ratio, total catastrophic losses, etc. in a quarter) and find none. Consequently, we find that inclusion of these variables in either the CCAPM or ICAPM does not materially affect our COE estimates. That happens even though some underwriting cycle variables seem to be related to the beta/realized returns of insurers: the underwriting cycle variables earn zero risk premium (controlling for other risk factors) because their effects can be diversified away by investing in multiple industries. Similarly, we find adding the insurance factors or financial industry factors neither improves the model goodness of fit of FF5 nor contributes to estimating COE (controlling for market-wide factors) due to their diversifiable nature.

The irrelevance of underwriting cycle (or any other insurance/financial industry specific) variables as candidate CCAPM/ICAPM factors goes beyond the application at hand. Even if such factors are correlated with insurance companies' realized returns, they will not contribute to expected returns due to being unrelated to the economy as a whole.

In the third major part of our empirical analysis, we apply four models (CAPM, FF5, CCAPM, and ICAPM) to estimate COE for all U.S. publicly traded insurers, and the two subgroups, P/L insurers and life insurers, over an 18-year period (1997–2014).[4] Since additional time-varying risks demand greater rewards, we find that on average

[4]In COE estimation, we lose 10 years as the initial estimation period for CCAPM, for which we need 120 months to estimate six parameters with enough precision.

ICAPM generates COE estimates that are significantly higher than CAPM COE and even higher than FF5 COE.[5]

We also apply a novel estimation technique for deriving COE from CCAPM by predicting, using business cycle variables, both the market beta of insurance firms and the expected market risk premium. The resulting COE series reflects well the risk shifts during our sample period; for example, in 2009–2011, during the aftermath of the Great Recession, the CCAPM's COE is higher than the COE estimate from any other model. The average level of COE from CCAPM in 1997–2014 is relatively low, due to the fact that the expected market risk premium is estimated at about 3 percent per annum (in contrast to 6 percent per annum *for all years* used in other models) before the Great Recession. This low level of the market risk premium is, however, consistent with alternative market risk premium estimates in Claus and Thomas (2001) and Fama and French (2002), who find that before the Great Recession investors deemed the market risk as historically low. If one plugs the 3 percent market risk premium estimated by these studies in the standard CAPM, the CAPM will produce significantly lower average COE than the CCAPM, consistent with the notion that CCAPM finds more risk in insurance firms.

ASSET PRICING MODELS AND LITERATURE

Fama-French Five-Factor Model

In response to actual and perceived weaknesses of the CAPM, Fama and French (1992, 1993) developed a three-factor model that became the most widely used alternative to the CAPM. Recently, Fama and French (2015) updated the model by including two additional factors.[6] The FF5 model is a single-period model that has the following specification:

$$R_i - RF = a_i + \beta_i(RM - RF) + s_i SMB + v_i HML + p_i RMW + i_i CMA + \varepsilon. \quad (1)$$

where R_i = return on asset i, RM = return on market portfolio, RF = return on riskless security, SMB (HML) = difference in returns to portfolios of small (value) and large (growth) stocks, RMW (CMA) = difference in returns to portfolios of high and low profitability (low and high investment) stocks. β_i, s_i, v_i, p_i, and i_i are the market, size, value, profitability, and investment betas, respectively.

The exact nature of the state variables (variables that describe the state of the economy and relevant risks) behind SMB and HML remains elusive despite

[5]We also evaluate the AFM model and add the volatility risk factor to FF5 (turning it into a six-factor model, FF6) and to the AFM model (turning it into AFM6) in Online Appendix A (Barinov, Xu, and Pottier, 2018). We observe that FF6 produces higher COE estimates than FF5, which generates higher COE estimates than the AFM model, and report the results in Online Appendix G (Barinov, Xu, and Pottier, 2018).

[6]Fama and French (1992) show that the CAPM cannot explain why size and book-to-market predict expected returns. Since then, the list of variables that predict expected returns controlling for beta and of implied trading strategies (also called anomalies) earning significant CAPM alphas has expanded to include dozens of variables. McLean and Pontiff (2016), Harvey, Liu, and Zhu (2016), and Hou, Xue, and Zhang (2015) provide the (largely overlapping) lists of violations of the CAPM documented as of today.

20 years of ongoing research. Some candidate state variables include GDP growth (Liew and Vassalou, 2000), investment (Zhang, 2005; Cooper, 2006), default risk (Vassalou and Xing, 2004), and changes in the slope of the yield curve (Hahn and Lee, 2006; Petkova, 2006). Another strand of research, started by Lakonishok, Shleifer, and Vishny (1994) and Daniel and Titman (1997), argues that *SMB* and *HML* represent market-wide mispricing, in which case, use of FF5 in the COE estimation becomes ambiguous.[7]

Conditional CAPM

As Cochrane (2005) points out, conditional asset pricing models start with an observation that the standard pricing equation, $p_t = E(m_t \cdot R_t)$, where p is the asset price, m is the pricing kernel, and R is returns, holds conditional on the information investors have as of time t, so that it should be written as $p_t = E(m_t \cdot R_t \mid I_t)$. Also, since the conditional expectation is essentially a projection on z_t, all variables in the information set I_t, we can write the unconditional moment condition with scaled payoffs, $E((m_t \cdot R_t - p_t) \cdot z_t) = 0$. If the pricing kernel is linear, as the CAPM and other factor models assume, then essentially in the unconditional model implied by the conditional one we have to use, as factors, not only the factors in the pricing kernel, such as the market return, but also the products of those factors with the variables in the information set, z_t.

In simpler terms, the CCAPM assumes that the expected return on an asset at any given point in time is linear in its conditional beta. The CCAPM allows the market beta and the expected market risk premium to vary with economic conditions by making them (linear) functions of economic variables or z_t. First, CCAPM recognizes that expected market risk premium is higher during economic recessions, as empirical studies in finance find (Fama and Schwert, 1977; Fama and French, 1989). In recessions, investors' wealth is lower and its marginal utility is higher, which makes investors' willingness to bear risk lower and the required risk premium higher. Second, the risk of stocks (market beta) also varies with economic conditions; for example, insurers can change the composition of their portfolio due to reaching for the yield (Becker and Ivashina, 2015).

The CCAPM states that the unconditional expected risk premium of a particular stock can be computed as follows, assuming both beta and the market risk premium are random variables:[8]

[7]Imagine, for example, that we are talking about a value firm that loads positively on *HML*. Using FF5 for COE estimation is likely to yield higher than average COE, reflecting the fact that value firms have high average returns. If the manager feels the need to beat the peers (also value firms), he/she will use the COE from FF5. However, if the value effect is mispricing and value firms have higher returns than warranted by their risk, using COE from FF5 will imply turning down some positive NPV projects (which earn more than what their risk warrants, but less than an average value firm makes).

[8]Equation (2) follows directly from the definition of covariance: $Cov(X,Y) = E[(X - E(X)) \cdot (Y - E(Y))] = E(X \cdot Y) - E(X) \cdot E(Y)$.

$$E(R_i - RF) = E[\beta_i \cdot (RM - RF)] = E(\beta_i) \cdot E(RM - RF) + Cov[\beta_i, (RM - RF)]. \quad (2)$$

The standard CAPM misses the covariance term ("beta-premium sensitivity"). In most COE applications, the CAPM assumes that expected market risk premium is constant at its long-term average, thus effectively setting the covariance term to zero even if the betas are allowed to change from one estimation period to another.

The economic meaning of the covariance term is that stocks with countercyclical betas (higher in bad times) are riskier than what their CAPM beta would imply. For such stocks, the covariance piece in Equation (2) will be positive because expected market risk premium, $E(RM-RF)$, is also higher in recession. Higher risk and higher beta in recessions are undesirable because marginal utility of consumption is higher during recessions and potential losses are more painful.

The fact that the covariance piece is the difference between the CAPM and CCAPM also guides our choice of conditioning variables that will be assumed to be driving the beta. These variables need to be related to the expected market risk premium (i.e., they have to predict the market return). If the beta is related to a variable that does not predict the market return, controlling for this relation will not affect our estimate of the covariance term and thus will not create extra difference between expected return/COE estimates from the CAPM and CCAPM.

For this study, we select four commonly used conditioning variables (z_t): dividend yield (*DIV*), default spread (*DEF*), Treasury bill rate (*TB*), and term spread (*TERM*), defined in the "Data and Variables" section, that are known to predict the market return.[9] Our choice of conditioning variables is standard for the CCAPM literature (Petkovand Zhang, 2005; O'Doherty, 2012).

Thus, we assume that the market beta is a linear function of the four variables above:

$$E(\beta_{it}) = b_{i0} + b_{i1}\ DEF_{t-1} + b_{i2}DIV_{t-1} + b_{i3}TB_{t-1} + b_{i4}TERM_{t-1}. \quad (3)$$

If we substitute Equation (3) into the standard CAPM equation and rearrange it, we get

$$\begin{aligned} R_{it} - RF_t = {} & \alpha_i + b_{i0} \cdot (RM_t - RF_t) + b_{i1}DEF_{t-1} \cdot (RM_t - RF_t) + b_{i2}DIV_{t-1} \cdot (RM_t - RF_t) \\ & + b_{i3}TB_{t-1} \cdot (RM_t - RF_t) + b_{i4}TERM_{t-1} \cdot (RM_t - RF_t) + \varepsilon. \end{aligned} \quad (4)$$

Equation (4) means the insurer stock returns are regressed not only on the excess market return, as in the CAPM, but also on the products of the excess market return with the four variables. Since *TB* is on average low in bad times, and *DEF*, *DIV*, and *TERM* are high, a negative loading on $TB_{t-1}(RM_t-RF_t)$ product and a positive loading on all other products implies higher beta during recessions and hence higher expected return/COE than what the CAPM predicts.

[9]Fama and French (1988) document that dividend yield predicts market returns. Fama and Schwert (1977) find similar evidence for *DEF* and *TB*. Fama and French (1989) find that the term spread is related to expected market risk premium.

Intertemporal CAPM

From the ICAPM's point of view, investors attempt to smooth their consumption over time by trying to push more wealth to the periods when consumption is scarcer and its marginal utility is higher. Therefore, investors will value the assets that pay them well when bad news arrives. Such assets are less risky than what the CAPM implies and command lower risk premium.

A bit more formally, in the most general case, the pricing kernel m_t, used to price all assets by $p_t = E(m_t \cdot R_t)$, equals $m_t = \delta U'(c_{t+1})/U'(c_t)$, where δ is the individual discount factor and $U(c_t)$ is investors' utility of consuming c_t in period t. The equation for m_t follows directly from the first-order condition to the investor's problem: the investor should be indifferent between consuming a marginal unit today and receiving $U'(c_t)$ benefit, or investing the marginal unit at R_{t+1} and getting $(1 + R_{t+1}) \cdot \delta U'(c_{t+1})$ in the future (rearranging the first-order condition and applying the law of iterated expectations yields $p_t = E(m_t \cdot R_t)$).

Merton (1973) shows that if consumption c_t is a function of state variables z_t, $c_t = c(z_t)$, and the investor solves a multiperiod problem, then the investor effectively maximizes the sum of future discounted utilities, which can be expressed as the value function $V(W_t, z_t)$, where W_t is investor's wealth as of time t. Then m_t can be rewritten as $m_t = \delta V'_W(W_{t+1,} z_{t+1})/V'_W(W_{t,} z_t)$, and the Taylor expansion of $p_t = E(m_t \cdot R_t)$, dropping second-order terms, yields

$$E_t(R_{t+1}) \approx -\frac{WV''_{WW}}{V'_W} \cdot Cov_t\left(R_{t+1}, \frac{\Delta W_{t+1}}{W_t}\right) - \frac{V''_{Wz}}{V'_W} \cdot Cov_t\left(R_{t+1}, \frac{\Delta z_{t+1}}{z_t}\right). \quad (5)$$

Equation (5) is the most general ICAPM equation. The first covariance term is usually approximated empirically by the covariance with the market return (or, effectively, by the market beta). The new part is that now the market risk premium is driven by the changes in relative risk aversion, $-WV''_{WW}/V'_W$ (so, assuming decreasing relative risk aversion, the market risk premium is higher in recessions). The second term introduces additional factor(s), represented by covariances with (or betas with respect to) unexpected changes in state variables. If the state variable z_t is procyclical, then the price of risk, $-V''_{Wz}/V'_W$, is positive because V''_{Wz} will be negative due to decreasing marginal utility of wealth, V'_W, and vice versa.

In this article, we follow a successful application of the ICAPM (Ang et al., 2006; Barinov, 2014) that uses market volatility as a state variable. Investors care about changes in volatility for two reasons. First, in Campbell (1993), an increase in volatility implies that in the next period risks will be higher, consumption will be lower, and savings in the current period have to be higher at the expense of lower current consumption to compensate for future consumption shortfall. Second, Chen (2002) also claims that, due to the persistence of the volatility, higher current volatility indicates higher future volatility. Accordingly, consumers will boost precautionary savings and lessen current consumption when they observe a surprise increase in expected volatility. Both Campbell (1993) and Chen (2002) demonstrate that stocks whose returns are most negatively correlated with surprise changes in expected market volatility are riskier because their value declines when consumption has to be reduced to increase savings.

To proxy for shocks to market volatility, we employ changes in the VIX index from the Chicago Board Options Exchange (CBOE).[10] The VIX index measures the implied volatility of at-the-money options on the S&P 100 index, and thus derives volatility expectations from option prices, effectively using all the information the traders have. Following Breeden, Gibbons, and Litzenberger (1989), Ang et al. (2006), and Barinov (2014), we form a portfolio that mimics the volatility risk factor, known as the *FVIX* factor/portfolio.[11] It is a zero-investment portfolio that tracks daily changes in expected volatility. By construction, *FVIX* earns positive returns when VIX increases, and consequently, has a negative risk premium because it is a hedge against volatility risk.[12] Hence, negative *FVIX* betas mean that the asset is exposed to volatility risk (and loses when both VIX and *FVIX* go up). The ICAPM specification is as follows:

$$R_i - RF = a_i + \beta_i(RM - RF) + \beta_{FVIX}FVIX + \varepsilon. \tag{6}$$

where RM = market portfolio return, RF = return on riskless security, $FVIX$ = factor-mimicking portfolio that mimics the changes in the VIX index, β_{FVIX} = asset i's $FVIX$ beta, and ε is the error term.

Prior Cost of Equity Capital Studies in the Insurance Literature

Cummins and Phillips (2005) estimate COE using CAPM and the older FF3 model. They find that the estimated COE is significantly different across sectors of the insurance industry: the COE of life insurers is approximately 200 basis points (bp) higher than P/L insurers. FF3 generates significantly higher COE estimates than the CAPM. Following Cummins and Phillips (2005), we use a time-series regression to obtain beta estimates and we use a longer time period to obtain the factor risk premia. Wen et al. (2008) compare CAPM COE estimates of P/L insurers to COE estimates from what the authors denote as the Rubinstein (1976)–Leland (1999), or RL, model. The authors find that while COE estimates are not significantly different for the full sample period, the estimates are significantly different in certain sub-periods. They also find that alphas (unexplained excess returns) are significantly smaller from the

[10] VIX is the CBOE market volatility index. There are two versions of VIX: the "original," based on S&P 100 options and dating back to 1986, and the new one, based on S&P 500 options, launched in 2003 and backfilled to 1990. The "original" VIX index current ticker is VXO. Following Ang et al. (2006), we use the "original" VIX to obtain a longer sample. Ang et al. (2006) document that the correlation between the new and the "original" indexes is 98 percent between 1990 and 2000.

[11] If one adds the change in VIX to the right-hand side of the CAPM equation to explain the firm returns, the intercept is no longer the abnormal return, referred to as alpha, since the market return is measured in percent and the VIX change in VIX unit, which is inconsistent. Therefore, a factor-mimicking portfolio, that is, a portfolio of stocks with the highest possible correlation with the VIX change, is needed. In addition, constructing the factor-mimicking portfolio from stock returns will allow us to keep the "return-relevant" portion of the VIX change and discard the noise and irrelevant information (Barinov, 2013).

[12] The detailed description of the factor-mimicking procedure that creates *FVIX* is in the "Data and Variables" section.

RL model than from the CAPM for insurers with highly skewed returns and for smaller insurers.

There are several other studies of insurer COE that follow approaches that differ from Cummins and Phillips (2005), Wen et al. (2008), and the present study.[13] Bajtelsmit, Villupuram, and Wang (2015) estimate upside and downside betas, coskewness, and cokurtosis in time-series regressions. Then they use these and other factors in cross-sectional regressions to explain realized insurer returns. They find that only downside risk is statistically and economically significant.[14] Ben Ammar, Eling, and Milidonis (2015), similar in spirit and method to Bajtelsmit, Villupuram, and Wang (2015), use the two-stage Fama and MacBeth (1973) method to identify risk factors and insurer characteristics that help explain the cross-sectional variation in insurer stock returns. However, they study which factors are priced using a cross-section of returns of one industry (insurance industry) *only* (rather than the whole stock market). A general problem with studies that attempt to identify industry-specific risks for asset pricing or COE purposes is that they are based on a false premise, namely, that the risk premium for a particular risk factor (*RM-RF*, *SMB*, *HML*, *RMW*, *CMA*, etc.) can be different for a particular industry. In equilibrium asset pricing models, such as the CAPM, CCAPM, and ICAPM, it is only the *beta* of a risk factor of an individual asset or industry portfolio that may differ from other individual assets or other industry portfolios. In addition, we examine several (insurance and financial) industry-specific factors and find that they are not priced.[15]

DATA AND VARIABLES

Due to the availability of VIX, which starts in January 1986, our sample spans 29 years (348 months) from January 1986 to December 2014. The insurers' value-weighted returns are from CRSP (market cap weight is lagged by 1 month). Fama–French five factors, the market return, and the risk-free rate are from Ken French's data library.[16] We calculate the financial industry factors according to Adrian, Friedman, and Muir (2016). All types of insurers are included and we further separate them into seven

[13]Lee and Cummins (1998) estimate CAPM and APT (multifactor) betas in a time-series regression, then use the estimated betas in a second-stage cross-sectional regression to estimate the risk premia, and then compare the estimated risk premia to the average realized risk premia over time. Cummins and Lamm-Tennant (1994) use Value Line betas to estimate insurer COE. They identify insurer characteristics that help explain the cross-sectional variation in Value Line betas, such as financial leverage. Nissim (2013) and Berry-Stölzle and Xu (2018) use an implied cost of capital method to estimate COE for insurance companies, but that method follows a different set of assumptions and is based on the dividend discount model (rather than the CAPM).

[14]In Online Appendix B (Barinov, Xu, and Pottier, 2018), we use liquidity, liquidity risk, and coskewness factors and find that they add little to insurers' COE.

[15]Ben Ammar, Eling, and Milidonis (2015) also consider several market-wide risk factors and insurer-specific characteristics, but they do not estimate COE in a manner consistent with Cummins and Phillips (2005), Fama and French (1993), or articles that begin by asking, "Does a risk factor reflect economy-wide risk, that is, nondiversifiable risk, or only risk related to one industry (diversifiable risk)?"

[16]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

major subsectors.[17] We perform major analysis on all insurers and the two largest subsets of P/L (SIC codes 6330–6331) and life insurers (SIC codes 6310–6311).

To estimate the CCAPM, we collect four commonly used conditioning variables, namely, *DEF*, *DIV*, *TB*, and *TERM*. *DEF* is the yield spread between Moody's Baa and Aaa corporate bonds. *DIV* is the sum, over the previous 12 months, of dividend yield (dividend divided by last year's price) to all CRSP stocks. *DIV* is obtained from CRSP as the difference between cum-dividend and ex-dividend market return. *TB* is the 1-month Treasury bill rate from Ken French's data library. *TERM* is the yield spread between the 10- and 1-year Treasury bond. The data source for *DEF* and *TERM* is the FRED database at the Federal Reserve Bank at St. Louis.[18]

To measure the exposure to volatility risk in the ICAPM, we follow the literature (Breeden, Gibbons, and Litzenberger, 1989; Ang et al., 2006; Barinov, 2014) and create a factor-mimicking portfolio, *FVIX*, that tracks innovations in expected market volatility. We use the VIX index from CBOE as a proxy of expected market volatility and its change as a proxy for innovations.

FVIX index is constructed by regressing changes in the VIX index on daily excess returns to five portfolios (base assets) sorted on past sensitivity to VIX changes: $\Delta VIX_t = \gamma_0 + \gamma_1 \cdot (VIX1_t - RF_t) + \gamma_2 \cdot (VIX2_t - RF_t) + \gamma_3 \cdot (VIX3_t - RF_t) + \gamma_4 \cdot (VIX4_t - RF_t) + \gamma_5 \cdot (VIX5_t - RF_t) + \varepsilon$, where $VIX1_t, \ldots,$ and $VIX5_t$ are the VIX sensitivity quintiles, with $VIX1_t$ being the quintile with the most negative sensitivity. The fitted part of the regression above less the constant is our volatility risk factor (*FVIX* factor). The daily returns to *FVIX* are then cumulated within each month to get the monthly return to *FVIX* used in the article.

The return sensitivity to VIX changes ($\gamma_{\Delta VIX}$) used to form the base assets is measured separately for each firm-month by regressing daily stock excess returns on daily market excess returns and the VIX index change (at least 15 nonmissing returns are required): $R_{i,t-1} - RF_{t-1} = a + \beta_i \cdot (RM_{t-1} - RF_{t-1}) + \gamma_{\Delta VIX} \cdot \Delta VIX_{t-1} + \varepsilon$. The VIX sensitivity quintiles in month t are formed using information from month $t-1$ and are rebalanced monthly.

We also hand-collect several underwriting cycle/insurance-specific variables as candidate CCAPM conditioning variables and candidate ICAPM additional factors.[19]

[17] All insurers are firms with SIC codes between 6300 and 6399. The seven subsectors are life insurance (6310–6311); accident and health insurance (6320–6329); property–liability insurance (6330–6331); surety insurance (6350–6351); title insurance (6360–6361); pension, health, welfare funds (6370–6379); and other insurance carriers (insurers falling into none of the above categories).

[18] See http://research.stlouisfed.org/fred2/.

[19] The variables include the industry-level *CatLoss* (catastrophic losses) and *CombRat* (combined ratio) from 1986 to 2014 and *Surplus*, *PremW* (premiums written), *PremE* (premiums earned), *NetInvInc* (net investment income), and *CapGain* (net realized capital gains) from 1987 to 2014. *CatLoss*, *Surplus*, *PremW*, *PremE*, and *CapGain* are CPI adjusted. *CatLoss*, *CombRat*, *Surplus*, *PremW*, *PremE*, *NetInvInc*, and *CapGain* are collected from the Insurance Services Office Inc. (ISO) quarterly publication "Property-Casualty Insurance Industry Financial Results." *CatLoss* is for property catastrophes only and the ISO obtains it from the Property Claim Services Company.

MODEL PERFORMANCE AND APPLICABILITY AND INSURER RISK SENSITIVITIES

Descriptive Statistics and Model Performance

Panel A of Table 1 reports the summary statistics of the monthly returns to the insurance industry, market risk premium, Fama–French factors (i.e., *SMB, HML, CMA*, and *RMW*), business cycle variables, and *FVIX*. The average value-weighted returns for all insurers, P/L insurers, and life insurers are close at 0.62 percent, 0.56 percent, and 0.76 percent per month, respectively, suggesting that P/L (life) insurers have somewhat lower (higher) risk than an average insurance company. The mean monthly market risk premium is 0.66 percent per month, very close to the mean for all insurers.

The rest of Table 1 verifies that the ICAPM and CCAPM have a good fit in a broad cross-section of stocks and generally outperform the CAPM and FF5. We employ the test suggested by Gibbons, Ross, and Shanken (1989), known as the GRS test in the asset pricing literature, to evaluate the performance of the models. The GRS test starts with fitting time-series models to a portfolio set that spans the whole economy and tests if the alphas of all portfolios are jointly zero, as should be the case for an asset pricing model that is able to explain the returns to a portfolio set.

The alphas are the primary focus of our article because all asset pricing models partition the in-sample return into the expected return (i.e., COE) and the alpha (and the zero-mean error term, which does not matter on average). Hence, the alpha is the systematic error in COE estimates and therefore the difference between COE estimates from different models.

Panel B of Table 1 performs the GRS test for the set of 30 industry portfolios from Fama and French (1997). This set is often used in the asset pricing literature (Lewellen, Nagel, and Shanken, 2010, e.g., advocate its use in all asset pricing tests). Panel B shows that the FF5 is rejected (it produces significant alphas for at least some of the industry portfolios, thus not getting their COE right), CAPM is not rejected, but the ICAPM produces a smaller test statistic (meaning that the average ICAPM alpha is closer to zero). CCAPM produces a test statistic that is larger than the CAPM one, but one still cannot reject the null that all CCAPM alphas are zero.

Panel C of Table 1 performs a test similar to the GRS test. Its first column tests whether in the ICAPM all *FVIX* slopes for the 30 industry portfolios are jointly equal to zero and decisively rejects the null, implying that a significant number of industry portfolios are exposed to (or are hedges against) volatility risk. The next column performs the same test for the slope on the $DEF_{t-1} \cdot (RM - RF)$ product in the CCAPM and finds that for a significant number of industry portfolios market beta is related to default premium. The next three columns reach a similar conclusion about the relation of market beta to dividend yield, Treasury bill rate, and term premium.

Panel D of Table 1 considers the possibility of reverse causality and uses the returns to the insurance industry (*INS*), property–liability (*PL*), or life insurers (*Life*) as a risk factor. Panel D adds the factors to the FF5 and checks whether the GRS test statistics have improved. Panel D finds that the GRS test statistics barely improve after the

TABLE 1
Summary Statistics and Factor Pricing

Panel A. Descriptive Statistics					
Variable	No. of Months	Mean	Std. Dev.	Min	Max
INS-RF (VW)	348	0.619	5.201	−23.051	22.233
PL-RF (VW)	348	0.558	4.962	−15.304	26.540
Life-RF (VW)	348	0.760	7.371	−46.984	41.765
INS-RF (EW)	348	0.820	4.641	−23.342	12.399
PL-RF (EW)	348	0.720	4.270	−22.990	12.871
Life-RF (EW)	348	0.861	6.341	−35.237	29.848
RM-RF	348	0.656	4.507	−23.240	12.470
SMB	348	0.106	3.064	−15.260	19.050
HML	348	0.231	3.008	−12.610	13.880
RMW	348	0.359	2.473	−17.570	12.190
CMA	348	0.322	2.052	−6.810	9.510
DEF	348	0.981	0.394	0.550	3.380
DIV	348	2.334	0.752	1.095	4.106
TB	348	0.291	0.206	0.000	0.790
TERM	348	1.493	1.060	−0.410	3.400
FVIX	347	−1.342	6.174	−16.279	31.241
Panel B. GRS Test, H_0: All Alphas Jointly Equal to Zero					
	CAPM	FF5	ICAPM	CCAPM	
Stat.	1.138	1.771	0.643	1.296	
p-value	0.287	0.009	0.928	0.143	
Panel C. GRS Test, H_0: All Slopes on the Variables in the First Row Jointly Equal to Zero					
	FVIX	DEF_{t-1}	DIV_{t-1}	TB_{t-1}	$TERM_{t-1}$
Stat.	7.126	3.993	6.293	2.901	2.501
p-value	0.000	0.000	0.000	0.000	0.000

TABLE 1
Continued

Panel D. GRS Test With Insurance and Financial Industry Factors, H_0: All Alphas Jointly Equal to Zero						
	FF5	FF5 + *INS*	FF5 + *PL*	FF5 + *Life*	AFM	FF5 + AFM
Stat.	1.771	1.706	1.717	1.814	1.449	1.614
p-value	0.009	0.014	0.013	0.007	0.065	0.025

Note: *INS/PL/Life* is the value-weighted return (if not indicated otherwise) to a portfolio of all the United States publicly traded insurance companies (SIC codes 6300–6399)/property–liability insurers (SIC codes 6330–6331)/life insurers (SIC codes 6310–6311). *VW* means value-weighted and *EW* means equal-weighted returns. *RF* is the risk-free rate, which is the 30-day Treasury bill rate. *RM* is the market return, which is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks. *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. *DEF* is default spread, defined as the yield spread between Moody's Baa and Aaa corporate bonds. *DIV* refers to dividend yield, defined as the sum of dividend payments to all CRSP stocks over the previous 12 months, divided by the current value of the CRSP value-weighted index. *TB* is the risk-free rate, which is the 30-day Treasury bill rate. *TERM* is term spread, defined as the yield spread between the 10-year and the 1-year Treasury bond. *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX, which measures the implied volatility of the S&P 100 stock index options. Panel A reports the descriptive statistics. Panel B performs the GRS (Gibbons, Ross, and Shanken, 1989) test for the set of 30 industry portfolios from Fama and French (1997). Panel C tests whether all *FVIX* slopes for the 30 industry portfolios in the ICAPM are jointly equal to zero in the first column. The next four columns perform the same test for the slope on $DEF_{t-1} \cdot (RM-RF)$, $DIV_{t-1} \cdot (RM-RF)$, $TB_{t-1} \cdot (RM-RF)$, or $TERM_{t-1} \cdot (RM-RF)$ in the CCAPM, respectively. Panel D performs the GRS test of all alphas being jointly zero for the 30 industry portfolios in FF5 augmented with the insurance factors (i.e., *INS*, *PL*, or *Life*), in the AFM model, or in FF5 augmented with the financial industry factors in the AFM model (*FROE*, the spread between high and low ROE financial firms, and *SPREAD*, the return spread between financial and nonfinancial firms), namely, FF5 + AFM.

insurance factors were added, consistent with the notion that industry-wide shocks are diversifiable and thus no industry portfolio can be an economy-wide risk factor (more on that in the "Underwriting Cycle Variables in the CCAPM and ICAPM?" section).[20]

The last two columns in Panel D of Table 1 report the GRS test for the AFM model, which adds the spread between high and low ROE financial firms (*FROE*) and the return spread between financial and nonfinancial firms (*SPREAD*) to the old FF3 model, as well as the FF5 model augmented with the financial industry factors, namely, *FROE* and *SPREAD* (FF5 + AFM). Adrian, Friedman, and Muir (2016) argue that the financial industry performance impacts the whole economy and thus can be a state variable. Panel D reveals that while the AFM and FF5 + AFM models outperform FF5, they still fall behind ICAPM and CCAPM (see Panel B). Also, additional analysis in Online Appendix C, which fits the AFM and FF5 + AFM models to alternative portfolio sets, reveals that in those portfolio sets these models trail the FF5 model. Thus, we conclude that the financial industry factors do not capture state variables and are likely to represent diversifiable risks, just as the "insurance factors" we also considered in Panel D.

Model Applicability and Insurer Risk Sensitivities

Table 2 reports the regression results of four asset pricing models for all publicly traded insurers, P/L insurers, and life insurers in Panels A, B, and C, respectively.[21] We observe that while the insurance industry as a whole seems less risky than the market (its market beta is 0.87, more than two standard errors below 1), life insurers are significantly more risky than the market ($\beta = 1.20$) and P/L insurers ($\beta = 0.73$) are less risky than an average insurer. The betas also align well with the average excess returns in Panel A of Table 1. FF5 additionally reveals that all insurers are value firms and profitable firms (see their positive and

[20]In Online Appendix C (Barinov, Xu, and Pottier, 2018), we test the robustness of the results in Panels B, C, and D to using other salient portfolios instead of the 30 industry portfolios. The portfolios include the well-known five-by-five sorts on size and book-to-market and four more salient double sorts (on size/momentum, size/reversal, size/profitability, and size/investment). With a few exceptions, we find that the ICAPM and CCAPM outperform the CAPM and FF5 in terms of the GRS statistic. We also find that *FVIX* and $DEF_{t-1} \cdot (RM-RF)$ are jointly significant in explaining returns to all alternative portfolio sets, and the other three variables from Panel C are jointly significant most of the time. The conclusion of Panel D also holds with alternative portfolio sets: adding the insurance factors or financial industry factors to FF5 (or any other model) barely improves the GRS test statistic and in some cases even makes it worse.

[21]In Online Appendix D (Barinov, Xu, and Pottier, 2018), we run analysis on two more insurance subsectors: accident and health (A/H) insurers (SIC codes 6320–6329) and other insurers (not P/L, A/H, or life), since the numbers of surety insurers, title insurers, pension, health, welfare funds, and other insurance carriers are so small that we have to analyze them together. We run analysis based on Table 2 (with the addition of the AFM model) and Table 3 for A/H and other insurers and find similar results: A/H and other insurers have countercyclical betas and are exposed to volatility risk.

Table 2
Asset Pricing Model Performance Comparison

	Panel A. All Insurers				Panel B. P/L Insurers				Panel C. Life Insurers			
	CAPM	FF5	CCAPM	ICAPM	CAPM	FF5	CCAPM	ICAPM	CAPM	FF5	CCAPM	ICAPM
RM-RF	0.87***	1.03***	0.50***	−0.28	0.73***	0.90***	0.40*	−0.67***	1.20***	1.35***	0.73***	0.76***
	(0.04)	(0.04)	(0.19)	(0.17)	(0.04)	(0.04)	(0.21)	(0.18)	(0.06)	(0.06)	(0.25)	(0.27)
SMB		−0.13**				−0.29***				0.06		
		(0.06)				(0.06)				(0.08)		
HML		0.59***				0.50***				1.10***		
		(0.07)				(0.08)				(0.11)		
RMW		0.25***				0.20**				0.03		
		(0.08)				(0.09)				(0.11)		
CMA		−0.09				−0.02				−0.31**		
		(0.11)				(0.12)				(0.16)		
FVIX				−0.86***				−1.05***				−0.33*
				(0.12)				(0.13)				(0.19)
$DEF_{t-1} \cdot (RM\text{-}RF)$			0.10				0.00				0.66***	
			(0.09)				(0.09)				(0.11)	
$DIV_{t-1} \cdot (RM\text{-}RF)$			0.30***				0.26***				0.32***	
			(0.07)				(0.08)				(0.09)	
$TB_{t-1} \cdot (RM\text{-}RF)$			−0.94**				−0.60				−2.23***	
			(0.39)				(0.43)				(0.51)	
$TERM_{t-1} \cdot (RM\text{-}RF)$			−0.10				−0.06				−0.24**	
			(0.07)				(0.08)				(0.10)	
Alpha	0.05	−0.24	−0.08	−0.37**	0.08	−0.18	−0.04	−0.44**	−0.03	−0.30	−0.11	−0.19
	(0.19)	(0.16)	(0.18)	(0.18)	(0.20)	(0.18)	(0.20)	(0.19)	(0.27)	(0.24)	(0.24)	(0.29)
Adj. R^2	0.567	0.714	0.604	0.620	0.440	0.600	0.463	0.528	0.540	0.685	0.662	0.542
Obs.	348	348	347	347	348	348	347	347	348	348	347	347

Note: This table shows the regression results based on CAPM, FF5, CCAPM, and ICAPM for all the publicly traded insurance companies, P/L insurers, and life insurers. The insurance portfolio returns are value weighted. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. We use four macroeconomic/business cycle variables as conditioning variables in the CCAPM, which include default spread (*DEF*), defined as the yield spread between Moody's Baa and Aaa corporate bonds, dividend yield (*DIV*), defined as the sum of dividend payments to all CRSP stocks over the previous 12 months divided by the current value of the CRSP value-weighted index, Treasury bill (*TB*), which is the 30-day Treasury bill rate, and term spread (*TERM*), defined as the yield spread between the 10- and 1-year Treasury bond. In the ICAPM, *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P 100 stock index options. "Obs." reports the number of months in the regressions. Standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

significant *HML* and *RMW* betas), and, if one views *HML* and *RMW* as risk factors, are riskier than their market betas suggest. Likewise, *SMB* betas suggest that insurance companies, with the exception of life insurers, are big firms, and thus somewhat less risky (the investment or *CMA* beta is small and insignificant).[22]

As discussed earlier, CAPM and FF5 are single-period models. However, investment and consumption decisions are made over multiple periods, and the insurance industry is exposed to business cycles. The ICAPM column adds *FVIX*, the volatility risk factor mimicking the changes in VIX (the expected market volatility). The negative *FVIX* beta of insurance companies suggests that when expected market volatility increases, insurers tend to have worse returns than firms with comparable CAPM betas, which makes insurers riskier than what the CAPM estimates.[23] This is true for all insurance companies, including P/L and life insurers, though we observe that life insurers have the lowest exposure to volatility risk, much lower than the average for all insurers, and P/L insurers have the highest volatility risk exposure (the most negative *FVIX* beta). The pattern in *FVIX* betas is opposite to the pattern in the CAPM betas. One reason why insurance firms load negatively on VIX is that volatility is positively related to the number of bankruptcies and layoffs. Bankrupt firms cancel their property insurance, and laid-off consumers can switch to cheaper health insurance, look for cheaper property insurance, cancel life insurance, and so on.

According to CCAPM, a higher beta in recessions is a source of risk missing from the CAPM. The beta cyclicality is captured in Table 2 by the slopes on the products of the market return and the business cycle variables. Panel A indicates that the beta of insurance companies significantly increases with *DIV* and significantly decreases with *TB*, and is not significantly related to either *DEF* or *TERM*. Since dividend yield is higher in recessions and the Treasury bill rate is lower, both significant coefficients indicate that the beta of insurance companies is countercyclical, which makes them riskier than what the CAPM would suggest. The same is true about Panel B, in which dividend yield stays a significant driver of the risk of P/L insurers, and the Treasury bill rate loses significance but keeps its sign. Panel C is more complicated because it suggests

[22]In Online Appendix A, we also fit the AFM model and the AFM model augmented by *FVIX* (AFM6) to the returns of all, P/L, and life insurance companies, and discuss the regression results in detail.

[23]In Online Appendix E, we look at the 48 industry portfolios from Fama and French (1997) to see how volatility risk exposure of other industries compares to that of insurers. The 48 portfolios span the whole economy and include insurers and other financial companies. We find that while negative *FVIX* betas dominate our sample (higher volatility is bad for the economy), roughly a third of *FVIX* betas are positive, and the average *FVIX* beta across all 48 industries is only −0.141 (compared to −0.866 for the insurance industry). We also document that the *FVIX* beta of the insurance industry is the 5th most negative (behind Food Products, Candy & Soda, Beer & Liquor, and Tobacco Products). Therefore, the insurance industry does differ from an average industry.

that beta of life insurers is related to all four business cycle variables, and the sign on *TERM* contradicts the other three.[24,25]

How do we conclude whether the beta is countercyclical or not if some slopes disagree? (One can also notice that in Panels A and B of Table 2 the $TERM_{t-1} \cdot (RM-RF)$ slope also contradicted the others, but was statistically insignificant.) An easy test is examining the alphas.[26] Comparing the alpha in the CAPM and CCAPM columns, we observe that it decreases by economically nonnegligible 8–12 basis point (bp) per month (1–1.5 percent per year) as we go from the CAPM to CCAPM. Hence, the CCAPM discovers more risk in insurers than CAPM, and for that to be true, the beta of the insurers has to be countercyclical (high in recessions representing more risks).[27]

We interpret the countercyclicality of insurers' beta as evidence that insurers tend to reach for higher yield and make their investment portfolios more risky in recessions, when the Treasury bill rate is low. We directly observe the negative link between the Treasury bill rate and insurers' risk for all insurers and life insurers; life insurers also reveal their tendency to reach for higher yield when Baa-rated companies start to offer relatively high yields (high *DEF*). Since insurers seldom invest in stocks, the dividend yield of the market, which seems to be related to the betas of all types of insurers, serves more as a proxy for the state of the economy (related to bond market yields).

A more formal test of whether the beta of insurers is countercyclical is presented in Table 3. In this table, we follow Petkova and Zhang (2005) in reporting the average beta in expansions and recessions and testing if their difference is zero using the standard difference-in-means test.[28] In the top row of each panel, we label the month as expansion or recession based on whether the predicted market risk premium (the fitted part of the regression predicting the market return) is below or above the in-

[24]The results in Table 2, which uses value-weighted returns, as well as the results in the rest of the article, are robust to using equal-weighted returns instead (see Online Appendix H for the evidence).

[25]The term spread, which measures the slope of the yield curve, is high in recessions, and thus the negative slope on $TERM_{t-1} \cdot (RM-RF)$ suggests the beta of life insurers is lower in recessions. The positive sign on $DEF_{t-1} \cdot (RM-RF)$ suggests higher beta in recessions because the default spread is higher in recessions.

[26]Effectively, all asset pricing models, including the CAPM and CCAPM, partition, in-sample, the average left-hand-side return (in our case, average realized return to insurance companies in 1986–2014) into expected return (COE, the risk-based part), which is the factor loadings times factor risk premiums, and the alpha (i.e., the average abnormal return, the unexplained part). In the same sample, a decrease in the alpha as one goes from one model to another implies an increase in the expected return (COE, risk) part, as the alpha and the risk-based part have to sum up to the same average realized return.

[27]Another way to come to the same conclusion is to look at Equation (2) and observe that in order for the difference in expected return based on the CCAPM and CAPM to be positive, the covariance between the beta and expected market return (which is this difference) has to be positive; that is, the beta has to be high when expected market return is high, that is, in recessions.

TABLE 3
Average Conditional CAPM Betas of Insurers in Expansions and Recessions

	Recessions	Expansions	Difference
	Panel A. All Insurers		
Median as cutoff point	0.994***	0.760***	0.235***
	(0.012)	(0.012)	(0.017)
Top and bottom 25% as cutoff point	1.048***	0.677***	0.371***
	(0.018)	(0.018)	(0.025)
	Panel B. P/L Insurers		
Median as cutoff point	0.851***	0.650***	0.201***
	(0.010)	(0.010)	(0.014)
Top and bottom 25% as cutoff point	0.882***	0.567***	0.315***
	(0.012)	(0.012)	(0.018)
	Panel C. Life Insurers		
Median as cutoff point	1.263***	0.995***	0.268***
	(0.031)	(0.031)	(0.044)
Top and bottom 25% as cutoff point	1.411***	0.970***	0.442***
	(0.053)	(0.053)	(0.074)

Note: The table labels the month as expansion or recession based on whether the predicted market risk premium is below or above the in-sample median (median as cutoff point), or whether the predicted market risk premium is in the bottom or top quartile of its in-sample distribution (top and bottom 25 percent as cutoff point). We measure expected market risk premium as the fitted part of the regression $RM_t - RF_t = b_{i0} + b_{i1}DEF_{t-1} + b_{i2}DIV_{t-1} + b_{i3}TERM_{t-1} + b_{i4}TB_{t-1} + \varepsilon$, where $RM-RF$ is the market risk premium, *DEF* is default spread, *DIV* is dividend yield, *TERM* is term spread, and *TB* is the 30-day Treasury bill rate. Standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

sample median.[29] In the second row, we use a more restrictive definition of expansions/recessions as the months when the predicted market risk premium is in the bottom/top quartile of its in-sample distribution, and omit from the sample the months when it is in the second or third quartile. In each month t, we compute predicted beta value by substituting the values of the four business cycle variables

[28]This definition is superior to defining expansions and recessions using statistical measures of business activity because it goes to the heart of things: it looks at whether investors have high marginal utility of consumption and demand a high risk premium.

[29]Following the seminal articles of Fama and Schwert (1977) and Fama and French (1989), the predictive regression includes the same four variables we use in the CCAPM: $RM_t - RF_t = b_{i0} + b_{i1}DEF_{t-1} + b_{i2}DIV_{t-1} + b_{i3}TERM_{t-1} + b_{i4}TB_{t-1} + \varepsilon$. In month t, we substitute the values of the four variables from month $t-1$ and estimate the predicted market risk premium.

from month $t-1$ in the beta equation (Equation (3)), and report in Table 3 the average predicted betas in expansions and recessions defined as above.

Table 3 shows that all insurers and the two subgroups of P/L insurers and life insurers have strongly countercyclical betas (which makes them riskier than what the CAPM suggests). For example, the first column in Table 2 reports the CAPM beta of all insurers, averaged across the whole sample, at 0.87. Panel A of Table 3 shows that this beta varies from 1.048 (0.994) in recessions to 0.677 (0.760) in expansion, with the difference (0.371 or 0.235, depending on the recession definition) being economically sizable and statistically significant. Thus, even if not all signs in the beta equation agree (see Table 2), average predicted betas show that insurance companies have higher risk exposure in bad times, which leads investors to demand higher COE.

In sum, Tables 2 and 3 suggest that insurance companies are exposed to time-varying market risk (CCAPM) as well as volatility risk (ICAPM), additional risk sources that the single-period models do not include.[30]

UNDERWRITING CYCLE VARIABLES IN THE CONDITIONAL CAPM AND INTERTEMPORAL CAPM?

Underwriting Cycles and the Market Risk Premium

The insurance industry is exposed to underwriting cycles, which are related to, but do not coincide with the business cycles the whole economy is going through. While underwriting cycles clearly affect the equity values (and actual stock returns) of insurance companies, they need not be related to insurers' COE (expected stock returns). Since equity value is the present value of cash flows, underwriting cycles can affect equity value of insurers by impacting cash flows, discount rates (i.e., COE), or both. Hence, underwriting cycles, while important to the insurance industry, can bring about only cash flow shocks and leave COE unaffected.

There is actually a good reason to believe that this is going to be the case. For a diversified investor investing in many industries, underwriting cycle shocks can be largely diversifiable, just as any industry shock is. If the marginal capital provider in the insurance industry is this diversified investor, underwriting cycles will be unrelated to COE, and thus underwriting cycle/insurance-specific variables will not be good candidates for inclusion into the CCAPM or ICAPM.

It is possible that underwriting cycle shocks will affect or be correlated with the state of the economy as a whole, and then underwriting cycle variables will have to be included in the CCAPM and ICAPM. An easy way to check whether this is the case is to see if the underwriting cycle variables are related to marginal utility of consumption and thus to expected market risk premium.

In Table 4, we try a host of underwriting cycle variables as potential predictors of the market risk premium. We find that none of the variables that measure the state of the

[30]In Online Appendix A, we also add *FVIX* and the four conditioning variables in FF5 and arrive at results similar to Table 2.

TABLE 4
Underwriting Cycles and Expected Market Risk Premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$CatLoss_{t-1}$	−0.1014						
	(0.2758)						
$CombRat_{t-1}$		−0.2007					
		(0.1278)					
$Surplus_{t-1}$			0.0022				
			(0.0141)				
$PremW_{t-1}$				0.0198			
				(0.1500)			
$PremE_{t-1}$					0.0098		
					(0.1619)		
$NetInvInc_{t-1}$						−0.4117	
						(1.4515)	
$CapGain_{t-1}$							0.5532
							(0.6396)
Constant	2.1410**	1.9335**	1.4000	0.8658	1.3405	4.1586	1.2786
	(0.9221)	(0.7834)	(2.6664)	(7.0719)	(7.4953)	(8.3766)	(0.9961)
Adj. R^2	−0.008	0.013	−0.009	−0.009	−0.009	−0.008	−0.002
Quarters	116	116	111	111	111	111	111

Note: This table reports the predictive regression results using lagged quarterly underwriting cycle/insurance-specific variables to predict the quarterly market risk premium from 1986 to 2014 for *CatLoss* (catastrophic losses) and *CombRat* (combined ratio), and from 1987 to 2014 for *Surplus*, *PremW* (premiums written), *PremE* (premiums earned), *NetInvInc* (net investment income), and *CapGain* (net realized capital gains). *CatLoss*, *CombRat*, *Surplus*, *PremW*, *PremE*, *NetInvInc*, and *CapGain* are collected from the Insurance Services Office Inc. (ISO) quarterly publication "Property-Casualty Insurance Industry Financial Results." *CatLoss*, *Surplus*, *PremW*, *PremE*, *NetInvInc*, and *CapGain* are CPI adjusted. *CatLoss* is for property catastrophes only and the ISO obtains it from the Property Claim Services Company. The CPI data were obtained from "Consumer Price Index for All Urban Consumers: All Items" Monthly, Seasonally Adjusted, CPIAUCSL from FRED at https://research.stlouisfed.org/fred2/series/CPIAUCSL#. Standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

insurance industry and underwriting cycles can predict the market risk as a whole (which is probably not surprising because the insurance industry is not large enough to change the fortunes of the U.S. consumers by itself). While the variables can be important for the insurance industry, they are unlikely to be priced in the stock market as a whole and therefore will not impact expected returns.

Underwriting Cycles and the Conditional CAPM

If we go back to Equation (2), we observe that the difference between expected return/COE estimates from the CAPM and CCAPM is equal to the covariance between the time-varying market beta and the expected market risk premium. Hence, if a variable is related to the beta but not the expected market risk premium, its inclusion in CCAPM will not change the estimate of expected return/COE, and the covariance piece in Equation (2) is unaffected by it. Thus, the shocks to the beta it can cause will be similar to random shocks and will average out in a long enough sample.

Given the results in Table 4, our prior is that the underwriting cycle variables will not be helpful for COE estimates if included in the CCAPM because these variables are unrelated to expected market risk premium. In Table 5, we present an empirical test of this hypothesis by adding the underwriting cycle variables to the CCAPM with the business cycle variables from Table 2. We observe that almost all variables are insignificant and thus appear unrelated to even the market beta of insurers. That does not mean that the variables are unimportant to the insurance industry: they can still affect the cash flows without affecting their covariance with the market return.[31]

One exception is the net realized capital gains variable, which seems to be significantly related to the beta of insurers. However, the alpha in the bottom row of Table 5 changes by only 2–3 bp per month after the inclusion of the capital gains variable, indicating that including this variable does not materially change our COE estimate for insurers. The case of the capital gains variable is a perfect illustration of the redundancy in asset pricing models of industry-specific variables that cannot predict the market risk premium. Even if such variables are related to the beta, they do not contribute to the average expected return because the part of the expected return that is unique to the CCAPM equals $Cov[\beta_i, (RM\text{-}RF)]$—in order for a variable to impact the expected return/COE, it has to be related both to the beta and the market risk premium.

Underwriting Cycles and the Intertemporal CAPM

In Table 6, we experiment with using insurance-specific variables to create ICAPM factors despite our initial suspicion that such variables will not matter in the ICAPM because they seem to be unrelated to the expected market risk premium shown in Table 4. We pick average combined ratio as the variable to create the factor-mimicking portfolio from because it summarizes well the state of the insurance industry. Since the combined ratio has the first-order autocorrelation of 0.98, we define the unexpected component as its simple change. Following Lamont's (2001) suggestion that the optimal base assets should have the richest possible variation in the sensitivity to the variable being mimicked, we choose quintiles sorted on historical sensitivity to changes in combined ratio.[32] We regress changes in combined ratio on

[31]Since the underwriting cycle variables are collected for the P/L insurance industry, to test the robustness of our results, we replicated the analyses in Table 5 (CCAPM) and Table 6 (ICAPM) for P/L insurers only and the untabulated results are very similar. Additionally, we replicated the analyses for life insurers only and the untabulated results are very similar as well.

[32]In each firm-quarter (underwriting cycle/insurance-specific variables such as combined ratio are collected quarterly) for every stock traded in U.S. market and listed on CRSP, we perform regressions of excess stock returns ($R_i - RF$) on $RM - RF$, SMB, HML, and changes in combined ratio. The regressions use quarterly returns and the most recent 20 quarters of data (i.e., in quarter t we use data from quarters $t-1$ to $t-20$) and omit the stocks with fewer than 12 nonmissing returns between $t-1$ and $t-20$. The slope on changes in combined ratio is our measure of historical stock sensitivity to changes in combined ratio.

TABLE 5
Underwriting Cycles in the Conditional CAPM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RM-RF	0.42**	0.25	0.12	0.97	−0.07	1.16	−0.95	1.71*	2.00	0.57
	(0.19)	(0.21)	(0.84)	(0.95)	(1.23)	(1.66)	(1.64)	(0.95)	(1.90)	(1.79)
$DEF_{t-1} \cdot (RM\text{-}RF)$	0.12	0.15*	0.12	0.16*	0.18**	0.17*	0.11	−0.27*	−0.25*	−0.25
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.15)	(0.15)	(0.15)
$DIV_{t-1} \cdot (RM\text{-}RF)$	0.32***	0.30***	0.32***	0.27***	0.29***	0.27***	0.30***	0.24***	0.23***	0.26***
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
$TB_{t-1} \cdot (RM\text{-}RF)$	−0.85**	−0.57	−0.89**	−0.37	0.29	−0.38	−0.12	−0.42	0.08	0.13
	(0.39)	(0.42)	(0.41)	(0.49)	(0.70)	(0.49)	(0.52)	(0.48)	(0.69)	(0.70)
$TERM_{t-1} \cdot (RM\text{-}RF)$	−0.10	−0.07	−0.10	−0.05	0.04	−0.05	−0.04	−0.07	0.00	−0.01
	(0.07)	(0.07)	(0.07)	(0.08)	(0.10)	(0.08)	(0.08)	(0.08)	(0.10)	(0.10)
$CatLoss_{t-1} \cdot (RM\text{-}RF)$		0.03*		0.04*	0.04*	0.05*	0.03	0.02	0.03	0.02
		(0.02)		(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)
$CombRat_{t-1} \cdot (RM\text{-}RF)$			0.00	−0.01	−0.00	−0.01	−0.00	−0.01	−0.01	−0.00
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$Surplus_{t-1} \cdot (RM\text{-}RF)$					0.00				0.00	0.00
					(0.00)				(0.00)	(0.00)
$PremW_{t-1} \cdot (RM\text{-}RF)$						−0.00			−0.01	
						(0.02)			(0.02)	
$PremE_{t-1} \cdot (RM\text{-}RF)$							0.03			0.00
							(0.02)			(0.02)
$CapGain_{t-1} \cdot (RM\text{-}RF)$								−0.16***	−0.16***	−0.15***
								(0.04)	(0.04)	(0.05)
Alpha	0.011	0.036	0.017	0.028	0.053	0.027	0.037	0.044	0.060	0.063
	(0.184)	(0.183)	(0.185)	(0.184)	(0.185)	(0.184)	(0.184)	(0.181)	(0.182)	(0.182)
Adj. R^2	0.603	0.605	0.602	0.605	0.606	0.604	0.606	0.619	0.619	0.618
Obs.	333	333	333	333	333	333	333	333	333	333

Note: This table reports the results adding the underwriting cycle/insurance-specific variables to the CCAPM for all the publicly traded insurance companies. It estimates equation $R_{it} - RF_t = \alpha + \gamma_0 (RM_t - RF_t) + \Gamma_1 Y_{t-1} (RM_t - RF_t) + \Gamma_2 X_{t-1} (RM_t - RF_t) + \varepsilon$, where R_i is the value-weighted returns to all insurers, *RM-RF* is the market risk premium, *Y* stands for the four business cycle variables (*DEF*, *DIV*, *TB*, and *TERM*), *X* stands for the underwriting cycle/insurance-specific variables from Table 4 (*CatLoss*, catastrophic losses, *CombRat*, combined ratio, *Surplus*, *PremW*, premiums written, *PremE*, premiums earned, and *CapGain*, net realized capital gains), and ε is the error term. *CatLoss*, *Surplus*, *PremW*, *PremE*, and *CapGain* are CPI adjusted. *DEF* is default spread, defined as the yield spread between Moody's Baa and Aaa corporate bonds. *DIV* refers to dividend yield, defined as the sum of dividend payments to all CRSP stocks over the previous 12 months divided by the current value of the CRSP value-weighted index. *TB* is the risk-free rate, which is the 30-day Treasury bill rate. *TERM* is term spread, defined as the yield spread between the 10- and 1-year Treasury bond. Because lagged *Surplus*, *PremW*, *PremE*, and *CapGain* are available starting from the second quarter of 1987, to make the regression sample periods consistent, all regressions are from April 1987 to December 2014. "Obs." reports the number of months in the regressions. Standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

TABLE 6
Underwriting Cycles in the Intertemporal CAPM (Combined Ratio Changes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RM-RF	0.87***	0.88***	0.87***	−0.27	−0.24	−0.29*	1.07***	1.07***	1.07***	0.52***	0.52***	0.49***
	(0.05)	(0.05)	(0.05)	(0.17)	(0.18)	(0.17)	(0.04)	(0.04)	(0.04)	(0.18)	(0.18)	(0.18)
SMB							−0.12**	−0.13**	−0.13**	−0.08	−0.09	−0.08
							(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
HML							0.52***	0.51***	0.52***	0.54***	0.54***	0.54***
							(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
RMW							0.32***	0.32***	0.31***	0.22***	0.23***	0.21**
							(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
CMA							0.07	0.08	0.07	0.00	0.01	0.00
							(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
FVIX				−0.87***	−0.85***	−0.88***				−0.39***	−0.39***	−0.41***
				(0.13)	(0.13)	(0.13)				(0.13)	(0.13)	(0.13)
FCombRat		−0.50*			−0.24			0.09			0.08	
		(0.28)			(0.26)			(0.23)			(0.23)	
ΔCombRat			0.03			0.04			0.03			0.03
			(0.03)			(0.03)			(0.02)			(0.02)
Alpha	0.15	0.12	0.15	−0.28	−0.28	−0.28	−0.20	−0.20	−0.19	−0.33*	−0.33*	−0.33**
	(0.20)	(0.20)	(0.20)	(0.19)	(0.19)	(0.19)	(0.16)	(0.16)	(0.16)	(0.17)	(0.17)	(0.17)
Adj. R^2	0.546	0.549	0.545	0.603	0.602	0.604	0.719	0.718	0.719	0.727	0.726	0.728
Obs.	312	312	312	312	312	312	312	312	312	312	312	312

Note: This table reports the regression results including the combined ratio factor (*FCombRat*) into the three models from Tables 2 (CAPM, FF5, and ICAPM) and FF5 augmented with *FVIX* (FF6) for all the publicly traded insurance companies. The results of estimating these four models are in columns 1, 4, 7, and 10, respectively. The combined ratio factor is added to the models in columns 2, 5, 8, and 11. In columns 3, 6, 9, and 12 each factor is replaced by the variable it mimics (changes in combined ratio). The left-hand-side variable is the value-weighted returns to all the publicly traded insurance companies. *RM−RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P 100 stock index options. *FCombRat* is the factor-mimicking portfolio that mimics the changes in combined ratio, namely, the combined ratio factor. *ΔCombRat* is the variable that *FCombRat* mimics, which is the changes in combined ratio. Since *FCombRat* and *ΔCombRat* are available from 1989, all regressions are from 1989 to 2014. "Obs." reports the number of months in the regressions. Standard errors appear in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

excess returns to the quintile portfolios to form the factor-mimicking portfolio (*FCombRat*) that tracks changes in combined ratio.[33,34]

Table 6 includes the combined ratio factor (*FCombRat*) in the three models from Table 2 (CAPM, FF5, ICAPM) and FF5 augmented with *FVIX* (FF6). The results of estimating the four models are in columns 1, 4, 7, and 10. *FCombRat* is added to the models in columns 2, 5, 8, and 11. In columns 3, 6, 9, and 12 *FCombRat* is replaced by the variable it mimics (change in average combined ratio). The left-hand-side variable is the monthly value-weighted returns to all insurers.[35]

First, we observe that the betas of all insurance companies with respect to the combined ratio factor are expectedly negative, but statistically insignificant once either *FVIX* or *SMB*, *HML*, *RMW*, and *CMA* are controlled for.[36] We also check that the insignificant betas of the combined ratio factor are not an artifact of our factor-mimicking procedure by replacing the factor-mimicking portfolio with the shocks to combined ratio the factor mimics (columns 3, 6, 9, and 12). That produces all insignificant loadings, which even turn puzzlingly positive.

Second, we observe that the impact of adding the combined ratio factor to either of the four models is minor. In particular, the change in the alpha is minuscule (0–3 bp per month).[37] Hence, adding the combined ratio factor as an insurance-specific factor does not change estimated COE. Again, the economic reason is that shocks specific to the insurance industry do not affect the economy as a whole and can be diversified away by investors who invest in many industries. Therefore, these shocks do not represent priced risks and should not be expected to affect COE of insurance companies (even if the shocks do affect their cash flows).

The irrelevance of underwriting cycle variables as candidate CCAPM/ICAPM goes beyond the application at hand, suggesting that "insurance-specific" factors should not be used to measure the expected returns to insurers. Even if such factors are correlated to insurance companies' realized returns, they will not contribute to

[33]In Online Appendix F, we present the factor-mimicking regression of the change in combined ratio on the base assets, and examine the alphas and betas of *FCombRat* in the CAPM, FF3, Carhart (1997), and FF5 models.

[34]The fact that combined ratio is quarterly and insurers returns are monthly is not a problem, since the factor-mimicking regression yields the weights, with which the base assets should be taken to mimic the combined ratio, and the weights can be multiplied by returns to the base assets taken at any (daily, monthly, etc.) frequency.

[35]Using other insurance-specific variables from Table 4 yields similar results. In Online Appendix F, we present the details on experimenting with catastrophic losses as an ICAPM factor.

[36]By construction, the factor posts high returns when combined ratio increases, which is bad news for insurers.

[37]The intercept of the regressions in columns 3, 6, 9, 12 cannot be interpreted as the alpha (abnormal return) because shocks to combined ratio are not returns to a tradable portfolio (which is one of the reasons why we construct the factor-mimicking portfolios).

expected returns due to being unrelated to the economy as a whole and thus having zero alphas controlling for market-wide risk factors.[38]

COST OF EQUITY ESTIMATION

Estimation Methods

In this study, we estimate the value-weighted average COE for 18 years (1997–2014) for all insurers combined and separately for P/L insurers and life insurers.[39] For CAPM, FF5, and ICAPM, we sum the products of the estimated insurer factor betas multiplied by long-term factor risk premiums, and then add in the risk-free rate to obtain COE. In each month, we estimate the factor betas by regressing monthly value-weighted insurer returns on monthly factor risk premiums in the previous 60 months. The factor risk premiums (*RM-RF*, *SMB*, *HML*, *RMW*, and *CMA*) are averaged from July 1926 to the month we estimate COE for.[40] Finally, the risk-free rate is the previous 60-month average ending in the month we estimate COE for. To obtain annual COE, we sum up each of the 12 months' COE estimates within that year.[41]

The CCAPM COE is estimated in a different and novel manner accounting for the time-varying nature of the market beta and expected market risk premium. We estimate insurer COE 1 year out. To calculate the predicted market risk premium in $t+1, t+2, \ldots,$ and $t+12$, we multiple the values of the four business cycle variables in $t-11$, $t-10$, $\ldots$, and t by the corresponding coefficients from $RM_t - RF_t = b_{i0} + b_{i1}\ DEF_{t-12} + b_{i2}DIV_{t-12} + b_{i3}TB_{t-12} + b_{i4}TERM_{t-12} + \varepsilon$, and sum the products up with the regression intercept. The regression is estimated in January 1928 to December 2014 (January 1928 is the first year when all the variables are available).

To predict the market beta, in each month we estimate the beta equation (Equation (3)) coefficients over the previous 120 months using equation

[38]In Online Appendix C, we also attempt using returns to the insurance industry or the subsectors (*INS*, *PL*, and *Life*) as a factor in cross-sectional regressions that include all stocks in the market. The insurance-industry factors come out insignificant. Adding them does not improve the R-squared or the estimate of the intercept of the cross-sectional regressions, consistent with the view that there is no "insurance risk" that would impact the whole market.

[39]In Online Appendix G, in order to control for potential bias resulting from infrequent trading, we follow the sum-beta approach of Dimson (1979) and Cummins and Phillips (2005). For CAPM, FF5, and ICAPM the sum-beta factor loadings are the sum of usual betas and betas with respect to lagged factor. The sum-beta COE estimates are very similar in each year from each model to the COE estimates discussed above, which means our estimates are robust to the potential infrequent trading bias.

[40]The risk premium for *FVIX* is averaged from February of 1986 (VIX starts from January 1986 and factor-mimicking regression is based on lagged variables) to the month we estimate COE for.

[41]In Online Appendix G, we also estimate the COE for all, P/L, and life insurance companies using the AFM model based on both the regular and the sum-beta approaches. The results show that, similar to the insurance factors, the diversifiable financial industry factors (*FROE* and *SPREAD*) do not contribute to the COE estimation for insurers, controlling for market-wide factors.

$R_{it}-RF_t = a_i + b_{i0}\cdot(RM_t-RF_t) + b_{i1}DEF_{t-12}\cdot(RM_t-RF_t) + b_{i2}DIV_{t-12}\cdot(RM_t-RF_t) + b_{i3}TB_{t-12}\cdot(RM_t-RF_t) + b_{i4}TERM_{t-12}\cdot(RM_t-RF_t) + \varepsilon$, where R_{it} is the value-weighted insurer stock returns of month t (we also run the regression on a 60-month rolling window basis and the results are similar). The estimated beta equation coefficients are applied to Equation (3) using DEF, DIV, TB, and $TERM$ in $t-11$, $t-10$, ..., and t to calculate the predicted market beta in $t+1$, $t+2$, ..., and $t+12$.

Then, in each month t, we estimate COE in $t+1$, $t+2$, ..., and $t+12$ by multiplying the predicted market risk premium in $t+1$, $t+2$, ..., and $t+12$ with the predicted market beta in the same time period and then adding in the risk-free rate in t. As a result, in each month t we obtain the $t+1$ to $t+12$ forecasts of COE. Then, we calculate the COE estimate of a given month by "horizontally" averaging the COE forecasted from the previous 12 months.[42] The annual COE, therefore, is calculated by summing up each of the 12 months' COE estimates within that year.[43]

Cost of Equity Estimation Results

The value-weighted average COE estimates of all publicly traded insurers are presented in Panel A of Table 7 for each of the 18 years (1997–2014) and 18 years combined. ICAPM produces the highest average COE estimate across the 18-year period with the value being 13.834 percent. FF5 generates the second highest estimate (12.662 percent), followed by CAPM (9.443 percent).[44,45]

The significantly higher ICAPM COE compared to CAPM are due to the volatility risk exposure of insurers (see Table 2). The 18-year average COE from ICAPM is even higher than that from FF5, which means that *FVIX* alone captures more risk than *SMB*, *HML*, *CMA*, and *RMW* taken together. Also, the ICAPM has a theoretical advantage over FF5, since it pinpoints the exact nature of risk faced by insurance companies (volatility risk), while *SMB*, *HML*, *CMA*, and *RMW* do not have a commonly accepted interpretation. Further, in Online Appendix G we find that if *FVIX* is added to FF5, the resulting FF6 model produces even higher COE estimates than FF5, further

[42]In other words, in month t we average 1-month-out COE estimate from $t-1$, 2-month-out COE estimate from $t-2$, ..., and 12-month-out COE estimate from $t-12$.

[43]In Online Appendix G, the sum-beta CCAPM COE is also calculated by summing the product of predicted contemporaneous beta with predicted contemporaneous market risk premium and the product of predicted lagged beta with predicted lagged market risk premium, plus current risk-free rate. The CCAPM COE estimates based on the regular and the sum-beta approach are similar.

[44]The sample period in Table 7 is shorter than in the rest of our analysis because we use the first 10 years of the sample as the learning period for the CCAPM.

[45]Our results in Table 7 are not directly comparable with those in some previous studies (e.g., Cummins and Phillips, 2005; Wen et al., 2008) because there are differences in the classification of insurers, definition of market return, risk-free rate, long-term factor risk premiums, value-weighted versus equal-weighted returns, estimation periods, and so on. Once we adjust the details to be as close as possible to the existing literature, we are able to obtain very similar COE estimates to those in the literature.

TABLE 7
Cost of Equity Estimates

	COE Estimates			
Year	CAPM (1)	FF5 (2)	CCAPM (3)	ICAPM (4)
Panel A. All Insurers				
1997	11.994	12.216	5.951	16.718
1998	12.779	14.289	4.672	17.523
1999	12.419	18.952	3.086	20.442
2000	11.906	20.945	4.439	26.400
2001	9.657	21.487	3.893	21.658
2002	8.369	19.120	2.617	17.007
2003	7.230	17.214	5.090	14.783
2004	6.505	15.434	6.109	15.399
2005	6.038	12.966	3.958	10.190
2006	7.324	10.693	4.437	8.481
2007	9.165	11.261	4.123	10.402
2008	10.291	10.032	2.994	11.136
2009	11.343	12.360	18.136	12.287
2010	10.704	8.470	28.765	11.064
2011	9.787	6.779	11.648	10.199
2012	8.852	5.627	8.532	9.229
2013	8.453	5.057	7.486	8.787
2014	7.152	5.017	6.520	7.314
Average	9.443	12.662	7.359	13.834
Panel B. P/L Insurers				
1997	10.648	9.464	5.678	18.315
1998	11.805	11.888	4.689	19.712
1999	11.324	18.926	3.109	22.797
2000	10.988	21.363	4.444	27.601
2001	8.989	21.305	3.985	22.197
2002	7.822	17.832	2.692	17.367
2003	6.864	16.262	5.483	15.366
2004	6.364	14.410	5.854	16.533
2005	5.956	12.300	3.179	11.214
2006	7.518	9.825	4.087	9.605
2007	9.521	11.564	4.282	11.594
2008	9.465	10.251	3.040	10.695
2009	9.228	10.666	16.867	10.099
2010	8.421	5.710	22.910	8.464
2011	7.437	3.665	9.419	7.593
2012	6.528	2.523	7.077	6.759
2013	6.076	2.334	6.179	6.186
2014	5.085	3.323	5.264	6.857
Average	8.336	11.312	6.569	13.831

(*Continued*)

TABLE 7
Continued

	COE Estimates			
Year	CAPM (1)	FF5 (2)	CCAPM (3)	ICAPM (4)
	Panel C. Life Insurers			
1997	12.664	19.831	6.094	20.394
1998	12.954	20.359	4.687	20.298
1999	12.745	18.533	3.127	18.932
2000	12.307	18.656	4.420	24.111
2001	10.415	19.815	3.499	20.132
2002	9.357	19.151	2.895	16.202
2003	8.476	17.795	6.139	14.330
2004	7.727	16.669	7.151	14.683
2005	7.223	13.389	5.656	9.315
2006	8.262	11.207	4.734	7.388
2007	9.571	10.252	4.177	8.243
2008	11.935	10.693	3.060	11.230
2009	17.882	18.525	24.145	17.902
2010	17.920	15.643	53.297	17.627
2011	16.981	13.658	20.048	16.584
2012	16.148	11.488	13.989	15.503
2013	16.335	10.883	11.819	16.215
2014	13.639	10.041	10.093	9.267
Average	12.363	15.366	10.502	15.464

Note: This table shows the value-weighted cost of equity (COE) estimates for all publicly traded insurers, P/L insurers, and life insurers based on CAPM, FF5, CCAPM, and ICAPM from 1997 to 2014 in columns 1–4, respectively. For each year, the annual COE estimate is the cumulative monthly COE estimates from January to December of that year. Average shows the average COE across the full sample period from 1997 to 2014.

confirming that *FVIX* contributes to COE estimation even controlling for the FF5 factors.[46]

CCAPM is a special case because it does not rely on the long-term average of the market risk premium to produce COE, but instead recognizes the time-varying nature of the market risk premium and predicts its values in each moment of time. On the one hand, this approach allows the CCAPM to better capture the variation of COE over the business cycle, which is evidenced by the fact that the CCAPM produces the highest estimates across all models during the Great Recession (2009–2011). On the other hand, in our sample, average predicted market risk premium hovers around 3 percent per annum, which is quite low compared to the long-run average market risk

[46]In Online Appendix G, we also used FF6 model for COE estimation for all, P/L, and life insurers, and obtained even higher COE estimates for each of these insurer groups (e.g., for all insurance firms FF6 pegs the average COE at 13.490 percent per annum) than those from FF5.

premium of roughly 6 percent.[47] As a result, on average the CCAPM produces lower COE than even the CAPM, not because the countercyclical beta risk it reveals is unimportant, but because the CCAPM has a different idea about the fair compensation for the market risk. If the standard CAPM used the same 3 percent market risk premium, it would produce an average COE of 4.818 percent per annum, much lower than the CCAPM's 7.359 percent per annum.

The COE estimates for the subsamples of P/L and life insurers are presented in Panels B and C of Table 7, respectively. Their ranking of average COE from different models is the same as that of all insurers. Specifically, ICAPM yields the highest average COE estimate (13.831 percent) for the entire 18-year period for P/L insurers, followed by FF5 (11.312 percent), CAPM (8.336 percent), and CCAPM (6.569 percent). For life insurers, again ICAPM produces the highest average COE estimate (15.464 percent) for the full sample period, followed by FF5 (15.366 percent), CAPM (12.363 percent), and CCAPM (10.502 percent). But still, CCAPM generates the highest estimates during the Great Recession across all models for both P/L and life insurers. An interesting observation is that COE estimates for life insurers tend to be higher on average than for P/L insurers. The differences between COE estimates for life insurers versus P/L insurers are between 1.6 and 4.1 percent, depending on the models, meaning that the required rate of return and risk for life insurers are higher than that of P/L insurers.

SUMMARY AND CONCLUSIONS

We extend prior literature by identifying new risk factors the insurance industry is exposed to. The CCAPM shows that insurers' risk exposure (market beta) is significantly higher in recessions (as characterized by high default spreads and low Treasury bill rates) when bearing risk is especially costly. The ICAPM adds that insurers' values drop in response to surprise increases in expected market volatility (VIX), which makes insurers riskier than what the CAPM predicts.

We also consider underwriting cycle/insurance-specific variables for potential inclusion into the CCAPM and ICAPM and find that while those variables apparently affect cash flows to insurers, they do not affect the insurers' cost of equity capital. Further, we add the insurance factors and financial industry factors to FF5 and find contribution to neither the model goodness of fit nor the COE estimation. Underwriting cycle/insurance-specific variables or insurance/financial industry factors do not affect the economy or the stock market as a whole, and their effect on insurance companies can be diversified away by an investor with exposure to many industries.

---

[47]The result used in the CCAPM estimation that the expected market risk premium was 3 percent per annum before the Great Recession of 2008 is not unique to our study. Using different estimation techniques, Claus and Thomas (2001) and Fama and French (2002) come to a similar conclusion that the Great Moderation of 1980s and 1990s resulted in a period of abnormally low discount rate. Both studies peg the expected market risk premium for 1980–2000 at roughly 3 percent, just as the expected market risk premium of our model does before 2008.

The analysis in the article is performed at the industry level and thus applies to an average/representative insurance firm. We do not exclude the possibility that some individual insurers can be not exposed to the risks the whole industry is exposed to and would suggest reestimating the models for an individual firm, if it is its COE that is of interest in a particular application.

In the COE estimates, based on an 18-year window (1997–2014), consistent with the notion that additional time-varying risks require greater rewards, the average COE estimates from the ICAPM are significantly higher than the ones from the CAPM and even higher than those from FF5. Moreover, adding *FVIX* to FF5 results in even higher COE than estimated by FF5.

We also employ a novel method of using CCAPM for estimating COE, which involves predicting both the market beta and the market risk premium. The resulting COEs are on average lower than those from the standard CAPM, but the CCAPM's estimates become much higher than those from any other model in 2009–2011, as would be expected given the extreme amount of risk in the market during the most recent recession. The low average COE produced by the CCAPM comes from low values of expected market risk premium between 1980 and 2007 (around 3 percent per annum, consistent with similar estimates in Claus and Thomas, 2001; Fama and French, 2002).

Our study adds to the literature in several ways. First, it is the first to examine CCAPM and volatility risk for insurers. Second, it provides empirical evidence supporting the pricing of time-varying market beta and volatility risk for insurers. Third, it provides evidence of meaningful economic and statistical differences between single- and multiperiod models. And, lastly, it demonstrates that industry-specific factors should not be used in factor models, since these factors do not have an impact on expected return/cost of capital and only affect cash flows.

The main contribution of the article is the introduction of the CCAPM and ICAPM with factor-mimicking portfolios to the insurance literature. We do not argue that the state variables we use are the only state variables that matter; to the contrary, we hope that our article opens the door to finding more risks and hedges in the insurance industry in addition to what we found. We also suggest a screening mechanism for choosing new state variables: such state variables should be able to predict the market risk premium.

References

Adrian, T., E. Friedman, and T. Muir, 2016, The Cost of Capital of the Financial Sector, Working Paper, Federal Reserve Bank of New York.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The Cross-Section of Volatility and Expected Returns, *Journal of Finance*, 61: 259-299.

Bajtelsmit, V. L., S. V. Villupuram, and T. Wang, 2015, Life Insurer Cost of Equity With Asymmetric Risk Factors, *Financial Review*, 50: 435-457.

Baker, M., and J. Wurgler, 2006, Investor Sentiment and the Cross-Section of Stock Returns, *Journal of Finance*, 61: 1645-1680.

Barinov, A., 2013, Analyst Disagreement and Volatility Risk, *Journal of Financial and Quantitative Analysis*, 48: 1877-1900.

Barinov, A., 2014, Turnover: Liquidity or Uncertainty? *Management Science*, 60: 2478-2495.

Becker, B., and V. Ivashina, 2015, Reaching for Yield in the Bond Market, *Journal of Finance*, 70: 1863-1901.

Ben Ammar, S., M. Eling, and A. Milidonis, 2015, Asset Pricing of Financial Institutions: The Cross-Section of Expected Stock Returns in the Property/Liability Insurance Industry, Working Paper, University of St. Gallen.

Berry-Stölzle, T. R., and J. Xu, 2018, Enterprise Risk Management and the Cost of Capital, *Journal of Risk and Insurance*, 85(1): 159-201.

Breeden, D. T., M. R. Gibbons, and R. H. Litzenberger, 1989, Empirical Tests of the Consumption-Oriented CAPM, *Journal of Finance*, 44: 231-262.

Campbell, J. Y., 1993, Intertemporal Asset Pricing Without Consumption Data, *American Economic Review*, 83: 487-512.

Campbell, J. Y., C. Polk, and T. Vuolteenaho, 2010, Growth or Glamour? Fundamentals and Systematic Risk in Stock Returns, *Review of Financial Studies*, 23: 305-344.

Carhart, M. M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52: 57-82.

Chen, J., 2002, Intertemporal CAPM and the Cross-Section of Stock Returns, Working Paper, University of Southern California.

Claus, J., and J. Thomas, 2001, Equity Premia as Low as Three Percent? Evidence From Analysts' Earnings Forecasts for Domestic and International Stock Markets, *Journal of Finance*, 56: 1629-1666.

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

Cochrane, J. H., 2007, Financial Markets and the Real Economy, in *International Library of Critical Writings in Financial Economics* (London: Edward Elgar).

Cooper, I., 2006, Asset Pricing Implications of Nonconvex Adjustment Costs and Irreversibility of Investment, *Journal of Finance*, 61: 139-170.

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

Daniel, K., and S. Titman, 1997, Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *Journal of Finance*, 52: 1-33.

Dimson, E., 1979, Risk Measurement When Shares Are Subject to Infrequent Trading, *Journal of Financial Economics*, 7: 197-226.

Fama, E. F., and K. R. French, 1988, Dividend Yields and Expected Stock Returns, *Journal of Financial Economics*, 22: 3-25.

Fama, E. F., and K. R. French, 1989, Business Conditions and Expected Returns on Stocks and Bonds, *Journal of Financial Economics*, 25: 23-49.

Fama, E. F., and K. R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance*, 47: 427-465.

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

Fama, E. F., and K. R. French, 1995, Size and Book-to-Market Factors in Earnings and Returns, *Journal of Finance*, 50: 131-155.

Fama, E. F., and K. R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance*, 51: 55-84.

Fama, E. F., and K. R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics*, 43: 153-193.

Fama, E. F., and K. R. French, 2002, The Equity Premium, *Journal of Finance*, 57: 637-659.

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

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

Fama, E. F., and G. W. Schwert, 1977, Asset Returns and Inflation, *Journal of Financial Economics*, 5: 115-146.

Gibbons, M. R., S. A. Ross, and J. Shanken, 1989, A Test of the Efficiency of a Given Portfolio, *Econometrica*, 57: 1121-1152.

Hahn, J., and H. Lee, 2006, Interpreting the Predictive Power of the Consumption-Wealth Ratio, *Journal of Empirical Finance*, 13: 183-202.

Harvey, C., Y. Liu, and H. Zhu, 2016, . . . and the Cross-Section of Expected Returns, *Review of Financial Studies*, 29: 5-68.

Hou, K., C. Xue, and L. Zhang, 2015, Digesting Anomalies: An Investment Approach, *Review of Financial Studies*, 28: 650-705.

Lakonishok, J., A. Shleifer, and R. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance*, 49: 1541-1578.

Lamont, O. A., 2001, Economic Tracking Portfolios, *Journal of Econometrics*, 105: 161-184.

Lee, A. C., and J. D. Cummins, 1998, Alternative Models for Estimating the Cost of Equity Capital for Property/Casualty Insurers, *Review of Quantitative Finance and Accounting*, 10: 235-267.

Leland, H. E., 1999, Beyond Mean-Variance: Performance Measurement in a Nonsymmetrical World, *Financial Analysts Journal*, 55: 27-36.

Lewellen, J. W., S. Nagel, and J. Shanken, 2010, A Skeptical Appraisal of Asset Pricing Tests, *Journal of Financial Economics*, 96: 175-194.

Liew, J., and M. Vassalou, 2000, Can Book-to-Market, Size and Momentum Be Risk Factors That Predict Economic Growth? *Journal Financial Economics*, 57: 221-245.

McLean, R. D., and J. Pontiff, 2016, Does Academic Research Destroy Stock Return Predictability? *Journal of Finance*, 71(1): 5-32.

Merton, R. C., 1973, An Intertemporal Capital Asset Pricing Model, *Econometrica*, 41: 867-887.

Nissim, D., 2013, Implied Cost of Equity Capital in the U.S. Insurance Industry, *Journal of Financial Perspectives*, 1: 1-17.

O'Doherty, M. S., 2012, On the Conditional Risk and Performance of Financially Distressed Stocks, *Management Science*, 58: 1502-1520.

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

Petkova, R., and L. Zhang, 2005, Is Value Riskier Than Growth? *Journal of Financial Economics*, 78: 187-202.

Rubinstein, M., 1976, The Valuation of Uncertain Income Streams and the Pricing of Options, *Bell Journal of Economics*, 7: 407-425.

Vassalou, M., and Y. Xing, 2004, Default Risk in Equity Returns, *Journal of Finance*, 59: 831-868.

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

Zhang, L., 2005, The Value Premium, *Journal of Finance*, 60: 67-103.

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's website.

Appendix A: Augmented Fama-French and AFM Models
Appendix B: Liquidity, Liquidity Risk, and Coskewness
Appendix C: Cross-Sectional Tests and GRS Tests of the Models
Appendix D: Other Types of Insurers
Appendix E: *FVIX* Exposures of 48 Fama-French (1997) Industry Portfolios
Appendix F: More Details on Underwriting Cycles and the Intertemporal CAPM
Appendix G: Cost of Equity Estimation from Augmented Fama-French and AFM Models and from Sum-beta Approach
Appendix H: Equal-Weighted Returns of Insurers

Appendices For "Estimating the Cost of Equity Capital for Insurance Firms with Multiperiod Asset Pricing Models"

Alexander Barinov[1]

Jianren Xu[*, 2]

Steven W. Pottier[3]

Appendix A: Augmented Fama-French and AFM Models

Fama and French (1995, 1996) argue that *SMB* and *HML* can pick up additional risk not picked up by the market beta and thus the three-factor Fama-French model (henceforth FF3) can be viewed as an empirical version of the intertemporal CAPM (ICAPM).[4] In a recent paper, Fama and French (2015) suggest two more factors, *RMW* and *CMA*, to augment the initial version of their model in order to explain recently discovered deviations from its predictions. The five-factor version of the Fama-French model (henceforth FF5) is quickly becoming the new standard benchmark model in finance. Following the trend, the FF5 model is used as a benchmark model in our paper.

While the precise economic nature of the risks that are allegedly behind *SMB* and *HML* remains elusive, and many papers contest the ICAPM interpretation of the Fama-French models, favoring the mispricing nature of *SMB* and *HML* (Lakonishok, Shleifer, and Vishny, 1994; Daniel and Titman, 1997), it is still possible that *SMB* and *HML* (and perhaps the newer factors of *RMW*

* Corresponding author
[1] Department of Finance, School of Business, University of California Riverside, 900 University Ave. Riverside, CA 92521, Tel.: +1-951-827-3684, alexander.barinov@ucr.edu.
[2] Corresponding author, Department of Finance, Insurance, Real Estate and Law, College of Business, University of North Texas, 1155 Union Circle #305339, Denton, TX 76203-5017, Tel.: +1-940-565-2192, Fax: +1-940-565-3803, jianren.xu@unt.edu.
[3] Department of Insurance, Legal Studies, and Real Estate, Terry College of Business, University of Georgia, 610 South Lumpkin Street, Athens, GA 30602, Tel.: +1-706-542-3786, Fax: +1-706-542-4295, spottier@uga.edu.
[4] The definitions of *RM*, *RF*, *SMB*, *HML*, *FVIX*, *DEF*, *DIV*, *TB*, and *TERM* are in Section II of the paper.

and *CMA*) can partly pick up the additional risks identified in the conditional CAPM (CCAPM) and the two-factor ICAPM with the market and volatility risk factors.

Table 1A adds *FVIX* to FF5 and finds that its beta is still negative and significant for all insurance companies and property-liability (P/L) insurance companies. The *FVIX* beta is smaller than in the ICAPM (see Table 2 in the paper), suggesting that there is some overlap between *FVIX* and *SMB*/*HML/RMW/CMA* (which is not surprising, because Barinov, 2011, finds that *FVIX* can at least partially explain the value effect, and Barinov, 2015, finds an even stronger overlap between *RMW* and *FVIX*). Likewise, the change in the alpha between FF5 and FF5 augmented with *FVIX* (FF6) is smaller than the change in the alpha between CAPM and ICAPM in Table 2, once again confirming the overlap between *FVIX* and *RMW*/*HML*. It is interesting though that the alphas in the ICAPM (Table 2 in the paper) and FF6 (Table 1A) are very similar (for all insurers and P/L insurers), suggesting that cost of equity (COE) estimates from ICAPM and FF6 will be similar (these models see about the same amount of risk in insurance companies). Thus, it seems that while the four Fama-French factors (*SMB*, *HML*, *RMW*, and *CMA*) overlap with *FVIX*, at least for the insurance industry as a whole and P/L insurers in particular they do not have much of explanatory power of their own that goes beyond the overlap. The reverse, however, is not true: the FF5 and FF6 alphas are quite different (see Table 1A), and so are COE estimates from FF5 and FF6 (see Table 15A). Thus, *FVIX* does have independent explanatory power that goes beyond its overlap with *RMW* and *HML*.

Overall, Table 1A shows that all insurance companies taken together and property-liability companies in particular trail not only the CAPM but also the FF5 model when market volatility unexpectedly increases, which makes them riskier than what CAPM and FF5 indicate.

Life insurers represent a special case, because for them *FVIX* becomes insignificant in FF6, and the ICAPM alpha in Table 2 in the paper is larger (less negative) than in FF5 and FF6. Thus, in the case of life insurers *SMB*/*HML/RMW/CMA* seem to dominate *FVIX*. In untabulated results, we have looked into this and found out that the cause of *FVIX* beta insignificance is the overlap between *HML* and *FVIX*: if we drop *SMB* from FF6, the *FVIX* beta barely changes; but if we drop *HML*, the *FVIX* beta goes back to almost its ICAPM value. Hence, we conclude that in the case of life insurers *HML* is a (probably empirically superior) substitute to *FVIX*, which does not change the central message of the ICAPM analysis: insurance companies are riskier than what the CAPM suggests, because insurance companies underperform in high volatility periods, and *HML*, which is related to volatility risk as Barinov (2011) shows, picks up this effect.

Table 1A also considers the Adrian, Friedman, and Muir (2016) model (henceforth the AFM model), which adds to the three traditional Fama-French factors (*RM-RF*, *SMB*, and *HML*) two more factors based on the performance of the financial industry. One factor is *FROE,* which is the return differential between top and bottom ROE quintiles formed using only financial firms, and the other is *SPREAD*, which is the return differential between financial and non-financial firms. Adrian et al. (2016) argue that performance of the financial industry affects the whole economy and thus the shocks to financial industry are not diversifiable, in contrast to other industry-wide shocks.

Table 1A shows that insurance firms are positively exposed to both *FROE* and *SPREAD* (the *SPREAD* exposure is somewhat tautological, since *SPREAD* is long in all insurance firms, among other financial firms). Adding *FROE* and *SPREAD* also makes the *HML* beta of insurers much smaller and increases the AFM model's alpha compared to the FF5 model (higher alpha implies smaller expected return / cost of capital, because all asset pricing models split the in-sample average return into the alpha and the part explained by the factors, i.e., expected return). Again, in a sense, the AFM model is explaining the insurance industry returns by using them on the right-hand side as well, so the move of the alpha towards zero is at least partly mechanical.

The rightmost column of Table 1A in each panel adds the *FVIX* factor to the AFM model (the result is the AFM6 model) and finds the *FVIX* betas are smaller than in the FF6 model (see the second column of each panel in Table 1A) and the ICAPM (see Table 2 in the paper), but all insurance firms and P/L insurers still have a significant exposure to volatility risk, and that makes the alpha of insurance companies smaller (more negative) (in AFM6 column) and their cost of capital greater than what the AFM model estimates, indicating that *FVIX* contributes to the COE estimates even controlling for the five factors in the AFM model.

In Table 2A, we try adding the four business cycle variables in the Fama-French five-factor model (conditional FF5 or C-FF5). We also make *SMB*, *HML*, *RMW*, and *CMA* betas time-varying, because untabulated analysis shows that the expected returns (and therefore risk) of these factors are also predictable by business cycle variables (in particular, the expected return of both *SMB* and *HML* seems high when the yield curve is steeper, i.e., when *TERM* is high, consistent with Hahn and Lee, 2006). We start with the “kitchen sink” approach in the middle column of each vertical panel, and then eliminate insignificant variables until we end up with the set of conditioning variables that are uniformly significant in all or almost all panels.

In the leftmost column in each panel (Conditional CAPM plus the four Fama-French factors), the market beta still looks countercyclical, though the results are weaker (the slopes on $DIV_{t-1}*(RM-RF)$ are significantly positive for all insurers and life insurers, but not for P/L insurers, and the slope on $TB_{t-1}*(RM-RF)$ is negative, but loses significance for all and P/L insurers, but not for life insurers). The alphas in the leftmost columns are more negative than the FF5 alphas from Table 2 in the paper, which implies that the market beta of insurance companies is still countercyclical even after controlling for the four Fama-French factors.

There are also signs of countercyclicality in the *SMB* beta and procyclicality in the *HML* and *CMA* betas, while the *RMW* beta delivers a split message. On the balance, it seems that the procyclical betas win in the C-FF5 model, since it has a higher (more positive) alpha and thus should generate lower cost of capital than FF5.

Appendix B: Liquidity, Liquidity Risk, and Coskewness

Several papers in the insurance literature (Jacoby et al., 2000; Wen et al., 2008) have brought up liquidity and skewness as potential determinants of expected returns (cost of capital) of insurance companies. In Table 3A, we attempt to add the respective factors to our analysis by constructing new factors that capture those variables. Just like what Fama and French (2015) did in the case of *SMB*, *HML*, *RMW*, and *CMA* and following the literature (see below), we form these factors as long-short portfolios that buy/short top/bottom quintile from the sorts of all firms in the market on the characteristic in question.[5]

For liquidity, we use two characteristics: *Zero*, the fraction of no-trade (zero return, zero trading volume) days, which is a catch-all trading cost measure suggested by Lesmond et al. (1999), and *Amihud*, the price impact measure from Amihud (2002). Lesmond et al. argued that firms with higher trading costs will see more days when investors perceive the costs of trading to be higher than benefits and refrain from trading. Amihud suggested averaging the ratio of absolute value of return to dollar trading volume over a month or a year (we use a year) to gauge by how much, on average, a trade of a given size (say, $1 million) moves the prices against the person trading (a large buy order, for example, makes prices increase and the buyer has to pay a higher price as a result).

The first panel of Table 3A reports the alphas of all insurers and two subgroups of P/L and life insurers for the baseline models (CAPM, FF5, ICAPM, and FF6), effectively collecting this

[5] The returns of all firms used for forming the liquidity factors, as well as trading volume data needed to compute the liquidity measures, are from CRSP.

information from Table 2 in the paper and Table 1A. The alphas are important, because the change in them, once we start adding more factors, will be the gauge of the economic importance of these factors. Any asset-pricing model partitions in-sample average return into the alpha (abnormal return) and the rest (expected return or cost of equity). Since the average return is the same (as long as the sample does not change), the change in the alpha has to equal the negative of the change in expected return.

Panel B of Table 3A adds the liquidity factor based on the no-trade measure (*Zero*) into the four models after which the columns are named and reports the alpha and the loading on the liquidity factor (all other betas are not reported for brevity). Panel B reveals three main results. First, in all models all groups of insurers load positively on the liquidity factor, suggesting that insurance companies are likely to be among the firms the factor buys (illiquid firms). Second, the liquidity factor is largely subsumed by *SMB*, *HML*, *RMW*, and *CMA*: as one goes from CAPM/ICAPM to FF5/FF6, the liquidity factor beta shrinks in 3-5 times and generally loses significance. Third, consistent with the above, adding the liquidity factor to CAPM/ICAPM changes the alpha (and hence, COE estimates) by economically sizeable 10-20 bp per month (1.2-2.4% per year), but adding it to FF5/FF6 changes the alpha and COE by at most 3 bp per month, which is economically small.

Panel C replaces the *Zero* liquidity factor by *Amihud* liquidity factor and finds even weaker results. The *Amihud* factor is rarely significant, the signs of the loadings alternate in different models, and even when the *Amihud* factor is significant (CAPM/ICAPM for life insurers), controlling for *SMB*, *HML*, *RMW*, and *CMA* effectively reduces it to zero. Consequently, the difference between alphas in Panels A and C is just a few bps, suggesting that controlling for the *Amihud* factor does not materially change COE estimates for insurance companies.

Summing up the evidence in Panels B and C, we conclude that liquidity has limited explanatory power for insurers' cost of equity, especially after we control for *SMB*, *HML*, *RMW*, and *CMA*, which are part of one of our benchmark models (FF5). Thus, we do not feel the need to further include liquidity factors in our analysis.

Panel D studies liquidity risk, which is a different concept. While liquidity refers to costs of trading that have to be compensated in the before-cost returns (i.e., the returns all asset-pricing literature uses), liquidity risk is a risk in the ICAPM sense and refers to losses during periods of market illiquidity. In their influential paper, Pastor and Stambaugh (2003) suggest their own price impact measure, compute it for each firm-month, and then average across all firms in each month. This series of monthly market-wide average of price impact is their liquidity measure, and the shocks to this series are liquidity shocks (constructed so that a positive shock means an increase in liquidity).

Panel D uses the Pastor-Stambaugh factor (*PS*), which is the return differential between firms with highest and lowest historical liquidity betas (high liquidity beta implies steep losses in response to liquidity decreases, i.e., liquidity risk). [6] Panel D reveals that while the factor loadings of insurance firms on the *PS* factor are uniformly negative (suggesting that insurers are hedges against liquidity risk), these loadings are insignificant, and controlling for the *PS* factor has little influence on alphas and hence on the cost of equity estimates.

Panel E looks at the role of skewness, which is known to be high in insurers' returns due to catastrophic losses. When it comes to measuring systematic risk though, the correct variable to look at is coskewness (covariance of stock returns of a portfolio with squared market returns),

[6] The values of the Pastor-Stambaugh factor are periodically updated by its creators and are available through WRDS to all subscribers.

because it measures the contribution of the asset to the skewness of a well-diversified portfolio.[7] We measure coskewness betas for each firm-month using the formula in Harvey and Siddique (2000):

$$\beta_{Skew} = \frac{E(\epsilon_{it} \cdot \epsilon_{Mt}^2)}{\sqrt{E(\epsilon_{it}^2)} \cdot E(\epsilon_{Mt}^2)} \quad (1)$$

where $\epsilon_{it} = R_{it} - RF_t - \alpha - \beta \cdot (RM_t - RF_t)$, and ϵ_{Mt} is the deviation of the market return from the long-run average. To form our coskewness factor (*Skew*), we sort all firms in the market on the historical coskewness betas and go long/short in the top/bottom quintile.

Panel E reveals that insurance companies have positive and significant exposure to the coskewness factor, indicating their exposure to the risk picked up by coskewness. However, the loading on the coskewness factor drastically decreases once we control for *SMB*, *HML*, *RMW*, *CMA*, and *FVIX*. Further, the alphas of FF6 in Panel A and the seven-factor model of FF6 plus *Skew* in Panel E differ by 1.5-5 bp per month, suggesting that the coskewness factor is economically insignificant once the other market-wide factors are controlled for.

Appendix C: Cross-Sectional Tests and GRS Tests of the Models

Cross-Sectional Test of the Models Used in the Paper

In this part we perform the cross-sectional test of the four main models (CAPM, FF5, CCAPM, and ICAPM) using industry portfolios as our cross-section. Table 4A presents the estimates from the second stage regression of returns on past betas and reports Fama-MacBeth (1973) *t*-statistics. The test follows the standard procedure: we first estimate the average betas (market beta, *FVIX* beta, etc.) for each industry portfolio formed as in Fama and French (1997)

---

[7] The standard CAPM uses a very similar logic: the non-systematic risk of an asset is the variance of the asset's returns, but the systematic risk of the asset is measured by the market beta, which is proportional to covariance between the asset's return and the market return, because the covariance measures the contribution of the asset to the variance of a diversified portfolio.

and then regress $t+1$ returns to the 30 industry portfolios on time t estimates of the betas. The time t betas are estimated individually for each firm in the industry portfolio using t-59 to t returns (at least 36 valid observations are required); the estimates are then trimmed at 1% and 99% in each month and averaged within each industry portfolio.

The main finding from Table 4A is that all the models except for ICAPM do not do a good job in the cross-section in our sample period (1986-2014, determined by the availability of *FVIX*). Our tests lack power to state that any of the betas (including market beta, *SMB* beta, *HML* beta, *RMW* beta, and *CMA* beta) are priced. *FVIX* is a fortunate exception with a t-statistic of -2.16. The scaled factors from CCAPM (DEF_{t-1}*(*RM-RF*), DIV_{t-1}*(*RM-RF*), and $TERM_{t-1}$*(*RM-RF*)) come close to 10% significance, but are not there. Therefore, we do not implement the standard errors corrections from Kan, Robotti, and Shanken (2013) – these corrections account for the estimation error and model misspecification error and always make the t-statistics smaller, and we already do not have any significant numbers in Table 4A, including the Fama-French five factor betas. In other words, using Kan, Robotti, and Shanken (2013) corrections will only exacerbate the conclusion that none of the factors in these tested models (except for *FVIX*) explain the cross-section of industry returns.

The insignificance of most factors in cross-sectional tests is a common problem that plagues those tests (see the results of testing many competing models in Kan, Robotti, and Shanken, 2013, and Lewellen, Nagel, and Shanken, 2010) and makes many asset-pricing papers starting with Fama and French (1993) revert to time-series regressions and alphas on the suspicion that cross-sectional regressions simply lack power to reject the null that an important factor is not priced. We also go this route in the paper.

Lewellen, Nagel, and Shanken (2010) suggest that asset pricing models should be evaluated on two “common sense” metrics. First, the risk premiums estimated from the second-stage regressions such as the ones in Table 4A have to be equal to the average risk premiums to the factors we observe in the sample. For example (and this is where almost all models fail), the slope on the market beta in the cross-sectional regression should be equal to the market risk premium (the difference between the average market return and the average risk-free rate). In 1986-2014, the average market risk premium is 0.656% per month (roughly 8% APR). This is somewhat high by historical standards and is probably driven by the sharp run-up in the market during the 1990s.

Second, Lewellen, Nagel, and Shanken (2010) suggest paying a close attention to the intercept. By definition, the intercept is the expected return to an asset with all betas equal to zero, that is, the risk-free rate. In our sample, the risk-free rate is 0.29% per month (roughly 3.5% APR). This is somewhat low by historical standards and is probably driven by the zero interest rates in 2008-2014.

If a model estimates, for example, the risk-free rate to be 15% APR and the market risk premium to be 1%, this model is bad no matter what the R-squared is, because such a model just does not make sense. In Table 4A this is what happens to both the CAPM and the FF5 model. Both estimate the risk-free rate at roughly 10% APR and the market risk premium is estimated to be at least twice smaller than it really is.

The ICAPM in the fourth column produces the most realistic estimates. While the risk-free rate is still too high, the observed average risk-free rate is now within the confidence interval, and the market risk premium estimate (0.717% per month) is almost exactly equal to its in-sample average (0.656% per month). The risk premium of *FVIX* estimated from the cross-sectional regression (-1.166% per month) is also close to the average *FVIX* return (-1.342% per month). The CCAPM in the third column produces an even more realistic estimate of the risk-free rate, but the market risk premium is too low (similar to FF5). Hence, on this “common sense” metric (realistic estimates of the market risk premium and the risk-free rate) the models rank as ICAPM, then CCAPM, then FF5, and then CAPM.

If one orders the models by the cross-sectional R-squared in the last row, the CCAPM comes out on top, followed by the FF5 model and the ICAPM. We do not believe, however, that R-squared is a good measure to compare the models on. First, as Lewellen, Nagel, and Shanken (2010) argue, if the model produces obviously biased estimates of the risk-free rate and risk premiums, it is a bad model regardless of the goodness of fit. Second, all asset-pricing tests mean to analyze the drivers of expected return, but use realized returns instead, since expected return is unobservable. Realized return is expected return plus the news component (in the case of the industry portfolios Table 4A is looking at, it is industry news). So, the model will not have a perfect fit even if it is 100% correct, because a perfect fit (R-squared =100%) is equivalent to industry news being non-existent (which is obviously false) or risk factors completely capturing them (which should not happen if the factors are truly economy-wide). Third, another reason why cross-sectional R-squared might be inappropriate to compare models is due to what Lewellen, Nagel, and Shanken (2010) discuss as "factor structure" – the returns to size-sorted portfolios, for example, can be very well explained, in terms of R-squared, by a size factor or something even remotely correlated with it. Likewise, if *HML* (or any other factor) is tilted towards a certain industry, its betas will be explaining the cross-section of realized returns to industry portfolios "better" in terms of R-squared due to their ability to pick up the industry-specific shocks to the industry/industries that the factor is tilted towards. (Again, this problem would not exist if we could observe expected returns and regress them on the factors/factor betas, but we can only observe realized returns).

In terms of the problem at hand (cost of equity estimation), we are also interested in expected returns (same thing as COE) and not that interested in the ability of the factors/factor betas to pick up industry-specific shocks. If these shocks are random and zero-mean, tracking them will increase the R-squared, but will not increase the expected return/COE estimate. Hence, we are interested mostly in the intercept in the second-stage regressions in Table 4A and in the intercept (aka alpha) from the first-stage factor regressions like the ones we report in the paper (Table 2 for example).

GRS test of the Models Used in the Paper

To make sure that the results in Panels B and C of Table 1 in the paper are not specific to the industry portfolios, we repeat the test suggested by Gibbons, Ross, and Shanken (1989), known as the GRS test in the asset-pricing literature, for several other salient portfolio sets. In particular, we look at five-by-five double sorts on size and market-to-book, five-by-five sorts on size and momentum (momentum is one of the most well-known anomalies; the momentum factor is used in another popular benchmark model originating from Carhart, 1997), and five-by-five sorts on size and long-term reversal, as well as five-by-five sorts on size and profitability and size and investment (profitability and investment are the two new factors in the five-factor model by Fama and French, 2015).[8]

Table 5A presents the test of the hypothesis that the alphas of the 25 portfolios (named in the panel heading) are jointly zero in the models named in the top row of each panel (failure to reject the null indicates the model is a good one based on GRS test). Since the portfolios represent important anomalies that have defied explanation, all models are rejected in almost all cases (the only exception is Panel C, in which FF5, ICAPM and CCAPM, but not CAPM and FF3, seem to explain the alphas of size-reversal sorts relatively well).

[8] All portfolio returns are from Ken French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

We notice also that CCAPM always has a smaller GRS statistic than CAPM and FF3, which means it produces, on average, smaller alphas (in Panel E, size-investment sorts, CCAPM and FF3 are tied). ICAPM is a bit behind CCAPM in terms of GRS test, but usually ahead of CAPM and FF3.

FF5 model is usually somewhat ahead of all other models, both because it is being fitted to the sorts that its factors largely come from, and because it has five factors as compared, say, to two factors in the ICAPM. Hence, the results of GRS test that uses the 30 industry portfolios are largely robust to using other portfolios to perform the test.

The next table, Table 6A, performs an analogue of the GRS test that tests the null hypothesis that all *FVIX* betas (or all slopes on $DEF_{t-1}*(RM - RF)$, or all slopes on $DIV_{t-1}*(RM - RF)$, etc.) are jointly equal to zero in a particular portfolio set. Rejection of the null hypothesis indicates the factor is an important factor significantly related to portfolio returns. We find that *FVIX* betas from ICAPM and the slope on $DEF_{t-1}*(RM - RF)$ from CCAPM are significant for all portfolios sets, and the rest of the CCAPM variables are significant for most of them, thus confirming that the results in Panel C of Table 1 in the paper, where we perform the same test with the 30 industry portfolios, are robust to using other portfolio sets.

Insurance and Financial Industry Factors: Cross-Sectional Test

In the second to fourth columns of Table 7A we perform the cross-sectional Fama-MacBeth regression that attempts to use the returns to the insurance industry as a factor for a full cross-section of firms (the first column reports the cross-sectional regression for the FF5 model as a benchmark). For each firm in the CRSP universe, we regress returns between *t*-59 and *t* on *RM-RF*, *SMB*, *HML*, *RMW*, and *CMA* and the returns to one of the insurance portfolios we use in the paper (all the publicly traded insurers, *INS*, property-liability insurers, *PL*, or life insurers, *Life*).

In the second stage, the *t*+1 returns to the 25 Fama and French (1992) size/book-to-market (size-BM) portfolios (Panel A) or the 30 Fama and French (1997) industry portfolios (Panel B), are regressed, in cross-section, on time *t* estimates of the betas from *t*-59 to *t*, as described above.

The main result in Panel A is that adding the insurance factors does not change much either in terms of the intercept (the risk-free rate is still being estimated at unreasonably high values that exceed 1% per month), or the market risk premium, or the R-squared. Also, none of the insurance factor betas are statistically significant and their estimated risk premiums controlling for the Fama-French five factors are small (just like their small Fama-French alphas in Table 2 (FF5 column) in the paper).

The two rightmost columns add the Adrian et al. (2016) financial industry factors instead of the insurance factors: first, to the three-factor Fama-French model, as Adrian et al. (2016) do (AFM column), and then to the FF5 model (FF5+AFM column). The only marginally significant beta is the *FROE* beta in the AFM model, but it has the wrong sign, because, first by construction, the average return to *FROE* is positive, and, second, the slope on the beta in cross-sectional regressions should equal the risk premium earned by the factor, so in our case if the AFM model had had a good fit, the slope on the *FROE* beta should have been positive. The intercepts of the AFM and FF5+AFM models are also very close to the intercept of the FF5 model, implying that *FROE* and *SPREAD* do not improve the goodness of fit of the models. The increases in the R-squared we observe comparing the AFM and FF5+AFM models with the FF5 model are likely to be driven by the wrong sign of *FROE* beta.

In Panel B, we redid the analysis again with the 30 industry portfolios. The results are very similar and even worse for the insurance factors: their risk premiums are now estimated to be much lower, and the risk premium of the *Life* factor flips its sign. All other factors (*RM-RF*, *SMB*, *HML*, *RMW*, and *CMA*) still lack significance, and the same is true about *FROE* and *SPREAD*. The AFM model is very close to the FF5 model in terms of R-squared, and the FF5+AFM model has a better R-squared, but worse (larger) intercept, which represents an unrealistically high estimate of the risk-free rate (0.815% per month, roughly 10% per year in the case of the FF5+AFM model).

Since the Fama-French factors are insignificant, we also tried dropping (some of) them and adding the insurance factors or AFM factors to the CAPM/FF3 (results not tabulated). In general, that would bias the test in favor of finding that the insurance factors matter – any diversified portfolio that is significantly correlated with either of the four Fama-French factors (*SMB*, *HML*, *RMW*, and *CMA*) (and, according to Table 2 in the paper, our insurance factors have significant *SMB*, *HML*, and *RMW* betas) can act as their proxy and seem to matter in addition to the market factor even if it has no additional information compared to *SMB*, *HML*, or *RMW* and thus is not priced controlling for those factors. However, Table 7A suggests that the four Fama-French factors are themselves not priced in our sample period, so the overlap between them and the insurance factors is less of a concern. Indeed, when we add the insurance factors to the CAPM, we find that they still do not price the five-by-five size-BM sorts or the 30 industry portfolios. None of the insurance/AFM factors is significant and what is even worse, the intercept (that estimates the risk-free/zero-beta rate) becomes noticeably larger and goes further into the implausible territory when we add the insurance/AFM factors to the CAPM/FF3.

We also tried extending the sample to 1963 to run the analyses in both Panels A and B in Table 7A (the start of Compustat data) to gain more power. We did achieve significance for the *HML* beta and marginal significance (along with a positive coefficient) for the *SMB* beta, but the betas of the insurance/AFM factors are still insignificant even in the longer sample, often negative, and adding them has a small effect on the R-squared and makes the intercept somewhat greater (that is, makes the overestimation of the risk-free rate slightly worse).

Insurance and Financial Industry Factors: GRS Test

Columns 2-4 of Table 8A test for the joint insignificance of alphas from time-series regressions with insurance factors on the left-hand side using the GRS test (column 1 of Table 8A performs the GRS test for the FF5 model as a benchmark). The point of Table 8A is the comparison of the FF5 model (first column) with the FF5 model augmented, in turn, by each of the insurance factors, as well as with the AFM and FF5+AFM models.

One can see from Panel A of Table 8A that adding the insurance factors does not change the test statistic in a material way, which implies that the effect of adding either of the insurance factors on the alphas of the 25 size-BM sorted portfolios is minimal and insurance factors are effectively not priced. This is not surprising, since, as we show in Table 2 in the paper, none of the insurance portfolios (all the publicly traded insurers, P/L insurers, or life insurers), now used as factors, have a significant alpha in the FF5 model. Hence, controlling for *RM-RF*, *SMB*, *HML*, *RMW*, and *CMA*, the risk premium of the insurance factors is essentially zero, and no matter whether some portfolios in the size-BM sorts load significantly on them or not, adding the insurance factors should not change the alphas of these size-BM portfolios (and it does not, as evidenced in Panel A of Table 8A).

In the subsequent panels of Table 8A, we also repeat the GRS test for the FF5 model and the FF5 model augmented with the insurance factors using four more portfolio sets, which are five-by-five sorts on size and other salient variables (momentum, long-term reversal, profitability, or investment). For all portfolio sets in the four panels B-E, adding the insurance factors either makes the GRS test statistics bigger, indicating that the insurance factors make the model fit worse, not better (size-momentum and size-reversal sorts) or does not affect the GRS test statistic at all, indicating that the insurance factors are useless (size-investment sorts).

Finally, in the two rightmost columns of each panel, we perform the GRS test for the AFM and FF5+AFM models. We observe that the AFM model is behind the FF5 model in terms of the GRS test statistic (which implies that the AFM model has larger pricing errors) and the FF5+AFM model generates GRS test statistics that are very close to the ones from FF5 (or FF5 augmented with an insurance factor). We conclude that the two financial industry factors suggested in Adrian et al. (2016), *FROE* and *SPREAD*, are close in their performance to the insurance factors – they do not add much to the explanatory power of the FF5 model and are largely unpriced.

Overall, our conclusion from both the cross-sectional Fama-MacBeth regressions and the time-series GRS tests is that the insurance and financial industry factors do not contribute to explaining the cross-section of returns in a material way, because they are industry-specific factors that can be diversified away if an investor invests in multiple industries. This is also consistent with related evidence in the paper (Tables 4-6), where we consider other potential insurance-industry-specific factors.

Appendix D: Other Types of Insurers

The insurance industry includes other types of companies with arguably very different risks and operating characteristics from the P/L and life insurance companies. In this section, we apply the same tests in Tables 2 and 3 in the paper to the other types of insurers and investigate whether the results are consistent with the P/L and life insurers that are usually considered to represent the insurance industry. Since the monthly average numbers of surety insurers, title insurers, pension, health, welfare funds, and other insurance carriers are very small (low teens for surety insurers and single digits for others), we put these insurers together as a combined category (other insurers).[9]

[9] The insurance industry is classified into seven categories, namely, life insurance (SIC 6310-6319), accident and health insurance (SIC 6320-6329), property-liability insurance (SIC 6330-6331), surety insurance (SIC 6350-6351),

Therefore we divide the insurance industry into four major groups, namely, property-liability (P/L) insurers (SIC codes 6330-6331), life insurers (6310-6311), accident and health (A/H) insurers (6320-6329), and other insurers (all other firms with 6300-6399).

We run the four asset pricing models (CAPM, FF5, CCAPM, and ICAPM as shown in Table 2 in the paper) as well as the AFM model (in Table 1A) on A/H insurers and other insurers in addition to all insurers, P/L insurers, and life insurers. The additional results are reported in Table 9A.

The results in Table 9A are consistent with the results of all, P/L, and life insurers reported in Table 2 in the paper and Table 1A. The CCAPM regression results in Panel A indicate that the beta of A/H insurers significantly increases with the dividend yield (*DIV*), and significantly decreases with the Treasury bill rate (*TB*) and term premium (*TERM*). Since dividend yield is higher and Treasury bill rate is lower in recessions, the significant coefficients on *DIV* and *TB* indicate that the beta of A/H insurance companies is countercyclical, which makes them riskier than what the CAPM would suggest. However, the significantly negative coefficient on *TERM* indicates that A/H insurers may have procyclical beta, since term premium is higher in recessions. When confronted with such conflicting evidence, we can compare the alpha in the CAPM and CCAPM column. We observe that it decreases by economically non-negligible 14.4 bp per month (1.73% per year) as we go from the CAPM to CCAPM. Hence, the CCAPM discovers more risk in insurance companies than CAPM, and for that to be true, the beta of the insurance companies has to be countercyclical (representing additional risk). Furthermore, a formal test of countercyclical or procyclical beta is performed in Panels C and D of Table 9A.

title insurance (SIC 6360-6361), pension, health, welfare funds (SIC 6370-6379), and other insurance carriers (SIC within 6300-6399 but do not fall into any of the previous six categories).

In Panel B, dividend yield and Treasury bill rate stay as the significant drivers of the risk of other insurers, and the signs suggest the countercyclicality of beta; *DEF* and *TERM* are insignificant, but the signs also indicate the countercyclicality of other insurers' beta.

The ICAPM column in Panels A and B of Table 9A adds *FVIX*, the volatility risk factor mimicking the changes in VIX (the expected market volatility). The negative and significant *FVIX* betas of A/H and other insurers suggest that when VIX increases unexpectedly, these insurance firms tend to have worse returns than firms with comparable CAPM betas, which makes A/H and other insurance companies riskier than what the CAPM estimates. The significant negative coefficients on *FVIX* are also observed for all, P/L, and life insurers in Table 2 in the paper.

It is interesting that in Panel A (A/H insurers) ICAPM produces the lowest (more negative) alpha, implying that the ICAPM generates higher COE and sees more risks (using two factors, *RM-RF* and *FVIX*) than the Fama-French five-factor model for accident and health insurers. In Panel B, the ICAPM has the second most negative alpha, but it still captures more risks than the five-factor AFM model.

Following Petkova and Zhang (2005), we also estimate the average betas of A/H insurers and other insurers in economic expansions and recessions. Expansions and recessions are defined as the periods with low and high expected market risk premium, respectively. The results are reported in Panels C and D of Table 9A, which have the same layout as Table 3 in the paper. We find that, based on both methods to classify expansions and recessions (expected market risk-premium above/below its historical median value or within the top/bottom quintile), A/H insurers and other insurers have significantly higher average betas in recessions, indicating that these two subgroups of insurers, in addition to P/L and life insurance subgroups shown in Table 3 in the paper, have strongly countercyclical betas (which makes them riskier than what the CAPM suggests). Thus, even though not all signs on the macroeconomic/business cycle variables in

Panels A and B of Table 9A agree, the average predicted betas show strong evidence that, consistent with all, P/L, and life insurers, A/H and other insurance companies have higher risk exposure in bad times, which is undesirable from investors' point of view and leads investors to demand higher cost of equity.

Appendix E: *FVIX* Exposures of 48 Fama-French (1997) Industry Portfolios

The question of how the other industries do in terms of volatility risk exposure, is an interesting one. In Table 10A we investigate the 48 industry portfolios from Fama and French (1997). The portfolios span the whole economy and include insurance and related industries (the bottom panel). We find that while negative *FVIX* betas dominate our sample (higher volatility is generally bad for everyone), roughly a third of *FVIX* betas are positive, and the average *FVIX* beta across all 48 industries is only -0.141 (compared to -0.866 for the insurance industry). We also notice that the *FVIX* beta of the insurance industry is the 5th most negative (behind Food, Soda, Beer, and Smoke in the top panel). Hence, the insurance industry does differ from an average industry.

Appendix F: More Details on Underwriting Cycles and the Intertemporal CAPM

In addition to the average combined ratio documented in Section V of the paper, we have experimented with another insurance-specific variable—total catastrophic losses to create the ICAPM factor. In this section, we demonstrate the results of the factor-mimicking regressions for both candidate insurance-specific variables (cat losses and the combined ratio) on the base assets, analyze the alphas and betas of the factor-mimicking portfolios in the CAPM, FF3, Carhart (1997), and FF5 models, and explore the regressions that try to add the factor-mimicking portfolio for inflation-adjusted catastrophic losses (in addition to change in combined ratio in Table 6 in the paper) to the models (CAPM, ICAPM, FF5, and FF5 augmented with *FVIX* (FF6)) we use in the paper.

Table 11A presents the results of factor-mimicking regressions on the base assets. The factor-mimicking regressions attempt to create a tradable portfolio that would correlate well with shocks to total catastrophic losses or average combined ratio. Since catastrophic losses are largely unpredictable and their autocorrelation is low, we treat the values of catastrophic losses as shocks. For combined ratio, a much more persistent variable with autocorrelation close to 1, we use its changes as a proxy for shocks.

Lamont (2001) suggests that the optimal base assets should have the richest possible variation in the sensitivity with respect to the variable being mimicked. Therefore, we choose quintiles based on historical sensitivity to catastrophic losses or change in combined ratio. In each firm-quarter (insurance-specific/underwriting cycle variables such as catastrophic losses and combined ratio are collected quarterly) for every stock traded in the US market and listed on CRSP, we perform regressions of excess stock returns on *RM-RF*, *SMB*, *HML*, and either inflation-adjusted catastrophic losses (*CatLoss*) or change in combined ratio (*ΔCombRat*). The slope on *CatLoss* or *ΔCombRat* is our measure of historical stock sensitivity to catastrophic losses or change in combined ratio.

The regressions use quarterly returns and the most recent 20 quarters of data (that is, in quarter *t* we use data from quarters *t*-1 to *t*-20) and omit stocks with less than 12 non-missing returns between *t*-1 and *t*-20.

To obtain the base assets for mimicking catastrophic losses or change in combined ratio, we sort all firms on CRSP on the historical stock sensitivity to catastrophic losses or change in combined ratio in five quintile portfolios. To minimize the impact of micro-cap stocks, we use NYSE breakpoints to form the quintiles and omit from the sample stocks those priced below $5 at the quintile formation date. Table 11A performs the standard factor mimicking regression with *CatLoss* (columns 1 and 2) or *CombRat* (columns 3 and 4) on the left-hand side and excess returns to value-weighted and equal-weighted quintile portfolios based on the historical stock sensitivity to catastrophic losses and change in combined ratio on the right-hand side, respectively.[10]

Table 11A shows that creating the factor-mimicking portfolio for either variable has limited success, because total catastrophic losses and shocks to average combined ratio seem to be unrelated to returns of any of the historical sensitivity quintiles. That is to say, when the insurance industry suffers a shock, the rest of the economy seems largely unaffected, consistent with similar findings in Table 4 of the paper that insurance-specific variables that drive the underwriting cycles do not predict the market risk premium. Consequently, the R-squared of the factor-mimicking regressions is only a few percent.[11]

Tables 12A and 13A look at the alphas and betas of the factor-mimicking portfolios constructed in Table 11A in the CAPM, FF3, Carhart, and FF5 models. The factor-mimicking portfolios are the fitted part from the regressions in Table 11A less the constant. The factor-mimicking regressions in Table 11A are performed at the quarterly frequency, since this is the frequency at which total catastrophic losses and average combined ratio are reported. However, the factor-mimicking portfolio returns are monthly, because returns to the base assets (stock sorted on historical stock sensitivity to catastrophic losses or change in combined ratio) are also available at the monthly frequency, and the factor-mimicking portfolio just multiplies them by the slopes from Table 11A.

[10] Column 3 effectively contains the equation for the combined ratio factor, *FCombRat*, used in Table 6 in the paper.
[11] In untabulated results, we also experimented with using different quintile breakpoints for the quintiles sorted on the historical stock sensitivity to catastrophic losses or change in combined ratio, or replacing these quintiles with two-by-three sorts on size and book-to-market from Fama and French (1993). The results in Tables 11A-14A and Table 6 in the paper are qualitatively the same when we do that.

We observe, first of all, that the alphas uniformly have the correct negative sign (the portfolios are constructed so that they win when total catastrophic losses or average combined ratio increases and insurance companies lose, and thus can be regarded as a hedge). However, the alphas are economically negligible (less than 1 bp per month) and mostly statistically insignificant for the factor-mimicking portfolio for *CatLoss* (see Table 12A); the alphas are economically small (1-3 bp per month on average) and all statistically insignificant for the factor-mimicking portfolio for *ΔCombRat* (see Table 13A). We conclude that investors are not willing to give up a significant return for a hedge against potential problems in the insurance industry, allegedly because the insurance industry losses do not impact the economy as a whole and the vast majority of investors are not materially affected by them, and also because the industry-specific risks can be diversified away.

The observation that the alphas of the factor-mimicking portfolios that track shocks to insurance-industry-specific variables are small is an important one. The alpha measures the unique risk captured by the factor (controlling for the other factors used in the alpha estimation). In terms of cost of capital, the alpha is the potential marginal contribution of the factor. Low-alpha factors (such as the factor-mimicking portfolios on catastrophic losses and changes in combined ratio in Tables 12A and 13A) have little chance to contribute materially to the cost of capital estimates if added into a factor model.

The betas of the factor-mimicking portfolios in Tables 12A and 13A are surprisingly significant, but numerically small. While the significance creates an (allegedly misleading) impression that shocks to the insurance variables are related to market-wide factors (*RM-RF*, *SMB*, *HML,* and sometimes *CMA* and *RMW*), the relation is economically negligible.

Table 14A contains regressions that try to add the value-weighted factor-mimicking portfolio for inflation-adjusted catastrophic losses (*FCatLoss*) to the models we use in the paper

(CAPM, ICAPM, FF5, and FF6) and thus repeats Table 6 in the paper replacing the factor that mimics combined ratio with the factor mimicking catastrophic losses. The results of estimating the models used in the paper are in columns 1, 4, 7, and 10. The factor is added to the models in columns 2, 5, 8, and 11. In columns 3, 6, 9, and 12 the factor is replaced by the variable the factor mimics (catastrophic losses, *CatLoss*). The left-hand side variable is the value-weighted returns to all publicly traded insurance companies. Changing it to equal-weighted returns or dividing the sample into P/L insurers and life insurers does not materially change the results.[12]

Similar to the results reported in Table 6 in the paper when adding the factor-mimicking portfolio for changes in combined ratio, in columns 8 and 11 of Table 14A we observe that the betas of all insurance companies with respect to the *FCatLoss* factor lose significance after we control for the factors our main analysis uses (*RM-RF*, *SMB*, *HML*, *CMA*, and *RMW*, or these factors plus *FVIX*). We checked (columns 9 and 12 of Table 14A) that the insignificant betas are not an artefact of our factor-mimicking procedure by replacing the factor-mimicking portfolio with catastrophic losses, which still produces insignificant loadings. In addition, we observe that the impact on the alphas of adding *FCatLoss* to models other than CAPM (namely, ICAPM, FF5, and FF5+*FVIX*) is minor, consistent with our findings regarding changes in combined ratio in Table 6 in the paper. In conclusion, adding the insurance industry factor-mimicking portfolios as insurance-specific factors does not change estimated cost of equity. The economic reason is that shocks specific to the insurance industry do not affect the economy as a whole and can be diversified away by investors who invest in many industries. Therefore, these shocks do not represent priced risks and should not be expected to affect the cost of equity of insurance companies (even if the shocks do affect their cash flows).

[12] This statement holds true when adding the factor-mimicking portfolio on changes of combined ratio (*ΔCombRat*) to the models (CAPM, ICAPM, FF5, and FF6) based on Table 6 in the paper.

Appendix G: Cost of Equity Estimation from Augmented Fama-French and AFM Models and from Sum-Beta Approach

In addition to the cost of equity capital estimated based on the four main models (CAPM, FF5, CCAPM, and ICAPM) in Table 7 in the paper, we estimate the value-weighted average COE using the AFM model and Fama-French five-factor model augmented with *FVIX* (FF6) for each of the 18 sample years (1997-2014) and 18 years combined. The results are presented in columns 5 and 6 in Table 15A in Panels A, B, and C for all publicly-traded insurance companies and the two major subgroups (P/L insurers and life insurers), respectively. For comparison purposes, the COE estimates from CAPM, FF5, CCAPM, and ICAPM are reported in columns 1-4 (same as Table 7 in the paper).

We document that the COE estimates from the AFM model are higher than the CAPM estimates, but they are lower than the FF5 estimates on average for all, P/L, and life insurance companies. It suggests that the financial industry factors (*FROE* and *SPREAD*) do not reflect as much risk as *RMW* and *CMA* for insurers. This is not surprising because the financial industry factors, similar to the insurance factors, are industry-specific factors that can be diversified away if the marginal financial portfolio investor also invests in many other industries. As a matter of fact, in untabulated results, we show that *FROE* has insignificant alpha controlling for FF5 factors and *SPREAD*'s alpha even has the "wrong" sign (implying that higher *SPREAD* beta means low expected return/COE, but by construction of *SPREAD* it should be the opposite). It indicates that adding the financial industry factors does not help in or even mislead (given the significant *SPREAD* betas for various groups of insurers in Tables 1A and 9A) the cost of equity estimation for insurance companies.

We find that the COE estimates from FF6 are even higher than those from FF5 on average for all insurance companies and the two subgroups. It suggests that *FVIX* contributes to COE estimation even controlling for *SMB*, *HML*, *RMW*, and *CMA*. Hence, it confirms the claim in Appendix A that *FVIX* has independent explanatory power that goes beyond its overlap with *RMW* and *HML*. The average COE for the 18-year period estimated from FF6 is 13.490%, 12.607%, and 15.688% per annum for all insurers, P/L insurers, and life insurers, respectively, as compared to 12.662%, 11.312%, and 15.366% per annum from FF5. For all insurance companies and the two subgroups, ICAPM generates very similar COE estimates to those from FF6, indicating that ICAPM finds about the same amount of risk in insurance companies during our sample period on average as FF6. It confirms our conclusion in Appendix A that *SMB*, *HML*, *RMW*, and *CMA* do not have much of explanatory power of their own for insurers beyond the overlap with *FVIX*.

Furthermore, following Cummins and Phillips (2005) we estimate the COE using the sum-beta approach (Dimson, 1979) based on all the six models mentioned above (CAPM, FF5, CCAPM, ICAPM, AFM, and FF6). The idea of Dimson is that for thinly traded stocks, the information in the market return can be incorporated into stock prices with a delay, and thus one should regress the stock returns on the market return from the same period *t* and also on the market return from period *t*-1. The market beta is then the sum of the slopes on those two market returns.

For CAPM, FF5, ICAPM, AFM, and FF6, the estimated sum-beta coefficients are obtained similarly by adding the slopes on the contemporaneous and lagged factor returns from these models. Then the sum-beta COE is calculated by summing the products of the estimated sum-beta coefficients multiplied by long-term factor risk premiums, plus the risk-free rate (more details on the estimation window and factor risk premiums are in Estimation Methods subsection in Section VI in the paper). For CCAPM the sum-beta COE is computed by summing the product of the predicted contemporaneous beta with predicted contemporaneous market risk premium and the product of the predicted lagged beta with predicted lagged market risk premium, plus current risk-free rate. The sum-beta version of COE estimates is reported in columns 7-12 in Table 15A based on different models for all insurance companies (Panel A), P/L insurers (Panel B), and life insurers (Panel C). The presented COE estimates are value-weighted averages across all firms for each of the 18 sample years (1997-2014) and 18 years combined.

The COE estimates based on the sum-beta approach are similar to those estimated without the sum-beta approach. For all insurance companies and the P/L subgroup the difference between the usual and sum-beta COE estimates is small across all models (generally under 1% per annum). For life insurers, the difference is more material (over 3% for FF5, ICAPM, and FF6). Moreover, we still find the ICAPM cost of equity estimates higher than those from the CAPM, AFM, and FF5 models.

Appendix H: Equal-Weighted Returns of Insurers

We have been using value-weighted returns of insurance companies throughout the paper and Online Appendices. As an additional robustness check, we replicated Tables 2, 3, 6, and 7 in the paper using equal-weighted insurer returns and report them in Tables 16A, 17A, 18A, and 19A, respectively.

Table 16A re-runs Table 2 in the paper using equal-weighted returns and fits several factor models to all insurers, P/L insurers, and life insurers, respectively. We find the following. First, the *FVIX* beta is still significant, though numerically smaller, for all insurers and P/L insurers, and and insignificant (as compared to marginally significant at 10% in Table 2) for life insurers. Second, the market beta of insurance companies is still countercyclical, positively related to dividend yield (*DIV*) and negatively related to Treasury bill rate. For life insurers, a positive dependence of the beta on default premium (*DEF*) and negative dependence on term premium (*TERM*) are added. Third, the equal-weighted CCAPM and ICAPM alphas are again significantly smaller than the CAPM alphas, implying that those models find additional sources of risk and will generate higher cost of capital estimates, though in equal-weighted returns, in contrast to value-weighted returns, the FF5 model sometimes generates even lower alphas (and finds even more risk) than the ICAPM.

Table 17A repeats Table 3 in the paper using equal-weighted returns and tabulates the market betas of the three groups of insurers (all, P/L, and life) in expansions and recessions. The differences in the betas recessions vs. expansions (the ultimate proof of the insurers' betas countercyclicality) are very close in Table 3 in the paper and Table 17A.

Table 18A repeats Table 6 and considers adding the change in combined ratio (*ΔCombRat*) and its factor-mimicking portfolio (*FCombRat*) to the CAPM, FF5, ICAPM, and FF6 models. Both *ΔCombRat* and *FCombRat* are still insignificant even when equal-weighted returns to all the publicly traded insurers are used on the left-hand side, and adding them to the models does not materially change the alphas or the *FVIX* betas.

We estimate the equal-weighted cost of equity for all, P/L, and life insurers and report the results in Table 19A. The equal-weighted COE estimates are usually lower than the value-weighted, but the difference is small with generally less than 1% on average across all models except for those from the ICAPM. The equal-weighted ICAPM COE estimates are about 3% lower than those value-weighted for all insurance companies and P/L insurers and 1.5% lower for life insurers on average. The lower equal-weighted COE can be due to the following reasons. First, the market betas across models are mostly lower in Table 16A (based on equal-weighted returns) than in Table 2 in the paper (based on value-weighted returns). Second, even though the insurer equal-weighted returns are higher than value-weighted returns (see Table 1 in the paper), the difference is smaller than the difference between the equal-weighted and value-weighted alphas. As a result, the equal-weighted COE estimates should turn out to be smaller than those value-weighted. Third, according to Table 4 in Adrian et al. (2016) (the mean of) *FSMB* (the return differential between the small financial and big financial firms) is less than zero, suggesting that the size effect is negative for financial firms, and consequently, small financial firms have lower COE. Since equal-weighted returns give more weights to small firms, the equal-weighted COE is lower. Further, for the ICAPM specifically, comparing Table 16A and Table 2 in the paper, we find that the *FVIX* betas are less than half in size using equal-weighted than value-weighted returns, indicating a lower explanatory power for equal-weighted than value-weighted returns. However, the ICAPM generates low COE estimates right before the Great Recession in 2008 and high estimates after it (well reflecting the reality), while the other models do not. In sum, even though the ICAPM is weaker when using equal-weighted insurer returns, our central message does not change: the ICAPM produces higher COE estimates than the CAPM and the insurance companies are exposed to the market volatility risk.

We also replicated all the other tables in the paper and most of the tables in Online Appendices using insurer equal-weighted returns (results not tabulated to save space) and find that the results with equal-weighted returns are qualitatively similar to the results with value-weighted returns that we usually report.

References

Adrian, T., E. Friedman, and T. Muir, 2016, The Cost of Capital of the Financial Sector, Working paper, Federal Reserve Bank of New York.

Amihud, Y., 2002, Illiquidity and Stock Returns: Cross-Section and Time Series Effects, *Journal of Financial Markets*, 5: 31-56.

Barinov, A., 2011, Idiosyncratic Volatility, Growth Options, and the Cross-Section of Returns, Working paper, University of California, Riverside.

Barinov, A., 2015, Profitability Anomaly and Aggregate Volatility Risk, Working paper, University of California, Riverside.

Carhart, M.M., 1997, On Persistence in Mutual Fund Performance, *Journal of Finance*, 52: 57-82.

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

Daniel, K., and S. Titman, 1997, Evidence on the Characteristics of Cross Sectional Variation in Stock Returns, *The Journal of Finance*, 52: 1-33.

Dimson, E., 1979, Risk Measurement when Shares are Subject to Infrequent Trading, *Journal of Financial Economics*, 7: 197-226.

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

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

Fama, E.F., and K.R. French, 1995, Size and Book-to-Market Factors in Earnings and Returns, *Journal of Finance*, 50: 131-155.

Fama, E.F., and K.R. French, 1996, Multifactor Explanations of Asset Pricing Anomalies, *Journal of Finance*, 51: 55-84.

Fama, E.F., and K.R. French, 1997, Industry Costs of Equity, *Journal of Financial Economics*, 43: 153-193.

Fama, E.F., and K.R. French, 2002, The Equity Premium, *Journal of Finance*, 57: 637-659.

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

Fama, E.F., and J.D. Macbeth, 1973, Risk, Return and Equilibrium: Empirical Tests, *Journal of Political Economy*, 81: 607-636.

Gibbons, M.R., S.A. Ross, and J. Shanken, 1989, A Test of the Efficiency of a Given Portfolio, *Econometrica*, 57: 1121-1152.

Hahn, J., and H.Lee, 2006, Interpreting the Predictive Power of the Consumption-Wealth Ratio, *Journal of Empirical Finance*, 13: 183-202.

Harvey, C. R., and A. Siddique, 2000, Conditional Skewness in Asset Pricing Tests, *Journal of Finance*, 55: 1263-1295.

Jacoby, G., D. J. Fowler, and A. A. Gottesman, 2000, The Capital Asset Pricing Model and the Liquidity Effect: A Theoretical Approach, *Journal of Financial Markets*, 3: 69-81.

Kan, R., C. Robotti, and J. Shanken, 2013, Pricing Model Performance and the Two-Pass Cross-Sectional Regression Methodology, *Journal of Finance*, 68: 2617-2649.

Lakonishok, J., A. Shleifer, and R. Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance*, 49: 1541-1578.

Lamont, O.A., 2001, Economic Tracking Portfolios, *Journal of Econometrics*, 105: 161-184.

Lesmond, D. A., J. Ogden, and C. Trzcinka, 1999, A New Estimate of Transaction Costs, *Review of Financial Studies*, 12: 1113-1141.

Lewellen, J.W., S. Nagel, and J. Shanken, 2010, A Skeptical Appraisal of Asset Pricing Tests, *Journal of Financial Economics*, 96: 175-194.

Pastor, L. and R.F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy*, 111: 642-685.

Petkova, R., and L. Zhang, 2005, Is Value Riskier than Growth? *Journal of Financial Economics*, 78: 187-202.

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

Table 1A. Fama-French Five-Factor and AFM Models Augmented by Volatility Risk Factor

	Panel A. All Insurers				**Panel B. P/L Insurers**				**Panel C. Life Insurers**			
	FF5	FF6	AFM	AFM6	FF5	FF6	AFM	AFM6	FF5	FF6	AFM	AFM6
RM-RF	1.03***	0.39**	0.89***	0.45***	0.90***	0.03	0.75***	0.13	1.35***	1.43***	1.24***	1.62***
	(0.04)	(0.18)	(0.03)	(0.13)	(0.04)	(0.20)	(0.03)	(0.15)	(0.06)	(0.28)	(0.05)	(0.22)
SMB	-0.13**	-0.08	-0.08**	-0.04	-0.29***	-0.22***	-0.22***	-0.16***	0.06	0.05	0.15**	0.11
	(0.06)	(0.06)	(0.04)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.08)	(0.08)	(0.07)	(0.07)
HML	0.59***	0.60***	0.10*	0.09*	0.50***	0.51***	0.04	0.03	1.10***	1.10***	0.44***	0.45***
	(0.07)	(0.07)	(0.06)	(0.05)	(0.08)	(0.08)	(0.07)	(0.06)	(0.11)	(0.11)	(0.09)	(0.09)
RMW	0.25***	0.15*			0.20**	0.07			0.03	0.04		
	(0.08)	(0.08)			(0.09)	(0.09)			(0.11)	(0.12)		
CMA	-0.09	-0.14			-0.02	-0.08			-0.31**	-0.30*		
	(0.11)	(0.11)			(0.12)	(0.12)			(0.16)	(0.16)		
FROE			0.05***	0.04**			0.05**	0.04*			0.03	0.04
			(0.02)	(0.02)			(0.02)	(0.02)			(0.03)	(0.03)
SPREAD			0.67***	0.65***			0.66***	0.63***			0.71***	0.73***
			(0.05)	(0.05)			(0.06)	(0.05)			(0.08)	(0.08)
FVIX		-0.45***		-0.32***		-0.62***		-0.46***		0.05		0.28*
		(0.13)		(0.09)		(0.14)		(0.11)		(0.19)		(0.16)
Alpha	-0.24	-0.40**	0.00	-0.15	-0.18	-0.41**	0.05	-0.17	-0.30	-0.29	-0.19	-0.06
	(0.16)	(0.16)	(0.12)	(0.13)	(0.18)	(0.18)	(0.15)	(0.15)	(0.24)	(0.24)	(0.21)	(0.22)
Adj R-sq	0.714	0.726	0.821	0.827	0.600	0.626	0.721	0.736	0.685	0.685	0.745	0.747
Obs	348	347	348	347	348	347	348	347	348	347	348	347

Note: This table shows the regression results based on Fama-French five-factor model (FF5), FF5 augmented with the volatility risk factor *FVIX* (FF6), Adrian, Friedman, and Muir (2016) model (AFM), and AFM augmented with *FVIX* (AFM6) for all the publicly traded insurance companies, P/L insurers, and life insurers. The insurance portfolio returns are value-weighted. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, and *HML* is the difference in the returns of high and low book-to-market portfolios. *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. *FROE* is the return spread between high and low ROE financial firms, and *SPREAD* is the return spread between financial and non-financial firms. *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P100 stock index options. Obs reports the number of months in the regressions. Standard errors appear in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 2A. Conditional Fama-French Five-Factor Model

	Panel A. All Insurers			Panel B. P/L Insurers			Panel C. Life Insurers		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
RM-RF	0.97***	1.30***	1.25***	0.87***	1.27***	1.11***	1.18***	1.39***	1.90***
	(0.17)	(0.18)	(0.15)	(0.19)	(0.21)	(0.17)	(0.23)	(0.27)	(0.23)
DEF_{t-1}*(RM-RF)*	-0.01	0.02		-0.10	-0.13		0.49***	0.67***	
	(0.08)	(0.12)		(0.09)	(0.14)		(0.11)	(0.18)	
DIV_{t-1}*(RM-RF)*	0.14**	0.02	0.03	0.12	0.04	0.00	0.17*	-0.01	0.23**
	(0.07)	(0.07)	(0.06)	(0.07)	(0.08)	(0.07)	(0.09)	(0.10)	(0.09)
TB_{t-1}*(RM-RF)*	-0.36	-0.33	-0.29	-0.11	-0.23	0.00	-1.51***	-1.25**	-2.24***
	(0.35)	(0.35)	(0.31)	(0.39)	(0.41)	(0.36)	(0.48)	(0.53)	(0.48)
$TERM_{t-1}$*(RM-RF)*	-0.10	-0.18***	-0.16***	-0.07	-0.19**	-0.16**	-0.23***	-0.29***	-0.32***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.09)	(0.09)	(0.09)
SMB	-0.15***	-0.39	-0.38**	-0.29***	-0.45	-0.43**	-0.02	-0.48	-0.63***
	(0.06)	(0.28)	(0.15)	(0.06)	(0.32)	(0.17)	(0.08)	(0.41)	(0.23)
DEF_{t-1}*SMB*		0.06			0.01			0.19	
		(0.15)			(0.17)			(0.22)	
DIV_{t-1}*SMB*		0.03	0.03		0.03	0.02		0.10	0.14
		(0.09)	(0.07)		(0.10)	(0.08)		(0.13)	(0.10)
TB_{t-1}*SMB*		-0.03			-0.03			-0.40	
		(0.56)			(0.64)			(0.83)	
$TERM_{t-1}$*SMB*		0.08	0.09*		0.04	0.06		0.12	0.19**
		(0.09)	(0.05)		(0.10)	(0.06)		(0.14)	(0.08)
HML	0.59***	0.72**	0.76***	0.55***	0.59	0.83***	0.80***	1.79***	0.85***
	(0.08)	(0.36)	(0.13)	(0.09)	(0.42)	(0.14)	(0.11)	(0.54)	(0.19)
DEF_{t-1}*HML*		0.04			0.19			-0.53**	
		(0.15)			(0.18)			(0.23)	
DIV_{t-1}*HML*		-0.07			-0.12			0.28	
		(0.14)			(0.15)			(0.20)	
TB_{t-1}*HML*		-0.03			0.34			-2.58**	
		(0.75)			(0.85)			(1.10)	
$TERM_{t-1}$*HML*		-0.08	-0.17***		-0.11	-0.25***		-0.29	0.01
		(0.13)	(0.06)		(0.15)	(0.07)		(0.19)	(0.10)
RMW	0.18**	0.79*	0.78**	0.12	0.76	0.69*	0.08	0.32	0.11
	(0.09)	(0.44)	(0.37)	(0.10)	(0.50)	(0.42)	(0.12)	(0.64)	(0.57)
DEF_{t-1}*RMW*		0.08			-0.06			0.33	
		(0.23)			(0.26)			(0.34)	
DIV_{t-1}*RMW*		-0.50***	-0.43***		-0.34**	-0.31**		-0.62***	-0.37**
		(0.13)	(0.12)		(0.15)	(0.14)		(0.19)	(0.19)
TB_{t-1}*RMW*		0.10	-0.06		-0.22	-0.23		0.88	0.48
		(0.83)	(0.76)		(0.95)	(0.87)		(1.23)	(1.18)
$TERM_{t-1}$*RMW*		-0.04	-0.04		-0.14	-0.13		0.13	0.11
		(0.14)	(0.13)		(0.16)	(0.15)		(0.20)	(0.20)
CMA	-0.10	1.59***	1.07***	-0.02	1.69***	1.15***	-0.24	0.87	0.72*
	(0.11)	(0.49)	(0.24)	(0.13)	(0.57)	(0.27)	(0.16)	(0.73)	(0.37)
DEF_{t-1}*CMA*		0.15			0.15			0.06	
		(0.30)			(0.34)			(0.44)	
DIV_{t-1}*CMA*		-0.35**	-0.50***		-0.27	-0.43***		-0.67***	-0.60***
		(0.17)	(0.11)		(0.19)	(0.13)		(0.25)	(0.17)
TB_{t-1}*CMA*		-2.17**	-0.79*		-2.70**	-1.15**		0.69	0.14
		(1.04)	(0.48)		(1.19)	(0.54)		(1.54)	(0.74)
$TERM_{t-1}$*CMA*		-0.38**			-0.41**			-0.01	
		(0.18)			(0.20)			(0.26)	
Alpha	-0.27*	0.02	-0.01	-0.24	0.08	0.05	-0.27	-0.11	-0.17
	(0.16)	(0.15)	(0.15)	(0.18)	(0.17)	(0.17)	(0.22)	(0.22)	(0.23)
Adj R-sq	0.718	0.775	0.774	0.610	0.674	0.673	0.725	0.755	0.731
Obs	347	347	347	347	347	347	347	347	347

Note: This table shows the conditional Fama-French five-factor model regression results for all the publicly traded insurance companies, P/L insurers, and life insurers. The insurance portfolio returns are value-weighted. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive investment portfolios. *DEF* is default spread, *DIV* is dividend yield, *TB* is the 30-day Treasury bill rate, and *TERM* is term spread. Obs reports the number of months in the regressions. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3A. Liquidity, Liquidity Risk, Coskewness

	All Insurers				P/L Insurers				Life Insurers			
	CAPM	FF5	ICAPM	FF6	CAPM	FF5	ICAPM	FF6	CAPM	FF5	ICAPM	FF6
Panel A. Baseline Models												
Alpha	0.048	-0.238	-0.369**	-0.399**	0.079	-0.179	-0.435**	-0.406**	-0.029	-0.296	-0.191	-0.287
	(0.185)	(0.159)	(0.183)	(0.161)	(0.201)	(0.179)	(0.195)	(0.179)	(0.271)	(0.236)	(0.286)	(0.245)
Panel B. Adding Liquidity Factor Based on No-Trade Days (*Zero*)												
Alpha	-0.154	-0.249	-0.520***	-0.419***	-0.095	-0.186	-0.558***	-0.421**	-0.313	-0.313	-0.421	-0.311
	(0.179)	(0.159)	(0.177)	(0.161)	(0.198)	(0.180)	(0.191)	(0.179)	(0.262)	(0.236)	(0.276)	(0.245)
Zero	0.371***	0.091	0.335***	0.109*	0.319***	0.058	0.272***	0.080	0.521***	0.139	0.510***	0.137
	(0.059)	(0.060)	(0.056)	(0.059)	(0.066)	(0.068)	(0.061)	(0.066)	(0.087)	(0.089)	(0.087)	(0.090)
Panel C. Adding Liquidity Factor Based on Price Impact (*Amihud*)												
Alpha	0.048	-0.224	-0.411**	-0.387**	0.106	-0.164	-0.445**	-0.394**	-0.110	-0.298	-0.330	-0.288
	(0.187)	(0.159)	(0.187)	(0.162)	(0.203)	(0.180)	(0.198)	(0.180)	(0.272)	(0.237)	(0.288)	(0.246)
Amihud	0.000	-0.079	0.086	-0.049	-0.081	-0.085	0.020	-0.045	0.241**	0.012	0.284***	0.005
	(0.074)	(0.067)	(0.070)	(0.066)	(0.080)	(0.075)	(0.074)	(0.074)	(0.107)	(0.099)	(0.108)	(0.101)
Panel D. Adding Pastor-Stambaugh Liquidity Risk Factor (*PS*)												
Alpha	0.081	-0.218	-0.338*	-0.381**	0.116	-0.150	-0.401**	-0.378**	0.007	-0.283	-0.152	-0.272
	(0.186)	(0.160)	(0.185)	(0.162)	(0.202)	(0.180)	(0.196)	(0.180)	(0.272)	(0.238)	(0.288)	(0.247)
PS	-0.078	-0.042	-0.062	-0.037	-0.091*	-0.062	-0.072	-0.055	-0.087	-0.028	-0.081	-0.029
	(0.048)	(0.039)	(0.045)	(0.039)	(0.052)	(0.044)	(0.048)	(0.043)	(0.070)	(0.059)	(0.070)	(0.059)
Panel E. Adding Coskewness Factor (*Skew*)												
Alpha	-0.133	-0.275*	-0.433**	-0.420***	-0.075	-0.205	-0.483**	-0.419**	-0.317	-0.378	-0.316	-0.340
	(0.174)	(0.158)	(0.174)	(0.159)	(0.195)	(0.179)	(0.190)	(0.179)	(0.250)	(0.230)	(0.263)	(0.238)
Skew	0.740***	0.294***	0.611***	0.259***	0.627***	0.204*	0.453***	0.153	1.176***	0.647***	1.181***	0.660***
	(0.099)	(0.096)	(0.098)	(0.095)	(0.111)	(0.110)	(0.107)	(0.107)	(0.143)	(0.141)	(0.147)	(0.142)

Note: This table shows the alphas for all the publicly traded insurance companies, P/L insurers, and life insurers from CAPM, FF5, ICAPM, and FF6, as well as liquidity factor betas (Panels B and C), liquidity risk loadings (Panel D), and coskewness factor loadings (Panel E). The models to which the liquidity/liquidity risk/coskewness factors are added are named in the heading of each column. The factors are added to the models one-by-one. The liquidity factors are the long-short portfolios that buy firms that are most frequently non-traded (Panel B) or have the highest price impact (Panel C) and short firms that are least frequently non-traded or have the lowest price impact. The liquidity risk factor (Pastor-Stambaugh factor) buys firms with the highest and shorts firms with the lowest historical return sensitivity to market liquidity shocks. The coskewness factor buys/shorts firms in the top/bottom coskewness quintile, and coskewness is defined, as in Harvey and Siddique (2000), the term proportional to covariance between firm-specific return shock with squared market return. Standard errors appear in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 4A. Fama-MacBeth Regressions for 30 Industry Portfolios

	CAPM	FF5	CCAPM	ICAPM
Intercept	0.949	0.764	0.569	0.618
t-stat	*3.52*	*2.50*	*2.13*	*2.26*
RM-RF beta	0.192	0.007	0.395	0.717
t-stat	*0.56*	*0.02*	*1.26*	*2.04*
SMB beta		0.335		
t-stat		*1.45*		
HML beta		0.289		
t-stat		*1.30*		
RMW beta		0.154		
t-stat		*1.21*		
CMA beta		-0.093		
t-stat		*-0.54*		
FVIX beta				-1.166
t-stat				*-2.16*
$DEF_{t-1}*(RM-RF)$			0.615	
t-stat			*1.44*	
$DIV_{t-1}*(RM-RF)$			1.039	
t-stat			*1.36*	
$TB_{t-1}*(RM-RF)$			0.048	
t-stat			*0.38*	
$TERM_{t-1}*(RM-RF)$			0.840	
t-stat			*1.37*	
R-sq	0.118	0.293	0.341	0.225

Note: The table reports the results of cross-sectional portfolio regressions run each month (1986-2014). It presents the estimates from the second stage regression of portfolio returns on past betas and reports Fama-MacBeth (1973) *t*-statistics. The portfolios are the 30 industry portfolios from Fama and French (1997), and the portfolio returns are downloaded from Ken French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The regressions run portfolio returns from *t*+1 on the portfolio-level betas from *t*. The betas are estimated for each individual firm using data from the previous 60 months, then trimmed at 1% and 99% to eliminate outliers, and then averaged across all firms within the portfolio.

Table 5A. GRS Test for Alternative Portfolio Sets

Panel A. 25 Size/market-to-book sorted portfolios

	CAPM	FF3	ICAPM	CCAPM	FF5
Stat	4.757	4.738	5.037	4.259	3.698
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Panel B. 25 Size/momentum sorted portfolios

	CAPM	FF3	ICAPM	CCAPM	FF5
Stat	2.868	2.963	2.632	2.292	2.396
p-value	*0.000*	*0.000*	*0.000*	*0.001*	*0.000*

Panel C. 25 Size/reversal sorted portfolios

	CAPM	FF3	ICAPM	CCAPM	FF5
Stat	1.803	1.758	1.542	1.342	1.175
p-value	*0.012*	*0.015*	*0.050*	*0.131*	*0.259*

Panel D. 25 Size/profitability sorted portfolios

	CAPM	FF3	ICAPM	CCAPM	FF5
Stat	2.18	2.142	1.923	1.889	1.512
p-value	*0.001*	*0.001*	*0.006*	*0.007*	*0.058*

Panel E. 25 Size/investment sorted portfolios

	CAPM	FF3	ICAPM	CCAPM	FF5
Stat	3.533	3.447	3.680	3.469	2.348
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Note: The table reports the results of the test with the null hypothesis that the alphas of all portfolios mentioned in the panel name are jointly zero in the time-series full-sample model named in the column heading. For example, the top left cell performs, in full 1986-2014 sample, 25 regressions of excess returns to each of the portfolios from five-by-five annual sorts on size and book-to-market on excess market return, and tests if all 25 intercepts are jointly zero. The returns to the portfolio sets, the detailed descriptions of the sorting variables, and the sorting procedure are available from Ken French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 6A. Joint Significance of the ICAPM/CCAPM factors for Alternative Portfolio Sets

Panel A. 25 Size/market-to-book sorted portfolios

	FVIX	DEF_{t-1}	DIV_{t-1}	TB_{t-1}	$TERM_{t-1}$
Stat	8.875	3.982	1.095	1.550	2.047
p-value	*0.000*	*0.000*	*0.346*	*0.048*	*0.003*

Panel B. 25 Size/momentum sorted portfolios

	FVIX	DEF_{t-1}	DIV_{t-1}	TB_{t-1}	$TERM_{t-1}$
Stat	9.157	5.743	2.518	2.029	1.040
p-value	*0.000*	*0.000*	*0.000*	*0.003*	*0.414*

Panel C. 25 Size/reversal sorted portfolios

	FVIX	DEF_{t-1}	DIV_{t-1}	TB_{t-1}	$TERM_{t-1}$
Stat	6.969	3.417	0.569	0.268	0.162
p-value	*0.000*	*0.000*	*0.954*	*1.000*	*1.000*

Panel D. 25 Size/profitability sorted portfolios

	FVIX	DEF_{t-1}	DIV_{t-1}	TB_{t-1}	$TERM_{t-1}$
Stat	8.311	3.602	3.051	2.342	0.497
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.981*

Panel E. 25 Size/investment sorted portfolios

	FVIX	DEF_{t-1}	DIV_{t-1}	TB_{t-1}	$TERM_{t-1}$
Stat	7.626	2.525	2.901	2.925	0.824
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.710*

Note: The table reports the results of the test with the null hypothesis that the *FVIX* betas (from ICAPM) or the interaction terms of the other four variables (*DEF*, *DIV*, *TB*, and *TERM*) with excess market return (from CCAPM) of all portfolios mentioned in the panel name are jointly zero. For example, the top right cell performs, in full 1986-2014 sample, 25 regressions of excess returns to each of the portfolios from five-by-five annual sorts on size and book-to-market on excess market return and its pairwise interactions with DEF_{t-1}, DIV_{t-1}, TB_{t-1}, and $TERM_{t-1}$, and tests if all 25 slopes on $(RM\text{-}RF)*TERM_{t-1}$ are jointly zero. The returns to the portfolio sets, the detailed descriptions of the sorting variables, and the sorting procedure are available from Ken French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 7A. Fama-MacBeth Regressions with Insurance and Financial Industry Factors

Panel A. 25 Size-BM Portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Intercept	1.156	1.245	1.267	1.160	1.249	1.085
t-stat	*4.53*	*4.89*	*4.95*	*4.59*	*4.31*	*3.90*
RM-RF beta	-0.042	-0.144	-0.145	-0.023	-0.227	-0.008
t-stat	*-0.13*	*-0.46*	*-0.46*	*-0.07*	*-0.67*	*-0.03*
SMB beta	0.013	0.014	0.001	0.019	0.004	0.020
t-stat	*0.08*	*0.08*	*0.01*	*0.11*	*0.02*	*0.10*
HML beta	0.209	0.211	0.233	0.253	0.119	0.131
t-stat	*1.06*	*1.08*	*1.21*	*1.28*	*0.61*	*0.68*
RMW beta	0.182	0.220	0.241	0.202		0.143
t-stat	*1.39*	*1.64*	*1.83*	*1.49*		*0.95*
CMA beta	0.009	0.046	0.037	0.056		-0.018
t-stat	*0.06*	*0.34*	*0.27*	*0.41*		*-0.13*
INS beta		0.346				
t-stat		*1.20*				
PL beta			0.527			
t-stat			*1.46*			
Life beta				0.095		
t-stat				*0.26*		
FROE beta					-1.012	-0.651
t-stat					*-1.69*	*-0.92*
SPREAD beta					0.014	0.345
t-stat					*0.06*	*1.40*
R-sq	0.472	0.507	0.509	0.505	0.539	0.595

Panel B. 30 Industry Portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Intercept	0.764	0.754	0.721	0.812	0.648	0.815
t-stat	*2.50*	*2.53*	*2.48*	*2.67*	*1.93*	*2.64*
RM-RF beta	0.007	0.002	0.035	-0.042	0.242	-0.132
t-stat	*0.02*	*0.01*	*0.10*	*-0.11*	*0.57*	*-0.34*
SMB beta	0.335	0.380	0.350	0.388	0.119	0.462
t-stat	*1.45*	*1.67*	*1.54*	*1.66*	*0.49*	*1.89*
HML beta	0.289	0.241	0.295	0.268	0.188	0.190
t-stat	*1.30*	*1.04*	*1.31*	*1.16*	*0.76*	*0.83*
RMW beta	0.154	0.099	0.102	0.085		-0.017
t-stat	*1.21*	*0.78*	*0.81*	*0.64*		*-0.12*
CMA beta	-0.093	-0.023	-0.042	-0.097		0.025
t-stat	*-0.54*	*-0.12*	*-0.23*	*-0.52*		*0.12*
INS beta		0.025				
t-stat		*0.07*				
PL beta			0.204			
t-stat			*0.42*			
Life beta				-0.374		
t-stat				*-0.77*		
FROE beta					0.700	0.291
t-stat					*1.02*	*0.35*
SPREAD beta					-0.336	-0.066
t-stat					*-1.25*	*-0.23*
R-sq	0.355	0.401	0.403	0.398	0.361	0.445

Note: The table reports the results of cross-sectional portfolio regressions run each month (1986-2014). It presents the estimates from the second stage regression of portfolio returns on past betas and reports Fama-MacBeth (1973) *t*-statistics. FF5 is Fama-French five-factor model in Fama and French (2015) and AFM is the model in Adrian, Friedman, and Muir (2016). In Panel A, the portfolios are five-by-five annual sorts on size and book-to-market, as in Fama and French (1993). In Panel B, the portfolios are the 30 industry portfolios from Fama and French (1997). *INS* (*PL* or *Life*) factor is the value-weighted returns to all publicly traded (P/L or life) insurance companies. The portfolio returns are downloaded from Ken French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The regressions run portfolio returns from *t*+1 on the portfolio-level betas from *t*. The betas are estimated for each individual firm using data from the previous 60 months, then trimmed at 1% and 99% to eliminate outliers, and then averaged across all firms within the portfolio.

Table 8A. GRS Test with Insurance Factors, Alternative Portfolio Sets

Panel A. 25 Size/market-to-book sorted portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Stat	3.698	3.586	3.62	3.658	4.254	3.463
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*

Panel B. 25 Size/momentum sorted portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Stat	2.396	2.466	2.449	2.429	2.781	2.305
p-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*

Panel C. 25 Size/reversal sorted portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Stat	1.175	1.215	1.207	1.192	1.728	1.276
p-value	*0.259*	*0.222*	*0.230*	*0.243*	*0.018*	*0.174*

Panel D. 25 Size/profitability sorted portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Stat	1.512	1.215	1.207	1.192	1.831	1.406
p-value	*0.058*	*0.222*	*0.230*	*0.243*	*0.010*	*0.097*

Panel E. 25 Size/investment sorted portfolios

	FF5	FF5+*INS*	FF5+*PL*	FF5+*Life*	AFM	FF5+AFM
Stat	2.348	2.254	2.281	2.324	3.073	2.214
p-value	*0.000*	*0.001*	*0.001*	*0.000*	*0.000*	*0.001*

Note: The table reports the results of the test with the null hypothesis that the alphas of all portfolios mentioned in the panel name are jointly zero in the model named in the column heading. For example, the top left cell performs, in full 1986-2014 sample, 25 regressions of excess returns to each of the portfolios from five-by-five annual sorts on size and book-to-market on excess market return, *SMB*, *HML*, *RMW*, and *CMA* (FF5), and tests if all 25 intercepts are jointly zero. The cell next to it adds the value-weighted return to all publicly traded insurance companies (*INS* factor) to FF5, re-estimates the 25 regressions and again tests if all intercepts are jointly zero. The next two cells in Panel A replace *INS* factor by value-weighted returns to P/L and life insurers (*PL* factor and *Life* factor), redo the regressions, and perform the same test. The last two cells in Panel A replace FF5 in the first cell with AFM model and FF5 augmented with the additional AFM factors (*FROE* and *SPREAD*), redo the regressions, and perform the same test. The returns to the portfolio sets, the detailed descriptions of the sorting variables, and the sorting procedure are available from Ken French's data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 9A. Other Types of Insurers

	Panel A. Accident and Health Insurers					Panel B. All Other Insurers				
	CAPM	FF5	AFM	CCAPM	ICAPM	CAPM	FF5	AFM	CCAPM	ICAPM
RM-RF	0.90***	1.03***	0.90***	0.65**	-0.21	1.11***	1.31***	1.12***	0.29	0.17
	(0.06)	(0.06)	(0.06)	(0.27)	(0.25)	(0.07)	(0.07)	(0.07)	(0.33)	(0.32)
SMB		0.05	-0.00				0.28***	0.31***		
		(0.09)	(0.08)				(0.11)	(0.10)		
HML		0.55***	0.04				0.73***	0.36***		
		(0.12)	(0.11)				(0.14)	(0.13)		
RMW		0.50***					0.45***			
		(0.12)					(0.15)			
CMA		-0.33**					0.17			
		(0.17)					(0.20)			
FROE			0.04					0.08*		
			(0.04)					(0.04)		
SPREAD			0.62***					0.73***		
			(0.09)					(0.11)		
FVIX					-0.84***					-0.70***
					(0.18)					(0.23)
DEF_{t-1}*(RM-RF)				0.14					0.03	
				(0.12)					(0.15)	
DIV_{t-1}*(RM-RF)				0.35***					0.49***	
				(0.10)					(0.12)	
TB_{t-1}*(RM-RF)				-1.33**					-1.17*	
				(0.56)					(0.69)	
$TERM_{t-1}$*(RM-RF)				-0.22**					0.02	
				(0.10)					(0.13)	
Alpha	0.16	-0.13	0.14	0.02	-0.24	0.03	-0.52*	-0.14	-0.17	-0.30
	(0.26)	(0.25)	(0.24)	(0.26)	(0.27)	(0.33)	(0.31)	(0.28)	(0.32)	(0.34)
Adj R-sq	0.415	0.507	0.539	0.444	0.448	0.406	0.522	0.573	0.454	0.420
Obs	348	348	348	347	347	348	348	348	347	347

Panel C. Accident and Health Insurers Betas	Recessions	Expansion	Difference
Median as cutoff point	1.049***	0.773***	0.276***
	(0.014)	(0.014)	(0.020)
Top and bottom 25% as cutoff point	1.123***	0.684***	0.439***
	(0.021)	(0.021)	(0.030)

Panel D. All Other Insurers Betas	Recessions	Expansion	Difference
Median as cutoff point	1.332***	0.942***	0.390***
	(0.023)	(0.023)	(0.032)
Top and bottom 25% as cutoff point	1.407***	0.788***	0.618***
	(0.030)	(0.030)	(0.042)

Note: Panels A and B show the regression results based on CAPM, FF5, AFM, CCAPM, and ICAPM for Accident and Health insurers (A/H insurers, SIC codes 6320-6329) and All Other Insurers (any insurers that are not P/L insurers (6330-6331), life insurers (6310-6311), or A/H insurers). The insurance portfolio returns are value-weighted. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, and *HML* is the difference in the returns of high and low book-to-market portfolios. *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. *FROE* is the return spread between high and low ROE financial firms, and *SPREAD* is the return spread between financial and non-financial firms. *DEF* is default spread, *DIV* is dividend yield, *TB* is the 30-day Treasury bill rate, and *TERM* is term spread. *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P100 stock index options. Panels C and D label the month as expansion or recession based on whether the predicted market risk premium is below or above in-sample median (median as cutoff point), or whether the predicted market risk premium is in the bottom or top quartile of its in-sample distribution (top and bottom 25% as cutoff point). We measure expected market risk premium as the fitted part of the regression $RM_t - RF_t = b_{i0} + b_{i1}DEF_{t-1} + b_{i2}DIV_{t-1} + b_{i3}TERM_{t-1} + b_{i4}TB_{t-1} + \varepsilon$. Obs reports the number of months in the regressions. Standard errors appear in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 10A. *FVIX* Exposures of 48 Fama-French (1997) Industry Portfolios

	Agric-RF	**Food-RF**	**Soda-RF**	**Beer-RF**	**Smoke-RF**	**Toys-RF**	**Fun-RF**	**Books-RF**	**Hshld-RF**	**Clths-RF**
RM-RF	0.689**	-0.685***	-0.462	-0.808***	-0.756**	0.750***	1.914***	0.998***	0.023	0.379
	(0.287)	(0.178)	(0.313)	(0.214)	(0.327)	(0.257)	(0.247)	(0.181)	(0.165)	(0.235)
FVIX	-0.064	-0.964***	-0.968***	-1.086***	-1.041***	-0.221	0.429**	-0.018	-0.519***	-0.538***
	(0.210)	(0.130)	(0.229)	(0.157)	(0.239)	(0.188)	(0.180)	(0.133)	(0.121)	(0.172)
Alpha	0.206	-0.012	-0.082	0.066	0.316	-0.244	0.251	-0.158	0.001	-0.143
	(0.309)	(0.192)	(0.337)	(0.231)	(0.351)	(0.277)	(0.265)	(0.195)	(0.178)	(0.252)
Adj R-sq	0.292	0.446	0.310	0.393	0.209	0.486	0.632	0.646	0.529	0.562
Obs	347	347	347	347	347	347	347	347	347	347

	Hlth-RF	**MedEq-RF**	**Drugs-RF**	**Chems-RF**	**Rubbr-RF**	**Txtls-RF**	**BldMt-RF**	**Cnstr-RF**	**Steel-RF**	**FabPr-RF**
RM-RF	0.404	0.911***	-0.161	0.787***	0.974***	1.313***	0.700***	1.143***	2.667***	1.580***
	(0.286)	(0.181)	(0.184)	(0.183)	(0.204)	(0.323)	(0.204)	(0.240)	(0.255)	(0.282)
FVIX	-0.332	0.042	-0.675***	-0.190	-0.065	0.086	-0.331**	-0.048	0.914***	0.383*
	(0.209)	(0.132)	(0.135)	(0.133)	(0.149)	(0.236)	(0.149)	(0.175)	(0.187)	(0.206)
Alpha	-0.079	0.303	0.144	0.040	0.074	0.036	-0.116	-0.151	0.022	-0.072
	(0.308)	(0.195)	(0.198)	(0.196)	(0.220)	(0.348)	(0.219)	(0.258)	(0.275)	(0.303)
Adj R-sq	0.336	0.561	0.499	0.652	0.607	0.440	0.645	0.593	0.657	0.454
Obs	347	347	347	347	347	347	347	347	347	347

	Mach-RF	**ElcEq-RF**	**Autos-RF**	**Aero-RF**	**Ships-RF**	**Guns-RF**	**Gold-RF**	**Mines-RF**	**Coal-RF**	**Oil-RF**
RM-RF	1.632***	0.968***	1.532***	0.030	0.690**	-0.448	0.838	1.514***	2.132***	0.194
	(0.189)	(0.177)	(0.278)	(0.217)	(0.316)	(0.297)	(0.568)	(0.330)	(0.530)	(0.226)
FVIX	0.275**	-0.205	0.198	-0.739***	-0.275	-0.772***	0.328	0.315	0.755*	-0.387**
	(0.138)	(0.129)	(0.203)	(0.158)	(0.231)	(0.217)	(0.416)	(0.241)	(0.388)	(0.165)
Alpha	0.101	0.071	-0.142	-0.167	-0.078	0.118	0.112	0.327	0.561	0.145
	(0.203)	(0.190)	(0.299)	(0.233)	(0.341)	(0.319)	(0.612)	(0.355)	(0.571)	(0.243)
Adj R-sq	0.723	0.739	0.544	0.569	0.390	0.201	0.024	0.388	0.209	0.367
Obs	347	347	347	347	347	347	347	347	347	347

	Util-RF	**Telcm-RF**	**PerSv-RF**	**BusSv-RF**	**Comps-RF**	**Chips-RF**	**LabEq-RF**	**Paper-RF**	**Boxes-RF**	**Trans-RF**
RM-RF	-0.358*	0.543***	0.382	2.100***	2.805***	2.795***	2.469***	0.415**	0.425*	0.313*
	(0.183)	(0.162)	(0.234)	(0.167)	(0.257)	(0.241)	(0.201)	(0.185)	(0.228)	(0.175)
FVIX	-0.583***	-0.282**	-0.443***	0.619***	1.086***	0.999***	0.882***	-0.383***	-0.410**	-0.466***
	(0.134)	(0.118)	(0.171)	(0.122)	(0.188)	(0.176)	(0.147)	(0.135)	(0.167)	(0.128)
Alpha	0.082	-0.095	-0.387	0.325*	0.316	0.375	0.309	-0.092	0.003	-0.099
	(0.197)	(0.174)	(0.251)	(0.180)	(0.277)	(0.260)	(0.216)	(0.199)	(0.245)	(0.189)
Adj R-sq	0.260	0.651	0.503	0.773	0.629	0.688	0.714	0.593	0.514	0.625
Obs	347	347	347	347	347	347	347	347	347	347

	Whlsl-RF	**Rtail-RF**	**Meals-RF**	**Banks-RF**	**Insur-RF**	**RlEst-RF**	**Fin-RF**	**Other-RF**
RM-RF	0.724***	0.374**	-0.106	0.153	-0.226	1.750***	1.754***	0.977***
	(0.142)	(0.167)	(0.177)	(0.201)	(0.174)	(0.288)	(0.172)	(0.238)
FVIX	-0.146	-0.451***	-0.713***	-0.690***	-0.866***	0.523**	0.325**	-0.101
	(0.104)	(0.122)	(0.129)	(0.147)	(0.127)	(0.210)	(0.125)	(0.174)
Alpha	-0.079	-0.014	-0.099	-0.332	-0.327*	-0.229	0.166	-0.483*
	(0.153)	(0.180)	(0.190)	(0.217)	(0.187)	(0.310)	(0.185)	(0.257)
Adj R-sq	0.707	0.666	0.583	0.629	0.639	0.439	0.774	0.555
Obs	347	347	347	347	347	347	347	347

Note: This table reports the ICAPM with *FVIX* regression results for all 48 industries defined by Fama-French (1997), available on http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html. *RM-RF* is the market risk premium, and *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index. Obs reports the number of months in the regressions. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 11A. Factor-Mimicking Regressions of *CatLoss* and the *CombRat*

Historical Sensitivity Quintiles	(1) *CatLoss* VW	(2) *CatLoss* EW	Historical Sensitivity Quintiles	(3) *CombRat* VW	(4) *CombRat* EW
Quint1-*RF*	0.007	0.045	Quint1-*RF*	0.287*	-0.067
	(0.091)	(0.128)		(0.170)	(0.277)
Quint2-*RF*	-0.012	-0.134	Quint2-*RF*	0.011	0.654
	(0.131)	(0.231)		(0.217)	(0.540)
Quint3-*RF*	-0.016	-0.028	Quint3-*RF*	-0.311	-0.369
	(0.124)	(0.235)		(0.282)	(0.602)
Quint4-*RF*	0.004	0.189	Quint4-*RF*	0.101	-0.276
	(0.141)	(0.278)		(0.266)	(0.582)
Quint5-*RF*	-0.013	-0.084	Quint5-*RF*	-0.136	0.024
	(0.077)	(0.125)		(0.157)	(0.234)
Constant	1.959***	1.952***	Constant	0.005	-0.076
	(0.319)	(0.339)		(0.660)	(0.708)
Adj. R-sq	-0.044	-0.041	Adj. R-sq	-0.013	-0.034
Obs	104	104	Obs	104	104

Note: This table performs the standard factor-mimicking regression with inflation-adjusted catastrophic losses (*CatLoss*) (in columns 1 and 2) or change in combined ratio (*ΔCombRat*) (in columns 3 and 4) on the left-hand side and excess returns to value-weighted (VW) and equal-weighted (EW) quintile portfolios based on the historical stock sensitivity to catastrophic losses and change in combined ratio, respectively. *RF* is risk-free rate. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 12A. *CatLoss* Mimicking Portfolio: Alphas and Betas

	(1) CAPM	(2) FF3	(3) Carhart	(4) FF5	(5) CAPM	(6) FF3	(7) Carhart	(8) FF5
	Panel A. Value-Weighted Returns				**Panel B. Equal-Weighted Returns**			
RM-RF	-0.029***	-0.030***	-0.029***	-0.030***	-0.017***	-0.017***	-0.016***	-0.016***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
SMB		0.003***	0.003***	0.003***		-0.012***	-0.012***	-0.013***
		(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.003)
HML		-0.004***	-0.004***	-0.003***		-0.007***	-0.007***	-0.010***
		(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.004)
Mom			0.003***				0.001	
			(0.000)				(0.002)	
RMW				-0.002				-0.001
				(0.001)				(0.004)
CMA				-0.002				0.008
				(0.001)				(0.005)
Alpha	-0.003	-0.002	-0.004**	-0.001	-0.008	-0.005	-0.006	-0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.008)	(0.008)	(0.008)
Adj. R-sq	0.909	0.927	0.936	0.927	0.214	0.272	0.270	0.274
Obs	312	312	312	312	312	312	312	312

Note: This table reports the alphas and betas of the factor-mimicking portfolios on inflation-adjusted catastrophic losses in the CAPM, FF3, Carhart, and FF5 models. The factor-mimicking portfolios in Panels A and B are the fitted part from the regressions in columns 1 and 2 in Table 11A less the constant, respectively. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios, and *Mom* is the return differential from investing long in past winners and shorting past losers. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 13A. *ΔCombRat* Mimicking Portfolio: Alphas and Betas

	(1) CAPM	(2) FF3	(3) Carhart	(4) FF5	(5) CAPM	(6) FF3	(7) Carhart	(8) FF5
	Panel A. Value-Weighted Returns				**Panel B. Equal-Weighted Returns**			
RM-RF	0.012	0.002	-0.013	-0.016	-0.010*	-0.011**	-0.015**	-0.009
	(0.009)	(0.009)	(0.009)	(0.010)	(0.005)	(0.006)	(0.006)	(0.006)
SMB		0.049***	0.052***	0.038***		0.020***	0.021***	0.024***
		(0.013)	(0.012)	(0.014)		(0.008)	(0.008)	(0.008)
HML		-0.015	-0.031**	0.034*		0.012	0.009	0.008
		(0.013)	(0.013)	(0.019)		(0.008)	(0.008)	(0.011)
Mom			-0.045***				-0.011**	
			(0.008)				(0.005)	
RMW				-0.052***				0.013
				(0.020)				(0.012)
CMA				-0.088***				0.002
				(0.027)				(0.016)
Alpha	-0.051	-0.049	-0.009	-0.002	-0.007	-0.013	-0.003	-0.019
	(0.040)	(0.039)	(0.038)	(0.041)	(0.023)	(0.023)	(0.023)	(0.024)
Adj. R-sq	0.002	0.049	0.134	0.086	0.008	0.029	0.040	0.027
Obs	312	312	312	312	312	312	312	312

Note: This table reports the alphas and betas of the factor-mimicking portfolios on change in combined ratio in the CAPM, FF3, Carhart, and FF5 models. The factor-mimicking portfolios in Panels A and B are the fitted part from the regressions in columns 3 and 4 in Table 11A less the constant, respectively. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios, and *Mom* is the return differential from investing long in past winners and shorting past losers. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 14A. Underwriting Cycles in the Intertemporal CAPM (*CatLoss*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RM-RF	0.87***	0.04	0.87***	-0.27	-0.64***	-0.27	1.07***	0.88***	1.07***	0.52***	0.41*	0.52***
	(0.05)	(0.14)	(0.05)	(0.17)	(0.19)	(0.17)	(0.04)	(0.14)	(0.04)	(0.18)	(0.21)	(0.18)
SMB							-0.12**	-0.11*	-0.12**	-0.08	-0.07	-0.08
							(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
HML							0.52***	0.50***	0.52***	0.54***	0.52***	0.54***
							(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)
RMW							0.32***	0.31***	0.32***	0.22***	0.22***	0.22***
							(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
CMA							0.07	0.06	0.07	0.00	-0.00	0.00
							(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
FVIX				-0.87***	-0.68***	-0.87***				-0.39***	-0.37***	-0.39***
				(0.13)	(0.13)	(0.13)				(0.13)	(0.13)	(0.13)
FCatLoss		-29.05***			-21.39***			-6.31			-4.44	
		(4.72)			(4.76)			(4.42)			(4.42)	
CatLoss			0.01			0.04			0.01			0.01
			(0.07)			(0.06)			(0.05)			(0.05)
Alpha	0.15	0.05	0.14	-0.28	-0.26	-0.35	-0.20	-0.20	-0.21	-0.33*	-0.32*	-0.35*
	(0.20)	(0.19)	(0.23)	(0.19)	(0.19)	(0.23)	(0.16)	(0.16)	(0.20)	(0.17)	(0.17)	(0.20)
Ad. R-sq	0.546	0.594	0.544	0.603	0.626	0.602	0.719	0.720	0.718	0.727	0.727	0.726
Obs.	312	312	312	312	312	312	312	312	312	312	312	312

Note: This table reports the regression results including the catastrophic losses factor into the three models from Tables 2 (CAPM, FF5, ICAPM) and FF5 augmented with *FVIX* (FF6) for all the publicly traded insurance companies. The results of estimating the four models are in columns 1, 4, 7, and 10, respectively. The catastrophic losses factor is added to the models in columns 2, 5, 8, and 11. In columns 3, 6, 9, and 12 factors is replaced by the variable it mimics (inflation-adjusted catastrophic losses). The left-hand side variable is the value-weighted returns to all insurance companies. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P100 stock index options. *FCatLoss* is the factor-mimicking portfolio that mimics the inflation-adjusted catastrophic losses, namely, the catastrophic losses factor. *CatLoss* is the variable that *FCatLoss* mimics, which is the inflation-adjusted catastrophic losses. Since *FCatLoss* and *CatLoss* are available from 1989, all regressions are from 1989 to 2014. Obs reports the number of months in the regressions. Standard errors appear in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 15A. Cost of Equity Estimates

Panel A. All Insurers

Year	COE Estimates						Sum-Beta COE Estimates					
	CAPM	FF5	CCAPM	ICAPM	AFM	FF6	CAPM	FF5	CCAPM	ICAPM	AFM	FF6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1997	11.994	12.216	5.951	16.718	11.672	13.263	11.945	12.506	5.901	17.780	10.727	10.808
1998	12.779	14.289	4.672	17.523	12.873	14.938	13.080	16.887	4.651	20.305	13.330	15.997
1999	12.419	18.952	3.086	20.442	13.859	20.236	12.977	21.254	2.904	22.000	14.538	21.260
2000	11.906	20.945	4.439	26.400	15.825	23.420	12.808	21.380	4.451	26.495	17.029	21.555
2001	9.657	21.487	3.893	21.658	16.769	23.516	9.851	22.530	3.795	21.426	17.717	22.466
2002	8.369	19.120	2.617	17.007	14.797	19.800	8.647	20.089	2.591	17.214	15.946	19.650
2003	7.230	17.214	5.090	14.783	14.385	17.552	7.445	16.456	5.482	15.506	15.795	16.510
2004	6.505	15.434	6.109	15.399	13.353	16.706	6.848	13.771	5.140	16.528	14.587	14.532
2005	6.038	12.966	3.958	10.190	12.234	13.540	6.430	12.023	3.251	11.716	12.751	12.176
2006	7.324	10.693	4.437	8.481	8.772	10.934	7.824	12.827	4.189	9.636	10.208	12.199
2007	9.165	11.261	4.123	10.402	10.409	12.186	9.422	14.428	4.134	11.424	11.410	13.918
2008	10.291	10.032	2.994	11.136	9.615	10.574	10.571	10.626	2.985	11.407	8.915	10.381
2009	11.343	12.360	18.136	12.287	11.708	12.472	11.267	13.926	18.246	12.486	9.486	12.868
2010	10.704	8.470	28.765	11.064	9.839	8.895	10.644	10.398	28.963	10.718	8.669	10.326
2011	9.787	6.779	11.648	10.199	8.780	7.412	9.625	8.443	12.118	9.525	7.664	8.787
2012	8.852	5.627	8.532	9.229	8.030	6.224	8.644	7.555	8.778	8.504	6.872	7.846
2013	8.453	5.057	7.486	8.787	7.659	5.767	8.294	6.971	8.407	7.913	8.178	7.243
2014	7.152	5.017	6.520	7.314	6.296	5.377	6.530	5.678	6.002	5.365	7.029	5.677
Avg.	9.443	12.662	7.359	13.834	11.493	13.490	9.603	13.764	7.333	14.219	11.714	13.567

Panel B. P/L Insurers

Year	COE Estimates						Sum-Beta COE Estimates					
	CAPM	FF5	CCAPM	ICAPM	AFM	FF6	CAPM	FF5	CCAPM	ICAPM	AFM	FF6
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1997	10.648	9.464	5.678	18.315	9.929	11.888	9.574	8.651	5.578	16.618	7.805	9.625
1998	11.805	11.888	4.689	19.712	11.531	14.399	11.332	13.566	4.662	19.785	11.485	14.298
1999	11.324	18.926	3.109	22.797	13.192	22.213	11.325	20.335	2.918	21.473	13.270	20.721
2000	10.988	21.363	4.444	27.601	16.926	24.995	11.957	20.786	4.468	25.172	16.972	20.636
2001	8.989	21.305	3.985	22.197	17.326	23.918	9.510	22.005	3.420	20.393	18.050	21.795
2002	7.822	17.832	2.692	17.367	14.632	18.765	8.246	18.160	2.595	16.372	15.055	17.480
2003	6.864	16.262	5.483	15.366	14.428	16.772	7.094	14.368	6.407	14.926	14.478	14.516
2004	6.364	14.410	5.854	16.533	13.368	16.293	6.824	11.777	4.974	16.641	13.496	13.201
2005	5.956	12.300	3.179	11.214	11.715	13.289	6.121	10.437	2.555	11.461	10.884	10.692
2006	7.518	9.825	4.087	9.605	7.939	10.334	7.390	12.191	4.031	8.941	10.241	11.048
2007	9.521	11.564	4.282	11.594	10.770	12.267	9.338	15.360	4.129	11.457	11.814	14.154
2008	9.465	10.251	3.040	10.695	8.332	10.766	9.443	11.125	2.914	10.220	7.270	10.640
2009	9.228	10.666	16.867	10.099	7.942	10.756	8.854	9.055	17.073	8.542	6.037	9.114
2010	8.421	5.710	22.910	8.464	6.319	5.937	8.107	4.692	21.954	6.269	4.495	4.763
2011	7.437	3.665	9.419	7.593	5.030	4.082	6.982	2.888	9.207	4.871	3.349	2.652
2012	6.528	2.523	7.077	6.759	4.404	2.926	6.039	1.880	6.700	3.939	2.557	1.552
2013	6.076	2.334	6.179	6.186	4.405	2.721	5.581	1.409	6.808	2.579	3.795	0.569
2014	5.085	3.323	5.264	6.857	4.362	4.603	3.839	3.375	4.605	3.342	4.526	3.458
Avg.	8.336	11.312	6.569	13.831	10.142	12.607	8.198	11.225	6.389	12.389	9.754	11.162

Panel C. Life Insurers

Year	COE Estimates						Sum-Beta COE Estimates					
	CAPM (1)	FF5 (2)	CCAPM (3)	ICAPM (4)	AFM (5)	FF6 (6)	CAPM (7)	FF5 (8)	CCAPM (9)	ICAPM (10)	AFM (11)	FF6 (12)
1997	12.664	19.831	6.094	20.394	15.631	21.997	13.636	22.230	6.209	25.200	15.612	22.828
1998	12.954	20.359	4.687	20.298	16.195	21.538	14.304	24.044	4.648	27.910	16.517	25.598
1999	12.745	18.533	3.127	18.932	14.808	18.359	14.436	22.383	2.664	26.066	15.422	24.864
2000	12.307	18.656	4.420	24.111	13.600	19.274	13.331	21.076	4.379	28.194	15.208	23.378
2001	10.415	19.815	3.499	20.132	15.095	20.536	10.415	22.570	3.879	22.259	16.841	22.799
2002	9.357	19.151	2.895	16.202	15.393	19.366	9.914	22.796	2.880	18.552	18.721	22.790
2003	8.476	17.795	6.139	14.330	15.370	17.824	9.161	20.235	5.127	17.229	19.848	20.137
2004	7.727	16.669	7.151	14.683	15.001	16.868	8.281	17.026	5.537	17.885	18.581	16.765
2005	7.223	13.389	5.656	9.315	13.863	13.130	8.337	14.921	4.957	13.619	17.103	15.027
2006	8.262	11.207	4.734	7.388	11.009	10.709	10.231	12.375	4.058	11.906	13.500	12.815
2007	9.571	10.252	4.177	8.243	10.219	9.703	10.873	10.547	4.462	11.391	12.797	10.320
2008	11.935	10.693	3.060	11.230	13.788	10.634	12.384	7.958	3.223	11.174	14.088	7.750
2009	17.882	18.525	24.145	17.902	22.526	18.672	19.255	27.730	24.827	23.168	21.371	23.803
2010	17.920	15.643	53.297	17.627	19.897	16.433	19.367	23.457	62.724	22.755	22.162	22.898
2011	16.981	13.658	20.048	16.584	18.462	14.664	18.069	18.928	23.070	21.098	20.171	21.311
2012	16.148	11.488	13.989	15.503	17.449	12.479	16.987	17.134	14.931	19.550	19.460	19.538
2013	16.335	10.883	11.819	16.215	15.526	12.432	17.583	18.292	12.467	22.503	19.373	22.358
2014	13.639	10.041	10.093	9.267	11.498	7.761	14.288	13.135	7.587	9.290	14.357	13.021
Avg.	12.363	15.366	10.502	15.464	15.296	15.688	13.381	18.713	10.979	19.431	17.285	19.333

Note: This table shows the value-weighted cost of equity (COE) estimates for all the publicly traded insurers, P/L insurers, and life insurers based on CAPM, FF5, CCAPM, ICAPM, AFM, and FF6 from 1997 to 2014 in columns 1-6. Columns 7-12 report the COE estimates based on the sum-beta approach. For each year, the annual COE estimate is the cumulative monthly COE estimates from January to December of that year. *Avg.* shows the average COE across the full sample period from 1997 to 2014.

Table 16A. Asset-Pricing Model Performance Comparison using Equal-Weighted Insurer Returns

	Panel A. All Insurers				Panel B. P/L Insurers				Panel C. Life Insurers			
	CAPM	FF5	CCAPM	ICAPM	CAPM	FF5	CCAPM	ICAPM	CAPM	FF5	CCAPM	ICAPM
RM-RF	0.81***	0.89***	0.64***	0.39**	0.71***	0.80***	0.32**	0.05	1.01***	1.10***	0.87***	0.80***
	(0.03)	(0.03)	(0.15)	(0.15)	(0.03)	(0.03)	(0.15)	(0.14)	(0.05)	(0.05)	(0.20)	(0.23)
SMB		0.43***				0.30***				0.46***		
		(0.04)				(0.05)				(0.07)		
HML		0.59***				0.46***				0.99***		
		(0.05)				(0.06)				(0.09)		
RMW		0.17***				0.19***				-0.05		
		(0.06)				(0.06)				(0.09)		
CMA		0.01				0.07				-0.10		
		(0.08)				(0.09)				(0.13)		
FVIX				-0.31***				-0.50***				-0.16
				(0.11)				(0.11)				(0.17)
$DEF_{t-1}*(RM-RF)$			0.09				-0.02				0.69***	
			(0.07)				(0.07)				(0.09)	
$DIV_{t-1}*(RM-RF)$			0.25***				0.26***				0.21***	
			(0.06)				(0.06)				(0.07)	
$TB_{t-1}*(RM-RF)$			-1.33***				-0.59*				-2.52***	
			(0.32)				(0.32)				(0.41)	
$TERM_{t-1}*(RM-RF)$			-0.07				-0.00				-0.24***	
			(0.06)				(0.06)				(0.08)	
Alpha	0.29*	-0.01	0.17	0.13	0.25*	-0.03	0.12	-0.00	0.20	-0.09	0.14	0.11
	(0.16)	(0.12)	(0.15)	(0.16)	(0.15)	(0.13)	(0.15)	(0.16)	(0.24)	(0.19)	(0.19)	(0.25)
Adj R-sq	0.613	0.805	0.675	0.622	0.560	0.704	0.606	0.592	0.518	0.720	0.712	0.518
Obs	348	348	347	347	348	348	347	347	348	348	347	347

Note: This table shows the regression results based on CAPM, FF5, CCAPM, and ICAPM for all the publicly traded insurance companies, P/L insurers, and life insurers. The insurance portfolio returns are equal-weighted. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. We use four macroeconomic/business cycle variables as conditioning variables in the CCAPM, which include default spread (*DEF*), defined as the yield spread between Moody's Baa and Aaa corporate bonds, dividend yield (*DIV*), defined as the sum of dividend payments to all CRSP stocks over the previous 12 months divided by the current value of the CRSP value-weighted index, Treasury bill rate (*TB*), which is the 30-day T-bill rate, and term spread (*TERM*), defined as the yield spread between the ten-year and the one-year T-bond. In the ICAPM, *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P100 stock index options. Obs reports the number of months in the regressions. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 17A. Average CCAPM Betas of Insurance Companies in Expansions and Recessions using Equal-Weighted Insurer Returns

Panel A. All Insurers	Recessions	Expansion	Difference
Median as cutoff point	0.932***	0.704***	0.228***
	(0.015)	(0.015)	(0.021)
Top and bottom 25% as cutoff point	1.021***	0.647***	0.375***
	(0.023)	(0.023)	(0.032)
Panel B. P/L Insurers	Recessions	Expansion	Difference
Median as cutoff point	0.837***	0.628***	0.209***
	(0.011)	(0.011)	(0.016)
Top and bottom 25% as cutoff point	0.873***	0.542***	0.331***
	(0.014)	(0.014)	(0.020)
Panel C. Life Insurers	Recessions	Expansion	Difference
Median as cutoff point	1.036***	0.832***	0.204***
	(0.035)	(0.035)	(0.050)
Top and bottom 25% as cutoff point	1.212***	0.857***	0.355***
	(0.058)	(0.058)	(0.082)

Note: The table labels the month as expansion or recession based on whether the predicted market risk premium is below or above in-sample median (median as cutoff point), or whether the predicted market risk premium is in the bottom or top quartile of its in-sample distribution (top and bottom 25% as cutoff point). We measure expected market risk premium as the fitted part of the regression $RM_t - RF_t = b_{i0} + b_{i1}DEF_{t-1} + b_{i2}DIV_{t-1} + b_{i3}TERM_{t-1} + b_{i4}TB_{t-1} + \varepsilon$, where *RM-RF* is the market risk premium, *DEF* is default spread, *DIV* is dividend yield, *TERM* is term spread, and *TB* is the 30-day Treasury bill rate. Standard errors appear in parentheses. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 18A. Underwriting Cycles in the Intertemporal CAPM using Equal-Weighted Insurer Returns (Combined Ratio Change)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RM-RF	0.81***	0.80***	0.81***	0.39**	0.35**	0.38**	0.90***	0.90***	0.90***	0.39***	0.40***	0.37***
	(0.04)	(0.04)	(0.04)	(0.16)	(0.16)	(0.16)	(0.03)	(0.03)	(0.03)	(0.14)	(0.14)	(0.14)
SMB							0.41***	0.40***	0.41***	0.45***	0.44***	0.45***
							(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
HML							0.57***	0.56***	0.57***	0.59***	0.58***	0.59***
							(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
RMW							0.18***	0.20***	0.18***	0.10	0.11*	0.09
							(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
CMA							0.08	0.11	0.09	0.02	0.05	0.02
							(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
FVIX				-0.32***	-0.34***	-0.32***				-0.36***	-0.36***	-0.37***
				(0.12)	(0.12)	(0.12)				(0.09)	(0.09)	(0.10)
FCombRat		0.27			0.37			0.29*			0.29*	
		(0.24)			(0.24)			(0.17)			(0.17)	
ΔCombRat			0.01			0.02			0.02			0.02
			(0.03)			(0.03)			(0.02)			(0.02)
Alpha	0.38**	0.40**	0.39**	0.23	0.23	0.22	0.05	0.05	0.05	-0.07	-0.07	-0.07
	(0.17)	(0.17)	(0.17)	(0.18)	(0.18)	(0.18)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
Adj R-sq	0.583	0.583	0.582	0.591	0.593	0.591	0.797	0.798	0.797	0.806	0.807	0.806
Obs	312	312	312	312	312	312	312	312	312	312	312	312

Note: This table reports the regression results including the combined ratio factor (*FCombRat*) into the three models from Tables 2 (CAPM, FF5, and ICAPM) and FF5 augmented with *FVIX* (FF6) for all the publicly traded insurance companies. The results of estimating these four models are in columns 1, 4, 7, and 10, respectively. The combined ratio factor is added to the models in columns 2, 5, 8, and 11. In columns 3, 6, 9, and 12 each factor is replaced by the variable it mimics (change in combined ratio). The left-hand side variable is the equal-weighted returns to all the publicly traded insurance companies. *RM-RF* is the market risk premium, *SMB* is the difference in the returns of small and large portfolios, *HML* is the difference in the returns of high and low book-to-market portfolios, *RMW* is the difference in the returns of robust and weak (high and low) operating profitability portfolios, and *CMA* is the difference in the returns of conservative and aggressive (low and high) investment portfolios. *FVIX* is the factor-mimicking portfolio that mimics the changes in VIX index, which measures the implied volatility of the S&P100 stock index options. *FCombRat* is the factor-mimicking portfolio that mimics the changes in combined ratio, namely, the combined ratio factor. *ΔCombRat* is the variable that *FCombRat* mimics, which is the change in combined ratio. Since *FCombRat* and *ΔCombRat* are available from 1989, all regressions are from 1989 to 2014. Obs reports the number of months in the regressions. Standard errors appear in parentheses. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 19A. Equal-Weighted Cost of Equity Estimates

Panel A. All Insurers

Year	COE Estimates			
	CAPM	FF5	CCAPM	ICAPM
	(1)	(2)	(3)	(4)
1997	10.100	13.305	5.609	9.923
1998	10.616	13.784	4.824	10.314
1999	10.889	16.993	3.717	14.741
2000	10.145	18.300	4.762	16.806
2001	8.716	18.295	4.465	14.427
2002	7.872	17.615	2.565	11.937
2003	7.061	16.852	2.646	10.330
2004	6.624	15.803	4.913	10.118
2005	6.811	14.285	4.307	8.029
2006	7.893	13.091	4.377	6.340
2007	9.665	13.871	4.336	7.118
2008	10.969	14.035	3.089	10.597
2009	11.396	13.714	15.623	13.173
2010	11.022	10.663	25.549	12.481
2011	10.134	9.420	11.643	11.808
2012	9.151	7.907	8.784	10.635
2013	8.762	6.801	7.556	10.256
2014	8.080	8.626	6.665	7.775
Average	9.217	13.520	6.968	10.934

Panel B. P/L Insurers

Year	COE Estimates			
	CAPM	FF5	CCAPM	ICAPM
	(1)	(2)	(3)	(4)
1997	9.364	14.095	5.474	13.724
1998	10.064	14.755	4.840	13.054
1999	10.114	16.502	3.785	15.343
2000	9.496	17.774	4.801	16.764
2001	8.205	17.288	4.474	14.241
2002	7.392	16.310	2.523	11.772
2003	6.682	15.791	2.655	10.304
2004	6.424	14.976	4.730	10.443
2005	6.598	13.248	3.977	8.214
2006	7.672	12.412	4.239	6.458
2007	9.441	13.747	4.416	7.055
2008	9.972	13.349	3.105	9.723
2009	9.158	12.354	12.057	10.823
2010	8.548	9.311	16.132	10.014
2011	7.650	7.805	9.481	9.431
2012	6.549	6.403	7.046	8.053
2013	6.059	5.946	5.660	7.544
2014	5.765	8.185	5.283	6.823
Average	8.064	12.792	5.815	10.544

Panel C. Life Insurers

Year	COE Estimates			
	CAPM	FF5	CCAPM	ICAPM
	(1)	(2)	(3)	(4)
1997	10.304	16.495	5.547	13.542
1998	10.690	16.468	4.801	13.788
1999	10.796	17.820	3.764	15.325
2000	10.121	17.852	4.828	16.622
2001	9.023	18.163	4.366	14.174
2002	8.381	17.841	2.822	11.789
2003	7.837	18.080	3.846	10.443
2004	7.465	17.511	5.549	10.316
2005	7.553	14.401	4.576	7.608
2006	8.737	12.467	4.239	5.537
2007	10.422	14.811	4.352	6.148
2008	12.257	15.551	3.113	10.795
2009	16.893	23.341	27.065	21.150
2010	16.952	17.628	50.852	21.213
2011	15.865	15.901	19.267	20.255
2012	14.871	14.283	14.201	19.039
2013	14.950	12.463	12.636	20.191
2014	12.349	10.917	9.326	11.442
Average	11.415	16.222	10.286	13.854

Note: This table shows the equal-weighted cost of equity (COE) estimates for all the publicly traded insurers, P/L insurers, and life insurers based on CAPM, FF5, CCAPM, and ICAPM from 1997 to 2014 in columns 1-4, respectively. For each year, the annual COE estimate is the cumulative monthly COE estimates from January to December of that year. *Average* shows the average COE across the full sample period from 1997 to 2014.