Estimating the Cost of Equity Capital for Insurance Firms with Multi-period Asset Pricing Models

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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 multi-period models—the conditional CAPM (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.

Keywords: Cost of equity; multi-period asset pricing models; time-varying risks

I. 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-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. Multi-period models account for the time-varying risks (factors) that reflect these cycles.

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.

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[1] In Section II, 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 Section II, while re-estimating beta(s) in CAPM/FF5 allows for the cost of equity 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".

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 papers 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 papers 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 not only want to know 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, Section IV 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? (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 multi-period models, such as the CCAPM and ICAPM, considered in our paper, 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.

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

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 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 cost of equity 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 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 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% per annum (in contrast to 6% 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% 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 CCAPM finding more risk in insurance firms.

II. Asset Pricing Models and Literature

Fama-French Five-Factor Model

In response to actual and perceived weaknesses of the CAPM, Fama and French (1992 and 1993) developed a three-factor model that became the most widely used alternative to the CAPM.

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[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.

[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. 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.

Recently, Fama and French (2015) updated the model by including two additional factors. [6] The five-factor (FF5) model is a single-period model that has the following specification:

$$R_i - RF = \alpha_i + \beta_i\,(RM\text{-}RF) + s_i\,SMB + v_i\,HML + p_i\,RMW + i_i\,CMA + \varepsilon \tag{1}$$

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 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), 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 $p_t=E(m_t{\cdot}R_t|I_t)$. Also, since the conditional expectation is essentially a projection on

[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), Hou, Xue, and Zhang (2015) provide the (largely overlapping) lists of violations of the CAPM documented as of today.

[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).

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: e.g., 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]

$$E(R_i\text{-}RF) = E[\beta_i \cdot (RM\text{-}RF)] = E(\beta_i) \cdot E(RM\text{-}RF) + Cov[\beta_i , (RM\text{-}RF)] \qquad (2)$$

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

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

(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 Section III, that are known to predict the market return.[9] Our choice of conditioning variables is standard for the CCAPM literature (Petkova and Zhang, 2005; O'Doherty, 2012).

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

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

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

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

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

[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.

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.

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 (re-arranging 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 multi-period 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 $p_t=E(m_t R_t)$, dropping second-order terms, yields

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

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 paper, 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&P100 index, and thus derives volatility expectations from option prices, effectively using all the information the traders have. Following Breeden et al. (1989), Ang et al. (2006), and Barinov (2014), we form a portfolio that mimics the volatility risk factor, known

[10] VIX is the Chicago Board Options Exchange (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% between 1990 and 2000.

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:

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

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

Prior Cost of Equity Capital Studies in 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 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 RL model than from the CAPM for insurers with highly skewed returns and for smaller insurers.

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[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, i.e., 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 next section.

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 et al. (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 et al. (2015), similar in spirit and method to Bajtelsmit et al. (2015), use the two-stage Fama-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]

III. 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

[13] Lee and Cummins (1998) estimate CAPM and APT (multi-factor) 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 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, we use liquidity, liquidity risk, and coskewness factors and find that they add little to insurers COE.

[15] Ben Ammar et al. (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 papers that begin by asking, "does a risk factor reflect economy-wide risk, that is, non-diversifiable risk, or only risk related to one industry (diversifiable risk)?"

CRSP (market cap weight is lagged by one 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 et al. (2016). All types of insurers are included and we further separate them into seven major subsectors.[17] We perform major analysis on all insurers and 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 price) to all CRSP stocks. *DIV* is obtained from CRSP as the difference between cum-dividend and ex-dividend market return. *TB* is the one-month Treasury bill rate from Ken French's data library. *TERM* is the yield spread between the ten-year and one-year Treasury bond. The data source for *DEF* and *TERM* is 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 et al., 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 $VIX1_t$,…, 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

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

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 paper.

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 non-missing returns are required): $R_{i,t-1} - RF_{t-1} = \alpha + \beta_i \cdot (RM_{t-1} - RF_{t-1}) + \gamma_{\Delta VIX} \cdot \Delta VIX_{t-1} + \varepsilon$. 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]

IV. 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%, 0.56%, and 0.76% 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% 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

[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.

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 paper, 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 thirty industry portfolios from Fama and French (1997). This set is often used in the asset pricing literature (Lewellen, Nagel, and Shanken, 2010, for example, 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 performs a test similar to the GRS test. Its first column tests whether in the ICAPM all *FVIX* slopes for the thirty 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 $DEF_{t-1}*(RM - RF)$ 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 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 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 Section V).[20]

The last two columns of Panel D 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 non-financial 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 et al. (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

[20] In Online Appendix C, we test the robustness of the results in Panels B, C, and D to using other salient portfolios instead of the thirty 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 $DEF_{t-1}*(RM - RF)$ 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, 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.

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 (β = 1.20) and P/L insurers (β = 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 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

[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.

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, etc.

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 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 Treasury bill rate loses significance but keeps its sign. Panel C is more complicated because it suggests 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 the $TERM_{t-1}*(RM - RF)$ 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 non-negligible 8-12 basis points (bp) per month (1-1.5% 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

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[24] The results in Table 2, which uses value-weighted returns, as well as the results in the rest of the paper, 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 $TERM_{t-1}*(RM - RF)$ suggests the beta of life insurers is lower in recessions. The positive sign on $DEF_{t-1}*(RM - RF)$ 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 (cost of equity, 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 (cost of equity, risk) part, as the alpha and the risk-based part have to sum up to the same average realized return.

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 Treasury bill rate is low. We directly observe the negative link between 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, 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 top row of each panel in Table 3, 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 in-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 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.

[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.

[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 papers 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.

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. The top panel 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 sizeable 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]

V. Underwriting Cycle Variables in the CCAPM/ICAPM?

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

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

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 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 US 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 into 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 into 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 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 (2001)'s suggestion that the optimal base assets should have the richest possible variation in the sensitivity to the

[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.

variable being mimicked, we choose quintiles sorted on historical sensitivity to changes in combined ratio.[32] We regress change in combined ratio on 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*) into 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 artefact 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.

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[32] In each firm-quarter (underwriting cycle/insurance-specific variables such as combined ratio are collected quarterly) for every stock traded in US market and listed on CRSP, we perform regressions of excess stock returns (R_i-*RF*) on *RM-RF*, *SMB*, *HML*, and 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 the stocks with less than 12 non-missing returns between *t*-1 and *t*-20. The slope on change in combined ratio is our measure of historical stock sensitivity to change in combined ratio.

[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).

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

VI. Cost of Equity Estimation

Estimation Methods

In this study, we estimate the value-weighted average cost of equity (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

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[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.

obtain annual cost of equity we sum up each of the 12 months' COE estimates within that year.[41]

The CCAPM cost of equity 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 one year out. To calculate the predicted market risk premium in *t*+1, *t*+2,…, and *t*+12, we multiple the values of the four business cycle variables in *t*-11, *t*-10,…, and *t* by the corresponding coefficients from $RM_t - RF_t = b_{i0} + b_{i1}DEF_{t-12} + b_{i2}DIV_{t-12} + b_{i3}TERM_{t-12} + b_{i4}TB_{t-12} + \varepsilon$, 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 $R_{it} - RF_t = \alpha_i + b_{i0} \cdot (RM_t - RF_t) + b_{i1}DEF_{t-12} \cdot (RM_t - RF_t) + b_{i2}DIV_{t-12} \cdot (RM_t - RF_t) + b_{i3}TB_{t-12} \cdot (RM_t - RF_t) + b_{i4}TERM_{t-12} \cdot (RM_t - RF_t) + \varepsilon$, 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 cost of equity, therefore,

[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.
[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.

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%. FF5 generates the second highest estimate (12.662%), followed by CAPM (9.443%).[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 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 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

[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 ten 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 (for example, 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 vs. equal-weighted returns, estimation periods, etc. 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.
[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 (for example, for all insurance firms FF6 pegs the average COE at 13.490% per annum) than those from FF5.

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% per annum, which is quite low compared to the long-run average market risk premium of roughly 6%.[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% market risk premium, it would produce the average COE of 4.818% per annum, much lower than the CCAPM's 7.359% 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%) for the entire 18-year period for P/L insurers, followed by FF5 (11.312%), CAPM (8.336%), and CCAPM (6.569%). For life insurers, again ICAPM produces the highest average COE estimate (15.464%) for the full sample period, followed by FF5 (15.366%), CAPM (12.363%), and CCAPM (10.502%). 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%, depending on the models, meaning that the required rate of return and risk for life insurers are higher than that of P/L insurers.

VII. Summary and Conclusions

We extend prior literature by identifying new risk factors the insurance industry is exposed

[47] The result used in the CCAPM estimation that the expected market risk premium was 3% 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%, just as the expected market risk premium of our model does before 2008.

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 cost of equity estimation. Underwiring 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.

The analysis in the paper 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 re-estimating the models for an individual firm, if it is its COE that is of interest in a particular application.

In the cost of equity 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% per annum, consistent with similar estimates in Claus and Thomas, 2001, and Fama and French, 2002).

Our study adds to the literature in several ways. First, it is the first to examine conditional CAPM 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-period and multi-period 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 paper 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 paper opens the door to finding more risks and hedges in 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.

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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

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 US 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 ten-year and the one-year T-bond. *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. Panel A reports the descriptive statistics. Panel B performs the GRS (Gibbons, Ross, and Shanken, 1989) test for the set of thirty industry portfolios from Fama and French (1997). Panel C tests whether all *FVIX* slopes for the thirty 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 $DEF_{t-1}*(RM - RF)$, $DIV_{t-1}*(RM - RF)$, $TB_{t-1}*(RM - RF)$, or $TERM_{t-1}*(RM - RF)$ in the CCAPM, respectively. Panel D performs the GRS test of all alphas being jointly zero for the thirty 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 non-financial firms), namely, FF5+AFM.

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}*(RM-RF)			0.10				0.00				0.66***	
			(0.09)				(0.09)				(0.11)	
DIV_{t-1}*(RM-RF)			0.30***				0.26***				0.32***	
			(0.07)				(0.08)				(0.09)	
TB_{t-1}*(RM-RF)			-0.94**				-0.60				-2.23***	
			(0.39)				(0.43)				(0.51)	
$TERM_{t-1}$*(RM-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-sq	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 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 brackets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 3. Average CCAPM Betas of Insurance Companies in Expansions and Recessions

Panel A. All Insurers	Recessions	Expansion	Difference
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	Recessions	Expansion	Difference
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	Recessions	Expansion	Difference
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 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 brackets. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

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-sq	-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 was 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 brackets. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

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}*(RM-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}*(RM-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}*(RM-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)
$TERM_{t-1}$*(RM-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)
$CatLoss_{t-1}$*(RM-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)
$CombRat_{t-1}$*(RM-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)
$Surplus_{t-1}$*(RM-RF)					0.00				0.00	0.00
					(0.00)				(0.00)	(0.00)
$PremW_{t-1}$*(RM-RF)						-0.00			-0.01	
						(0.02)			(0.02)	
$PremE_{t-1}$*(RM-RF)							0.03			0.00
							(0.02)			(0.02)
$CapGain_{t-1}$*(RM-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-sq	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 ten-year and the one-year T-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 1987/04 to 2014/12. Obs reports the number of months in the regressions. Standard errors appear in brackets. ∗∗∗, ∗∗, and ∗ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 6. Underwriting Cycles in the Intertemporal CAPM (Combined Ratio Change)

	(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-sq	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 (change 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&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 brackets. $***$, $**$, and $*$ denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 7. Cost of Equity Estimates

Panel A. All Insurers

Year	CAPM (1)	FF5 (2)	CCAPM (3)	ICAPM (4)
	COE Estimates			
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

Year	CAPM (1)	FF5 (2)	CCAPM (3)	ICAPM (4)
	COE Estimates			
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

Panel C. Life Insurers

Year	CAPM (1)	FF5 (2)	CCAPM (3)	ICAPM (4)
	COE Estimates			
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 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.