

Cost of Capital Estimates for Insurance Stocks with Jump Risk Premia: Evidence from U.S. Life and P&C Insurers

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Abstract: We estimate the cost of capital of insurance companies based on a high-frequency factor model that captures jump risk and time-varying factor loadings. Using a large panel of intraday returns, we obtain cost of equity estimates for U.S. property and casualty (P&C) insurers and life insurers over the period 2004 to 2020. We find that P&C and life insurers exhibit markedly different continuous and jump risk exposures, reflecting differences in their business models. We confirm prior findings that P&C insurers' cost of equity is below the U.S. market average. In contrast, the evidence for life insurers is mixed. While cost of equity estimates for life insurers are higher when using traditional specifications based on the market factor alone, the estimates decrease markedly when additional risk factors and jump components are included. Overall, our findings suggest that cost of capital estimates for insurance companies should take systematic jump risk exposure into account.

Keywords: Cost of Capital, Insurance, High-Frequency Asset Pricing, Jump Risk

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1 Introduction

The cost of capital is one of the most critical financial metrics for evaluating a firm’s performance and determining the required return on its projects. For insurance companies, its significance tends to be even greater. It not only influences how policies are priced (Cummins, 1991) but also plays a central role in determining the level of regulatory reserves that must be maintained to withstand potential adverse outcomes (Albrecher et al., 2018). Despite the importance of cost-of-capital estimates, there is still no widespread consensus in the insurance literature on which method practitioners should apply. In practice, the capital asset pricing model (CAPM), estimated from realized daily or longer-horizon return data, is likely still the most common choice despite its well-known deficiencies (Graham and Harvey, 2001; Kielholz, 2000; Levi and Welch, 2017).

A large literature in empirical finance has proposed extensions to the CAPM (1) by including additional factors, which recently led to a debate on how to “tame the factor zoo” (Feng et al., 2020) and (2) by applying improved techniques for estimating the relevant factor loadings and risk premia (Aletti, 2022; Bollerslev et al., 2025). In particular, a recent strand of the literature focuses on exploiting the information content of high-frequency price data for calibrating factor models (Aletti et al., 2025; Pelger, 2020). An important feature of such models is that they make it possible to distinguish jump risk¹ from continuous price variation. Specifically, measuring exposure to jump risk allows us to identify compensation that investors require for extreme market movements, which have been shown to be substantial components of systematic risk premia (Bollerslev et al., 2016). A separate measurement of jump risk premia is of particular importance if continuous and jump risk premia have opposing signs and partially offset each other.

In this paper, we apply such high-frequency estimation methods to determine the cost of capital for insurance firms. More specifically, we adopt the methodology recently developed by Aït-Sahalia et al. (2025) (hereafter ASJX (2025)). This approach can be seen as an adaptation of classical Fama and MacBeth (1973) regressions to a high-frequency setting. It extends the standard multi-factor models previously used in the literature along three dimensions: (1) it leverages the information content of high-frequency returns, (2) it naturally captures time-varying risk exposures (without imposing parametric assumptions (Ang et al., 2006; Cosemans et al., 2016)), and (3) it separately identifies risk premia for systematic exposure to jumps of the priced factors.

We apply this method to a comprehensive insurance sample consisting of U.S. property and casualty (P&C) and life insurance firms. Our analysis proceeds in two stages. First, we estimate prices of risk (or lambdas) and factor loadings using a broad cross-section of the overall U.S. stock market, defined as all liquid common shares in the CRSP universe traded on major exchanges. For this purpose, we build a large panel dataset of fifteen-minute returns sampled from the NYSE Trade and Quote (TAQ)

¹Jumps are generally defined in the literature as return movements that deviate so strongly from the time-varying mean that they are unlikely to be caused by the Brownian component of the pricing process (Bollerslev et al., 2013; Mancini, 2001).

database for the period 2004 to 2020. We then run time-series regressions to estimate continuous and jump betas for a selection of standard factor specifications. Similar to ASJX (2025), we allow for time variation in continuous factor betas via rolling-window estimation and estimate time-invariant jump betas over the entire sample period. Further, jump betas are estimated separately for positive and negative factor jumps. Following Fama and MacBeth (1973), we then run cross-sectional regressions of one-month-ahead returns on the estimated factor betas and aggregate the estimates over the entire sample period to obtain the corresponding prices of risk. Second, we determine the cost of equity for our insurance sample based on these estimation results.

Our main findings can be summarized as follows. First, we find that P&C insurers and life insurers exhibit distinct continuous and jump risk exposures, reflecting fundamental differences in their business models. Second, for most factors, jumps are significantly priced and earn a higher premium than the corresponding continuous components. Both the sign and magnitude are economically meaningful. Third, we confirm previous findings that P&C insurers, which make up the majority of insurance firms, have lower cost of capital compared to the broad cross-section of U.S. stocks and compared to life insurers in particular, when using the standard model specification. Lastly, we demonstrate that the estimated cost of equity of life insurers strongly depends on the model and factor specification. Under the standard model specification, life insurers exhibit higher cost of capital estimates relative to the cross-section of U.S. stocks, consistent with prior findings. However, this pattern reverses in the high-frequency model with jumps, where the estimates fall below the average of the broader cross-section.

To the best of our knowledge, our study is the first to employ a high-frequency factor model to estimate the cost of equity for insurance companies. It thus extends previous studies on the cost of equity in insurance by applying intraday data and high-frequency methods that allow for a more granular identification of the relevant risk premia. In particular, we are able to isolate the compensation required for jump risk by separating exposure to large, discontinuous factor variation from small continuous changes in the priced factors.

The rest of the paper proceeds as follows. In Section 2, we review related literature. Section 3 presents model assumptions and the estimation framework developed by ASJX (2025). In Section 4, we introduce the high-frequency return dataset used in our analysis. Section 5 summarizes our estimation results on factor loadings, risk pricing and the resulting high-frequency cost of equity for our insurance sample. In Section 6, we offer concluding remarks.

2 Related Literature

2.1 High-Frequency Asset Pricing Literature

Our analysis exploits two important insights from the high-frequency asset pricing literature.

First, it has been shown that sampling returns at higher frequencies than the traditional daily or monthly ones allows for more accurate estimation of second moments (Barndorff-Nielsen and Shephard, 2004b). This finding carries over to covariances and, by extension, realized betas (Andersen et al., 2006; Barndorff-Nielsen and Shephard, 2004a).

Second, a series of studies has demonstrated that jumps are an integral feature of asset price dynamics (Andersen et al., 2007; Bandi and Russell, 2008; Barndorff-Nielsen et al., 2008). Building on their insights, subsequent work, such as Todorov and Bollerslev (2010) and Bollerslev et al. (2016), formalized the distinction between systematic continuous and jump risk exposure as captured by separate continuous and jump betas. While these models were restricted to a single factor, namely the market portfolio, papers such as Aït-Sahalia et al. (2020) and ASJX (2025) extended them to allow for multi-factor specifications, more in line with the standard in the broader empirical asset pricing literature.

We particularly build on ASJX (2025), who develop a two-pass regression framework, conceptually identical to the Fama and MacBeth (1973) framework, which enables the estimation of risk premia associated specifically with jump components. This approach allows a direct comparison of standard, low-frequency risk premia to high-frequency premia, which include a separate compensation for jump risk.

2.2 Literature on Time-Varying Risk Exposure

Previous research in empirical asset pricing has shown that both risk exposures (betas) and risk premia can be time-varying, reflecting evolving firm-specific characteristics and macroeconomic conditions (Gagliardini et al., 2020; Martin, 2017). Traditionally, parametric techniques were applied to capture such time variation with the conditional capital asset pricing model, introduced by Jagannathan and Wang (1996), as one of the best-known examples. This model conditions both market beta and market risk premium on the economic cycle by modeling them as linear functions of economic state variables and is motivated by the notion that market risk premia should move countercyclically since investors demand higher compensation for risky assets during market downturns.

This conventional parametric approach of incorporating conditioning variables to model time-varying risk premia and factor loadings has been criticized by Lewellen and Nagel (2006), who argue that this framework is highly sensitive to the choice of conditioning variables. An alternative approach, adopted by studies such as Ang et al. (2006), captures time-variation in the factor exposures implicitly through the use of rolling-window regressions. Similarly, a number of more recent studies (Aït-Sahalia et al., 2020; Bollerslev et al., 2025) have exploited the substantially higher number of observations provided by high-frequency data to non-parametrically estimate time-varying factor loadings without imposing potentially restrictive assumptions on the model dynamics.

2.3 Insurance Asset Pricing Literature

Finally, our analysis builds on the previous literature studying the cost of capital of insurance companies, which has largely concentrated on estimating insurers' cost of equity (Barinov et al., 2020; Ben-Ammar et al., 2018; Cummins and Phillips, 2005).² In accordance with this convention, we use the terms *cost of capital* and *cost of equity* interchangeably throughout this paper. Previous papers show that the continuous market beta of insurers exhibits non-negligible time variation and differs by line of insurance and across estimation methods. The existing literature does not provide a clear consensus on whether insurance firms command higher costs of capital than the broader cross-section of stocks. However, there is a widespread view that insurers are particularly sensitive to market declines and that life and health insurers tend to have higher costs of capital than P&C insurers (Nissim, 2013). Bajtelsmit et al. (2015) and Barinov et al. (2020) additionally find evidence for counter-cyclicalities in insurers' betas, implying that during recessions and downturns insurers' cost of capital increases. Bajtelsmit et al. (2015) employ a two-stage Fama and MacBeth (1973) regression to show that systematic downside risk is significantly priced among the cross-section of life insurance stocks.

3 Methodology

In this section, we discuss the application of the methodology proposed by ASJX (2025) to determine the cost of capital of insurance companies.

3.1 Model Set-Up

We consider M risky assets with log-prices $P_{m,t}$, $m = 1, \dots, M$, that follow a linear factor model driven by K traded factors with log-prices $Z_{k,t}$, $k = 1, \dots, K$, together with one risk-free asset, and idiosyncratic components with log-prices $P_{m,t}^I$, $m = 1, \dots, M$, where $t \in \mathbb{R}_+$ is the time index. Each factor is assumed to consist of a continuous component $Z_{k,t}^C$, a negative jump component $Z_{k,t}^{J-}$, and a positive jump component $Z_{k,t}^{J+}$.³ Based on the common factor specification, the m th log-price $P_{m,t}$ exhibits the following continuous dynamics at time t :

$$P_{m,t} = P_{m,0} + \sum_{k=1}^K \int_0^t \beta_{m,k,s}^C dZ_{k,s}^C + \sum_{k=1}^K \int_0^t \beta_{m,k}^{J+} dZ_{k,s}^{J+} + \sum_{k=1}^K \int_0^t \beta_{m,k}^{J-} dZ_{k,s}^{J-} + P_{m,t}^I, \quad (1)$$

where $\beta_{m,k,t}^C$ denotes the continuous beta of asset m with respect to factor k at time t . $\beta_{m,k}^{J+}$ and $\beta_{m,k}^{J-}$ denote the corresponding betas with respect to positive and negative jump exposure, which are

²Some earlier insurance papers also tried to provide estimates for the weighted average cost of capital of insurers by estimating the risk exposure of the underwriting business, an approach motivated by the Insurance CAPM (Cummins and Harrington, 1985; Fairley, 1979; Hill and Modigliani, 1987). Cox and Rudd (1991) find, however, that these underwriting betas are highly unstable and mostly insignificant. Later papers motivated their primary focus on cost of equity by arguing that insurance firms typically do not issue conventional debt in the form of bonds and notes, as industrial firms do, due to regulatory requirements (Berry-Stölzle and Xu, 2018). Moreover, policyholder liabilities, which effectively function as leverage, are not directly associated with debt costs.

³In single-jump specifications, we consider combined jump components $Z_{k,t}^J = Z_{k,t}^{J-} + Z_{k,t}^{J+}$.

assumed to be time-invariant in this specification.⁴

Under the assumptions laid out in ASJX (2025), the drift term $\mu_{m,t}$ associated with $P_{m,t}$ in model (1) can be written as:

$$\mu_{m,t} - r_t^f = \lambda_{m,t}^I + \sum_{k=1}^K (\beta_{m,k,t}^C \lambda_{k,t}^C + \beta_{m,k,t}^{J+} \lambda_{k,t}^{J+} + \beta_{m,k,t}^{J-} \lambda_{k,t}^{J-}). \quad (2)$$

Here, $\lambda_{k,t}^C$ measures the compensation for bearing exposure to continuous variation in risk factor k and is referred to as the corresponding price of risk. Similarly, $\lambda_{k,t}^{J+}$ and $\lambda_{k,t}^{J-}$ measure the compensation for exposure to positive and negative jump risk of factor k . Taken together, equation (2) can be seen as an extension of the Arbitrage Pricing Theory (APT) of Ross (1976) to a continuous model with jump components. The component $\lambda_{m,t}^I$ in equation (2) represents a potential mispricing of asset m due to the idiosyncratic component $P_{m,t}^I$ and is assumed to be equal to zero. Since equation (2) can be interpreted as the excess return investors require at time t for holding the risky asset m , it also provides the foundation for calculating the cost of equity in Subsection 3.4.

3.2 Time-Series Regressions

For estimating the betas from model (1), we rely on price data sampled at the frequency Δ (e.g., 1/27 for fifteen-minute intervals including an overnight return). Assuming that $N + 1$ price observations per asset are available, we can define the intraday asset and factor returns as:

$$R_{m,i} = P_{m,i} - P_{m,i-1} \quad (3)$$

$$F_{k,i} = Z_{k,i} - Z_{k,i-1} \quad (4)$$

with $P_{m,i}$ and $Z_{k,i}$ as the observed log-prices at time index $i \in \{1, \dots, N\}$.

Since jumps are not directly observable, we rely on asset- and factor-specific thresholds to identify jumps. In particular, we classify an asset (factor) return as a jump if its absolute value exceeds a jump-threshold $u_{m,i}^R$ ($u_{k,i}^F$).⁵ Based on these thresholds, we introduce the continuous asset and factor returns

$$R_{m,i}^C = R_{m,i} \mathbf{1}(|R_{m,i}| \leq u_{m,i}^R) \quad \text{and} \quad F_{k,i}^C = F_{k,i} \mathbf{1}(|F_{k,i}| \leq u_{k,i}^F) \quad (5)$$

and the factor jump returns

$$F_{k,i}^{J+} = F_{k,i} \mathbf{1}(F_{k,i} > u_{k,i}^F) \quad \text{and} \quad F_{k,i}^{J-} = F_{k,i} \mathbf{1}(F_{k,i} < -u_{k,i}^F), \quad (6)$$

where $\mathbf{1}(\cdot)$ denotes the indicator function. For the single-jump beta specification, we also define $F_{k,i}^J = F_{k,i} \times \mathbf{1}(|F_{k,i}| > u_{k,i}^F)$.

⁴This assumption follows ASJX (2025). It avoids unstable parameter estimates resulting from the infrequent occurrence of jumps over shorter time periods.

⁵The calculation of these thresholds will be detailed in Subsection 4.2.

Our factor loadings are defined analogously to standard OLS betas.⁶ Using the previously defined truncated asset and factor returns, the continuous betas of asset m with respect to factors $k = 1, \dots, K$ at the end of month t are estimated by running the following time-series regression:

$$R_{m,i}^C - r_i^f = \sum_{k=1}^K \beta_{m,k,t}^C F_{k,i}^C + \varepsilon_{m,i}^C, \quad (7)$$

where we use all valid intraday observations i over the preceding 252 trading days.

To estimate the jump betas of asset m with respect to the same factors, we rely on the regression:

$$R_{m,i} - r_i^f = \sum_{k=1}^K (\beta_{m,k}^{J+} F_{k,i}^{J+} + \beta_{m,k}^{J-} F_{k,i}^{J-}) + \varepsilon_{m,i}^J. \quad (8)$$

In this case, we use all available intraday observations $i = 1, \dots, N$ for the regression since we do not allow for time variation in the jump exposures.⁷ A crucial implication of equation (8) is that only factor returns are truncated while asset returns remain untruncated. This means we estimate an asset's sensitivity to factor jumps independently of whether the asset return itself is classified as a jump. The approach is similar to the Li et al. (2017) procedure for estimating standard multivariate jump regressions.⁸

Running these time-series regressions for all M assets and T months generates an (unbalanced) panel of estimated continuous betas $\hat{\beta}_{m,k,t}^C$ for each factor $k = 1, \dots, K$. Moreover, we obtain $2K$ jump betas $\hat{\beta}_{m,k}^{J+}$ and $\hat{\beta}_{m,k}^{J-}$ for the assets in our sample. These betas are used to determine the prices of risk as explained in the following subsection.

3.3 Cross-Sectional Regressions

To obtain the prices of risk, we run standard cross-sectional regressions of one-month-ahead returns on the relevant asset betas. Let $R_{m,t}^d$ denote the discrete return of asset m in month t . Then, the cross-sectional regression for month t can be written as:

$$R_{m,t+1}^d = \lambda_{0,t} + \sum_{k=1}^K (\hat{\beta}_{m,k,t}^C \lambda_{k,t}^C + \hat{\beta}_{m,k}^{J+} \lambda_{k,t}^{J+} + \hat{\beta}_{m,k}^{J-} \lambda_{k,t}^{J-}) + \varepsilon_{m,t+1}^\lambda, \quad \forall m = 1, \dots, M \quad (9)$$

where $\lambda_{0,t}$ denotes the intercept and $\varepsilon_{m,t+1}^\lambda$ the pricing error. The aggregate prices of risk are then simply given by the time-series average of the monthly estimates obtained from equation (9):

$$\hat{\lambda}_0 = \frac{1}{T-1} \sum_{t=1}^{T-1} \hat{\lambda}_{0,t}, \quad \hat{\lambda}_k^C = \frac{1}{T-1} \sum_{t=1}^{T-1} \hat{\lambda}_{k,t}^C, \quad \hat{\lambda}_k^{J+} = \frac{1}{T-1} \sum_{t=1}^{T-1} \hat{\lambda}_{k,t}^{J+}, \quad \hat{\lambda}_k^{J-} = \frac{1}{T-1} \sum_{t=1}^{T-1} \hat{\lambda}_{k,t}^{J-}. \quad (10)$$

⁶Consistent with the existing literature, the first-stage regression is estimated without an intercept, reflecting the small absolute size of high-frequency returns used in the construction of realized betas (Barndorff-Nielsen and Shephard, 2004a).

⁷In the single-jump beta case, the time-series regression for asset m is given by: $R_{m,i} - r_i^f = \sum_{k=1}^K \beta_{m,k}^J F_{k,i}^J + \varepsilon_{m,i}^J, \forall i = 1, \dots, N$.

⁸The fact that both asset and factor returns are truncated when estimating continuous betas, whereas only factor returns are truncated for jump betas, stems from econometric considerations. For continuous betas, we truncate both asset and factor returns to capture the covariation solely attributable to the diffusive components (Aït-Sahalia and Jacod, 2014). For jump betas, we do not truncate the asset returns, since co-jumps between asset and factor returns are infrequent and would complicate accurate identification. There are also studies such as Aletti (2022) that truncate the asset return for estimating jump betas.

We follow the classical [Fama and MacBeth \(1973\)](#) procedure for calculating the standard errors of the aggregate prices of risk by relying on the sum of squared demeaned spot prices of risk $\hat{\lambda}_t$ to form an estimator. [ASJX \(2025\)](#) show that under standard regularity assumptions the aggregate risk premium estimators asymptotically follow a standard normal distribution with a $\sqrt{T}$ -convergence rate, so that we are able to perform standard inference procedures.

3.4 Cost of Capital Estimator

Based on the results from the time-series and cross-sectional regressions described above, we estimate the cost of equity for firm m at the end of month t as:

$$\hat{\mu}_{m,t} = \hat{r}_t^f + \hat{\lambda}_0 + \sum_{k=1}^K (\hat{\beta}_{m,k,t}^C \hat{\lambda}_k^C + \hat{\beta}_{m,k}^{J+} \hat{\lambda}_k^{J+} + \hat{\beta}_{m,k}^{J-} \hat{\lambda}_k^{J-}). \quad (11)$$

This approach makes two adjustments compared to the model in equation (2). First, we allow for a general intercept term λ_0 which captures the excess returns not attributed to the risk factors included. Second, we replace the unobservable spot prices of risk with the aggregate estimates defined in equation (10). The use of the two-step Fama-MacBeth approach ([Fama and MacBeth, 1973](#)) to determine the prices of risk instead of relying on average realized factor returns naturally handles (1) the separation of continuous and jump components⁹ and (2) the correlation of the risk factors in our model.

According to Equation (11), the time-series variation of $\hat{\mu}_{m,t}$ can be fully attributed to the variation in the observable risk-free rate $\hat{r}_t^f$ and the continuous factor loadings $\hat{\beta}_{m,k,t}^C$, whereas its cross-sectional variation stems from the jump and continuous betas.

4 Data & Implementation

4.1 Constructing High-Frequency Returns

For our high-frequency returns, we rely on intraday transaction observations from the NYSE TAQ database in combination with low-frequency CRSP prices for the period 2004 to 2020. We sample prices at fifteen-minute intervals, resulting in twenty-six intraday returns and one overnight return per trading day. We choose the fifteen-minute frequency, a common choice in the literature that represents a reasonable trade-off between the improved jump identification accuracy and the negative effects of market microstructure noise at higher sampling frequencies ([Bandi and Russell, 2008](#)). Our return construction process proceeds in three steps.

First, we only consider the transaction prices for all securities that are U.S. common shares, i.e., with CRSP share codes 10 or 11, and are traded on either NYSE, NYSE American (formerly AMEX), or NASDAQ. While processing the returns, we remove all trades that exhibit violated trade conditions, so that condition codes Z, B, U, T, L, G, W, K are filtered out, and we only keep trades with correction

⁹Note that the jump and continuous components of the risk factors in our model are not tradable.

indicator 00 or 01. We also drop all transactions with negative price, zero size, or non-empty suffix code (i.e., preferred shares). We identify the opening trade as the trade that either meets the eligible opening conditions (O, Q, OI, QI) or is the first trade after 09:30:00 and the closing price accordingly as the price that either meets the eligible closing conditions (6, M, 6I, MI) or is the last trade before 16:00:00, and drop all observations that are outside this window. This filtering procedure for the TAQ transaction data follows [Da and Xiu \(2021\)](#). We finally filter out small and relatively illiquid stocks. In particular, we apply the microcap filter proposed by [Hou et al. \(2020\)](#), that is, we exclude all firms with a market capitalization below the 20th percentile of NYSE market capitalization at the end of the previous calendar year. In addition, we exclude penny stocks by imposing the common minimum price threshold of USD 5 ([Bollerslev et al., 2022](#)).

Second, we link the TAQ prices with the low-frequency CRSP dataset to correctly handle overnight returns and de-listings ([Aït-Sahalia et al., 2020](#); [Bollerslev et al., 2016](#)). The merger is conducted using the CRSP PERMNO identifier, which acts as the unique security identifier in our dataset. On each day, we replace the TAQ open and close prices with the corresponding CRSP prices.

Third, at the endpoints of each fifteen-minute interval, we assign the nearest transaction price, except for the first and last price observations, where we use the CRSP-adjusted open and close prices, as noted above. Intraday returns are then computed as the difference in consecutive log-prices. For overnight returns, we begin by calculating the open-to-close returns from the CRSP open and close prices. Subsequently, we combine these returns with the CRSP-adjusted close-to-close (i.e., total) returns to calculate CRSP-implied overnight returns ([Bollerslev et al., 2016](#)). This overnight return correctly handles dividends, share splits, and de-listings. This overnight return is used as first observation of the trading day associated with the date of the corresponding CRSP total return.¹⁰ By aligning the TAQ returns with the CRSP open and close prices, the cumulative return of the two datasets coincide, allowing a direct comparison between low-frequency and high-frequency premia.

To ensure our beta estimations are based on a sufficient number of returns, we only retain day-stock observations with at least ten non-zero intraday returns.¹¹ This requirement is similar to [Da and Xiu \(2021\)](#) and is motivated by the intuition that an excessive number of zero returns may distort the sample return distribution and thereby induce biased estimates. More generally, a high proportion of zeros leads to inflated tails of the distribution, thus complicating the accurate identification of jumps ([Bandi et al., 2020](#); [Kolokolov and Renò, 2024](#)). To obtain excess returns, we subtract the risk-free

¹⁰This does not result in an excessive number of jumps being attributed to the opening trade, as we account for the intraday volatility pattern when determining the appropriate jump threshold in Section 4.2 Specifically, the threshold is adjusted to reflect the dependence of the return volatility on the intraday interval.

¹¹For the estimation of the risk premia, we employ a more restrictive filter that permits a maximum of eight zero returns per day. This choice is motivated by the [Epps \(1979\)](#) effect, which refers to the empirical observation that a higher proportion of zero returns leads to a downward bias in the realized covariances and realized beta estimates, which in turn translates to a bias in the estimated risk premia. To mitigate this issue while preserving a sufficiently large number of assets with non-zero beta and cost of capital values, we adopt this stricter threshold only for the estimation of the risk premia. Nevertheless, our results for the risk premia and cost of capital estimates are robust to relaxing this restriction.

Table 1: Summary Statistics for High-Frequency and Monthly Excess Returns

Group	Mean	SD	Skew	Kurt	Min	10%	Median	90%	Max	M
Panel A: 15-Minute Excess Returns										
All Stocks	0.00	0.40	0.28	39.70	-3.51	-0.35	-0.00	0.36	3.76	3996
Insurance	0.00	0.29	0.07	5.47	-0.89	-0.27	0.00	0.28	0.93	119
P&C Insurance	0.00	0.27	0.05	4.28	-0.69	-0.24	0.00	0.25	0.71	67
Life Insurance	0.00	0.26	0.03	1.21	-0.41	-0.24	0.00	0.25	0.42	23
Panel B: Monthly Excess Returns										
All Stocks	1.13	9.87	1.10	22.84	-52.25	-9.24	0.80	11.59	91.52	3996
Insurance	1.12	7.19	0.18	3.05	-17.00	-6.40	0.87	8.69	23.90	119
P&C Insurance	0.98	6.57	0.14	2.61	-13.43	-5.55	0.82	7.57	18.67	67
Life Insurance	1.15	5.83	0.02	0.56	-7.65	-4.59	0.95	6.95	11.28	23

Note: This table presents summary statistics for the fifteen-minute excess log-returns in Panel A and the monthly excess returns in Panel B (both are multiplied by 100) using the TAQ dataset for the years 2004 to 2020 based on our data filtering procedure for U.S. stocks, the aggregate insurance group, the P&C insurance group, and the life insurance group. For both sampling frequencies, we first calculate the cross-sectional values for the mean (Mean), standard deviation (SD), minimum (Minimum), 10th percentile (10%), median (Median), 90th percentile (90%), and maximum (Maximum) and then display the time-series averages. We also provide the number of valid assets which is simply the sum of unique assets in the dataset.

rate from the raw asset returns. We proxy it by the one-month T-Bill rate from Kenneth French’s website adjusted for the sampling frequency.

To identify insurance companies, we rely on NAICS industry codes provided by Compustat. We consider three insurance subsamples. Our P&C insurance sample includes all stocks with year-end NAICS code 524126, while the life insurance sample is defined analogously using NAICS code 524113. Our aggregate insurance sample comprises all firms that provide direct insurance services, identified using the following NAICS codes: 524113 (Life), 524114 (Health), 524126 (P&C), 524127 (Title), 524128 (Other Direct), and 524130 (Reinsurance). Our return dataset contains 67 P&C and 23 life insurers, and 119 firms in the aggregate insurance sample. Table 1 reports summary statistics of high-frequency returns for U.S. stocks, the aggregate insurance group, P&C insurers, and life insurers. As expected, the first two moments of the fifteen-minute returns are substantially smaller, whereas the higher moments tend to be more extreme than those of monthly returns.¹² Interestingly, we find in line with previous papers that the average realized return of P&C insurers is lower than for the aggregate insurance sector (Barinov et al., 2020).

For the factor return data, we rely on the high-frequency factor data library provided by Aletti (2022, 2025). Since their returns are sampled at a one-minute frequency, we use cumulative fifteen-minute returns in our regressions. We employ the five classical Fama and French (2015) factors, i.e., market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA), plus the

¹²In unreported results, we further find that the realized volatility, kurtosis, and skewness increase notably after 2006, reflecting the inclusion of smaller stocks in the sample that did not meet our minimum observation requirement during the first years of the sample period.

momentum (MOM) factor. Aleti (2022) defines these factors in accordance with the methodology of Fama and French (2015) so that the daily cumulative returns of his factors largely match the ones from Kenneth French’s website.

4.2 Implementation

4.2.1 Jump Thresholds

As outlined in Section 3.2, our beta estimation requires the specification of the jump thresholds $u_{m,i}^R$ and $u_{k,i}^F$ for each asset m , factor k and time index i . To estimate these thresholds, we follow the approach of Bollerslev et al. (2013). The overall idea of this approach is that returns are classified as jumps if their magnitude exceeds the continuous variation on a given trading day by a factor τ . Furthermore, this approach extends the standard procedure of Mancini (2001) by including a time-of-day (TOD) adjustment to account for the diurnal pattern of intraday volatility.¹³

We detail the threshold calculation for the case of asset m (with the steps for the factors being defined analogously). The threshold calculation requires an estimate of the integrated variance $\widehat{IV}_{m,t}$ of asset m in month t . Following Mancini (2009), we use the truncated realized variance defined as the sum of squared truncated intraday returns for this purpose.¹⁴ The time-of-day adjustment $\widehat{TOD}_{m,i}$ for asset m and the return period i is defined as the proportion of quadratic variation in the intraday period corresponding to observation i relative to the average continuous quadratic variation over the entire sample period.

Based on these definitions, the jump threshold for intraday observation i in month t is defined as

$$u_{m,i}^R = \tau \times \Delta^\omega \times \sqrt{\widehat{IV}_{m,t} \times \widehat{TOD}_{m,i}} \quad (12)$$

with tuning parameters τ and ω .

Following ASJX (2025), we choose $\omega = 0.47$ and $\tau = 3.0$ for our estimations.¹⁵ With these choices, we classify 1.36 percent of intraday returns of the overall panel as jumps, which is similar to previous findings in the literature (Pelger, 2020).¹⁶

¹³Typically, volatility is elevated after the market opens, as investors process the overnight information flow, and near the close, when institutional investors rebalance their portfolios and close intraday positions. In contrast, price moves are more muted and stable during the middle part of the active trading day (Aleti et al., 2025).

¹⁴This approach proceeds in two steps. First, we calculate the realized variance $\widehat{RV}_{m,t}$ as the sum of squared intraday returns: $\widehat{RV}_{m,t} = \sum_{i \in \mathcal{M}_t} R_{m,i}^2$, where $\mathcal{M}_t$ denotes the set of time indices in month t . Second, we only keep returns whose absolute values are below $\tau \times \Delta^\omega \times \sqrt{\widehat{RV}_{m,t}}$ and again calculate the sum of squared returns.

¹⁵Changing the threshold τ within a reasonable range, i.e., between 2.0 and 3.5, does not materially affect the results, since the jump beta is driven by relatively large jumps.

¹⁶Note that the share of returns that are three times larger than the time-varying volatility is considerably higher than what would be expected under a pure continuous Brownian motion (Ait-Sahalia and Jacod, 2009; Barndorff-Nielsen and Shephard, 2004b).

4.2.2 Continuous Betas

We use rolling windows of 252 trading days to estimate the continuous betas. Accordingly, at the end of each month in our sample, we rely on (at most) 6,804 return observations recorded during the previous 252 trading days to estimate the continuous betas as shown in equation (7).

Similar to Frazzini and Pedersen (2014) and Levi and Welch (2020), we impose a minimum observation number condition and require that 70 percent of an asset’s total intraday return observations are available for a given window when estimating the continuous betas. If this condition is violated, we do not calculate the stock’s continuous beta for month t and discard it when estimating the month t spot risk premia, as outlined in equation (9).

4.2.3 Jump Betas

Due to the assumption of time-invariant jump risk exposures, we do not use rolling windows but leverage the entire sample period for each stock to obtain jump beta estimates. Given that the cross-section of stocks changes over time, the length of the estimation period varies across stocks.

To ensure the stability of our results, we impose a minimum jump-count requirement, retaining only stocks with at least $80K$ jump observations over the estimation period with K denoting the number of factors included in the model. This restriction is motivated by the fact that jump beta estimates based on a limited number of observations are inherently unstable.¹⁷ Stocks that do not meet this requirement are omitted from all cross-sectional regressions (9).

We further consider two alternative specifications of jump betas. The first distinguishes between negative and positive jumps by estimating separate jump betas and their corresponding prices of risk, whereas the second employs a unified jump beta that captures all jump events irrespective of their sign.¹⁸

5 Empirical Results

We consider three model specifications throughout the empirical section. First, the standard multi-factor model based on daily return data, which are calculated as daily cumulated intraday returns.¹⁹ This specification is denoted by [1] and forms the standard model in empirical asset pricing. For this model, we will also estimate the betas over rolling windows of 252 trading days. Second, our high-frequency factor model, outlined in Section 3.1 and denoted by [2], using intraday observations

¹⁷The resulting estimation error tends to generate in extreme realized jump beta estimates that disproportionately affect the risk premia. Imposing a minimum requirement mitigates this issue and reduces the impact of estimation noise. In this sense, the restriction can be viewed as an alternative to the direct winsorization of jump beta estimates.

¹⁸In contrast to ASJX (2025), we do not discard jumps smaller than 0.5 percent in absolute size, but instead retain all detected jumps. Their motivation is that investors may focus primarily on large jumps, whereas small jumps are perceived similarly to continuous factor movements and therefore carry a comparable risk premium.

¹⁹These intraday cumulative returns are by construction equivalent to the day-to-day returns using the CRSP dataset.

Table 2: Summary Statistics for Beta Estimates in the CAPM Specification

Model	Beta	Mean	SD	Skew	Kurt	Min	10%	Median	90%	Max	M
Panel A: All Stocks											
[1]	$\hat{\beta}^{MKT}$	1.12	0.40	0.56	0.82	0.10	0.65	1.09	1.64	2.94	3082
[2 ^d]	$\hat{\beta}^{MKT,C}$	1.03	0.34	0.67	1.05	0.20	0.63	1.00	1.48	2.56	3082
	$\hat{\beta}^{MKT,J-}$	0.91	0.34	-0.31	4.74	-2.44	0.51	0.92	1.31	2.83	3082
	$\hat{\beta}^{MKT,J+}$	1.02	0.41	0.91	5.44	-0.73	0.55	1.00	1.51	4.55	3082
[2 ^s]	$\hat{\beta}^{MKT,J}$	0.96	0.34	0.29	1.95	-0.30	0.55	0.96	1.38	3.61	3082
Panel B: Insurance											
[1]	$\hat{\beta}^{MKT}$	1.03	0.33	0.79	0.85	0.49	0.69	0.96	1.49	1.99	91
[2 ^d]	$\hat{\beta}^{MKT,C}$	0.94	0.28	0.66	0.63	0.48	0.64	0.89	1.33	1.69	91
	$\hat{\beta}^{MKT,J-}$	0.87	0.33	-0.12	0.87	0.01	0.44	0.92	1.18	1.77	91
	$\hat{\beta}^{MKT,J+}$	1.04	0.45	0.83	2.67	0.00	0.51	1.03	1.60	2.90	91
[2 ^s]	$\hat{\beta}^{MKT,J}$	0.95	0.38	0.36	1.49	0.01	0.50	0.96	1.38	2.24	91
Panel C: P&C Insurance											
[1]	$\hat{\beta}^{MKT}$	0.97	0.30	0.96	1.52	0.56	0.69	0.92	1.36	1.79	53
[2 ^d]	$\hat{\beta}^{MKT,C}$	0.88	0.26	0.74	0.90	0.51	0.64	0.83	1.22	1.51	53
	$\hat{\beta}^{MKT,J-}$	0.81	0.33	-0.27	0.97	0.01	0.40	0.84	1.14	1.68	53
	$\hat{\beta}^{MKT,J+}$	0.95	0.39	0.12	1.40	0.00	0.53	0.97	1.36	2.11	53
[2 ^s]	$\hat{\beta}^{MKT,J}$	0.87	0.35	-0.02	1.49	0.01	0.50	0.89	1.19	1.89	53
Panel D: Life Insurance											
[1]	$\hat{\beta}^{MKT}$	1.38	0.29	-0.28	-0.42	0.94	1.05	1.39	1.69	1.78	16
	$\hat{\beta}^{MKT,C}$	1.23	0.24	-0.08	-0.28	0.90	0.97	1.22	1.49	1.58	16
	$\hat{\beta}^{MKT,J-}$	1.04	0.45	-0.41	-0.64	0.27	0.38	1.14	1.53	1.77	16
	$\hat{\beta}^{MKT,J+}$	1.38	0.65	0.30	1.00	0.32	0.43	1.44	2.01	2.90	16
[2 ^s]	$\hat{\beta}^{MKT,J}$	1.21	0.51	-0.07	-0.10	0.38	0.44	1.24	1.73	2.24	16

Note: This table presents summary statistics for the betas for U.S. stocks in Panel A, the P&C insurance group in Panel B, and the life insurance group in Panel C for the CAPM specification. Specification [1] shows the results for a low-frequency standard regression and specification [2^d] and [2^s] implement our high-frequency model specification with two jumps and an aggregate jump component, respectively. For the continuous beta (estimated over rolling 252 trading days), we calculate each month, the mean, standard deviation (SD), minimum (Min), 10th percentile (10%), median, 90th percentile (90%), and maximum (Max) values for the cross-sectional distribution and present the time-series average for each cross-sectional value. We also provide the number of valid assets which is simply the sum of assets with non-zero jump betas in the dataset.

and separating the factor returns into continuous and jump components. We will denote the model with a negative and positive jump beta for each factor as [2^d] and the model with an aggregate jump beta as [2^s].

5.1 Factor Betas

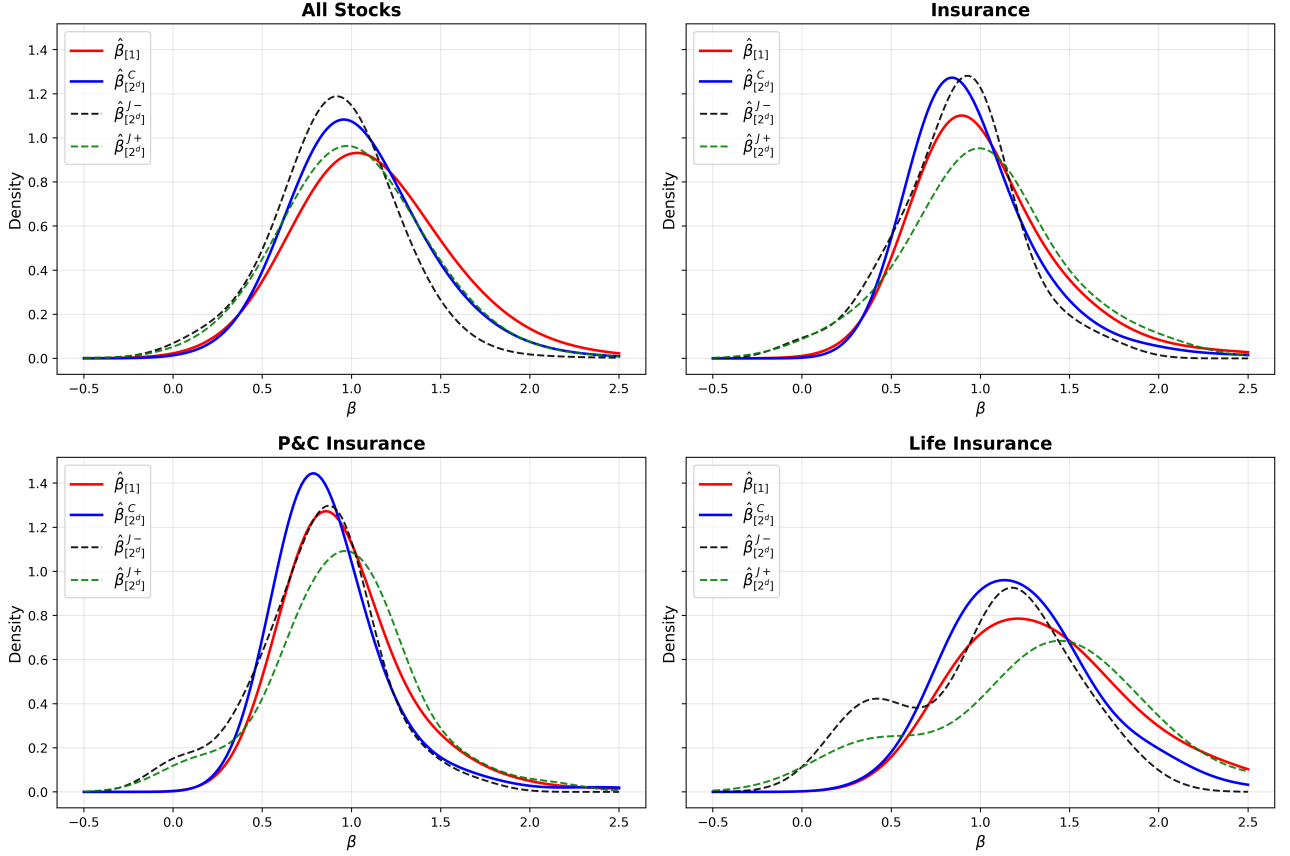
In this subsection, we present the estimated factor loadings for both the insurance groups and the cross-section of U.S. stocks. Table 2 presents the time-series average of the cross-sectional betas for the standard CAPM specifications.

Table 3: Summary Statistics for Beta Estimates in the FF3/FF4/FF5 Specification

Model	Beta	Factor Specification								
		FF3			FF4			FF5		
		All Stocks	P&C	Life	All Stocks	P&C	Life	All Stocks	P&C	Life
[1]	$\hat{\beta}^{MKT}$	1.03	0.91	1.28	1.02	0.93	1.27	1.02	0.92	1.25
[2 ^d]	$\hat{\beta}^{MKT,C}$	1.02	0.87	1.20	0.99	0.87	1.17	1.00	0.87	1.18
	$\hat{\beta}^{MKT,J-}$	0.90	0.75	0.97	0.89	0.75	0.95	0.89	0.74	0.96
	$\hat{\beta}^{MKT,J+}$	0.95	0.80	1.16	0.94	0.78	1.12	0.94	0.77	1.15
[2 ^s]	$\hat{\beta}^{MKT,J}$	0.92	0.77	1.06	0.91	0.76	1.03	0.91	0.76	1.04
[1]	$\hat{\beta}^{SMB}$	0.49	0.19	0.20	0.47	0.25	0.20	0.49	0.20	0.18
[2 ^d]	$\hat{\beta}^{SMB,C}$	0.35	0.13	0.17	0.32	0.15	0.15	0.34	0.13	0.15
	$\hat{\beta}^{SMB,J-}$	0.68	0.41	0.44	0.63	0.36	0.38	0.67	0.40	0.42
	$\hat{\beta}^{SMB,J+}$	1.08	1.02	1.34	1.09	0.99	1.28	1.04	0.94	1.24
[2 ^s]	$\hat{\beta}^{SMB,J}$	0.73	0.57	0.67	0.69	0.50	0.61	0.74	0.62	0.69
[1]	$\hat{\beta}^{HML}$	0.12	0.56	0.93	0.07	0.67	0.94	0.10	0.54	0.96
[2 ^d]	$\hat{\beta}^{HML,C}$	0.15	0.55	0.86	0.09	0.60	0.84	0.14	0.51	0.84
	$\hat{\beta}^{HML,J-}$	0.24	0.53	1.25	0.13	0.42	0.93	0.25	0.51	1.20
	$\hat{\beta}^{HML,J+}$	1.08	1.02	1.34	1.09	0.99	1.28	1.04	0.94	1.24
[2 ^s]	$\hat{\beta}^{HML,J}$	0.30	0.80	1.05	0.15	0.57	0.52	0.33	0.77	1.03
[1]	$\hat{\beta}^{MOM}$				-0.02	0.04	-0.11			
[2 ^d]	$\hat{\beta}^{MOM,C}$				0.01	-0.01	-0.10			
	$\hat{\beta}^{MOM,J-}$				-0.18	-0.26	-0.63			
	$\hat{\beta}^{MOM,J+}$				-0.18	-0.26	-0.63			
[2 ^s]	$\hat{\beta}^{MOM,J}$				-0.20	-0.24	-0.60			
[1]	$\hat{\beta}^{RMW}$							-0.00	-0.17	-0.36
[2 ^d]	$\hat{\beta}^{RMW,C}$							-0.01	-0.18	-0.33
	$\hat{\beta}^{RMW,J-}$							-0.10	-0.41	-0.56
	$\hat{\beta}^{RMW,J+}$							-0.16	-0.08	-0.55
[2 ^s]	$\hat{\beta}^{RMW,J}$							-0.13	-0.25	-0.59
[1]	$\hat{\beta}^{CMA}$							-0.01	0.10	-0.20
[2 ^d]	$\hat{\beta}^{CMA,C}$							-0.04	0.12	-0.06
	$\hat{\beta}^{CMA,J-}$							-0.04	-0.01	0.03
	$\hat{\beta}^{CMA,J+}$							-0.18	-0.13	-0.12
[2 ^s]	$\hat{\beta}^{CMA,J}$							-0.11	-0.10	-0.04
<i>M</i>		2714	50	16	2787	50	16	2643	52	16

Note: This table presents the time-series average for the betas for U.S. stocks, the P&C insurance group, and the life insurance group for the Fama-French three-factor (FF3), the Fama-French three-factor plus momentum (FF4) model, and the Fama-French five-factor (FF5) specifications. Specification [1] shows the results for a low-frequency standard regression and specification [2^d] and [2^s] implement our high-frequency model specification with two jumps and an aggregate jump component, respectively. In the last row we provide the number of assets with non-zero jump betas.

Figure 1: Density Plot of Market Beta Estimates in the CAPM Specification



Note: This figure displays kernel density estimates of the unconditional distribution of the monthly (estimated over rolling 252 trading days) low-frequency standard market betas $\hat{\beta}_{[1]}$ from model specification [1] (in red) and high-frequency continuous market betas $\hat{\beta}_{[2^d]}^C$ (in blue), negative jump market betas $\hat{\beta}_{[2^d]}^{J-}$ (dotted black), and positive jump market betas $\hat{\beta}_{[2^d]}^{J+}$ from specification [2^d] (dotted green) for the period 2004 to 2020 for U.S. stocks, the aggregate insurance group, the P&C insurance group, and the life insurance group. For both types of regressions, we used the CAPM specification. We choose Gaussian kernel functions with a bandwidth of 0.5.

The continuous market betas²⁰ $\hat{\beta}^{MKT,C}$ of specification [2] only reflect the continuous part in the covariation between asset and the market returns and are generally of smaller magnitude with lower standard deviations compared to the standard market betas $\hat{\beta}^{MKT}$ of specification [1]. For the insurance sample, we find that the continuous and standard market betas are significantly smaller for the P&C insurance group and significantly larger for the life insurance group compared to the aggregate group of stocks. This finding is in line with the previous literature and suggests that, as a result of the aforementioned institutional differences, life insurers are disproportionately affected by market fluctuations.

The aggregate jump betas $\hat{\beta}^{MKT,J}$ of specification [2^s], which measure an asset's sensitivity to market jumps irrespective of their sign, are, on average, smaller than the corresponding continuous betas and exhibit higher standard deviation and kurtosis.²¹ For the separate jump betas, we see that

²⁰By construction, the same continuous betas are obtained under specification [2^d] and [2^s].

²¹This finding contrasts with the results of [Todorov and Bollerslev \(2010\)](#), who find jump betas to be larger than continuous betas on average. However, their analysis is restricted to a sample of forty large-cap stocks over a five-year period, whereas our estimates are obtained for a broader cross-section of stocks. When we restrict our sample to large-cap stocks and a comparable

$\hat{\beta}^{MKT,J-}$ tends to be smaller in size than $\hat{\beta}^{MKT,J+}$ but both exhibit a similarly high kurtosis. Similar to the continuous market betas, we find that, on average, P&C insurers have lower jump betas and life insurers have higher jump betas compared to the aggregate cross-section of U.S. stocks. This implies that life insurance stocks exhibit greater sensitivity to market jump risk than the average firm in our sample, strengthening our intuition that life insurers are more exposed to tail risk.

To help visualize the differences, Figure 1 displays Gaussian kernel density estimates of the unconditional distributions of the market beta estimates. Consistent with Table 2, the continuous market betas obtained under specification [2] are more densely centered around unity and exhibit lower kurtosis than the standard betas of specification [1], which is mechanically transmitted to the corresponding jump beta estimates. As a result, the distribution of jump betas display higher kurtosis and more pronounced tail behavior. This effect is particularly pronounced for the insurance stocks due to the smaller sample size and the, by construction, higher presence of idiosyncratic effects.

In Table 3 we additionally report the average beta estimates for the Fama-French three-factor (FF3), the Fama-French three-factor plus momentum (FF4) model, and the Fama-French five-factor (FF5) specification.

5.2 Prices of Risk

In Tables 4 and 5 we report the results for the second-stage Fama and MacBeth (1973) regression and provide the annualized aggregate risk premia for the cross-section of U.S. stocks. We show the results for three factor model specifications: the FF3 model, the FF4 model, and the FF5 model.²² Table 4 shows the result for model specification [2^s] with a single jump beta and Table 5 for the model [2^d] with two separate jump betas. Since our estimation approach differs substantially from ASJX (2025), we report the estimated prices of risk in detail in this subsection.²³

The first result, also reported by ASJX (2025), is that not a single risk factor is significantly priced for the standard model [1]. Only the intercept estimate $\hat{\lambda}_0$ is significantly different from zero for the three factor models at conventional significance levels. A statistically significant intercept of economically meaningful magnitude is commonly viewed as a sign of model misspecification, indicating the presence of omitted risk factors in the cross-sectional regression that are not spanned by the included

time period, we likewise find jump betas to exceed continuous betas on average.

²²We focus our attention here on these three models because the estimated risk premia are more significant. Results for the CAPM and five-factor plus momentum (FF6) models are presented in Tables A1 and A2 in the Appendix.

²³The findings reported in ASJX (2025) are restricted to model specifications [1] and [2^d]. While their findings are qualitatively similar, they report risk premium estimates that differ in both sign and magnitude from our estimates. The differences arise from several aspects in which their estimation approach differs from ours: (1) Sample period: Their sample begins on January 1, 1996, whereas our return dataset only starts on January 1, 2004; (2) Jump risk premium: As mentioned before, they consider compensation only for large jumps, i.e., jumps that are exceeding 0.5 percent in absolute size; (3) Monthly returns: For the Fama and MacBeth (1973) regression, they use monthly log-returns as the dependent variable, while we use monthly discrete returns; (4) Intercept: They do not include an intercept in the Fama and MacBeth (1973) regression, whereas we do; (5) Sample selection: Their analysis is restricted to stocks that are constituents of the S&P 1500 index; (6) Rolling window size: They estimate the continuous betas using rolling windows of 21 trading days, whereas we use rolling windows of 252 trading days; In unreported findings, we are able to replicate their results when we use a similar setup.

Table 4: Fama-MacBeth Regressions with Continuous and Jump Components – Single Jump

Factor	Comp.	Factor Specification					
		FF3		FF4		FF5	
		[1]	[2 ^s]	[1]	[2 ^s]	[1]	[2 ^s]
λ_0	Cont.	6.38** (1.96)	5.05 (1.03)	6.69** (2.09)	6.68 (1.47)	5.68* (1.79)	7.83* (1.78)
MKT	Cont.	4.23 (0.91)	−2.30 (−0.45)	3.65 (0.81)	−2.58 (−0.54)	4.87 (1.13)	−2.85 (−0.62)
	Jump		12.57** (2.31)		10.30** (2.35)		10.43** (2.14)
SMB	Cont.	3.56 (1.58)	5.50 (1.21)	2.90 (1.40)	5.46 (1.12)	3.29 (1.58)	7.67* (1.78)
	Jump		−5.78*** (−2.68)		−6.88*** (−2.88)		−8.48*** (−3.63)
HML	Cont.	0.54 (0.23)	2.35 (0.87)	−0.26 (−0.12)	0.75 (0.29)	0.08 (0.04)	4.44* (1.67)
	Jump		−5.26* (−2.60)		−3.34* (−1.76)		−3.95** (−2.24)
MOM	Cont.			−2.13 (−0.53)	−2.60 (−0.66)		
	Jump				7.29** (2.18)		
RMW	Cont.					0.29 (0.21)	−0.62 (−0.33)
	Jump						2.66** (2.11)
CMA	Cont.					−1.36 (−1.04)	0.53 (0.26)
	Jump						−2.28* (−1.75)
R^2		26.75%	33.50%	28.13%	35.86%	28.92%	37.11%

Note: This table reports the estimated annualized aggregate prices of risk (multiplied by 100) for a variety of commonly used factor models from two-pass Fama-MacBeth type regressions. Specification [1] shows the results for a low-frequency standard regression and specification [2^s] implements our high-frequency model specification with a single jump. The jump risk premium captures the compensation for all jumps. In parentheses, t -statistics are reported. The R^2 represents the time-series average of cross-sectional R^2 estimates. The returns are sampled at a fifteen-minute frequency from January 2, 2004 to December 31, 2020. The indicators *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

risk factors (Horenstein and Maio, 2026). This suggests that the standard model [1] may be inappropriate to fully explain the cross-section of expected returns. Interestingly, model specification [2^s] with a single jump beta produces intercepts of similar magnitude, although these are only statistically significant at the 10 percent level in the FF5 model. By contrast, the estimated intercepts decline substantially and cease to be significant once positive and negative jump exposures are included separately as in Table 5. This finding may suggest that the two-beta specification [2^d] more effectively captures the risk premia in the cross-section of returns.

The second finding is that jump risks earn larger premia that are more significantly priced than their continuous counterparts for model specifications [2^s]. This finding also holds to a lesser extent for specification [2^d]. For example, in Table 4 the jump component of the market factors earns a statistically significant premium of 10.43 to 12.57 percent per year, whereas exposure to jump risk for size is negatively priced, yielding a significant annual premium of −8.48 to −5.78 percent. For specifications [2^s] and [2^d], only the continuous components of size and value are to a certain degree significantly priced. The observation that the continuous factor returns are for the most part not yielding significant premia reflects the intuition that investors care more about factor jumps and

Table 5: Fama-MacBeth Regressions with Continuous and Jump Components - Double Jump

Factor	Comp.	Factor Specification					
		FF3		FF4		FF5	
		[1]	[2 ^d]	[1]	[2 ^d]	[1]	[2 ^d]
λ_0	Cont.	6.38** (1.96)	4.43 (0.90)	6.69** (2.09)	4.93 (1.05)	5.68* (1.79)	4.61 (1.04)
MKT	Cont.	4.23 (0.91)	-1.28 (-0.26)	3.65 (0.81)	-1.08 (-0.22)	4.87 (1.13)	-1.47 (-0.33)
	Neg. Jump		8.58* (1.69)		5.12 (1.32)		7.94** (2.00)
	Pos. Jump		5.12 (1.02)		7.65* (1.65)		6.29 (1.36)
SMB	Cont.	3.56 (1.58)	8.44* (1.89)	2.90 (1.40)	8.90* (1.93)	3.29 (1.58)	8.76 (1.95)
	Neg. Jump		-8.11*** (-3.22)		-8.30*** (-3.43)		-8.38*** (-3.52)
	Pos. Jump		-1.03 (-0.62)		-1.73 (-1.00)		-2.87 (-1.60)
HML	Cont.	0.54 (0.23)	4.02 (1.53)	-0.26 (-0.12)	2.89 (1.10)	0.08 (0.04)	6.31** (2.37)
	Neg. Jump		-6.62*** (-3.20)		-5.27** (-2.53)		-7.63*** (-3.82)
	Pos. Jump		-1.71 (-0.93)		-0.14 (-0.09)		-0.26 (-0.18)
MOM	Cont.			-2.13 (-0.53)	-4.50 (-1.13)		
	Neg. Jump				-1.00 (-0.36)		
	Pos. Jump				13.54*** (4.96)		
RMW	Cont.					0.29 (0.21)	-0.96 (-0.51)
	Neg. Jump						1.40 (1.32)
	Pos. Jump						2.41* (1.88)
CMA	Cont.					-1.36 (-1.04)	0.94 (0.47)
	Neg. Jump						-2.21* (-1.76)
	Pos. Jump						0.71 (0.68)
R^2		26.75%	35.20%	28.13%	37.57%	28.92%	39.41%

Note: This table reports the estimated annualized aggregate prices of risk (multiplied by 100) for a variety of commonly used factor models from two-pass Fama-MacBeth type regressions. Specification [1] shows the results for a low-frequency standard regression and specification [2^d] implements our high-frequency model specification with two separate jumps. The jump risk premia capture the compensation for all jumps. In parentheses, t -statistics are reported. The R^2 represents the time-series average of cross-sectional R^2 estimates. The returns are sampled at a fifteen-minute frequency from January 2, 2004 to December 31, 2020. The indicators *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

will charge or pay a premium accordingly, whereas continuous factor returns are less likely to be significantly priced.

Table 5 further allows us to distinguish whether the estimated jump risk premia are driven by exposure to negative or positive factor jumps. Consistent with the economic intuition that investors care more about negative than positive market jump risk, we find that the compensation for exposure to negative market jumps is higher than the one for positive jumps. The asymmetry between negative and positive jump components is even more pronounced for the momentum factor in the FF4 model. While exposure to positive momentum jumps commands a strikingly significant premium of 13.54 percent, the premium associated with negative momentum jumps is close to zero and statistically insignificant.

As mentioned before, a key motivation for including separate jump component is that they allow

for the correct estimation of premia when the prices of continuous and jump risk have opposite signs. This intuition is reflected in Tables 4 and 5 where we see for most factors that the coefficients for the continuous and jump components carry opposing signs²⁴ and that the significance is mostly restricted to the jump component. The significance of the several jump components is particularly noteworthy as all the factors yields insignificant results when aggregating the continuous and jump components as in model specification [1].

As expected, augmenting the model with jump components materially improves the in-sample explanatory power of the cross-sectional regressions. Model specifications [2] exhibit substantially higher in-sample R^2 values than specification [1]. While the time-series average R^2 ranges from 26.75 to 28.92 percent under specification [1], it increases to between 35.20 and 39.41 percent under the double-jump specification [2^d].²⁵

5.3 Cost of Capital

The results reported in the previous subsection strongly suggest that jump risk is significantly priced for the majority of factors in the cross-section of stock returns. The significance of the risk premia, thereby, motivates applying the same decomposition when estimating the cost of capital using equation (11) as we will do in this subsection.

For each valid stock-month observation²⁶, we first form the capital cost estimate $\hat{\mu}_{m,t}$ and then calculate the cross-sectional average for the corresponding groups in which we are interested. In Table 6 we show the time-series average of the resulting cost of equity estimates for both the cross-section of U.S. stocks and the insurance groups across all three previously mentioned factor model specifications plus the CAPM for model specification [1] and both model specifications [2].^{27,28}

Our first finding is that, for the cross-section of U.S. stocks, average cost of equity estimates are higher and exhibit lower cross-sectional dispersion, except for the CAPM specification, under model [1] than under either variant of specification [2]. The greater variation in cost of equity estimates under models [2^s] and [2^d] is attributable to the larger set of risk factors through the inclusion of factor jump components. Given that these additional factors are significantly priced in the cross-

²⁴The result that the continuous and jump risk components exhibit opposing signs does not arise mechanically from the regression specification. Tables A3 and A4 in the Appendix replicate the Fama and MacBeth (1973) regressions for the post-2007 subsample. Here we find for several risk factors that the estimated prices of continuous and jump risk share the same sign. This result indicates that the opposing signs observed in the full sample is driven by the data rather than the model specification [2] itself.

²⁵In unreported findings we further see that the in-sample mean absolute pricing error defined in accordance with Maio and Santa-Clara (2012) tends to be higher for model specification [1] which also implies inferior in-sample pricing performance.

²⁶We require for each stock-month observation that a stock has both a non-zero jump beta and a non-zero continuous beta.

²⁷Figures A1 and A2 in the Appendix additionally provide Gaussian kernel density estimates of the cost of equity estimates for the CAPM and FF5 specifications.

²⁸In Table A5 of the Appendix, we present the cost of equity estimates for model specification [1] using the historically realized factor premia (defined as the arithmetic monthly average factor return between January 1963 and December 2020), sourced from Kenneth French's website, as the input for $\hat{\lambda}$ instead of the estimated risk premia from the Fama and MacBeth (1973) regression. While the estimated costs of equity are smaller in magnitude, the main qualitative conclusions are consistent with our baseline analysis. In particular, P&C insurers exhibit lower costs of equity than the broader cross-section of stocks, whereas life insurers consistently display higher estimates across factor specifications.

Table 6: Summary Statistics for Cost of Capital

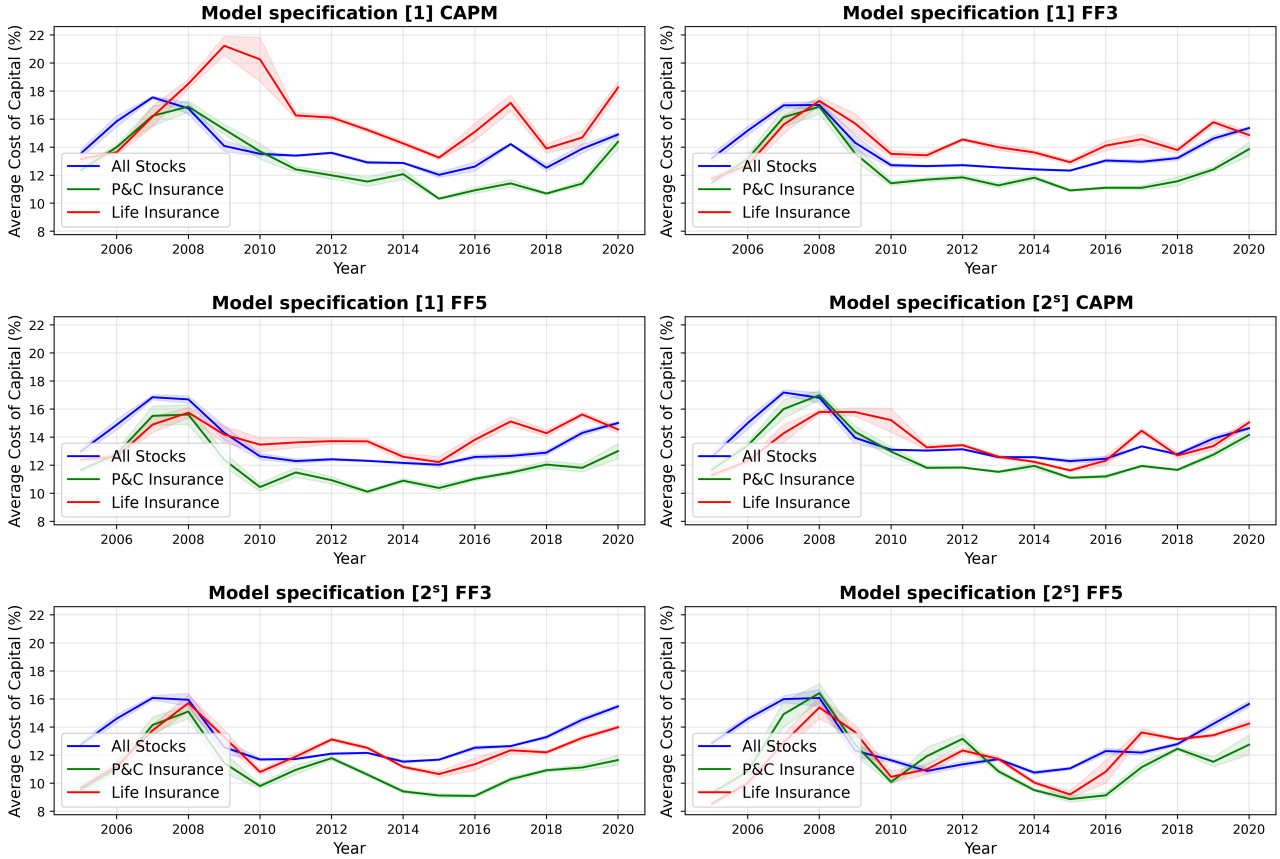
Model	CAPM		FF3		FF4		FF5		Mean	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: All Stocks										
[1]	14.01	3.18	13.81	2.90	13.04	2.53	13.55	3.20	13.60	2.95
[2 ^d]	13.78	2.13	13.09	5.39	11.19	5.78	12.39	5.82	12.61	4.78
[2 ^s]	13.70	1.61	13.19	3.84	11.16	3.83	12.87	4.47	12.73	3.44
Panel B: Insurance										
[1]	13.31	2.67	12.69	2.06	11.98	1.70	12.29	2.17	12.56	2.15
[2 ^d]	12.64	1.87	11.68	3.96	11.15	4.48	11.75	4.57	11.81	3.72
[3]	12.95	1.34	11.82	2.59	10.24	2.86	12.16	2.89	11.79	2.42
Panel C: P&C Insurance										
[1]	12.83	2.37	12.50	1.89	11.82	1.53	11.96	1.93	12.28	1.93
[2 ^d]	12.45	1.57	10.72	3.01	10.67	3.50	11.07	3.15	11.23	2.81
[2 ^s]	12.82	1.31	11.00	2.35	9.83	2.55	11.59	2.39	11.31	2.15
Panel D: Life Insurance										
[1]	16.05	2.32	14.25	1.77	13.15	1.53	13.90	1.95	14.34	1.89
[2 ^d]	13.24	1.92	10.17	3.48	8.08	4.05	9.62	4.02	10.28	3.37
[2 ^s]	13.46	1.23	12.29	2.37	9.13	2.74	11.88	2.37	11.69	2.18

Note: This table presents summary statistics for the annualized cost of capital (multiplied by 100) estimates for U.S. stocks in Panel A, the aggregate insurance group in Panel B, the P&C insurance group in Panel C, and the life insurance group in Panel D. Specification [1] shows the results for a low-frequency standard regression, specification [2^d] implements our high-frequency model specification with two jumps, and specification [2^s] implements our high-frequency model specification with a single jump component for the period 2004–2020. Each month, the mean and standard deviation values for the cross-sectional distribution are calculated. The table presents the time-series average for each cross-sectional value. The Mean column shows the average across model specifications per row.

section, it is likely that the increase in dispersion for models [2^s] and [2^d] in cost of equity estimates genuinely reflects economically meaningful differences in underlying risk exposure. We also find, that the estimates are fairly stable across factor specifications for the average U.S. stock ranging between 13.04 and 14.01 percent for specification [1], 11.19 and 13.78 percent for specification [2^d], and 11.16 and 13.70 percent for specification [2^s]. This relative stability of the mean cost of equity estimates across model and factor specifications, particularly when compared to earlier studies such as [Cummins and Phillips \(2005\)](#), arises somewhat mechanically from our estimation approach. Since we do not rely on the realized historical factor premia as an estimator for λ , but estimate the prices of risk directly from the cross-section of stock returns, the estimated risk premia are determined such that the fitted expected returns match more closely the realized monthly returns. As a consequence, differences in model specification primarily affect the cost of equity estimates of individual stocks and industries rather than the aggregate mean.

For the P&C insurance group, we find evidence supporting the notion that these insurers are less exposed to common risk factors, resulting in lower expected returns. As a result, their estimated

Figure 2: Yearly Cost of Capital Estimates - Single Jump



Note: This figure displays the yearly average of monthly (multiplied by 100) cross-sectional averages cost of equity estimates from the low-frequency standard regression model [1] and the high-frequency model [2^s] with a single jump component for the period 2005–2020 for U.S. stocks (blue line), the P&C insurance group (green line), and the life insurance group (red line). The estimates result from the CAPM, Fama-French three factor (FF3), and the Fama-French five-factor (FF5) specifications. The shaded areas represent the 90% confidence intervals.

cost of equity is lower than that of the the cross-section of U.S. stocks across all model and factor specifications, ranging between 9.83 and 12.50 percent. While they have lower cost of equity values for specifications [2^s] and [2^d], changing the model specifications does not materially affect the mean value. Consistent with prior findings and the previously mentioned institutional differences, we see that for the standard model [1] P&C insurers have consistently lower cost of equity values compared to life insurers. A similar pattern applies for the aggregate insurance group, which exhibits slightly higher average costs of equity than the P&C insurance group, ranging on average from 11.23 to 12.56 percent across model specifications.

For the life insurance group, the standard model specification [1] likewise yields the expected result that firms operating in this segment possess higher costs of equity than the average firm in the broader equity market. The cost of equity estimates range from 13.15 to 16.05 percent. Strikingly, this ranking reverses partially for the model specifications [2] where the average cost of equity estimates across factor specifications lie below the corresponding estimates for the aggregate stock market.²⁹

²⁹In unreported findings, we document the opposite effect for health insurance firms, whose cost of capital increase when

This pattern is particularly pronounced for the multi-factor specifications (i.e., FF3, FF4, and FF5). For both models $[2^s]$ and $[2^d]$, the estimated cost of equity of life insurers declines when moving from the CAPM to the multi-factor specifications. The primary reason why life insurance stocks have lower cost of equity estimates for these multi-factor specifications stems from their particular jump risk exposure. While life insurers have a higher exposure to market jump risk, which is positively priced, they also have, as can be seen in Table 3, lower than average exposure to momentum jump risk, which is also positively priced, and a higher exposure to value jump risk, which is negatively priced. This implies that the CAPM model without jump risk components may inadequately capture the sources of risk for life insurers, thereby generating disproportionately high cost of equity estimates.

Figure 2 shows the time-series of yearly average cost of equity estimates for model specification [1] and the single-jump specification $[2^s]$. The time-series paths of the estimates cost of equity are broadly similar under models [1] and $[2^s]$. Estimates are relatively muted in 2005, rise during the GFC as systematic risk increases, remain relatively stable throughout the 2010s, and increase again in 2020 with the onset of the COVID-19 crisis. Moreover, the plot for the CAPM specification [1] is consistent with the traditional view that life insurers face high cost of equity. The estimated cost of equity reaches approximately 21 percent during the GFC and remain elevated thereafter, which is broadly consistent with the findings of Nissim (2013). A similar increase is observed during the COVID-19 crisis in 2020. These dynamics underscore the sensitivity of life insurers to market fluctuations given the importance of investment assets to their business model. Interestingly, the effect of the strong and rapid increase in capital costs during the GFC largely disappears in the other specifications, indicating that countercyclical changes in the remaining factor loadings partially offset the increase in market exposure. In particular, for the single-jump model $[2^s]$ the yearly estimates for the life insurers are broadly similar with the aggregate stock group and P&C insurers.

6 Conclusion

The preceding section has demonstrated that incorporating jump components for estimating the cost of capital of insurance firms, can materially affect the resulting estimates. Our findings for life insurers suggest that the widely-held belief³⁰ that life insurers face higher costs of equity may be sensitive to the underlying asset-pricing specification. In particular, models based solely on a continuous market factor, which are still widely used in industry, tend to produce higher estimated expected returns, which reduce once other risk factors and especially once jump risk components are incorporated.

Although our current analysis reveals meaningful differences in the cost of equity across insurance firms for different asset-pricing model specifications, we cannot establish how these differences are

including jump components.

³⁰A noteworthy example is a report by Boston Consulting Group (2018), which suggests that insurers face disproportionately high costs of capital that, under the current conditions in the insurance sectors, are difficult to earn.

related to underlying firm characteristics. Therefore, our subsequent follow-up analysis will focus on the determinants of insurers' cost of capital. There is a rich literature documenting firm characteristics associated with expected returns that are common to all firms, including leverage, size, and liquidity. Further, there is a range of factors that are likely specific to insurance firms. It is therefore of interest how these the relation between these characteristics and the cost of equity estimates depends on the chosen model and factor specification.

A Appendix: Tables

Table A1: Fama-MacBeth Regressions with Continuous and Jump Components - Single Jump

Factor	Comp.	Factor Specification			
		CAPM		FF6	
		[1]	[2 ^s]	[1]	[2 ^s]
λ_0	Cont.	3.76 (1.09)	10.06** (2.17)	6.37** (2.06)	9.19** (2.25)
MKT	Cont.	8.01 (1.50)	5.74 (1.02)	3.94 (0.94)	-4.69 (-1.05)
	Jump		-3.39 (-0.62)		10.40** (2.23)
SMB	Cont.			2.29 (1.15)	6.10 (1.33)
	Jump				-8.81*** (-3.85)
HML	Cont.			-0.32 (-0.15)	3.08 (1.21)
	Jump				-3.38* (-1.73)
MOM	Cont.			-1.86 (-0.48)	-3.30 (-0.84)
	Jump				7.59** (2.33)
RMW	Cont.			0.25 (0.19)	1.05 (0.57)
	Jump				1.59 (1.28)
CMA	Cont.			-1.16 (-0.92)	0.37 (0.19)
	Jump				-2.00 (-1.55)
R^2		26.54%	32.12%	27.65%	33.88%

Note: This table reports the estimated annualized aggregate prices of risk (multiplied by 100) for a variety of commonly used factor models from two-pass Fama-MacBeth type regressions. Specification [1] shows the results for a low-frequency standard regression and specification [2^s] implements our high-frequency model specification with a single jump. The jump risk premium captures the compensation for all jumps. In parentheses, *t*-statistics are reported. The R^2 represents the time-series average of cross-sectional R^2 estimates. The returns are sampled at a fifteen-minute frequency from January 2, 2004 to December 31, 2020. The indicators *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A2: Fama-MacBeth Regressions with Continuous and Jump Components - Double Jump

Factor	Comp.	Factor Specification			
		CAPM		FF6	
		[1]	[2 ^d]	[1]	[2 ^d]
λ_0	Cont.	3.76 (1.09)	8.35* (1.75)	6.37** (2.06)	5.47 (1.33)
MKT	Cont.	8.01 (1.50)	6.59 (1.21)	3.94 (0.94)	-1.29 (-0.29)
	Neg. Jump		5.11 (0.84)		6.52* (1.66)
	Pos. Jump		-7.10 (-1.40)		6.57 (1.44)
SMB	Cont.			2.29 (1.15)	7.26 (1.52)
	Neg. Jump				-8.46*** (-3.52)
	Pos. Jump				-2.87 (-1.57)
HML	Cont.			-0.32 (-0.15)	5.00* (1.89)
	Neg. Jump				-5.03** (-2.38)
	Pos. Jump				-0.69 (-0.46)
MOM	Cont.			-1.86 (-0.48)	-5.28 (-1.32)
	Neg. Jump				-0.51 (-0.16)
	Pos. Jump				13.40*** (4.70)
RMW	Cont.			0.25 (0.19)	0.76 (0.40)
	Neg. Jump				0.89 (0.81)
	Pos. Jump				0.97 (0.73)
CMA	Cont.			-1.16 (-0.92)	0.86 (0.45)
	Neg. Jump				-2.49** (-2.00)
	Pos. Jump				0.87 (0.79)
R^2		26.54%	33.34%	27.65%	35.23%

Note: This table reports the estimated annualized aggregate prices of risk (multiplied by 100) for a variety of commonly used factor models from two-pass Fama-MacBeth type regressions. Specification [1] shows the results for a low-frequency standard regression and specification [2^d] implements our high-frequency model specification with two separate jumps. The jump risk premia capture the compensation for all jumps. In parentheses, t -statistics are reported. The R^2 represents the time-series average of cross-sectional R^2 estimates. The returns are sampled at a fifteen-minute frequency from January 2, 2004 to December 31, 2020. The indicators *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A3: Fama-MacBeth Regressions with Continuous and Jump Components - Post-2007

Factor	Comp.	Factor Specification					
		FF3		FF4		FF5	
		[1]	[2 ^s]	[1]	[2 ^s]	[1]	[2 ^s]
λ_0	Cont.	5.86 (1.38)	8.28 (1.45)	5.91 (1.40)	5.49 (0.95)	4.89 (1.25)	5.42 (1.05)
MKT	Cont.	6.00 (0.99)	-1.83 (-0.34)	5.97 (1.00)	1.73 (0.34)	6.86 (1.20)	1.07 (0.20)
	Jump		10.59* (1.66)		10.16* (1.75)		10.99* (1.87)
SMB	Cont.	3.32 (1.46)	12.03*** (3.60)	2.49 (1.24)	12.07*** (3.72)	3.48 (1.62)	13.14*** (4.00)
	Jump		-8.40*** (-4.07)		-9.07*** (-4.26)		-9.31*** (-4.28)
HML	Cont.	-0.21 (-0.08)	1.08 (0.34)	-1.21 (-0.47)	0.50 (0.17)	-0.47 (-0.18)	4.07 (1.34)
	Jump		-4.28* (-1.87)		-4.53* (-1.77)		-5.38** (-2.37)
MOM	Cont.			-6.04 (-1.27)	-8.10* (-1.89)		
	Jump				8.30** (2.14)		
RMW	Cont.					0.34 (0.20)	0.25 (0.12)
	Jump						2.27 (1.54)
CMA	Cont.					-1.68 (-1.18)	0.11 (0.06)
	Jump						-2.87** (-2.03)
R^2		26.54%	32.12%	27.65%	33.88%	28.51%	35.41%

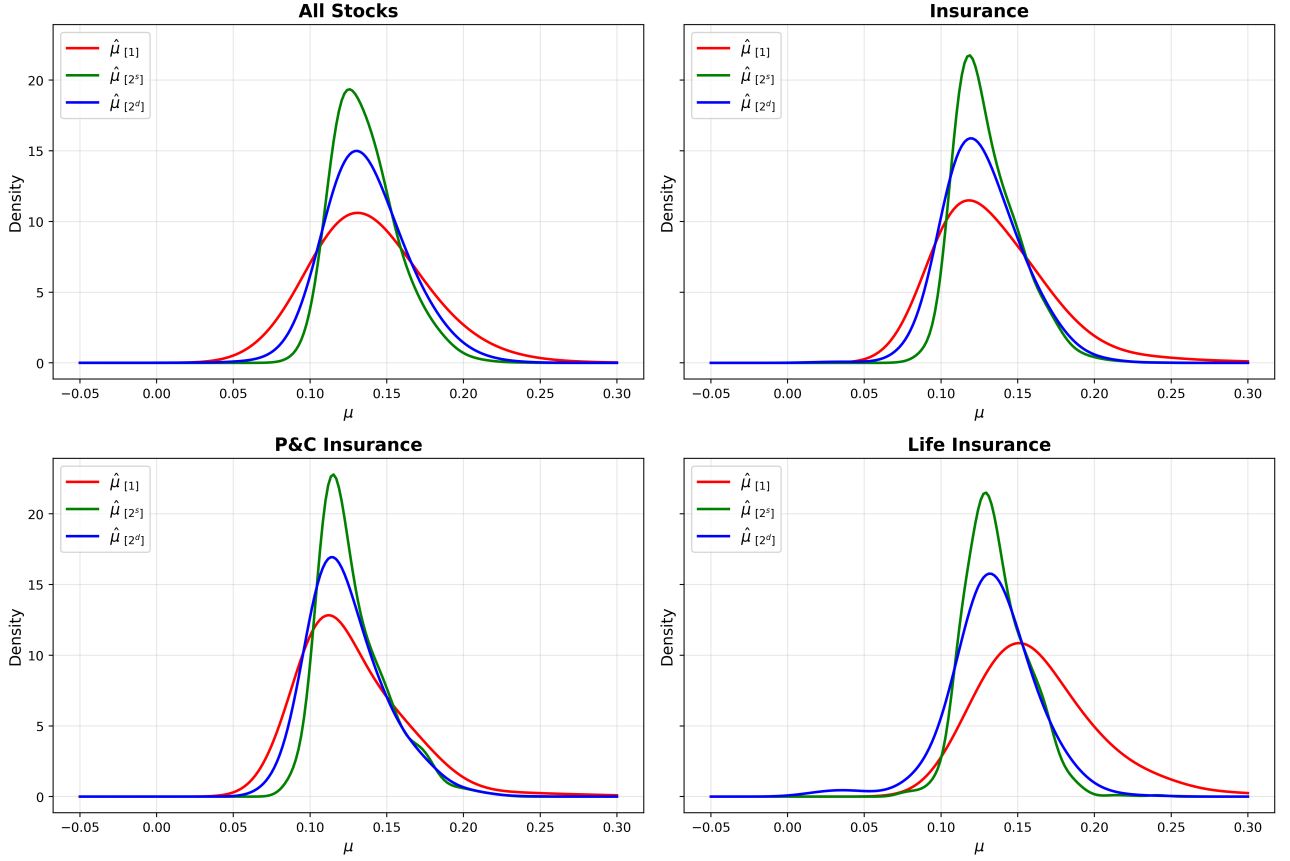
Note: This table reports the estimated annualized aggregate prices of risk (multiplied by 100) for a variety of commonly used factor models from two-pass Fama-MacBeth type regressions. Specification [1] shows the results for a low-frequency standard regression and specification [2^s] implements our high-frequency model specification with a single jump. The jump risk premium captures the compensation for all jumps. In parentheses, t -statistics are reported. The R^2 represents the time-series average of cross-sectional R^2 estimates. The returns are sampled at a fifteen-minute frequency from January 2, 2007 to December 31, 2020. The indicators *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A4: Fama-MacBeth Regressions with Continuous and Jump Components - Post-2007

Factor	Comp.	Factor Specification					
		FF3		FF4		FF5	
		[1]	[2 ^d]	[1]	[2 ^d]	[1]	[2 ^d]
λ_0	Cont.	5.86 (1.38)	8.22 (1.47)	5.91 (1.40)	4.25 (0.75)	4.89 (1.25)	4.86 (0.99)
MKT	Cont.	6.00 (0.99)	−1.59 (−0.31)	5.97 (1.00)	2.92 (0.57)	6.86 (1.20)	1.92 (0.37)
	Neg. Jump		1.67 (0.35)		2.78 (0.68)		3.63 (0.96)
	Pos. Jump		10.29* (1.83)		9.58* (1.79)		8.79* (1.66)
SMB	Cont.	3.32 (1.46)	14.50*** (4.36)	2.49 (1.24)	14.88*** (4.60)	3.48 (1.62)	15.38*** (4.82)
	Neg. Jump		−9.68*** (−4.74)		−9.03*** (−4.83)		−10.38*** (−5.32)
	Pos. Jump		−2.55* (−1.70)		−3.14*** (−1.94)		−2.54 (−1.58)
HML	Cont.	−0.21 (−0.08)	3.33 (1.13)	−1.21 (−0.47)	2.76 (0.97)	−0.47 (−0.18)	5.31* (1.88)
	Neg. Jump		−5.94** (−2.53)		−4.29* (−1.92)		−5.95*** (−2.81)
	Pos. Jump		−1.73 (−0.86)		−1.63 (−0.82)		−2.40 (−1.29)
MOM	Cont.			−6.04 (−1.27)	−10.54** (−2.49)		
	Neg. Jump				0.10 (0.03)		
	Pos. Jump				15.26*** (4.86)		
RMW	Cont.					0.34 (0.20)	0.51 (0.26)
	Neg. Jump						1.63 (1.64)
	Pos. Jump						0.75 (0.62)
CMA	Cont.					−1.68 (−1.18)	0.43 (0.22)
	Neg. Jump						−2.17* (−1.81)
	Pos. Jump						−0.33 (−0.30)
R^2		26.54%	33.34%	27.65%	35.23%	28.51%	36.95%

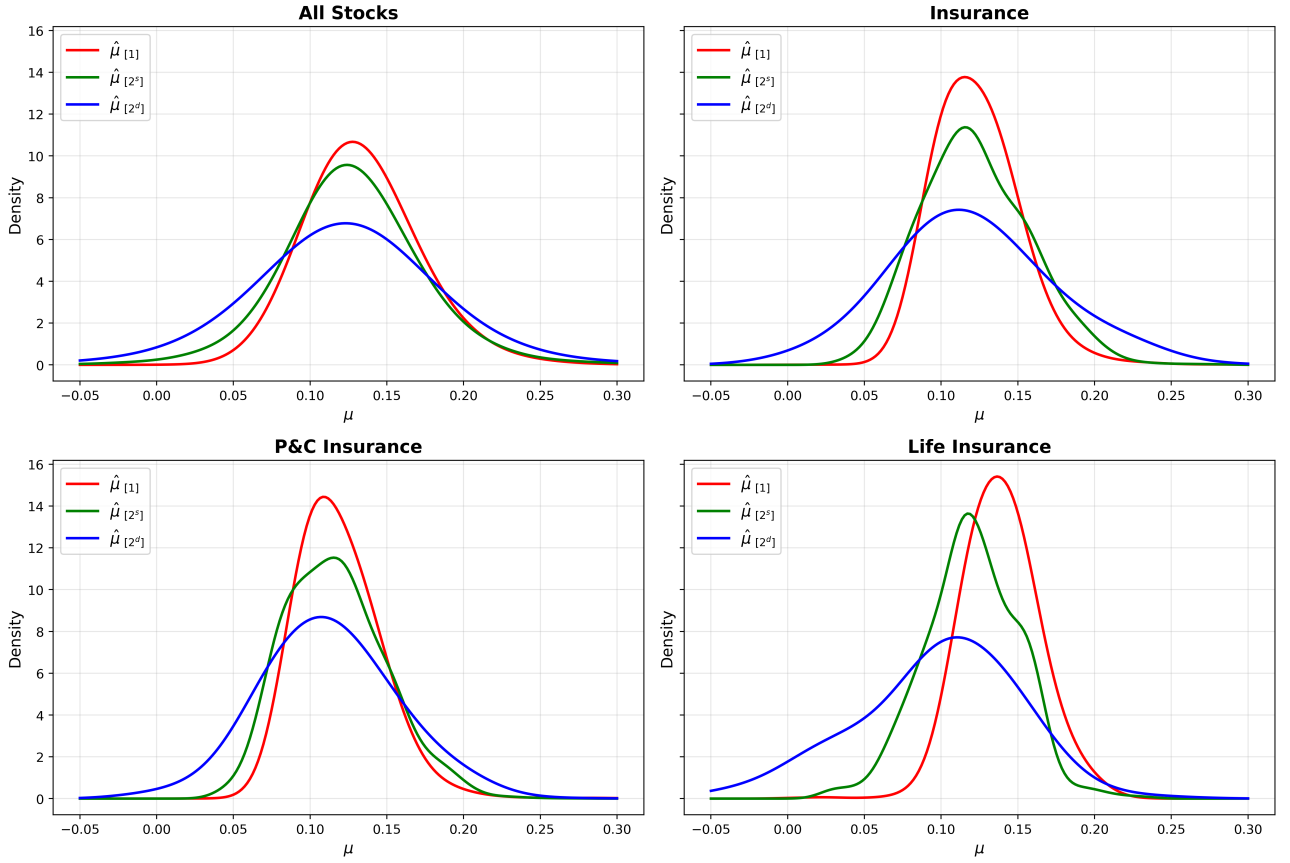
Note: This table reports the estimated annualized aggregate prices of risk (multiplied by 100) for a variety of commonly used factor models from two-pass Fama-MacBeth type regressions. Specification [1] shows the results for a low-frequency standard regression and specification [2^d] implements our high-frequency model specification with two separate jumps. The jump risk premia capture the compensation for all jumps. In parentheses, t -statistics are reported. The R^2 represents the time-series average of cross-sectional R^2 estimates. The returns are sampled at a fifteen-minute frequency from January 2, 2007 to December 31, 2020. The indicators *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Figure A1: Density Plot of Cost of Capital in the CAPM Specification



Note: This figure displays kernel density estimates of the unconditional distribution of the monthly low-frequency standard cost of capital estimates $\hat{\mu}_{[1]}$ from model specification [1] (in red), the high-frequency model specification with two jumps $[2^d]$ (in blue), and the high-frequency model specification with a single jump $[2^s]$ (in green) for the period 2005–2020 for U.S. stocks, aggregate insurance group, the P&C insurance group, and the life insurance group. For both types of regressions, we used the CAPM specification. We choose Gaussian kernel functions with a bandwidth of 0.5.

Figure A2: Density Plot of Cost of Capital in the FF5 Specification



Note: This figure displays kernel density estimates of the unconditional distribution of the monthly low-frequency standard cost of capital estimates $\hat{\mu}_{[1]}$ from model specification [1] (in red), the high-frequency model specification with two jumps [2^d] (in blue), and the high-frequency model specification with a single jump [2^s] (in green) for the period 2005–2020 for U.S. stocks, aggregate insurance group, the P&C insurance group, and the life insurance group. For both types of regressions, we used the Fama-French five-factor (FF5) specification. We choose Gaussian kernel functions with a bandwidth of 0.5.

Table A5: Summary Statistics for Cost of Capital - Realized premia

Model	CAPM		FF3		FF4		FF5		FF6	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: All Stocks										
[1]	8.94	2.73	10.02	4.28	11.96	5.82	9.81	5.54	9.61	8.67
Panel B: Insurance										
[1]	8.35	2.30	10.03	3.40	11.72	4.63	9.61	3.52	9.44	5.29
Panel C: P&C Insurance										
[1]	7.94	2.03	9.78	2.95	11.79	4.37	9.63	2.97	9.51	4.76
Panel D: Life Insurance										
[1]	10.70	2.06	13.40	2.81	14.17	4.16	11.74	3.29	10.29	5.42

Note: This table presents summary statistics for the annualized cost of capital (multiplied by 100) estimates for U.S. stocks in Panel A, the aggregate insurance group in Panel B, the P&C insurance group in Panel C, and the life insurance group in Panel C. Specification [1] shows the results for a low-frequency standard regression using realized factor premia (defined as the arithmetic monthly average factor return between January 1963 and December 2020) for the period 2004–2020. Each month, the mean and standard deviation values for the cross-sectional distribution are calculated. The table presents the time-series average for each cross-sectional value.

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