The Price of News Arrivals: Evidence from Equity Options*

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Abstract

It is well-known that individual stock returns often exhibit large discrete movements, or jumps. In addition, it is documented that jump risk is necessary to explain observed equity options prices. However, very little is known about the source of jumps and its premium, perhaps due to the latent nature of jumps. I propose to identify jumps using a comprehensive news dataset from Factiva. This enables me to model the time-varying probability of jumps and it allows me to impose flexible risk premiums showing how the uncertainty of news arrivals is priced. When estimating a continuous-time stochastic volatility jump diffusion model on individual equity options with news arrivals driving the jump dynamics, I find that (1) the arrival of news itself is positively priced and (2) the size of jumps due to news arrival carries a significantly negative risk premium. The results are consistent with previous theories highlighting both positive and negative effects of public news arrival.

JEL Classification: G12, G14

Keywords: Public news; Time-varying jump intensity; Information risk; Options

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1 Introduction

One of the first empirical puzzles found in the financial literature is the leptokurtic distribution of stock returns. Earlier research tried to explain the puzzle by the so called Mixture of Distributions Hypothesis (MDH) (e.g., Clark (1973), Epps and Epps (1976), Tauchen and Pitts (1983)). MDH conjectures that trading activities are triggered by randomly spaced arrivals from a latent information process. However, the biggest problem with the empirical testing of MDH lies in the latent nature of the information process. The literature has thus largely focused on testing the implications of MDH, namely the volume-volatility relationship. Instead of relying on the implications of the hypothesis, in this paper, I directly test the role of specific information process, the firm-specific public news arrival, and how the uncertainty of its arrival is priced in the market.

To construct a measure of public news arrival, I use one of the most widely used database, Factiva. For each of the 20 firms in my sample, I construct two measures of public news arrival. The first is a simple count of the daily number of news articles appearing in the database while the second measures the news tone associated with individual article by applying the textual analysis technique developed in Loughran and McDonald (2011).

Large amounts of public news arrival coincides with large discrete movements in daily stock returns. For example, Microsoft's stock price dropped by 14.47% on Apr 3^{rd}, 2000 following a judge's ruling that Microsoft had violated antitrust laws. Of course, the day came with excessive amount of news articles, 348 news articles in my sample compared to the average news articles per day of 71, reporting the judge's ruling. On the theoretical side, Andersen (1996) proposes a modified Mixture of Distributions Hypothesis where the information arrival induces Poisson-type jumps in returns and finds strong empirical support. Along these lines, I conjecture that public news arrivals are related to the stock return jumps, rather than its continuous movements, and I find supporting empirical evidences.

Detecting jumps in stock returns has been one of the most active research area in financial econometrics in last decade.[1] I employ the method developed in Lee and Mykland (2008) to identify individual daily stock returns as jump or no jump days. Using the identified jump days, I find strong evidence linking public news count with the probability of jumps. In particular, the news tone that measures the tone of each news article, does not have a significant relationship to the occurrence of jumps, but it is strongly correlated with the size of a jump conditional on its occurrence. This evidence is consistent with Tetlock (2007) who has found the correlation between pessimistic tones extracted from the Wall Street Journal and large negative returns. I also find additional evidence from the equity options market using the slope of the implied volatility surface. Both news counts and news tones are shown to be related with the IV-SKEW that proxies for the embedded risk-adjusted jump risk.

I then use the findings from the daily returns as a guidance to build a continuous time stochastic-volatility jump-diffusion model of daily returns, with the goal to study the market price of risk associated with the public news arrival. The major innovation of the model is to feature a time-varying jump-intensity where its variation solely depends on the observed public news arrival. By fitting the model to the daily returns, news arrivals, and equity options prices, I find a significant positive risk premium associated with the public news innovation while the actual jump size due to the news carries a large negative risk premium. This suggests that a public news arrival is not viewed as redundant, but rather viewed as something investors prefer to have. Through this public news interpretation, I am able to both reconcile and explain the previously documented puzzling positive jump-timing risk premium.

There are mainly two channels for public news and its contents to cause stock returns to jump. The first channel is by influencing the beliefs of either noise or liquidity traders. The seminal paper by De Long, Shleifer, Summers, and Waldmann (1990) studies how noise trader risk can explain various empirical puzzles, while Campbell, Grossman, and Wang (1993) focuses on how sudden changes in liquidity traders can affect short-term returns. Tetlock (2007) provides empirical evidence consistent with these theoretical models. On the other

[1] For reference, see Huang and Tauchen (2005) and Gilder, Shackleton, and Taylor (2014) for concise summary.

hand, public news arrival can be viewed as a resolution of information asymmetry. If the public news articles do contain information that was only know to a group of privately informed investors, the arrival of such news instantaneously resolves the information asymmetry, thus causing the stock price to jump.

Furthermore, it is not clear how the public information should be priced in the market. If the noise trading effect is true, then public information is nothing more than exogenous shocks that cause short-term market movements that in turn quickly revert to the fundamental, hence should carry a negative risk premium. On the other hand, if the public information indeed resolves the information asymmetry, then it should carry a positive risk premium as shown in Easley and O'hara (2004). My findings suggest that, at least when using Factiva based news counts and contents as a proxy for public information, both theories co-exist in the market. Specifically, the positive jump-timing risk premium can be viewed as evidence of resolution of information asymmetry via a public news arrival story. On the other hand, the significantly negative jump-size premium can be viewed as a negative risk premium associated with risk aversion against the effect of noise trading induced price jumps. Thus, I conclude that public news arrival is an important economic factor that is strongly priced in the market, and the resulting evidences are consistent with both views from the previous theories.

This paper is perhaps most closely related to the work by Engle, Hansen, and Lunde (2012). They use the same news dataset from Factiva and study whether the news information can improve the forecasting power of daily realized volatility. In contrast, I emphasize the contemporaneous relationship between news arrival and stock return jumps. Also, I focus on using news arrivals as an exogenous observable to extract the risk premium associated with it instead of forecasting. In this respect, Lee (2012)'s work serves as good evidence why I focus on jumps. Lee (2012) finds that there is a higher chance of observing intra-day jumps in returns during scheduled firm-specific news announcement times. I follow the same intuition, with the notable difference that I study the impact of a daily time-series of news arrival instead of focusing on specific events. In other words, I am specifically interested in the role played by the unexpected and mostly unscheduled component of public news arrival.

There exists an extensive amount of literature studying the time-varying jump-intensity in returns and options prices.[2] The typical approach, mostly taken for its analytical tractability, is to assume an affine functional form for the jump-intensity in the latent variance process.[3] However, this approach does not allow for separate interpretations of the diffusive variance risk premium and jump-timing risk premium because two come from the same source. Particularly, two risk premiums are forced to have the same sign, which is not a required restriction. Perhaps due to this analytical complexity, the jump-timing premium has been mostly neglected and assumed away from in most studies. My model contributes to this literature by proposing to bypass this issue by allowing a purely public news dependent process that enters the jump-intensity equation, thus allowing one to identify the two premiums separately.

In terms of methodology, my paper is also related to the literature on explaining derivatives prices using economic co-variates. Usage of stochastic co-variates has been a popular approach in the credit derivatives literature.[4] There are way fewer studies linking economic co-variates to the pricing of options, perhaps due to the different modeling approach and difficulties associated with assigning appropriate co-variates. I contribute to this literature by proposing an observed news process as a possible candidate for an economic co-variate.

The remainder of the paper is organized as follows. Section 2 describes the dataset used for the analysis and provides preliminary non-parametric evidence from both equity and options markets. In Section 3, I develop the structural model that builds on the findings from Section 2 and discuss the estimation strategy. Section 4 focuses on the resulting implications from the estimated parameters and its properties. Section 5 concludes.

[2] Too cite few, see Maheu and McCurdy (2004), Maheu, McCurdy, and Zhao (2013), Andersen, Benzoni, and Lund (2002), Eraker (2004), Broadie, Chernov, and Johannes (2007a), Christoffersen, Jacobs, and Ornthanalai (2012), Ornthanalai (2014), and Andersen, Fusari, and Todorov (2015).

[3] Santa-Clara and Yan (2010) is a notable exception where the jump-intensity process is modeled as a separate latent process.

[4] See Altman (1968), Shumway (2001), Duffie, Saita, and Wang (2007), etc.

2 Data and Non-Parametric Analysis

In this section, I first describe the data sets used in the paper. I then perform non-parametric analysis to look for the evidence that links firm-specific news arrivals to jumps in returns.[5] The result non only indicates that firm-specific news arrival is related to return jumps but also provides good intuition on how the parametric models should be structured.

2.1 Data

The main variable of interest is firm-specific news arrival. The focus of this paper is placed on the role played by the daily arrival of firm-specific news instead of specific corporate events with large news flows, including both scheduled and unscheduled. Therefore, I require a comprehensive database that contains as many firm-specific news articles as possible. In this regard, I use Factiva database to search for comprehensive list of news articles.[6] Due to the technological advances such as Internet, the number of daily news articles have dramatically increased since the early 2000s. For this reason, I start my sample period at January, 2000 and ends at July, 2012 to avoid issues with obvious trend in news data.

Factiva database conveniently identifies each news article by its own ticker, which allows me to easily merge CRSP database with Factive news articles at daily level by its unique ticker. I identify 20 firms with the most amount of news articles for this study as the firms with smaller variation in its amount of daily news flow would not provide as much reliable conclusions as the firms with large amount of news flows. For each firm, I simply count the number of news articles with its ticker that appears in the Factiva database.[7] Table 1 shows descriptive statistics of daily news counts for 20 selected firms. The mean number of news articles observed each day is around 44 while median number is 32, indicating significant amount of weight is placed on the large news counts out-lier. Table 1 also shows that daily

[5]The author would like to acknowledge that dataset and most of non-parametric analysis in this section are taken from Jeon, McCurdy, and Zhao (2016).

[6]Bajgrowicz and Scaillet (2011) and Engle, Hansen, and Lunde (2012) also use Factiva database.

[7]Ederington and Lee (1993), Mitchell and Mulherin (1994), and Berry and Howe (1994) show that simple count of number of news articles is a good measure of public information arrival.

news counts are highly volatile. Standard deviation of each firm is is very large, sometime being much bigger than the mean, indicating that there are significant variation associated with the amount of news flowing into the equity market.

Besides the absolute number of news articles, its individual content might be also very relevant for investors. To quantify the individual content, I rely on the recent development in textual analysis (Cite papers) to measure the tone of each individual news articles. Due to the limitation of computing power and resources, I only download the first paragraph of each article. Then, I count the number of positive and negative words used in the first paragraph using the words list provided by Loughran and McDonald (2011). The final measure of news tone of each individual article is simply the difference between the percentage of positive and negative words. To ensure that longer articles carry more weight, I value-weight them by the number of words in each article to the daily level. Table 2 shows descriptive statistics of daily news tones for 20 selected firms. News tone measure of 0 thus corresponds to the neutral news tone day that had equal amount of positive and negative wordings. The news tone is negative in average with an exception of IBM and Cisco. Like the news counts reported in Table 1, the news tones are also highly volatile.

2.2 Evidences from Daily Jump Detection

In this section, I show preliminary evidence on the relationship between firm-specific news arrivals and daily return jumps. In order to classify each day as jump day or no jump day, I rely on the non-parametric method developed in Lee and Mykland (2008). It normalizes each return observation by the non-parametric spot variance estimator then compares it to the specific quantiles provided by the limiting distributions of interest.[8] To be conservative, I consider four different statistics that differ in its significance level and asymptotic distributions. Specifically, $J99$ and $J95$ denote the jumps detected at 99% and 95% significance level using Gumbel distribution as in Lemma 1 of Lee and Mykland (2008), while $J_0 99$ and $J_0 95$ denote

[8] I have used the corrections pointed out by Gilder, Shackleton, and Taylor (2014) in deriving the quantiles of the asymptotic distribution.

the jumps detected at 99% and 95% significance level using more relaxed normal distribution as in Theorem 1 of Lee and Mykland (2008).[9]

Having identified the jumps at daily level for individual securities, I first run the following pooled logit regression to test whether the jumps are more likely to occur on days with more news arrivals. NewsCount and NewsTone denote the daily count and tone of news articles described in the previous section, where I standardize them to have same mean and standard deviation across 20 firms.

$$\text{logit}(p_{it}) = a + b_1 \times \text{NewsCount}_{it} + b_2 \times \text{NewsTone}_{it} + b_3 \times \text{ret}_{i,t-1} + \epsilon_{it} \tag{1}$$

Table 3 reports the pooled logit regression result for four different threshold of detecting jumps. Same findings hold across all four cases: more news counts are associated with higher probability of having jump while news tone does not have statistically significant relationship to the probability of jump. The result shows that jumps are more likely to occur when excessive amount of information flows regardless of its actual content.

Next, I further explore the role of news tone given that it does not affect the occurrence of jumps itself. Tetlock (2007) shows the level of news pessimism extracted from Wall Street Journal is related to the downward pressure on market prices. In other words, the news tone is linked to the size of the market price movements, or jumps. Motivated by this, I run the following regression to test whether the news tone matters for the size of jumps conditional on having jumps.

$$r_{it}|\text{Jump} = a + b_1 \times \text{NewsCount}_{it} + b_2 \times \text{NewsTone}_{it} + \epsilon_{it} \tag{2}$$

For each of four jump detection statistics, I first take subsamples classified as jump days only. Then, I assume the entire daily return of those days are due to the jump component. Ta-

[9] Each of four statistics $\{J99, J95, J_0 99, J_0 95\}$ thus identifies the jump day if the absolute value of daily return is above $\{5.1024, 4.4881, 3.2283, 2.4565\}$ times of the daily spot volatility.

ble 4 reports the OLS regression result. First panel provides the estimates of coefficients when entire subsample of jump days are used. Again, no qualitative differences are found among four different jump detection statistics. NewsTone variable shows statistically significant positive coefficient, meaning negative NewsTone comes with negative jump returns, consistent with Tetlock (2007). Coefficients estimates for NewsCount shows much weaker statistical significance and even has a negative sign. The potential issue with NewsCount variable is that it can take only positive values while the dependent variable, size of jump return, can be both positive and negative. Thus, I further divide the jump days into two subsamples, one with positive jump returns and other with negative jump returns.

Middle panel reports the result for positive jumps only subsample. First and most interestingly, the significance associated with NewsTone variable disappears and the sign becomes negative. In other words, the actual content of news matters less for positive jump returns and actually it even reduces the size of jumps, given that NewsTone will be in general positive on those days. Second, NewsCount is now strongly related with the size of jumps, carrying a statistically significant positive coefficient.

Bottom panel shows the coefficient estimates on negative jumps only subsample. In this case, all coefficients for both NewsTone and NewsCount are statistically significant at 1% level. The signs of estimated coefficients for NewsTone and NewsCount are positive and negative, respectively, indicating that pessimistic news tone and more number of negative news come with larger negative returns. Looking at the size of the coefficients, NewsTone dominates the NewsCount in its impact on the jump returns. Using the estimated coefficients from the $J99$ statistic in column (1), one standard deviation decrease in NewsTone decreases jump size by 1.47% while one standard deviation increase in NewsCount decreases jump size by 0.66%.

The subsample results are largely consistent with the findings by Chen and Ghysels (2011). Using intra-day returns as the sign of news, they find that moderately good-news actually reduces the volatility while bad news and very good news increase volatility. News tone result implies the same conclusion that negative news tone increases volatility via having larger jump sizes while positive news actually reduces, or does not impact, volatility.

2.3 Evidences from Implied Volatility

Having established the linkage between news measures and jumps in the previous section, I now move on to find evidences from the options market. Options market reflects investor's risk-adjusted expectation, thus reveals forward-looking information. The most well-known pattern of implied volatility is perhaps around the scheduled earnings announcement (Rogers, Skinner, and Buskirk (2009)). Empirically, implied volatility spikes a day before the earnings announcement, then shows a slight drop on the announcement date followed by sudden drops. One way to think about earnings announcement is to classify it as a day with large information arrival, as the number of news counts is excessively high around the earnings announcement date. However, there is a fundamental difference between earnings announcement date and other dates with large news flows. That is, the timing of earnings announcements are known in advance, while other large news flows come at surprise without fixed date in advance.

Figure 2 compares the behavior of implied volatility in [-5,+5] days window around scheduled earnings announcement date and unscheduled large news flow dates. The top panel plots the average one-month maturity at-the-money (ATM) implied volatility within 5 days window around the quarterly earnings announcement dates. Similarly, in the bottom panel, I plot the average ATM implied volatilities four dates each year with largest news count that does not belong to within 5 days of quarterly earnings announcement dates. First, top panel reveals consistent pattern with what was reported in the literature, both peak a day before and sudden drop afterwards, around the scheduled earnings announcement dates. On the other hand, bottom panel shows very different pattern. The level of average implied volatility now peaks on the day of large news flow instead of the day before. Also, there is no sudden drop in average implied volatility afterwards, but it rather persists. With this interesting differences between the impact of scheduled and unscheduled news in mind, I move on to study how the jump risk component in equity options is related to the public news arrival.

To measure perceived jump risk embedded in equity options prices, I choose the steepness of volatility smirk, or implied volatility skew (IV-SKEW), as the measure of investor's risk aversion to expected negative jumps. This measure was explored in Xing, Zhang, and Zhao (2010) where they show the predictability of cross-sectional returns using IV-SKEW. I closely follow their definition of IV-SKEW where I use Black-Schole delta as the definition of moneyness where Xing, Zhang, and Zhao (2010) uses the ratio of the strike price to the stock price. To construct IV-SKEW measure, I first obtain end-of-day option prices and implied volatility as well as Black-Scholes delta from IVY OptionMetrics database for 20 firms in my sample. The sample period is again from Jan, 2000 to Jul, 2012. Then, for each day with options traded, I choose OTM puts with maturity being closest to 30 days and BS-delta value being closest to -0.25. Similarly, I choose ATM calls by looking for options having maturity closest to 30 days and BS-delta closest to 0.5. The final daily measure of IV-SKEW is computed as the difference between the implied volatilities of average OTM puts and ATM calls selected.

$$\text{IV-SKEW}_{it} = \text{IV}_{it}^{OTMP} - \text{IV}_{it}^{ATMC} \tag{3}$$

The famous volatility smirk puzzle basically translates to this measure of IV-SKEW being positive. I also find this in my sample where the average daily IV-SKEW is 3.86%. Larger IV-SKEW reflects larger risk-adjusted expected jump risk for investors. Hence, I next run the simple linear regression of news variables from the previous section on the IV-SKEW. To avoid noise associated with daily measure of IV-SKEW, I average them at monthly level as well as all explanatory variables. Following equation summarizes the regression model used.

$$\text{IV-SKEW}_{it} = a + b_1\text{NewsCount}_{it} + b_2\text{NewsTone}_{it} + b_3\text{ATM IV} + \epsilon_{it} \tag{4}$$

Table 5 summarizes the result where column (1), (2), and (3) report different combinations while column (4) reports the full model result. The resulting estimates of coefficients are all statistically significant in all models and generally agrees with the results from Table 4. For instance, NewsCount is positively related with the IV-SKEW, meaning that more news comes with steeper smirk. Also note that sign for NewsTone variable is negative, indicating pessimistic news content also makes IV smirk steeper. In terms of its magnitude, one standard deviation increase in NewsCount will increase IV-SKEW by 0.17% while one standard deviation decrease in NewsTone will increase IV-SKEW by 0.61%. Given that IV-SKEW embeds both information about the occurrence and size of jumps, where it is hard to disentangle them non-parametrically under the risk-neutral measure, the results are largely consistent with the findings from Table 3 and Table 4.

Having all preliminary evidences above established, I next move on to build a reduced-form model that features findings of this section. The goal of reduced-form study is to identify the prices associated with the inherent news arrival process, which is shown to be related to stock return jumps.

3 Reduced-Form Model of News and Jumps

In this section, I build a reduced-form model of stock price process that features the empirical findings of the previous section. Specifically, I embed the news process, to be filtered from the observed information from daily news counts and news tones, in the standard affine stochastic volatility jump-diffusion model. Then, I discuss the risk-neutralization of the process that delivers closed-form option pricing formula. Lastly, I outline the two-step filtering process used to estimate parameters and infer the latent states of the proposed dynamics from the observable data.

3.1 Reduced-Form Model of Stock Price Dynamics

I begin by specifying the process governing the log stock variance, spot variance, and news under the physical measure ($\mathbb{P}$). I use S_t, V_t, and I_t to denote stock price, spot variance, and spot news at time t. The following dynamics fully describe the process of three factors under the physical measure $\mathbb{P}$:

$$
\begin{aligned}
d\log(S_t) &= (\mu - \frac{1}{2}V_t - \xi\lambda_t)dt + \sqrt{V_t}(\sqrt{1-\rho^2}dW_t^1 + \rho dW_t^2) + q_t dN_t && (5)\\
dV_t &= \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_t^2 && (6)\\
dI_t &= \kappa_I(\theta_I - I_t)dt + \sigma_I\sqrt{I_t}dW_t^3 && (7)
\end{aligned}
$$

where μ denotes the return drift of individual equity. For simplicity, I treat μ as a constant and fix it at the sample average of daily returns throughout the paper. All Brownian motions $dW_t^i, i = 1$ to 3 are assumed to be independent to each other.

I assume standard square-root process for the variance and news process, V_t and I_t, as in Heston (1993). The log stock price $\log(S_t)$ also follows standard jump-diffusion process with $q_t dN_t$ representing the compound Poisson distributed jump process with time-varying intensity λ_t. Each individual jump is assumed to be independent and identically distributed normal distribution with mean jump size η and jump standard deviation δ. The jump compensation term ξ is set to be equal to $e^{(\eta+\frac{1}{2}\delta^2)} - 1$ to ensure log stock price is a martingale process.

What is new to the model is the specification of jump intensity, λ_t, dynamics. Standard assumptions made in the literature is to define it as either a constant or an affine function of spot variance V_t.[10] In this paper, I take different approach to use observed firm-specific news flow to anchor the jump intensity in contrast to using latent process V_t. The empirical findings of the previous section ensures the validity of this specification which I re-confirm in the reduced-form estimation later. To keep the model within affine class for the analytical tractability, I impose the following affine functional form of jump intensity:

$$
\lambda_t = \gamma_0 + \gamma_1 I_t \tag{8}
$$

where γ_0 is a constant term that captures the residual of jump-intensity not explained by the news process I_t. This specification belongs to the two-factor affine stochastic volatility

[10] For example, see Pan (2002) and Bates (2006).

jump-diffusion framework and thus the option pricing can be done analytically using the general result of Duffie, Pan, and Singleton (2000).

Note that I only model the dynamics of individual firm's returns, thus abstracting away from the potential factor structure in returns.[11] I do so because the paper focuses on firm-level dynamics and risk premium only, instead of at portfolio level. Thus, the loss by not considering the potential factor structure is rather minimal while the gain from analytical tractability is huge.

3.2 Risk Neutralization

The model has three sources of diffusive risk represented by Brownian increments and one source of jump risk. I impose linear form of price of risk for three diffusive Brownian motions to preserve same square-root functional form under the risk-neutral measure as in Heston (1993). As discussed in Pan (2002), the pricing kernel for jump risk under the incomplete market can take virtually any arbitrary form by allowing it to change its entire distribution.

In this paper, I only consider two sources of jump risk premium, namely jump-timing and jump-size premium. Because the jump intensity λ_t is driven by the news process that is independent of the diffusive variance process V_t, the risk premium imposed on the Brownian motion dW_t^3, denoted by λ_I, effectively controls the jump-timing premium by allowing risk-neutral jump-intensity to differ from its physical counterpart. Lastly, jump-size premium is introduced by simply shifting the mean of normally distributed individual jumps by the amount of $\eta^{\mathbb{Q}} - \eta$. Below summarizes the change of measure where λ_V and λ_I denote the diffusive risk premium placed on variance and news, respectively.

[11] The factor structure and pricing of idiosyncratic risk in equity options markets have been started to gain attention only recently. See Christoffersen, Fournier, and Jacobs (2015), Gourier (2016), and Bégin, Dorion, and Gauthier (2016) for the recent development in this subject.

$$dW_t^{2,\mathbb{Q}} = dW_t^2 + \lambda_V \sigma \sqrt{V_t} dt \quad (9)$$

$$dW_t^{3,\mathbb{Q}} = dW_t^3 + \lambda_I \sigma_I \sqrt{I_t} dt \quad (10)$$

$$\eta^{\mathbb{Q}} = \eta + (\eta^{\mathbb{Q}} - \eta) \quad (11)$$

I do not specify the risk premium associated with the Brownian motion dW_t^1 associated with log stock price as it has to be fixed to have risk-neutral drift equal to the risk-free rate r. Under this change of measure, the risk-neutral dynamics preserves the following same functional form:

$$d\log(S_t) = (r - \frac{1}{2}V_t - \xi^{\mathbb{Q}}\lambda_t)dt + \sqrt{V_t}(\sqrt{1-\rho^2}dW_t^{1,\mathbb{Q}} + \rho dW_t^{2,\mathbb{Q}}) + q_t^{\mathbb{Q}} dN_t \quad (12)$$

$$dV_t = \kappa^*(\theta^* - V_t)dt + \sigma\sqrt{V_t}dW_t^{2,\mathbb{Q}} \quad (13)$$

$$dI_t = \kappa_I^*(\theta_I^* - I_t)dt + \sigma_I\sqrt{I_t}dW_t^{3,\mathbb{Q}} \quad (14)$$

where the mapping between physical and risk-neutral parameters are given by:

$$\kappa^* = \kappa + \lambda_V \sigma \quad (15)$$

$$\kappa_I^* = \kappa_I + \lambda_I \sigma_I \quad (16)$$

$$\theta^* = \frac{\kappa\theta}{\kappa^*} \quad (17)$$

$$\theta_I^* = \frac{\kappa_I \theta_I}{\kappa_I^*} \quad (18)$$

3.3 Filtering and Estimation

As all latent state continuous models do, my model also needs to jointly estimate the parameters and filter the latent states. Given that my focus is on identifying the risk premiums associated with news process, I follow the approach from Christoffersen, Heston, and Jacobs (2013) and perform a sequential estimation.[12] Specifically, the estimation procedure is divided into two steps. The first step identifies all parameters and spot states under the physical measure only using the daily returns and observed news data. Then, I take the physical parameters and states as given in the second step and only estimates the risk premium parameters using equity options data. Pros of this approach is that I can avoid the difficulty of weighting the likelihood between physical and risk-neutral counterparts. Meanwhile, the obvious cons of this approach is that it is not statistically efficient as the joint estimation procedure. Since my focus is placed heavily on the qualitative outcome of resulting pricing kernel estimates rather than exactly quantifying the risks, I argue that sequential estimation procedure is better-suited for my model.

3.3.1 Estimated under the Physical Measure

I first define the state-space system by discretizing $\mathbb{P}$-measure equations (5), (6), and (7) using Euler scheme at daily interval. The discretized state-space equations are written as below:

$$
\begin{aligned}
r_{t+1} &= (\mu - \frac{1}{2}V_t - \xi\lambda_t)\Delta t + \sqrt{\Delta t V_t}(\sqrt{1-\rho^2}\epsilon^1_{t+1} + \rho\epsilon^2_{t+1}) + \sum_{j=0}^{N_{t+1}} y_{j,t+1} && (19)\\
V_{t+1} &= V_t + \kappa(\theta - V_t)\Delta t + \sigma\sqrt{\Delta t V_t}\epsilon^2_{t+1} && (20)\\
I_{t+1} &= I_t + \kappa_I(\theta_I - I_t)\Delta t + \sigma_I\sqrt{\Delta t I_t}\epsilon^3_{t+1} && (21)\\
N_{t+1} &\sim \text{Poisson}(\gamma_0 + \gamma_1 I_t) && (22)
\end{aligned}
$$

where the innovation terms ϵ^i_{t+1} for $i = 1$ to 3 are i.i.d. standard normal random variables, the counting process N_{t+1} denotes the number of jumps between time t and $t+1 = t+\Delta t$, and individual jump terms $y_{j,t+1}$ are i.i.d. normally distributed random variables with mean η and standard deviation δ. I set the daily time interval to Δt to be 1/252 so that all parameters are expressed in annual terms.

[12] Christoffersen, Fournier, and Jacobs (2015) and Andersen, Fusari, and Todorov (2015) take the opposite approach by starting from the risk-neutral measure and sequentially estimate risk premium parameters by matching it to the physical measure.

Under the physical probability measure, I have three observables, namely daily returns, news count, and news tone. In order to simplify the filtering procedure while maintaining the empirical findings from the previous section, I first construct the tone-adjusted news count measure as follows:

$$\tilde{I}_t = \text{NewsCount} \times \exp(-\text{NewsTone}) \tag{23}$$

The intuition behind this measure is as follows. It was shown that negative news tones emphasize the size of jumps where positive news tones reduces the size of jumps (although statistically less significant) in Table 4. Since the size of individual jumps is fixed to be constant, η, in the model, I effectively embed the effect of news tone on the jump size into the news count measure by the above adjustment. The negative news tone thus results in higher tone-adjusted news count $\tilde{I}_t$ as $\exp(-\text{NewsTone})$ is greater than 1 when NewsTone is negative, and positive news tone will lower the tone-adjusted news count in the same fashion.

After the adjustment, I end up with two observables under the physical probability measure, daily log-returns r_{t+1} and tone-adjusted news count $\tilde{I}_t$. They are linked to the state equation by the simple measurement relationship that the daily log-returns are observed without an error and the news process I_t is observed with normally distributed measurement error ($\tilde{I}_t = I_t + \epsilon_t^m$). Then, I estimate the physical parameters and filter the latent states at the same time by maximizing the likelihood of observing daily log-returns and tone-adjusted news count via Particle Filtering (PF) algorithm.

3.3.2 Pricing Kernel Parameter Estimation

Given the estimated physical parameters and latent states from the previous section, I next estimate parameters associated with pricing kernel where I treat all else being fixed. The end-of-day options prices for 20 firms in the sample are obtained from OptionMetrics database. I follow literature and pick only Wednesday prices in order to avoid potential issues using daily data.[13] Commonly-used option data filters, such as strictly positive volume and in-violation of put-call parity, are applied to raw data. For each day, I pick options with maturity between 15 and 250 calendar days to ensure only liquid options are considered. Lastly, I pick six strike prices with the highest trading volume for each fixed maturity every Wednesday.

Since I am dealing with the individual equity options that are American, I follow Broadie, Chernov, and Johannes (2007b) and convert them into the corresponding European options prices.[14] All put options are converted into corresponding call options via put-call parity for the ease of implementation later. This leaves us with a total of 191,625 options for 20 individual firms.

The pricing kernel equations defined in (9), (10), and (11) mean that there are only three extra parameters to be estimated once physical parameters and states are fixed. The estimation is performed by minimizing vega-weighted root mean squared error (VWRMSE) proposed by Trolle and Schwartz (2009). It is based on simplifying assumption that vega-weighted option errors are i.i.d. normally distributed. Thus, I estimate three parameters $\Theta^{\mathbb{Q}} = \{\lambda_V, \lambda_I, \eta^{\mathbb{Q}} - \eta\}$ by minimizing the following VWRMSE-based likelihood:

$$\tilde{\Theta}^{\mathbb{Q}} = \arg\min_{\Theta} \; -\frac{1}{2}\sum_{i=1}^{N}[\log(VWRMSE^2) + e_i^2/VWRMSE^2] \tag{24}$$

$$\text{VWRMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e_j^2} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}((C_i^{Mkt} - C_i^{Mod}(\Theta))/BSV_i^{Mkt})^2} \tag{25}$$

where C_i^{Mkt}, C_i^{Mod}, and BSV_iMkt denote market price of call option, model-implied price of call option, and market-implied Black-Scholes Vega, respectively.

The option pricing formula is available in closed-form up to the Fourier transform, as the model falls into the class of affine stochastic-volatility jump-diffusion model. The following proposition summarizes the characteristic function of the log-spot stock price under the

[13] I use the previous business day if Wednesday turns out to be holiday. See Dumas, Fleming, and Whaley (1998) for more detailed description of advantage using Wednesday options data.

[14] OptionMetrics provides implied volatility computed using CRR binomial-tree model, zero-rates, and ex-post divided rates that are sufficient for this conversion.

physical measure. Since the model preserves identical functional form under the risk-neutral measure, the same formula is applied with the appropriate parameter mappings.

Proposition 1 *Denote the risk-neutral characteristic function of log-spot price by* $E_t[\exp(iu\log(S_{t+\tau})])] = S_t^{iu} f(u,\tau,V_t,I_t)$. *Then function* f *is given by*

$$f(u,\tau,V_t,L_t) = \exp(A(u,\tau) + B_1(u,\tau)V_t + B_2(u,\tau)I_t)$$

$A, B_1,$ *and* B_2 *are given as the solution to the following Ricatti ODE with the initial conditions* $A(0) = B_1(0) = B_2(0) = 0$.

$$\frac{dA}{d\tau} = (r - \xi\gamma_0)iu + \gamma_0\theta_u + \kappa\theta B_1 + \kappa_I\theta_I B_2 \tag{26}$$

$$\frac{dB_1}{d\tau} = -\frac{1}{2}u(i+u) - (\kappa - \rho\sigma iu)B_1 + \frac{1}{2}\sigma^2 B_1^2 \tag{27}$$

$$\frac{dB_2}{d\tau} = \gamma_1\theta_u - \gamma_1\xi iu - \kappa_I B_2 + \frac{1}{2}\sigma_I^2 B_2^2 \tag{28}$$

where $\theta_u = \exp(\theta iu - \frac{1}{2}\delta^2u^2) - 1$. *All three ODEs have closed-form analytical solution similar to the Heston (1993)'s expression.*

Proof. *Direct application of Duffie, Pan, and Singleton (2000) result.* ■

Once the characteristic function is available in the closed-form, European call options can be valued using the following formula following Heston (1993).

$$C_t = S_t P_1 - Ke^{-r\tau}P_2 \tag{29}$$

where the P_1 and P_2 probabilities are computed using Fourier inversion:

$$P_1 = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re[\frac{e^{iu\log(\frac{S_t}{K})}f(u+1,\tau,V_t,I_t)}{iuS_te^{r\tau}}]du \tag{30}$$

$$P_2 = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re[\frac{e^{iu\log(\frac{S_t}{K})}f(u,\tau,V_t,I_t)}{iu}]du \tag{31}$$

The integrands in the above expression vanish quickly and can be computed effectively using a numerical integration scheme such as quadrature.

4 Estimation Results

4.1 Physical Parameter Estimates

Table 6 reports parameter estimates for 20 firms in the sample. For brevity, I omit the parameter estimates associated with the information process I_t.

The speed of mean-reversion parameter κ for the diffusive variance V_t has average of 1.90 in average. Cisco has the slowest mean-reversion speed having estimated κ equal to 0.10 while Pfizer mean-reverts the fastest with κ being equal to 3.99. The magnitudes are in general consistent with those reported in the prior literature. The long-run mean level of diffusive variance θ has average estimate of 0.084, or 28.98% of annual volatility. Overall, estimates for diffusive variance process are mostly consistent with previous studies.

The estimates of individual jump-distribution parameters are summarized by its mean η and standard deviation σ. Average estimate of η is 0.3% where it varies from -5.2% of Merck & Co. to 8.1% of Amazon. In average, it is consistent with the previous findings that positive and negative jumps are equally likely for individual equity returns. Note that my model does not feature separate positive and negative sized jumps, hence the estimated average jump-size is close to 0. Along the same intuition, the expected standard deviation of individual jumps must be large. This is indeed the case, the average estimated δ is 8.2%, enormously larger than the mean.

The parameters of focus in this paper are γ_1 that measures the relationship between the news process I_t and jump-intensity λ_t. Estimated parameter γ_1 is positive in all 20 firms which is consistent with the previous non-parametric findings that more information comes with higher probability of jumps. In terms of magnitude, the average γ_1 is 0.072. Given that average I_t in the entire sample is 47.45, this roughly translates to 3.4 jumps per year explained by the news process I_t. The average total number of jumps per year is then given by γ_0, which is 1.11 in average, plus news induced jumps. Thus, news process carries the first-order importance in explaining jumps in which roughly 75% of the time-varying jump-intensity is captured by the news.

Overall, physical parameter estimates emphasize the benefit of having news process, which is filtered from observable public news arrival data, in capturing time-varying jump-intensity just using physical observables. Having established the estimates and states, I next discuss the pricing kernel estimates, which is the central findings of this paper.

4.2 Pricing Kernel Parameter Estimates

Table 7 reports estimates of three pricing kernel parameters defined in equation (9), (10), and (11) for 20 firms in the sample. Three parameters λ_V, λ_I, and $\eta^{\mathbb{Q}} - \eta$ each represents the diffusive variance risk premium, news risk premium, and jump-size risk premium.

The variance risk premium (VRP) is arguably one of the most actively researched topic in recent finance literature. The significantly negative variance risk premium, often measured by the difference between physical realized volatility and risk-neutral volatility such as VIX, is found in index options market. However, relatively little is known about the VRP at individual firm levels. Existing studies such as Carr and Wu (2009) and Drissen, Maenhout, and Vilkov (2009) have found much smaller amount of VRP in individual firm levels that are sometimes indistinguishable from being zero. In this paper, rather than trying to pin down the exact mechanisms behind why individual variance risk premiums are smaller, I focus on extracting risk premium components involving news process and studies its further implications.

The estimated diffusive variance risk premium parameter λ_V is in mostly negative with an average value of -0.119. This value is much smaller than what was estimated for index options market in the prior literature.[15] It is also consistent with the prior non-parametric findings documenting much smaller magnitude of variance risk premium in individual equity options.

[15]For example, Christoffersen, Fournier, and Jacobs (2015) reports estimated λ_V to be -1.48 without jumps in the index returns process.

Overall, the estimated diffusive variance risk premium is consistent with the prior findings.

Recall that there are two distinct risk premiums associated with the jump component, namely jump-timing risk premium λ_I and jump-size premium $\eta^{\mathbb{Q}} - \eta$. The unique feature of my model is that estimated pricing kernel jointly identifies these two parameters. The estimated jump-timing risk premium λ_I is mostly positive with a single exception of Wal Mart, averaging to the value of 1.951 across 20 firms. What this means is that instead of having a negative risk premium on the jump-timing, there is a large positive risk premium associated with the jump-timing. In other words, risk-neutral world has higher probability weight on the state of the world with smaller number of jumps. This is highly counter-intuitive, because risk-averse investors do not like jumps. Instead, estimated result implies that risk-averse investors favor having more jumps.

This puzzling finding was acknowledged in the prior literature that studied index options. For instance, in her seminal paper, Pan (2002) (Section 5.2) found that jump-intensity estimates become smaller when it was allowed to vary. Aït-Sahalia, Karaman, and Mancini (2015) (Section 5.3), using OTC variance swap data, has also found this positive jump-timing premium and concluded it as an evidence of limited ability of estimating flexible change of measure. My result, although estimated using individual equity options, is consistent with their findings. In particular, I used observed news process as an exogenous identifier of jump-intensity in order to circumvent the problem of limited ability in estimating general pricing kernel.

In order to explain the positive jump-timing premium, I rely on two arguments. First, my pricing kernel jointly identifies the jump-timing and jump-size premium. Looking at the estimated jump-size risk premium parameter $\eta^{\mathbb{Q}} - \eta$, it is found to be largely negative with a single exception of Cisco. The average jump-size premium is very large being -5.4% where the average jump-size under the physical measure was found to be only 0.3% in Table 6. Thus, aggregated jump-risk premium still remains negative once both timing and size premiums are considered. Therefore, I interpret the result as a decomposition of individual equity jump risk premium, rather than an evidence of positive jump risk premium. Second, recall that the source of jump-timing, or jump-intensity, in my model solely comes from the news process I_t. Thus, resulting estimates of the jump premiums have a direct interpretation in terms of how investors view news uncertainty. The fact that jump-timing being positive implies that investors prefers the state of the world with more news arrivals. On other hand, the negative jump-size premium implies that investors are really afraid of having large negative jumps in returns due to the news arrival. Putting these together, I conclude that news is viewed as preferable to investors once the negative impact is accounted for.

To engage economic interpretation of the findings, I consider two channels for public news to cause jumps in equity returns. The first channel argues that sudden arrival of massive amount of public information triggers the rapid increase in the noise or liquidity trading activity via distorting their belief. Other possible channel is that the arrival of public information comes together with the resolution of information asymmetry, thus resulting in sudden movements in the equity price. Both channels have same implications that public news arrival is related with return jumps, but have opposite interpretation in terms of risk premium. If the public information merely serves as a channel to increase noise trading activity, it should be negatively priced as it only increases potential jump risk faced by investors. On the other hand, if it indeed resolved the information asymmetry between privately informed and uninformed investors, it should be positively priced. Indeed, Easley and O'hara (2004)'s noisy rational expectations equilibrium model implies that firms facing higher information asymmetry requires higher return. Empirically, Zhao (Forthcoming) shows this is true by measuring firm's information intensity by its form 8-K filing frequency.

My findings are consistent with both theories. The somewhat puzzling positive jump-timing risk premium associated with the positive estimates of λ_I can be explained by the resolution of information asymmetry story. Investors seek to have more public information, although it can cause prices to jump, because it resolves the potential information asymmetry. On the other hand, they do not like public information to increase the noise trading activity and cause returns to jump, especially negatively signed jumps, thus placing more subjective probability weight on the state of the world with large negative jumps in returns. Therefore, the estimated jump-size risk premium parameter $\eta^{\mathbb{Q}} - \eta$ is largely negative. In recent article, Han, Tang, and Yang (2016) theoretically studies conflicting role of public information and shows that public information improves market liquidity but at the same time can harm price efficiency. Thus, their result is perhaps most closely related to my results that document both positive and negative implications of public information arrival.

Overall, the findings of this section highlights the importance of separating the precise source of jump risk premium. In future research, it would be interesting to study the quantitative implications of the estimated parameters in the context of noisy rational expectations equilibrium model featuring both positive and negative effect of public news arrival.

5 Conclusion

I first study the role of firm-specific public news arrival on equity return jumps. Using comprehensive news data from Factiva database, I find news to be strongly related with jumps in both physical and risk-neutral measure. I then estimate a continuous-time model with stochastic volatility and news driven jump-intensity. In particular, the variation in probability of jump is driven by the observable news process instead of latent state variables. The model is estimated in sequential fashion to ensure the clean identification of risk premium parameters associated with news. Resulting estimates reveal an important finding: jump-timing risk is positively priced while jump-size risk is significantly negatively priced. I interpret this result as investor's preference for having more public news arrivals while disliking the potential large negative returns news can induce. Thus, public news is not redundant and it carries significant risk premium. The question of exact source of news arrival risk premium is left unresolved and is left as a venue for future research.

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Table 1: **Summary Statistics of News Counts. 2000-2012**

	Summary Statistics			
Company Name	Total	Mean	Median	Std. Dev.
Microsoft	325,150	71.0	92	53.4
GE	265,302	57.9	72	82.9
IBM	165,213	36.3	45	31.2
Chevron	106,356	23.7	29	21.8
UTC	53,809	12.6	14	13.1
Pfizer	111,363	24.7	29	26.5
Johnson & Johnson	103,271	23.3	26	26.5
Merck & Co.	51,170	12.3	12	26.2
Disney	160,245	34.9	41	15.5
JP Morgan	232,971	51.2	63	48.2
WalMart	165,220	36.0	43	100.4
American Express	54,216	12.3	13	83.6
Intel	171,146	37.8	41	17.5
Bank of America	202,898	44.9	45	86.0
Verizon	159,291	35.8	42	113.6
AT&T	139,631	31.0	37	99.3
Cisco	113,818	25.4	29	78.4
Yahoo	85,902	19.6	20	30.9
Amazon	60,519	13.6	14	17.5
Ebay	73,672	16.5	19	18.3
Total	3,303,317	44.3	32	67.9

This table reports summary statistics of daily news counts downloaded from the Factiva database. The first column reports the total number of news articles for each firm during the sample period. The last three columns report the daily mean, median, and standard deviation of news counts for each firm. The sample period is from January 2000 to July 2012.

Table 2: **Summary Statistics of Daily News Tones. 2000-2012**

	Summary Statistics				
Company Name	Mean	Std. Dev.	25 Prctile	Median	75 Prctile
Microsoft	-5.33	13.67	-11.79	-3.06	3.35
GE	-2.32	11.32	-7.78	-1.72	3.39
IBM	4.32	12.98	-2.18	5.01	11.68
Chevron	-7.21	17.58	-15.68	-6.96	0.23
UTC	-2.93	18.91	-11.08	-0.78	6.28
Pfizer	-6.96	16.99	-15.27	-5.90	1.74
Johnson & Johnson	-3.32	16.26	-10.03	-1.61	4.36
Merck & Co.	-4.53	23.91	-12.75	-0.44	5.47
Disney	-1.46	13.02	-7.84	-0.49	5.65
JP Morgan	-9.39	12.79	-16.11	-7.40	-1.39
WalMart	-10.30	13.61	-17.31	-8.99	-1.84
Americal Express	-2.19	21.48	-12.42	-0.37	8.20
Intel	-0.16	15.08	-7.48	1.10	8.58
Bank of America	-10.67	15.07	-17.78	-9.51	-1.71
Verizon	-6.16	15.57	-13.15	-4.70	2.33
AT&T	-5.64	14.88	-12.73	-4.39	2.59
Cisco	3.71	16.29	-5.01	4.34	12.78
Yahoo	-2.52	18.21	-11.48	-1.28	7.77
Amazon	-0.76	19.65	-9.93	0.00	9.68
Ebay	-4.85	20.06	-13.53	-3.27	4.88
Total	-3.92	17.13	-12.05	-2.67	4.93

This table reports the summary statistics of daily news tones (in percentage). The daily news tone variable is constructed by analyzing the first paragraph of each news article. I search for the percentage of positive and negative words using the list from Loughran and McDonald (2011). Then, tones from each individual articles are aggregated to the daily level using the total number of words in each article as a weight. The sample period is from January 2000 to July 2012.

Table 3: **Effect of News Counts on the Probability of a Daily Jump. 2000-2012**

	(1) $J99$	(2) $J95$	(3) J_099	(4) J_095
Intercept	-4.9743^{***}	-4.5062^{***}	-3.3069^{***}	-2.4112^{***}
	(0.0847)	(0.0596)	(0.0282)	(0.0131)
NewsCount	0.1944^{***}	0.1885^{***}	0.1747^{***}	0.1579^{***}
	(0.0452)	(0.0443)	(0.0405)	(0.0328)
NewsTone	-0.0710	-0.0693	-0.0062	-0.0061
	(0.0495)	(0.0427)	(0.0233)	(0.0164)
Ret_{t-1}	-1.8709	-2.6763	-2.7729^{**}	-3.6652^{***}
	(2.6206)	(1.8715)	(1.1521)	(0.8004)

This table reports the coefficients from the pooled logit regression of daily news count, news tone, and lagged return on the daily jump indicator defined using Lee and Mykland (2008). The explanatory variables are the total number of news reported on Factiva database each day and its news tone, standardized to have same mean and standard deviation across firms, and lagged daily returns. News tone measure is constructed first at each individual article level by counting the number of positive and negative words from Loughran and McDonald (2011), they are then aggregated by a value-weighting scheme using the total number of words in the article. The daily return jump indicator is identified using 4 different statistics. $J99$ and $J95$ indicators use Lee and Mykland (2008)'s Lemma 1 statistic at 99% and 95% significance, respectively. I use the correction term from Gilder, Shackleton, and Taylor (2014). The J_099 and J_095 indicators use looser bound from the normal distribution as in Theorem 1 of Lee and Mykland (2008). Each of four statistics $\{J99, J95, J_099, J_095\}$ thus identifies the jump day if the absolute value of daily return is above $\{5.1024, 4.4881, 3.2283, 2.4565\}$ times of the daily spot volatility. The sample period is from January 2000 to July 2012. Statistical significance levels of 1%, 5%, and 10% are indicated with ***, **, and *, respectively. Standard errors clustered at individual firm levels are reported in parentheses.

Table 4: **Effect of News Counts and Tones on Daily Jump Size. 2000-2012**

	(1) $J99$	(2) $J95$	(3) $J_0 99$	(4) $J_0 95$
Intercept	0.0148***	0.0117***	0.0100***	0.0063***
	(0.0047)	(0.0034)	(0.0014)	(0.0009)
NewsCount	-0.0006	-0.0007	-0.0008	-0.0008
	(0.0021)	(0.0017)	(0.0010)	(0.1074)
NewsTone	1.8468***	1.4412***	0.8202***	0.5045***
	(0.2355)	(0.1721)	(0.0786)	(0.0432)
N	452	713	2267	5243
R^2	12.65%	9.33%	4.72%	2.61%
Positive Jumps Only	(1) $J99$	(2) $J95$	(3) $J_0 99$	(4) $J_0 95$
Intercept	0.0609***	0.0583***	0.0485***	0.0414***
	(0.0044)	(0.0032)	(0.0013)	(0.0007)
NewsCount	0.0168***	0.0127***	0.0086***	0.0053***
	(0.0025)	(0.0019)	(0.0011)	(0.0006)
NewsTone	-0.2758	-0.1853	-0.0793	−0.0899**
	(0.2418)	(0.1823)	(0.0794)	(0.0429)
N	241	374	1256	2816
R^2	16.96%	10.42%	4.75%	2.57%
Negative Jumps Only	(1) $J99$	(2) $J95$	(3) $J_0 99$	(4) $J_0 95$
Intercept	−0.0553***	−0.0514***	−0.0429***	−0.0371***
	(0.0037)	(0.0026)	(0.0012)	(0.0007)
NewsCount	−0.0066***	−0.0073***	−0.0064***	−0.0046***
	(0.0013)	(0.0011)	(0.0007)	(0.0004)
NewsTone	0.8593***	0.7561***	0.5142***	0.3807***
	(0.1736)	(0.1264)	(0.0607)	(0.0342)
N	211	339	1011	2427
R^2	25.85%	24.20%	15.55%	9.75%

This table reports the coefficients from the linear regression of daily news counts and news tones on the daily jump size. I assume the entire daily return is due to the jump component on the jump days detected using Lee and Mykland (2008). NewsCount measures the absolute number of news articles appeared in the Factiva database per each day. The NewsTone measure is constructed first at each individual article level by counting the number of positive and negative words from Loughran and McDonald (2011), then they are aggregated by a value-weighting scheme using total number of words in the article. The daily return jump indicator is identified using 4 different statistics. $J99$ and $J95$ indicator uses Lee and Mykland (2008)'s Lemma 1 statistic at 99% and 95% significance, respectively. We use the correction term from Gilder, Shackleton, and Taylor (2014). $J_0 99$ and $J_0 95$ indicator uses looser bound from the normal distribution as in Theorem 1 of Lee and Mykland (2008). Each of the four statistics $\{J99, J95, J_0 99, J_0 95\}$ thus identifies the jump day if the absolute value of daily return is above $\{5.1024, 4.4881, 3.2283, 2.4565\}$ times the daily spot volatility. The sample period is from January 2000 to July 2012. Statistical significance levels of 1%, 5%, and 10% are indicated with ***, **, and *, respectively. Standard errors are reported in parentheses.

Table 5: **Effect of News Counts and Tones on IV-SKEW. 2000-2012**

	(1)	(2)	(3)	(4)
Intercept	-0.0065^{***}	0.0070^{***}	-0.0067^{***}	-0.0073^{***}
	(0.0011)	(0.0011)	(0.0011)	(0.0011)
NewsCount			0.0018^{**}	0.0017^{**}
			(0.0008)	(0.0008)
NewsTone		-0.3563^{***}		-0.3547^{***}
		(0.0548)		(0.0548)
ATM IV	0.2035^{***}	0.1996^{***}	0.2047^{***}	0.2008^{***}
	(0.0044)	(0.0044)	(0.0044)	(0.0045)
N	3020	3020	3020	3020
R^2	41.29%	42.10%	41.38%	42.18%

This table reports the coefficients from the linear regression of monthly average news counts and news tones on the monthly average IV-SKEW. IV-SKEW is defined as the difference between the implied volatility of the call option having Black-Scholes delta closest to 0.5 and put option having delta closest to -0.25. Both options are chosen to have maturity as close as possible to 30 days. NewsCount measures the absolute number of news articles that appeared in Factiva database during each month. The NewsTone measure is constructed first at each individual article level by counting the number of positive and negative words from Loughran and McDonald (2011), then they are aggregated by value-weighting scheme using total number of words in the article. Statistical significance levels of 1%, 5%, and 10% are indicated with ***, **, and *, respectively. Standard errors are reported in parentheses.

Table 6: **Model Parameter Estimates under the Physical Measure**

	Estimated Parameters							
Company Name	κ	θ	σ	η	δ	γ_0	γ_1	ρ
Microsoft	2.46	0.045	0.53	0.015	0.105	0.42	0.035	-0.43
GE	1.36	0.074	0.45	0.004	0.075	0.89	0.036	-0.49
IBM	2.56	0.057	0.56	0.012	0.066	1.00	0.037	-0.50
Chevron	2.51	0.074	0.31	0.005	0.074	1.00	0.012	-0.50
UTC	2.60	0.091	0.31	0.007	0.050	0.95	0.091	-0.49
Pfizer	3.99	0.049	0.44	-0.011	0.065	1.07	0.064	-0.45
Johnson & Johnson	3.20	0.032	0.45	0.004	0.046	1.14	0.130	-0.42
Merck & Co.	0.45	0.049	0.53	-0.052	0.087	1.02	0.173	-0.45
Disney	0.60	0.058	0.48	0.014	0.053	1.15	0.056	-0.60
JP Morgan	1.25	0.274	0.90	-0.002	0.086	0.70	0.047	-0.38
Wal Mart	2.53	0.050	0.45	0.015	0.043	1.18	0.043	-0.38
Americal Express	1.40	0.114	0.60	0.003	0.085	0.96	0.178	-0.30
Intel	1.61	0.138	0.48	-0.039	0.084	0.96	0.058	-0.35
Bank of America	0.64	0.048	0.55	-0.010	0.147	0.51	0.024	-0.50
Verizon	1.87	0.047	0.49	0.002	0.051	1.25	0.049	-0.50
AT&T	1.69	0.075	0.43	0.006	0.067	1.01	0.054	-0.48
Cisco	0.10	0.161	0.56	0.002	0.082	1.03	0.056	-0.49
Yahoo	1.93	0.064	0.64	-0.003	0.184	3.56	0.007	-0.26
Amazon	1.97	0.130	0.65	0.081	0.165	1.00	0.214	-0.50
Ebay	3.19	0.050	0.52	-0.001	0.032	1.49	0.073	-0.47
Average	1.90	0.084	0.52	0.003	0.082	1.11	0.072	-0.45

This table reports the estimated model parameters under the physical measure using daily returns and news counts from Jan, 2000 to Jul, 2012 for 20 individual equities. A Particle Filtering (PF) algorithm was used to estimate the parameters by maximizing the likelihood of observing daily returns and tone-adjusted news counts. The tone-adjusted news counts is defined as below:

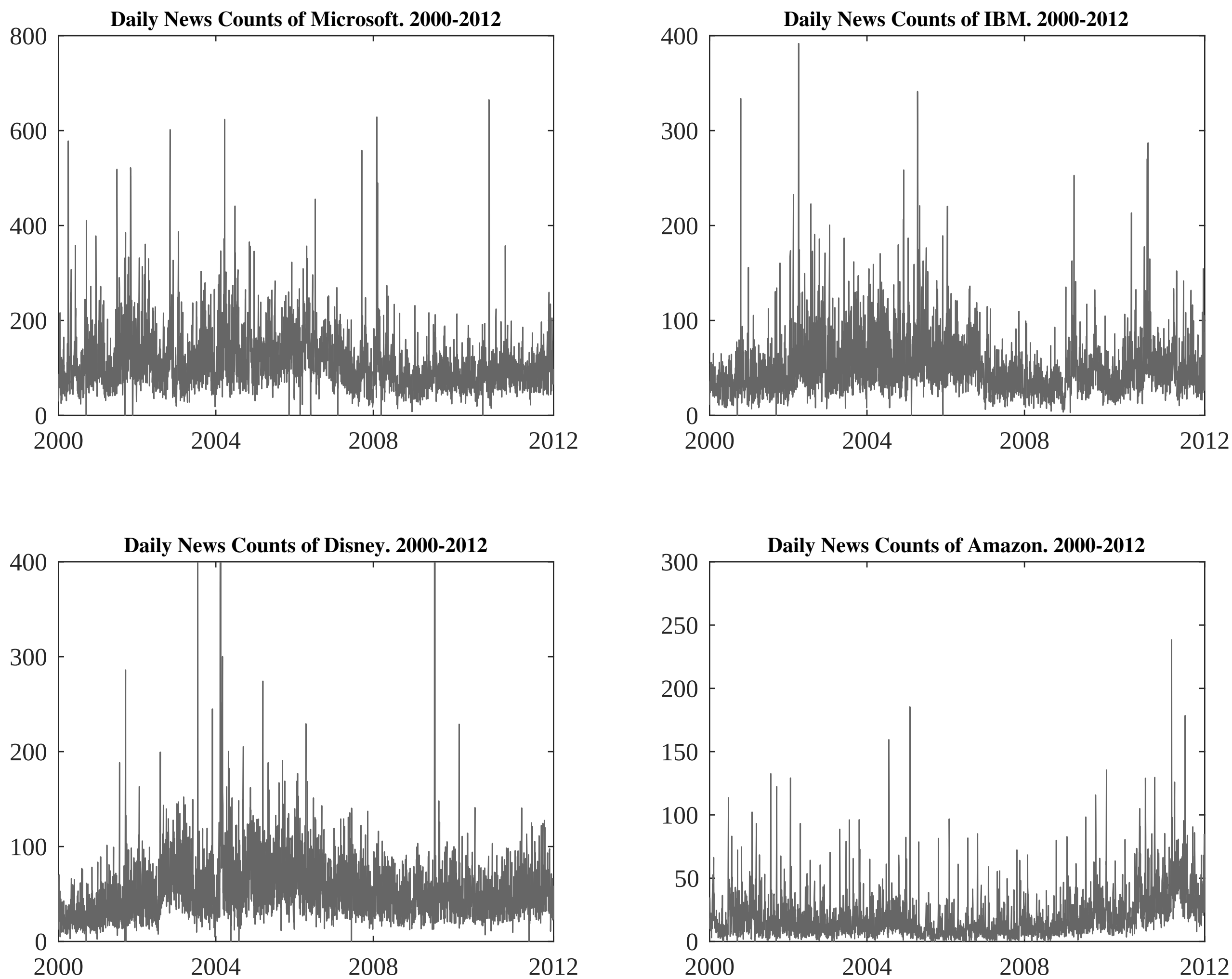
$$\tilde{I}_t = \text{NewsCount} \times \exp(-\text{NewsTone})$$

Table 7: **Pricing Kernel Parameter Estimates**

	Estimated Parameters		
Company Name	λ_V	λ_I	$\eta^{\mathbb{Q}} - \eta$
Microsoft	-0.888	1.629	-0.088
GE	-0.623	1.626	-0.074
IBM	-0.509	0.167	-0.051
Chevron	-0.353	1.799	-0.139
UTC	-1.842	1.008	-0.028
Pfizer	0.060	0.033	-0.059
Johnson & Johnson	0.007	0.007	-0.035
Merck & Co.	0.000	0.000	-0.009
Disney	0.002	1.398	-0.032
JP Morgan	0.497	1.027	-0.021
Wal Mart	-0.042	-0.006	-0.026
Americal Express	-0.384	2.647	-0.099
Intel	0.448	6.528	-0.079
Bank of America	0.202	0.787	-0.057
Verizon	-0.191	0.358	-0.041
AT&T	-0.073	0.096	-0.033
Cisco	0.087	0.064	0.007
Yahoo	1.282	18.222	-0.025
Amazon	-0.015	1.609	-0.147
Ebay	-0.039	0.017	-0.041
Average	-0.119	1.951	-0.054

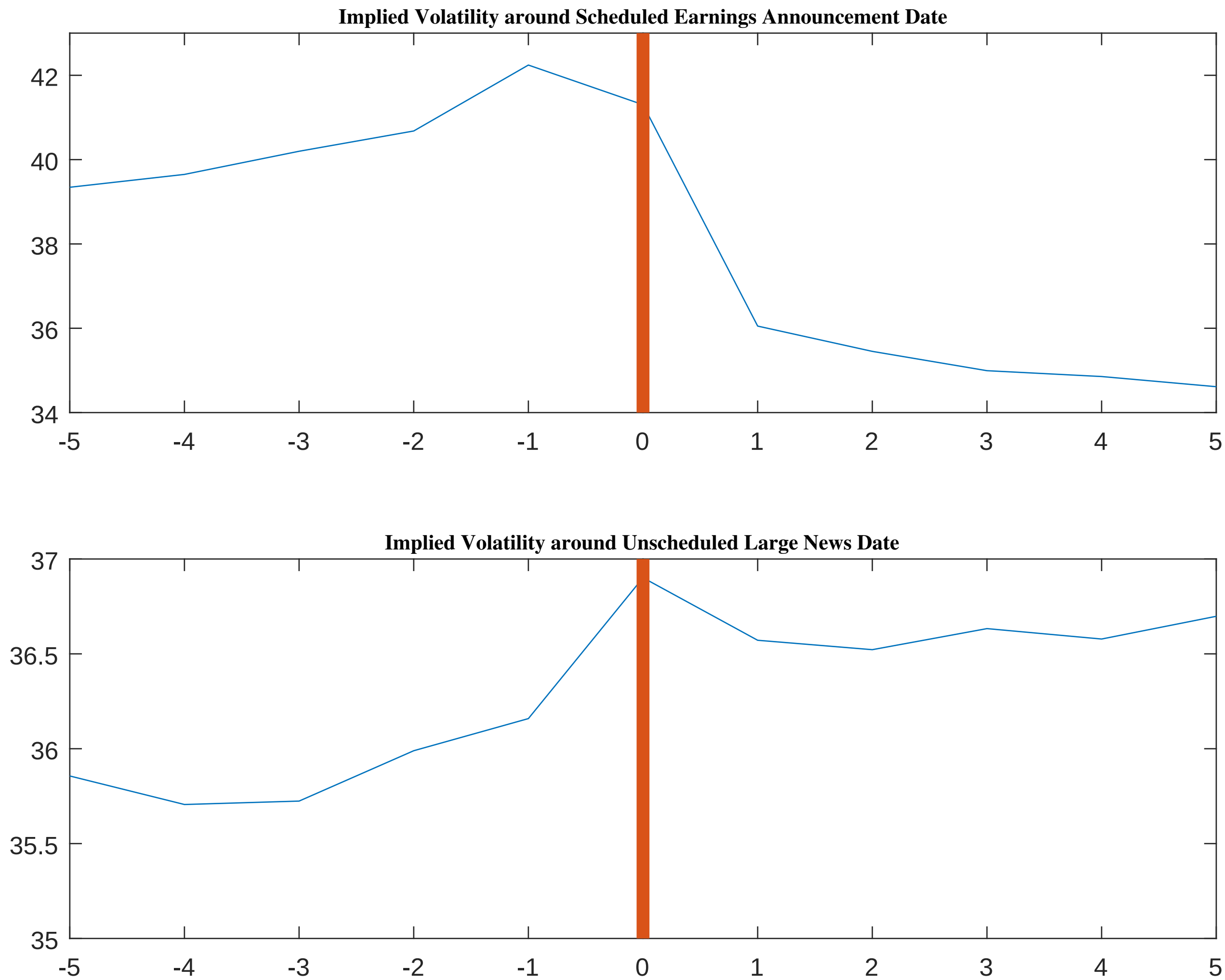
This table reports the pricing kernel parameters estimated by minimizing Vega-weighted root mean squared error (VWRMSE). Estimation was performed first by fixing the physical dynamics parameters and spot variances filtered from Table 6, then only allowing the pricing kernel parameters to vary. Three pricing kernel parameters λ_V, λ_I, and $\eta^{\mathbb{Q}} - \eta$ each represents the diffusive variance risk premium, news risk premium, and jump size risk premium, respectively.

Figure 1: **Time-series Plot of Daily News Counts for Selected Firms. 2000-2012**



This figure plots the time-series of daily news counts of four selected firms. The sample begins in Jan, 2000 and ends Jul, 2012. Y-axis represents absolute counts of news articles that appear in Factiva database each day.

Figure 2: **Implied Volatility Around Scheduled vs. Unscheduled Dates**



This figure plots the behavior of the average implied volatility around scheduled vs. unscheduled news dates. The top panel plots the average implied volatility in the [-5,5]-day window around the scheduled quarterly earnings announcement dates. The bottom panel plots the average implied volatility in the [-5,5]-day window around the dates in top 2% range of news counts that are not within 5 days from the earnings announcement date. Both panels plot the average implied volatility of all 20 firms in the sample from Jan, 2000 to Jul, 2012.

Appendix

A Benchmark Model

In this section, I provide a result comparing the performance of my model to the benchmark model. Benchmark model considered is the plain stochastic-volatility jump-diffusion (SVJ) model with constant jump-intensity, thus serves as a special case of my model. Specifically, it corresponds to the case $\gamma_1 = 0$.

Table A.1 reports the estimated parameter for the benchmark model. The estimated parameters are mostly similar to the full news model estimates reported in Table 6. To compare the performance of two models, Table A.2 provides the negative log-likelihood of observing daily returns as well as model-implied number of expected jumps per year. Improvement in return likelihood is observed in virtually all 20 firms in-sample, with varying degree of the differences between two. News model implies mostly more expected number of jumps, average being 3.72 jumps per year compared to 3.17 of the benchmark model case.

B Variance Risk Premium

So far, I have focused on the implications of point estimates of each parameters, and thus have not quantified model-implied risk premiums for individual firms. Given the parameter estimates and the affine structure of the model, it is straightforward to extract the relevant measures.

First, the model-implied variance risk premium is computed as the difference between the unconditional variance of log-returns under the risk-neutral and physical probability measures. As the model features two sources of risks, diffusive and jump, the resulting functional form for variance risk premium has also two component stemming from each of two. The following proposition provides an expression for the variance risk premium.

Proposition 2 *The unconditional variance risk premium is given by*

$$VRP = \underbrace{(\theta^* - \theta)}_{Diffusive} + \underbrace{[(\gamma_0 + \gamma_1\theta_I^*)((\eta^{\mathbb{Q}})^2 + \delta^2) - (\gamma_0 + \gamma_1\theta_I)(\eta^2 + \delta^2)]}_{Jump} \tag{32}$$

Table A.3 reports the model-implied variance risk premiums. The first three columns report diffusive, jump, and total variance risk premiums, respectively. Consistent with the previous literature, the resulting variance risk premium is very small. Also, diffusive and jump components have similar magnitude of contribution on average to total variance risk premium.

To convert the numbers into more conventional definition of variance risk premium that uses the difference between annualized volatility, the last column reports the following expression.

$$\text{VRP in Vol.} = \sqrt{\theta^* + (\gamma_0 + \gamma_1 \theta_I^*)((\eta^{\mathbb{Q}})^2 + \delta^2)} - \sqrt{\theta + (\gamma_0 + \gamma_1 \theta_I)(\eta^2 + \delta^2)} \tag{33}$$

Again, the average variance risk premium is very small, being only -0.36% in annualized volatility terms.

Table A.1: **Benchmark Model Parameter Estimates under the Physical Measure**

	Estimated Parameters						
Company Name	κ	θ	σ	η	δ	λ	ρ
Microsoft	2.51	0.057	0.45	0.013	0.084	2.74	-0.48
GE	2.36	0.052	0.39	0.007	0.061	2.73	-0.18
IBM	2.56	0.057	0.56	0.012	0.066	2.70	-0.24
Chevron	2.54	0.075	0.30	0.005	0.073	1.42	-0.52
UTC	2.57	0.089	0.31	0.007	0.050	2.62	-0.51
Pfizer	2.59	0.077	0.32	-0.013	0.058	2.48	-0.49
Johnson & Johnson	2.62	0.045	0.31	0.005	0.041	3.82	-0.49
Merck & Co.	0.44	0.050	0.51	-0.051	0.085	4.78	-0.09
Disney	2.61	0.113	0.33	0.012	0.076	2.50	-0.49
JP Morgan	0.49	0.100	0.59	0.010	0.163	4.55	-0.50
Wal Mart	2.58	0.067	0.32	0.011	0.042	2.95	-0.49
Americal Express	1.64	0.074	0.50	0.003	0.081	2.78	-0.17
Intel	2.58	0.071	0.45	-0.029	0.082	2.19	-0.41
Bank of America	0.64	0.047	0.53	-0.010	0.149	2.70	-0.50
Verizon	1.29	0.076	0.39	0.002	0.065	2.49	-0.47
AT&T	2.09	0.056	0.39	0.006	0.089	2.00	-0.40
Cisco	0.10	0.156	0.55	0.002	0.079	4.83	-0.43
Yahoo	1.93	0.064	0.64	-0.003	0.176	3.56	-0.26
Amazon	1.97	0.129	0.62	0.081	0.165	6.55	-0.37
Ebay	1.50	0.060	0.50	-0.001	0.036	3.00	-0.41
Average	1.88	0.076	0.45	0.003	0.086	3.17	-0.40

This table reports the estimated benchmark model parameters under the physical measure using daily returns from Jan, 2000 to Jul, 2012 for 20 individual firms. Particle Filtering (PF) algorithm was used to estimate the parameters by maximizing the likelihood of observing daily returns.

Table A.2: **Comparison between Benchmark Model and News Model**

Company Name	Benchmark Likelihood	News Model Likelihood	Benchmark λ	News Model $E[\lambda]$
Microsoft	-8402.44	-8418.78	2.74	4.30
GE	-8481.90	-8488.88	2.73	3.95
IBM	-8920.27	-8921.26	2.70	2.88
Chevron	-8822.36	-8824.40	1.42	1.44
UTC	-8595.54	-8602.05	2.62	2.54
Pfizer	-8705.53	-8730.83	2.48	3.50
Johnson & Johnson	-9887.53	-9931.67	3.82	5.56
Merck & Co.	-8583.35	-8593.89	4.78	4.01
Disney	-8179.39	-8231.86	2.50	4.05
JP Morgan	-7830.30	-7845.75	4.55	4.61
Wal Mart	-9080.98	-9114.28	2.95	3.71
Americal Express	-8044.31	-8048.48	2.78	4.13
Intel	-7595.94	-7629.32	2.19	4.18
Bank of America	-8010.00	-8024.50	2.70	2.32
Verizon	-8949.93	-8952.91	2.49	3.95
AT&T	-8822.86	-8826.19	2.00	3.55
Cisco	-7459.82	-7459.40	4.83	3.33
Yahoo	-6744.76	-6745.92	3.56	3.76
Amazon	-6574.41	-6604.12	6.55	5.22
Ebay	-8749.92	-8750.22	3.00	3.31
Average	-8322.08	-8337.23	3.17	3.72

This table compares the return likelihood and estimated unconditional number of jumps per year between the benchmark model and the news model. In the benchmark model, parameter λ represents unconditional number of jumps per year. In the news model, the annual jump-intensity is equal to $\gamma_0 + \gamma_1 I_t$, thus $E[\lambda] = \gamma_0 + \gamma_1 E[I_t]$, where $E[I_t]$ is computed as the in-sample average of filtered sates I_t.

Table A.3: **Variance Risk Premium implied by Model Parameters**

Company Name	Diffusive VRP	Jump VRP	Total VRP	VRP in Vol.
Microsoft	0.0107	-0.0125	-0.0019	-0.31%
GE	0.0191	0.0006	0.0198	3.04%
IBM	0.0071	0.0030	0.0102	1.86%
Chevron	0.0034	0.0206	0.0240	3.92%
UTC	0.0255	-0.0004	0.0251	3.79%
Pfizer	-0.0003	0.0167	0.0164	3.05%
Johnson & Johnson	0.0000	0.0049	0.0049	1.13%
Merck & Co.	0.0000	0.0040	0.0040	0.67%
Disney	-0.0001	-0.0034	-0.0035	-0.66%
JP Morgan	-0.0720	-0.0174	-0.0894	-8.72%
Wal Mart	0.0004	-0.0004	0.0000	-0.01%
Americal Express	0.0224	0.0049	0.0273	3.44%
Intel	-0.0163	-0.0062	-0.0225	-2.79%
Bank of America	-0.0070	-0.0032	-0.0102	-1.69%
Verizon	0.0025	0.0032	0.0057	1.16%
AT&T	0.0014	0.0006	0.0020	0.32%
Cisco	-0.0514	-0.0013	-0.0528	-6.64%
Yahoo	-0.0191	-0.0036	-0.0226	-2.67%
Amazon	0.0006	-0.0775	-0.0768	-7.46%
Ebay	0.0003	0.0059	0.0062	1.32%
Average	-0.0036	-0.0031	-0.0067	-0.36%

This table reports the variance risk premium implied by the estimated model parameters. The first three columns report diffusive, jump, and total variance risk premium, respectively, computed using the expression given in the equation (32). The last column (VRP in Vol.) reports the total variance risk premium computed as the difference between annualized volatility under the risk-neutral and physical measure. The exact expression is given in the equation (33), also shown below.

$$\text{VRP in Vol.} = \sqrt{\theta^* + (\gamma_0 + \gamma_1 \theta_I^*)((\eta^{\mathbb{Q}})^2 + \delta^2)} - \sqrt{\theta + (\gamma_0 + \gamma_1 \theta_I)(\eta^2 + \delta^2)}$$