Jumps and Information Flow in Financial Markets

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*I am very grateful to Per Mykland, George Constantinides, Federico Bandi, Ruey Tsay, Pietro Veronesi, Geert Bekaert (the Co-Editor), and two anonymous referees for their helpful advice, suggestions, and comments. I also thank Gurdip Bakshi, Tim Bollerslev, Yacine Ait-Sahalia, Cheol Eun, Narayan Jayaraman, Jonathan Clarke, Chayawat Ornthanalai, Amit Goyal, and Frank Yu for their comments and encouragements and the participants of the Volatility Conference at the University of Chicago, the 8th SAET Conference on Current Trend in Economics, Workshop on Financial Econometrics at the University of Toronto, and Finance Seminars at the University of Maryland, University of Wisconsin-Madison, University of Houston, Arizona State University, and Georgia Tech for their comments. Financial support for this research from the Stevanovich Center for Financial Mathematics at the University of Chicago is gratefully acknowledged. Comments are welcome and errors are mine. Please address any correspondence to: Suzanne S. Lee, address: Georgia Institute of Technology, College of Management, Atlanta, GA 30332, phone: 404.822.1552, fax:404.894.6030, e-mail: suzanne.lee@mgt.gatech.edu.

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Abstract

This paper investigates the predictability of jump arrivals in U.S. stock markets. Using a new test that identifies jump predictors up to the intraday level, I find that jumps are likely to occur shortly after macroeconomic information releases such as Fed announcements, nonfarm payroll reports, and jobless claims as well as market index jumps. I also find firm-specific jump predictors related to earnings releases, analyst recommendations, past stock jumps, and dividend dates. Evidence suggests that distinguishing systematic jumps from idiosyncratic jumps is possible using the characteristics of jump predictors. Finally, I present a short-term jump size clustering.

JEL classification: G10, C14

Key words: mixed unobservability, jump predictor tests, partial likelihood, systematic vs. idiosyncratic risk, jump size clustering, high frequency data

Much recent research in finance has found empirical evidence of jumps in equity returns. Their presence has been successfully used to better explain various market phenomena.[1] Nevertheless, the role of real-time information for predicting jumps in stock markets has not been thoroughly investigated in the literature. In this article, I analyze the predictability of jumps in individual stock returns, using both macroeconomic and firm-specific news releases and I present how the information is reflected in stock prices as jumps.[2] This analysis naturally allows a novel decomposition of individual stock jumps into systematic and idiosyncratic jumps.

To accomplish this goal, I identify important jump predictors and assess their relative importance and precision for the purpose of developing stochastic jump intensity models. Assuming that an individual equity price follows a jump diffusion process with stochastic jump intensity, I must resolve the econometric problem of identifying jump predictors using discrete data from continuous-time models. I refer to this as the mixed unobservability problem. It arises from the simultaneous presence of two unobservability problems. The first is caused by the difficulty we usually face when making an inference for a continuous-time jump counting process (without diffusion) using discrete observations. The second problem results from the presence of the diffusion process. The mixture of these two makes jumps in jump diffusion models unobservable; thus, the identification of jump predictors becomes difficult.

As a resolution, I propose an inference technique called the Jump Predictor Test (JPT). It allows us to estimate a regression-type jump intensity model and apply standard hypothesis tests in order to identify significant jump predictors. In this way, we can predict ex ante whether jumps are likely to occur, what kind of jumps are more likely to occur, and when they are more likely to occur, given the available information. The idea underlying this JPT is simple. I first detect the location of jumps from the return series by multiple nonparametric jump detection tests.[3] This is a necessary step before applying the JPT. Then, I suggest a likelihood inference for the JPT using time-series data for both jumps and information covariates. I prove that this technique asymptotically makes the effect of the mixed unobservability problem negligible, allowing good jump predictors to be identified. I discuss a theory of likelihood inference justifying this approach and provide a guide for tests and general applications.

Using the JPT, an empirical study is performed to refine our understanding of how jumps in U.S. individual stock returns respond to market information releases. Using high frequency data from January 4, 1993 to December 31, 2008 for Dow Jones Industrial Average component stocks, I demonstrate that jumps are predictable to some extent. I link stochastic jump arrivals to the most important predictors related to four macroeconomic and four firm-specific information variables: U.S. Federal Open Market Committee (FOMC) decisions, overall market jumps detected in the S&P 500 market index, U.S. nonfarm payroll employment reports, initial unemployment claims, earnings releases, analyst recommendations, dividend dates, and past jump arrivals for each firm.

Jumps are likely to occur within a short time horizon such as 30 minutes following macroeconomic information releases. The indicator for the 30 minutes following FOMC announcements turns out to be the most influential predictor of U.S. individual stock jumps, followed by overall market jumps. Macroeconomic predictors tend to play a more important role in pinning down intraday jump dynamics for individual stocks than do firm-specific predictors, evidence which has not been clearly uncovered in the literature. The JPT enables us to uniquely capture an unusual impact of real-time information on price jumps up to the intraday level, which is difficult to show with conventional methodologies.

I also find that firm-specific predictors perform differently from macroeconomic predictors. The firm-specific predictors are indicators for time horizons within one day before earnings releases, within the first 30 minutes following analyst recommendations, within three hours of the arrival of previous jumps in the same stock, and within the morning hours of ex-dividend dates. The jump probability being higher within one day before earnings releases suggests the possibility of information leakage before the pre-scheduled announcements.

I further investigate the role of information characteristics in distinguishing systematic jumps from idiosyncratic jumps. This distinction between systematic jumps and idiosyncratic jumps is expected to be beneficial in portfolio or risk management, with better understanding of the determinants of non-diversifiable risk in highly volatile markets. After classifying systematic and idiosyncratic jumps, I separately estimate the systematic and idiosyncratic jump intensity models for each firm, where all the aforementioned predictors are used. I find that all the macroeconomic information predictors remain strongly significant for systematic jumps, emphasizing their important role in systematic jump prediction. Idiosyncratic jumps are strongly induced by earnings and analysts' recommendation releases. In general, idiosyncratic jump prediction is less precise than systematic jump prediction using the available information. Finally, I use the JPT methodology to investigate jump size dynamics, showing that they tend to cluster by size. This simple application demonstrates the possibility of the JPT being applied to other studies on jump modeling using various types of jumps in other markets.

The remainder of the paper is organized as follows. Section 1 sets up the general theoretical framework. Section 2 explains the inference theory for the JPT. Section 3 reports the JPT's finite sample performance. Readers who are interested mainly in application of the JPT may turn directly to Section 4, which presents the empirical evidence. Section 5 concludes.

1 Theoretical Model

I employ a one-dimensional asset return process with a complete probability space $(\Omega, \mathcal{F}_t, \mathcal{P})$, where Ω is the set of market events, $\{\mathcal{F}_t : t \in [0,T]\}$ is an information filtration[4] for market participants up to time t, and $\mathcal{P}$ is a data-generating measure in continuous time. Let the continuously compounded return be written as $d\log S(t)$ for $t \geq 0$, where $S(t)$ is the asset price at t under $\mathcal{P}$. The log return process $d\log S(t)$ is represented by the following stochastic differential equation (SDE):

$$d\log S(t) = \mu(t)dt + \sigma(t)dW(t) + Y(t)dJ(t), \tag{1}$$

where $W(t)$ is an $\mathcal{F}_t$-adapted standard Brownian motion and drift $\mu(t)$ and spot volatility $\sigma(t)$ are $\mathcal{F}_t$-adapted and bounded processes. This model without its jump component describes diffusive risk in returns due to normal randomness in markets.

In order to frame the dynamic jump arrivals, which depend on heterogeneous information flow over time, I set $J(t) = \int_0^t dJ(s)$ to be a doubly stochastic Poisson process, that is, a non-homogeneous Poisson process with an integrated stochastic intensity $\Lambda_\theta(t) = \int_0^t d\Lambda_\theta(s)ds$.[5] The instantaneous intensity process with respect to the filtration up to time t is $d\Lambda_\theta(t) = E(dJ(t)|\mathcal{F}_{t-})$. Its integrated intensity process $\Lambda_\theta(t)$ is specified by a q-dimensional parameter $\theta = (\theta_1, .., \theta_q) \in \Theta$, which is a subset of the q-dimensional Euclidean space. I can thus write

$$\Lambda_\theta(t) = \int_0^t d\Lambda_\theta(s)ds = \gamma(t, X(t); \theta), \tag{2}$$

where $X(t)$ denotes the conditional information predictors that affect the likelihood of jump arrivals, and γ is a general function of time and the predictors. The counting process considered in this paper is assumed to be nonexplosive with finite jump intensity. This assumption excludes models with infinite-activity jumps.[6] The term $Y(t)dJ(t)$ describes more dramatic and unusually large risk occurring with the aforementioned stochastic intensity. Here, $Y(t)$ represents the jump size and has a mean of $\mu_y(t)$ and a standard deviation of $\sigma_y(t)$, which can be time-varying. The jump counting process $J(t)$ and the diffusion $W(t)$ are independent from one another.

I assume a time horizon T and a number of observations n within the horizon. The observation of asset prices $S(t)$ and informational predictor $X(t)$ occur only at discrete times $0 = t_0 < t_1 < ... < t_n = T$. For simplicity, I set observation times for both $S(t)$ and $X(t)$ as equally spaced: $\Delta t = t_i - t_{i-1} = \frac{T}{n}$. This simplified assumption can be easily generalized to non-equidistant cases by letting $\max_i |t_i - t_{i-1}| \to 0$. Assumptions (**Assumptions C** and **D**) on the drift and volatility as well as the intensity function are given in the Appendix for the readers' convenience. Simply put, these assumptions allow for stochastic drift and volatility. The integrated jump intensity function $\Lambda_\theta(t)$ is only required to be continuous and three times differentiable with respect to θ. $X(t)$ can include multiple covariates and these covariates should be determined according to information available at any time up to t.

2 Inference for Stochastic Jump Predictors

In making statistical inferences using discrete data from the jump diffusion model as stated in equation (1), econometricians face two different unobservability problems. The first is the problem usually faced when making inferences for a continuous-time counting process (without diffusion) using discrete observations. The second problem is due to the presence of a diffusion process. The combination of these two problems renders jumps in continuous time unobservable, and hence they become latent variables. This particular econometric problem, which I refer to in this paper as *mixed unobservability*, complicates the identification of jump predictors, which is the purpose of this study.

As a solution, I suggest the Jump Predictor Test (JPT). The intuition underlying the JPT is simple. Notice that our inference problem requires linking jumps to information arrivals in continuous-time, and likelihood inference is therefore desirable. Since we do not have continuous observations to use in optimizing the true likelihood function for the jump intensity model within jump diffusion processes, one needs to approximate the true likelihood function using discrete data. If there is no diffusion term in the model, one obvious solution is to approximate the true likelihood function by a simple time discretization method (referred to later as the full likelihood). This takes care of the first unobservability problem mentioned above. In the jump diffusion models I consider in this study, the presence of a diffusion term makes this likelihood function unavailable for direct application. To resolve this problem, in an initial step, jumps are detected from the return time series by multiple nonparametric jump detection tests. Using these estimated jumps, an auxiliary (or pseudo) likelihood is created, which I refer to as the partial likelihood in this paper. I show that this partial likelihood is equivalent to the full likelihood. Because the full likelihood approximates the true likelihood in continuous time, the partial likelihood based on detected jumps can be applied to determine jump predictors in continuous time models. The limiting distribution of parameter estimates is derived from the likelihood function and can be used to test whether any information predictor is important or not by the usual significance tests.

Figure 1 illustrates the intuition behind the proposed procedure using a simple example of seven stochastic jump arrivals. In particular, the figure shows that the test is designed to identify the information covariates that predict the jump arrivals. Before applying the JPT, these jump arrivals in continuous time are estimated by jump detection tests using discrete observations from jump diffusion models. A time-series indicator for these estimated jump arrivals is created and linked in the intensity model to the time-series data for information covariates. Figure 2 illustrates how the mixed unobservability is resolved by the proposed method. In paricular, Figure 2 shows that the true likelihood function is approximated by the partial likelihood function, which is the empirical likelihood for actual application. In the approximation, there are three likelihoods involved, and the lines represent how they are linked to each other in resolving the unobservability problems. The partial likelihood function (which depends on detected jumps) converges to the true likelihood function in continuous time (by going through the full likelihood function) as we increase the frequency of observations.

In the following subsection, the JPT is discussed in more detail, with mathematical definitions given for the aforementioned three likelihoods, and a user's guide is provided for selecting good jump predictors. Since it is often useful to learn the possible error that can be made in any prediction analysis, the prediction error distribution is also provided.

2.1 Likelihood Inference for the Jump Predictor Test

In this subsection, I explain why one can naively use the "usual" maximum likelihood estimation and related tests in order to determine jump predictors. As mentioned above, since the stochastic jumps are modeled by a continuous-time process but the data are sampled only at discrete times, the likelihood function must be approximated. To illustrate the approximation, I use a notion of *product integration*, as follows:

Definition 1. Product Integration

The product integration $\widetilde{\prod}$ *over* $[0, T]$ *of any cadlag (left continuous and right limit) function with* $t_i \in [0, T]$ *is defined as*

$$\widetilde{\prod}_{s \in [0,T]} (c_1 + c_2 dg(s))^{c_3 + c_4 dh(s)} = \lim_{\Delta t \to 0} \prod_{1 \le i \le n} (c_1 + c_2 dg(t_i))^{c_3 + c_4 dh(t_i)}, \tag{3}$$

where c_1*,* c_2*,* c_3*, and* c_4 *are constants,* $dg(t_i) = g(t_i) - g(t_{i-1})$*,* $dh(t_i) = h(t_i) - h(t_{i-1})$*, and* $\Delta t = |t_{i+1} - t_i|$*, when* $t_0 = 0 < t_1 < t_2 < ... < t_n = T$ *are discrete times to make a partition of* $[0, T]$*.*

This product integration can be understood as a product in continuous time.[7] This notation is used below to define the true likelihood for a continuous-time jump intensity model within jump diffusion, and the other two approximate likelihood functions involved in the analysis are listed in the following definitions.

Definition 2. Three Likelihoods

A. True Likelihood

$$\widetilde{L(\theta|\mathcal{F}_T)} = \widetilde{\prod}_{s\in[0,T]} d\Lambda_\theta(s)^{dJ(s)} \widetilde{\prod}_{s\in[0,T]} (1 - d\Lambda_\theta(s))^{1-dJ(s)}, \tag{4}$$

where the instantaneous jump intensity $d\Lambda_\theta(t)$ *satisfies equation (2),* $\Lambda_\theta(t) = \int_0^t d\Lambda_\theta(s) = \gamma(t, X(t); \theta)$*, and* $X(t)$ *is a* $\mathcal{F}_t$*-predictable process.*

B. Full Likelihood

$$L_n(\theta|\mathcal{F}_T) = \prod_{1\le i\le n} d\Lambda_\theta(t_i)^{dJ(t_i)} \prod_{1\le i\le n} (1 - d\Lambda_\theta(t_i))^{1-dJ(t_i)}, \tag{5}$$

where $dJ(t_i) = J(t_i) - J(t_{i-1})$ *and* $d\Lambda_\theta(t_i) = \Lambda_\theta(t_i) - \Lambda_\theta(t_{i-1})$*.*

C. Partial Likelihood

$$PL_n(\theta|\mathcal{F}_T) = \prod_{1\le i\le n} d\hat{\Lambda}_\theta(t_i)^{d\hat{J}(t_i)} \prod_{1\le i\le n} (1 - d\hat{\Lambda}_\theta(t_i))^{1-d\hat{J}(t_i)}, \tag{6}$$

where $d\hat{\Lambda}_\theta(t_i) = E[I_{\{\mathcal{L}(i)\in\mathcal{R}_n(\alpha_n)\}}]$ *and* $d\hat{J}(t_i) = I_{\{\mathcal{L}(i)\in\mathcal{R}_n(\alpha_n)\}}$*, with jump detection test statistic* $\mathcal{L}(i) \equiv \frac{\log S(t_i)/S(t_{i-1})}{\widehat{\sigma(t_i)}\sqrt{\Delta t}}$*, rejection region for the jump detection test* $\mathcal{R}_n(\alpha_n)$*, and overall error rate*

*α_n. The instantaneous volatility estimator $\widehat{\sigma(t_i)}$ can be based on bipower variation (***Definition 2.C.a***) as in*

$$\widehat{\sigma(t_i)}^2 \equiv \frac{1}{(K-2)c^2} \sum_{j=i-K+2}^{i-1} |\log S(t_j)/S(t_{j-1})||\log S(t_{j-1})/S(t_{j-2})|,$$

*where $K = b\Delta t^a$ with $-1 < a < -1/2$ for some constant b, and $c = E|u| \approx 0.7979$ with u being a standard normal random variable. Alternatively, it can be based on truncated power variation (***Definition 2.C.b***) as follows. For any $g > 0$ and $0 < \widetilde{\omega} < 1/2$,*

$$\widehat{\sigma(t_i)}^2 \equiv \frac{\Delta t^{-1}}{K} \sum_{j=i-K}^{i-1} (\log S(t_j)/S(t_{j-1}))^2 \, I_{\{|\log S(t_j)/S(t_{j-1})| \leq g\Delta t^{\widetilde{\omega}}\}},$$

where $K = b\Delta t^a$ with $-1 < a < 0$, for some constant b.[8]

For the continuous-time jump models, we have the well-defined continuous-time (conditional) likelihood function $\widetilde{L(\theta|\mathcal{F}_T)}$, as in **Definition 2.A**. The definition of product integration and the (conditional) likelihood function suggest that we can approximate the likelihood function by replacing the instantaneous changes by the increments of $J(t)$ and $\Lambda_\theta(t)$ over t_{i-1} to t_i and forming the corresponding finite products. Hence, if there is no diffusion term, the actual data analysis can be done by the full likelihood, as in **Definition 2.B**. However, because of the diffusion term, we do not have direct data for the full likelihood function, in which case, we should use the partial likelihood, as in **Definition 2.C**. The intuition for this approach is that this partial likelihood uses the "jumps" that are pre-identified with a suggested jump detection test and treats them as data for jump intensity model. Currently, there is no theoretical basis in the literature for us to simply use **Definition 2.C** for significance tests to determine jump predictors in continuous time. Below I show that this partial likelihood based on the detected jumps is sufficient as an objective function to be maximized, and thus, naive likelihood methods are valid.

In order to apply the partial likelihood, the jump locations must be estimated. These jumps are required to satisfy certain properties discussed in the following proposition.

Proposition 1. Properties of Estimated Jump Arrivals

Let $\mathcal{L}(i)$ be as in **Definition 2.C** *and let* **Assumption C** *(see Appendix) be satisfied. Further, let the rejection region for a chosen test be $\mathcal{R}_n(\alpha_n) = (-\infty, -q_{\alpha_n}S_n - C_n) \cup (q_{\alpha_n}S_n + C_n, \infty)$, where q_{α_n} is the $(1-\alpha_n)$th percentile of a standard Gumbel distribution with α_n being the overall error rate, $C_n = (2\log n)^{1/2} - (\log \pi + \log(\log n))/(2(2\log n)^{1/2})$, and $S_n = 1/(2\log n)^{1/2}$ with n being the number of observations. Then, as $n \to \infty$ $(\Delta t \to 0)$,*

$$d\hat{J}(t_i) = \hat{J}(t_i) - \hat{J}(t_{i-1}) = I_{\{\mathcal{L}(i)\in\mathcal{R}_n(\alpha_n)\}} \xrightarrow{P} dJ(t_i) = 1,$$

for any $(t_{i-1}, t_i]$ with a jump, and

$$d\hat{J}(t_i) = \hat{J}(t_i) - \hat{J}(t_{i-1}) = I_{\{\mathcal{L}(i)\in\mathcal{R}_n(\alpha_n)\}} \xrightarrow{P} dJ(t_i) = 0,$$

for any $(t_{i-1}, t_i]$ without a jump.

Notice that the null hypothesis for the jump detection test is the absence of a jump. This proposition indicates that for every set of discrete-time intervals during which we do (or do not) have a jump, we do (or do not) detect the jump by conducting the tests. In other words, jump or no jump arrival in an interval must be determined by the test, and the interval should shrink to zero as we increase the frequency of observations. Remember that because we have the diffusion term, the jump indicator over each interval (t_{i-1}, t_i) is not directly observable and must be estimated by a jump detection technique, which depends on several observations in the rolling window of size K before the time interval. Unless the jump detection test is properly chosen, the probability of a jump event calculated with the jump detection test (using discrete data from a jump diffusion model) may not necessarily be the same as the probability of a jump event over each discrete time interval. As a first step for likelihood approximation, **Proposition 1** ensures that the limiting support of the two probabilities above is indeed the same asymptotically.[9]

Threshold $q_{\alpha_n} S_n + C_n$ for the rejection region $\mathcal{R}_n(\alpha_n)$ is dominated in the limit (when $n \to \infty$) by the C_n term. In particular, it is of the order of $\sqrt{2 \log n}$. One can achieve this exact order of $\sqrt{2 \log n}$ when the overall error rate α_n satisfies $\alpha_n = 1 - exp(-\frac{1}{\sqrt{\pi \log n}})$, which converges to zero as $n \to \infty$. Econometricians can arbitrarily require that $\alpha_n \to 0$ at a faster rate than this (if preferred) and can thus marginally decide how conservative they would like the outcome to be.

With the local properties in **Proposition 1** satisfied, I show in the following proposition how the second unobservability problem due to the presence of the diffusion process is resolved as $\Delta t \to 0$.

Proposition 2. Asymptotic Equivalence of Partial Likelihood and Full Likelihood
Suppose that **Assumptions C** *and* **D** *(see Appendix) hold. Let* $L_n(\theta|\mathcal{F}_T)$ *and* $PL_n(\theta|\mathcal{F}_T)$ *be as in* **Definition 2.B** *and* **2.C**, *with* $\mathcal{F}_T$ *being the information filtration up to time* T. *The estimated jumps satisfy the properties stated in* **Proposition 1**. *Then, as* $\Delta t \to 0$ *and* $\alpha_n \to 0$,

$$\frac{PL_n(\theta|\mathcal{F}_T)}{L_n(\theta|\mathcal{F}_T)} \xrightarrow{P} 1, \tag{7}$$

when there is a finite number of jumps during time horizon $[0, T]$.

This proposition tells us that the probability that the full likelihood and partial likelihood are different from each other becomes negligible as we increase the frequency of observations. In other words, this asymptotic equivalence justifies performing likelihood inference based on detected jumps as if they were from pure jump models in the absence of a diffusive component.[10] However, this proposition does not shed light on the relationship between $PL_n(\theta|\mathcal{F}_T)$ and $\widetilde{L(\theta|\mathcal{F}_T)}$. Therefore, this result by itself does not guarantee that the outcome from partial likelihood inference holds in continuous time. We need the following important proposition to resolve the first unobservability problem. In particular, **Proposition 3** connects the partial likelihood, which we can use for actual analysis, and the true likelihood.

Proposition 3. Partial Likelihood is Sufficient

Suppose that **Assumptions C** *and* **D** *(see Appendix) hold. Let* $\widetilde{L(\theta|\mathcal{F}_T)}$ *and* $PL_n(\theta|\mathcal{F}_T)$ *be as in* **Definition 2.A** *and* **2.C***, with* $\mathcal{F}_T$ *being the information filtration up to time* T*. The estimated jumps satisfies the properties stated in* **Proposition 1***. Then, as* $\Delta t \to 0$ *and* $\alpha_n \to 0$*,*

$$\frac{PL_n(\theta|\mathcal{F}_T)}{\widetilde{L(\theta|\mathcal{F}_T)}} \xrightarrow{P} 1, \tag{8}$$

when there is a finite number of jumps during time horizon $[0, T]$*.*

Although this simple result with the likelihood ratios may appear subtle, it is in fact a crucial step in enabling us to provide the asymptotic distributions for jump predictor tests because now the limiting behavior between the partial likelihood and the true likelihood in continuous time becomes clear. This likelihood approximation technique has not been used previously for making inferences on jump predictors for stochastic jump intensity, and it can be applied to other contexts.[11]

Once the above convergence is established, the main results of the selection of jump predictors directly follow along with the implication of the prediction error distribution, as stated in **Theorem 1** below.

Theorem 1. Jump Predictor Test (JPT)

Suppose that **Assumptions C** *and* **D** *(see Appendix) hold. Let* $X(t) = [X_1(t), X_2(t), .., X_p(t)]$ *be the vector of the investor's jump predictor candidates that could affect* $\Lambda_\theta(t)$ *and let* $\hat{\theta} = [\hat{\theta}_1, ..., \hat{\theta}_p]$ *be the maximum likelihood estimate for effect parameter* θ *based on* $PL_n(\theta|\mathcal{F}_T)$*, as in* **Definition 2.C**. *Then, the following results hold as* $\Delta t \to 0$.

A. $X_k(t)$ *is selected as a jump predictor if* $Prob\left(z > \frac{\hat{\theta}_k}{SE(\hat{\theta}_k)}\right) < \beta$*, where* β *is the chosen significance level and* z *is a standard normal random variable.* $SE(\hat{\theta}_k)$ *can be found in the usual manner from the covariance matrix of* $\mathcal{Z}^{-1}(\hat{\theta})$*, with* $-\mathcal{Z}(\theta)$ *being the matrix of second-order partial derivatives of the log-*$PL_n(\theta|\mathcal{F}_T)$*.*[12]

B. The investor's prediction error for jump intensity, $d\hat{\Lambda}_\theta(t) - d\Lambda_\theta(t)$*, asymptotically follows a normal distribution with mean 0 and variance* $\triangledown d\Lambda_\theta' Z^{-1}(\theta) \triangledown d\Lambda_\theta$*, where* $\triangledown d\Lambda_\theta$ *is the partial derivative of* $d\Lambda_\theta(t)$ *with respect to* θ*.*[13]

My final solution appears similar to the usual MLE methods. However, this work is distinguished from others in that I solve the "mixed unobservability" problem described earlier and I discuss the necessary requirements for the estimated jumps to be used in the analysis. I also develop a theoretical justification for the naively applied likelihood inference. Finally, the term "partial likelihood" is also used in the statistics literature for continuous-time counting process inference using the full likelihood, as in **Definition 2.B**. The partial likelihood in this paper is different from the existing approach and is specific to the aforementioned mixed unobservability problem.

3 Simulation Study

In this subsection, I examine the finite sample performance of the JPT using a Monte Carlo simulation. The purpose of this simulation study is to prove whether important jump predictors can be identified correctly. In summary, the overall results show that the JPT performs well in distinguishing the effects of jump predictors under general market conditions, including market interruptions (opening and closing at deterministic times of the day), an asymmetric U-shaped intraday volatility pattern due to the trading mechanism, leverage effects, jumps in volatility, and time-varying jump sizes. Although the JPT was developed assuming the absence of some of these more realistic conditions, this simulation is performed under a realistic setup in order to demonstrate that the proposed technique provides evidence that is fairly robust to their presence.

For return series generation, I use the Euler-Maruyama Stochastic Differential Equation (SDE) scheme [see Kloeden and Platen (1992)], which is one of the most widely used methods for simulating data from continuous-time models. I avoid the starting value effects by discarding five hundred observations during the burn-in period each time I generate a time series. I generate 15-minute returns over a 1-year horizon from the general model represented as

$$d \log S(t) = u(t)\sigma(t)dW(t) + Y(t)dJ(t), \tag{9}$$

where the stochastic volatility model is specified as

$$d\sigma^2(t) = \kappa\left(\theta - \sigma^2(t)\right)dt + \omega\sigma(t)dB(t) + Y_\sigma(t)J_\sigma(t). \tag{10}$$

The terms $W(t)$ and $B(t)$ denote standard Brownian Motion processes, $J(t)$ and $J_\sigma(t)$ denote Poisson processes, and $E(dB(t)dW(t)) = \rho dt$. The parameter values used are the estimates from the empirical study by Eraker (2004). Specifically, they are $\kappa = 0.0162, \theta = 0.573$, $\omega = 0.58$, and $\rho = -0.46$.

For the stochastic jump intensity for both price and volatility, I assume $d\Lambda_\theta(t) = \frac{1}{1+\exp(-\theta_0-\theta_1 X(t))}$ with $\theta_0 = -4$ and $\theta_1 = 3$. This parameterization ensures that the intensity (probability) is within the admissible range of [0,1]. The predictor $X(t)$ is set to one every week at 10:00am and zero otherwise in order to mimic real-time news events. The volatility jump size $Y_\sigma(t)$ is set to follow the exponential distribution with mean $\mu_\sigma = 1.25$, and the price jumps size $Y(t)$ is set relative to $\sigma(t-)$, the level of stochastic volatility immediately before time t. In other words, jump sizes in prices are assumed to be time-varying.

The number of trading days per year is 252, with 6.5 trading hours per day, interrupted overnight, and opening at 9:30am and closing at 4:00pm each day to mimic the New York Stock Exchange. An asymmetric U-shaped intraday volatility pattern is accommodated in the model by $u(t)$ specified as in Andersen, Dobrev, and Schaumburg (2008). In particular, $u(t)$ is specified by the sum of two exponentials with different coefficients to produce the asymmetry, as in

$$u(t) = c_1 + c_{open} \exp(-a_{open} \times t_{open}) + c_{close} \exp(-a_{close} \times t_{close}), \tag{11}$$

where t_{open} denotes the length of time that has passed since market opening and t_{close} denotes the length of time that remains until the market closes on the same trading day. The constant parameters used are $c_1 = 0.8892, c_{open} = 0.75, c_{close} = 0.25, a_{open} = 10$, and $a_{close} = 10$, following the calibrated setup of Andersen, Dobrev, and Schaumburg (2008).

Table 1 reports the simulation results. Every time the return data are generated, the suggested method is applied and parameter estimates ($\hat{\theta_0}$ and $\hat{\theta_1}$) are obtained along with their standard errors ($SE(\hat{\theta_0})$ and $SE(\hat{\theta_1})$) and p-values ($Prob(z > \frac{\hat{\theta_i}}{SE(\hat{\theta_i})})$ with $i = 1, 2$) associated with the estimates. Reported are their averages over three thousand simulation runs. Results based on both **Definition 2.C.a** and **Definition 2.C.b** are provided in the table. As can be seen, the parameter estimates are on average slightly biased in this type of analysis due to the fact that we only use discrete data for this continuous-time model. One way to reduce this bias is to increase the time horizon. Despite the presence of bias, the results show that the test allows us to identify the importance of jump predictors fairly precisely with p-values much lower than usual significance levels such as 1%. This proves that this test is powerful in finite samples.

To save space, I only report results on whether one can correctly identify the jump predictors using the proposed method. I have also confirmed that the small sample distribution of the parameter estimates under the null hypothesis is as suggested by the asymptotic theory used in this paper. The empirical size of the test is close to its theoretical value and there is no over-rejection problem. Related results are available upon request.

The overall results indicate that the presence of intraday volatility patterns, market closures, volatility jumps, and time-varying jump sizes will not strongly affect the ultimate conclusion on the significance of jump predictors. Therefore, the JPT seems to be robust in various market conditions. The reason for this robust result is that the predicting information is required to be released often enough before jump arrivals in order to be selected as a significant and important predictor. This simulation evidence emphasizes the importance of using time-series information on both jumps and information covariates when identifying the economic determinants of jump dynamics.[14]

In the implementation of jump detection techniques such as the tests introduced by Lee and Mykland (2008) and Lee and Hannig (2010), it is important to use proper window sizes and truncation levels for volatility estimation. As is often the case with various nonparametric methods, the jump detection tests are sensitive to these tuning parameters. In theory, window sizes K for both **Definition 2.C.a** and **Definition 2.C.b** must be large enough (but obviously smaller than the total number of observations) to remove the effect of price jumps in volatility estimation. I use the rules used by Lee and Mykland (2008) and Lee and Hannig (2010) in this simulation and find that the JPT performs well with the optimal window size, that is, the smallest integer that satisfies condition $K = \Delta t^{\alpha'}$ with $-1 < \alpha' < -0.5$ for detecting jumps.

Furthermore, **Definition 2.C.b** requires the optimal truncation level as well. In selecting these parameters, I follow the suggestion made by Aït-Sahalia and Jacod (2009b), who also use the truncated power variation estimator for their analysis. The parameter values used are $\tilde{\omega} = 0.47$ and $g = 4 \times \tilde{\sigma}$. Since the $\tilde{\sigma}$ is unknown in practice and can be time-varying, it is determined using a data-dependent method. In this simulation study, I apply a jump robust volatility estimator based on bipower variation using returns in the upcoming window of size K after each truncation time, which can be applied in the test with **Definition 2.C.b**.[15] With these properly chosen tuning parameters, as can be seen in Table 1, the JPT is robust to various realistic market conditions. The ultimate conclusions drawn from both of the jump detection tests are qualitatively similar. For the empirical analysis in Section 4, results using **Definition 2.C.a** are reported.

4 Empirical Analysis for U.S. Individual Equity Jumps

4.1 Data for Equity Jumps

This subsection describes jumps filtered by applying jump detection tests on equity returns. I select the most actively traded U.S. large-cap component stocks in the Dow Jones Industrial Average (DJIA) traded on the New York Stock Exchange (NYSE). Data are collected from the TAQ database, which contains tick-by-tick data for trading information such as transaction time, price, exchange, and volume information beginning with 1993. My sample extends from January 4, 1993 to December 31, 2008, for a total of 4,017 trading days over 16 years. It is based on price data from 9:30am to 4:00pm, the normal trading hours on the NYSE. I select transactions on the NYSE in order to maintain sufficient degrees of liquidity and a similar organization of trading mechanisms and trading hours across different stocks. For this reason, two of the 30 stocks are excluded because they are traded on the NASDAQ. I also exclude an additional five stocks because of a significant incidence of missing data or unusual name changes, either of which could create significant bias in empirical results.

Table 2 lists the names of the 23 stocks and the S&P 500 index, along with their ticker symbols.[16] This table includes basic descriptive statistics of log returns such as standard deviation, skewness, kurtosis, and autocorrelations. I use 15-minute stock returns by taking the differences of log transaction prices. Although a 5-minute frequency has been a popular choice for studying the volatility of liquid stocks, an even lower frequency is chosen for this jump analysis to ensure minimal distortion or bias due to noise. Table 2 shows that the sample autocorrelations of returns are sufficiently small. Furthermore, this sampling frequency is close to 17.5 minutes, the frequency chosen by Bollerslev, Law, and Tauchen (2009), who utilize volatility signature plots for similar large-cap companies to determine optimal frequency in their analysis. The simulation study also confirms that the JPT using this frequency provides satisfactory power. The statistics suggest that the index and individual stocks have different patterns in return variations. The index has on average lower mean, lower standard deviation, lower skewness, and higher kurtosis than do the individual stocks, which means that the variation in index return tends to be driven more by infrequent extreme negative movements.

Table 2 also includes the descriptive statistics for detected jump counts, that is, the number of tests undertaken, the number of detected jumps over the sample period, and the average jump frequencies over a day, a month, and a year. The significance level for the nonparametric jump detection test is 5%, and I do not exclude the possibility of detecting jumps in overnight returns.

Results indicate that each year, stocks in the sample experience approximately 21 jumps, from 15 for XOM to 25 for AA, BA, or HPQ. The daily average rate of jump arrival is 8%. This rate is calculated with the assumption that the jump arrival rate is constant over time. I observe, however, that jumps do not occur regularly. Therefore, models with constant jump intensities are not appropriate.

Table 2 also shows that the S&P 500 index has more jumps than an equally weighted index of the analyzed stocks. It is worth mentioning that unlike evidence in recent studies using high frequency data, I find a larger number of jumps in the index than in individual stocks.[17] The main reason is the difference in sample periods. For example, Bollerslev, Law, and Tauchen (2009) use a sample period of January 1, 2001 to December 31, 2005, Lee and Mykland (2008) use a sample period of September 1, 2005 to November 30, 2005, and Lee and Hannig (2010) use a sample period of January 1, 2002 to December 2006. In contrast, my sample extends from January 4, 1993 to December 31, 2008. It turns out that the S&P 500 index fund had a greater number of jumps in years in my sample that are missing from the other studies, namely 1993-1995 and 2007-2008. This result may appear counterintuitive, since we generally expect the index to jump less than individual stocks due to a diversification effect. However, this is not impossible. First, it is possible that small co-jumps induced by correlated news escape detection at the individual level but show up at the aggregate level, as noted by Bollerslev, Law, and Tauchen (2009). Second, the result is based on the S&P 500 index, which includes many component stocks that are not analyzed in this study. It is also possible that jumps in other stocks create jumps in this index.

Table 3 presents the times during a day when the jumps arrive. That is, it reports the percentage of detected jumps during specific time intervals in a trading day among all realized jumps. I divide the trading hours of the NYSE, 9:30am to 4:00pm, into nine categories. I find that more than 86% of individual equity jumps arrive before 11:00am, at approximately the time of market opening.[18] The jumps in the S&P 500 index appear to show a different arrival pattern within a day. The tendency of index jumps near opening (64% between 9:30am to 11:00am) is not as high as the tendency for stocks (86%). A significantly higher rate of jumps near market opening is similar to that of Bollerslev, Law, and Tauchen (2009), who find a significant number of jumps around 10:00am using a different approach.

Summarizing Tables 2 and 3, I conclude that if jumps occur, they tend to take place in the morning, while overnight returns do not necessarily include jumps. In fact, there are far fewer jumps than the number of trading days. The NYSE trading mechanism for opening markets provides a naturally controlled experiment framework to study whether the market interruption itself is the cause of jumps in stock prices. Based on my results, I conclude that without information that will be reflected in prices, the interruption itself does not trigger jumps. At this stage, I hypothesize that jumps are triggered when investors' demand for trading increases due to information flow in a relatively illiquid market. The jump predictor analysis, to which I now turn, allows disentangling which information is important enough to trigger jump arrivals.

4.2 Data for Jump Predictors X(t)

This subsection describes the raw data used to create jump predictors. I used a pre-test procedure to reduce a large number of potential jump predictors to the eight most important predictors. The procedure is based on how broadly each variable is significant when it is used as a jump predictor of the individual stocks I consider in this study. To measure the breadth, I use the number of firms for which each predictor is significant. More detailed descriptions of the pre-test procedure, alternative information variables, and their data sources are presented in the Appendix.

Table 4 provides details on information variables related to four macroeconomic and four firm-specific jump predictors I focus on in this study. It contains the names of the information variables, their mnemonic abbreviations, the total number of raw data, all dates and times for each variable, the data source, and the sample period which is matched exactly to the sample period for the jump data shown in Table 2. The sampling frequency of all information data is set at 15 minutes to match the sampling frequency of jump data presented in Subsection 4.1.

4.2.1 Macroeconomic Information Variables

The macroeconomic variables I consider in creating jump predictors are U.S. market jumps (MARKET) in the S&P 500 index, Federal Open Market Committee news releases (FOMC), nonfarm payroll employment report releases (NONFARM), and initial unemployment claims news releases (JOBLESS). Four different time series of indicators for the arrival times of the information are used.

For example, the U.S. market jump variable MARKET(t) is a time series of indicators for the arrival times of jumps in the S&P 500 index. The significance level α applied to detect U.S. market jumps is 5%, and the total number of detected market jumps during the sample period is 446. FOMC announcements occur every six weeks, and I have 134 observations. Nonfarm payroll employment information is released monthly, and 191 observations are incorporated. Jobless claims information is released weekly, and thus there are many more observations for this variable than for the other variables. Since the NONFARM and JOBLESS numbers are released outside trading hours at 8:30am in the morning, I set the indicators for NONFARM(t) and JOBLESS(t) to one at the earliest possible time at which the information can be reflected. In this particular case, the earliest time is 9:30am. Except for U.S. market jumps, these macroeconomic variables are released regularly at a pre-scheduled time, as noted in Table 4, for most of the sample period.[19]

4.2.2 Firm-specific Information Variable

In the presence of the aforementioned macroeconomic variables, for each firm I consider the following firm-specific variables in creating jump predictors: earnings announcements (EARNINGS), analyst recommendations (ANALYST), individual stocks' past jumps (CLUSTER), and dividend related dates (DIVIDEND). Similar to the macroeconomic variables, for firm c, for example, I first create a time series of indicators for the arrival times of these information releases and denote them by $\text{EARNINGS}_c(t)$, $\text{ANALYST}_c(t)$, $\text{CLUSTER}_c(t)$, and $\text{DIVIDEND}_c(t)$.

For earnings announcements, I collected release times and dates from the First Call Historical Database, a subsidiary of Thomson Corporation, which many brokerage firms and institutional investors depend on to disseminate their research reports electronically to their clients through a news wire service. To minimize data errors, release dates were compared between the First Call Historical Database and I/B/E/S database. If the dates from these sources were different, I used the timing information from a Factiva search. For those earnings that are released after trading hours, I set the indicator of $\text{EARNINGS}_c(t)$ for firm c to one at the earliest possible time at which the information can be reflected. As noted in Table 4, I include all the quarterly earnings announcements and revisions (if any) by firms over the sample period. The cross-sectional average number of announcements and revisions is 70 for the 23 firms and the standard error is 10.14.

For analyst recommendations, I collected the comprehensive real-time release history from the First Call Historical Database. This system provides the dates and time-stamps of analyst recommendation updates, measured within one minute, which allows us to learn when the information becomes available to investors and whether it affects jump arrivals. To reduce bias due to sample selection, I include all types of recommendation changes by all analysts reported in the database. Note that Womack (1996) examines immediate market reactions to dramatic recommendation changes [added to buy (sell) recommendations] made by the highest rated U.S. brokerage research departments. In contrast, I include not only those dramatic recommendation changes but also other changes, such as from buy to strong buy. Each recommendation record from the database contains the ticker symbol of the corresponding firm, the date and time of the update (up to minutes), and a one-to-five point recommendation scale, with one being most favorable and five being least favorable. For those analyst recommendations released during non-trading hours, I again set the indicator of $\text{ANALYST}_c(t)$ for firm c to one at the earliest possible time at which the information can be reflected. As noted in Table 4, the cross-sectional average number of recommendations is 519 for the 23 firms over the sample period, and the standard error is 129.85.

I also examine whether past jump arrivals in a specific stock change the likelihood of future jump arrivals during normal trading hours. In short, I test for evidence of jump clustering, by which I mean that jump arrivals tend to follow previous jump arrivals. To capture this jump clustering effects, I use stock jump arrival times in the jump dataset and create a time series of jump time indicator variables $\text{CLUSTER}_c(t)$ for firm c. As noted in Table 4, the cross-sectional average number of jumps is 348 for the 23 firms over the sample period, and the standard error is 45.30. Further details on the jump data used for this CLUSTER variable can be found in Table 2.

For dividend-related dates, I collected data from the CRSP database. Four major dates related to dividend payments are available: the dividend announcement date, when the board of directors announces to shareholders and the market that the firm will pay a dividend; the ex-dividend date, on (or after) which a stock holder can sell the stock and still receive the declared dividend payments; the date of record, when investors must be listed as holders to ensure the right to a dividend payout; and the date of payment, when the firm mails the dividend to the listed holders. I found the ex-dividend date to be significant for the majority of firms and hence include it in my analysis. For firm c, I create a time series of $\text{DIVIDEND}_c(t)$ indicators that are set to be one on those dates. As noted in Table 4, the cross-sectional average number of dividend related dates is 190 for the 23 firms over the sample period, and the standard error is 23.79. (Since I set the information variable $\text{DIVIDEND}_c(s)$ to be measured every 15 minutes, I use a divisor of 26 (number of 15-minute observations per trading day) in this case to report the average number of dates.)

4.3 General Jump Prediction

In this subsection, I specify and estimate a model for general jump prediction with the information predictors $X(t)$ derived from the indicators discussed previously. In particular, I consider the following logistic parameterization of the instantaneous jump intensity model for firm c:

$$d\Lambda_\theta(t) = \frac{1}{1 + \exp(-\theta_0 - \sum_{j=1}^{10} \theta_j X_j(t))}, \tag{12}$$

where $X_1(t) = I(9:30 \leq h(t) < 10:00)$ is the time-of-day indicator for times between 9:30am and 10:00am, with $h(t)$ being the hour:minute of time t,

$X_2(t) = I(10:00 \leq h(t) < 11:00)$ is the time-of-day indicator for times between 10:00am and 11:00am,

$X_3(t) = I(\int_{t-30min}^{t} \text{MARKET}(s) > 0)$ is the indicator for MARKET taking a value of one within the 30 minutes prior to t,

$X_4(t) = I(\int_{t-30min}^{t} \text{FOMC}(s) > 0)$ is the indicator for FOMC taking a value of one within the 30 minutes prior to t,

$X_5(t) = I(\int_{t-30min}^{t} \text{NONFARM}(s) > 0)$ is the indicator for NONFARM taking a value of one within the 30 minutes prior to t,

$X_6(t) = I(\int_{t-30min}^{t} \text{JOBLESS}(s) > 0)$ is the indicator for JOBLESS taking a value of one within the 30 minutes prior to t,

$X_7(t) = I(\int_{t}^{t+1day} \text{EARNINGS}_c(s) > 0)$ is the indicator for EARNINGS for firm c taking a value of one within one day after t,

$X_8(t) = I(\int_{t-30min}^{t} \text{ANALYST}_c(s) > 0)$ is the indicator for ANALYST for firm c taking a value of one within the 30 minutes prior to t,

$X_9(t) = I(\int_{t-3hour}^{t} \text{CLUSTER}_c(s) > 0)$ is the indicator for CLUSTER for firm c taking a value of one within the 3 hours prior to t, and

$X_{10}(t) = I(\text{DIVIDEND}_c(t) \times (X_1(t) + X_2(t)) > 0)$ is the indicator for morning hours between 9:30am and 11:00am on DIVIDEND dates of firm c.[20]

Table 5 contains the parameter estimates for all firms listed in Table 2. Coefficients on controls for intraday seasonal patterns of jump arrivals (in particular, morning hours) appear in the two left columns after the coefficient for the intercept. I then report coefficients on the four macroeconomic jump predictors and finally coefficients on the four firm-specific jump predictors in the subsequent columns. *,**,*** indicate the JPT results, showing that the corresponding predictors are significant at the 10%, 5%, and 1% levels, respectively. As recognized earlier in Table 3, the significance of $X_1(t)$ and $X_2(t)$ on the time of day between 9:30am and 11:00am confirms that jumps often tend to occur early in the morning.[21]

The significance of predictors depending on market jump arrivals ($X_3(t)$) provides strong evidence that overall market jump arrivals increase the likelihood of individual equity jumps within 30 minutes. This predictor is significant at the 1% level for all firms except for GE, for which it is significant at the 5% level. Another noteworthy macroeconomic variable is FOMC announcements on federal fund rate changes ($X_4(t)$). Results indicate that FOMC announcements are likely to induce individual equity jump arrivals within 30 minutes. Since this information is usually released in the afternoon at 2:15pm, this means that the jumps are likely to arrive between 2:15pm and 2:45pm on these announcement dates. Considering the magnitude of the coefficient on this predictor, this is the most influential predictor of U.S. individual equity jumps among all those considered. The other two macroeconomic predictors ($X_5(t)$ and $X_6(t)$) are indicators of times shortly after the release of employment and unemployment reports. Given their actual release times, which is 8:30am for both cases, the results show that jumps are likely to occur during the first half hour of NYSE trading (9:30am to 10:00am). Except for the case of CVX for nonfarm payroll reports and the cases of DIS and GE for initial jobless claims, these two jump predictors are significant mostly at the 1% level.

Among the firm-specific jump predictors, the largest coefficient is found for $X_7(t)$, which indicates times within one day before earnings releases, and it is the second most influential predictor after $X_4(t)$, related to FOMC announcements. Earnings announcement information is the only information that tends to induce jump arrivals *before* their release time. This exception may occur because of possible information leakage or because firms sometimes do not release information at pre-scheduled times. All the other pre-scheduled variables such as FOMC, NONFARM, and JOBLESS tend to induce jump arrivals within the first 30 minutes *after* the news releases.

Another important firm-specific jump predictor is $X_8(t)$, which indicates times within the 30 minutes after analysts publish their recommendations. As can be seen in Table 5, it is significant at the 1% level for all firms except for XOM, for which it is significant at the 5% level. Notice that in this paper, this predictor is created to indicate the first 30 minutes after analysts' recommendation releases. Therefore, investors are supposed to observe recommendation releases before jump times, making a short-term prediction in real-time. Controlling for all the aforementioned predictors, I find that the third and fourth most important among the firm-specific predictors are $X_9(t)$ indicating morning hours (from 9:30am to 11:00am) of ex-dividend dates (significant at the 10% level for 14 out of 23 firms) and $X_{10}(t)$ indicating arrivals of the same stock jumps within the previous three trading hours (significant at the 5% level for 15 out of 23 firms), which provides evidence of jump clustering.[22]

Of most economic interest in this type of study would be the magnitude of the coefficient estimates and their interpretation. Since the instantaneous jump intensity for each firm is estimated using the time-series logistic regression model (which links jumps to the various information predictors), one can express the instantaneous odds in favor of jump arrival (relative intensities of jump and no jump arrival) at time t as follows:

$$\frac{d\Lambda_\theta(t)}{1 - d\Lambda_\theta(t)} = \exp\left(\theta_0 + \sum_{j=1}^{10} \theta_j X_j(t)\right). \tag{13}$$

Because the jump predictors are set up to be the indicators of times around information releases, taking values of either 0 or 1, one can conclude that the jth jump predictor $X_j(t)$ allows us to predict an increase of θ_j units in the log-odds in favor of jump arrival in the corresponding stock price. Alternatively, but perhaps preferably, one can also conclude that the impact of the jth information arrivals is to increase the predicted odds of jump arrival in the individual stock price, multiplicatively by the factor of $\exp(\theta_j)$. If there is no information release at time t, and hence all the jump predictors ($X_j(t)$'s) are set at 0 at time t, the predicted odds of observing a jump at that time is then $\exp(\theta_0)$. To give an example, Table 5 shows that the parameter estimate of θ_4 for Home Depot (HD) is 4.01. This means that the predicted odds of jump arrivals in the Home Depot stock price are generally increased by a factor of $\exp(4.01) = 55.15$ within 30 minutes after FOMC announcements relative to that in other times without the news. If the information is released in morning hours, the increase in the predicted odds of jump arrivals is interpreted relative to the odds during morning hours without the news releases. Other parameter estimates can be interpreted similarly and represent strong economic significance for the selected predictors.

It is worth emphasizing here that jumps associated with the ex-dividend dates are most likely not linked to information shocks but rather are probably due to short-term trading activity on the ex-day to take advantage of possible arbitrage profits. A sizable amount of the literature focuses on short-term trading activity on ex-dividend dates and abnormal returns in relation to differential taxation between dividend and capital gains.[23] In a similar vein, I also investigated whether the magnitude of dividend yield matters for price jumps and whether dividend-related jump intensities were affected by a significant change in tax policy on dividend and capital gains taxation since the Jobs and Growth Tax Relief Reconciliation Act (signed in May of 2003) falls within the sample period of this study. I find no strong evidence to support these hypotheses using the JPT.

4.4 Separate Predictions for Systematic and Idiosyncratic Jumps

In this subsection, I investigate whether it is possible to distinguish systematic and idiosyncratic jumps using the JPT. To accomplish this goal, I specifically define systematic jumps to be jumps detected in the S&P 500 index. Idiosyncratic jumps are defined to be all the detected jumps for each firm after excluding the systematic jumps as well as cojumps that occurred simultaneously in at least two firms. These simultaneous jumps are further excluded in order to remove any industry effect or some other common effect that is unidentified by the S&P 500 index jumps but is not considered to be entirely idiosyncratic.

Once jumps are classified as mentioned above, the separate intensity models for systematic and idiosyncratic jumps are set up as

$$d\Lambda_\theta^{systematic}(t) = \frac{1}{1+\exp(-\theta_0 - \sum_{j=1}^{10}\theta_j X_j(t))}, \tag{14}$$

$$d\Lambda_\theta^{idiosyncratic}(t) = \frac{1}{1+\exp(-\theta_0 - \sum_{j=1}^{10}\theta_j X_j(t))}, \tag{15}$$

where the definitions of $X_j(t)$ are described in Subsection 4.3. As in the general jump intensity model, both models include the terms to control for intraday seasonal patterns of jump arrivals. The macroeconomic and firm-specific predictors are included for both models. Tables 6 and 7 contain the parameter estimates of the systematic and idiosyncratic jump intensity models for each firm. *,**,*** indicate the JPT results, showing that the corresponding predictors are significant at the 10%, 5%, and 1% levels, respectively.

Table 6 shows that distinguishing systematic jumps is possible using the important macroeconomic predictors. All the macroeconomic predictors ($X_3(t), X_4(t), X_5(t)$ and $X_6(t)$) are shown to be strongly significant at the 1% level without exception. $X_4(t)$ related to FOMC announcements is proven to be the most influential systematic jump predictor, followed by $X_5(t)$ related to nonfarm payroll employment information. $X_3(t)$ and $X_6(t)$ related to overall market jumps and jobless news releases are also shown to be fairly important and precise predictors. The significance of the predictors indicating times after market jump arrivals ($X_3(t)$) suggests strong evidence of systematic jump clustering, which means that systematic jumps tend to increase the likelihood of systematic jumps within a short-time horizon of 30 minutes.

Comparing the average magnitudes of the coefficients for the firm-specific predictors to those for the macroeconomic predictors, the macroeconomic predictors are much more important for systematic jump prediction in U.S. stock markets. As expected, the firm-specific predictors are mostly insignificant in the systematic jump prediction. One exception is $X_9(t)$, which is the predictor indicating three trading hours after individual stock jumps. Individual stock jumps are shown to increase the likelihood of systematic jumps within three trading hours (for 19 out of 23 firms at the 5% level). Given that I consider large stocks included in the Dow Jones Industrial Average Index for this study, it is possible that an extreme shock realized in one large individual firm may increase uncertainty in the overall market, triggering systematic jumps due to short-term cross-autocorrelation effects in jump components.

Table 7 reveals that $X_7(t)$ related to corporate earnings announcements is the most important idiosyncratic jump predictor, followed by $X_8(t)$ related to analysts' recommendation releases. Both predictors are strongly significant at the 1% level for all firms (with one exception of XOM for $X_8(t)$) and are associated with the two largest coefficients among all predictors considered. Individual stock jumps and dividend information remain influential for some firms ($X_9(t)$ ($X_{10}(t)$) is significant for 14 (9) out of 23 firms at the 5% level). Comparing the average magnitudes of the coefficients for the macroeconomic predictors to those for the firm-specific predictors, the firm-specific predictors are proven to be more useful for idiosyncratic jump prediction in these individual stock markets.

Results show that for some firms, macroeconomic jump predictors remain important in predicting their idiosyncratic jumps. Hence, the macroeconomic news releases not only are likely to trigger jumps in the overall market, but also occasionally induce stock price jumps in the absence of systematic jumps. This could be because some macroeconomic news may not be broadly influential enough to trigger jump at the market level, whereas one individual stock could be more sensitive to the news to experience dramatic changes in prices. This evidence simply demonstrates the important role of macroeconomic information in extremely volatile stock markets.

4.5 Jump Size Clustering and Implications

In the analysis of jump dynamics, it is also important to understand how jump sizes changes over time. Jump size dynamics can be easily investigated by applying the JPT to jumps with different jump sizes after classifying them according to their size. Using the suggested technique, I show evidence of jump size clustering in this subsection.

As an initial step, I classify all the detected jumps for each firm into two size groups after observing its jump size distribution as presented in Table 8. The first group (inner-quartile jump group) includes jumps whose jump sizes are less than the upper quartile and greater than the lower quartile of the jump size distribution for the firm. The second group (outer-quartile jump group) includes jumps whose jump sizes are greater than the upper quartile and less than the lower quartile of the jump size distribution for the same firm. Then, I create the inner and outer quartile jump group indicators ($\text{CLUSTER}_c^{gr}(t)$) with $gr = inner$ or $outer$, for firm c.

The jump intensity model for jump size clustering is specified as

$$d\Lambda_\theta^{gr}(t) = \frac{1}{1 + \exp(-\theta_0 - \sum_j \theta_j X_j^{gr}(t))}, \tag{16}$$

where $X_1^{gr}(t) = X_1(t) = I(9:30 \leq h(t) < 10:00)$ is the time-of-day indicator for times between 9:30am and 10:00am, with $h(t)$ being hour:minute of the time t,

$X_1^{gr}(t) = X_2(t) = I(10:00 \leq h(t) < 11:00)$ is the time-of-day indicator for times between 10:00am and 11:00am,

$X_3^{gr}(t) = I(\int_{t-3hours}^{t} \text{CLUSTER}_c^{gr}(s) > 0)$ is the indicator for CLUSTER_c^{gr} for firm c's gr-quartile jumps, taking a value of one within 3 hours prior to t, and

$X_4^{gr}(t) = I(\int_{t-10hours}^{t-3hours} \text{CLUSTER}_c^{gr}(s) > 0)$ is the indicator for CLUSTER_c^{gr} for firm c's gr-quartile jumps, taking a value of one between 3 and 10 trading hours prior to t. As in the previous application, time-of-day indicators for the morning hours are included to control for the intraday seasonal pattern of jump arrivals.

Table 8 reports the characteristics of the detected jump size distribution for all firms listed in Table 2. The estimation results for inner(outer)-quartile jump clustering are also presented. As in other tables, *,**,*** indicate the JPT results, showing that the corresponding predictors are significant at the 10%, 5%, and 1% levels, respectively. It shows that both inner and outer quartile jumps are likely to cluster separately within a short time horizon of 3 trading hours and up to 10 trading hours. The results are consistent with the jump clustering evidence presented in Table 5. Both sized jumps are shown to be short-lived up to 10 trading hours. The outer-quartile jumps are more likely to cluster over longer trading hours than are inner-quartile jumps. The impact sizes (measured by the average magnitudes of coefficients) of outer-quartile jumps on similar jumps in the future tend to be slightly greater than those of inner-quartile jumps.

The evidence found in this study offers explanations for some existing evidence documented in the literature. For example, it is worth noting that the jump size clustering can influence the well-known volatility clustering, since traditional volatility measures do not treat returns due to jump components separately from returns due to diffusion components. Another related study is on aggregate idiosyncratic variance by Bekaert, Hodrick, and Zhang (2010). The authors study the idiosyncratic variances estimated using realized variances of the residuals from empirical asset pricing models as in Campbell, Lettau, Malkiel, and Xu (2001) and Fama and French (1996). They identify a large number of structural breaks in their idiosyncratic variances and investigate the dynamics of idiosyncratic variances using regime shifting models. They also document the importance of macroeconomic uncertainty in explaining time-variation in idiosyncratic variance.

If the idiosyncratic realized variance is estimated by their approach, their estimates essentially represent total variations from both diffusion and jump components in jump diffusion models (including systematic jumps). In other words, variations from jump components are embedded in their traditional idiosyncratic variance estimates. Therefore, one can interpret that structural breaks in the idiosyncratic variances are partially due to the presence of jumps in returns. In particular, if (sizes of) jumps cluster as shown in this paper, their idiosyncratic variance will stay in a higher-variance regime for a period of time in their two-regime shifting model until it comes back to a lower-variance regime without jump clustering. Moreover, their finding of macroeconomic information as important determinants of idiosyncratic variances can be explained, since the presence of jumps (especially, systematic jumps that are likely to be driven by macroeconomic predictors and market index jumps) contributes to the time variation in idiosyncratic variance.

5 Concluding Remarks

This article examines the predictability of jumps in individual stock returns. Assuming that stock prices move continuously, following the jump diffusion models, but that econometricians can only observe stock price data at discrete times, I first resolve the technical problem of identifying jump predictors and propose a new empirical test which allows us to discover multiple predictors up to the intraday level and assess their relative importance and precision. The theoretical result for statistical inference is very general and can be useful for other empirical studies. As long as high frequency observations for target returns and jump predictors are available for a sufficiently long sample period, this technique can be applied to analyzing general jump dynamics as well as any specific types of jumps in various financial markets.

I show that one can predict general jump arrivals in U.S. individual stock returns using both macro-level and micro-level information. In particular, macroeconomic information arrivals such as Fed announcements, nonfarm payroll reports, overall market jumps, and initial jobless claims tend to significantly increase the likelihood of individual stock jump arrivals within a short time horizon such as 30 minutes. I also find strong evidence that stock price jumps tend to occur within one day before earnings announcement times, within the first 30 minutes after analysts' recommendation releases, within three trading hours immediately after the same stock experiences jumps, and during the morning hours on ex-dividend dates. I further examine whether one can distinguish systematic jumps and idiosyncratic jumps using these important predictors. All the aforementioned macro-level information variables are proven to be very important in systematic jump prediction, while earnings and analyst recommendation releases are associated with better predictors for idiosyncratic jumps than dividend and individual stock jump information. Overall, the evidence demonstrates an important role of macroeconomic fundamentals in extreme stock returns, "jumps" with important implications for asset pricing, hedging strategies, portfolio diversification, and risk management.

Figure legends

Figure 1: Intuition of Jump Predictor Test

This graph illustrates an example of seven jump arrivals over a given time horizon and shows how the proposed test identifies the information covariates predicting those jump arrivals. These arrivals of jumps are not directly observable from discrete data from continuous-time models in practice. The JPT requires estimating the location of those jump arrival times (from the 1st to the 7th) by jump detection tests (for example, see Lee and Mykland (2008) or the big jump test in Lee and Hannig (2010)) as a necessary step. The time-series data for both these estimated jumps and information covariates are employed for the JPT. The likelihood approximation for this regression-type analysis is explained in Figure 2. A time-series indicator for jump arrivals is created and linked to the predictors related to information variables. The multiple candidates for jump predictors (to become independent variables) should be from the information set available up to each time jumps arrive and the information set is updated over time. The jump arrival indicators based on the jump detection tests are required to satisfy the properties listed in **Proposition 1**. See Section 2 for more details.

Figure 2: How the Mixed Unobservability Problem is Resolved

This graph illustrates how the jump predictors are identified in continuous-time models. Note that the goal of the inference is to approximate the true likelihood $\widetilde{L(\theta|\mathcal{F}_T)}$ for stochastic jump intensity models within jump diffusion processes with an empirical likelihood which depends on available discrete data. I suggest using partial likelihood $PL_n(\theta|\mathcal{F}_T)$, depending on jumps filtered by multiple jump detection tests and available covariates. The line between partial likelihood $PL_n(\theta|\mathcal{F}_T)$ and full likelihood $L_n(\theta|\mathcal{F}_T)$ represents their asymptotic equivalence, indicating that partial likelihood $PL_n(\theta|\mathcal{F}_T)$ approximates full likelihood $L_n(\theta|\mathcal{F}_T)$. The line between full likelihood $L_n(\theta|\mathcal{F}_T)$ and true likelihood $\widetilde{L(\theta|\mathcal{F}_T)}$ again indicates that full likelihood $L_n(\theta|\mathcal{F}_T)$ approximates true likelihood $\widetilde{L(\theta|\mathcal{F}_T)}$, which is the ultimate likelihood that needs to be optimized in order to identify the jump predictors in continuous-time models. Mathematical definition of three likelihoods can be found in **Definition 2**. More details are in Section 2.

Footnotes

1. See Bakshi, Cao, and Chen (1997), Duffie, Pan, and Singleton (2000), Aït-Sahalia (2002), Andersen, Benzoni, and Lund (2002), and the references therein.

2. See Andersen and Bollerslev (1998), Andersen, Bollerslev, Diebold, and Vega (2003), Wongswan (2006), and the references therein for the impact of macroeconomic fundamentals on foreign currency exchange markets, futures markets, treasury (bond) markets, and international stock markets.

3. Econometricians have explored ways to distinguish jump risk from volatility risk using discrete observations from continuous-time models. See Aït-Sahalia (2004), Andersen, Bollerslev, and Dobrev (2007), Huang and Tauchen (2005), Barndorff-Nielsen and Shephard (2006), Jiang and Oomen (2008), Aït-Sahalia and Jacod (2009b), Lee and Mykland (2008), and the references therein.

4. See Protter (2004) for the usual technical conditions that this filtration satisfies.

5. This doubly stochastic Poisson process is also known as a Cox process and applied in modeling corporate default events in recent studies by Duffie, Saita, and Wang (2007) and Das, Duffie, Kapadia, and Saita (2007), among others.

6. There is some evidence of extremely small jumps (see Aït-Sahalia and Jacod (2009a), and Todorov and Tauchen (2008), among others). Although it would be interesting to characterize the dynamics of extremely small jumps, doing so is beyond the scope of this paper.

7. This definition of product integration is created for this study in order to explain the likelihood approximation. Though a similar concept is used in Andersen, Borgan, Gill, and Keiding (1992) for counting processes, these authors do not intend to describe it in the presence of the diffusion term in their model.

8. For the jump detection test, the null hypothesis is the absence of a jump, and hence, rejecting the null indicates the presence of a jump. The simulation study in Section 4 is based on these two estimators, and various parameter choices are suggested for actual applications therein. Term K in the definition is a window size within which a local movement in the process is considered. These are used in Lee and Mykland (2008) and Lee and Hannig (2010) for conducting jump detection tests. For the asymptotic arguments, K needs to satisfy slightly different conditions depending on the choice of volatility estimator. However, all the conditions are imposed to make the effect of jumps in volatility estimation negligible. Other candidates for $\widehat{\sigma(t_i)}$ are consistent stochastic volatility estimators such as the multipower variation based estimators, which include tripower or quadpower variations as special cases. In finite samples, the bipower variation has finite sample bias due to jumps, and multipower variations share similar finite sample bias. The simulation study suggests that the marginal benefit of using more orders in power variation is not significant in the JPT application.

9. The global property of one of the jump detection tests (**Definition 2.C.a**) was mentioned in Lee and Mykland (2008), but this local property must be satisfied.

10. This result can essentially be achieved by the application of jump tests that satisfy the properties stated in **Proposition 1**, which enables us to separate jumps from the jump diffusion models. See Lee and Mykland (2008) and Lee and Hannig (2010) for more details on this issue.

11. A similar technique is applied in Mykland and Zhang (2009) for estimating the volatility or leverage effect, which is the correlation between return and volatility processes in asset prices.

12. The formula for $-\mathcal{Z}(\theta)$, the matrix of second-order partial derivatives of the log-partial likelihood function, is

$$\mathcal{Z}(\theta) = -\sum_{1\le i\le n} \frac{\partial^2}{\partial\theta_j\theta_l} \log d\hat{\Lambda}_\theta(t_i) d\hat{J}(t_i) - \sum_{1\le i\le n} \frac{\partial^2}{\partial\theta_j\theta_l} \log(1 - d\hat{\Lambda}_\theta(t_i))(1 - d\hat{J}(t_i)). \tag{17}$$

13. As usual, $\nabla d\Lambda_\theta$ can be estimated by replacing θ with $\hat{\theta}$. $\hat{\theta}$ is asymptotically normal under the null hypothesis around its mean θ_0 with its covariance matrix $-\mathcal{Z}^{-1}(\theta_0)$.

14. It is ideal to adjust individual returns for intra-day volatility patterns when detecting jumps before applying JPT. However, as also mentioned in Bollerslev, Law, and Tauchen (2009), there is no obvious solution for this adjustment in most realistic settings because the relative importance of volatility and jumps changes continuously over time (also across days) and any volatility measurements which depend on observations at particular times of the days still will not completely resolve this problem. As stated, this intraday volatility problem does not matter in the identification of jump predictors by the JPT.

15. Though other jump robust estimators based on multipower variation can be used for the same purpose, applying estimators based on multipower variation here does not significantly change the results.

16. I list in the table the symbols used as of December 31, 2008. For the data collection, I first checked if there were changes in the symbol and confirmed that the observations are from the same firm before and after the change.

17. This finding on the relative number of jumps in the index and in individual stocks is robust to the choice of the diffusive volatility estimator, and also holds for the estimator based on multipower variation.

18. To mitigate the noisy data problem, I removed from the sample all the observations that might be driven by the bounce-back effect. One could further improve the results by modeling noise explicitly in the analysis.

19. Before April 1995, FOMC news was not released regularly at the time specified in Table 4.

I follow Andersen, Bollerslev, Diebold, and Vega (2003) for the irregular release time as in the table note and regular release times of 11:30am for the years before 1994.

20. As noted in the earlier section, depending on application, other functions for jump intensity can be applied instead of the simple logistic function.

21. Note that these time-of-day indicators only depend on time, and hence are deterministic. Therefore, they can be created before time t.

22. In order to make sure that the overall conclusions based on the proposed method is not the outcome of in-sample overfitting, I check whether the relative importance of the selected predictors is stable over time. Specifically, I split the total sample period from 1993 to 2008 into two subsample periods. I estimate the same jump intensity models separately over the two non-overlapping subsample periods and find that their relative importance stays the same.

23. For example, Michaely (1991) analyzes the effect of the 1986 Tax Reform Act (TRA) on the ex-dividend day stock price behavior and finds that the tax change had no effect on the ex-dividend stock price behavior. Also, see Lasfer (1995) and related references therein.

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Figure 1: **Intuition of Jump Predictor Test (JPT)**

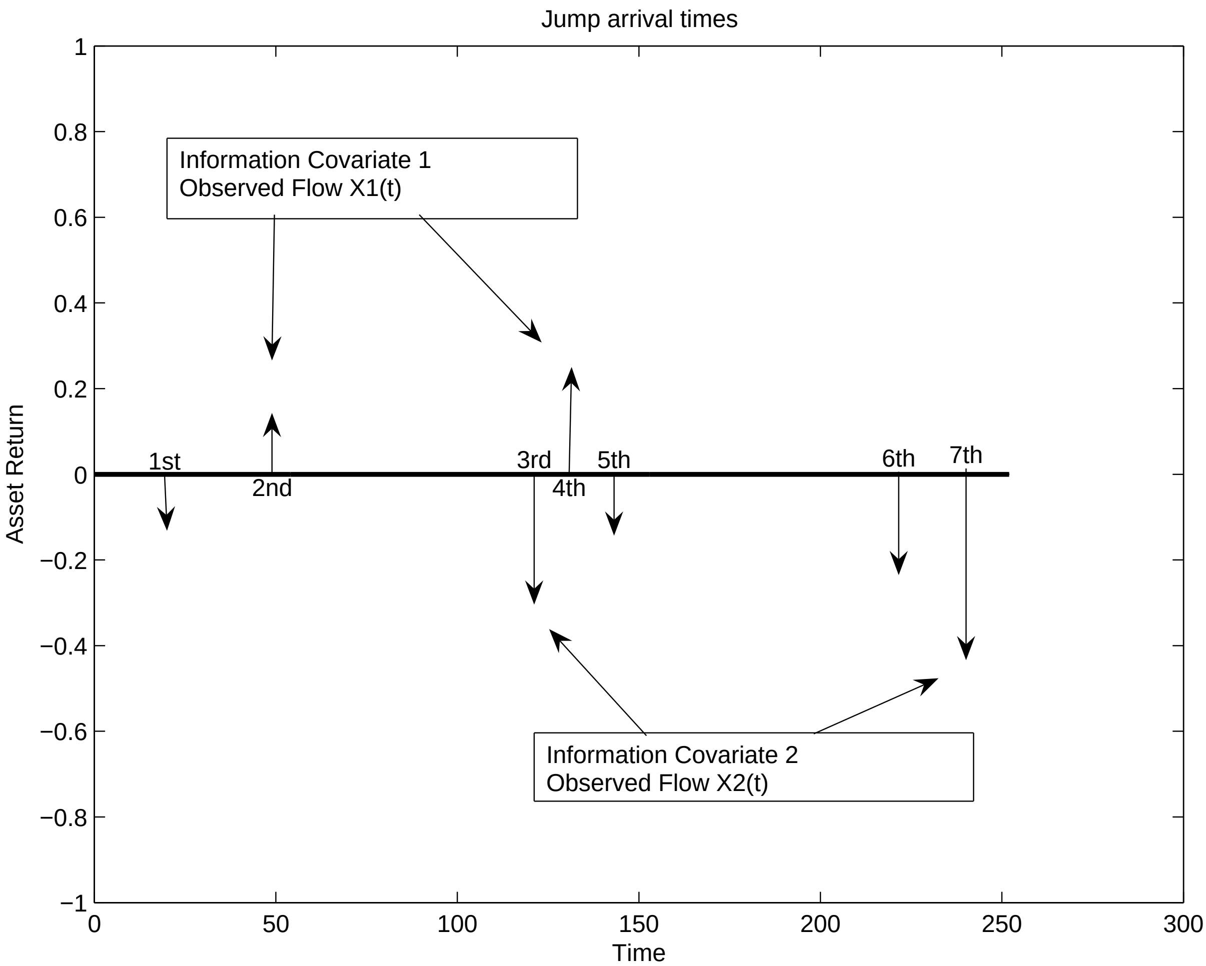

Figure 2: **How the Mixed Unobservability Problem is Resolved**

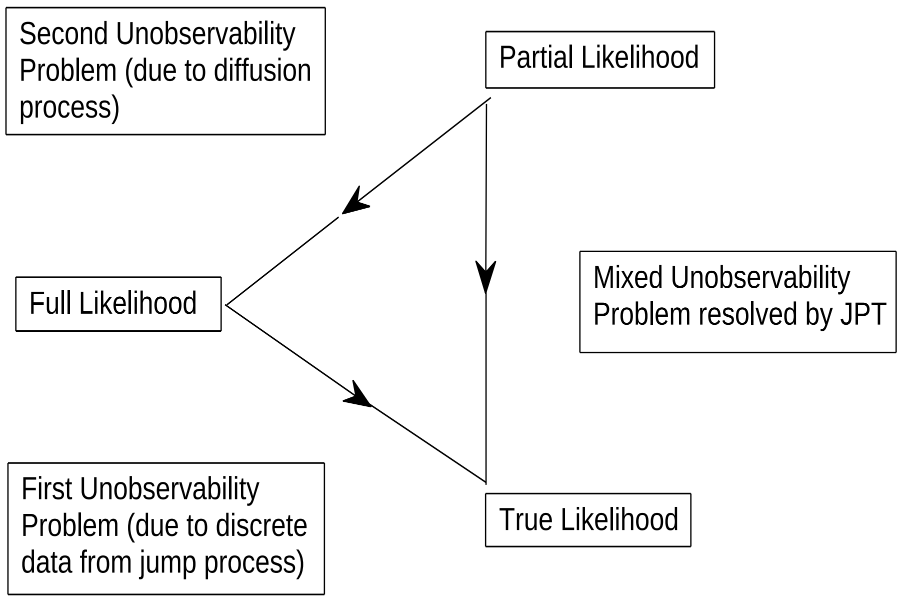

Table 1: **Simulation Results of the Jump Predictor Test (JPT)**[†]

	Definition 2.C.a			**Definition 2.C.b**		
	In the presence of U-shaped intraday volatility and jumps in volatility					
σ_y	$\hat{\theta}_0$	$SE(\hat{\theta}_0)$	p-value	$\hat{\theta}_0$	$SE(\hat{\theta}_0)$	p-value
$4\sigma(t^-)$	-3.9986	0.0934	0.0000	-4.0202	0.0943	0.0000
$8\sigma(t^-)$	-3.9992	0.0934	0.0000	-4.0211	0.0944	0.0000
$12\sigma(t^-)$	-4.0034	0.0936	0.0000	-4.0250	0.0946	0.0000
σ_y	$\hat{\theta}_1$	$SE(\hat{\theta}_1)$	p-value	$\hat{\theta}_1$	$SE(\hat{\theta}_1)$	p-value
$4\sigma(t^-)$	2.9506	0.3372	4.4562e-006	2.9456	0.3395	5.8270e-006
$8\sigma(t^-)$	2.9478	0.3373	7.0656e-007	2.9421	0.3397	9.9900e-007
$12\sigma(t^-)$	2.9510	0.3374	5.9852e-007	2.9434	0.3400	5.1609e-007

[†] This table contains averaged simulation results from the proposed procedure described in Section 2 using the two tests as defined in **Definition 2.C.a** and **2.C.b**. All the figures in this table are results averaged over 3,000 simulation runs. 15-minute returns over 1 year are generated from the general model that accommodates the presence of price jumps with stochastic jump intensity, U-shaped asymmetric intraday volatility, jumps in volatility, time-varying jump sizes, and leverage effect. It is assumed that market opens at 9:30am and closes at 4:00pm. The model is specified as $d\log S(t) = u(t)\sigma(t)dW(t) + Y(t)dJ(t)$, and the stochastic volatility model is specified as $d\sigma^2(t) = \kappa\left(\theta - \sigma^2(t)\right)dt + \omega\sigma(t)dB(t) + Y_\sigma(t)J_\sigma(t)$, where $W(t)$ and $B(t)$ denote standard Brownian Motion processes and $J(t)$ and $J_\sigma(t)$ denote Poisson processes, $E(dB(t)dW(t)) = \rho dt$. The parameter values used for the simulation are the estimates from the empirical study by Eraker (2004). They are $\kappa = 0.0162, \theta = 0.573$, and $\omega = 0.58, \rho = -0.46$. For the jump intensity model, I assume that $d\Lambda_\theta(t) = \frac{1}{1+\exp(-\theta_0-\theta_1 X_1(t))}$ with $\theta_0 = -4$ and $\theta_1 = 3$. Here, the predictor $X_1(t)$ is set to become 1 every week at 10:00am to mimic real-time news events. Sizes for jumps in volatility $Y_\sigma(t)$ follow the exponential distribution with its mean $\mu_v = 1.25$ and time-varying sizes for jumps in prices $Y(t)$ are set in comparison to $\sigma(t^-)$ volatility level immediately before time t. $u(t)$ for the asymmetric U-shaped intra-day volatility pattern is modeled as in Andersen, Dobrev, and Schaumburg (2008) and their calibrated parameter setup. See further details in Section 3.

Table 2: **Descriptive Statistics for Jump Counts and Returns from DJIA Individual Equities and the S&P 500 Index**[†]

Name (Ticker)	# of tests	# of jumps	per year	per month	per day	Stdev	Skew	Kurt	Autocorr(1)	Autocorr(2)
S&P 500 (SPY)	107929	446	27.87	2.32	0.11	0.0023	-0.5236	58.28	-0.0788	-0.0007
ALCOA (AA)	106299	409	25.56	2.13	0.11	0.0045	0.0286	37.38	-0.0181	0.0037
AMERICAN EXPRESS (AXP)	106406	338	21.12	1.76	0.08	0.0044	-0.2928	44.05	-0.0559	-0.0023
BOEING (BA)	106756	409	25.56	2.13	0.10	0.0039	-0.1562	34.17	-0.0412	-0.0045
CATERPILLAR (CAT)	105840	391	24.43	2.03	0.10	0.0041	-0.2746	32.70	-0.0236	-0.0091
CHEVRON CORPORATION(CVX)	105872	284	17.75	1.48	0.07	0.0032	-0.1865	20.23	-0.0230	0.0063
DU PONT (DD)	106741	313	19.56	1.63	0.08	0.0037	-0.0734	16.50	-0.0568	0.0040
WALT DISNEY (DIS)	106527	368	23.00	1.91	0.09	0.0040	-0.1808	34.06	-0.0669	-0.0072
GENERAL ELECTRIC (GE)	107577	291	18.18	1.51	0.07	0.0036	-0.0007	39.43	-0.0452	-0.0117
HOME DEPOT (HD)	106529	392	24.50	2.04	0.10	0.0043	-0.4156	50.75	-0.0576	-0.0003
HEWLETT PACKARD (HPQ)	106588	411	25.68	2.41	0.10	0.0043	-0.4156	50.75	-0.0576	-0.0003
INTL. BUSINESS MACH. (IBM)	107335	363	22.68	1.89	0.09	0.0037	0.7954	59.60	-0.0266	-0.0028
JOHNSON & JOHNSON (JNJ)	106368	358	22.37	1.86	0.09	0.0031	0.2544	21.89	-0.0721	-0.0092
JP MORGAN & CHASE (JPM)	106624	346	21.62	1.80	0.09	0.0044	0.5689	41.81	-0.0379	-0.0007
COCA COLA (KO)	106420	281	17.56	1.46	0.07	0.0032	-0.1931	23.55	-0.0582	0.0010
MCDONALD (MCD)	106418	374	23.37	1.94	0.09	0.0036	-0.1960	19.55	-0.0792	-0.0052
3M (MMM)	105901	320	20.00	1.66	0.08	0.0032	-0.2309	34.90	-0.0442	-0.0067
MERCK & CO INC(MRK)	105878	388	24.25	2.02	0.10	0.0036	-0.5656	32.41	-0.0399	0.0102
PFIZER (PFE)	105955	387	24.18	2.01	0.10	0.0037	-0.2976	41.75	-0.0668	-0.0042
PROCTOR & GAMBLE (PG)	106316	276	17.25	1.43	0.07	0.0031	-0.4345	27.35	-0.0719	-0.0141
AT&T (T)	106531	293	18.31	1.52	0.07	0.0040	0.3408	29.30	-0.0740	0.0120
UNITED TECHNOLOGIES (UTX)	106005	365	22.81	1.90	0.09	0.0036	0.0422	30.11	-0.0224	-0.0126
WALMART STORES (WMT)	106178	354	22.12	1.84	0.09	0.0039	0.0163	23.69	-0.0775	0.0048
EXXON MOBIL (XOM)	106640	253	15.81	1.31	0.06	0.0031	-0.4102	25.85	-0.0614	0.0048
AVERAGE	106447	348	21.79	1.82	0.08	0.0038	-0.0731	34.73	-0.0498	-0.0022
Standard Error	(418)	(45.30)	(2.83)	(0.25)	(0.012)	(0.0004)	(0.3290)	(11.62)	(0.01966)	(0.0069)

[†] This table includes the descriptive statistics for jump counts and returns for each individual component stock of the DJIA (as of December 31, 2008) and the S&P 500 index. For returns, summary statistics such as standard deviation, skewness, kurtosis, and autocorrelations are listed. For jump counts, the total number of jump tests, the total number of detected jumps, and the average numbers of detected jumps are listed, with their cross-sectional averages at the bottom. Observations are based on trades in the New York Stock Exchange (NYSE) from January 4, 1993 to December 31, 2008 with a total of 4,017 trading days. The component stocks traded on the Nasdaq are excluded to keep consistent trading mechanisms across different securities for comparison purposes. Kraft (KFT) is excluded due to a significant amount of missing data because it only started to be traded in 2001. CITI GROUP (C), BANK OF AMERICA (BAC), and VERIZON (VZ) are also excluded because of unusual firm name changes in order to avoid any complication due to the change. The 15-minute returns from transaction prices are applied. Ticker denotes the ticker symbol of each series as of December 31, 2008.

Table 3: **At What Times do Jumps Occur more often?**†

Ticker	9:30am	9:45am	10:00am	10:15am	11:00am	12:00pm	1:00pm	2:00pm	3:00pm
SPY	0.6300	0.0157	0.0314	0.0650	0.0269	0.0336	0.0291	0.0605	0.0561
AA	0.5917	0.1320	0.0636	0.0685	0.0318	0.0318	0.0098	0.0244	0.0269
AXP	0.6065	0.1272	0.0207	0.0621	0.0237	0.0089	0.0325	0.0355	0.0533
BA	0.5892	0.1516	0.0636	0.0733	0.0244	0.0147	0.0244	0.0196	0.0269
CAT	0.6087	0.1535	0.0716	0.0486	0.0179	0.0230	0.0153	0.0205	0.0256
CVX	0.6021	0.1725	0.0387	0.0387	0.0070	0.0106	0.0141	0.0317	0.0599
DD	0.6198	0.1725	0.0575	0.0511	0.0256	0.0096	0.0096	0.0160	0.0288
DIS	0.6576	0.1603	0.0462	0.0408	0.0136	0.0054	0.0190	0.0109	0.0190
GE	0.6632	0.0687	0.0241	0.0790	0.0412	0.0069	0.0206	0.0172	0.0378
HD	0.6224	0.1607	0.0408	0.0536	0.0230	0.0128	0.0204	0.0357	0.0128
HPQ	0.6399	0.1582	0.0535	0.0389	0.0268	0.0122	0.0195	0.0195	0.0219
IBM	0.6501	0.1405	0.0386	0.0523	0.0220	0.0165	0.0138	0.0193	0.0138
JNJ	0.6341	0.1229	0.0447	0.0531	0.0168	0.0112	0.0223	0.0223	0.0475
JPM	0.6272	0.1069	0.0405	0.0578	0.0434	0.0145	0.0173	0.0289	0.0434
KO	0.7544	0.1103	0.0320	0.0285	0.0142	0.0142	0.0142	0.0071	0.0214
MCD	0.6070	0.1551	0.0294	0.0428	0.0348	0.0187	0.0241	0.0348	0.0374
MMM	0.5156	0.1656	0.0906	0.0469	0.0375	0.0219	0.0156	0.0125	0.0656
MRK	0.5851	0.1598	0.0387	0.0490	0.0258	0.0155	0.0103	0.0232	0.0670
PFE	0.6176	0.1628	0.0413	0.0413	0.0439	0.0207	0.0181	0.0155	0.0310
PG	0.6594	0.1377	0.0290	0.0906	0.0000	0.0181	0.0036	0.0145	0.0326
T	0.6280	0.1297	0.0444	0.0410	0.0205	0.0239	0.0171	0.0239	0.0478
UTX	0.5233	0.1699	0.0548	0.0877	0.0521	0.0219	0.0219	0.0137	0.0384
WMT	0.6243	0.1469	0.0367	0.0508	0.0169	0.0226	0.0226	0.0169	0.0508
XOM	0.6877	0.0830	0.0356	0.0593	0.0158	0.0158	0.0158	0.0316	0.0356
AVE	0.6224	0.1412	0.0451	0.0546	0.0252	0.0161	0.0175	0.0215	0.0367

† The table reports the percentages of jumps in individual equities and the S&P 500 index detected at specific time intervals in a trading day among all detected jumps during the sample period from January 4, 1993 to December 31, 2008 for a total of 4,017 trading days. The NYSE trading hours (9:30am to 4:00pm) are divided into 9 time intervals. Column names are the starting points of the time intervals. For example, the first column (9:30am) includes the percentages of jumps that occurred during the time interval starting at 9:30am and ending at 9:45am.

Table 4: **Description of Data for Jump Predictors in U.S. Individual Equity Markets**†

Macroeconomic Variable Names	Total	Times	Dates	Data Source
U.S. Market Jump (MARKET)	446	Irregular	1993.01.04-2008.12.31	Trade and Quote (TAQ)
Federal Open Market Committee Meeting (FOMC)	134	14:15◇	1993.01.04-2008.12.31	Federal Reserve Board & Bloomberg
Nonfarm Payroll Employment (NONFARM)	192	8:30	1993.01.04-2008.12.31	Bureau of Labor Statistics & Bloomberg
Initial Unemployment Claims (JOBLESS)	834	8:30	1993.01.04-2008.12.31	Employment and Training Administration & Bloomberg
Firm-specific Variable Names	**Total§**	**Times**	**Dates**	**Data Source**
Earnings Announcements (EARNINGS)	70 (10.14)	Irregular	1993.01.04-2008.12.31	First Call Historical Database
Analyst Recommendation Release (ANALYST)	519 (129.85)	Irregular	1993.01.04-2008.12.31	First Call Historical Database
Past Jumps (CLUSTER)	348 (45.30)	Irregular	1993.01.04-2008.12.31	Trade and Quote (TAQ)
Dividend Dates (DIVIDEND)	190 (23.79)§§	Irregular	1993.01.04-2008.12.31	Center for Research in Security Prices (CRSP)

† This table shows the source, dates, times, and number of observations of each information variable. Total denotes the total number of times in which the corresponding event happened over the sample period, as stated in the Dates column. § For the firm-specific variables, I report the averages of total numbers across all the firms along with their standard error in parentheses. Times are local U.S. Eastern times. U.S. market jumps and past jumps denote variables based on the jumps in the S&P 500 and individual equity returns, respectively. Jumps are detected by the nonparametric jump test statistic as defined in **Definition 2.C.a** using the 15-minute returns. The significance level α applied for detecting both U.S. market jumps and individual equity jumps is 5%. All the observations are in real time up to 1 minute, except Dividend Dates, for which daily observations are available. GENERAL MOTORS (GM) is excluded due to significant missing data in the First Call Historical Database. §§ Since the observations for DIVIDEND are available in daily frequency, I report the average number of daily observations. ◇ Before April 1995, FOMC news were not released regularly at the specified time. I follow Andersen, Bollerslev, Diebold, and Vega (2003) for the irregular release times of FOMC news release, which are 11:05am on 1994.2.4, 2:20pm on 1994.3.22 and 1994.7.6, 2:30pm on 1994.11.15, 2:26pm on 1994.5.17, 2:23pm on 1994.12.20, 1:17pm on 1994.8.16, 2:22pm on 1994.9.27, and 2:24pm on 1995.2.1. Before 1994, I use 11:30am.

Table 5: **Jump Predictor Test Results for U.S. Individual Equity Markets**†

Related Variable		9:30-10:00	10:00-11:00	MARKET	FOMC	NONFARM	JOBLESS	EARNINGS	ANALYST	CLUSTER	DIVIDEND
Ticker	Intercept	$X_1(t)$	$X_2(t)$	$X_3(t)$	$X_4(t)$	$X_5(t)$	$X_6(t)$	$X_7(t)$	$X_8(t)$	$X_9(t)$	$X_{10}(t)$
AA	-7.8144***	3.6418***	1.8084***	1.5326***	3.6508***	1.2330***	0.9882***	1.4039***	1.2981***	0.95378***	-0.5298
AXP	-7.7531***	3.4042***	1.2469***	1.9561***	3.1663***	1.4879***	0.7655***	1.4932***	1.1224***	0.92842***	1.1995***
BA	-7.9999***	3.9836***	1.9775***	1.1086***	2.1912***	1.0610***	0.5417***	2.2272***	1.1460***	0.7856***	0.1997
CAT	-8.0818***	3.8428***	2.0611***	1.6874***	3.8204***	1.2347***	0.9712***	2.0695***	1.2969***	0.6643***	0.4924*
CVX	-8.1292***	3.6083***	1.5752***	1.8762***	2.9845***	0.5167	1.0633***	1.0199***	1.0021***	1.0327***	2.0428***
DD	-8.4827***	4.0620***	2.1965***	1.2496***	3.9256***	1.6242***	1.0490***	2.3641***	1.1901***	0.3525	1.2100***
DIS	-8.0831***	3.7731***	1.7896***	1.3690***	1.6904***	0.9829***	1.4441	1.3044***	1.4369***	1.4733***	0.6911
GE	-8.0210***	3.8356***	1.2015***	0.8198**	3.6902***	0.7399**	-0.4940	1.6548***	0.8496***	1.0862***	1.2008***
HD	-8.0724***	3.9520***	1.9986***	1.4200***	4.0128***	1.3721***	0.9442***	2.3218***	0.8497***	0.2880	1.0947***
HPQ	-8.0351***	4.0713***	1.8896***	1.1256***	3.3822***	0.8238***	0.7690***	1.4297***	1.1971***	0.64140***	-0.3814
IBM	-8.0761***	4.0309***	1.6760***	0.7944***	3.3143***	1.1395***	0.5880***	1.7858***	1.4604***	0.0690	0.2185
JNJ	-7.9060***	3.6711***	1.5072***	1.5687***	3.3266***	1.1265***	1.1194***	2.1832***	0.9213***	0.5559**	1.0080***
JPM	-7.8185***	3.5438***	1.3923***	1.6798***	3.8022***	1.2384***	0.9482***	1.9435***	0.9370***	0.2926	1.2376***
KO	-8.8063***	4.4579***	1.9059***	1.6545***	1.9381***	1.3850***	0.6545***	2.2853***	1.4942***	0.1379	0.9913**
MCD	-7.6797***	3.5861***	1.1577***	1.5203***	2.6346***	1.0066***	0.5497***	1.5543***	1.0218***	1.1421***	0.8517*
MMM	-7.8196***	3.2633***	1.7792***	1.7631***	2.3914***	1.6108***	0.4482**	2.3990***	1.4641***	0.1769	0.6819
MRK	-7.6606***	3.3771***	1.5106***	1.8177***	2.4264***	1.2788***	1.1487***	1.8247***	0.9554***	0.5873***	0.9024**
PFE	-7.8430***	3.7069***	1.5421***	1.3149***	2.5535***	1.4551***	0.9195***	1.7234***	0.8047***	1.0330***	1.4674***
PG	-8.7633***	4.3661***	2.2297***	1.6371***	2.7987***	0.6228	0.6867***	2.3072***	0.9834***	0.7624***	0.4922
T	-8.0451***	3.5796***	1.2137***	2.1107***	2.0850***	0.9886***	0.8000***	1.7980***	0.9498***	0.9444***	1.8488***
UTX	-7.7814***	3.4414***	1.7798***	1.7532***	2.7354***	1.4421***	0.8144***	2.2252***	1.3406***	0.4870**	0.5611
WMT	-8.0105***	3.6988***	1.6869***	1.6252***	3.5814***	1.4561***	1.2996***	2.5700***	1.1536***	-0.4644	0.0629
XOM	-8.4024***	3.9781***	1.5942***	1.9345***	3.8401***	0.9399***	0.5122**	1.9373***	0.6535**	0.1565	1.5759***
Average	-8.0472	3.7772	1.6835	1.5356	3.0410	1.1142	0.7644	1.9055	1.1099	0.5686	0.7445

† This table contains the parameter estimates for general jump intensity models applied to the individual equity price data to assess the relative importance of jump predictors. Firm names associated with ticker symbols are listed in Table 2, and descriptions of relevant jump data can also be found therein. The jumps are detected based on NYSE transaction price data sampled every 15 minutes as a necessary step for the jump predictor test as defined in **Definition 2.C.a**. The jump predictors are assumed to be related to doubly stochastic Poisson jump arrivals as in the following fashion: $d\Lambda_\theta(t) = \frac{1}{1+\exp(-\theta_0 - \sum_{j=1}^{10} \theta_j X_j(t))}$, where the definitions of $X_j(t)$'s are in Subsection 4.3. The sample period extends 16 years from January 4, 1993 to December 31, 2008. *,**,*** indicate the significance at the 10%, 5%, and 1% levels, respectively. The averages in the last row are taken after setting the insignificant parameter values equal to zero.

Table 6: **Systematic Jump Predictor Test Results for U.S. Individual Equity Markets**†

Related Variable		9:30-10:00	10:00-11:00	MARKET	FOMC	NONFARM	JOBLESS	EARNINGS	ANALYST	CLUSTER	DIVIDEND
Ticker	Intercept	$X_1(t)$	$X_2(t)$	$X_3(t)$	$X_4(t)$	$X_5(t)$	$X_6(t)$	$X_7(t)$	$X_8(t)$	$X_9(t)$	$X_{10}(t)$
AA	-7.1221***	3.2396***	0.5544***	1.3868***	3.7379***	1.8166***	0.5609***	-0.3328	0.3213	0.9835***	0.1188
AXP	-7.0892***	3.2190***	0.6024***	1.4804***	3.7477***	1.8141***	0.5615***	0.5534	0.0586	0.2389	0.3583
BA	-7.1057***	3.2392***	0.5825***	1.4449***	3.7632***	1.8090***	0.5401***	0.0297	0.1787	0.7403***	-1.2161
CAT	-7.1238***	3.2479***	0.5545***	1.3766***	3.7248***	1.8217***	0.5406***	0.5472*	0.0058	0.8976***	0.4751
CVX	-7.0859***	3.2262***	0.6011***	1.4677***	3.7404***	1.8233***	0.5520***	-0.3239	0.1700	0.5679**	-0.6180
DD	-7.1128***	3.2491***	0.5666***	1.3988***	3.7232***	1.7727***	0.5717***	0.4495	0.1178	0.9307***	-1.2169
DIS	-7.1184***	3.2235***	0.5490***	1.4146***	3.7336***	1.7979***	0.5365***	0.3879	0.2362	0.9338***	0.3256
GE	-7.1430***	3.2625***	0.5526***	1.0698***	3.6839***	1.7840***	0.4993***	-0.1423	-0.1740	1.4822***	0.1700
HD	-7.1114***	3.2435***	0.5512***	1.3964***	3.6873***	1.7993***	0.5629***	0.2772	-0.1751	0.8490***	0.8008**
HPQ	-7.1045***	3.2085***	0.5411***	1.3704***	3.6216***	1.8185***	0.5458***	0.1189	0.1791	0.8100***	0.8849**
IBM	-7.1124***	3.2163***	0.5445***	1.2795***	3.6546***	1.7658***	0.5548***	-0.3236	0.4324**	1.0558***	-0.4304
JNJ	-7.0995***	3.2245***	0.5747***	1.4549***	3.7190***	1.8170***	0.5583***	0.2655	0.1229	0.6684***	0.1745
JPM	-7.1109***	3.1936***	0.5561***	1.3266***	3.7251***	1.8189***	0.5643***	1.0076***	0.2197	0.5780***	1.2331***
KO	-7.1114***	3.2556***	0.5512***	1.3968***	3.7308***	1.8099***	0.5450***	0.3741	-0.2427	1.0739***	-0.3234
MCD	-7.1023***	3.2192***	0.5770***	1.4765***	3.7500***	1.8127***	0.5315***	0.4351	0.2341	0.5831***	0.5330
MMM	-7.0972***	3.2252***	0.5974***	1.4769***	3.7488***	1.8072***	0.5508***	0.3986	0.3014	0.5087*	-0.4226
MRK	-7.0981***	3.2209***	0.5796***	1.4834***	3.7396***	1.8132***	0.5586***	0.3362	0.1162	0.5294**	0.3309
PFE	-7.1008***	3.2396***	0.5909***	1.4560***	3.7284***	1.8236***	0.5489**	0.4304	0.0142	0.5982***	-0.5868
PG	-7.0980***	3.2125***	0.5405***	1.4083***	3.7155***	1.8847***	0.5976***	0.2488	-0.6007*	0.8195***	1.5502***
T	-7.0865***	3.2258***	0.5930***	1.4855***	3.7436***	1.7914***	0.5631***	-0.0053	0.0002	0.4948*	0.2851
UTX	-7.1092***	3.2706***	0.5975***	1.4268***	3.7579***	1.8131***	0.5472***	0.2373	-0.5598	0.8037***	-1.1444
WMT	-7.0882***	3.2252***	0.5982***	1.4914***	3.7503***	1.8308***	0.5600***	0.3640	-0.1109	0.2959	0.6089
XOM	-7.1023***	3.2302***	0.5759***	1.3996***	3.7366***	1.8035***	0.5385***	0.1483	0.1787	0.9283***	0.1142
Average	-7.1058	3.2312	0.5710	1.4073	3.7245	1.8108	0.5517	0.0676	-0.0073	0.7320	0.1943

† This table contains the parameter estimates for systematic jump intensity models to assess the relative importance of jump predictors. Firm names associated with ticker symbols are listed in Table 2, and description of relevant jump data can also be found therein. The systematic jumps are detected in the S&P 500 index as a necessary step for the systematic jump predictor test as defined in **Definition 2.C.a**. The jump predictors are assumed to be related to doubly stochastic Poisson jump arrivals as in the following fashion: $d\Lambda_\theta^{systematic}(t) = \frac{1}{1+\exp(-\theta_0-\sum_{j=1}^{10}\theta_j X_j(t))}$, where the definitions of $X_j(t)$'s are in Subsection 4.3. The sample period extends 16 years from January 4, 1993 to December 31, 2008. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The averages in the last row are taken after setting the insignificant parameter values equal to zero.

Table 7: **Idiosyncratic Jump Predictor Test Results for U.S. Individual Equity Markets**†

Related Variable		9:30-10:00	10:00-11:00	MARKET	FOMC	NONFARM	JOBLESS	EARNINGS	ANALYST	CLUSTER	DIVIDEND
Ticker	Intercept	$X_1(t)$	$X_2(t)$	$X_3(t)$	$X_4(t)$	$X_5(t)$	$X_6(t)$	$X_7(t)$	$X_8(t)$	$X_9(t)$	$X_{10}(t)$
AA	-7.9363***	2.4758***	1.6724***	0.6588	2.0155**	0.4114	0.9894***	1.6873***	1.6395***	0.9917***	0.4719
AXP	-8.2021***	2.3469***	1.3860***	1.4438***	2.5358***	0.3582	0.6635*	2.2778***	1.2000***	1.1763***	0.7742
BA	-8.2781***	3.2449***	2.0307***	0.4465	0.0000	0.0080	0.5893**	2.4116***	1.1929***	0.7152***	-0.3901
CAT	-8.3654***	2.9568***	2.0309***	1.2146***	2.3323**	1.0718*	1.0264***	2.2106***	1.4771***	0.1379	0.8519**
CVX	-8.4792***	2.7210***	1.6319***	1.3523***	0.0000	0.6666	1.2022***	1.0746**	1.3022***	1.1535***	2.4072***
DD	-8.8742***	3.3244***	2.1784***	-0.4521	2.3075**	1.3560***	1.1483***	2.6048***	1.4092***	0.5882*	1.5896***
DIS	-8.6378***	3.4382***	2.0985***	1.1767***	0.0000	0.9387**	0.2081	1.3365***	1.3990***	0.8932***	0.3082
GE	-8.5663***	3.2028***	1.2665***	-0.9003	3.1230***	0.0000	-0.3699	1.7864***	1.3424***	1.4834***	1.1222*
HD	-8.2000***	2.8436***	1.8642***	0.1827	2.9942***	0.6104	1.0260***	1.9746***	1.3097***	0.7591***	0.7725
HPQ	-8.3449***	3.3812***	1.8789***	-0.1609	0.0000	0.6968	0.6806***	1.8070***	1.1010***	0.9643***	-0.4216
IBM	-8.4305***	3.2232***	1.7844***	0.1369	0.0000	1.0910**	0.3130	2.1974***	1.4234***	0.4374	0.7540
JNJ	-8.0988***	2.7578***	1.5884***	0.6880	1.7963*	-0.4491	1.0811***	1.7360***	0.9816***	0.5920*	1.7116***
JPM	-8.0772***	2.6858***	1.4022***	1.1237***	0.0000	0.0000	0.8528***	1.5624***	1.1556***	0.5558*	1.5197***
KO	-9.1329***	3.8300***	2.1107***	-0.4557	2.8787***	-0.2498	0.2397	2.1323***	1.5533***	-0.2410	-0.0021
MCD	-7.8472***	2.9162***	1.1768***	0.5483	1.9416*	0.3724	0.4381	1.5584***	1.0183***	1.1853***	1.1221*
MMM	-8.1022***	2.2236***	1.7134***	1.0197**	0.0000	1.5741***	0.6977**	2.5714***	1.5889***	0.2380	0.8871
MRK	-7.8078***	2.3416***	1.3484***	0.5024	0.0000	0.2140	1.2862***	1.7729***	1.0478***	1.0112***	1.1229**
PFE	-8.2045***	2.8938***	1.5371***	0.2899	0.0000	1.3538***	0.6828**	1.5861***	0.9460***	1.2912***	1.5468***
PG	-9.3901***	4.0060***	2.5535***	1.0019**	0.0000	0.2699	0.2377	2.5889***	1.3286***	0.7410**	0.7740
T	-8.3327***	2.9468***	1.2626***	0.6099	0.0000	-0.6685	1.0241***	1.8102***	0.8428***	1.3290***	2.1022***
UTX	-7.9386***	2.3433***	1.6682***	0.8607**	2.0532**	0.6112	1.0754***	2.0923***	1.8286***	0.7807***	1.1186*
WMT	-8.3501***	2.9808***	1.6563***	0.5007	0.0000	1.5990***	1.3301***	2.7184***	1.0968***	0.0028	-0.1019
XOM	-8.8659***	3.2563***	1.5986***	0.3457	2.9570***	0.5026	0.4764	2.3308***	0.4011	0.2345	2.2325***
Average	-8.3679	2.9713	1.7147	0.3997	1.1711	0.3906	0.6676	1.9926	1.2254	0.7048	0.8021

† This table contains the parameter estimates for idiosyncratic jump intensity models to assess the relative importance of jump predictors. Firm names associated with ticker symbols are listed in Table 2, and descriptions of relevant jump data can also be found therein. The idiosyncratic jumps for each firm are obtained by applying the jump detection test as defined in **Definition 2.C.a** and by removing any systematic jumps as well as any common jumps that simultaneously occurred in at least two stocks. The jump predictors are assumed to be related to doubly stochastic Poisson jump arrivals as in the following fashion: $d\Lambda_\theta^{idiosyncartic}(t) = \frac{1}{1+\exp(-\theta_0 - \sum_{j=1}^{10} \theta_j X_j(t))}$, where the definitions of $X_j(t)$'s are in Subsection 4.3. The sample period extends 16 years from January 4, 1993 to December 31, 2008. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The averages in the last row are taken after setting the insignificant parameter values equal to zero.

Table 8: **Jump Size Clustering for U.S. Individual Equity Markets**†

	Detected Jump Size Distribution				Inner-Quartile Jump Clustering					Outer-Quartile Jump Clustering				
	Min	Lower	Upper	Max	Intercept	$X_1^{in}(t)$	$X_2^{in}(t)$	$X_3^{in}(t)$	$X_4^{in}(t)$	Intercept	$X_1^{out}(t)$	$X_2^{out}(t)$	$X_3^{out}(t)$	$X_4^{out}(t)$
AA	-0.098	-0.019	0.021	0.104	-8.100***	3.457***	1.765***	1.735***	0.4803	-8.855***	4.442***	2.289***	1.759***	0.635**
AXP	-0.123	-0.019	0.021	0.096	-8.313***	3.578***	1.618***	1.408***	0.6173*	-8.435***	3.757***	1.407***	1.914***	0.7826**
BA	-0.097	-0.018	0.021	0.084	-8.656***	4.180***	2.272***	1.570***	0.462	-8.568***	4.096***	1.868***	1.553***	1.0914***
CAT	-0.092	-0.018	0.021	0.085	-8.236***	3.637***	1.713***	1.537***	0.564*	-9.254***	4.718***	2.958***	1.624***	0.994***
CVX	-0.072	-0.015	0.014	0.047	-8.553***	3.510***	1.935***	1.691***	1.081***	-9.073***	4.376***	1.725***	1.621***	0.856**
DD	-0.070	-0.018	0.018	0.048	-8.764***	3.987***	2.274***	1.216***	0.5133	-9.313***	4.652***	2.413***	1.493***	1.113***
DIS	-0.107	-0.020	0.020	0.087	-8.611***	4.101***	1.723***	1.497***	0.666**	-9.603***	5.067***	3.158***	1.198***	1.090***
GE	-0.102	-0.018	0.018	0.080	-8.478***	3.662***	1.319***	1.589***	0.551	-8.727***	3.992***	1.043***	2.013***	0.953***
HD	-0.131	-0.020	0.022	0.101	-8.249***	3.584***	1.870***	0.858***	1.122***	-9.092***	4.680***	2.368***	1.245***	1.013***
HPQ	-0.142	-0.026	0.025	0.128	-8.574***	4.201***	1.643***	1.402***	0.705**	-8.779***	4.331***	2.218***	1.716***	0.939***
IBM	-0.111	-0.019	0.020	0.112	-8.410***	3.928***	1.293***	1.107***	0.0812	-9.050***	4.596***	2.254***	1.0128**	0.5967*
JNJ	-0.051	-0.016	0.014	0.073	-8.488***	3.844***	1.897***	0.915**	0.972***	-8.537***	3.974***	1.386***	2.075***	0.816***
JPM	-0.097	-0.017	0.018	0.096	-8.257***	3.489***	1.564***	1.363***	1.092***	-8.607***	4.030***	1.513***	1.500***	0.838***
KO	-0.060	-0.018	0.014	0.065	-9.453***	4.783***	2.316***	1.393***	0.416	-9.362***	4.718***	1.849***	1.478***	0.611
MCD	-0.073	-0.019	0.017	0.052	-8.173***	3.538***	1.347***	1.641***	0.776***	-8.464***	3.991***	1.254***	2.054***	0.287
MMM	-0.078	-0.015	0.015	0.060	-8.287***	3.355***	1.918***	0.813	0.6216*	-8.541***	3.668***	2.030***	1.710***	0.943***
MRK	-0.080	-0.019	0.016	0.064	-8.295***	3.714***	1.701***	0.781*	1.034***	-8.296***	3.661***	1.851***	1.369***	0.874***
PFE	-0.094	-0.021	0.018	0.105	-8.273***	3.736***	1.418***	1.417***	0.815***	-8.712***	4.233***	2.077***	2.042***	0.282
PG	-0.070	-0.016	0.014	0.053	-9.2613***	4.563***	2.066***	1.667***	-0.455	-9.280***	4.436***	2.594***	1.580***	0.615
T	-0.091	-0.019	0.018	0.067	-8.525***	3.671***	1.620***	1.513***	0.809**	-8.899***	4.149***	1.446***	1.915***	1.409***
UTX	-0.100	-0.015	0.017	0.071	-8.128***	3.366***	1.657***	1.342***	0.790***	-8.725***	4.099***	2.357***	1.663***	0.3172
WMT	-0.087	-0.018	0.019	0.076	-8.393***	3.800***	1.659***	1.243***	0.400	-8.672***	4.142***	1.999***	0.6868	-0.271
XOM	-0.074	-0.017	0.012	0.049	-8.913***	4.007***	1.572***	1.337***	1.328***	-9.044***	4.177***	1.8787***	0.8948	0.813*
Average	-0.091	-0.018	0.018	0.078	-8.495	3.812	1.746	1.314	0.564	-8.864	4.260	1.997	1.531	0.685

† This table contains the parameter estimates showing jump size clustering in U.S. individual stock markets. Firm names associated with ticker symbols are listed in Table 2. The detected jump sizes are based on NYSE transaction price data sampled every 15 minutes with a significance level α of 5% for the jump detection test as defined in **Definition 2.C.a**. Inner-quartile and outer-quartile jumps are classified for each firm. Inner (outer)-quartile jump group for each firm includes jumps whose sizes are less (greater) than the upper quartile and greater (less) than lower quartile of the jump size distribution of that firm. The model for inner (outer)-quartile jump clustering is specified as $d\Lambda_\theta^{gr}(t) = \frac{1}{1+\exp(-\theta_0-\sum_{j=1}^4 \theta_j X_j^{gr}(t))}$, where $gr = inner$ or $outer$ and the definitions of $X_j(t)$'s are in Subsection 4.5. The sample period extends 16 years from January 4, 1993 to December 31, 2008. *, **, and *** indicate the significance at the 10%, 5%, and 1% levels, respectively. The averages in the last row are taken after setting the insignificant parameter values equal to zero.

Appendix

A.1. Assumption C on $\mu(t)$ and $\sigma(t)$ in equation (1)

It is assumed that the drift and diffusion coefficients do not change dramatically over a short time interval, allowing them to depend on the process itself. It satisfies most of continuous-time models in the asset pricing literature. See Lee and Mykland (2008) for more detailed mathematical assumptions on the $\mu(t)$ and $\sigma(t)$ coefficients.

A.2. Assumption D on $\Lambda_\theta(t)$ in equation (2)

Here, a note is made on the minimal assumption imposed on $X(t)$. $X(t)$ is required to be a $\mathcal{F}_t$-predictable process. In other words, each of $X(t)$'s components is supposed to be determined according to information observable at any time up to t. $X(t)$ can be deterministic variables such as time (time of the day or day of the week), exogenous information variables available before t, jump indicators observed at any time up to t, waiting time since the last jump time, jump indicators from other markets observed at any time up to t, or other state variables forecasted using a conditional expectation based on dynamic (time-series) models. For the formation of the expectation, there is no restriction on the type of static or dynamic model specification or estimation procedures. The integrated intensity function $\Lambda_\theta(t)$ is only required to be continuous and differentiable so that the Martingale central limit theorem can hold and the solution for the corresponding score function exists and is consistent.

The following assumptions are imposed on $\Lambda_\theta(t)$, which is a modified version of Condition VI.1.1. in Andersen, Borgan, Gill, and Keiding (1992). Denote by θ_0 the true value of parameter and θ the free parameter. Let T be a given terminal time, $0 < T \leq \infty$, and n be the number of observations within terminal time T.

D.1. There exists a neighborhood Θ_0 of θ_0 such that for all n and $\theta \in \Theta_0$, $\log d\Lambda_\theta(t)$ and $d\Lambda_\theta(t)$ are three times differentiable with respect to $\theta \in \Theta_0$.

D.2. There exist finite functions $\sigma_{jl}(\theta)$ defined on Θ_0 such that for all j, l,

$$\frac{1}{n}\int_0^T \{\frac{\partial}{\partial\theta_j}\log d\Lambda_{\theta_0}(t)\}\{\frac{\partial}{\partial\theta_l}\log d\Lambda_{\theta_0}(t)\}d\Lambda_{\theta_0}(t)dt \xrightarrow{p} \sigma_{jl}(\theta_0),$$

as $n \to \infty$. Moreover, the matrix $\Sigma = \{\sigma_{jl}(\theta_0)\}$ is positive definite.

D.3. For all j and $\epsilon > 0$, we have

$$\frac{1}{n}\int_0^T \{\frac{\partial}{\partial\theta_j}\log d\Lambda_{\theta_0}(s)\}^2 I\left(|\frac{1}{\sqrt{n}}\frac{\partial}{\partial\theta_j}\log d\Lambda_{\theta_0}(s)| > \epsilon\right) d\Lambda_{\theta_0}(s)ds \xrightarrow{p} 0,$$

as $n \to \infty$.

D.4. For any n, there exist G_n and H_n such that

$$\sup_{\theta\in\Theta_0} |\frac{\partial^3}{\partial\theta_j\partial\theta_l\partial\theta_m} d\Lambda_\theta(t)| \leq G_n(t)$$

and

$$\sup_{\theta\in\Theta_0} |\frac{\partial^3}{\partial\theta_j\partial\theta_l\partial\theta_m}\log d\Lambda_\theta(t)| \leq H_n(t)$$

for all j, l, m. Further,

$$\frac{1}{n}\int_0^T G_n(t)dt,\ \frac{1}{n}\int_0^T H_n(t)d\Lambda_{\theta_0}(t)dt,\ \frac{1}{n}\int_0^T \{\frac{\partial^2}{\partial\theta_j\partial\theta_l}\log d\Lambda_{\theta_0}(t)\}^2 d\Lambda_{\theta_0}(t)dt$$

all converge in probability to finite quantities as $n \to \infty$, and for all $\epsilon > 0$,

$$\frac{1}{n}\int_0^T H_n(t) I\left(\sqrt{\frac{H_n(t)}{n}} > \epsilon\right) d\Lambda_{\theta_0}(t)dt \xrightarrow{p} 0.$$

A.3. Proof of Proposition 1

With the rejection region $\mathcal{R}_n(\alpha_n) = (-\infty, -q_{\alpha_n}S_n - C_n, q_{\alpha_n}S_n + C_n, \infty)$, if $dJ(t_i) = 0$ for each single interval $(t_{i-1}, t_i]$,

$$P(d\hat{J}(t_i) = 0 = dJ(t_i)) = 1 - P(\mathcal{L}(i) \in \mathcal{R}_n(\alpha_n))$$

$$= 1 - 2(1 - \Phi(q_{\alpha_n} S_n + C_n)) \approx 1 - 2(1 - \Phi(\sqrt{2\log n})) \sim 1 - \frac{1}{\sqrt{\pi} n \sqrt{\log n}} \to 1, \tag{18}$$

as $n \to \infty$, i.e., $\Delta t \to 0$. $\Phi(x)$ is the standard normal cumulative distribution function. The last approximation is due to the asymptotic expression for $1 - \Phi(x)$ as $x \to \infty$, which is $\lim_{x\to\infty} x(1 - \Phi(x))e^{x^2/2} = (2\pi)^{-1/2}$. See Galambos (1978) for its derivation.

If $dJ(t_i) = 1$ for an interval with its jump time $\tau \in (t_{i-1}, t_i]$,

$$P(d\hat{J}(t_i) = 1 = dJ(t_i)) = P(\mathcal{L}(i) \in \mathcal{R}_n(\alpha_n)) \approx P(|Y(\tau)| > (q_{\alpha_n} S_n + C_n)\sigma(\tau)\sqrt{\Delta t})$$

$$\approx 1 - F_{|Y|}\left(\sigma(\tau)\sqrt{-2\Delta t \log(\Delta t)}\right) \sim 1 - \frac{2}{\sqrt{2\pi}}\sigma(\tau)\sqrt{-2\Delta t \log(\Delta t)} \to 1, \tag{19}$$

as $\Delta t \to 0$, and hence $\sigma(\tau)\sqrt{-2\Delta t \log(\Delta t)} \to 0$. $F_{|Y|}(y)$ is the distribution function of absolute jump sizes $|Y|$ and $\sigma(\tau)$ denotes the local volatility level at jump time τ.

A.4. Proof of Proposition 2

I decompose the full likelihood function into two different mutually exclusive parts for actual jump times and non-jump times, as follows:

$$L_n(\theta|\mathcal{F}_T) = \underbrace{\prod_{1\le i\le n, dJ(t_i)=1} d\Lambda_\theta(t_i)^{dJ(t_i)}}_{(20.1)} \underbrace{\prod_{1\le i\le n, dJ(t_i)=1} (1 - d\Lambda_\theta(t_i))^{1-dJ(t_i)}}_{(20.2)}$$
$$\times \underbrace{\prod_{1\le i\le n, dJ(t_i)=0} d\Lambda_\theta(t_i)^{dJ(t_i)}}_{(20.3)} \underbrace{\prod_{1\le i\le n, dJ(t_i)=0} (1 - d\Lambda_\theta(t_i))^{1-dJ(t_i)}}_{(20.4)}, \tag{20}$$

where $\Lambda_\theta(t) = \gamma(t, X(t); \theta)$.

The second (20.2) and third (20.3) products are one under the full observations from the jump models without diffusion term. Hence, it is enough to show that both of these two products (20.2) and (20.3), based on results by the jump detection tests, become one, with probability one, as

$\Delta t \to 0$, so that the other two products based on the results by the jump detection tests match the corresponding ones, (20.1) and (20.4).

For term (20.2), let H be the finite number of jumps during the time horizon and τ_h be the jump times in $[0, T]$ with $h = 1, ..., H$. Then, from Proposition 1, as $\Delta t \to 0$,

$$P\left(\prod_{1\le i\le n, dJ(t_i)=1} \left(1 - d\hat{\Lambda}_\theta(t_i)\right)^{1-d\hat{J}(t_i)} = 1|H\right) = P\left(\text{for all } i \text{ s.t. } dJ(t_i) = 1,\ d\hat{J}(t_i) = 1|H\right)$$

$$\approx \prod_{1\le h\le H} \left[1 - F_{|Y|}\left(\sigma(\tau_h)\sqrt{-2\Delta t \log(\Delta t)}\right)\right] \sim 1 - \frac{2}{\sqrt{2\pi}} \sum_{h=1}^{H} \sigma(\tau_h)\sqrt{-2\Delta t \log(\Delta t)} \to 1, \quad (21)$$

where $F_{|Y|}(y)$ is the distribution function of absolute jump sizes $|Y|$ and $\sigma(\tau_h)$ denotes the local (bounded) volatility level at the hth jump time. Notice here that only the finite activity jumps are allowed with finite number H of jumps to obtain this result.

For the term (20.3),

$$P\left(\prod_{1\le i\le n, dJ(t_i)=0} d\hat{\Lambda}_\theta(t_i)^{d\hat{J}(t_i)} = 1|H\right) = P\left(\text{for all } i \text{ s.t. } dJ(t_i) = 0,\ d\hat{J}(t_i) = 0|H\right)$$

$$\sim P\left(\max_{1\le i\le n, dJ(i)=0} |\mathcal{L}(i)| \in \mathcal{R}(\alpha_n)^c\right) = G(q_{\alpha_n}) = 1 - \alpha_n \to 1, \quad (22)$$

as $q_{\alpha_n} \to \infty$ and $\alpha_n \to 0$, with the distribution function of a standard Gumbel variable $G(q_{\alpha_n})$. Therefore, the result holds, because

$$P\left(\frac{PL_n(\theta|\mathcal{F}_T)}{L_n(\theta|\mathcal{F}_T)} = 1|H\right)$$

$$= P\left(\prod_{1\le i\le n, dJ(t_i)=1} \left(1 - d\hat{\Lambda}_\theta(t_i)\right)^{1-d\hat{J}(t_i)} = 1|H\right) \times P\left(\prod_{1\le i\le n, dJ(t_i)=0} d\hat{\Lambda}_\theta(t_i)^{d\hat{J}(t_i)} = 1|H\right)$$

$$\sim \left(1 - \frac{2}{\sqrt{2\pi}} \sum_{h=1}^{H} \sigma(\tau_h)\sqrt{-2\Delta t \log(\Delta t)}\right) \times (1 - \alpha_n) \to 1, \quad (23)$$

as $\Delta t \to 0$ and $\alpha_n \to 0$. Note that this pointwise convergence in probability combined with the results of Newey (1991) imply uniform convergence in probability in a compact subset of Θ due to Condition D.

A.5. Proof of Proposition 3

By the definition of product integration,

$$\frac{L_n(\theta|\mathcal{F}_T)}{\widetilde{L(\theta|\mathcal{F}_T)}} \xrightarrow{a.s.} 1, \text{ which implies } \frac{L_n(\theta|\mathcal{F}_T)}{\widetilde{L(\theta|\mathcal{F}_T)}} \xrightarrow{P} 1. \tag{24}$$

Thus, due to Proposition 2,

$$\frac{PL_n(\theta|\mathcal{F}_T)}{\widetilde{L(\theta|\mathcal{F}_T)}} = \frac{PL_n(\theta|\mathcal{F}_T)}{L_n(\theta|\mathcal{F}_T)} \times \frac{L_n(\theta|\mathcal{F}_T)}{\widetilde{L(\theta|\mathcal{F}_T)}} \xrightarrow{P} 1. \tag{25}$$

A.6. Proof of Theorem 1

Given **Assumption C**, we know that as $\Delta t \to 0$, for any θ, $\log(L_n(\theta|\mathcal{F}_T)) - \log(PL_n(\theta|\mathcal{F}_T)) \xrightarrow{P} 0$, which also implies uniform convergence in probability from Proposition 2. Here, let $\mathcal{U}_L(\theta)$ and $\mathcal{U}_{PL}(\theta)$ be the score functions based on $\log(L_n(\theta|\mathcal{F}_T))$ and $\log(PL_n(\theta|\mathcal{F}_T))$. Then, the two estimators $\hat{\theta}_{L,n}$ and $\hat{\theta}_{PL,n}$ such that $\mathcal{U}_L(\hat{\theta}_{L,n}) = 0$ and $\mathcal{U}_{PL}(\hat{\theta}_{PL,n}) = 0$ are asymptotically equivalent. In other words, as $\Delta t \to 0$ (as $n \to 0$), $\hat{\theta}_{L,n} - \hat{\theta}_{PL,n} \to 0$ in probability: this is proved by contradiction. Now, according to the Slutsky Theorem as in Ferguson (1996), it is enough to show that the estimator based on $L_n(\theta|\mathcal{F}_T)$, $\hat{\theta}_{L,n}$, is consistent and converges in law to a normal distribution around its mean θ_0. For this part, I apply a modified version of proofs for Theorem VI.1.1. and VI.1.2 in Andersen, Borgan, Gill, and Keiding (1992). Due to a Taylor expansion, $1 - d\Lambda_\theta(t) = exp(-d\Lambda_\theta(t))$, $\mathcal{U}_L(\theta)$ can be written as

$$\mathcal{U}_L(\theta) = \int_0^{\cdot} \frac{\partial}{\partial\theta} \log d\Lambda_\theta(s) dM(s),$$

where $M(t) = J(t) - \int_0^t d\Lambda_\theta(s)ds$ and is a local square integrable martingale. Here, Lenglart's inequality is first applied to establish the existence of a consistent estimator that is the solution for the score function. Next, the Martingale central limit theorem is used to establish the convergence of estimators in distribution to normal. Finally, it is obvious that the last result can be obtained by the delta method.

An alternative to the proof given above is to consider two equivalent probability measures $\mathcal{P}$ and $\mathcal{P}_{PL_n}$. $\mathcal{P}$ is the true (latent) data-generating measure for $\widetilde{L(\theta|\mathcal{F}_T)}$ in continuous time, as in Definition 2.A and $\mathcal{P}_{PL_n}$ is the observable data-generating measure for $PL_n(\theta|\mathcal{F}_T)$ in discrete time, as in Definition 2.C. Instead of going through $L_n(\theta|\mathcal{F}_T)$, the above weak convergence proof can be directly applied on $\mathcal{U}_{PL}(\theta)$ because of the convergence of $\mathcal{P}_{PL_n}$ to $\mathcal{P}$, as shown in Proposition 3.

A.7. Equity Price Data Cleaning Procedure

To avoid unnecessary data recording errors, I also preprocess the raw data as follows. All stocks selected are assured to pass the active trade filter (50 trades per day), which is usual for high frequency data analysis. For transactions that happen at the same time, I take the first transaction price recorded in the database. I exclude obvious outliers and all recording errors such as zero prices. High frequency data may contain *bounce-back* type data errors caused by extreme round trips of recorded prices to unreasonably different price levels. If returns from a stock are followed by returns with opposite signs and similar magnitudes and if the magnitudes of any jumps in the stock are significantly different from those without the bounce-back effect, I exclude those returns from consideration.

A.8. Pre-search Procedure for Jump Predictors

I describe a pre-test procedure I employed to determine the most important jump predictors listed in Table 4. Since the JPT is applied to link the one dimensional time series indicator of jumps detected from one stock to multiple jump predictors, I initiate my estimation for each firm using all the eight predictors described in Section 4 as well as various alternative predictors. Table A.1 lists all the alternative information variables (along with their data source) I consider for creating predictors but reject due to their relative lack of significance. These news information variables are selected to capture real-time information releases regarding the real activity of the overall economy, inflation, and monetary policy as well as firm-specific fundamental information. The sample periods for all variables are matched exactly with the sample period for jump data in Table 2, which is from January 4, 1993 to December 31, 2008.

For each variable, I create the predictors based on a time-series indicator of the information release times (unless defined otherwise). These predictors are designed to test the impact of information on stock price jumps over the time horizon, such as 15 minutes, 30 minutes, 60 minutes, 90 minutes, 120 minutes, and 180 minutes, etc., around the information releases. In addition to these predictors, the terms controlling for the intraday seasonality of jump arrivals are added in this pre-search.

The jump predictor is selected if it is proven to be broadly significant. In order to measure the breadth of significance, I obtain the parameter estimates and p-values associated with all the predictors for each firm. Then, for each predictor, I count the number of firms for which the predictor is significant at the 5% level. Finally, all the predictors are ranked according to these number of firms, and the eight predictors are selected according to this ranking. To give an example using Table 5, $X_1(t), X_2(t), X_3(t), X_4(t), X_7(t)$ and $X_8(t)$ are significant for 23 out of 23 firms and they are ranked first to be included in the model. Then, $X_5(t)$ and $X_6(t)$ are selected as they are significant for 21 firms in the sample. The last two are included subsequently. Some predictors related to the alternative variables listed in Table A.1 are found to be significant, but they are not ranked highly enough by the aforementioned measure. They are not as broadly significant as the predictors related to variables listed in Table 4, and hence omitted in the model. The time-of-day variables for times beyond 11:00am and up to 4:00pm are also found to be insignificant, and hence omitted in the model.

Table A.1. Data for Alternative Jump Predictors in U.S. Individual Equity Markets[†]

Macroeconomic Variable Names	Data Source	Macroeconomic Variable Names	Data Source
GDP advance	Bureau of Economic Analysis (BEA)	GDP preliminary	Bureau of Economic Analysis (BEA)
GDP final	Bureau of Economic Analysis (BEA)	Retail Sales	Bureau of the Census (BC)
Industrial Production	Federal Reserve Board (FRB)	Capacity Utilization	Federal Reserve Board (FRB)
Personal Income	Bureau of Economic Analysis (BEA)	Consumer Credit	Federal Reserve Board (FRB)
Personal Consumption Expenditures	Bureau of Economic Analysis (BEA)	New Home Sales	Bureau of the Census (BC)
Durable Goods Orders	Bureau of the Census (BC)	Construction Spending	Bureau of the Census (BC)
Factory Orders	Bureau of the Census (BC)	Business Inventory	Bureau of the Census (BC)
Government Budget Deficit	Bloomberg	Trade Balance	Bureau of Economic Analysis (BEA)
Producer Price Index	Bureau of Labor Statistics (BLS)	Consumer Price Index	Bureau of Labor Statistics (BLS)
Consumer Confidence	Conference Board (CB)	Housing Starts	Bureau of the Census (BC)
NAPM Index	Nat'l Assoc of Purchasing Managers (NAPM)	Leading Indicator	Conference Board (CB)

Firm-specific Variable Names	Data Source
Earnings Estimates (issued by brokers)	First Call Historical Database
Analyst Forecasts Dispersion	First Call Historical Database
Dividend Announcement Dates, Dates of Record, & Payout Dates	Center for Research in Security Prices (CRSP)
Stock Split-related Dates	Center for Research in Security Prices (CRSP)

[†] The information variables listed in Table 4 are selected based on the pre-test procedure described in Appendix A.8. This table contains the names and sources of the information variables that are considered in addition to the selected variables in Table 4 but not included in the jump intensity models due to relative lack of significance. The sample period for all variables is the same as that for jump data in Table 2 and for the other information variables listed in Table 4, which is from January 4, 1993 to December 31, 2008. Dividend-related dates and stock split-related dates are available in daily frequency, while the other variables are available in intraday frequency. Analysts forecast dispersion is defined as the standard deviation of analyst earnings forecast values reported in the database.