Lévy (co)jumps across international equity markets and FOMC news announcements *

Kam Fong CHAN [+]

Zheyao PAN

Abstract:

This study characterizes the discontinuous price movements and comovements of international equity markets using the Lévy model which distinguishes jumps with different amplitudes. The model identifies many large and infinitely small Lévy jumps in the international equity indices sampled at high frequency. By contrast, the conventional Poisson jump model misses particularly many of the small jumps. We also demonstrate that the high-frequency trading strategy triggered by large Lévy jumps yields sizeable realized returns. Furthermore, we find that concurrent large jumps across the international equity markets tend to occur more frequently than concurrent small jumps. We show that the Federal Open Market Committee (FOMC) announcements predominantly drive large jumps and cojumps in close proximity of the news releases. Large price jumps observed post FOMC announcements are associated with market uncertainty pertaining to monetary policy.

JEL classifications: C14; C58; G12; G15

Keywords: Lévy jumps; Cojumps; FOMC news announcements; High-frequency trading

---

* We gratefully acknowledge Christopher Neely for constructive comments and suggestions. We thank Jan Hannig, Suzanne Lee and Hanlin Shang for useful discussions on the implementation of the Lee-Hannig test. We also thank Marianne Lown for editorial assistance. All remaining errors are ours.

[+] Chan is from the UQ Business School, The University of Queensland, Australia (k.chan@business.uq.edu.au). Pan (corresponding author) is from the Otago Business School, The University of Otago, New Zealand (zheyao.pan@otago.ac.nz).

Lévy (co)jumps across international equity markets and FOMC news announcements *

Abstract:

This study characterizes the discontinuous price movements and comovements of international equity markets using the Lévy model which distinguishes jumps with different amplitudes. The model identifies many large and infinitely small Lévy jumps in the international equity indices sampled at high frequency. By contrast, the conventional Poisson jump model misses particularly many of the small jumps. We demonstrate that the high-frequency trading strategy that relies on large negative Lévy jump as a signal yields sizeable realized returns. We also find that concurrent large jumps across the international equity markets tend to occur more frequently than concurrent small jumps, and the Federal Open Market Committee (FOMC) announcements drive predominantly large jumps and cojumps. Large price jumps observed post FOMC announcements are associated with market uncertainty pertaining to monetary policy.

JEL classifications: C14; C58; G12; G15

Keywords: Lévy jumps; Cojumps; FOMC news announcements; High-frequency trading

---

* We gratefully acknowledge Christopher Neely for constructive comments and suggestions. We thank Jan Hannig, Suzanne Lee and Hanlin Shang for useful discussions on the implementation of the Lee-Hannig test and Marianne Lown for editorial assistance. We acknowledge the help for SIRCA for the access to the TRTH database. All remaining errors are ours.

1. Introduction

Numerous studies have established that the prices of financial markets display discontinuous sample paths or jumps; see, for example, Andersen et al. (2007), Jiang et al. (2011) and Lee (2012). These studies typically consider a special class of jump-diffusion models – the Poisson model – which does not distinguish between jumps with different amplitudes. Recent advances in the financial econometrics literature (for example, Aït-Sahalia, 2004; Rachev et al., 2011), however, have documented two different types of jumps in financial asset prices. The first are *small jumps*, which are many infinite and rare asset price movements with non-trivial jump magnitude that cannot be captured by the continuous diffusive process. The second are infrequent and severe perturbations to asset prices or *large jumps*. Collectively, small and large jumps form the Lévy class of jumps and they are different from the Poisson jumps. We review the existing literature that distinguishes both classes of jumps shortly.

The present study analyzes high-frequency Lévy jumps and cojumps (i.e., concomitant jumps) across international equity indices in the U.S. (S&P 500 index or SPX), Canada (TSX) and Mexico (MXX). These markets share common trading hours and this element is crucial in our cojump analyses. We find that the prices of the equity markets display many large and small (yet non-trivial) intraday Lévy jumps. By contrast, the Poisson-like jump test misses particularly many of the small infinite activity jumps. We also show that the high-frequency trading strategy that uses *large negative* jump as a signal dominates other strategies. We then explore whether scheduled Federal Open Market Committee (FOMC) monetary policy announcements are a driving force behind these uniquely behaved jumps. We demonstrate that they are, but that FOMC announcements trigger mostly *large* jumps and cojumps in near proximity of the news announcements. International portfolio managers interested in hedging global cojump risk should take note because the finding of this study suggests there little room for them to avoid the

FOMC announcement risk; instead, it systematically affects individual and concurrent price jumps, especially those with large amplitude, in international equity markets.

In order to analyze the Lévy jump–news announcement relationship, it is paramount to methodologically detect and isolate small jumps from large jumps, and to also separate both types of jumps from the continuous diffusive process. The Lévy jump test of Lee and Hannig (2010) is ideally suited for this purpose. The non-parametric (i.e., model-free) nature of the Lee-Hannig test ensures that its implementation is relatively straightforward and not as computationally over-intensive as in other methods commonly used to estimate Lévy jumps.[1] The Lee-Hannig test also allows us to pin down precisely when Lévy jumps occur at high frequency. These attributes are crucial because the multi-market data set that we consider is sampled at high frequency over an extended 20-year sample period.

Our study complements and significantly extends the literature in two major respects along important dimensions. First, existing empirical studies have almost exclusively focused on linking macroeconomic announcements to jumps and cojumps without considering whether the announcements play different roles in triggering (co)jumps with different amplitudes. For example, Dungey et al. (2009) and Lahaye et al. (2011) scrutinize the impact of macroeconomic announcements on jumps and cojumps across different asset classes. Other relevant studies include Evans (2011), Jiang et al. (2011), Dungey and Hvozdyk (2012), Lee (2012), Boudt and Petitjean (2014), Dewachter et al. (2014) and Novotný et al. (2015). The jumps and cojumps assumed in these studies are invariably Poisson in nature, and Poisson jumps do not distinguish between small infinite activity jumps and rare jumps with substantially larger amplitudes.[2]

[1] The Bayesian Markov Chain Monte-Carlo method employed by Li et al. (2008), Yu et al. (2011), and Yang and Kanniainen (2017) is a prime example.

[2] We refer interested readers to Tankov and Cont (2003) and Rachev et al. (2011) for technical details on the differences between Poisson and Lévy jumps.

Nonetheless, the large versus small (co)jump distinction is crucial for various reasons. In particular, Aït-Sahalia and Jacod (2012) argue that small infinite activity jumps are idiosyncratic because they tend to reflect stock-specific information, such as earnings announcements. On the other hand, market-wide news, such as macroeconomic announcements, is a catalyst for stock price movements with a significantly large magnitude. Li et al. (2008) show that Lévy jump models are essential and more powerful than the affine-jump (Poisson-like) diffusion models of Duffie et al. (2000) in modelling equity index returns. Lee and Hannig (2010) argue that distinguishing jumps with different amplitudes and analyzing their separate and systematic patterns are vital for investors with different risk aversions for diversification and risk management purposes. In line with Lee and Hannig (2010), Ornthanalai (2014) finds that rare jumps with considerably large magnitude are important in modelling derivatives and designing optimal portfolio allocation. Yet, investors should not overlook small jumps; else, they could significantly understate the jump risk in the economy. When taken together, the insights from these studies underscore the importance of classifying jumps and cojumps into large and small a priori to linking them to macroeconomic news and investment (particularly high-frequency trading strategies), and the present study makes the first concerted effort to empirically address this issue.

Second, studies that have examined Lévy jumps have focused mainly on the equity market at the national (i.e., non-cross-border) level. For example, Li et al. (2008) and Lee and Hannig (2010) analyze Lévy jumps using U.S. equity market indices. We extend the literature by considering international equity market indices of SPX, TSX and MXX, and we also scrutinize Lévy cojumps, an important aspect that the aforementioned studies have overlooked.

We summarize our novel findings as follows. First, we use the Lee-Hannig test and identify many large and infinitely small (but non-trivial) Lévy jumps in the equity market indices. By contrast, the Poisson-like jump test of Lee and Mykland (2008), which many regard as the "golden non-parametric test" commonly used to estimate intraday jumps, misses many of the pronounced jumps, especially small infinite activity jumps.[3] For example, it categorizes only one-fifth of the small Lévy jumps detected in the SPX as "jumps".

We also find that Lévy jumps occur more frequently in the MXX emerging market than in the SPX and TSX developed markets, a finding that is in line with prior studies that examine Poisson-like jumps in international equity markets (see, for example, Pukthuanthong and Roll (2015)). Interestingly, large cross-border cojumps occur more frequently than small cross-border cojumps, even though, individually, small jumps occur nearly two to three times more frequently than large jumps. Furthermore, we do not find significant evidence of discernible asymmetry in positive and negative Lévy jump frequency in the markets considered, and this finding holds for both large and small jumps. In sharp contrast, the Lee-Mykland jump test shows significantly more Poisson-type negative jumps than positive jumps (Lahaye et al., 2011).

To put the economic benefits of separating jumps into large and small in perspective, we compare various high-frequency trading strategies. On average, we find that the high-frequency trading strategy that utilizes large negative Lévy jump as a signal dominates other strategies, including the one that relies on the signal provided by the Poisson-like jump.

What drives Lévy jumps and cojumps? Our empirical result points primarily to FOMC announcements; they influence predominantly (co)jumps with large amplitudes. For example, we find that nearly one-tenth of the FOMC announcements trigger large cojumps across the trivariate markets in near proximity to the news releases, but none of them generates small cojumps. We also find that unexpected FOMC news exerts a statistically significant influence particularly on large Lévy (co)jumps. Finally, we relate large price jumps identified in the SPX market to uncertainty associated with monetary policy. Consistent with our hypothesis, we show that a heightening in monetary policy uncertainty is related to large price declines, whereas the

[3] Recent studies that have employed the Lee-Mykland test to estimate intraday jumps and cojumps include Lahaye et al. (2011), Boudt and Petitjean (2014), Bradley et al. (2014) and Gilder et al. (2014).

resolution of uncertainty is related to large positive price jumps. Overall, our findings support Aït-Sahalia and Jacod's (2012) contention that key macroeconomic news in the form of FOMC announcements primarily drives extreme stock price movements with large magnitudes (i.e., large jumps and cojumps).

We organize the remainder of the paper as follows. Section 2 details the Lee-Hannig's jump test. Section 3 describes the high-frequency stock index data. Section 4 presents the empirical results and Section 5 concludes.

2. Lee-Hannig Test for Lévy Jumps

This section describes the non-parametric Lévy jump test of Lee and Hannig (2010). Erdemlioglu et al. (2013) show that ignoring intraday volatility periodicity leads to spurious jump identification in the Lee-Hannig test.[4] To correct for this bias, we follow Lahaye et al. (2011), Erdemlioglu et al. (2013) and Gilder et al. (2014) and adopt the weighted standard deviation (WSD) estimator of Boudt et al. (2011) to de-periodize the equity returns prior to implementing the Lee-Hannig jump test. Appendix A discusses this de-periodicity adjustment procedure in detail.

2.1. General framework

Let $[0, T]$ be the fixed time interval with T representing maturity. Assume that the stock price at time t, S_t, occurs at discrete times $0 = t_0 < t_1 < \ldots < t_n = T$ over the time interval $[0, T]$ and the time increment $\Delta t = t_i - t_{i-1}$ is equally spaced.

In the absence of jumps, the log of the stock price follows a Brownian process:

$$\mathrm{d}\log S_t = \mu_t \mathrm{dt} + \sigma_t \mathrm{dW}_t \ , \tag{1}$$

where μ_t is the drift term and W_t denotes the standard Brownian motion with σ_t spot volatility.

In the presence of Lévy jumps, however, the log of the stock price is characterized as

[4] Boudt and Petitjean (2014) argue that ignoring periodicity could result in an over-detection (under-detection) of intraday jumps in times when volatility is periodically high (low).

$$\mathrm{d}\log S_t = \mu_t \mathrm{dt} + \sigma_t \mathrm{dW}_t + \mathrm{dL}_t, \tag{2}$$

where L_t is an adapted Lévy jump process with the Lévy jump measure υ independent of W_t and all other variables are defined above.

2.2. Detecting large jumps

The intuition of the large jump test is straightforward: after controlling for local volatility, the log stock price return should be greater (in magnitude) than those drawn from a diffusion process when a jump occurs. The test statistic $\tau(t_i)$ to determine whether a large Lévy jump occurs at time t_i is given by

$$\tau(t_i) = \frac{\log\left(\dfrac{S_{t_i}}{S_{t_{i-1}}}\right)}{\widehat{\sigma}_{t_i} \widehat{f}_i^{\mathrm{WSD}} \Delta t^{1/2}}, \tag{3}$$

where $\widehat{f}_i^{WSD}$ refers to Boudt et al.'s (2011) de-periodicity filter of intraday volatility discussed in Appendix A.

For any $g > 0$ and $0 < \omega < 0.5$, the truncated power variation is specified as

$$\widehat{\sigma}_t^2 = \frac{\Delta t^{-1}}{K} \sum_{j=i-K}^{i-1} \left[\log\left(\frac{S_{t_i}}{S_{t_{i-1}}}\right)\right]^2 I_{\left\{\left|\log\left(\frac{S_{t_i}}{S_{t_{i-1}}}\right)\right| \le g\Delta t^{\omega}\right\}}, \tag{4}$$

where I is an indicator function, $K = \tilde{b}\Delta t^{c}$ with $-1 < \tilde{c} < 0$ and $\tilde{b}$ is a constant, and $\Delta t = \dfrac{1}{78 \times 252}$. Following Lee and Hannig (2010), we set $\tilde{b} = 1$, $\tilde{c} = 0.5$, $g = 1.2$ and $\omega = 0.47$.

As $\Delta t \to 0$,

$$\frac{\max_{t \in (t_{i-1}, t_i] \text{ for } 0 \le i \le n} |t(t)| - C_n}{S_n} \xrightarrow{D} X, \tag{5}$$

where ξ has a cumulative distribution function $P(\xi \le x) = \exp(-e^{-x})$, $C_n = \sqrt{2\log n} - \dfrac{\log \pi + \log(\log n)}{2(2\log n)^{1/2}}$, $S_n = \dfrac{1}{2(2\log n)^{1/2}}$ and n is the total number of observations.

Eq. (5) suggests that the identification of a large jump at time t_i if $\frac{|\tau(t_i)|-C_n}{S_n} > q_{\tilde{\alpha}}$ where $q_{\tilde{\alpha}}$ is the $\tilde{\alpha}$ quantile of the limiting distribution of maximum ξ.

2.3. Detecting small jumps

Lee and Hannig (2010) show that in the absence of Lévy jumps,

$$\tau_t \xrightarrow{D} \mathrm{N}(0,\ 1)\,, \tag{6}$$

where N(0, 1) denotes the standard normal distribution. Therefore, as $\Delta t \rightarrow 0$,

$$\Phi(\tau_t) \xrightarrow{D} \mathrm{U}(0, 1)\,, \tag{7}$$

where Φ(.) is the cumulative distribution function of the standard normal distribution and U(0, 1) denotes the uniform distribution.

Eq. (7) implies that in the absence of jumps, the distribution of statistic τ_t converges to a standard normal distribution. In this case, the QQ-plot graph for τ_t is a straight line with a 45^o gradient.[5] However, if the QQ-test rejects the null hypothesis of no Lévy jumps, we then calculate the following test statistic:

$$\tilde{l}(r) = 1-(n-K+1)\left[\Phi(0.5(T_r+T_{r+1}))-\Phi(0.5(T_{r-1}+T_r))\right]\ , \tag{8}$$

where $r = 1, \ldots, n-K$ and T_r are the order statistics of τ_t.

The first item, 1, denotes the number of test statistics within the interval $\left[(T_r+T_{r+1})/2,\ (T_{r-1}+T_r)/2\right]$, and the second term, $(n-K+1)\left[\Phi(0.5(T_r+T_{r+1}))-\Phi(0.5(T_{r-1}+T_r))\right]$, approximates the expected number of test statistics observed in the same interval under the no-jump model, which is closer to 1.[6] As a result, if the smoothed value of $\tilde{l}(r)$,[7] denoted as $l(r)$, is

---

[5] One can use the method of Hernandez-Campos et al. (2004) to examine the significance of the QQ-test.

[6] Lee and Hannig (2010) show that the expected number of the test statistics within the interval in the null of no jumps is equal to 1/(1+n).

[7] We smooth $\tilde{l}(r)$ so that the variance of $\tilde{l}(r)$ remains bounded away from zero. Following Lee and Hannig (2010), we locally average the $\tilde{l}(r)$ with the Nadaraya-Watson estimator and select the bandwidth based on the "direct plug in" method of Ruppert et al. (1995).

further away from unity, then this particular test statistic is more likely due to a jump. As a result, we can define the belief measure for a return at time t to identify the exact locations of Lévy jumps:

$$b(t_i) = \max(0, l(r(i))), \quad (9)$$

where $b(t_i)$ is a measure of the belief that a particular return is a jump event. When $b(t_i) \geq (1-\hat{\alpha})$ for a given significance level $\hat{\alpha}$, we determine a jump at time t_i. Finally, we define small jumps as those that are not detected by the large-jump rule but are identified by the belief measure. Following Lee and Hannig (2010), we set the significance levels ($\tilde{\alpha}$) for both the large-jump test and the small-jump test at 5%.

3. Data

Our empirical analyses feature the SPX, TSX and MXX stock market indices. We focus on these markets because they share common trading hours between 9:30 Eastern Standard Time (EST) and 16:00 EST. This element is crucial to our subsequent cojump analysis. The sample period covers an extended 20-year sample period from January 2, 1996 to December 30, 2015.

We source the high frequency tick data from the Thomson Reuters Tick History database. Following Bollerslev et al. (2009), we first convert the tick data into five-minute prices using the nearest tick, and then use them to obtain the five-minute continuously compounded log returns. The five-minute interval sampling is a popular choice in most prior related literature. It also strikes a satisfactory balance between the desire to obtain as finely sampled observations as possible (as required by the asymptotic theory underlying the Lee-Hannig test), on the one hand, and the confounding effects of microstructure frictions typically found in ultra-high frequency data (Hansen and Lund, 2006), on the other.

We adopt the data-cleaning procedure of Andersen et al. (2010) and pre-filter the data prior to computing the five-minute returns; this includes removing extreme outliers and mis-recorded price observations. We also remove zero five-minute returns (which account for approximately

0.6% of the total SPX observations), days associated with public holidays in the respective countries and trading days which have stale prices for at least two consecutive hours.[8] In total, we have 4,911 trading days for SPX, 4,930 for TSX and 4,880 for MXX, and each trading day has 78 five-minute return observations.

4. Empirical Results

4.1. Lévy jumps and cojumps

We begin by assessing the adequacy of the Lee-Hannig test in detecting Lévy jumps in the multi-markets. Figure 1 visualizes the finding by plotting the large jumps (marked in blue) and small jumps (marked in green) identified by the Lee-Hannig test, along with the five-minute SPX intraday log returns series, which are expressed in percentages. To ease readability, Figure 1 focuses on the first four years of the full sample (1996–1999). The figure provides strong evidence of Lévy jumps, with the Lee-Hannig test identifying many of the severe log SPX price movements as large jumps and abrupt log SPX price movements with moderate (but non-trivial) changes as small jumps.

< Insert Figure 1 here >

< Insert Table 1 here >

Table 1 underscores the evidence of Lévy jumps in the equity indices by reporting some summary statistics along with some novel findings. The SPX, for example, has large and small jumps for 0.15% and 0.38% of the time, respectively,[9] and small jumps contribute over two-thirds $\left(\frac{1426}{574+1426}=71.3\%\right)$ of all the estimated Lévy jumps.

[8] The findings of our final analysis are insensitive to the removal of zero return observations, but the inclusion of zero returns could result in spurious detection of small jumps. The result of this sensitivity check is available upon request. We have greatly benefited from personal discussion with Professor Hannig on the issue concerning zero returns.

[9] Our estimates are marginally lower than those estimated by Lee and Hannig (2010); they identify 0.32% (0.49%) of the SPX return observations as large (small) jumps. A possible explanation is that unlike Lee and Hannig (2010), we de-periodize the data prior to estimating the Lévy jumps and this thus alleviates the Type I error in detecting spurious jumps. Unreported analysis (which is available upon request) provides support for this contention.

By contrast, Panel D of Table 1 shows that the Lee-Mykland test misses many of the pronounced jumps.[10] Using the SPX market for discussion, the Lee-Mykland test identifies only 740 of all the return observations as jumps. This estimate is several times lower than the total number of large and small Lévy jumps (574+1426) estimated under the Lee-Hannig test. Not surprisingly, the Lee-Mykland test misses many of the small (but non-trivial) infinite activity jumps, with the probability of Lee-Mykland jumps coinciding with small Lévy jumps and divided by the number of small Lévy jumps being 19% (see Panel E). In other words, the Lee-Mykland test only categorizes one-fifth of the small Lévy jumps as "jumps". Intuitively, the Lee-Mykland test assumes a Poisson counting process governing the jump dynamics; hence, it is unable to identify particularly many of the *moderately* large price movements (i.e., infinite small jumps). [11]

Pukthuanthong and Roll (2015) and others find that jump occurrences are considerably more pronounced in emerging markets than in developed markets,[12] as one would reasonably expect, since emerging stock market returns are more leptokurtic than developed stock market returns (Bekaert et al., 1998). We reach a similar finding using the Lee-Hannig jump test: large MXX jumps make up $\frac{740}{740+574} = 56\%$ of the total number of large jumps detected in both SPX and MXX and this proportion is statistically different from 50% (*t*-statistic=4.6).[13] Likewise,

[10] We use the similar criteria that we employed in the Lee-Hannig test to estimate the Lee-Mykland model. These include purging the intraday period pattern of volatility using the de-periodicity procedure of Boudt et al. (2011) and setting the jump test significance level at 5%.

[11] A figure (which we omit to save space) analogous to Figure 1 which superimposes the identified Lee-Mykland jumps on the large and small Lévy jumps provides further supporting graphical evidence that the Lee-Mykland test misses many of the moderately large log price movements in SPX.

[12] These earlier studies employ coarser (i.e., daily) data frequency to detect jumps.

[13] The corresponding standard error to compute the statistical significant test is defined as $\sqrt{\left(1-\frac{N_1}{N_2}\right)\frac{N_1}{N_2}\Big/N_2}$ where N_1 = number of large jumps in MXX and N_2 = total number of large jumps in both SPX and TSX.

$\frac{1555}{155+1426}=52\%$ of the total number of SPX and MXX small jumps belong to the MXX market and this ratio is also significantly different from 50% (*t*-statistic=2.4).

The Lévy jump amplitudes are economically meaningful. To see this, Table 1 reports the sample mean and standard deviation of the jump size as measured using the absolute five-minute returns $|r_{i,t}|$ and expressed in basis points (bps). Consider the SPX market: the large-jump-size distribution has a mean of 64.9 bps versus 7.0 bps for periods with no jumps. These estimates translate to a large mean difference of 67.9 bps between large-jump and no-jump periods, and the two-sample unequal variance *t*-test for the difference in means yields a significant *t*-statistic =30. The absolute return mean difference between small-jump and no-jump periods is 4.7–7.0 =34.7 bps with *t*-statistic =45. The large (small) jump size variation is 46.2 bps (29.0) versus 8.9 bps for no-jump periods. When taken together, the estimates imply that the five-minute pseudo-Sharpe ratios (calculated as $E(|r_{i,t}|)/\text{stdev}(|r_{i,t}|)$) on large- and small-jump periods are nearly two times higher than on no-jump periods. Similarly, the pseudo-Sharpe ratio for investing in the MXX on large-jump (small-jump) periods is 1.3 (1.7) times higher than on no-jump periods.

Another noteworthy aspect of Table 1 concerns the asymmetry in Lévy jumps. Panel D shows that there are significantly more negative Poisson-type jumps than positive jumps (for example, 57.3% of the SPX jumps identified by the Lee-Mykland test are negative), a finding that is also echoed by Lahaye et al. (2011). The Lee-Hannig jump test, however, paints a slightly different story. For example, negative large jumps identified in SPX only marginally outnumber positive large jumps (50.9% of the large jumps are negative), but there are significantly more small negative jumps than small positive jumps (53.2% versus 46.8%). We also reach a similar conclusion for the TSX and MXX markets. As such, the evidence of asymmetry in Lévy jumps in the markets is less clear-cut.[14]

[14] Kou et al. (2016) use an affine-diffusion model to show that negative jump sizes have become larger in the period following the 2007–2009 financial crisis relative to the pre-crisis period. Our Lévy jump results, however, are different: the jump amplitudes of negative small Lévy jumps have become less negative in the post-crisis period

A useful metric to gauge the economic benefits of separating jumps into large and small takes the perspective of a high-frequency trader who strategically times her investment in the equity markets under different strategies. In particular, we first assume the high-frequency trader to invest in the equity market between t_{i+1} and t_{i+36} (which represents a short three-hour investment window) as soon as she had identified a large Lévy jump at t_i.[15] We label this as the "large Lévy jump signalling strategy". We compare this strategy to three other strategies: the "small Lévy jump signalling strategy" which relies on small Lévy jumps detected at t_i, the "LM jump signalling strategy" which utilizes Poisson jump signals detected at t_i using the Lee-Mykland test and the "naive strategy" in which we assume the non-savvy investor to put her money into the equity market even though there were no jumps detected at t_i.[16]

< Insert Figure 2 here >

The solid lines in Figure 2 graph the mean pointwise cumulative intraday percentage returns of the aforementioned strategies in SPX, TSX and MXX over the three-hour window.[17] The result is striking. Using Panel C for discussion, the MXX displays a strong upward drift within an hour after being triggered by large Lévy jump signals. Put it differently, ignoring transaction cost, the high-frequency trader who uses the "large Lévy jump signalling strategy" would have realized a sizable 0.45% returns within an hour (see the blue line in Figure 2). This estimate is threefold to fourfold more than what she would have earned under the "small Lévy jump signalling strategy" (pink line) and the "LM jump signalling strategy" (green line). The

compared with the pre-crisis period, whereas negative large jump size in the post-crisis period reverts to that observed in the pre-crisis period. To save space, we report these findings in the online appendices.

[15] For simplicity, we assume the high-frequency trader identifies jumps between 9:30 EST (when the market opens) and 13:00 EST. This allows her to unwind her position prior to the market closing at 16:00 EST. To ensure that our trading strategies are robust to jumps commonly detected in the first half an hour following the market opening, we rerun the trading strategies assuming the trader to begin identifying jumps post 10:00 EST. The qualitative findings of this robustness test are similar to those reported here and hence are not reported to save space.

[16] We construct the "naive strategy" by bootstrapping (with sampling replacement) 10,000 indexes of t_i that do not contain Lévy jumps.

[17] In practice, one would have to invest in the futures markets.

cumulative returns for the "naïve strategy", as depicted by the dotted black line, are essentially zero.

< Insert Figure 3 here >

Figure 3 is similar to Figure 2 except that we condition the trading strategies on the jump signs, with the right (left) column of Figure 3 plotting the cumulative returns of the respective strategies as soon as they have been triggered by positive (negative) jump signals detected at t_i. The figure shows that the cumulative returns earned post large negative Lévy jump signal considerably outweigh those earned post large positive Lévy jump signal (for example, the SPX cumulative returns earned within the three-hour window following large negative Lévy jump signals is 0.6% versus an inconsequential 0.2% cumulative returns for the large positive Lévy jump signalling strategy). Nonetheless, the signed "small Lévy jump" and "LM jump" signalling strategies yield no discernible difference in the realized cumulative returns. Overall, the superior performance of the large negative Lévy jump signalling strategy suggests investors to have overreacted to pronounced market-wide bad news.[18]

< Insert Table 2 here >

We then extend the above univariate jump findings to cojumps, with results reported in Table 2. In a spirit similar to Lahaye et al. (2011), we define large cojumps (small cojumps) as significant large jumps (small jumps) that occur concomitantly in the markets. We also report the findings pertaining to large-small cojumps, that is, a combination of large and small jumps that occur concurrently in the markets. As expected, bivariate cojumps occur more frequently

[18] Our results that negative jumps lead to positive short-run returns is in contrast to the recent study of Jiang and Zhu (2017) who document that investors underreact to information shocks (using jumps as a proxy) at the firm level. However, there are three distinctions between our study and theirs. First, we apply the Lee and Hannig jump testing method whereas Jiang and Zhu (2017) use the Jiang and Oomen (2008) method. Second, we focus on the high-frequency trading returns whereas Jiang and Zhu's (2017) trading strategy focuses on coarser (i.e., daily and monthly) frequencies. Third, we use the market-level jumps whereas they focus on firm-level jumps. It is probable that investors have underreacted to firm-level news and overreacted to market-level news. As evidence, Peng and Xiong (2006) surmise that investors tend to process more market-wide information than firm-specific information because of their limited attention and cognitive resources.

across the developed markets of SPX and TSX than between the developed and emerging markets. This finding continues to hold for all types of cojumps (i.e., large, small and large-small cojumps). Interestingly, large cojumps occur more frequently than do small cojumps, even though Table 1 has shown that small individual jumps occur nearly two to three times more frequently than large individual jumps. The trivariate cojump analysis reported in Table 2 underscores this finding: trivariate large cojumps occur 58 times versus 20 times for trivariate small cojumps.

The two rightmost panels of Table 2 report the probability of cojumps in the respective markets, conditional on large/small jumps detected in one of the markets. Consider the trivariate analysis: P(trivariate coj | large SPX jumps) = 10.5%, implying that 10.5% of the large jumps detected in the SPX coincide with (i.e., "spillover to") large jumps in both TSX and MXX. In contrast, P(trivariate coj | small SPX jumps) = 1.5%, suggesting that merely 1.5% of small jumps identified in the SPX coincide with small jumps detected in the other two markets.

4.2. FOMC news announcements

Section 1 of this study reviews the voluminous amount of recent literature that has documented the significant price jump–macroeconomic news announcement relationship, but these studies do not distinguish between jumps with different jump amplitudes. Aït-Sahalia and Jacod (2012) conjecture that most systematically large price movements are driven primarily by important macroeconomic news, whereas stock-specific news announcements result in idiosyncratic and small infinite activity jumps.

We empirically examine the above hypothesis by investigating the extent to which macroeconomic news announcements influence Lévy jumps. To do so, we focus exclusively on scheduled FOMC announcements. Two considerations dictate our choice. First, the FOMC news report release time is unique – it is typically scheduled between 14:00 EST and 14:15 EST, [19] a

[19] Instead of using the FOMC official (scheduled) release time, we rely on the actual FOMC announcement time-stamps corresponding to when the news announcements become first available. We first extract the 1996–2011

period when there are rarely other key activities or scheduled news taking place. As such, it is highly unlikely that the significant Lévy jump–FOMC news relationship, if any, is confounded by other events. Second, the FOMC announcement is one of the most closely watched global announcements, since it serves as a critical indication of U.S. monetary policy and has serious implications for the global economy (Bernanke and Kuttner, 2005).

< Insert Figure 4 here >

We begin by revisiting the Lee-Hannig versus Lee-Mykland debate in detecting intraday jumps on FOMC news announcement days. To do so, Figure 4 plots the five-minute SPX price levels and log returns on August 8, 2006, when a scheduled FOMC news is time-stamped at 14:14 EST. The figure shows that the SPX had risen *modestly* by nearly 30 bps immediately upon the FOMC news release, but it plunged *sharply* by 62 bps several minutes thereafter. The Lee-Mykland jump test, as expected, identifies both sizeable price movements as jumps, but it makes no distinction with respect to their jump amplitudes. As such, investors and asset managers alike risk assuming the SPX price index to revert to its level prior to the FOMC news announcement, when in reality it did not. In contrast, the Lee-Hannig test correctly identifies the first price movement as a "small jump" and the latter as a "large jump" with a higher magnitude.

< Insert Figure 5 here >

Figure 5 plots the number of significant Lévy jumps estimated on FOMC announcement days. We restrict the visual analysis to 30 minutes prior to and 60 minutes after the time-stamped news arrival. The evidence is striking: FOMC announcements trigger predominantly large jumps in all the equity markets, with the effect particularly pronounced in the five-minute interval

FOMC time-stamps from the study by Lucca and Moench (2015). We then splice these time-stamps with the 2012–2013 time-stamps from Bernile et al. (2016), and finally with the 2014–2015 time-stamps obtained from Bloomberg and from the earliest Dow Jones newswires story mentioning the news. In total, we have 157 scheduled FOMC news announcements over the 1996–2015 sample period. We lose the FOMC news announcement on January 31, 1996, because the Lee-Hannig jump test requires a "training" estimation period over the first two months of the full sample period. We also omit the FOMC news released on July 1, 1998, and August 21, 2001; the former was also identified by Lucca and Moench (2015) as having missing intraday data, whereas the latter was excluded due to the data filtering rule defined in Section 3.

containing the actual time-stamped announcement (i.e., at τ =0) and in the two ensuing five-minute intervals (i.e., at τ ={1, 2}). For example, Panel A shows that within the first 10 minutes post an FOMC news release, large jumps make up $\frac{46}{46+35} = 57\%$ of the combined large and small Lévy jumps in the SPX market.[20]

Another revelation from Figure 5 is the absence of significant Lévy jumps prior to an FOMC news release. In a related study, Bernile et al. (2016) provide evidence of informed trading activities during news embargoes prior to scheduled FOMC news announcements, a finding which the authors interpret as consistent with information leakage. Our finding extends Bernile et al.'s (2016) and suggests that informed trading that occurs ahead of FOMC scheduled news is not large enough to trigger extreme price movements (i.e., Lévy jumps).

< Insert Table 3 here >

Table 3 reports some descriptive statistics, including the number of "large events" and its proportion over the number of FOMC announcements P(J | N), and the analogous proportions for "small events" and "strictly small events". An event is deemed as "large" ("small") if there is a large jump (small jump) in one of the three five-minute intervals (i.e., τ ={0, 1, 2}), and it is categorized as "strictly small" if τ ={0, 1, 2} contains strictly small jumps. One can interpret the P(J | N) probability as the proportion of FOMC news that "generates" jumps.[21] Table 3 shows that a quarter of the FOMC announcements trigger large jumps in the SPX within the first 10 minutes of a news release, but only 13.4% of them generate strictly small jumps in the same

[20] In the online appendices, we plot the jump amplitudes (calculated as the mean of absolute stock returns) of large and small jumps on FOMC announcement days. The plots show that the mean amplitude of large jumps at τ ={0, 1, 2} are typically 1.5 to two times the mean amplitude of small jumps.

[21] Beber and Brandt (2010) note that the probability estimates reported in Table 4 of the present study do not indicate a formal causality between jumps and FOMC news. Rather, one can only argue that jumps are likely attributed to the FOMC news because they occur in close proximity to each other.

intervals. Similarly, nearly 23% of the FOMC news triggers large jumps in TSX within the $\tau = \{0, 1, 2\}$ intervals but less than 8% of them result in strictly small jumps.[22]

Having established that FOMC news announcements are associated particularly with large Lévy jumps, we now investigate whether the large SPX price jumps are related to monetary policy uncertainty attributed to the news announcements. Following prior studies such as Beber and Brandt (2009), we use the Chicago Board Options Exchange market volatility index (VIX) as a measure of monetary policy uncertainty. We hypothesize that an elevation of uncertainty in monetary policy is associated with "bad" news and this results in a substantial price drop in the equity market (i.e., increases in the VIX are associated with large negative price jumps). Nonetheless, a large price increase in the SPX would suggest that the news announcement resolves uncertainty among the market participants (i.e., decreases in the VIX are associated with large positive price jumps).

< Insert Figure 6 here >

Figure 6 plots the five-minute cumulative log changes in the VIX around the FOMC announcement. Consistent with the findings in Beber and Brandt (2009), Boguth et al. (2017) and Fernandez-Perez et al. (2017), the VIX decreases by 2% on days following FOMC news announcements. The figure also reveals a striking contrasting pattern for FOMC news days associated with large price jumps in the SPX of opposite signs.[23] On the one hand, the VIX

[22] We have conducted three robustness tests to corroborate our finding that FOMC news announcements predominantly trigger Lévy jumps. First, we experimented with several other key macroeconomics news released at 10:00 EST (which is within the active trading hours of the respective equity markets). The second and third tests are placebo tests where we target non-FOMC announcement days and (i) analyze significant Lévy jumps detected over the 14:10–14:25 EST intervals and (ii) randomly select (with replacement) 10,000 five-minute intervals. The findings, which we report in the online appendices to conserve space, show that the "events" in the respective robustness tests are inconsequential in triggering Lévy jumps.

[23] We obtain the signs of large SPX price jumps as follows: First, we use the Lee-Hannig test to detect large Lévy jumps on FOMC announcement days. Table 3 shows that there were 40 "large events", that is, there were 40 FOMC news days when one of the three five-minute intervals in $\tau = \{0, 1, 2\}$ contains at least a large price jump in the SPX market. For each of these 40 news days, we aggregate the log SPX returns on intervals which are identified as containing large jumps. We use the sign of the aggregated log stock returns as a reference for positive or negative large price jumps. In total, there were 19 large positive jumps and 21 large negative jumps.

increases by nearly 1% over the first half hour post news release and such an increase in uncertainty is associated with a large price drop in the SPX. On the other hand, the VIX exhibits a pronounced 8% drop over the first two hours following the FOMC news release and this decrease in uncertainty relates to large positive SPX price jumps.

< Insert Figure 7 here >

Does FOMC news also trigger *cojumps*? Figure 7 illustrates our findings by visualizing large cojumps and non-large cojumps over the [–30, +60] minute intervals on FOMC announcement days. We define large cojumps as significant large jumps that occur concurrently in the markets considered and non-large cojumps when the intervals contain a combination of large and small or strictly small concurrent jumps. Figure 7 reveals that FOMC announcements generate mainly large cojumps, especially within the first five minutes post news release. For instance, both SPX and TSX have 22 large cojumps versus 11 non-large cojumps at $\tau = \{0, 1\}$. For the trivariate analysis, there were 12 cases when the three markets concurrently exhibited large jumps at $\tau = \{0, 1\}$, with nine of them coinciding instantaneously with the FOMC release at $\tau = 0$. In contrast, all the markets have merely four non-large cojumps at $\tau = 0$ and a cumulative of seven non-large cojumps at $\tau = \{0, 1\}$.

< Insert Table 4 here >

Table 4 provides further supporting evidence by showing pronounced large cojumps, particularly in the bivariate case involving SPX and TSX. Of the 156 FOMC announcements that occur over the common sample between SPX and TSX, 15.4% generate large jumps in both markets at $\tau = \{0, 1\}$, but none of the news triggers strictly small cojumps over the same interval. The trivariate panel shows that 7.5% of the FOMC news announcements coincide with large cojumps at $\tau = \{0, 1\}$. but none of the news influences strictly small cojumps.

Our findings therefore suggest that the scheduled FOMC announcements trigger large cojumps across international markets. This confirms and extends the arguments of Bollerslev et al. (2008) and Gilder et al. (2014) that scheduled macroeconomic announcements drive common jumps across the market portfolio's underlying components.

4.3. FOMC news surprises

This sub-section explores whether the Lévy cojumps that we have established earlier are related to the unexpected information content in the FOMC news.[24] Following prior related studies, we define the FOMC news surprise component $\left(\Delta i_t^u\right)$ using the now standard decomposition algorithm of Kuttner (2001):

$$\Delta i_t^u = \frac{D}{D-d}\left(f_{m,t}^0 - f_{m,t-1}^0\right), \tag{10}$$

where $f_{m,t}^0$ is the Federal funds rate implied in the current month Federal funds futures contract, d refers to the day of the month of the current FOMC meeting, D is the number of days in the month and $\frac{D}{D-d}$ is a scaling factor to account for the timing of the FOMC announcement within a given month. We source the Δi_t^u surprise data from Kenneth Kuttner's personal website (http://econ.williams.edu/people/knk1). Note that most of the non-zero Δi_t^u news surprises were observed prior to July 2008; after this period, the Federal funds rate has been constantly at approximately 15–25 bps and the FOMC did not report a point target until December 2015.

We estimate the following ordered probit model:

$$Y_t = \beta \times \left|S_t\right| + \varepsilon_t \ , \tag{11}$$

where Y_t =2 if the markets have at least a large cojump over the τ ={0, 1} interval on scheduled FOMC announcement day t, 1 if the markets have at least a non-large cojump (and no large cojump) in the interval and 0 if the markets have no concurrent jumps estimated over the interval. Our cojump analysis focuses on the narrower τ ={0, 1} interval, since Figure 7 shows that most

[24] We reach a similar finding for univariate Lévy jumps. For brevity purposes, we report the findings in the online appendices.

of the concurrent jumps tend to occur in the five-minute interval containing the FOMC news release and in the ensuing five-minute interval.

Three remarks are in order before we present the empirical findings. First, the ordered probit model Eq. (11) is in a similar spirit to the probit model commonly adopted by prior studies on examining the relationship between intraday jump occurrences (as measured by dichotomous 0/1 dummy variable) and macroeconomic news surprises; see, for example, Lahaye et al. (2011). The present study extends the literature by considering the trichotomy case of no jump, strictly small jump and large jump. Second, we standardize the Δi_t^u FOMC news surprise by its time-series standard deviation to obtain the S_t independent variable; this facilitates the interpretation of the empirical analysis presented below. Third, consistent with Jiang et al. (2011) and Lahaye et al. (2011), we emphasize the importance of considering the magnitude (instead of the sign) of FOMC standardized news surprises in relation to Lévy jumps. This explains our modelling choice of $| S_t |$ rather than S_t in Eq. (11).

< Insert Table 5 here >

Table 5 reports the findings. The trivariate panel shows that the estimated β coefficient is positive and statistically significant at 1%. This suggests that surprising FOMC standardized news significantly increases the probability of observing Lévy cojumps in all the markets. The "marginal effect" rows show that a unit increase in the absolute standardized FOMC news surprises increases the probability of observing concurrent large jumps in all the markets by almost 4.4%. This estimate is two times higher than the impact that the same unit increase in the news surprise has had in inducing non-large cojumps. Overall, the results in Table 5 reaffirm our hypothesis that unexpectedly large FOMC news tends to catch market participants by surprise, and this translates to an increase in the probability of observing particularly large Lévy cojumps in the equity markets.

5. Conclusions

Using 20 years of intraday data, we detect many large and infinitely small Lévy jumps in the SPX, TSX and MXX equity markets. By contrast, the conventional Poisson jump-diffusion model misses many of the pronounced jumps, especially small jumps. We also find that concurrent large jumps across the international equity markets tend to occur more frequently than concurrent small jumps. We further identify that the FOMC news announcements predominantly drive large jumps and cojumps. We also find that FOMC news surprises are associated with an increase in the probability of observing particularly large Lévy jumps and cojumps in the equity markets. Finally, we find that a heightening in monetary policy uncertainty is associated with large price declines, whereas the resolution of uncertainty is related to large positive price jumps.

Identifying when and to what extent the international markets (co)jump is vital for investors and portfolio managers seeking to hedge discontinuous sample paths and diversify across border. One implication from our study is that investors and portfolio managers should pay particular attention to scheduled FOMC news announcements since they drive predominantly large (co)jumps. We also explore various trading strategies that relies on signals provided by Lévy and Poisson jumps. High-frequency traders should take note, because our results show the strategy that uses large negative Lévy jump as a signal yields the highest realized returns, on average.

Appendix A: De-periodicity filtering of intraday volatility

We follow Lahaye et al. (2011) and Gilder et al. (2014) and adopt the weighted standard deviation (WSD) estimator of Boudt et al. (2011) to de-periodize the intraday volatility of log stock returns. We specify the standardized intraday log stock return as

$$\bar{r}_{t_i} = \frac{\log\left(\dfrac{S_{t_i}}{S_{t_{i-1}}}\right)}{\sqrt{\hat{\sigma}_{t_i}^2 \Delta t}}, \tag{A.1}$$

with $\hat{\sigma}_{t_i}^2$ as defined in Eq. (3). We then construct the shortest half-scale estimator as

$$\mathrm{ShortH}_i = 0.741 \times \min\left\{\bar{r}_{(h_i),i} - \bar{r}_{(h_1),i}, \cdots, \bar{r}_{(T_i),i} - \bar{r}_{(T_i-h_i+1),i}\right\}, \tag{A.2}$$

where T_i is the total number of observations of intraday interval i, $h_i = \left[\frac{T_i}{2}\right] + 1$ and $\bar{r}_{(j),i}$ denotes the order statistics of $\bar{r}_{(t),i}$. We estimate the shortest half estimator for periodicity as

$$\hat{f}_i^{ShortH} = \frac{\mathrm{ShortH}_i}{\frac{1}{M}\sum_{j=1}^{M}\mathrm{ShortH}_j^2}, \tag{A.3}$$

where M = 78 refers to the number of intraday intervals within one day. Finally, we define the WSD estimator ($\hat{f}_i^{WSD}$) for $i \in [1, M]$ as

$$\hat{f}_i^{WSD} = \frac{\mathrm{WSD}_i}{\frac{1}{M}\sum_{j=1}^{M}\mathrm{WSD}_j^2}, \tag{A.4}$$

where

$$\mathrm{WSD}_j = \sqrt{1.081 \times \frac{\sum_{l=1}^{n,j} I\left[\left(\frac{\bar{r}_{t,j}}{\hat{f}_j^{\mathrm{ShortH}}}\right)^2\right]\bar{r}_{t,j}^2}{\sum_{l=1}^{n,j} I\left[\left(\frac{\bar{r}_{t,j}}{\hat{f}_j^{\mathrm{ShortH}}}\right)^2\right]}}, \tag{A.5}$$

with n, j denoting the total number of observations within the interval j, and $I(z)$=1 if z ≤ 6.635 and 0 otherwise.

References

Aït-Sahalia, Y., and Jacod, J. (2012). Analyzing the spectrum of asset returns: Jump and volatility components in high frequency data. *Journal of Economic Literature* 50, 1007-1050.

Aït-Sahalia, Y. (2004). Disentangling diffusion from jumps. *Journal of Financial Economics* 74, 487-528.

Andersen, T., Bollerslev, T., and Diebold, F. (2007). Roughing it up: Including jump components in measuring, modelling and forecasting asset return volatility. *Review of Economics and Statistics* 89, 701-720.

Andersen, T. G., Bollerslev, T., Frederiksen, P., and Ørregaard Nielsen, M. (2010). Continuous-time models, realized volatilities, and testable distributional implications for daily stock returns. *Journal of Applied Econometrics* 25, 233-261.

Beber, A., and Brandt, M. (2009). Resolving macroeconomic uncertainty in stock and bond markets. *Review of Finance* 13, 1-45.

Beber, A., and Brandt, M. (2010). When it cannot get better or worse: the asymmetric impact of good and bad news on bond returns in expansions and recessions. *Review of Finance* 14(1), 119-155.

Bekaert, G., Erb, C., Harvey, C., and Viskanta, T. (1998). Distributional characteristics of emerging market returns and asset allocation. *Journal of Portfolio Management* 24, 102-116.

Bernanke, B., and Kuttner, K. (2005). What explains the stock market's reaction to Federal Reserve policy? *Journal of Finance* 60, 1221-1257.

Bernile, G., Hu, J., and Tang, Y. (2016). Can information be locked up? Informed trading ahead of macro-news announcements. *Journal of Financial Economics* 121, 496-520.

Boguth, O., Gŕegoire, V., and Martineau, C. (2017). Shaping expectations and coordinating attention: The unintended consequences of FOMC press conferences. *Working Paper*, Arizona State University.

Bollerslev, T., Law, T. H., and Tauchen, G. (2008). Risk, jumps, and diversification. *Journal of Econometrics* 144(1), 234-256.

Bollerslev, T., Kretschmer, U., Pigorsch, C., and Tauchen, G. (2009). A discrete-time model for daily S & P500 returns and realized variations: Jumps and leverage effects. *Journal of Econometrics* 150, 151-166.

Boudt, K., Croux, C., and Laurent, S. (2011). Robust estimation of intraweek periodicity in volatility and jump detection. *Journal of Empirical Finance* 18(2), 353-367.

Boudt, K., and Petitjean, M. (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets* 17, 121-149.

Bradley, D., Clarke, S., Lee, S., and Ornthanalai, C., (2014). Are analysts' recommendation informative? Intraday evidence on the impact of time-stamp delays. *Journal of Finance* 69, 645-673.

Dewachter, H., Erdemlioglu, D., Gnabo, J., and Lecourt, C. (2014). The intra-day impact of communication on euro-dollar volatility and jumps. *Journal of International Money and Finance* 43, 131-154.

Duffie, D., Pan, J., and Singleton, K. (2000). Transform analysis and asset pricing for affine jump-diffusions. *Econometrica* 68, 1343-1376.

Dungey, M., McKenzie, M., and Smith, L. (2009). Empirical evidence on jumps in the term structure of the US Treasury market. *Journal of Empirical Finance* 16, 430-445.

Dungey, M., and Hvozdyk, L. (2012). Cojumping: Evidence from the US Treasury bond and futures markets. *Journal of Banking and Finance* 36, 1563-1575.

Erdemlioglu, D., Laurent, S., and Neely, C. J. (2013). Econometric modelling of exchange rate volatility and jumps. *Working Paper*, Federal Reserve Bank of St. Louis.

Evans, K. (2011). Intraday jumps and US macroeconomic news announcements. *Journal of Banking and Finance* 35, 2511-2527.

Fernandez-Perez, A., Frijns, B., and Tourani-Rad, A. (2017). When no news is good news – The decrease in investor fear after the FOMC announcement. *Journal of Empirical Finance* 41, 187-199.

Gilder, D., Shackleton, M., and Taylor, S. (2014). Cojumps in stock prices: Empirical evidence. *Journal of Banking and Finance* 40, 443-459.

Hansen, P., and Lunde, A. (2006). Realized variance and market microstructure noise. *Journal of Business & Economic Statistics* 24, 127-161.

Hernandez-Campos, F., Marron, J., Samorodnitsky, G., and Smith, F. (2004). Variable heavy tails in internet traffic. *Performance Evaluation* 58, 261-284.

Jiang, G., Lo, I., and Verdelhan, A. (2011). Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the US treasury market. *Journal of Financial and Quantitative Analysis* 46, 527-551.

Jiang, G., and Oomen, R. (2008). Testing for jumps when asset prices are observed with noise – a "swap variance" approach. *Journal of Econometrics* 144, 352-370.

Jiang, G., and Zhu, K. (2017). Information shocks and short-term market underreaction. *Journal of Financial Economics* 124, 43-64.

Kou, S., Yu, C., and Zhong, H., (2016). Jumps in equity index returns before and during the recent financial crisis: A Bayesian analysis. *Management Science* 63, 988-1010.

Kuttner, K. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics* 47, 523-544.

Lahaye, J., Laurent, S., and Neely, C. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics* 26, 893-921.

Lee, S. (2012). Jumps and information flow in financial markets. *Review of Financial Studies* 25, 439-479.

Lee, S., and Hannig, J. (2010). Detecting jumps from Lévy jump diffusion processes. *Journal of Financial Economics* 96, 271-290.

Lee, S., and Mykland, P. (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies* 21, 2535-2563.

Li, H., Wells, M., and Yu, C. L. (2008). A Bayesian analysis of return dynamics with Lévy jumps. *Review of Financial Studies* 21, 2345-2378.

Lucca, D., and Moench, E. (2015). The pre-FOMC announcement drift. *Journal of Finance* 70, 329-371.

Novotný, J., Petrov, D., and Urga, G., (2015). Trading price jump clusters in foreign exchange markets. *Journal of Financial Markets* 24, 66-92.

Ornthanalai, C. (2014). Levy jump risk: Evidence from options and returns. *Journal of Financial Economics* 112, 69-90.

Peng, L., and Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics* 80, 563-602.

Pukthuanthong, K., and Roll, R. (2015). Internationally correlated jumps. *Review of Asset Pricing Studies* 5, 92-111.

Rachev, S., Kim, Y., Bianchi, M., and Fabozzi, F., (2011). *Financial Models with Lévy Processes and Volatility Clustering*, Wiley Finance.

Ruppert, D., Sheather, S., and Wand, M. (1995). An effective bandwidth selector for local least squares regression. *Journal of the American Statistical Association* 90, 1257-1270.

Tankov, P., and Cont, R., (2003). *Financial Modelling with Jump Processes*, Chapman and Hall/CRC Financial Mathematics Series.

Yang, H., and Kanniainen, J. (2017). Jump and volatility dynamics for the S&P 500: Evidence for infinite-activity jumps with non-affine volatility dynamics from stock and option markets. *Review of Finance* 21, 811-844.

Yu, C. L., Li, H., and Wells, M. T. (2011). MCMC estimation of Lévy jump models using stock and option prices. *Mathematical Finance* 21, 383-422.

Table 1: Summary statistics of significant jumps (full sample period)

Panel A reports the sample mean and standard deviation of absolute intraday returns (expressed in basis points) on intervals containing no Lévy jumps. Panel B reports the number of large Lévy jumps identified by the Lee-Hannig test, sample mean and standard deviation of the amplitude of large Lévy jumps, and the corresponding statistics for positive and negative large Lévy jumps. The final two rows of the panel report the percentages of jumps that are negative $\left(100\times\frac{\#\text{–ve of jumps}}{\#\text{ of jumps}}\right)$ and its corresponding standard error $\left(100\sqrt{\left(1-\frac{N_1}{N_2}\right)\frac{N_1}{N_2}\Big/N_2}\right)$ where N_1 = # of –ve jumps and N_2 = # of jumps. Panels C and D report the analogous statistics for small Lévy jumps and jumps detected by the Lee-Mykland test. Panel E reports some conditional probability estimates: (i) Pr(LM jump | Large & small Lévy jumps) is the probability of jumps detected by the Lee-Mykland test and coinciding with large and small Lévy jumps divided by the number of large and small Lévy jumps; (ii) Pr(LM jump | Large Lévy jumps) is the probability of jumps detected by the Lee-Mykland test and coinciding with large Lévy jumps divided by the number of large Lévy jumps; and (iii) Pr(LM jump | Small Lévy jumps) is the probability of jumps detected by the Lee-Mykland test and coinciding with small Lévy jumps divided by the number of small Lévy jumps. Although the full sample period covers the period from January 2, 1996 to December 30, 2015, the starting date for the estimates reported in this table is March 1, 1996, since the Lee-Hannig test requires a "training" estimation period from January 2, 1996 to February 28, 1996.

	SPX	TSX	MXX
# of obs	379860	381264	377442
Panel A: No Lévy jumps			
E($\lvert r_{i,t}\rvert$ | no jumps)	7.0	5.2	5.7
Std($\lvert r_{i,t}\rvert$ | no jumps)	8.9	8.4	7.4
Panel B: Large Lévy jumps			
# of jumps (% of # of obs)	574 (0.15%)	730 (0.19%)	740 (0.20%)
E($\lvert r_{i,t}\rvert$ | jumps)	64.9	54.1	69.5
Std($\lvert r_{i,t}\rvert$ | jumps)	46.2	84.9	69.6
# of +ve jumps (% of # of obs)	282 (0.07%)	341 (0.09%)	376 (0.10%)
E($r_{i,t}$ | +ve jumps)	67.2	55.2	67.9
Std($r_{i,t}$ | +ve jumps)	45.2	97.8	67.6
# of –ve jumps (% of # of obs)	292 (0.08%)	389 (0.10%)	364 (0.10%)
E($r_{i,t}$ | –ve jumps)	-62.6	-53.1	-71.1
Std($r_{i,t}$ | –ve jumps)	47.2	71.9	71.6
Pr(–ve jumps)	50.9%	53.3%	49.2%
Std error	2.09%	1.85%	1.84%
Panel C: Small Lévy jumps			
# of jumps (% of # of obs)	1426 (0.38%)	1723 (0.45%)	1555 (0.41%)
E($\lvert r_{i,t}\rvert$ | jumps)	41.7	32.6	39.5
Std($\lvert r_{i,t}\rvert$ | jumps)	29.0	35.4	32.1
# of +ve jumps (% of # of obs)	667 (0.18%)	736 (0.19%)	742 (0.20%)
E($r_{i,t}$ | +ve jumps)	43.5	31.9	39.1
Std($r_{i,t}$ | +ve jumps)	30.7	25.3	30.3
# of –ve jumps (% of # of obs)	759 (0.20%)	987 (0.26%)	813 (0.22%)
E($r_{i,t}$ | –ve jumps)	-40.0	-33.2	-39.8
Std($r_{i,t}$ | –ve jumps)	27.4	41.4	33.7
Pr(–ve jumps)	53.2%	57.3%	52.3%
Std error	1.32%	1.19%	1.27%
Panel D: Lee-Mykland jumps			
# of jumps (% of # of obs)	740 (0.19%)	1053 (0.28%)	802 (0.21%)
E($\lvert r_{i,t}\rvert$ | jumps)	43.6	35.9	60.2
Std($\lvert r_{i,t}\rvert$ | jumps)	37.9	70.3	67.2
# of +ve jumps (% of # of obs)	316 (0.08%)	413 (0.11%)	383 (0.10%)
E($r_{i,t}$ | +ve jumps)	45.9	37.0	57.1
Std($r_{i,t}$ | +ve jumps)	38.5	84.7	63.2
# of –ve jumps (% of # of obs)	424 (0.11%)	640 (0.17%)	419 (0.11%)
E($r_{i,t}$ | –ve jumps)	-42.0	-35.1	-62.9
Std($r_{i,t}$ | –ve jumps)	37.4	59.2	70.7

Pr(–ve jumps)	57.3%	60.8%	52.2%
Std error	1.82%	1.50%	1.76%
Panel E: Conditional probability			
Pr(LM jump | Large & small Lévy jumps)	77%	76%	83%
Pr(LM jump | Large Lévy jumps)	51%	55%	54%
Pr(LM jump | Small Lévy jumps)	19%	24%	17%

Table 2: Summary statistics of significant cojumps

The top panel reports the following statistics for concurrent large jumps identified in the markets: the number of observations (# obs) over the common sample between two or more markets, number of cojumps (# coj), probability of cojumps P(coj) (in %) over the common sample and the probability of cojumps conditional on large jumps identified in one of the markets P(coj | large) (in %). For example, the probability of large cojumps identified in both SPX and TSX, conditional on significant large jumps detected in the SPX (P(large coj | large jumps in SPX)) is calculated as 215/567 = 37.9%, where the denominator refers to the number of large SPX jumps detected over the common sample between SPX and TSX. The middle panel reports analogous statistics for a combination of large and small concurrent jumps detected in the markets, whereas the bottom panel reports similar statistics for concurrent small jumps identified in the markets. The full sample covers the period from March 1, 1996 to December 30, 2015.

	# obs	# coj	P(coj)	P(coj | large)			P(coj | small)		
				SPX	TSX	MXX	SPX	TSX	MXX
Large cojumps									
SPX–TSX	371358	215	0.06	37.9	30.0	-	-	-	-
SPX–MXX	365820	84	0.02	15.0	-	11.5	-	-	-
TSX–MXX	366834	91	0.02	-	12.9	12.6	-	-	-
SPX–TSX–MXX	357630	58	0.02	10.5	8.4	8.1	-	-	-
Large-small cojumps									
SPX–TSX	371358	270	0.07	47.5	37.7	-	19.4	15.9	-
SPX–MXX	365820	102	0.03	18.2	-	14.0	7.4	-	6.6
TSX–MXX	366834	112	0.03	-	15.9	15.4	-	6.8	7.4
SPX–TSX–MXX	357630	94	0.03	17.0	13.6	13.1	7.0	5.7	6.3
Small cojumps									
SPX–TSX	371358	230	0.06	-	-	-	16.6	13.5	-
SPX–MXX	365820	69	0.02	-	-	-	5.0	-	4.5
TSX–MXX	366834	69	0.02	-	-	-	-	4.2	4.6
SPX–TSX–MXX	357630	20	0.01	-	-	-	1.5	1.2	1.3

Table 3: Jump–FOMC news analysis

The table reports the following statistics: (i) the number of FOMC announcements (which is lower than the total of 157 FOMC announcements reported over the entire sample period since some days are omitted due to the data filtering criteria discussed in Section 3), (ii) number of large events and its corresponding proportion P(J | N), (iii) number of small events and its corresponding P(J | N), (iv) number of strictly small events and its corresponding P(J | N), (v) the mean size of large jumps and (vi) the mean size of small jumps. "Large event" is counted if it contains large jumps in one of the three corresponding five-minute intervals surrounding the FOMC news release (i.e., at $\tau = \{0, 1, 2\}$), whereas "small event" ("strictly small event") is counted if it contains at least a small jump (strictly small jumps) over the intervals. The sample period covers from March 1, 1996 to December 30, 2015.

	SPX	TSX	MXX
# of anct	157	156	147
# of large events (%)	40 (25.5%)	36 (23.1%)	19 (12.9%)
# of small events (%)	32 (20.4%)	23 (14.7%)	24 (16.3)
# of strictly small events (%)	21 (13.4%)	12 (7.7%)	19 (12.9)
Mean size of large jumps (in bps)	65.96	43.60	62.79
Mean size of small jumps (in bps)	36.08	25.63	32.76

Table 4: Cojump–FOMC news analysis

The table reports the following statistics: (i) the number of FOMC announcements that occur over the common sample between the markets, (ii) number of large-cojump events and its corresponding proportion P(J | N), (iii) number of non-large-cojump events and its corresponding P(J | N), (iv) number of strictly small-cojump events and its corresponding P(J | N), (v) the mean size of large cojumps and (vi) the mean size of non-large cojumps. "Large-cojump event" is counted if it contains concurrent large jumps in the markets in one of the three corresponding five-minute intervals surrounding the FOMC news release (i.e., at $\tau = \{0, 1, 2\}$). "Non-large-cojump event" is counted if it contains a combination of large and small jumps, or small cojumps, in one of intervals. "Strictly small–cojump event" is counted if it contains strictly small jumps concurrently in the markets. The sample period covers from March 1, 1996 to December 30, 2015.

	SPX-TSX	SPX-MXX	TSX-MXX	SPX-TXX-MXX
# of anct	156	147	146	146
# of large-cojump events (%)	24 (15.4%)	13 (8.8%)	11 (7.5%)	11 (7.5%)
# of non-large-cojump events (%)	16 (10.3%)	8 (5.4%)	12 (8.2%)	9 (6.2%)
# of strictly small–cojump events (%)	0 (0.0%)	1 (0.7%)	3 (2.1%)	0 (0.0%)
Mean size of large cojumps (in bps)	42.41	56.00	38.51	36.52
Mean size of non-large cojumps (in bps)	17.38	23.03	14.03	9.81

Table 5: Ordered probit estimation results for cojumps

The table reports the coefficient estimate and corresponding *z*-statistic (in parentheses) of Eq. (11). The dependent variable is defined as follows: $Y_t = 2$ if there is at least a large cojump detected at $\tau = \{0, 1\}$, and $Y_t = 1$ if there is at least a non-large cojump (and strictly no large cojumps) detected $\tau = \{0, 1\}$ and 0 if no jumps are detected over the intervals. The specification is estimated using the Huber-White sandwich estimation of variance. The Estrella-R^2 is a nonlinear transformation of the likelihood ratio test and serves to measure how well the estimated model fits against a model that only includes the intercept variable. The sample period exclusively covers scheduled FOMC news announcement days from March 1, 1996 to December 30, 2015. *** denotes statistical significance at the 1% level.

	SPX-TSX	SPX-MXX	TSX-MXX	SPX-TSX-MXX
β	0.32	0.35	0.38	0.35
	(2.59)***	(2.82)***	(2.97)***	(2.81)***
Marg. effect dP[Y=1]/dS	0.023	0.015	0.027	0.022
Marg. Effect dP[Y=2]/dS	0.064	0.051	0.046	0.044
R^2 (%)	5.27	5.39	6.55	5.52
# of obs	156	147	146	146

Figure 1: Detecting Lévy jumps in SPX

This figure plots the five-minute SPX log returns (expressed in percentages and in grey) and large jumps (marked in blue) and small jumps (marked in green) identified through the Lee-Hannig test. The time-series covers from 1996 to 1999.

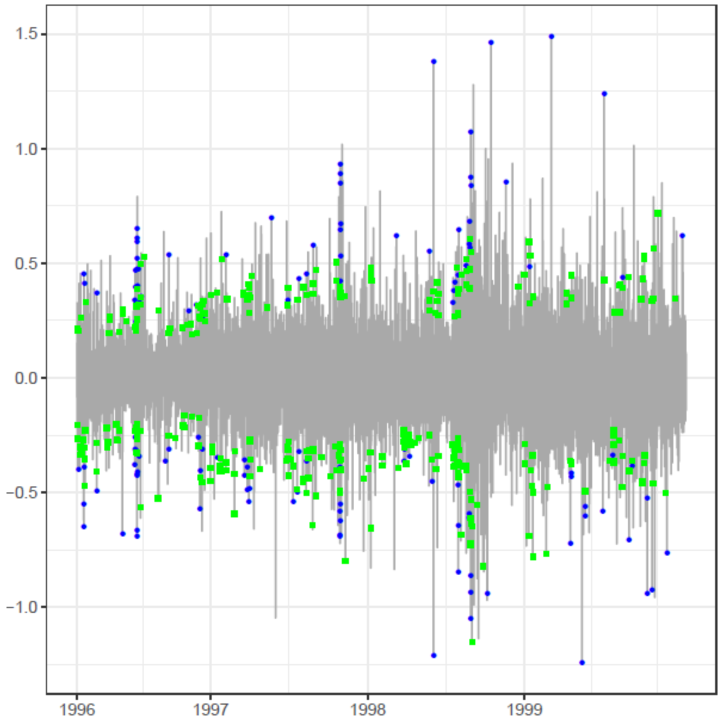
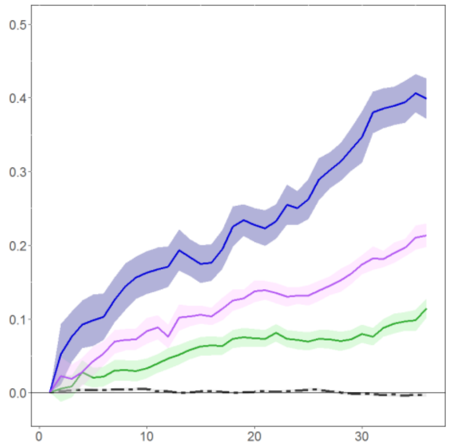
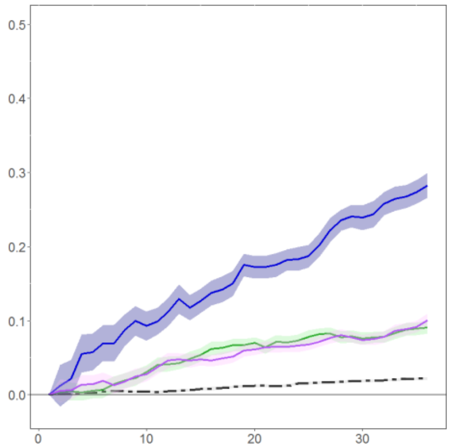


Figure 2: Cumulative returns unconditional on jump signs

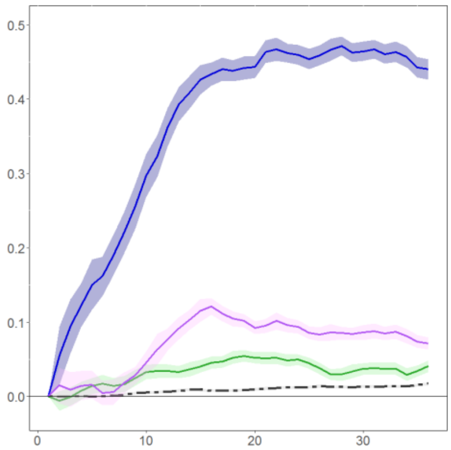
The solid lines in this figure plot the mean pointwise cumulative returns (expressed in percentages) of four different strategies over a three-hour window: the "large Lévy jump signalling strategy" (blue line), the "small Lévy jump signalling strategy" (green line), the "LM jump signalling strategy" (pink line) and the "naïve strategy" (black dotted line). The gray shaded areas are pointwise 95% confidence bands around the respective average cumulative returns. To facilitate comparison, we normalize all the cumulative returns to 0% at the start of the respective trading strategies.



Panel A: SPX



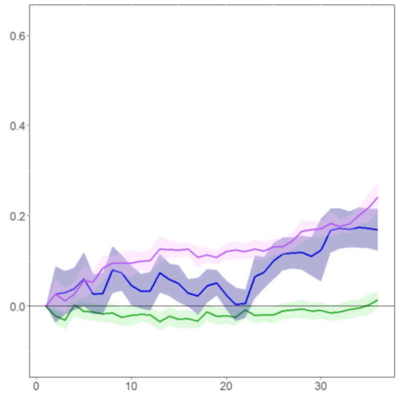
Panel B: TSX



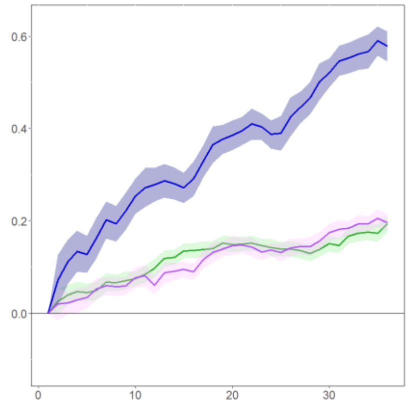
Panel C: MXX

Figure 3: Cumulative returns conditional on jump signs

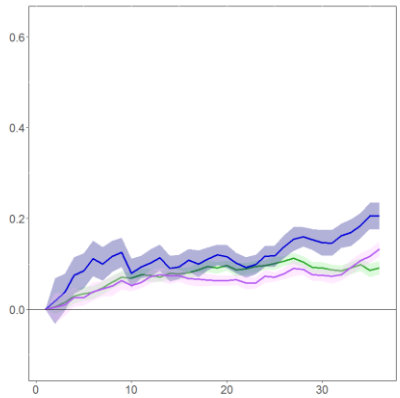
The solid lines in this figure plot the mean pointwise cumulative returns (expressed in percentages) of three different strategies over a three-hour window: the "large Lévy jump signalling strategy" (blue line), the "small Lévy jump signalling strategy" (green line) and the "LM jump signalling strategy" (pink line). The gray shaded areas are pointwise 95% confidence bands around the respective average cumulative returns. The strategies in the left and right columns use positive and negative jumps as signals, respectively. To facilitate comparison, we normalize all the cumulative returns to 0% at the start of the respective strategies.



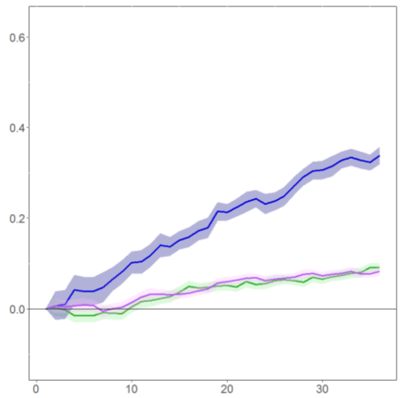
Panel A.1: +ve SPX jumps



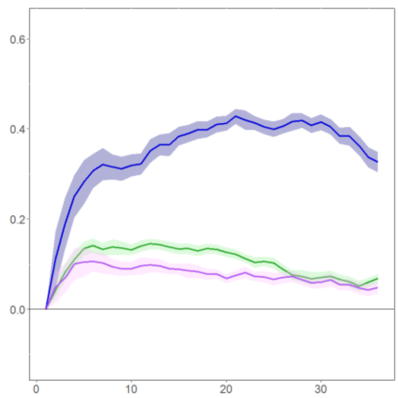
Panel A.2: –ve SPX jumps



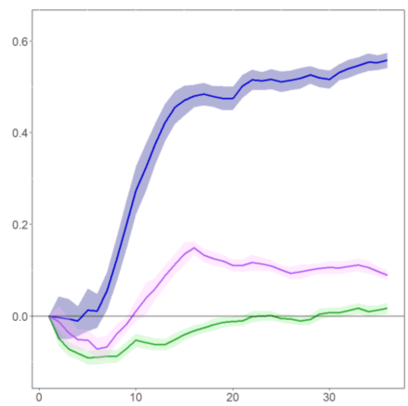
Panel B.1: +ve TSX jumps



Panel B.2: –ve TSX jumps



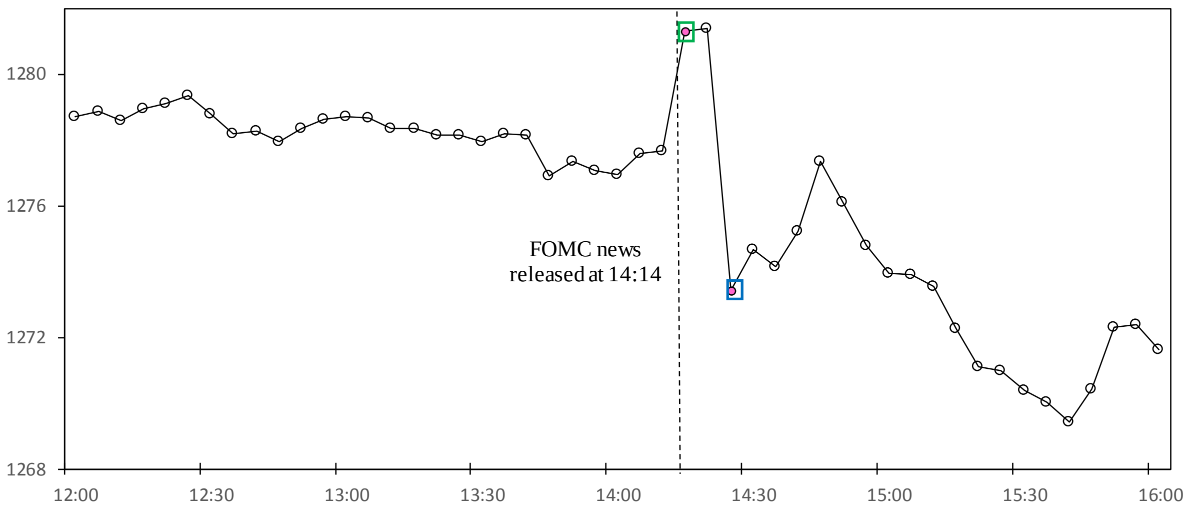
Panel C.1: +ve MXX jumps



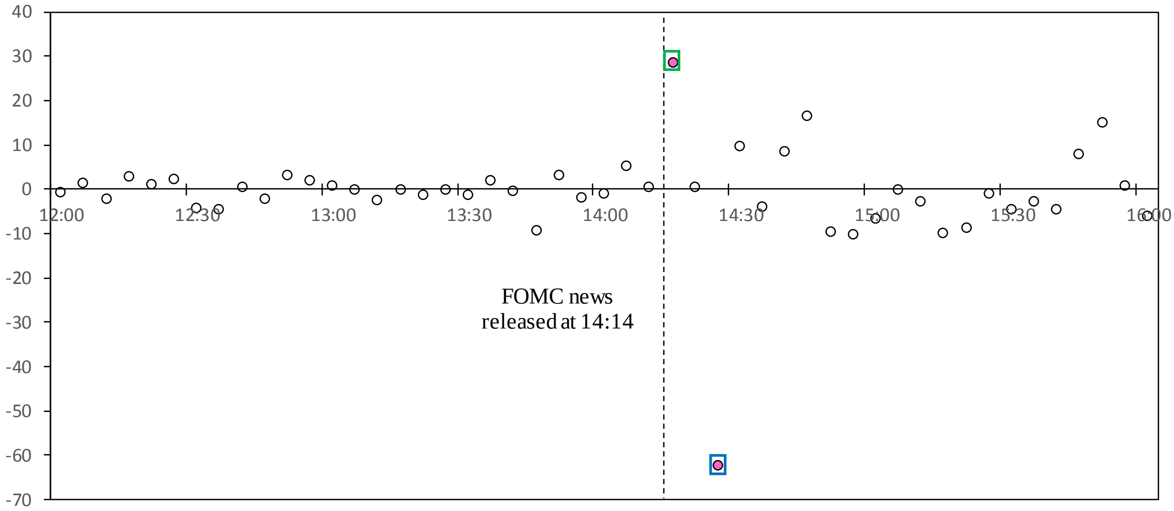
Panel C.2: –ve MXX jumps

Figure 4: Lévy jumps versus Poisson jumps

This figure plots the five-minute SPX price levels (Panel A) and price returns (Panel B) on August 8, 2006. To ease readability, we restrict the plots to between 12:00 EST and 16:00 EST. The dotted line in the respective panels indicates the actual FOMC news release which was time-stamped at 14:14 EST. The purple dots (●) correspond to jumps identified by the Lee-Mykland test. The blue boxes (□) correspond to large Lévy jumps identified by the Lee-Hannig test, whereas the green boxes (□) correspond to small Lévy jumps.



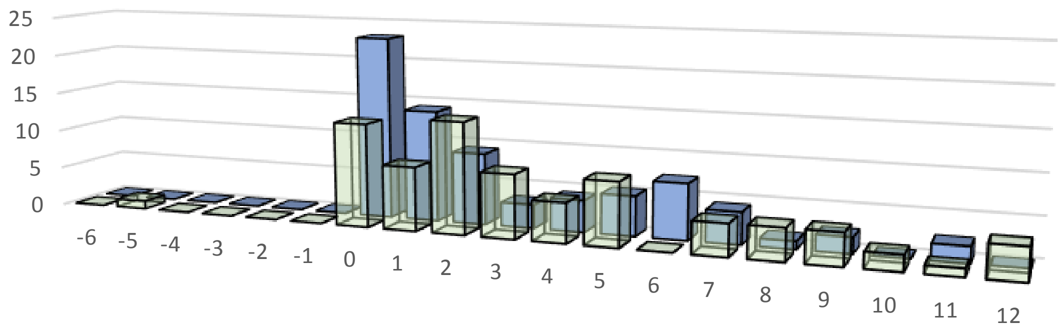
Panel A: SPX price levels



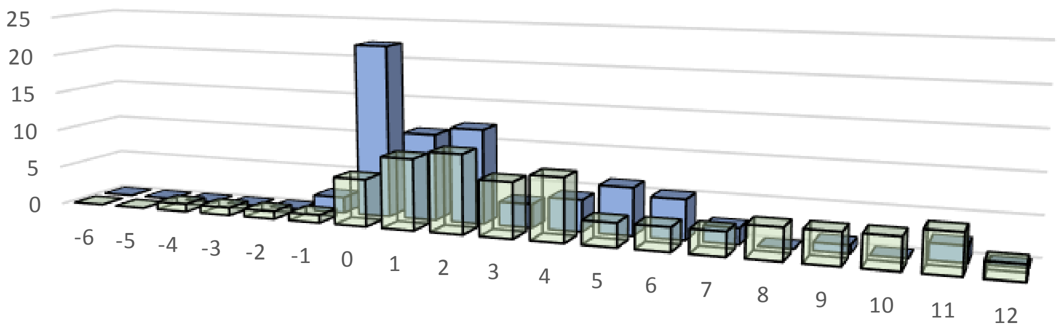
Panel B: SPX log price returns (in basis points)

Figure 5: Lévy jumps on FOMC announcement days

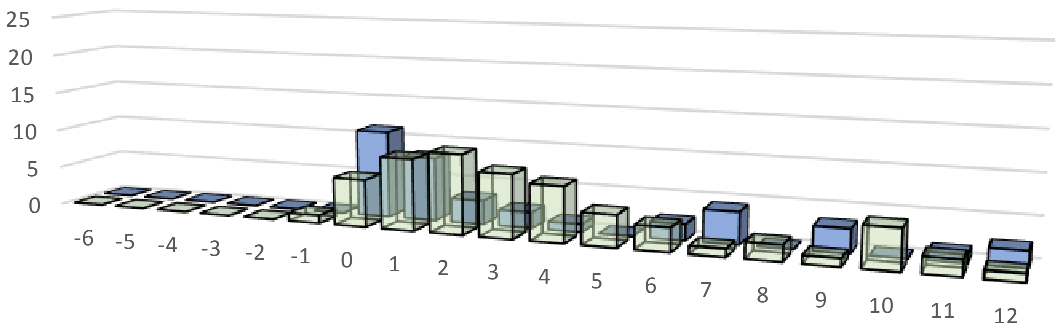
This figure plots the number of significant large jumps (in blue) and small jumps (in green) detected on FOMC announcement days. The event time τ =0 refers to the five-minute interval containing the FOMC actual time-stamped announcement, whereas τ =1 is the ensuing five-minute interval. The sample estimation period covers from March 1, 1996 to December 30, 2015.



Panel A: SPX



Panel B: TSX



Panel C: MXX

Figure 6: Large Lévy jumps and market uncertainty on FOMC announcement days

The dotted line plots the log cumulative change (expressed in percentages) in the VIX on all FOMC announcement days. The dark line (dashed line) plots the log cumulative change in the VIX on FOMC news days when there are large positive (negative) SPX price jumps identified by the Lee-Hannig test in one of the three corresponding five-minute intervals surrounding the FOMC news release (i.e., at $\tau = \{0, 1, 2\}$). To ease readability, the log cumulative changes are normalized to 0 at $\tau = -6$. The sample estimation period covers from March 1, 1996 to December 30, 2015.

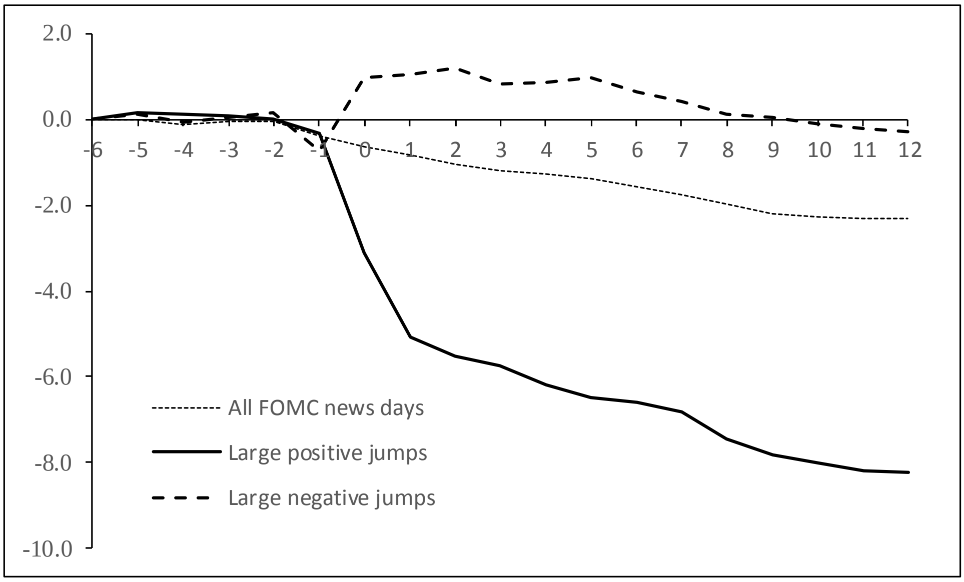
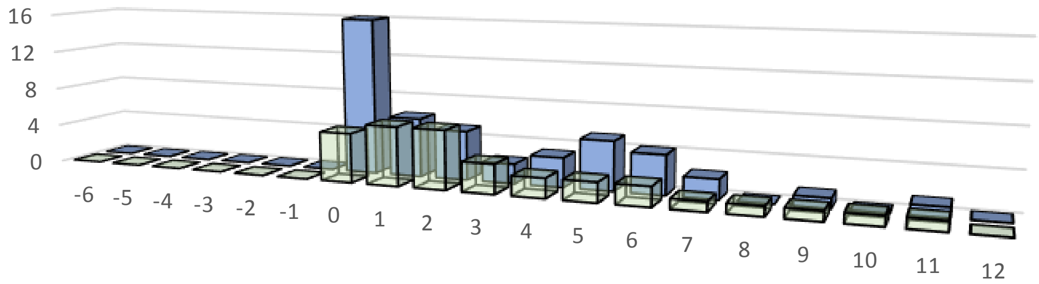
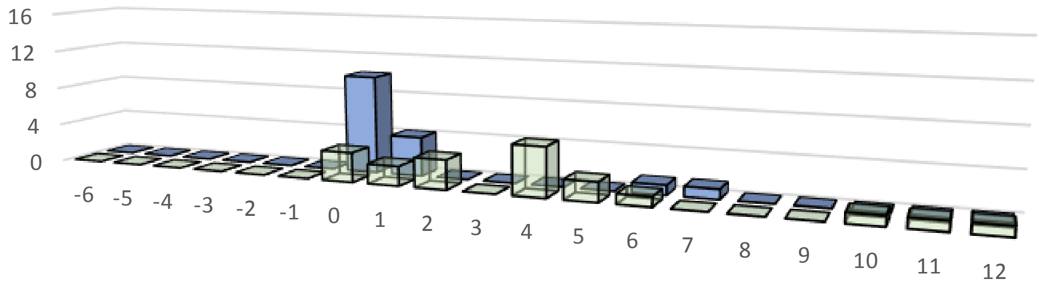


Figure 7: Lévy cojumps on FOMC announcement days

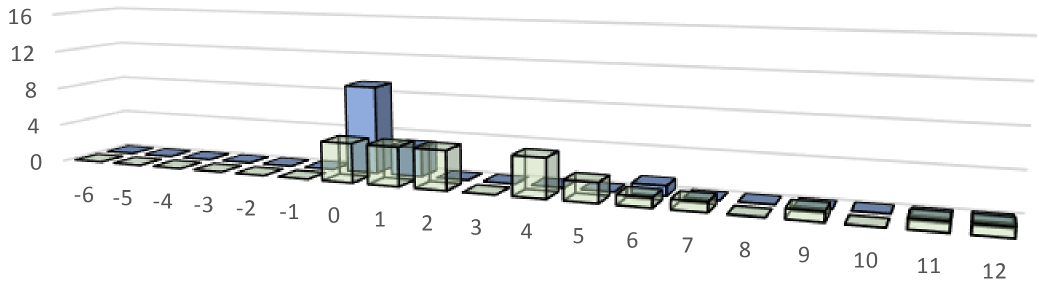
This figure plots the number of significant large cojumps (in blue) and non-large cojumps (in green) detected on FOMC announcement days. The event time τ =0 refers to the five-minute interval containing the FOMC actual time-stamped announcement, whereas τ =1 is the ensuing five-minute interval. The sample estimation period covers from March 1, 1996 to December 30, 2015.



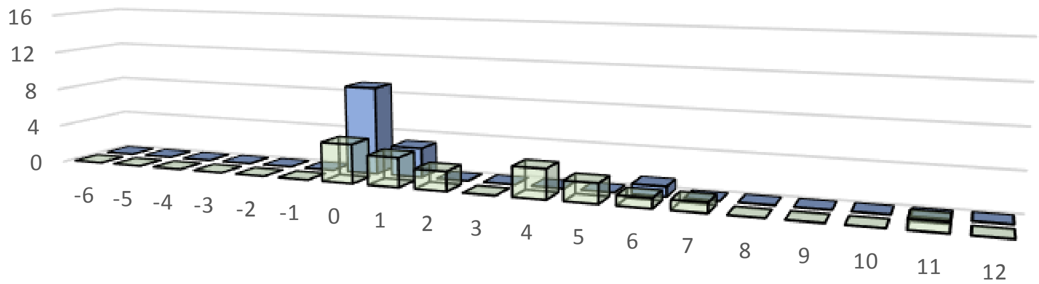
Panel A: SPX–TSX



Panel B: SPX–MXX



Panel C: TSX–MXX



Panel D: SPX–TSX–MXX

Lévy (co)jumps across international equity markets and FOMC news announcements

Online Appendices

Online Appendix I

In this appendix, we characterize the Lévy jump dynamics in different market conditions. Kou et al. (2016) use an affine-diffusion model that augments both stochastic volatility and double-exponential jumps[25] to show that the negative daily jump rate in the S&P 500 index has decreased significantly after the 2007–2009 financial crisis period, but negative jump sizes have become larger in the post-crisis period relative to the pre-crisis period. Following Kou et al. (2016), we partition the full sample period into pre-crisis period (May 1996 –July 2007), crisis period (August 2007–June 2009) and post-crisis period (July 2009–December 2015) and re-estimate the Lévy jump analysis.

Exhibit I reports the results for the SPX market; the results for TSX and MXX are qualitatively similar and hence are not reported to save space. As what one would reasonably expect, during the 2007–2009 crisis period, the intensity of large Lévy jumps has increased relative to other periods. Large negative jumps also outnumber large positive jumps during the crisis period (52.7% of the large jumps are negative). Contradicting the finding of Kou et al. (2016), however, is the result pertaining to the negative jump sizes: the negative large-jump-size pattern in the post-crisis period reverts to that observed in the pre-crisis period (E($r_{i,t}$| –ve large jumps) = –63.2 in the post-crisis period versus E($r_{i,t}$| –ve large jumps) = –61.5 in the pre-crisis period), but the jump amplitude of the small negative jumps has become considerably

[25] Kou et al.'s (2016) model only admits a finite number of large and monotonic jumps in returns.

less negative after the crisis (E($r_{i,t}$| –ve small jumps) = –33.1 in the post-crisis period versus E($r_{i,t}$| –ve small jumps) = –42.7 in the pre-crisis period).

Exhibit I: Summary statistics of significant SPX jumps in different sub-periods

This table reports the Lévy jump statistics for three sub-periods: March 1996 to July 2007 (pre-crisis period), August 2007 to June 2009 (crisis period) and August 2009 to December 2015 (post-crisis period). Table 1 of the main text provides the description of this table.

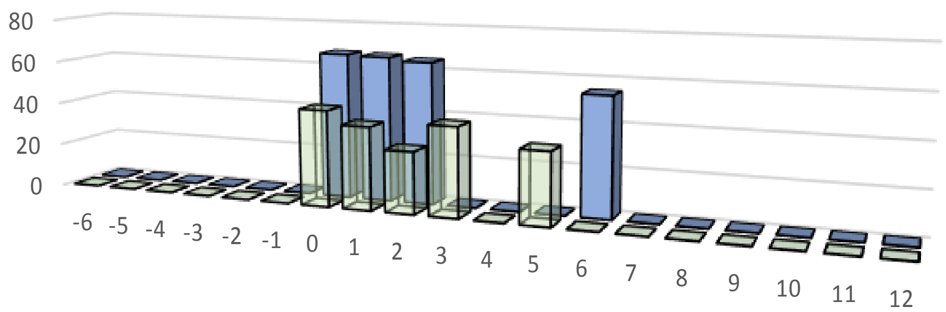
	Pre-crisis	Crisis	Post-crisis
# of obs	218830	37762	128138
Panel A: No Lévy jumps			
E($\|r_{i,t}\|$ | no jumps)	7.0	7.4	6.9
Std($\|r_{i,t}\|$ | no jumps)	8.9	9.9	8.6
Panel B: Large Lévy jumps			
# of jumps (% of # of obs)	352 (0.16%)	75 (0.20%)	147 (0.11%)
E($\|r_{i,t}\|$ | jumps)	64.2	66.9	65.6
Std($\|r_{i,t}\|$ | jumps)	46.1	58.6	39.4
# of +ve jumps (% of # of obs)	171 (0.08%)	34 (0.09%)	77 (0.06%)
E($r_{i,t}$ | +ve jumps)	67.0	67.4	67.8
Std($r_{i,t}$ | +ve jumps)	49.6	31.3	40.2
# of –ve jumps (% of # of obs)	181 (0.08%)	41 (0.11%)	70 (0.05%)
E($r_{i,t}$ | –ve jumps)	-61.5	-66.5	-63.2
Std($r_{i,t}$ | –ve jumps)	42.4	74.4	38.5
Pr(–ve jumps)	51.4%	54.7%	47.6%
Std error	2.66%	5.75%	4.12%
Panel C: Small Lévy jumps			
# of jumps (% of # of obs)	866 (0.40%)	158 (0.42%)	402 (0.31%)
E($\|r_{i,t}\|$ | jumps)	43.0	46.2	37.0
Std($\|r_{i,t}\|$ | jumps)	29.4	30.4	27.1
# of +ve jumps (% of # of obs)	389 (0.18%)	80 (0.21%)	198 (0.15%)
E($r_{i,t}$ | +ve jumps)	43.3	50.2	41.1
Std($r_{i,t}$ | +ve jumps)	26.4	35.8	35.6
# of –ve jumps (% of # of obs)	477 (0.22%)	78 (0.21%)	204 (0.16%)
E($r_{i,t}$ | –ve jumps)	-42.7	-42.1	-33.1
Std($r_{i,t}$ | –ve jumps)	31.7	23.1	13.5
Pr(–ve jumps)	55.1%	49.4%	50.7%
Std error	1.69%	3.98%	2.49%

Online Appendix II

In this appendix, we plot the mean of absolute stock returns for large jumps (in blue) and small jumps (in green) on FOMC announcement days for the SPX market; the results for the TSX and MXX are omitted to conserve space. To ensure the mean estimates are statistically meaningful, we only calculate the mean absolute jump returns at interval τ if there are more than five significant large/small jumps detected over that interval. Exhibit II shows that the mean amplitudes of large jumps at τ ={0, 1, 2} are typically 1.5 to two times the mean amplitude of small jumps. This highlights the impact of FOMC news releases in triggering large jumps, especially within the first 10 minutes post news arrival.

Exhibit II: Magnitude of Lévy jumps on FOMC announcement days

The SPX index returns are expressed in basis points (bps). The sample estimation period covers from March 1, 1996 to December 30, 2015.



Online Appendix III

To further corroborate the empirical finding reported in the main text that the main driver underlying Lévy jumps is FOMC announcements, Panel A of Exhibit III reports statistics analogous to those in Table 4 for the aggregate of four other key macroeconomic news announcements: the monthly consumer confidence index, Conference Board leading indicator, new home sales index and the Institute of Supply Management (ISM) index. We choose these variables because of their importance (for example, Yao and Tian (2015) use the Lee-Mykland jump test and show that SPX jumps are associated with ISM news announcements) and their news report release time is within the active trading hours of the respective equity markets. Panel A shows that these four macro variables hardly trigger Lévy jumps in all the markets considered, with only two out of 866 news announcements (0.2%) coinciding with large SPX jumps detected within the first 10 minutes post news release.

We also experimented with two further analyses to corroborate the finding. Panel B analyzes significant Lévy jumps detected over the 14:10–14:25 EST interval on non-FOMC-announcement days. Panel C reports the results where we randomly select (with replacement) 10,000 five-minute intervals on non-FOMC-announcement days. By construction, the tests in both panels serve as placebo tests and we hypothesize them to be inconsequential in triggering Lévy jumps. The results support our hypothesis: for the SPX market, the probability for a large (small) jump is only 0.3% (0.9%) (compare, for example, the probability for a large (small) jump in the SPX index, which is 25.5% (13.4%) in Table 4).

Exhibit III: Robustness tests

Panel A reports the following statistics – number of announcements, number of "large events" and ""strictly small events" and their corresponding P(J | N)s, and mean jump size of large and small jumps – for key macroeconomic announcements that are typically released at 10:00 EST. Panel B reports similar statistics assuming an "event"' occurs at 14:15 EST on non-FOMC-announcement days, and Panel C reports analogous statistics by randomly drawn "10,000 events" at any time on non-FOMC-announcement days. The sample period covers from March 1, 1996 to December 30, 2015.

	SPX	TSX	MXX
Panel A			
# of anct	866	830	819
# of large events (%)	2 (0.2%)	3 (0.4%)	5 (0.6%)
# of strictly small events (%)	18 (2.1%)	15 (1.8%)	17 (2.1%)
Mean size of large jumps(in bps)	81.24	69.86	81.90
Mean size of small jumps(in bps)	58.79	36.04	52.39
Panel B			
# of anct	4713	4732	4692
# of large events (%)	12 (0.3%)	15 (0.3%)	17 (0.4%)
# of strictly small events (%)	36 (0.8%)	55 (1.2%)	46 (1.0%)
Mean size of large jumps(in bps)	57.41	41.10	40.59
Mean size of small jumps(in bps)	36.88	27.24	34.60
Panel C			
# of anct	10000	10000	10000
# of large events (%)	28 (0.3%)	46 (0.5%)	40 (0.4%)
# of strictly small events (%)	93 (0.9%)	119 (1.2%)	84 (0.8%)
Mean size of large jumps(in bps)	52.27	44.55	88.78
Mean size of small jumps(in bps)	39.79	29.38	38.78

Online Appendix IV

We estimate the following ordered probit model for each individual equity market:

$$Y_t = \beta \times |S_t| + \varepsilon_t \ , \qquad \text{(D.1)}$$

where Y_t =2 if there is at least one large jump estimated over the τ ={0, 1, 2} interval on scheduled FOMC announcement day t, 1 if there is at least one strictly small jump (and no large jump) identified over the interval and 0 if there is no jump identified over the interval.

Exhibit IV reports the results. The absolute FOMC standardized news surprise variable enters with a positive sign and is statistically significant. This reaffirms our hypothesis that unexpectedly large FOMC news tends to catch market participants by surprise, and this translates to an increase in the probability of observing Lévy jumps in the stock indices. The "marginal effect" estimates reported in the table imply that while the release of a unit absolute FOMC standardized news surprise increases the probability of observing a strictly small jump in the SPX by 1.4%, the same unit news release increases the probability of observing a large, fivefold SPX jump of 7.0%.

Exhibit IV: Ordered probit estimation results for univariate jumps

The table reports the statistics analogous to those reported in Table 5 of the main text for univariate jumps detected in the respective SPX, TSX and MXX markets. * and *** denote statistical significance at the 10% and 1% levels, respectively.

	SPX	TSX	MXX
β	0.22	0.42	0.42
	(1.79)*	(3.56)***	(3.52)***
Marg. effect dP[Y=1]/dS	0.014	0.022	0.052
Marg. Effect dP[Y=2]/dS	0.070	0.123	0.080
R^2 (%)	2.68	9.48	9.99
# of obs	157	156	147

References used in online appendices

Kou, S., Yu, C., and Zhong, H. (2016). Jumps in equity index returns before and during the recent financial crisis: A Bayesian analysis. *Management Science* 63, 988-1010.

Yao, W., and Tian, J. (2015). The role of intra-day volatility pattern in jump detection: Empirical evidence on how financial markets respond to macroeconomic news announcements. Working Paper, University of Tasmania.