Detecting spurious jumps in high-frequency data *

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Abstract

We propose a technique to avoid spurious detections of jumps in high-frequency data via an explicit thresholding on available test statistics. We prove that it eliminates asymptotically all spurious detections. Monte Carlo results show that it performs also well in finite samples. In Dow Jones stocks, spurious detections represent up to 50% of the jumps detected initially. For the majority of stocks, we do not detect clustering in time of jump occurrences. During the three years of our study (2006-2008), we find no single cojump affecting all stocks, although on a few occasions, more than 50% of the Dow Jones constituents jump simultaneously. However, if we consider industry sectors separately, we observe a significant number of cojumps which indicates the presence of sector-level news. Finally, we relate detected jumps to macroeconomic and company-specific news releases. Only announcements directly affecting the balance sheet such as share buybacks increase the likelihood of a jump. Fed funds rate target news have a visible but not significant impact.

1 Introduction

Numerous methods to test for the presence of jumps in high-frequency data have been introduced recently. These techniques are usually applied to test the null hypothesis of no jumps in a particular day, over a series of days. When implementing such a procedure, we are conducting a multiple test, since we simultaneously test for the presence of jumps over several days (instead of just one). By construction, such a multiple testing setting leads to a number of spurious detections. The first contribution of this paper is to propose a technique to avoid spurious detections of jumps via an explicit thresholding on available test statistics. We prove that if we consider test statistics above a certain threshold level only, the likelihood of making spurious detections disappears asymptotically. Monte Carlo results show that our approach behaves also well in finite samples. Spurious detections are eliminated completely, and the effect on the power to detect genuine jumps is not significant in most settings. We use the adjusted ratio statistic of Barndorff-Nielsen and Shephard (2006) (henceforth BNS) as the underlying test to detect jumps. However, our method to eliminate spurious detections can be applied just as easily on other existing jump detection techniques, such as Aït-Sahalia and Jacod (2009), or Andersen, Bollerslev and Dobrev (2007).

We start by investigating the number of jump days selected by error in the U.S. equity market if we do not account for spurious detections. We collect high-frequency returns from the Trades and Quotes (TAQ) database for the Dow Jones Industrial Average Index (DJIA) stocks, over the three-year period of January 2006 to December 2008. We find that the number of jumps is reduced by 50% after thresholding the spurious detections, and amounts to around 40 per year.

The second contribution is the investigation of the dynamic features of irregular jump arrivals and the relation between simultaneous jumps in the individual stocks and jumps in the index. Our Monte Carlo simulations illustrate the importance of eliminating the spurious detections in order to be able to observe the true dynamics of jumps. We show for example that the power of the test we use to detect clustering of jump arrivals decreases significantly if we do not remove the spurious jumps. The different results obtained before and after thresholding further highlight the impact of spurious detections. For the majority of Dow Jones stocks, we do not detect clustering in time of jumps occurrences. During the three years of our study there is no day where the 30 stocks all jump simultaneously, although we do detect a jump in 50% or more of the stocks on a few occasions. However, if we consider industry sectors separately, we observe a number of cojumps significantly larger than if the stocks jumped independently which indicates the presence of sector-level news.

The third contribution of our paper is to relate jumps occurrences and news announcements. Jumps in individual stocks can be generated by either stock-specific news or common market-level news. Market-level news can cause jumps in many stocks simultaneously and can induce discontinuities even in a diversified index. We first study whether macroeconomic news cause stock prices to jump and find no statistically significant effect. The press releases following scheduled Federal Open Market Committee (FOMC) meetings are the only announcements which increase the likelihood of a jump, and are also the main reason explaining the rare cojumps affecting more than 50% of the stocks. The importance of removing spurious detections with e.g. our thresholding technique is highlighted once again since the FOMC meeting effect is not apparent before thresholding. Our conclusion that in the equity market a majority of announcements are not followed by a jump differs from the findings in other markets, e.g. Dungey, McKenzie and Smith (2009) find that two thirds of cojumps in bond prices coincide with a scheduled US news release.

Next, we focus on stock-specific news. We find that jumps do not occur systematically on scheduled events such as quarterly earnings or dividend announcements. Finally, we use the Factiva news database to relate jumps to a wider set of company-specific events. In particular, we consider news stories from two major newswires, i.e., Dow Jones News Service (DJNS) and Reuters News. By examining the content of news, we can analyze the impact of a variety of unscheduled and uncategorized events and are not limited to a predetermined set of event types such as earnings announcements, mergers, or analysts' recommendations. To our knowledge, we are the first to perform an extensive analysis of the relation between news media publications and jumps. Our results show that news releases are not very likely to cause jumps. Companies purposefully shift most important announcements after the bell or early in the morning in order to avoid uncontrolled investor reactions and the consequent impact on the stock price. The only news type for which the increase in the likelihood of a jump is statistically significant is "Share Buybacks". Our conclusions differ from the findings of Lee and Mykland (2008) who find a story for each day they detect a jump.

From our results it is evident that a number of jumps in the equity market occur in the absence of any news events. One explanation is that these jumps without a news release are the consequence of liquidity pressures captured in the order book. Jiang, Lo and Verdelhan (2010) show that liquidity shocks, such as changes in the bid-ask spread and market depth, have significant predictive power for jumps in bond prices.

The remaining of the article is organized as follows. Section 2 presents our methodology to eliminate spurious detections of jumps. Section 3 shows results of our Monte Carlo study, and Section 4 presents empirical results on the number of jumps. Section 5 investigates the dynamics of jump arrival times. Section 6 examines the occurrences of cojumps, and Section 7 the relation between jump arrivals and news releases. The appendix contains the proof of the theorem and our Monte Carlo study showing the good properties of the runs test when detecting time clustering of jumps.

2 Detecting spurious jumps

2.1 Setting and assumptions

Let X_t for continuous time $t \geq 0$ denote the log-price of the asset. The workhorse model of modern asset pricing theory assumes that X follows an Itô semimartingale. The semimartingale assumption rules out arbitrage opportunities. A semimartingale can be decomposed into the sum of a drift, a continuous Brownian-driven part, and a discontinuous, or jump, part:

$$X_t = X_0 + \underbrace{\int_0^t b_s ds + \int_0^t \sigma_s dW_s}_{\text{continuous part}} + \underbrace{J_t}_{\text{jump part}},$$

where W denotes a standard Brownian motion and J is a pure jump process. If we focus on finite activity jumps, the jump part can be written as

$$J_t = \sum_{j=1}^{N_t} c_j,$$

where N is a simple counting process (which is assumed finite for all t) and the c_j are nonzero random variables.

In this section we present our technique to improve results from existing methods to detect jumps in high-frequency financial returns when we apply them over many days. The idea of detecting jumps deserves clarification, especially as in discretely sampled data, every change in the price is by nature a discrete jump. In reality, the jump detection literature is attempting to answer the following question. Given that we observe in discrete data a change in the asset return of a large magnitude, what does that tell us about the likelihood that such a change involves a jump, as opposed to just a large realization of the Brownian part?

2.2 Thresholding technique

Numerous jump detection methods have been developed since high-frequency data have become easily available. In a typical empirical application, the jump tests are applied to detect the jump days over a sample period. For each day a test statistic S is computed to test the null hypothesis of no jumps. As we perform the tests for many days simultaneously, we are actually conducting a multiple test, which by nature leads to making a proportion of spurious detections equal to the significance level of the individual tests. For example, if we perform the individual tests at the 5% level during a one-year period with no single jump, by construction we erroneously select on average more than 12 days as containing a jump. These spurious detections have an important impact when studying the distribution of jumps dynamics, as shown in our simulation experiments.

One major contribution of the present paper is to propose a technique that allows to eliminate the spurious detections, based on the following theoretical result developed in detail in the appendix. Denote by N the number of days in the study, and by n the number of observations per day used to compute each individual test statistic. We obtain a series of daily statistics which can be written as $(S_1^n, \dots, S_N^n)$. For most available tests, under the null hypothesis of no jumps, the statistics converge to independent standard normal random variables. Theorem 1 of the appendix states that, under some technical conditions about the relative rate of convergence of n with respect to N and about the underlying price process, we get, under the null hypothesis of no jumps,

$$P\left[\sup_t |S_t^n| \leq \sqrt{2\log N}\right] \to 1, \quad \text{as} \quad N, n \to \infty.$$

This means that, if there are no jumps, the event that the largest and the smallest of the entries of the vector $(S_1^n, \dots, S_N^n)$ stay within $\left[-\sqrt{2\log N}, \sqrt{2\log N}\right]$

becomes certain for large n and N. The bound $\sqrt{2 \log N}$ is the so-called universal threshold for a sample of size N. As explained in Donoho and Johnstone (1994), it is asymptotically the expected maximum absolute value of a sequence of N independent standard normal random variables.

Using the theorem, we obtain a method to eliminate spurious detections that can be applied very easily on top of most existing jump detection techniques. In the first step, we compute the test statistics individually for each day. In the second step, we discard statistics below the threshold $\sqrt{2 \log N}$. This way, spurious detections of jumps become negligible with high probability. The precise statement and the proof of the theorem are in the appendix, for a general test statistic, as well as for the specific example of the adjusted ratio statistic of BNS[1].

2.3 Available jump detection tests

Determining from high-frequency data whether an asset returns process has jumps has been considered by a number of authors. Carr and Wu (2003) exploit the differential behavior of short-dated options. Barndorff-Nielsen and Shephard (2006) introduce a test based on the difference between the bipower variation and the quadratic variation. Andersen, Bollerslev and Diebold (2007) and Huang and Tauchen (2005) study financial datasets using multipower variations, in order to assess the proportion of quadratic variation attributable to jumps. Andersen, Bollerslev and Dobrev (2007) and Lee and Mykland (2008) introduce two very similar tests which compare each intra-day return to a local measure of volatility. Fan and Wang (2007) develop wavelet methods to estimate jump locations and jump sizes from a discretely observed process with market microstructure noise. Jiang and Oomen (2008) construct a test motivated by the hedging error of a variance swap replication strategy. Aït-Sahalia and Jacod (2009) propose a test based on truncated power variations computed at different sampling frequencies. A test for jumps could be easily constructed using the MedRV or MinRV measures of Andersen, Dobrev and Schaumburg (2009). Other tests include Mancini (2009), and Lee and Hannig (2010).

[1]The jump detection methods of Andersen, Bollerslev and Dobrev (2007) and Lee and Mykland (2008) result in performing a number of tests simultaneously within each day. Andersen, Bollerslev and Dobrev (2007) control for the size of the multiple jump tests using a Bonferroni correction. Lee and Mykland (2008) use the extreme value theory. To our knowledge we are the first to rigorously account for multiple testing over many days.

2.4 BNS jump detection technique

Our thresholding technique can be applied to most existing jump detection techniques. In the present paper, we use the standard test of BNS. The essence of the BNS jump detection method is to compare the realized quadratic variation which incorporates volatility originating from jumps (if present) to the realized bipower variation which is robust to jumps. Each day $t = 1, \ldots, N$, we observe the log price process X at the discrete times $i\Delta_n$, $i = 1, \ldots, n+1$, Δ_n is the sampling interval and n is large. We denote by $X_{t,i\Delta_n}$ the i^{th} intraday price observation on day t, and by $\Delta X^n_{t,i} \equiv X_{t,(i+1)\Delta_n} - X_{t,i\Delta_n}$ the i^{th} intraday return on day t, $i = 1, \ldots, n$. The realized quadratic variation (RV) and the realized bipower variation (BV) of X are defined as follows and converge to different quantities of the underlying jump-diffusion process.

$$RV^n_t \equiv \sum_{i=1}^{n} (\Delta X^n_{t,i})^2 \quad \xrightarrow[n\to\infty]{} \quad \int_{t-1}^{t} \sigma^2_s ds + \sum_{i>N_{t-1}}^{N_t} c^2_i,$$

$$BV^n_t \equiv \sum_{i=2}^{n} |\Delta X^n_{t,i}||\Delta X^n_{t,i-1}| \quad \xrightarrow[n\to\infty]{} \quad \mu_1^2 \int_{t-1}^{t} \sigma^2_s ds,$$

where μ_1 is a constant. If the jumps are of finite activity, the probability of observing jumps in two consecutive returns approaches zero. Consequently, the product of any two consecutive returns is asymptotically driven by the diffusion component only and the contribution of jumps is eliminated in the bipower variation. In the remaining of the paper we use the adjusted ratio statistic of BNS defined below. It is the preferred test in Huang and Tauchen (2005). Up to a scaling factor, the ratio $\frac{\mu_1^{-2} BV^n_t}{RV^n_t} - 1$ converges to a standard normal random variable under the null hypothesis of no jumps:

$$S^n_t \equiv \frac{\Delta_n^{-1/2}}{\sqrt{\vartheta \max\left(t^{-1}, QV^n_t/(BV^n_t)^2\right)}} \left(\frac{\mu_1^{-2} BV^n_t}{RV^n_t} - 1 \right) \to \mathcal{N}(0,1),$$

where QV^n_t is the realized quadpower variation:

$$QV^n_t \equiv \Delta_n^{-1} \sum_{i=4}^{n} |\Delta X^n_{t,i}||\Delta X^n_{t,i-1}||\Delta X^n_{t,i-2}||\Delta X^n_{t,i-3}|.$$

2.5 FDR thresholding

In addition to the Universal threshold, we also report results using the data-adaptive thresholding scheme of Abramovich, Benjamini, Donoho and Johnstone (2006), based on the control of the false discovery rate (FDR). FDR control is a relatively recent innovation in simultaneous testing, which ensures that at most a certain expected fraction of the rejected null hypothesis correspond to spurious detections. Throughout the paper, we set the FDR target level at 10%, which results in a less conservative threshold level than with the universal threshold, and eliminates fewer jump days. We obtain qualitavily similar results with an FDR level between 5% and 20%. Setting the FDR target level to zero is equivalent to using the universal threshold.

3 Monte Carlo study

In this section, we examine the effectiveness of our method to remove spurious detections by performing Monte Carlo experiments. The asymptotic result of Theorem 1 requires that N and n tend to infinity. Here we assess the finite sample performance of our method. We use a sample path of 756 days, consisting of 6.5 hours of trading, which corresponds to the three-year period in our empirical study. We perform 1,000 Monte Carlo iterations.

The data generating process for the log-price is the stochastic volatility with rare jumps model employed by Barndorff-Nielsen and Shephard (2004) and Huang and Tauchen (2005):

$$\begin{aligned} dX_t &= \mu dt + \exp(\beta_0 + \beta_1 v_t) dW_t + j_s dN_t, \\ dv_t &= \alpha_v v_t dt + dB_t, \end{aligned}$$

where W_t and B_t are both Brownian motions and $\mathrm{E}[dW_t dB_t] = \rho dt$. The parameters are the same as in Huang and Tauchen (2005)—calibrated to be realistic for the US equity market. Using one day as the time unit, $\mu = 0.03$, $\beta_0 = 0$, $\beta_1 = 0.125$, $\alpha_v = -0.1$, $\rho = -0.62$. Our jump component is slightly different. N_t is a Poisson process with intensity $\lambda = 40$ (jumps per year) chosen to correspond to what we observe in our data. Contrary to Huang and Tauchen (2005), we use jumps of constant size j_s. We avoid the trivial situation where the jump sizes are very large, and perform our study for $j_s = 0.25$ (small jump), $j_s = 0.5$ (medium jump), and $j_s = 1$ (large jump). We approximate the diffusion process through the Euler scheme with an Euler tick of one second. We discard the burn-in period, i.e., the first 500 data points of the whole series, to avoid the starting value effect.

To detect the jumps, we use the adjusted ratio statistic of BNS. The individual tests are performed at the 5% significance level. In order to meet the conditions of the theorem, which states that the number of observations within the day must be larger than the number of days, we apply our thresholding technique over six-month periods. This constraint arises because the sampling frequency is limited by the increasing microstructure noise at higher frequencies. If we apply our method to the foreign exchange market open non-stop and not only during the 6.5 daily trading hours of the equity market, the constraint dissapears. The impact of splitting the sample into six-month periods is very small, i.e., the universal threshold moves from 3.6 to 3.1.

Table 1 shows the size across different sampling frequencies with respectively, no account for spurious detections, use of the universal threshold, and use of the FDR threshold. The results show that our thresholding technique eliminates almost all spurious detections. Table 2 displays the proportion of days erroneously identified as containing a jump, for different sampling frequencies and jump sizes. Applying the FDR threshold leaves around 2.5% of spurious detections, consistent with the fact that we control the FDR at 10%[2]. Table 3 shows the percentage of true jumps detected. Our thresholding technique has an impact on the ability to detect jumps only in situations where the power of the underlying test is low, e.g., small jumps or low sampling frequency. Moreover, a little drop in power is in many cases compensated by the elimination of the spurious detections.

[Tables 1, 2, and 3]

4 Empirical results

4.1 Data

We conduct our analysis over the three-year period from January 2006 to December 2008, on the 30 stock composing the Dow Jones Industrial Average (DJIA) index between November 21, 2005 and February 19, 2008. Most stocks are traded on the NYSE, except for Microsoft and Intel which trade on the NASDAQ. The data is extracted from the TAQ database. In addition to the individual stocks, we also study the behavior of the index. The TAQ database

[2] Assume there are 252 trading days in a year, among which 40 are jump days. Before thresholding, we detect the 40 jumps and, supposing we perform the individual tests at the 5% level, make on average (252-40)0.05=10.6 spurious detections. Applying the FDR threshold with a target rate of 10%, we remain with $10.6 \times 0.1 = 1.06$ spurious detections, or $1.06/(40 + 1.06) = 2.58\%$ of the selected days.

does not have Dow Jones intraday data. Therefore, we use the DIAMONDS Trust (DIA) exchange-traded fund (ETF) which tracks the Dow Jones index[3]. In addition to using the DIAMONDS ETF, we also construct a price-weighted portfolio comprised of the 30 stocks as in Bollerslev, Law and Tauchen (2008). We refer to this index as PWI in the sequel[4].

The degree of preprocessing and the choice of the sampling frequency are crucial aspects of volatility estimation and jump detection in high-frequency data. The cleaning of high-frequency data has been discussed in e.g. Dacorogna, Gencay, Müller, Olsen and Pictet (2001), and Hansen and Lunde (2006) and the consecutive discussion. Hansen and Lunde (2006) argue that tossing out a large number of observations can in fact improve volatility estimators. Our data cleaning procedure closely follows Barndorff-Nielsen, Hansen, Lunde and Shephard (2009). We consider only trades with a time stamp between 9:35 a.m. and 4:00 p.m., i.e., we remove the first five minutes of the day. This period incorporates adjustments to the information accumulated overnight, and consequently displays a much higher average return variability than any other 5-minute interval. We eliminate obvious data errors such as transaction prices reported at zero, transaction times that are out of order, trades with a non-zero 'correction indicator'. We aggregate all transactions with the same time stamp to the median price. Finally, we discard 'bounce back' outliers as defined in Aït-Sahalia, Mykland and Zhang (2009).

The empirical results also depend on the sampling frequency. There is a trade-off between preserving the continuous time assumption and avoiding microstructure noise effects. If data is sampled too sparsely, jumps disappear because of time averaging. For example, sampling every 15 minutes leads to only 26 daily observations. Although the validity of the corresponding results is questionable, such a large sampling interval has been used in numerous studies. On the other hand, when sampling at increasing frequency, it becomes difficult to separate the price process from the microstructure noise. Microstructure effects include bid-ask bounces, the discreteness of price changes, the gradual response of prices to a block trade, the strategic component of the order flow, etc. In our empirical study, we sample at the two-minute frequency. At that

[3]DIAMONDS trade on NYSE Arca. The all-electronic NYSE Arca is the largest listing and trading platform for ETFs in the U.S.

[4]The Dow Jones index is a price-weighted average scaled by the Dow Divisor to compensate for the effects of stock splits and other adjustments.

frequency, the noise is negligible for the stocks and the time period we consider. The volume of transactions has increased dramatically in the last few years, probably due to the emergence of high-frequency trading. The tick size reduction from 1/16 of 1 dollar to 1 cent on January 29, 2001 has also greatly reduced the problem of bid-ask bounce. Hence, previous recommendations concerning a reasonable frequency to avoid microstructure noise are probably too conservative today.

Another issue when working with high-frequency data, is whether to sample in tick time or in calendar time. Oomen (2006) discusses the benefits of tick-time sampling for the estimation of volatility, and Andersen, Dobrev and Schaumburg (2009) study their volatility estimators under both calendar and tick time sampling. As the limit theories underlying the individual jump tests we use are derived under the assumption of equidistant sampling, we sample in calendar time.

4.2 Number of jumps after removing spurious detections

[Figure 1]

Figure 1 illustrates the thresholding process for Microsoft (MSFT) during the first six months of 2007. For each day in the sample, the points show the value of the BNS adjusted ratio statistic. Dashed lines show the critical value of the individual tests, the FDR threshold, and the universal threshold. The jumps selected after applying the FDR threshold are shown by asterisks, and the spurious detections are depicted by circles. Table 4 displays the average number of jumps per year for each stock, respectively before thresholding, after applying the universal threshold, and after applying the FDR threshold. Around 50% of the jump days selected initially are eliminating after applying the FDR threshold. The resulting average number of jumps per year amounts to around 40. Table 4 also shows the number of jumps in the exchange-traded DIA fund and in our price-weighted portfolio PWI. Once we remove spurious detections, the PWI jumps less often than its average constituents. This smaller amount of jumps is probably explained by an averaging phenomenom in the PWI. On the contrary, we detect more jumps in DIA than in the stocks it is supposed to track. The ETF is an asset subject to its own microstructure effects. The smaller amount of jumps in DIA than in PWI is consistent with the results of Bollerslev, Law and Tauchen (2008). We come back to the different results obtained with DIA and PWI when we study cojumps and the relation between jumps and news announcements.

The Monte Carlo shows the good properties of the underlying jump detection method and of our thresholding technique. Although the power deteriorates with diminishing jump size and sampling frequency, the results in a simulation setting are very good. In practice however, the results can be heavily influenced by different phenomena acting simultaneously. Not knowing which effect is stronger (e.g. very small jumps, microstructure noise) renders the analysis of the results even more difficult. One illustration of the difficulty to run the tests on real data is the low intersection between jumps detected by different tests. For example, Gilder (2009) shows that the methods of Andersen, Bollerslev and Dobrev (2007) and BNS agree on only 50% of detected jump days. There are more phenomena at hand than simply spurious detections due to multiple testing which cause the discrepancies between the number of jumps before and after applying the different thresholds. The ideal threshold lies probably between the universal and the FDR threshold. The universal threshold eliminates nearly 100% of the spurious detections, but also discards some true jumps. On the other hand, the FDR threshold is less likely to remove actual jumps, but leaves some spurious detections. The reader must be aware of these issues in the remaining of this study, just as when looking at empirical results obtained with any existing jump detection technique.

[Table 4]

5 Dynamics of jump occurrences

[Tables 5]

Since the work of Merton (1976) on the application of jump processes in option pricing, the inclusion of jumps in financial modeling has gained a lot of attention amongst academics and practitioners. For example, the empirical option pricing literature shows that jumps are necessary to capture the short term skew. The widely used assumption is that jump arrival times follow a simple Poisson process. In the present section, we study the dynamics of jump arrivals to asses whether this assumption is not overly simplistic.

The jump test of BNS indicates whether one or more jumps occurred on a given day but does not give the exact number of jumps. As a result, we cannot observe the durations between successive jumps and are unable to test whether they follow an exponential distribution. For the same reason, because the corresponding probability of more than one jump in a day is high, we cannot use the standard methods to test whether jumps occurrences are driven by a simple Poisson process. To circumvent this difficulty, we use the runs test developed by Mood (1940)[5]. As we show in the appendix by performing a Monte Carlo study, the runs test is a powerful method to detect clustering of jumps in time in our setting. Our simulations also illustrate the importance of removing the spurious detections e.g. with our thresholding technique in order to get a correct picture of the jumps dynamics. In our simulations, the power of the runs test to detect non-Poisson jump arrivals drops from 86% to 65% if we do not eliminate the spurious jumps (see Table 14). Table 5 reports the results of the runs test for the 30 Dow Jones stocks over the period from January 2006 to December 2008. With no account for spurious detections, we detect the presence of clustering in only three stocks (AIG, Microsoft and AT&T). After applying the FDR threshold, the proportion of stocks with non-random jump arrival increases to almost 25%. After applying the universal threshold, we detect clustering of jumps in only less than 7% of the stocks. However, this latter result is probably biased by the decrease of power of the runs test due to the small number of observations remaining after applying the universal threshold. Looking at our two index proxies, the runs test indicates that jumps in DIA cluster in time whereas jumps in PWI do not. Once again, the DIA index behaves as a proper asset, whereas effects affecting the individual components are averaged out in the PWI portfolio.

Even if we do not observe exactly the durations between successive jumps, in particular if there are many jumps within the same day, we can still estimate the parameters of the simple Poisson process that would have most likely generated the observations. If we suppose that the durations between jumps follow an

[5]The runs test compares the number of sequences of consecutive days with jump and without jump, or runs, against its sampling distribution under the hypothesis of random arrival. For example, a particular sequence of 10 jump tests may be represented by 0011101001, containing three runs of 1s, and three runs of 0s. In contrast, the sequence 1111100000 contains the same number of 0s and 1s, but only two runs. Too few runs indicate the presence of clustering. Too many runs indicate an oscillation. The runs test has been used in Fama (1965) to test the random walk hypothesis of stock returns. See Section 2.2.2 of Campbell, Lo and MacKinlay (1996) for details and the exact test statistic. We use the runstest function from the MATLAB Statistics Toolbox.

exponential distribution with parameter λ, then the probability of one or more jumps occurring on a given day is $1 - e^{-\lambda}$. Hence, even if we do not observe the exact number of jumps within days, we can estimate λ as $\widehat{\lambda} = -\ln(1 - \widehat{p})$, where $\widehat{p}$ denotes the estimated probability of occurrence of a jump, obtained as the ratio of the number of days with jumps over the total number of days. For the stocks for which the runs test indicates no time clustering of jumps, $\widehat{\lambda}$ ranges from 0.06 to 0.27, when using the FDR threshold. This corresponds to a mean duration between successive jumps of respectively 16.1 and 3.7 days. Figure 2 displays an example of the exponential distribution fitted for Microsoft, along with the histogram of the durations. Panel (a) shows the results before thresholding and Panel (b) after applying the FDR threshold. Remember that we do not observe the inter jump durations exactly. Therefore, the bars of the histogram represent grouped data, and do to take into account the possibility of more than one jump per day. For example, if we detect a first jump on day t and the following jump on day $t+2$, the true duration between both jumps can range from one to three days, depending on when exactly the jumps occur within the day. That is without considering the event of multiple jumps per day. Therefore, the first bar of the histogram shows the number of times two consecutive days are detected to contain jumps, which corresponds to durations ranging from zero to two days. A visual inspection of the histogram does not lead to reject the Poisson hypothesis. The bottom of Figure 2 plots the durations between successive jumps.

[Figure 2]

6 Cojumps

Jumps in individual stocks can be generated by either stock-specific news or common market-level news. Market-level news can cause jumps in many stocks simultaneously and can induce discontinuities even in a diversified index. In this section, we study simultaneous jumps (cojumps) in the Dow Jones stocks and their relation to jumps in the index. We examine in detail the relation between jumps and news announcements in the next section. Other empirical studies of cojumps include Bollerslev, Law and Tauchen (2008) who examine the relationship between jumps in a sample of forty large-cap U.S. stocks and the corresponding aggregate market index, Lahaye, Laurent and Neely (2010) who investigate cojumps between stock index futures, bond futures, and exchange rates, and Dungey, McKenzie and Smith (2009) who consider simultaneous jumps across the term structure.

We define cojumps with the univariate BNS test as simultaneous significant jumps, i.e., occurring on the same day, rather than using any of the multivariate tests proposed e.g. by Bollerslev, Law and Tauchen (2008), or Jacod and Todorov (2009). Even if there is no day in our sample where the 30 stocks all jump together, we do detect a jump in 50% or more of the stocks on a few occasions, i.e., on 29 days before thresholding, on two days when applying the FDR threshold (September 18, 2007 and February 25, 2008), and on one day when applying the universal threshold (February 25, 2008). September 18, 2007 is an exmple of a market-level annoucement, i.e., the Federal Open Market Committee (FOMC) decision to lower its target for the federal funds rate 50 basis points to 4-3/4 percent. After applying the FDR threshold, 54% of the Dow Jones stocks are detected to cojump on that day. Figure 3 displays the simultaneous jump at 2:15 p.m. in JPMorgan Chase, IBM, Microsoft, and 3M.

[Figure 3]

6.1 Cojumps with index

In this section, we investigate the relation between jumps in our index proxies and jumps in the individual Dow Jones stocks. Table 6 shows the likelihood of a jump in DIA or PWI conditional on the proportion of stocks cojumping, for respectively no thresholding, use of the universal threshold, and use of the FDR threshold. The probability of a jump in the index increases with the number of stocks jumping simultaneously and becomes significantly more important if more than 40% of the stocks jump. From the second column of Table 6 which gives the corresponding number of occurrences, we see that this is a rare event. For example, after applying the FDR threshold, we observe more than 40% of the stocks jumping simultaneously on only 7 out of 747 days. Once again, the FDR threhold results show that PWI jumps less often than DIA. The DJIA index is a price-weighted average, which gives higher-priced stocks more influence than to their lower-priced counterparts. As a robustness check, we perform our analysis using the price-weighted proportion of stocks jumping simultaneously. We obtain very similar results.

Table 7 displays information on the distribution of the proportion of stocks jumping simultaneously, depending on whether or not there is a jump in the index. When applying the FDR threshold, the average percentage of stocks jumping raises from 12.5% to 17.7% when there is a jump in DIA, and can reach 70%. With no jump in the index, the percentage of stocks jumping on the same day never exceeds 40%.

[Tables 6 and 7]

6.2 Cojumps within industry sectors

During the three years of our study, we find no single cojump affecting all Dow Jones constituents. However, we observe a significant number of cojumps if we group stocks by industry sectors. Table 8 shows the repartition of our thirty stocks among the different Global Industry Classification Standard[6] (GICS) sectors, and Table 9 displays the number of cojumps within each sector for respectively, no account for spurious detections, use of the universal threshold, and use of the FDR threshold. An asterisk indicates that there are no more cojumps than if the stocks jumped independently[7]. For all but two sectors the number of cojumps is significant. Hence, at least part of the simultaneous jumps must be driven by sector-level events.

[Tables 8 and 9]

7 Relation to news releases

In this section we investigate the relation between jumps and information arrival. We consider successively macroeconomic news, which can explain simultaneous jumps in many stocks, and news specific to a particular company.

7.1 Macroeconomic news

[Tables 10 and 11]

[6]The Global Industry Classification Standard (GICS) is an industry taxonomy developed by Morgan Stanley Capital International (MSCI) and Standard & Poor's.

[7]Under the null hypothesis that stocks jump independently, the probability that the stocks jump simultaneously on a given day is the product of the jump probabilities of the individual stocks. The distribution of the corresponding test statistic is obtained from a simple application of the Central Limit Theorem and the Delta method. See supplementary appendix for details.

We investigate whether jumps occurring in many stocks simultaneously or in our index proxies can be explained by macroeconomic news. There is a long literature on market reaction to macroeconomic news. Cutler, Poterba and Summers (1989) estimate the fraction of the variance in aggregate stock returns that can be attributed to various kinds of news, including major political and world events. Ederington and Lee (1993) and Ederington and Lee (1996) are the first to investigate the intraday reaction of bond prices to macro announcements. More recently, Andersen, Bollerslev, Diebold and Vega (2007) show using high-frequency data that reaction times to news are very short, and Aït-Sahalia, Andritzky, Jobst, Nowak and Tamirisa (2010) examine the market response to policy initiatives during the recent financial crisis. To our knowledge, however, the only papers studying the link between jumps in assets and macroeconomic news are Dungey, McKenzie and Smith (2009), Lahaye, Laurent and Neely (2010), and Huang (2007). Numerous other studies which mention the relation of jumps to macroeconomic announcements merely investigate the timing of jumps to see whether an unusual pattern corresponds to a regularly scheduled news announcement.

For all announcements except the target Fed funds rate, we use the International Money Market Services (MMS) data on expected (surveyed) and realized (announced) macroeconomic fundamentals. MMS conducts a Friday telephone survey of about 40 money managers, collects forecasts of all indicators to be released during the next week, and reports the median forecasts from the survey. One of the first article to use the MMS survey data is Andersen, Bollerslev, Diebold and Vega (2003). The authors study the effect of macro announcements on U.S. dollar spot exchange rates but do not look at jumps. The target Fed funds rate forecasts are obtained from Action Economics, which also gathers estimates on economic data once a week from economists, strategists, and a few traders. We obtain the data from Haver Analytics. As of December 16, 2008, the funds target rate is a range, i.e., zero to 0.25%, rather than a specific rate. The Federal Open Market Committee (FOMC) can also surprise the market by changing the Fed funds target between scheduled meetings. In our sample, the decisions following such unscheduled meetings are always released early on the next morning and therefore do not cause jumps during market hours.

We consider only the announcements released during the trading hours, listed in Table 10. Table 11 presents the results with respectively no thresholding, use of the universal threshold, and use of the FDR threshold. For each macroeconomic news, the table displays the number of announcement days in our sample, the average probability of a jump in individual stocks on an announcement day, the probability of a jump in the Diamonds ETF, and the probability of a jump in our PWI portfolio. The last row presents corresponding results based on all days in our sample independently on the presence or absence of news. The only announcement which increases the likelihood of a jump is the target Fed funds rate. After applying the FDR threshold, the unconditional average probability of a jump in stocks on a given day is 14.4%. On a day with a scheduled FOMC meeting, this proportion increases to 18%, but the difference is not statistically significant[8]. Figure 3 displays an example of a simultaneous jump in many stocks immediately following an FOMC announcement. Even if no jump is detected, however, most FOMC meetings are followed by a strong reaction in stock prices as illustrated in Figure 4. Following the news, the volatility increases but the variation is caused by the Brownian part only and not by a jump. Hence, our results show that in the equity market, a majority of announcements are not followed by a jump. This conclusion differs from the findings in other markets. For example, Dungey, McKenzie and Smith (2009) find that two thirds of cojumps in bond prices coincide with a scheduled US news release. The importance of removing spurious detections with e.g. our thresholding technique is highlighted once again as the effect just described is not apparent before thresholding. For example, before thresholding the probability of a jump in DIA appears larger on days with no FOMC meeting.

As already noticed in the previous sections, the results of Table 11 show that the PWI portfolio jumps less often than the DIA fund. The ability to detect jumps of the BNS test depends on the size of the jump relative to the total variation of the process. Therefore, when the discontinuities in the individual stocks are averaged out in the PWI portfolio, some jumps can no longer be detected. This explains the lower amount of jumps in PWI. On the other hand, DIA is a proper asset subject to its own microstructure effects. The discrepancies between DIA and PWI show that the exchange-traded fund is sometimes subject to a decoupling from the index it is tracking. For example,

[8]Denote by p_1 and p_2 the probabilities of a jump on respectively a news day and a day with no announcement. Let n_1 be the number of news days and n_2 the number of days with no announcement. For $\frac{n_1}{n_1+n_2} \longrightarrow \lambda$, we can test the null hypothesis of no link between jumps and announcements using the following asymptotic normality result: $\sqrt{\frac{n_2}{n_1+n_2}}\widehat{p}_1 - \sqrt{\frac{n_1}{n_1+n_2}}\widehat{p}_2 \sim \mathcal{N}\left(0, (1-\lambda)p_1(1-p_1) + \lambda p_2(1-p_2)\right)$, where the $\widehat{p}$'s denote estimated probabilities.

imagine a news release that causes only a few stocks to jump. The resulting discontinuities disappear in PWI when we add them to the movements of the other stocks. The DIA fund however is traded as one proper asset and can still be affected by the announcement. Table 11 illustrates indeed that DIA is more likely to jump after a news release.

It may not be the act of releasing information to the market itself that is important. Rather, it may be the extent to which the actual announcement differs from the market expectation, i.e. the surprise content of each announcement, that determines whether assets jump in reaction to the information release. We capture the surprise content of the announcements using the survey data from MMS and Action Economics. To account for the discrepancies across the various news items, we compute the standardized surprise, defined as the difference between expectations and realizations, divided by the standard deviation. We do not observe any effect caused by the surprise component of macro news announcements, even if we consider separately surprises above and below expectations. The detailed analysis is available upon request.

[Figure 4]

7.2 Scheduled company-specific announcements

In the previous section, we have looked at the impact of different market-wide announcements. We now switch the focus to company-specific announcements. First, we investigate whether dividends can cause the stock price to jump. We obtain data from COMPUSTAT and CRSP (for the declaration date). We do not observe significantly more jumps on the ex-dividend date. This result is not surprising, given that companies usually commit to dividend policy for the long run, that the amounts are known in advance, and that dividends are settled after the bell. The likelihood of a jump does not increase on the dividend declaration date either. The observed probability of a jump on a dividend declaration day (pooling all the stocks together) is actually lower than the overall proportion of days with jump, i.e., 12.2% against 14.4% when applying the FDR threshold.

Second, using data from I.B.E.S., we perform a similar analysis for quarterly earnings announcements[9]. Again, we find that jumps do not occur more often on earnings announcement days. This is explained by the fact that earnings

[9] Patton and Verardo (2009) show that the beta of individual stocks increases by an economically significant amount on quarterly earnings announcement days.

are most often announced outside of the trading hours. If we focus on the 15 announcements made during trading hours, which represent only 4.2% of all the announcements for the 30 stocks during our three-year sample, we observe that the likelihood of a jump increases slightly to 20% (when using the FDR threshold). Remember that the average unconditional probability of a jump after applying the FDR threshold is 14.4%. The difference is not significant. Hence, our results put into perspective the findings of Lee and Mykland (2008) who always detect a jump on the three earnings announcement days in their sample. The detailed analysis of the impact of dividends and quarterly earnings announcements is available upon request.

7.3 Company-specific news releases

[Table 12]

In this section, we investigate whether jumps can be explained by news stories from two major newswires, i.e., Dow Jones News Service (DJNS) and Reuters News. By examining the content of news, we can analyze the impact of a variety of unscheduled and uncategorized events and are not limited to a predetermined set of event types such as earnings announcements, mergers, or analysts' recommendations. To our knowledge, the present study is the first to perform an extensive analysis of the relation between news media publications and price discontinuities. Cutler, Poterba and Summers (1989) is one of the first empirical studies to explore the link between news coverage and stock prices. Lee and Mykland (2008) examine the association of financial news releases with jump arrivals on a small sample of three stocks over three months. Tetlock (2007) and Tetlock, Saar-Tsechansky and Macskassy (2008) attempt to quantify the language used in financial news stories. They are the first to investigate the relation of investor sentiment to stock market activity by analyzing news media content. The two papers are different from our study, however, as our aim is not to extract the qualitative content of media publications.

We access the DJNS and Reuters News newswires through Factiva. Factiva is a news database that aggregates content from thousands of leading news and business sources. Retrieving information effectively from such a huge repository is a difficult task. The perfect mix of getting everything and avoiding irrelevant or erroneous stories is difficult to achieve. The technology to automatically quantifying language content is not ripe for the scope of our study[10]. Therefore, we rely on the taxonomy applied by Factiva which provides a hierarchy of company names, industries, regions, and subjects. Such an indexing allows for example to narrow search results on a specific topic, or retrieve stories which are actually about a particular company, and not all the stories where the company name merely occurs.

One problem with the Factiva web interface is that it does not allow to perform queries on the "publication time" field. To circumvent this problem, we export all the news stories in XML format. We then parse the XML files and reconstruct our own database. Although the "publication time" field is not searchable using the web interface, it is encoded properly when exporting documents in XML format. As we can download the full articles with indexing, we do not loose any information. This process also allows us to perform text analysis inside the articles, and run custom searches efficiently. Keeping news published in the US only, we are left with 30,071 DJNS stories and 31,228 Reuters stories about our thirty companies during our three-year sample[11]. The stocks we consider are large multinational companies and are the subject of one or more stories almost every day. We further eliminate irrelevant stories by selecting news published during market hours only and by requiring that the company name appears in the headline[12]. This allows us to reduce the number of stories to 8,498 for DJNS and 6,520 for Reuters News, which corresponds to around one story every three days for each stock.

Having eliminated the irrelevant stories, we analyze the probability of jumps occurring on specific news types using the Factiva indexing hierarchy. We also investigate the impact of news flagged as "Down Jones/Reuters Top Wire News" in order to capture any uncategorized and unusual story. An important proportion of the "Top Wire News" are stories about earnings. The majority of

[10]Tetlock (2007) and Tetlock, Saar-Tsechansky and Macskassy (2008) are only able to construct a simple indicator of media pessimism, or look at the fraction of negative words.

[11]These numbers are obtained by using the Factiva option to remove duplicates and exclude republished news, recurring pricing and market data, and non-business stories such as obituaries, sports or calendars. occurence

[12]The Factiva indexing system does not solve the aboutness vs occurrence issue perfectly. For instance, an article containing a "Top Wire News" story about Microsoft and secondarily mentioning Intel will also be retrieved in a search for "Top Wire News" and Intel, although the information might be not very important for Intel. When imposing that the headline mentions the company name, we must account for the fact that one company can have different denominations. For example, Bank of America appears as BofA, Bank of Amer, or B. of A.

them is discarded, however, when we eliminate news released outside market hours. Table 12 presents results for a selection of news types susceptible to cause jumps. Results for further kinds of news are available upon request. As one additional precaution, we require that a particular news appears simultaneously on both the DJNS and Reuters News wires. For each news type, the first two columns indicate the total number of stories and the number of stories published during market hours. 78 percent of the announcements are made outside market hours. Once again, only by reconstructing our own database are we able to filter out news outside market hours automatically. The remaining columns show the conditional pooled probability of a jump on days a news is released, for each type of news. Results are reported for respectively no account for spurious detections, use of the universal threshold, and use of the FDR threshold. An asterisk indicates that the likelihood of a jump is significantly larger after a news is released than on days with no news of the same type. After applying the FDR threshold, the unconditional probability of a jump computed over all days and stocks is 14.4 percent. The news types for which we observe an increased probability of jumps are "Down Jones/Reuters Top Wire News" (27.1%), "Government Contracts" (29.5%), "Divestitures/Asset Sales" (28.6%), "Share Capital" (33.3%), "Share Buybacks" (42.9%) (a subcategory of "Share Capital"), and "Sales Figures" (23.1%). Recall that the probability of a jump on FOMC meeting days is 18 percent. The only news type for which the increase in the likelihood of a jump is statistically significant is "Share Buybacks". Our results show that news releases are not very likely to cause jumps. Companies purposefully shift most important announcements after the bell or early in the morning in order to avoid uncontrolled investor reactions and the consequent impact on the stock price.

Our findings differ from the conclusions of Lee and Mykland (2008). First, Lee and Mykland (2008) sample at the low 15-minute frequency and keep the opening transactions, which leads them to systematically detect jumps in the first return of a day. The opening transactions of each day are very erratic and do not correspond to normal returns as they result from information accumulated over the night. Second, the companies under consideration are the subject of articles every day. It is therefore not surprising that Lee and Mykland (2008) are able to find a story for each day they detect a jump. If all such events would systematically induce jumps, we should observe jumps scattered across the day, and not just when the market opens.

Finally, we take a closer look at the stock price reaction when a company announces a share repurchase program, as it is the only kind of news to significantly increase the probability of a jump. Our entire sample contains 35 news about share buybacks, from which 7 are released during market hours. We want to verify that if a jump is caused by the publication of a news, then the jump immediately follows the news. The BNS jump test does not return the precise moment the jump occurs. However, in our example it is easy to spot the jump by visually inspecting the price trajectories displayed in Figure 5. Table 13 displays the headline and publication time of the corresponding news and indicates whether the BNS test detects a jump. For the three announcements where a jump is detected, i.e., IBM, Johnson & Johnson, and JPMorgan Chase, the timing match is perfect. A buyback increases earnings per share prospects and, as expected, the jumps are positive. We also observe an abnormal sudden price increase after three other announcements of shares repurchase programs, i.e., Alcoa, American Express, and AT&T. The BNS test does not identify these as jumps, however, because the reaction to the news is spread over two or three consecutive returns. Probably, the announcement merely increases the volatility and the large returns are produced by the Brownian part only. The jump in AT&T is the less visible. This is maybe due to the fact that the buyback appears only in the Reuters News headline. Readers of the DJNS must scan the entire message to obtain the information. For Johnson & Johnson, we do not observe a jump because the news does not announce a new share repurchase program, but signals on the contrary a pause in a repurchase plan already accepted.

[Table 13]

[Figure 5]

Appendices

A Proof of theorem

Under the null hypothesis of no jumps the asymptotic distribution of jump test statistics can be shown to converge to independent standard normal random variables. These results follows from showing asymptotic negligibility of the drift contributions and application of a CLT for triangular arrays of martingale differences.

For each integer $n \geq 1$, let the real-valued random variables $Y^n_{t,i}$, $1 \leq t \leq N$, $1 \leq i \leq n$, form N square integrable martingale difference sequences w.r.t. the σ-fields $\mathcal{F}^n_{t,0} \subset \mathcal{F}^n_{t,1} \subset \ldots \subset \mathcal{F}^n_{t,n}$, that is, suppose that $Y^n_{t,i}$ is measurable w.r.t. $\mathcal{F}^n_{t,i}$ with $\mathrm{E}[(Y^n_{t,1})^2] < \infty$ and $\mathrm{E}[Y^n_{t,i}|\mathcal{F}^n_{t,i}] = 0$ a.s. for all n, i and t. The CLT is applied to quantities which can be written as $S^n_t = \sum_{i=1}^{n} Y^n_{t,i}$. In the following theorem we show that the event that the largest and the smallest of the entries of the vector $(S^n_1, \ldots, S^n_N)$ stay within $[-\sqrt{2\log N}, \sqrt{2\log N}]$ becomes certain for large n and N. We use two conditions on higher moments, which imply the conditions to apply the CLT for triangular arrays of martingale differences when n goes to infinity, and require that N is not too large w.r.t. the asymptotics in n.

Theorem 1. *Let* $S^n_t = \sum_{i=1}^{n} Y^n_{t,i}$, $1 \leq t \leq N$. *If, for* $0 < \gamma < \infty$,

$$L^n_{t,2\gamma} = E\left[\sum_{i=1}^{n} |Y^n_{t,i}|^{2+2\gamma}\right] \to 0, \quad \text{as} \quad n \to \infty, \tag{1}$$

$$M^n_{t,2\gamma} = E\left[\left|\sum_{i=1}^{n} E\left[(Y^n_{t,i})^2|\mathcal{F}^n_{t,i}\right] - 1\right|^{1+\gamma}\right] \to 0, \quad \text{as} \quad n \to \infty, \tag{2}$$

and

$$(1 + \sqrt{2\log N})^{3+6\gamma} N \leq \alpha(L^n_{t,2\gamma} + M^n_{t,2\gamma})^{-1}, \tag{3}$$

with $\alpha > 0$. *Then,*

$$P\left[\sup_t |S^n_t| \leq \sqrt{2\log N}\right] \to 1, \quad \text{as} \quad N, n \to \infty. \tag{4}$$

Proof. Conditions (1) and (2) imply the conditions of the CLT for triangular arrays of martingale differences, and we get the weak convergence of the distribution $P\left[S^n_t \leq x\right]$ to the standard normal distribution $\Phi(x)$ as $n \to \infty$.

Now $P\left[\sup_t |S_t^n| \leq \sqrt{2\log N}\right] = P\left[|S_1^n| \leq \sqrt{2\log N}, \ldots, |S_N^n| \leq \sqrt{2\log N}\right] = \prod_{t=1}^{N} P\left[|S_t^n| \leq \sqrt{2\log N}\right]$ by independence.

From Grama (1997) Theorem 2.1, Condition (3) ensures that we can use exact bounds for the departure from normality of $P\left[S_t^n \geq \sqrt{2\log N}\right]$ and $P\left[S_t^n \leq -\sqrt{2\log N}\right]$ (see also Hauesler (1988) Theorem 2 for exact uniform bounds, and Lipster and Shiryayev (1989) Section 5.7 Theorems 1 and 2 for uniform bounds, i.e., Berry-Esseen type bounds, instead of the exact nonuniform bounds for moderate deviations that we use here), so that

$$\begin{aligned}\prod_{t=1}^{N} P\left[|S_t^n| \leq \sqrt{2\log N}\right] &= \prod_{t=1}^{N}\Big(1 - P\left[S_t^n \geq \sqrt{2\log N}\right] \\ &\quad - P\left[S_t^n \leq -\sqrt{2\log N}\right]\Big) \\ &= \prod_{t=1}^{N}\left[1 - 2\Phi(-\sqrt{2\log N})\left\{1 + R_t(\alpha,\gamma,N)\right\}\right],\end{aligned}$$

where the remainder term is

$$R_t(\alpha,\gamma,N) = \theta C(\alpha,\gamma)\left\{(1+\sqrt{2\log N})^{3+6\gamma} N (L_{t,2\gamma}^n + M_{t,2\gamma}^n)\right\}^{1/(3+2\gamma)}$$

with $|\theta| < 1$ and $C(\alpha,\gamma)$ being a constant only depending on α and γ. Using $\Phi(-\sqrt{2\log N}) \leq \phi(\sqrt{2\log N})/\sqrt{2\log N}$ with ϕ denoting the density of the standard normal distribution, we deduce the stated result from

$$\prod_{t=1}^{N}\left[1 - 2\Phi(-\sqrt{2\log N})\right] = \left[1 - \frac{2}{\sqrt{2\pi}\sqrt{2\log N}N}\right]^N \to 1, \quad \text{as} \quad N \to \infty,$$

and the asymptotic negligibility of the contribution of the remainder term as $N, n \to \infty$ since $R_t(\alpha,\gamma,N)$ is bounded by $\theta C(\alpha,\gamma)\alpha^{3+6\gamma}$ because of (3). □

Condition (3) is rather weak as clearly illustrated in the case of independent random variables by Grama (1997). Let $Y_{t,i}^n = \eta_{t,i}/\sqrt{n}$, where $\eta_{t,i}$ form N given independent sequences of i.i.d. random variables which satisfy $E[\eta_{t,1}] = 0$, $\mathrm{E}[(\eta_{t,1})^2] = 1$, $m_{2\gamma} = E[|\eta_{t,1}|^{2+2\gamma}] < \infty$ with $0 < \gamma < \infty$. In this case $M_{t,2\gamma}^n = 0$ and $L_{t,2\gamma}^n = n^{-\gamma} m_{2\gamma}$. Thus for standard Gaussian $\eta_{t,1}$, condition (3) is easily met for various (n, m, α, γ) since $m_{2\gamma} = \frac{(2+2\gamma)!}{2^{1+\gamma}(1+\gamma)!}$.

BNS test: We can write the adjusted ratio test statistic of Barndorff-Nielsen and Shephard (2006) in the above form using

$Y_{t,i}^n := (\vartheta\mu_1^{-4}\Delta_n QV_t^n)^{-1/2}\left(\mu_1^{-2}|\Delta X_{t,i}^n||\Delta X_{t,i-1}^n| - |\Delta X_{t,i}^n|^2\right)$. Since

$$|X_{t,i}^n|^{2+2\gamma} \leq (\vartheta\mu_1^{-4}\Delta_n QV_t^n)^{-1/2}\sum_{l=0}^{\infty}\begin{pmatrix} 2+2\gamma \\ l \end{pmatrix}\left(|\Delta X_{t,i}^n||\Delta X_{t,i-1}^n|\right)^{2(2+2\gamma-l)} |\Delta X_{t,i}^n|^{2l},$$

where $\begin{pmatrix} 2+2\gamma \\ l \end{pmatrix} = \frac{1}{l!}\prod_{t=0}^{l-1}(2+2\gamma-t)$, Condition (1) holds from the convergence of $\Delta_n^{-1/2}\Delta_n^{1-2(1+\gamma)}\sum_{i=2}^{n}\left(|\Delta X_{t,i}^n||\Delta X_{t,i-1}^n|\right)^{2(2+2\gamma-l)}|\Delta X_{t,i}^n|^{2l}$, $p \geq 2$, in law to Gaussian variables for X continuous, the equality $\Delta_n^{-(1+\gamma)} = \Delta_n^{-1/2}\Delta_n^{1-2(1+\gamma)}$ $\Delta_n^{2+\gamma-3/2}$, and $\Delta_n \to 0$. Condition (2) holds since $\sum_{i=2}^{n}\mathrm{E}\Big[(\mu_1^{-2}|\Delta X_{t,i}^n||\Delta X_{t,i-1}^n| - |\Delta X_{t,i}^n|^2)^2|\mathcal{F}_{t,i}^n\Big]$ converges to $A(4)_t$ (see BNS, proof of Proposition 4.2).

Theorem 1 can be applied to numerous other jump detection tests, such as Aït-Sahalia and Jacod (2009). The proof is available on request.

B Runs test Monte Carlo study

In the Monte Carlo study of this section, we assess the statistical properties, i.e. size and power, of the runs test applied to detect time clustering of jumps. Our simulations also illustrate the importance of eliminating the spurious detections in order to obtain the true picture of the jumps dynamics. We generate a total of 10,000 price trajectories corresponding to the setting of our empirical application, i.e. three years of high-frequency returns. As in Section 3, we use the model of Huang and Tauchen (2005). Under the null hypothesis of simple Poisson jumps, the jumps are generated from an exponential distribution with parameter $\lambda = 40$ (jumps per year), calibrated to correspond to what we observe empirically. Under the alternative hypothesis that jumps cluster in time, we use an Autoregressive Conditional Duration (ACD) model[13]. The ACD model specifies the density of the ith duration between two jumps d_i, conditional on past durations. We use the Weibull ACD(1,1) or WACD(1,1) specification. $\psi_i \equiv \mathrm{E}[d_i|d_{i-1},\ldots,d_1]$, the expectation of the ith duration, is given by

$$\psi_i = \omega + \alpha d_{i-1} + \beta\psi_{i-1}.$$

The WACD model further assumes that $d_i = \psi_i\epsilon_i$, where $\{\epsilon_i\} \sim$ i.i.d. Weibull with parameters (λ, γ). We set the values of the parameters to obtain the same

[13]See Engle and Russel (1998).

mean number of jumps as under the null: $\omega = 0.6$, $\alpha = 0.3$, $\beta = 0.6$, $\lambda = 0.79$, and $\gamma = 0.7$. The jump size is set to $j_s = 1$. We sample at the two-minute frequency, and use the test of BNS at the 5% significance level to detect jumps. We then apply the runs test (see Mood (1940)) to test the null hypothesis that jumps arrive randomly, i.e., do not cluster in time.

The first column of Table 14 presents results on the size of the runs test. It displays the proportion of times the null hypothesis is rejected when jumps durations are generated from the exponential distribution. The first three lines display results from the BNS test, for respectively no account for spurious detections, use of the universal threshold, and use of the FDR threshold. The last line of the table reports results based on the true (simulated) jumps. The second column present corresponding results for the power of the runs test, i.e., when jumps durations are obtained from the ACD model. The results show the good size and power properties of the runs test in the setting of our empirical study, and highlight the importance of eliminating the spurious detections when investigating the dynamics of jumps. When we do not account for multiple testing, the power to detect time clustering of jumps drops from 85% to only 65%.

[Table 14]

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	Sampling frequency					
	30 sec		2 min		5 min	
No thresholding	5.5	(0.8)	6.1	(0.9)	6.9	(0.9)
Universal threshold	0.2	(0.1)	0.3	(0.2)	0.5	(0.3)
FDR threshold	4.8	(1.0)	5.0	(1.1)	4.9	(1.3)

Table 1: Monte Carlo: Size. Numbers in parenthesis correspond to standard deviations.

		Sampling frequency					
Jump size		30 sec		2 min		5 min	
Large	No thresholding	5.5	(0.9)	6.1	(0.9)	6.9	(1.0)
	Universal threshold	0.2	(0.2)	0.3	(0.2)	0.4	(0.3)
	FDR threshold	1.1	(0.5)	1.5	(0.5)	1.9	(0.6)
Medium	No thresholding	5.5	(0.9)	6.1	(1.0)	6.9	(1.0)
	Universal threshold	0.2	(0.2)	0.3	(0.2)	0.5	(0.3)
	FDR threshold	1.1	(0.4)	0.9	(0.4)	1.6	(1.0)
Small	No thresholding	5.5	(0.9)	6.1	(1.0)	7.0	(1.0)
	Universal threshold	0.2	(0.2)	0.3	(0.2)	0.4	(0.3)
	FDR threshold	1.2	(0.9)	4.2	(1.3)	4.7	(1.4)

Table 2: Monte Carlo: Proportion of spurious detections. Numbers in parenthesis correspond to standard deviations.

		Sampling frequency					
Jump size		30 sec		2 min		5 min	
Large	No thresholding	99.9	(0.3)	99.5	(0.7)	96.1	(1.8)
	Universal threshold	99.9	(0.3)	99.2	(0.9)	83.0	(3.4)
	FDR threshold	99.9	(0.3)	99.4	(0.7)	91.2	(2.7)
Medium	No thresholding	99.7	(0.5)	75.2	(4.0)	40.5	(4.8)
	Universal threshold	97.2	(1.6)	37.5	(4.5)	11.0	(3.1)
	FDR threshold	99.0	(0.9)	50.3	(5.6)	17.7	(4.7)
Small	No thresholding	46.9	(4.9)	16.4	(3.6)	10.8	(3.0)
	Universal threshold	11.1	(2.9)	1.7	(1.3)	1.0	(1.0)
	FDR threshold	19.9	(5.6)	11.6	(3.7)	7.4	(2.8)

Table 3: Monte Carlo: Proportion of jumps detected. Numbers in parenthesis correspond to standard deviations.

Ticker	Company name	No thresholding	Universal threshold	FDR threshold
Dow Jones stocks:				
AA	Alcoa	73.3	16.3	35.0
AIG	American International Group	75.3	23.3	41.3
AXP	American Express	72.0	17.7	35.7
BA	Boeing	57.7	14.0	27.7
C	Citigroup	57.7	12.0	21.7
CAT	Caterpillar	59.0	15.7	23.3
DD	DuPont	81.0	16.3	37.3
DIS	Walt Disney	86.7	25.7	52.0
GE	General Electric	76.7	23.0	50.7
GM	General Motors	77.0	16.3	33.3
HD	The Home Depot	70.7	17.7	32.3
HON	Honeywell	61.7	13.0	23.3
HPQ	Hewlett-Packard	66.7	17.3	31.7
IBM	IBM	55.0	11.0	20.7
INTC	Intel	89.0	25.3	58.3
JNJ	Johnson & Johnson	68.0	18.0	36.0
JPM	JPMorgan Chase	60.0	13.3	25.7
KO	Coca-Cola	73.7	17.3	37.7
MCD	McDonald's	75.7	21.3	44.7
MMM	3M	62.7	16.3	32.7
MO	Altria Group	73.3	20.7	37.0
MRK	Merck	69.3	21.7	36.7
MSFT	Microsoft	94.0	27.7	64.3
PFE	Pfizer	93.0	25.7	55.0
PG	Procter & Gamble	61.0	15.0	26.3
T	AT&T	82.0	22.7	48.7
UTX	United Technologies Corporation	59.3	12.7	23.0
VZ	Verizon Communications	75.0	20.7	38.3
WMT	Wal-Mart	50.3	7.0	31.3
XOM	ExxonMobil	43.7	10.7	15.0
Index:				
DIA	Diamonds Trust	91.7	25.3	54.3
PWI	Price-weighted index	72.7	13.0	33.7
Summary for stocks:				
Mean		70.0	17.8	35.9
Median		71.3	17.3	35.3
Minimum		43.7	7.0	15.0
Maximum		94.0	27.7	64.3

Table 4: Average number of jumps per year. Two-minute sampling frequency. Tests performed over 2006–2008.

Ticker	Company name	No thresholding	Universal threshold	FDR threshold
Dow Jones stocks:				
AA	Alcoa	0.93	0.40	0.15
AIG	American International Group	0.00*	0.00*	0.00*
AXP	American Express	0.14	0.13	0.32
BA	Boeing	0.89	0.82	1.00
C	Citigroup	0.08	0.91	0.98
CAT	Caterpillar	0.49	1.00	0.95
DD	DuPont	0.65	1.00	0.92
DIS	Walt Disney	0.40	0.57	0.02*
GE	General Electric	0.40	0.17	0.53
GM	General Motors	0.09	0.45	0.07
HD	The Home Depot	0.15	0.35	0.53
HON	Honeywell	0.14	0.74	0.63
HPQ	Hewlett-Packard	0.55	0.61	0.84
IBM	IBM	0.51	0.84	0.85
INTC	Intel	0.23	0.26	0.35
JNJ	Johnson & Johnson	0.36	0.67	0.37
JPM	JPMorgan Chase	0.29	1.00	0.16
KO	Coca-Cola	0.45	0.56	0.65
MCD	McDonald's	0.52	0.07	0.06
MMM	3M	0.70	0.40	0.04*
MO	Altria Group	0.16	0.77	0.04*
MRK	Merck	0.92	0.98	0.04*
MSFT	Microsoft	0.00*	0.65	0.00*
PFE	Pfizer	0.12	0.02*	0.30
PG	Procter & Gamble	0.49	0.54	0.11
T	AT&T	0.02*	0.52	0.00*
UTX	United Technologies Corporation	0.17	0.25	0.17
VZ	Verizon Communications	0.49	1.00	0.58
WMT	Wal-Mart	0.47	1.00	0.21
XOM	ExxonMobil	0.35	0.29	0.54
Index:				
DIA	Diamonds Trust	0.10	0.01*	0.00*
PWI	Price-weighted index	0.21	0.64	0.74
Summary for stocks:				
Percentage of stocks with clustering		10.0	6.7	23.3

Table 5: p-values of runs testss of the Null hypothesis that jumps arrive randomly.

Proportion of stocks jumping simultaneously	Number of occurrences	P(jump in DIA) (%)	P(jump in PWI) (%)
No thresholding:			
0–20%	148	14.2	9.5
20–40%	469	36.0	27.3
40–60%	121	63.6	55.4
60–80%	8	87.5	100.0
80–100%	1	100.0	100.0
Universal threshold:			
0–20%	716	9.2	4.3
20–40%	29	27.6	20.7
40–60%	1	100.0	100.0
60–80%	1	100.0	100.0
80–100%	0	-	-
FDR threshold:			
0–20%	533	15.2	9.8
20–40%	207	36.7	22.2
40–60%	6	83.3	33.3
60–80%	1	100.0	100.0
80–100%	0	-	-

Table 6: Likelihood of a jump in the index conditional on the proportion of its constituents cojumping.

Proportion of stocks	Jump in DIA:		Jump in PWI:	
jumping simultaneously	No	Yes	No	Yes
No thresholding:				
Mean (%)	25.1	33.4	25.3	35.0
Median (%)	23.3	30.0	26.7	33.3
Maximum (%)	60.0	93.3	53.3	93.3
Universal threshold:				
Mean (%)	6.1	9.0	6.2	9.4
Median (%)	6.7	6.7	6.7	6.7
Maximum (%)	23.3	66.7	26.7	66.7
FDR threshold:				
Mean (%)	12.5	17.7	12.7	18.5
Median (%)	10.0	16.7	13.3	16.7
Maximum (%)	40.0	70.0	40.0	70.0

Table 7: Proportion of stocks jumping simultaneously conditional on a jump in the index.

Industry sector	Dow Jones constituents
Energy	ExxonMobil
Materials	Alcoa, DuPont
Industrials	Boeing, Caterpillar, General Electric, Honeywell, 3M, United Technologies Corporation
Consumer Discretionary	Walt Disney, General Motors, The Home Depot, McDonald's
Consumer Staples	Coca-Cola, Altria Group, Procter & Gamble, Wal-Mart
Health Care	Johnson & Johnson, Merck, Pfizer
Financials	American International Group, American Express, Citigroup, JPMorgan Chase
Information Technology	Hewlett-Packard, IBM, Intel, Microsoft
Telecommunication Services	AT&T, Verizon Communications

Table 8: Sectors.

		Number of cojumps		
Sector	Nb stocks in sector	No thresholding	Universal threshold	FDR threshold
Materials	2	76*	5*	19*
Industrials	6	3*	0	0
Consumer Discretionary	4	9*	0	1*
Consumer Staples	4	3	0	0
Health Care	3	31*	1*	6*
Financials	4	10*	1*	2*
Information Technology	4	18*	0	1*
Telecom. Services	2	97*	6*	27*

Table 9: Number of cojumps within industry sectors. An * indicates that there are significantly more cojumps than if the stocks were independent.

Announcement	Source	Announcement time
Monthly announcements:		
Consumer credit	FRB	3:00 p.m.
Construction spending	BC	10:00 a.m.
Factory orders	BC	10:00 a.m.
Business inventories	BC	10:00 a.m.
Government budget deficit	FMS	2:00 p.m.
Consumer confidence index	CB	10:00 a.m.
ISM manufacturing composite index	ISM	10:00 a.m.
Six-week announcements:		
Target federal funds rate	FRB	2:15 p.m.

Table 10: Macroeconomic news announcements. The sources are: Federal Reserve Board (FRB), Bureau of the Census (BC), Financial Management Service (FMS), Conference Board (CB), Institute for Supply Management (ISM).

Announcement	Nb of ann.	P(jump in stocks)	P(jump in DIA)	P(jump in PWI)
No thresholding:				
Monthly announcements:				
Consumer credit	35	28.6 (7.6)	42.9 (8.4)	34.3 (8.0)
Construction spending	35	27.9 (7.6)	20.0 (6.8)	11.4 (5.4)
Factory orders	35	29.7 (7.7)	40.0 (8.3)	31.4 (7.8)
Business inventories	36	28.7 (7.5)	41.7 (8.2)	25.0 (7.2)
Government budget deficit	36	25.3 (7.2)	36.1 (8.0)	33.3 (7.9)
Consumer confidence index	36	24.6 (7.2)	33.3 (7.9)	27.8 (7.5)
ISM manufacturing composite index	35	28.4 (7.6)	34.3 (8.0)	25.7 (7.4)
Six-week announcements:				
Target federal funds rate	23	29.3 (9.5)	34.8 (9.9)	34.8 (9.9)
All days	747	28.1 (1.6)	36.9 (1.8)	29.2 (1.7)
Universal threshold:				
Monthly announcements:				
Consumer credit	35	7.2 (4.4)	5.7 (3.9)	0.0 -
Construction spending	35	6.6 (4.2)	8.6 (4.7)	0.0 -
Factory orders	35	7.8 (4.5)	11.4 (5.4)	5.7 (3.9)
Business inventories	36	7.1 (4.3)	11.1 (5.2)	5.6 (3.8)
Government budget deficit	36	5.7 (3.9)	5.6 (3.8)	0.0 -
Consumer confidence index	36	5.7 (3.9)	8.3 (4.6)	5.6 (3.8)
ISM manufacturing composite index	35	7.3 (4.4)	17.1 (6.4)	2.9 (2.8)
Six-week announcements:				
Target federal funds rate	23	11.0 (6.5)	17.4 (7.9)	13.0 (7.0)
All days	747	7.2 (0.9)	10.2 (1.1)	5.2 (0.8)
FDR threshold:				
Monthly announcements:				
Consumer credit	35	13.6 (5.8)	17.1 (6.4)	8.6 (4.7)
Construction spending	35	13.4 (5.8)	14.3 (5.9)	5.7 (3.9)
Factory orders	35	14.0 (5.9)	11.4 (5.4)	14.3 (5.9)
Business inventories	36	14.5 (5.9)	22.2 (6.9)	11.1 (5.2)
Government budget deficit	36	12.5 (5.5)	30.6 (7.7)	8.3 (4.6)
Consumer confidence index	36	11.8 (5.4)	16.7 (6.2)	16.7 (6.2)
ISM manufacturing composite index	35	14.7 (6.0)	22.9 (7.1)	14.3 (5.9)
Six-week announcements:				
Target federal funds rate	23	18.0 (8.0)	26.1 (9.2)	21.7 (8.6)
All days	747	14.4 (1.3)	21.8 (1.5)	13.5 (1.3)

Table 11: Probability of a jump on macroeconomic news announcements in stocks, the DIAMONDS trust, and the PWI index (%). Numbers in parenthesis correspond to standard deviations.

	Number of news		Conditional probability of jump in stocks					
		During	No		Universal		FDR	
News subject	All	market hours	thresholding		threshold		threshold	
Dow Jones/Reuters Top Wire News	949	196	46.6*	(3.6)	10.8	(2.2)	27.1	(3.2)
Government Contracts	44	14	34.1	(12.7)	29.5	(12.2)	29.5	(12.2)
Non-governmental Contracts	125	40	6.9	(4.0)	0.4	(1.1)	0.9	(1.5)
Dividends	82	31	20.0	(7.2)	1.7	(2.3)	8.3	(5.0)
Ownership Changes	807	173	28.4	(3.4)	4.1	(1.5)	16.1	(2.8)
- Acquisitions/Mergers/Takeovers	660	148	30.2	(3.8)	5.0	(1.8)	16.9	(3.1)
- Divestitures/Asset Sales	48	9	50.0*	(16.7)	0.0	(0.0)	28.6	(15.1)
Share Capital	53	10	33.3	(14.9)	22.2	(13.1)	33.3	(14.9)
- Share Buybacks	35	7	42.9*	(18.7)	28.6	(17.1)	42.9*	(18.7)
Corporate Crime/Legal/Judicial	167	57	48.4*	(6.6)	13.0	(4.4)	16.4	(4.9)
- Insider Dealing	3	2	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)
Corporate Credit Ratings	34	12	14.6	(10.2)	4.2	(5.8)	4.2	(5.8)
Management Moves	243	79	22.4	(4.7)	2.9	(1.9)	11.1	(3.5)
Sales Figures	58	13	30.8	(12.8)	7.7	(7.4)	23.1	(11.7)
Earnings Projections	693	109	25.3	(4.2)	6.8	(2.4)	14.2	(3.3)
Analyst Comment/Recommendation	65	11	7.1	(7.8)	7.1	(7.8)	7.1	(7.8)
All days	747	747	28.1	(1.6)	7.2	(0.9)	14.4	(1.3)

Table 12: Probability of a jump in stocks on different types of news. Numbers in parenthesis correspond to standard deviations.

						Jump, after thresholding:		
Ticker	Company name	Date	Source	Pub. time	News headline	None	Universal	FDR
AA	Alcoa	19/01/2007	Reuters	12:27:51	UPDATE 1-Alcoa to buy back shares, raises dividend.	No	No	No
			DJNS	12:12:00	Alcoa Bd OKs New Share Repurchase Program, Div Increase And Debt Restructuring To Enhance Shareholder Value.			
AXP	American Express	22/05/2006	Reuters	14:22:00	American Express boosts payout, sets buyback	No	No	No
			DJNS	14:13:00	American Express Announces 25 % Div Increase Plans To Repurchase Up To 200 M Additional Shrs			
HD	The Home Depot	26/02/2008	Reuters	09:43:12	Home Depot says big share buyback 'on pause'	No	No	No
			DJNS	09:34:00	2nd UPDATE: Home Depot 4Q Net Falls 27%, Issues Weak Outlook			
IBM	IBM	26/02/2008	Reuters	11:02:32	IBM says board approves $15 bln share buyback	Yes	No	Yes
			DJNS	11:17:00	UPDATE: IBM Plans Another $15B Buyback, Boosts EPS View			
JNJ	Johnson & Johnson	09/07/2007	Reuters	12:09:49	UPDATE 2-J&J OKs $10 bln stock buyback plan, shares rise	Yes	Yes	Yes
			DJNS	15:11:00	UPDATE: J&J To Buy Back Up To $10 Billion In Stock			
JPM	JPMorgan Chase	21/03/2006	Reuters	12:39:28	UPDATE 1-JPMorgan authorizes $8 bln share buyback	Yes	Yes	Yes
			DJNS	12:34:00	JPMorgan Chase Announces $8 B Shr Repurchase Authorization			
T	AT&T	31/01/2006	Reuters	12:46:16	AT&T to buy back $2 bln in shares in '06	No	No	No
			DJNS	12:30:00	AT&T Updates Outlook On Merger Synergies, Details Plans For Growth In Wireless, Broadband And Business Services			

Table 13: DJNS and Reuters news headlines about the 7 share buybacks in our sample announced during market hours.

	Inter-jumps duration:			
	Exponential (H_0)		ACD	
No thresholding	4.6	(2.0)	65.4	(4.7)
Universal threshold	4.0	(2.1)	85.4	(4.2)
FDR threshold	4.2	(2.0)	83.6	(4.0)
True jumps	4.2	(2.1)	86.9	(3.8)

Table 14: Power and size results of runs test. Numbers in parenthesis correspond to standard deviations.

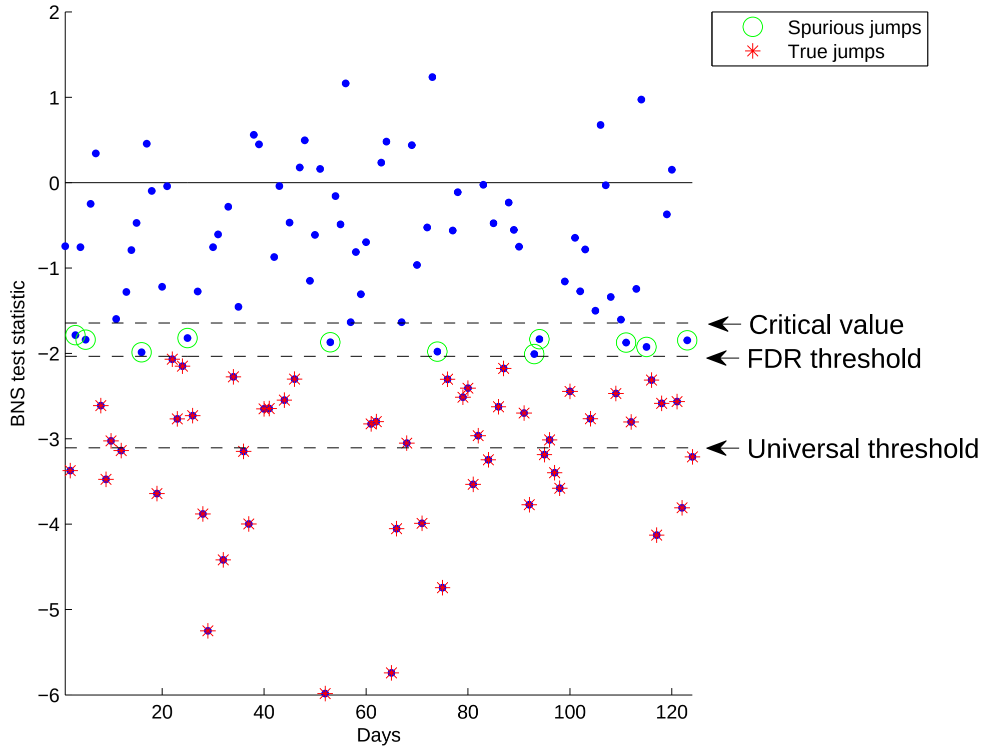
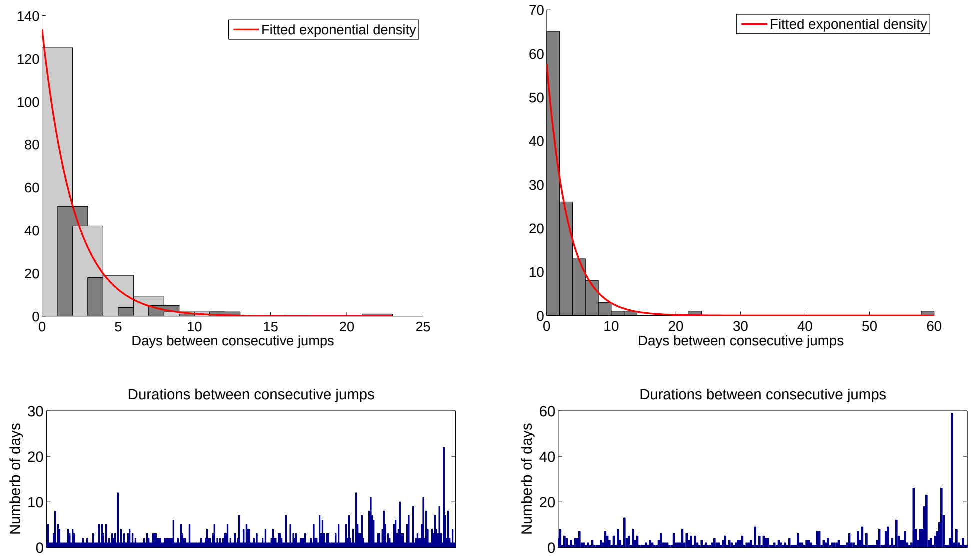


Figure 1: Daily test statistics obtained from the BNS test (points), and with our thresholding methodology (asterisks), for the period between January and June 2007, MSFT, two-minute sampling frequency.



(a) No thresholding

(b) FDR thresholding

Figure 2: MSFT: histogram (top) and plot (bottom) of durations between consecutive jumps. In Panel (b), only bars for odd durations are displayed to avoid clutter.

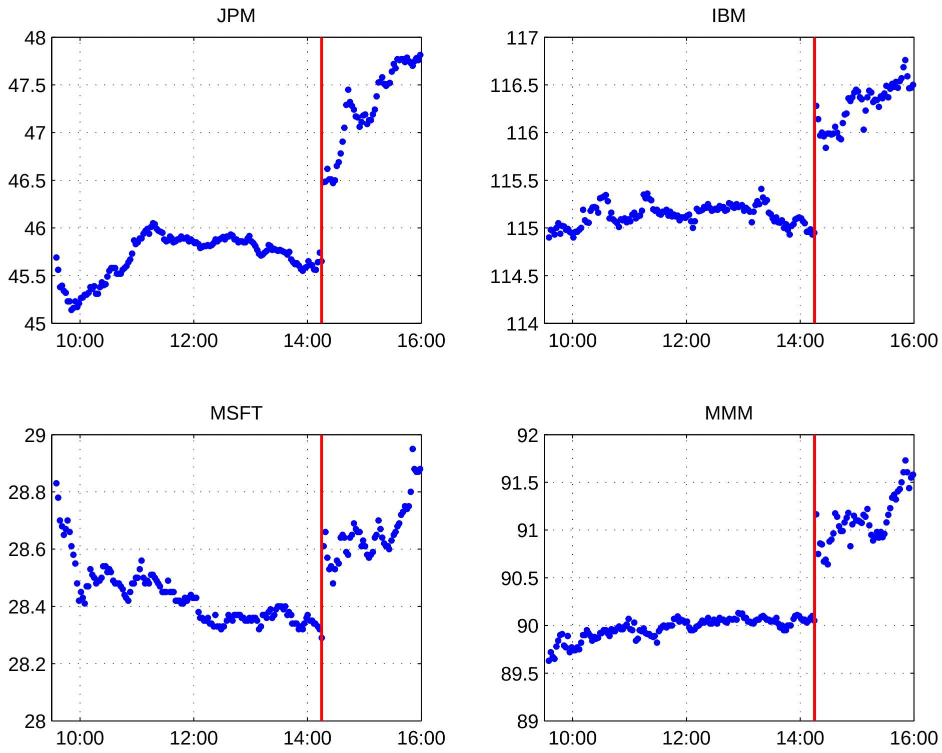


Figure 3: On September 18, 2007, the FOMC lowers its target for the federal funds rate 50 basis points to 4-3/4 percent. As a consequence, 54% of Dow Jones stocks are detected to jump simultaneously (after applying the FDR threshold).

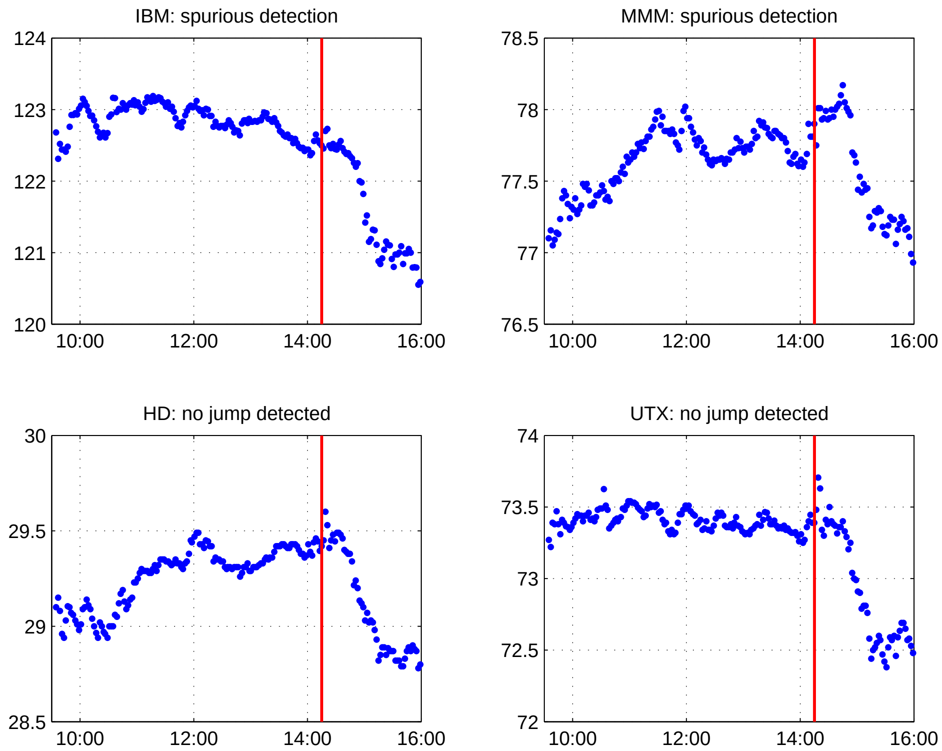


Figure 4: On April 30, 2008, the Federal Open Market Committee lowers its target for the federal funds rate 25 basis points to 2 percent. Very few stocks are detected to jump, although the reaction of the stock price is strong.

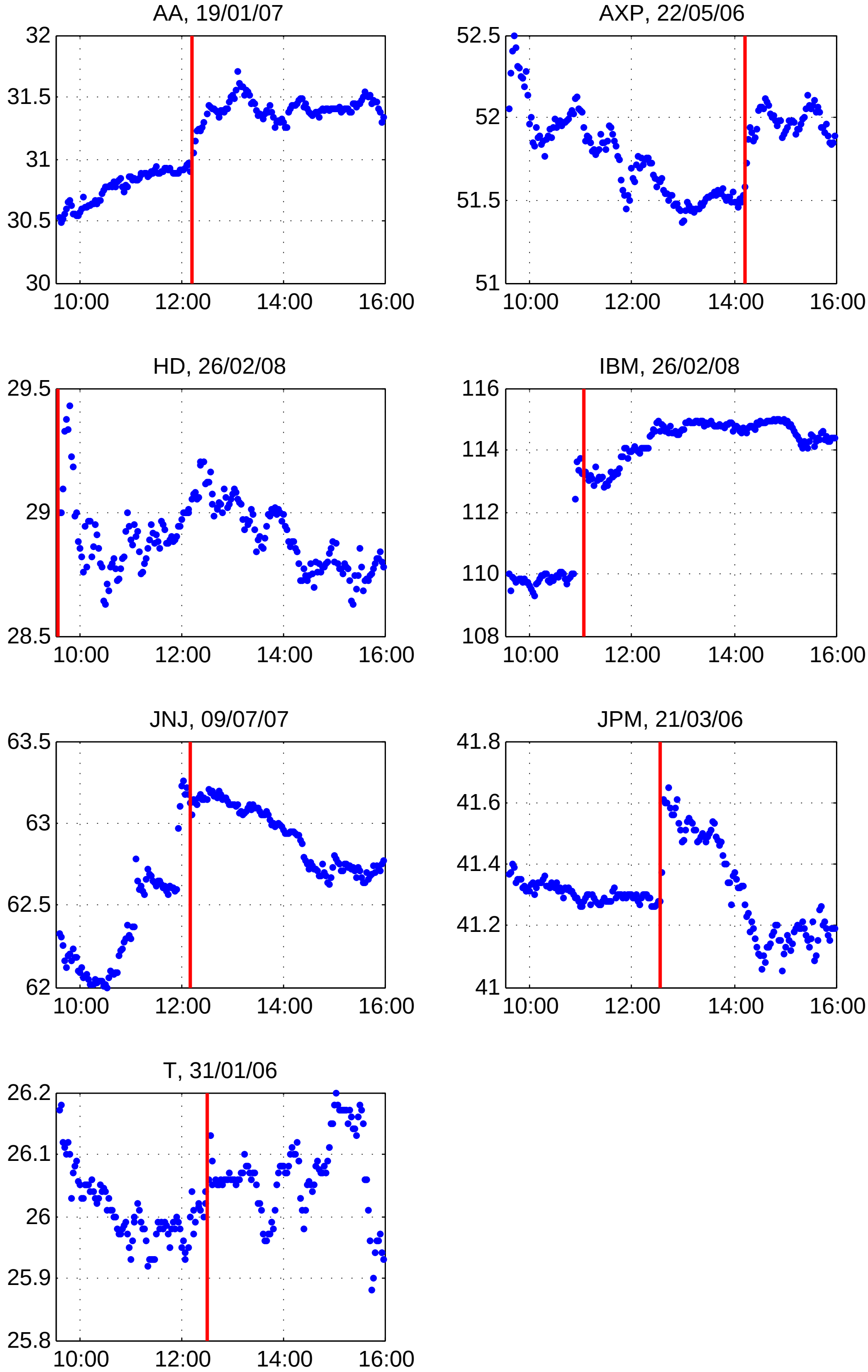


Figure 5: This figure displays how stock prices react following the 7 announcements about share buybacks in our sample.