Cojumps in Stock Prices: Empirical Evidence

Dudley Gilder[1], Mark B. Shackleton[2], and Stephen J. Taylor[2]

[1]Corresponding author. Finance and Accounting Group, Aston Business School, Aston University, Birmingham, B4 7ET, UK. e-mail: d.gilder@aston.ac.uk.
[2]Department of Accounting and Finance, Lancaster University Management School, Lancaster University, Lancaster, LA1 4YX, UK

Feb, 2012

Abstract

We examine contemporaneous jumps (cojumps) among individual stocks and a proxy for the market portfolio. We examine two hypotheses. The first posits that there should be a tendency for stocks to be involved in (systematic) cojumps with the market portfolio (Hypothesis 1). The second posits that systematic cojumps should be associated with macroeconomic news announcements (Hypothesis 2). Evidence from a variety of daily and intraday cojump detection methods shows that although a small number of stocks are often detected to be involved in systematic cojumps, there is a *tendency* for stocks to be involved in cojumps with the market portfolio, supporting Hypothesis 1. We find only partial support for Hypothesis 2. There is evidence of an association between systematic cojumps and the news announcements concerning the Federal Funds Target Rate.

JEL Classification Codes: G10

Keywords: High-Frequency Data, Non-parametric Jump Tests, Realised Volatility, Macroeconomic News

1 Introduction

An important question in understanding which stochastic processes should be used to model the dynamics of asset prices is whether price changes are consistent with the presence of discontinuities, or jumps. In a continuous time framework, this is often considered equivalent to asking whether in addition to a Brownian motion component, the building block of diffusion processes, prices are also driven by a compound Poisson process, generating sporadic large price changes. There is now a large body of evidence suggesting jumps should be included. For example, Andersen et al. (2002), Eraker et al. (2003), Chernov et al. (2003) and Eraker (2004) find jump-diffusions provide a superior fit relative to pure diffusion models when modelling equity indices. In discrete time, Chan and Maheu (2002), Maheu and McCurdy (2004), Duan et al. (2006), Daal et al. (2007) and Christoffersen et al. (2008) also provide support for the presence of jumps based on GARCH models augmented with jump processes.

More recently, non-parametric tests have been developed to detect (large) jumps using high-frequency data. The seminal work in this area was Barndorff-Nielsen and Shephard (2004a) and Barndorff-Nielsen and Shephard (2006) (BNS), who developed a technique to identify jumps which relied on separating realised measures of volatility into a component driven by continuous price changes and a component driven by jumps. Subsequently, many additional tests based on non-parametric volatility estimators have been developed (Jiang and Oomen (2008),Andersen et al. (2009b), Corsi et al. (2010), Podolskij and Ziggel (2010), Christensen et al. (2011)). All of these non-parametric tests identify whether jumps were present over a given interval of time, which is usually selected to be one day. Tests which explicitly identify intraday jumps have been deveoped by Andersen et al. (2007) (ABD) and Lee and Mykland (2008) (LM). Similar to the parametric evidence, application of these non-parametric tests to various markets has supported the presence of price jumps[1].

However, there has been little research into cojumps; that is, the tendency for (large) jumps to arrive simultaneously in the prices of more than one stock. Exceptions include Dungey et al. (2009) and Dungey and Hvozdyk (2011) who investigate cojumps in Treasury bond prices and link them to macroeconomic news announcements. Lahaye et al. (2010) also investigate cojumps between an equity index, bond index and exchange rates and link

[1]For example, jumps in equity indices and individual stocks have been documented in Huang and Tauchen (2005), Andersen et al. (2007), Lee and Mykland (2008), Lee and Hannig (2010), Lahaye et al. (2010) and Evans (2011). Evidence for the presence of jumps in foreign exchange and Treasury bond markets is given by Dungey et al. (2009), Dungey and Hvozdyk (2011) and Jiang et al. (2011).

them to macroeconomic news announcements. The contribution of this paper is to add to the empirical evidence on the tendency for stock prices to cojump. We are motivated both theoretically and empirically. Specifically, existing empirical evidence from non-parametric jump tests indicates that jumps occur relatively frequently. For example, Lee (2009) finds 21 jumps per year on average for 23 stocks and Lee and Hannig (2010) find on average 82 (large) jumps per year in 30 stocks comprising the Dow Jones Industrial Average. It is therefore interesting to ask how many of the jumps detected in the individual stock prices are involved in cojumps?

Asset pricing theory also tells us that for a risk premium to be associated with jump risk, the jumps must not all be idiosyncratic. There needs to be occasions on which jumps occur simultaneously and cannot be diversified away. Bollerslev et al. (2011) use high-frequency data to present evidence that a large fraction of the equity risk premium is attributable to the fear of large price movements and Bollerslev and Todorov (2011) provide empirical evidence for dependence in the extreme tails of the distributions governing stock price jumps. Implicitly, these studies suggest cojumps in the individual stock prices should occur.

We investigate two hypotheses. The first hypothesis posits that a large number of stocks should be involved in cojumps with the market portfolio (Hypothesis 1). We refer to these cojumps as systematic cojumps. Previous work by Bollerslev et al. (2008) suggests there is little association between large jumps in an equally-weighted portfolio of 40 stocks, their proxy for the market portfolio, and the stocks from which the portfolio is constructed. Instead, they present evidence that cojumps between individual stocks usually involve small jumps which are not detectable by the previously mentioned non-parametric tests. However, the lack of association is based on the correlation between the values of BNS test statistics. Similarly, Bajgrowicz and Scaillet (2011) do not find simultaneous jumps in all 30 DJIA stocks when employing the BNS test and suggest this is indicative of jump risk being diversifiable.

In contrast, we present comprehensive evidence on cojumps for a large panel of 60 stocks and the SPDR ETF (SPY), which replicates the S&P 500 and acts as a proxy for the market portfolio, using both daily and intraday jump tests. Although a relatively large number of non-parametric jump tests now exist, there are few dedicated to detecting cojumps[2]. We therefore predominantly employ univariate jump tests in conjunction with

[2]Barndorff-Nielsen and Shephard (2004b) started to develop a multivariate extension of their popular jump test, but this work remains incomplete. Gobbi and Mancini (2007) have developed a method for

a coexceedance criterion to detect cojumps, whereby a cojump is detected if jumps are detected in the prices of more than one stock for the same time interval.

To detect cojumps at the daily frequency we use the BNS test. Given its popularity in empirical applications, this test acts as a benchmark[3]. One problem with the BNS test is that it is not robust to disjoint cojumps; the arrival of jumps in the prices of more than one asset on the same day but at different intraday times. We therefore also employ the cojump test of Jacod and Todorov (2009) (JT test) to examine the extent of disjoint cojump detection. The JT test determines whether cojumps between any two stocks detected using the coexceedance criterion with the BNS test (or other "daily" jump test) are disjoint or true cojumps. To detect intraday cojumps, we use the intraday jump tests of Andersen et al. (2007) and Lee and Mykland (2008) and the sequential BNS test of Andersen et al. (2010). The intraday jump tests have the advantage of being robust to disjoint cojumps. Lastly, we employ the intraday cojump test of Bollerslev et al. (2008). The advantage of the BLT test is that it is able to aggregate information in large panels of stocks to detect cojumps in which jumps in the individual stocks involved are potentially small.

In employing the intraday jump tests we are careful to correct for the intraday volatility pattern and size distortions which have been highlighted by Dumitru and Urga (2011)[4]. Similar to Lahaye et al. (2010) we use methods from Boudt et al. (2008) to correct for the intraday volatility pattern. To correct the size of the intraday tests, we use bootstrapped critical values and combine non-parametric tests, as recommended by Dumitru and Urga (2011).

The second hypothesis we examine posits that cojumps will be associated with the release of macroeconomic news, which has a market-wide influence on stock prices (Hypothesis 2). An association between macroeconomic news and the arrival of jumps has been demonstrated in the bond market (Dungey et al. (2009);Dungey and Hvozdyk (2011)), foreign exchange market (Lahaye et al. (2010)) and equity futures market (Lahaye et al. (2010);Evans (2011)). Bajgrowicz and Scaillet (2011) have also demonstrated an association between jumps in individual stock prices and macroeconomic news, but rely on

identifying the continuous component of quadratic covariation, but it does not offer a means of testing for cojumps. The test of Jacod and Todorov (2009) is an exception, which allows cojumps in bivariate price series to be detected.

[3]The question of which daily non-parametric jump tests to employ to maximise the probability of detecting cojumps is not addressed here and is left to future research.

[4]Dumitru and Urga (2011) have shown that intraday non-parametric jump tests are over-sized in finite samples.

the daily BNS jump test and do not distinguish whether such an association exists with systematic cojumps.

Our main results can be summarised as follows. We show in a Monte Carlo study that the methods used for correcting for the intraday volatility pattern and size distortions in the non-parametric jump tests are effective. Bivariate simulations show that the intraday jump tests are more powerful than the daily BNS test and that the JT test has very low power, at least for the sampling frequency we use. Empirically, many of the cojumps detected using the BNS test appear to be disjoint cojumps, highlighting the importance of employing detection methods that are robust to disjoint cojumps. On many occasions, only a small fraction of stocks are detected to be involved in systematic cojumps (the median ranges between 3 and 8 stocks). Although this appears to support the claims of Bollerslev et al. (2008) and Bajgrowicz and Scaillet (2011), when we compare the results to what would be expected if jump arrivals were independent, the probability of observing cojumps involving the numbers of stocks we detect to be involved is effectively zero for the majority of systematic cojumps. This contrasts with non-systematic cojumps (which do not involve the market portfolio), where the number of stocks involved in the majority of cases could be explained by independent jump arrivals. Therefore, we claim that there is a *tendency* for a *relatively* large number of stocks to be involved in systematic cojumps, supporting Hypothesis 1.

We find only partial support for Hypothesis 2. There is evidence of an association between systematic cojumps and the release of the Federal Fund Target Rate, but not for other macroeconomic announcements released during trading hours.

The remainder of the paper is organised as follows. Section 2 describes our (co)jump detection methodology. Sections 3 and 3.2 present results from Monte Carlo simulations and describes our size-correction procedures. Section 4 describes our data. Results from applying the jump tests to the individual stock and SPY series are given in Section 5, whilst Section 6 provides our results on cojumps. The association between macroeconomic news and (co)jumps is analysed in Section 7. Section 8 concludes.

2 Jump and Cojump Identification

2.1 Nonparametric Volatility Metrics

Essential to nonparametric jump tests are two high-frequency volatility metrics: Realised variance (RV) and realised bipower variation (BV) [5]. The theoretical relevance of these volatility metrics is based on the assumption that prices follow a semi-martingale, which ensures no-arbitrage. Log prices, $p(t)$, are assumed to be generated by,

$$\mathrm{d}p(t) = \mu(t)\mathrm{d}t + \sigma(t)\mathrm{d}W(t) + \kappa(t)\mathrm{d}N(t), \tag{1}$$

where $\mu(t)$ is a process of finite variation, $\sigma(t)$ is a càdlàg volatility process, $W(t)$ is a Brownian motion, $N(t)$ is a finite activity counting process with intensity $\lambda(t)$, which may also be stochastic, and $\kappa(t)$ represents the random jump sizes.

Given a set of $M+1$ intraday log prices for day t, equally spaced in time, $\{p_{t,0}, \ldots, p_{t,M}\}$, M intraday returns can be formed by $r_{t,i} = p_{t,i} - p_{t,i-1}$, $i = 1, \ldots, M$. For day t, RV can then be computed from,

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2.$$

The probability limit of RV equals the quadratic variation (QV) of the process generating prices on day t (Andersen and Bollerslev, 1998a; Andersen et al., 2001, 2003). In the absence of jumps, QV is equivalent to integrated variance (IV),

$$\operatorname*{plim}_{M\to\infty} RV_t \quad = \quad QV_t = IV_t = \int_{t-1}^{t} \sigma^2(u)\mathrm{d}u, \tag{2}$$

with day t interpreted as commencing at time $t-1$ and concluding at time t. If jumps are present then,

$$\operatorname*{plim}_{M\to\infty} RV_t \quad = \quad QV_t = \int_{t-1}^{t} \sigma^2(u)\mathrm{d}u + \sum_{(t-1)\leq s\leq t} (\Delta p(s))^2,$$

where $\Delta p(s)$ represents the instantaneous change in the log price resulting from a jump at time s. Therefore, when there are jumps in prices, RV_t incorporates both the integrated variance for day t and the sum of the squared jumps realised during day t.

[5] For a review of RV see McAleer and Medeiros (2008) and Andersen et al. (2009a).

In contrast, BV is robust to jumps and is computed from (Barndorff-Nielsen and Shephard, 2004a, 2006),

$$BV_t = \mu_1^{-2}\left(\frac{M}{M-1}\right)\sum_{j=2}^{M}|r_{t,j}||r_{t,j-1}|,$$

where, $\mu_p = \mathbb{E}[|u|^p]$ and $u \sim \mathcal{N}(0,1)$. Hence, $\mu_1^{-2} = (\mathbb{E}[|u|])^{-2} = \pi/2$. The probability limit is

$$\operatorname*{plim}_{M\to\infty} BV_t = IV_t,$$

irrespective of whether jumps are present or not. Andersen et al. (2009b) have suggested MinRV and MedRV as alternatives to BV which they claim are more robust to jumps in finite samples,

$$\begin{aligned} MinRV_t &= \frac{\pi}{\pi-2}\frac{M}{M-1}\sum_{i=2}^{M}\min\left(|r_{t,i}|,|r_{t,i-1}|\right)^2 \\ MedRV_t &= \frac{\pi}{6-4\sqrt{3}+\pi}\frac{M}{M-2}\sum_{i=2}^{M-1}\operatorname{med}\left(|r_{t,i+1}|,|r_{t,i}|,|r_{t,i-1}|\right)^2. \end{aligned}$$

2.2 Jump Tests

We employ the daily non-parametric jump test of Barndorff-Nielsen and Shephard (2004a) and Barndorff-Nielsen and Shephard (2006) and the non-parametric intraday jump tests of Andersen et al. (2007), Lee and Mykland (2008) and Andersen et al. (2010).

We apply the ratio form of BNS test as recommended by Huang and Tauchen (2005). Jump(s) are detected for day t if,

$$Z_{BNS} = \frac{\frac{RV_t - BV_t}{RV_t}}{\sqrt{\left(\left(\frac{\pi}{2}\right)^2+\pi-5\right)\frac{1}{M}\max\left(1,\frac{QV_t}{BV_t^2}\right)}} > \Phi_{1-\alpha}^{-1},$$

where,

$$QV_t = M\left(\frac{\pi}{2}\right)^2\left(\frac{M}{M-3}\right)\sum_{i=4}^{M}|r_{t,i}||r_{t,i-1}||r_{t,i-2}||r_{t,i-3}|.$$

where $\Phi_{1-\alpha}^{-1}$ represents the inverse of the standard normal cumulative distribution function

evaluated at a cumulative probability of $1-\alpha$. If the MinRV or MedRV estimators are employed we use,

$$
\begin{aligned}
Z_{BNS,MinRV} &= \frac{\frac{RV_t - MinRV_t}{RV_t}}{\sqrt{\left(1.81\frac{1}{M}\max\left(1, \frac{MinRQ_t}{MinRV_t^2}\right)\right)}} > \Phi^{-1}_{1-\alpha}, \\
Z_{BNS,MedRV} &= \frac{\frac{RV_t - MedRV_t}{RV_t}}{\sqrt{\left(0.96\frac{1}{M}\max\left(1, \frac{MedRQ_t}{MedRV_t^2}\right)\right)}} > \Phi^{-1}_{1-\alpha},
\end{aligned}
$$

where,

$$
\begin{aligned}
MinRQ_t &= \frac{\pi M}{3\pi - 8}\frac{M}{M-1}\sum_{i=2}^{M}\min\left(|r_{t,i}|, |r_{t,i-1}|\right)^4 \\
MedRQ_t &= \frac{3\pi M}{4\pi + 72 - 52\sqrt{3}}\frac{M}{M-2}\sum_{i=2}^{M-1}\mathrm{med}\left(|r_{t,i+1}|, |r_{t,i}|, |r_{t,i-1}|\right)^4.
\end{aligned}
$$

The sequential BNS test (s-BNS test) of Andersen et al. (2010) detects intraday jumps by firstly detecting jump days using the BNS test and then selecting the maximum intraday return to be the intraday jump. To detect all intraday jumps, the procedure is repeated until the BNS test is insignificant. At each iteration, RV is re-calculated with the previously identified intraday jump/return set to zero. We modify the procedure by selecting the maximum standardised return, $\max|r_{t,i}|/\sqrt{\hat{s}^2_{\mathcal{M},i}\cdot\Delta\cdot BV_t}$, for $i = 1, \ldots, M$. Note, $\Delta = 1/M$ and $\hat{s}^2_{\mathcal{M},i}$ corrects for the, U-shaped, intraday volatility pattern observed in equity markets (Wood et al. (1985) and Harris (1986)). The methods, $\mathcal{M}$, used to estimate the intraday volatility pattern are described in Appendix C.

A jump is detected with the ABD test on day t in intraday interval i when,

$$
|r_{t,i}| > \Phi^{-1}_{1-\beta/2}\cdot\sqrt{\hat{s}^2_{\mathcal{M},i}\cdot\Delta\cdot BV_t}, \tag{3}
$$

where $(1-\beta)^M = 1-\alpha$ and α represents the daily significance level.

To apply the LM test, first define $\mathcal{L}_i = r_{t,i}/(\hat{s}_{\mathcal{M},i}\hat{\sigma}_{LM,t,i})$, where,

$$
\hat{\sigma}^2_{LM,t,i} = \frac{1}{K-2}\sum_{j=i-1}^{i-K+1}|r_{t,j}||r_{t,j-1}|.
$$

Lee and Mykland (2008) suggest $K = \sqrt{M \times 252}$. A jump is detected if,

$$|\mathcal{L}_i| \quad > \quad \frac{\xi}{c\sqrt{2\ln M}} + \frac{\sqrt{(2\ln M)}}{c} - \frac{(\ln\pi + \ln(\ln M))}{2c\sqrt{2\ln M}},$$

where $c = \sqrt{\pi/2}$ and $\xi = -\ln(-\ln(1-\alpha))$.

When a jump is detected by the ABD, LM or s-BNS tests, we assume its size dominates that of any diffusion component. Thus, the size of a jump detected on day t for intraday interval i, $\kappa_{t,i}$, is set equal to the value of the return for that interval.

2.3 Cojump Test

We take three approaches to cojump detection. Firstly, we use the following coexceedance rule,

$$\sum_{j=1}^{N} \mathbb{I}\{\text{Jump}_{t,i,j} > 0\} \begin{cases} \geq 2 & \text{Cojump} \\ \leq 1 & \text{No Cojump,} \end{cases}$$

where $\mathbb{I}\{\text{Jump}_{t,i,j} > 0\}$ is an indicator function taking the value 1 when a jump is detected in asset j during intraday interval i on day t. We use the coexceedance rule in conjunction with the ABD, LM and s-BNS and BNS tests to detect both intraday jumps and jump days.

Secondly, we use the cojump test of Jacod and Todorov (2009) (JT test). This test is employed after a cojump has been detected in the prices of two stocks by the coexceedance rule employed with the BNS test. The JT test is used to distinguish disjoint cojumps from true cojumps. Disjoint cojumps occur when jumps arrive in the prices of two assets on the same day, but do not occur at the same intraday time. In contrast, a true cojump occurs when the jumps arrive at the same intraday time. The JT test is a bivariate test and in what follows $X_{t,i} = (p^1_{t,i}, p^2_{t,i})'$ refers to the bivariate vector of prices of stocks 1 and 2 on day t at intraday time i. In order to conduct the test, two statistics are estimated,

$$\phi^{(j)}_{JT,t} \quad = \quad \frac{V(f, k\Delta)_t}{V(f,\Delta)_t} \qquad \text{and} \qquad \phi^{(d)}_{JT} = \frac{V(f,\Delta)_t}{\sqrt{V(g_1,\Delta)_t V(g_2,\Delta)_t}},$$

where,

$$
\begin{aligned}
V(f,\Delta)_t &= \sum_{i=1}^{M} f(\Delta_i X_{t,i}), \\
V(f,k\Delta)_t &= \sum_{i=1}^{M} f(\Delta_{ki} X_{t,i}), \\
f(X) &= (x_1 x_2)^2, \\
g_1(X) &= (x_1)^4, \\
g_2(X) &= (x_2)^4, \\
\Delta_{ki} X_{t,i} &= X_{t,ki} - X_{t,k(i-1)}.
\end{aligned}
$$

The null hypothesis underlying $\phi_{JT,t}^{(j)}$ is that the cojump on day t is a true cojump, which is rejected when $|\phi_{JT,t}^{(j)} - 1| > c_t^{(j)}$. The null hypothesis underlying $\phi_{JT,t}^{(d)}$ is that the cojump on day t is a disjoint cojump, which is rejected when $\phi_{JT,t}^{(d)} > c_t^{(d)}$. Therefore, to detect a cojump, $\phi_{JT,t}^{(j)}$ should not be significant whilst $\phi_{JT,t}^{(d)}$ should be significant. To detect a disjoint cojump, $\phi_{JT,t}^{(j)}$ should be significant whilst $\phi_{JT,t}^{(d)}$ should not be significant. Other combinations are unclassified. We refer to Jacod and Todorov (2009) for further discussion on the construction of the tests and critical values $c_t^{(j)}$ and $c_t^{(d)}$. Note, we use Theorem 5.1(a) in Jacod and Todorov (2009) to construct $c_t^{(j)}$ and Theorem 5.3(b) to construct $c_t^{(d)}$. In applying the JT test, we follow the empirical application in Section 7 of Jacod and Todorov (2009).

Lastly, we use the intraday cojump test of Bollerslev et al. (2008). This is used to detect intraday cojumps in a large panel of stocks. The test statistic is,

$$
Z_{mcp,t,i} = \frac{mcp_{t,i} - \overline{mcp_t}}{\hat{\sigma}_t},
$$

where,

$$
\begin{aligned}
mcp_{t,i} &= \frac{2}{n(n-1)} \sum_{u=1}^{n-1} \sum_{v=u+1}^{n} \frac{r_{u,t,i}}{\hat{s}_{u,\mathcal{M},i}} \frac{r_{v,t,i}}{\hat{s}_{v,\mathcal{M},i}}, \\
\overline{mcp_t} &= \frac{1}{M} \sum_{i=1}^{M} mcp_{t,i}, \\
\hat{\sigma}_t &= \sqrt{\frac{1}{M-1} \sum_{i=1}^{M} (mcp_{t,i} - \overline{mcp_t})^2}.
\end{aligned}
$$

Note, we differ from Bollerslev et al. (2008) in using intraday returns standardised by an intraday volatility corrector. We find this helps mitigate the effect of a U-shaped intraday correlation pattern. To find critical values, we follow the bootstrap procedure of Bollerslev et al. (2008).

To clarify terminology, cojumps involving the market proxy are said to be systematic cojumps, whilst cojumps amongst the individual stocks that exclude the market proxy are said to be non-systematic cojumps. Similarly, if a jump in an individual stock is involved in a systematic cojump, then the jump is classified as a systematic jump. If a jump in an individual stock is involved in a non-systematic cojump, then the jump is classified as a non-singular idiosyncratic jump. If a jump in an individual stock occurs independently of any cojump, then the jump is classified as a singular idiosyncratic jump. In general, jumps not involved in systematic cojumps are referred to as idiosyncratic jumps. We refer to the various methods for cojump detection collectively as detection methods and we may refer to (co)jumps detected using daily detection methods as (co)jump days.

3 Monte Carlo Study

We conduct a Monte Carlo study to examine whether the methods we employ to correct for the intraday volatility pattern and size distortions in the jump tests are effective. We follow Dumitru and Urga (2011) in using a Monte Carlo simulation set-up similar to Huang and Tauchen (2005). The simulation results presented below are not intended to be comprehensive, but to reflect our empirical application of the (co)jump tests. However, to the best of our knowledge, the performance of the ABD, LM and s-BNS tests have not been compared in a Monte Carlo study before. We also present evidence from bivariate simulations and a simple multivariate simulation (of 60 assets) to assess the performance of the different tests in detecting cojumps.

3.1 Univariate Simulations

Following Dumitru and Urga (2011) and Huang and Tauchen (2005), we generate log prices from two models estimated in Chernov et al. (2003), modified to incorporate the

U-shaped intraday volatility pattern. The first is a one factor model with jumps,

$$\begin{aligned} dp(t) &= \sigma_u(t)\exp(\beta_0 + \beta_1 V(t))dW_1(t) + \kappa(t)dN(t), \\ dV(t) &= \alpha_v dt + dW_2(t), \end{aligned} \tag{4}$$

where $W_1(t)$ and $W_2(t)$ are correlated Brownian motions, $Corr(dW_1(t), dW_2(t)) = \rho$, $N(t)$ is a Poisson counting process with constant intensity, λ, and $\kappa(t) \sim \mathcal{NID}(0, \sigma_J^2)$. The multiplicative term $\sigma_u(t)$ introduces a U-shape intraday volatility pattern. We follow Andersen et al. (2009b) and model $\sigma_u(t)$ according to Hasbrouck (1999) where,

$$\sigma_u(t) = C + A\exp(-at) + B\exp(-b(1-t)), \qquad t \in [0,1],$$

where $A = 0.75$, $B = 0.25$, $C = 0.88929198$, $a = 10$ and $b = 10^6$. The second model is a two factor model, which Chernov et al. (2003) show to be able to mimic the dynamics of (4) despite an absence of jumps. The model is given by,

$$\begin{aligned} dp(t) &= \sigma_u(t)\mathrm{s}-\exp(\beta_0 + \beta_1 V_1(t) + \beta_1 V_2(t))dW_1(t), \\ dV_1(t) &= \alpha_{v1} V_1 dt + dW_{21}(t), \\ dV_2(t) &= \alpha_{v2} V_2 dt + (1 + \beta_{v2} V_2(t))dW_{22}(t), \end{aligned} \tag{5}$$

where $W_{21}(t)$ and $W_{22}(t)$ are independent Brownian motions, but correlated with $W_1(t)$, with $Corr(dW_1(t), dW_{21}(t)) = \rho_1$ and $Corr(dW_1(t), dW_{22}(t)) = \rho_2$. The function $\mathrm{s}-\exp(u)$ is defined by,

$$\mathrm{s}-\exp(u) = \begin{cases} \exp(u) & \text{if} \quad u \le u_0 = \ln(1.5) \\ \frac{e^{u_0}}{\sqrt{u_0}}\sqrt{u_0 - u_0^2 + u^2} & \text{Otherwise.} \end{cases} \tag{6}$$

This ensures a unique solution exists for the volatility specification in (5) (see Chernov et al. (2003)).

Parameter values are given in Table 1 1 and are identical to those used by Huang and Tauchen (2005)[7]. Note, when λ equals 0, 0.1 (large jumps), 0.2 (medium jumps) or 0.5 (small jumps) we refer to (4) as the SV, SVJL, SVJM and SVJS models. We refer to the

[6] As stated in Andersen et al. (2009b), these parameters mean that volatility at $t = 0$ is 3 times the volatility at $t = 0.5$ and volatility at $t = 1$ is 1.5 times the volatility at $t = 0.5$.

[7] In the case of the SVJ models, we restrict our attention to the medium value of volatility mean reversion (α_v) given in Huang and Tauchen (2005).

SVJL, SVJM and SVJS models collectively as the SVJ models. The two factor model is referred to as the SV2F model. The corresponding values of σ_J^2 for each of the SVJ models mean that the proportion of QV due to jump variation is expected to be constant.

In order to simulate prices from (4) and (5), we use an Euler discretisation. We simulate prices every second for 55,000 days, where we assume there is 385 mins in a day to match our empirical data. The first 5,000 days are a burn-in period and are dropped from the final analyses. Since we are interested in the performance of the jump tests in a setting that reflects our empirical data, we sample (log) prices every 11-mins. In addition, we introduce microstructure noise by adding an iid random variable to the (log) price so that we sample,

$$y_{t,i} = p_{t,i} + e_{t,i},$$

where $y_{t,i}$ is the log price sampled on day t at intraday time i, $e_{t,i} \sim \mathcal{NID}(0, \omega_{t,i}^2)$ and $\omega_{t,i}^2 = 0.001\, IV_t$[8]. Finally, we impose sparse sampling by randomly removing simulated prices such that the average time between observed prices is 5 seconds; this is the approximate median time observed between trades in the empirical data[9].

3.1.1 Univariate Simulation Results

In this section we compare the effective size and power of the jump tests when applied to prices generated by the five models described in Section 3.1. All jump tests were applied using a significance level of 1%.

Dumitru and Urga (2011) show that the ABD/LM test is over-sized in finite samples, whereas the size of the BNS is largely unaffected. Therefore, when applying the ABD and LM tests we apply the solutions proposed by Dumitru and Urga (2011). The first combines tests. Specifically, we investigate combining ABD with s-BNS (ABD∩s-BNS) and LM with s-BNS (LM∩s-BNS) and ABD with LM (ABD∩LM). The idea is to find the intersection between the jumps detected by the two tests and retain only the intersection of detected jumps. However, the "sizes" of the combined tests are far below the nominal significance levels applied to the ABD and LM and BNS tests.

[8] A noise-to-signal ratio of 0.001 is consistent with the estimates in Hansen and Lunde (2006). It also results in a first-order autocorrelation in the simulated 17.5-min returns comparable to that observed in the empirical data.

[9] Andersen et al. (2009b) introduce these features into some of their simulations to more closely reflect empirical reality.

The second solution is to adjust (reduce) the significance levels of the tests. For the ABD test, we find an appropriate size-correction can be based on simulating 50,000 days of M normally distributed intraday returns with constant volatility. The adjusted significance level is selected such that the number of spurious jumps detected is consistent with what would be expected under the nominal significance level[10]. In order to achieve an effective size of 1%, we find a significance level of 0.5% is required. Under constant volatility, the LM test was under-sized and we were unable to use this size correction method. We base our size correction on returns simulated according to the SV model. In this case, we find a significance level of 0.5% is required in order to achieve an effective size of 1%.

The results of applying the ABD∩s-BNS, LM∩s-BNS, ABD∩LM and the size-corrected ABD and LM tests are given in Table 2. In applying the tests we use BV as our preferred estimator of IV and the weighted standard deviation (WSD) intraday volatility corrector. Results for alternative intraday volatility estimators and IV correctors are given in Appendix C. There is little variation in the results when the alternative intraday volatility estimators are employed. We use the WSD corrector because it is one of the intraday volatility correctors recommended by Boudt et al. (2008). It is also shown that there is little benefit in using the MinRV and MedRV estimators over BV.

Table 2 shows that, as expected, application of the ABD∩s-BNS, LM∩s-BNS and ABD∩LM tests is associated with very low effective sizes for the SVJL, SVJM and SVJS models, which results from a substantially reduced number of spurious jumps being detected. The effective powers of the ABD∩s-BNS and LM∩s-BNS tests are capped by the s-BNS test, which has the lowest power of the three intraday tests (Appendix C), but the effective power of the ABD∩LM test is comparable to the size-corrected ABD and LM tests. However, one benefit from combining the the tests is that, when applied to the SV2F model, the effective sizes of the ABD∩s-BNS, LM∩s-BNS and ABD∩LM tests do not become overly inflated. The size correction for the ABD test appears to work well, with the effective size of the test approximately 1% for the SVJ models and only becoming inflated (11%) for the SV2J model. For the LM test, since it is based on the results for the SV model, it is not surprising the size correction works very well when applied to the SV model. When applied to the SVJL, SVJM and SVJS models, the test is slightly under-sized, but not dramatically. However, the LM test does become severely over-sized

[10]Dumitru and Urga (2011) propose a slightly different solution. They recommend simulating 10,000 days of M intraday returns at each intraday interval, where volatility is set equal to the volatility estimate for that interval. Using this method, critical values are updated for each intraday interval.

when applied to the SV2F model (57%).

3.2 Bivariate Monte Carlo Simulation

To examine the performance of our coexceedance cojump test procedure outlined in Section 2.3, we apply it to simulated bivariate price series using the daily and intraday jump tests. We also apply the cojump test of Jacod and Todorov (2009) (JT).

3.2.1 Bivariate Simulation Set-Up

We simulate a bivariate price series such that the individual price series have dynamics that follow (4) and (5). In the Euler discretisation, the correlation between the Brownian motion components of log prices for each time increment is selected randomly from the set $\{0.25, 0.32, 0.4, 0.5\}$. These values represent the 25th, 50th, 75th and 90th percentiles of the sample correlations from our empirical data.

In the SVJL, SVJM and SVJS models, the jump intensity, λ, in each price series is 0.05, 0.1 and 0.25, respectively, and the $\kappa(t) \sim \mathcal{NID}(0, \sigma_J^2)$, σ_J^2 is 3, 1.5 and 0.6, respectively. Cojumps are drawn from a common compound Poisson process. For the SVJL, SVJM and SVJS models, the cojump intensity and sizes are identical to those previously stated for the individual price series. Hence, the size of a cojump is identical in each of the individual price series and half of the jump variation component of the QV in each price series is expected to be due to cojumps.

3.2.2 Bivariate Simulation Results

We report the percentage of spurious and the percentage of correctly identified cojumps in Table 3. Panel A shows the results for the size-corrected ABD, size-corrected LM, ABD∩s-BNS, LM∩s-BNS and ABD∩LM tests. In summary, the percentage of spurious cojumps detected is very low in all cases, including for the SV2F model. Although the results from the tests are not directly comparable, because the ABD∩s-BNS and LM∩s-BNS detect a relatively higher proportion of spurious cojumps, the ABD∩LM test and the size-corrected ABD and LM tests do appear to be more powerful.

Panel B of Table 3 reports the results for the daily BNS and JT tests. We report results for the JT test employing both $\phi_{JT,t}^{(j)}$ and $\phi_{JT,t}^{(d)}$ (JT-JD test) and results based on employing $\phi_{JT,t}^{(j)}$ (JT-J test) only. Results for the size-corrected ABD and LM tests and the ABD∩s-BNS, LM∩s-BNS and ABD∩LM tests have also been re-expressed in terms of the

percentage of spurious and correctly identified cojump days to enable comparisons across the approaches. In addition to the percentages of spurious and true cojumps detected, the percentage of disjoint cojumps detected as cojumps by the BNS test are reported. For the JT test, we also report the percentage of days spuriously identified as containing disjoint cojumps as well as the percentage of days on which true disjoint cojumps were correctly identified.

All tests detect similarly low numbers of spurious cojump days and the ABD∩LM test and size-corrected ABD and LM tests detect the highest proportion of true cojumps. The coexceedance procedure based on the BNS test performs very similarly to the ABD∩s-BNS and LM∩s-BNS tests, leading to similar proportions of spurious and true cojump days being detected. The proportion of disjoint cojumps erroneously detected as cojump days by the BNS test is also low. Note, because the JT test is applied after detecting cojumps with the BNS test, the proportions of correctly detected cojumps for the BNS test represent maximum values that can be achieved with the JT test. In contrast, the performance of the JT test is relatively poor, with the proportion of true cojumps detected by the JT-JD test being approximately 1/3 of the proportion detected using the BNS test in all cases. The proportion of disjoint cojump days correctly detected JT-JD is also very low (<2.5%) in all cases. The propotion of true cojump days detected increases marginally when the JT-D test is employed, although the largest improvement is observed in the detection of disjoint cojump days. For example, for the SVJL model, the proportion of disjoint cojump days correctly detected is larger than the proportion of true cojump days detected. However, these improvements come at the cost of a large increase in the proportion of spuriously detected disjoint cojump days.

In conclusion, the ABD∩LM test and size-corrected ABD and LM tests appear to provide the best overall performance in detecting cojumps. There appears to be little benefit in adopting the JT test in addition to the BNS test, although the JT-D form of the test does, on balance, outperform the JT-JD test.

3.3 Multivariate Monte Carlo Simulation

To further reflect our empirical application, we examine how well the cojump detection methods perform on a panel of 60 return series and compare them against the BLT test. We are particularly interested in how well the BLT test detects small (co)jumps vis-á-vis the other detection methods.

Extending the SVJ and SV2F models to a panel of 60 stocks is computationally very demanding. Therefore, we simulated 50,000 days of 35 $\mathcal{NID}(0,1)$ intraday returns for the 60 stocks. Cojumps were introduced by adding a jump of size $\sqrt{\frac{1}{19} \times 35}$ (small), $\sqrt{\frac{1}{4} \times 35}$ (medium) or $\sqrt{\frac{2}{3} \times 35}$ (large) to the same intraday return across the 60 stocks[11]. A total of 5000 cojumps were introduced in all cases. A 1% significance level was used in all cases. Note, to make the BLT results comparable to those of the other detection methods, we applied the test using a 0.0287% intraday significance level such that the daily significance level was 1%[12]. Given the simplicity of the simulations, the results should be taken as indicative only.

The proportions of true and spurious cojumps detected along with the mean number of stocks detected to be involved in each cojump are given in Table 4. The results confirm the claim of Bollerslev et al. (2008) that their test is able to detect cojumps involving small jumps in a large panel of stocks. The alternative detection methods are only useful in detecting cojumps which involve large jumps in the constituent stocks. Results for the BNS test are noteworthy. The proportion of spurious cojumps detected for this detection method is always large (>20%) relative to the other detection methods (≤0.1%). Lastly, the mean number of stocks detected to be involved in the cojumps by all detection methods is low on average. Even large (co)jumps do not necessarily lead to the detection of a large number of stocks being involved in the cojumps. This is important to remember when analysing the empirical results in Section 6.

4 Data

We obtained high-frequency transaction data from the trades and quotes (TAQ) database for the period January 2002 to June 2011. We sampled prices with time stamps falling within 09:35-16:00 EST. The first 5 minutes of the trading day, which officially starts at 09:30 EST, is ignored due to the erratic price behaviour potentially induced by the market opening procedure. Appendix A explains our data cleaning methods. Our sample consists of 60 liquid stocks and a proxy for the market portfolio, the Spider ETF (SPY), which replicates the S&P 500. Appendix B explains our sample selection procedure.

[11]The jumps are expected to contribute either 5%, 20% or 40% to the QV of each stock on the days of cojump arrivals. The mean value of $\frac{RV_t - BV_t}{RV_t}$ across our sample of stocks is approximately 20%. The absolute value of the simulated returns was taken before adding the positive jumps, which does not affect the (co)jump detection methods.

[12]This is same Bonferroni adjustment that is made for the ABD test $(1-(1-\alpha)^{\frac{1}{M}})$.

Although theoretically the accuracy of RV and BV estimates increases as the sampling interval over which intraday returns are measured decreases, empirically such a relationship is limited by the presence of microstructure noise, such as bid-ask bounce, price discreteness and irregular trading. These bias the RV and BV estimates, with the effects increasing in magnitude as the time interval over which intraday returns are sampled decreases. Using volatility signature plots (Andersen, Bollerslev, Diebold, and Labys, 2000), we decide to sample prices over intraday intervals of 11-mins ($M = 35$).

5 Intraday Jumps

Before examining cojumps, we summarise results from applying our jump tests to the individual securities. To provide robustness against a potentially time-varying intraday volatility pattern, we estimate the WSD intraday volatility correctors for non-overlapping windows of six months of data. We use a 1% significance level, but analogous results are obtained using either a 5% or 0.1% significance level.

Table 5 presents the mean number of jumps detected by each test as well as the mean number and size (absolute values) of positive and negative standardised jumps detected by the intraday jump tests[13]. Note, each test detects a larger number of jumps than the 16 jumps we would expect from type I errors. Based on the mean numbers of jumps detected, the (daily) jump intensities are estimated to be between 10.3% (25.7 jumps per year) and 1.5% (3.8 jumps per year), which are higher than those obtained from parametric models, but within the range of estimates obtained from other studies applying non-parametric jump tests to high-frequency data.

Table 5 is also informative with respect to some of the jump properties. In particular, it shows that, on average, the number and mean sizes of positive and negative jumps detected for each security are similar. To test for significant differences between the number and sizes of positive and negative jumps, we conducted Wilcoxon rank sum tests and Chi-squared goodness-of-fit tests, respectively[14]. Table 5 shows very few significant differences were identified in either case. Therefore, the detected jumps appear to be symmetrically distributed. This supports Lee and Mykland (2008) and Lahaye et al. (2010) who report similar findings of symmetrically distributed jumps for individual stocks and stock index

[13]The size of a standardised jump is given by $\frac{|r_{t,i}|}{\sqrt{\frac{1}{M} BV_t s^2_{WSD,i}}}$.

[14]Taking absolute values means the distributions of positive and negative jump sizes are non-normal. We therefore preferred the Wilcoxon rank sum test over two-sample t-tests.

futures, T-bond futures and three major exchange rates, respectively.

Dumitru and Urga (2011) and Schwert (2011) show that different non-parametric jump tests do not agree on the times of jump arrivals. This incongruence between the jumps detected by the different tests is indicative of each test either detecting some jumps that cannot be detected by the other tests or of spurious jump detection. Dumitru and Urga (2011) suggest that by taking the union of the results from several tests, the power of jump detection can be improved. Conversely, they suggest that taking the intersection of the results will minimise spurious jump detection. Table 6 provides the percentage intersections between the jumps detected by each of the detection methods we apply. Although the percentages are affected by the different number of jumps detected by the tests, they are low overall. Hence, this may be indicative of each test detecting some jumps that cannot be detected by the other tests or of each test detecting a relatively large number of spurious jumps. Either explanation would have a large impact on the number of detected jumps. For example, if the union of jumps detected by each test is taken, the mean number of detected jumps is 470.3, whereas if the intersection is taken it is 25.7. We defer further discussion to Section 6.

5.1 Illustrative Detected Jumps

To illustrate what is meant by a detected jump, Figure 1 plots the price series for the days on which the largest, detected in XRX, and smallest, detected in EP, standardised jump were identified. The largest standardised jump was detected by all jump tests and the smallest was detected by the LM test only. We also plot a jump in the SPY which corresponds to a day on which a large number of stocks were observed to be involved in a systematic cojump by all detection methods.

The jumps in XRX and the SPY are consistent with our expectations of what a jump should look like. The small detected jump in EP appears to be part of a more prolonged price decrease. However, this does not mean a jump has not occurred. The behaviour of the price series is consistent with what Barndorff-Nielsen et al. (2009) refer to as a gradual jump. If there is available liquidity between the pre-jump and post-jump prices, then this will be consumed, which takes time, before the price fully reflects the jump. Indeed, the price changes do not appear to be driven by volatility[15].

[15]Christensen et al. (2011) has questioned whether jumps detected using sparse sampling of high-frequency data can be classified as jumps or whether they are driven by volatility bursts. We take the view that jumps do exist.

5.2 Intraday Distribution of Detected Jumps

Figure 2 shows the proportion of jumps detected by each of the intraday jump tests within each intraday interval, aggregated across all stocks. Generally, the distributions are relatively flat except for noticeable increases in the proportion of jumps detected during the first and last intraday intervals. There appears to be a disproportionate number of jumps detected during the first intraday interval for the LM, ABD∩s-BNS and LM∩s-BNS tests, whilst there is a disproportionate number of jumps detected during the last four intraday interval for the LM∩s-BNS test. Therefore, even after correcting for the intraday volatility pattern, we appear to detect some spurious jumps during the first and last intraday intervals.

Figure 2 also provides us with a preliminary understanding of whether an association exists between jumps and macroeconomic news announcements (Hypothesis 2). If macroeconomic news released at 10:00, 14:15 or 15:00 EST is associated with jumps, we would expect to detect an unusually large number of jumps during the intervals from 09:57-10:08, 14:10-14:21 and 14:54-15:05. However, there does not appear to be a particularly large number of jumps associated with any of these intervals[16].

6 Cojump Results

Table 7 summarises our cojump results. Both systematic (which do involve the market portfolio) and non-systematic (which do not involve the market portfolio) cojumps were detected using our seven detection methods. In addition, we include results from taking the intersection and union of jumps detected using all our intraday detection methods. We subsequently refer to these as the intersection and union methods. Results from the BLT cojump test are also included. All results are obtained using a 1% significance level and the SPY as the market proxy. Analogous results are found when either a 5% or 0.1% significance level is employed.

6.1 Comparison Across Detection Methods

Across all detection methods, a large number of cojumps are detected and a large proportion of individual stock jumps are involved in the cojumps. However, a majority of cojumps are non-systematic with a relatively low proportion ($< 20\%$) of individual stock

[16] A closer examination of this issue is made in Section 7.

jumps being involved in systematic cojumps. Nevertheless, consistent with Hypothesis 2, more stocks are involved in systematic cojumps on average than non-systematic cojumps. In analogy to the individual stock jump results, the much lower (higher) number of cojumps identified by the intersection (union) method is indicative of incongruent cojumps being detected by the alternative detection methods[17].

6.2 Disjoint Cojumps

The results for the BNS and s-BNS test are noteworthy. The BNS test detects cojumps on nearly all days and the number of stocks involved in the cojumps is, generally, large. In contrast, the results for the s-BNS test are comparable to those obtained by the other intraday jump tests, suggesting many (daily) cojumps detected by the BNS test are disjoint cojumps. To further demonstrate, we conduct two additional analyses. Firstly, we employ the JT test. We apply the JT-J form of the test only and compare results for all pairs of stocks identified to be involved in a cojump by the BNS test. Secondly, we use our intraday jump tests to identify jump days. Any day on which a jump is detected by an intraday jump test is classified as a jump day. These are then employed in the coexceedance criterion to identify cojump days in an analogous manner to the BNS test.

Results from the two analyses suggest many BNS cojumps are disjoint cojumps. The discrepancy between the number of pairwise cojumps detected by the BNS and JT tests is large. The mean proportion of pairwise BNS cojumps confirmed to be cojumps by the JT test is 16%. Of course, we suspect the power of the JT test is low and that it does not provide the most reliable evidence for disjoint cojumps. However, if nothing else, the results demonstrate the difference that may occur between employing the JT test and the BNS test in detecting cojumps.

Applying the intraday tests to identify cojump days also leads to a large increase in the number of detected cojump days (median number of stocks involved in the cojumps). We detect 1923 (4) for the size-adjusted ABD test and 1671 (4) for the size-adjusted LM test. Although not as high as for the BNS test, the number of cojump days approximately doubles for the ABD and LM tests.

[17] If the intersection between (systematic and non-systematic) cojump times are examined, we find results comparable to those in Table 6 (available upon request).

6.3 Comparison of the Number of Stocks Involved in Cojumps

In spite of the incongruence between the cojumps detected, the median number of stocks detected to be involved in systematic cojumps is higher, relative to non-systematic cojumps, across all detection methods. However, except for the BNS test, these numbers are low relative to the 61 securities (60 stocks plus the SPY) in our sample. Bollerslev et al. (2008) believe that the evidence for cojumps is weak based on the BNS test. Our results suggest the evidence from the BNS test may overstate the prevalence of cojumps due to disjoint cojumps. Thus, the evidence from intraday jump tests would appear weaker still. Nevertheless, we show the relative frequencies of systematic cojumps involving different numbers of stocks is consistent with systematic cojumps involving more stocks, supporting Hypothesis 1.

Table 8 summarises the relative frequencies of systematic and non-systematic cojumps involving different numbers of stocks. To provide an illustration of the results we would expect if cojumps were the result of independent jumps arriving during the same interval by chance, Table 8 includes the relative frequency of intraday cojumps and cojump days, involving different numbers of stocks, we would expect if jump arrivals were independent (and therefore diversifiable). To construct the relative frequencies, the probability of an intraday jump in each interval is set equal to the sample maximum (number of jumps/number of intervals) taken across all intraday detection methods; the probability of a jump day is set equal to the sample maximum from the BNS test results. We use the sample maximum to emphasise any difference between the results and what we would expect if jump arrivals were independent.

The first result to note is that a relatively large proportion, between 8.4% and 47%, of systematic (co)jumps detected with the intraday detection methods involve 1 or 2 securities (either the SPY alone or the SPY plus one other stock). Although the numbers for the independent jumps in Table 8 are indicative only, it is reasonable to suggest that such proportions of systematic cojumps involving low numbers of stocks could be a result of independent jumps. This accords with Bollerslev et al. (2008) who suggest there is little evidence that systematic cojumps are associated with large jumps in the underlying stocks. Instead, they provide evidence that systematic cojumps are associated with small jumps in the underlying stocks. It is also noteworthy that although the systematic cojumps detected with the BNS test tend to involve many more stocks than the systematic cojumps detected by the intraday methods, many could potentially be explained by independent

jumps.

However, between 15.4% and 69.7% of the systematic cojumps detected by the intraday detection methods involve 5 or more stocks (8.3% of the stocks in our sample). From the indicative numbers in Table 8, it is reasonable to suggest that if intraday jumps were independent we would expect no systematic cojumps to involve 5 or more 5 stocks[18]. Therefore, we conclude there is a *tendency* for systematic cojumps to be associated with large jumps in the underlying stocks, consistent with Hypothesis 1. The evidence suggests that although the number of stocks involved may not be large in absolute terms, the numbers involved are large *relative* to what would be expected if jumps were independent.

Our conclusion is further supported by the proportions of non-systematic cojumps involving different numbers of stocks being much closer to what we would expect if jumps/jump days were independent. In addition, the maximum numbers of stocks we detect to be involved in systematic cojumps is larger than the maximum numbers involved in non-systematic cojumps for each respective intraday detection method. However, like Bajgrowicz and Scaillet (2011), we do not observe one day on which all the stocks in our sample are detected to cojump. Nevertheless, there is a tendency for systematic cojumps to involve a larger number of stocks *relative* to non-systematic cojumps, consistent with Hypothesis 1.

Table 89 also shows that there may be some benefit in aggregating results across the intraday detection methods. Apart for the LM detection method, there is a larger proportion of systematic cojumps involving 10 or more stocks (32.1%) for the union detection method compared to all other intraday detection mehtods and a smaller proportion involving fewer than 5 stocks (37.7%). The maximum number of stocks involved in a systematic cojump also increases to 54 for the union detection method. This is consistent with the intraday detection methods detecting distinct and different systematic jumps to one another so that when their results are aggregated, larger numbers of stocks are found to be involved in the cojumps. The same result is observed for non-systematic cojumps.

Lastly, although the proportions are low, there remains a relatively large number of non-systematic cojumps involving relatively large numbers of stocks which cannot be explained

[18]Chi-squared goodness-of-fit tests reject the null hypothesis (p-value <0.001) that the distribution of systematic cojumps, generated by each detection method, involving different numbers of stocks is a result of independent jumps/jump days. The expected numbers of cojumps for each detection method were calculated by setting the probability of a jump in any given time interval equal to the mean sample probability for that detection method. However, the null was also rejected (p-value <0.001) for the distribution of non-systematic cojumps generated by each detection method.

by independent jump arrivals. We would expect these to be systematic rather than non-systematic cojumps. There are two potential explanations for this and the large proportion of systematic cojumps involving small numbers of stocks. The first is that our market proxy, the SPY, is not perfectly linked to the stocks included in our sample. It is possible that some of the singular SPY jumps are spurious or not linked to the underlying stocks because the SPY has its own price dynamics. Similarly, the sample of 60 stocks is only a fraction of the S&P 500. Stocks in the S&P 500 excluded from our sample could be involved in cojumps with the SPY, leading to the detection of singular jumps in the SPY.

The second potential explanation is the argument of Bollerslev et al. (2008) that there are many small, undetectable, jumps. Bollerslev et al. (2008) consider the situation where a large jump in the market proxy may be associated with small undetectable cojumps in the underlying stocks, which would lead to the detection of singular jumps in the SPY. We also consider the converse situation of cojumps between the underlying stocks involving large, detectable, jumps, but the accompanying jump in the SPY being small and undetectable. This would lead to non-systematic cojumps involving large numbers of stocks.

6.3.1 Using the EQW as the Market Proxy

To establish a perfect link between jumps in the market proxy and jumps in the prices of the underlying stocks, we follow Bollerslev et al. (2008) and replace the SPY with (the equally-weighted portfolio) EQW. In the following, we use the prefixes EQW- and SPY- to highlight when we are referring to systematic and non-systematic cojumps identified using the EQW or SPY market proxies.

The relative frequencies of EQW-systematic and EQW-non-systematic cojumps involving different numbers of stocks are given in Table 9. Establishing a perfect link clearly helps explain singular jumps in the market proxy. Compared to the relative frequencies of SPY-systematic cojumps, lower proportions of EQW-systematic cojumps involve 1 and 2 securities and the proportion of EQW-systematic cojumps involving 5 or more stocks are all higher for the intraday detection methods, except the intersection method. This provides further support for our conclusion that there is a tendency for systematic cojumps to involve *relatively* large numbers of the underlying stocks. In contrast, there is little difference between the results for EQW-non-systematic cojumps and SPY-non-systematic cojumps. A non-trivial number of non-systematic cojumps continue to involve relatively

large numbers of stocks.

6.3.2 Small (Co)Jumps

Thus far we have ignored the results from the BLT test. We now use the results from this test to examine whether we find an intersection with the times at which systematic cojumps involving only a few stocks are found. Such intersections would be indicative of these cojumps involving more stocks with small jumps, as conjectured by Bollerslev et al. (2008) and demonstrated in our multivariate Monte Carlo simulation study. This would offer an explanation of why we do not detect more stocks being involved in the cojumps. Since we believe the results from our union detection method are reliable, the discussion below refers to the intersections between the detected BLT cojumps and cojumps from our union detection method[19].

Surprisingly only 27.2% of SPY-systematic cojumps and 32.4% of EQW-systematic cojumps from the union detection method are also detected as cojumps by the BLT test. Furthermore, there appears to be a positive association between the results obtained with the BLT test and the number of stocks involved in systematic (co)jumps detected with the other detection methods. For example, only 24.1% and 29.3% of SPY- and EQW-systematic cojumps involving fewer than 20 stocks are also detected by the BLT test, whilst 47.8% and 49% of SPY- and EQW-systematic cojumps involving more than 20 stocks are also detected by the BLT test. Hence, small (co)jumps may not be the only explanation of why we observe systematic cojumps involving small (absolute) numbers of stocks. It may be sufficient for large (co)jumps in a relatively large number of stocks to generate a jump in the market portfolio; we do not expect all stocks to react in the same way to information that enters the market.

There is also some evidence that the SPY- and EQW-non-systematic cojumps may involve more stocks with small jumps. However, only 0.5% of SPY- and EQW-non-systematic cojumps involving fewer than 10 stocks are also detected by the BLT test, whereas 24.3% and 7.7% of SPY- and EQW-non-systematic cojumps, respectively, involving 10 or more stocks are also detected by the BLT test. This provides further support that, at least, some of the non-systematic cojumps involving relatively large numbers of stocks may be systematic.

[19] Bollerslev et al. (2008) do not explicitly state the intersection between the cojumps detected by their test and the BNS test in their study. Hence, to the best of knowledge, we are the first to do so.

To investigate the likelihood of a type II error in the detection of a small jump in the market proxy when a large number of stocks are found to be involved in non-systematic cojumps, we calculated the p-values of the ABD, LM and BNS tests applied to the SPY and EQW for the times at which non-systematic cojumps were found to involve a large number of stocks. Small p-values slightly larger than the (nominal) threshold of 1% would be indicative of type II errors. We exclude non-systematic cojumps involving fewer than 10 stocks and use the results for the union detection method. We find tentative evidence of type II errors in the detection of jumps in SPY and EQW market proxies. Of the 52 SPY-non-systematic cojumps involving more than 10 stocks, 20 of the ABD and 18 of the BNS p-values for the SPY were found to be less than 10%. None of the LM p-values were particularly low. Similarly, of the 40 EQW-non-systematic cojumps involving more than 10 stocks 23 of the ABD p-values and 14 of the BNS p-values for the EQW were found to be less than 10%. Again, none of the LM p-values were particularly low. Hence, we believe some of non-systematic cojumps should be classified as systematic.

6.3.3 Non-systematic Cojumps

After taking into consideration the non-systematic cojumps that are likely to have been misclassified, there remain some non-systematic cojumps that involve relatively large numbers of stocks. Two further possible explanations include diversifiable (co)jumps and industry (co)jumps. If the stocks involved in non-systematic cojumps have jumps of opposite signs, then we refer to them as diversifiable as they potentially have no net effect on the market portfolio. Alternatively, if all the stocks involved in a non-systematic cojump are from the same industry, then we refer to the non-systematic cojump as an industry cojump. To keep the analysis manageable, we consider these two possibilities using the results from our union detection method. Stocks are sorted into 12 industry portfolios by SIC code[20]. Although alternative groupings were available, we found that using 12 industries ensured a reasonable number of stocks are associated with each industry. A non-systematic cojump was classified as an industry cojump if it involved stocks from within the associated industry exclusively.

We found no evidence that the SPY- or EQW-non-systematic cojumps are diversifiable. We also do not find that industry cojumps explain the presence of non-systematic cojumps

[20]The allocation of the SIC codes to the industry portfolios are obtained from the website of Kenneth R. French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

involving large numbers of stocks either. We find that 5.4% and 5.3% of SPY- and EQW-non-systematic cojumps represent industry cojumps and, across all industries, the mean number of stocks involved in the industry cojumps ranges from 2 to 2.3. This differs to Bajgrowicz and Scaillet (2011) who find many industry cojumps amongst the 30 DJIA stocks. However, their results are based exclusively on the BNS test.

7 Association between Macroeconomic News and Cojumps

Our analysis of Hypothesis 2 is based on cojumps detected using the union detection method with a significance level of 1%[21]. A total of 6 regularly scheduled macroeconomic news announcements, which are released during trading hours (09:30-16:00), were included in the analysis. These included Construction Spending, Factory Orders, ISM Report on Business and New Home Sales, all released at 10:00; the Federal Funds Target Rate, released at 14:15; and Consumer Credit, released at 15:00. Although a full analysis should take into consideration the surprise component of news announcements, this is beyond the scope of our paper. We therefore examine the relationship between the timing of detected (co)jumps and the release times of the macroeconomic news announcements.

We follow Lahaye et al. (2010) and report estimates, for all, systematic and non-systematic (co)jumps, of the probabilities of (co)jump arrivals conditional on the release of macroeconomic news in Table 10. We also report the numbers of (co)jumps detected to coincide with the release of the macroeconomic news announcements and the mean number of stocks involved in each type of (co)jump. To obtain unconditional estimates, we include (co)jumps detected to occur during the intraday intervals which are associated with the news releases, without conditioning on the release of news.

From Table 10 it can be seen that conditioning on the release of macroeconomic news leads to an increase (>2 times) in the probability of a (co)jump arrival. However, the number of stocks detected to be involved in the (co)jumps increases substantially for the Federal Funds Target Rate announcement only. When the (co)jumps are separated into systematic and non-systematic (co)jumps, it can be seen that conditioning on the release of macroeconomic news leads to a large relative increase in the probability of either type of (co)jump. Surprisingly, the conditional probability of a non-systematic cojump is higher than a systematic cojump. Indeed, the numbers of systematic (co)jumps

[21] Analogous results hold when the 0.1% and 5% significance levels are adopted and other detection methods are used.

found to be associated with the release of macroeconomic news are low (except, arguably, for those associated with news released about the Federal Funds Target Rate). However, the number of stocks involved in systematic (co)jumps associated with the release of macroeconomic news is large, especially when compared to the results in Table 10. In addition, conditioning on the release of macroeconomic news, except factory orders, leads to an increase in the number of stocks involved in systematic (co)jumps. In comparison, the mean number of stocks involved in non-systematic (co)jumps associated with the release of macroeconomic news is <2 (except for the Federal Funds Target Rate), suggesting that many are singular jumps. Therefore, it is unlikely that a causal effect exists between the release of macroeconomic news and the occurrence of many of the non-systematic (co)jumps.

The results in Table 10 suggest there is a particularly strong relationship between Federal Funds Target Rate announcements and the arrival of systematic (co)jumps. This announcement is associated with the largest (relative increase in the) probability of systematic (co)jumps and the largest number of stocks involved in systematic (co)jumps. The same is true of non-systematic (co)jumps, which, again, suggests some non-systematic (co)jumps may in fact be systematic. This evidence is consistent with Lahaye et al. (2010), Bajgrowicz and Scaillet (2011) and Lee (2009) who also find a strong association between jumps in equity markets and Federal Funds Target Rate news announcements.

7.1 Systematic Cojumps and Other News

To examine whether there was evidence that the remaining systematic cojumps could be explained by news other than macroeconomic announcements, we investigated whether press articles could explain systematic cojumps involving the 10 largest numbers of stocks which were not associated with macroeconomic news announcements. We obtained relevant news articles from the Nexis database. A summary of the dates, numbers of stocks involved and the news identified is given in Table **??**. All information related to relevant news is paraphrased from The Associated Press newswire. In each case there was some, ostensibly, important news. However, whether the news was responsible for the systematic cojumps is difficult to determine. For example, on 22 Feb 2008 the news article indicates prices "shot up" and on 3 March 2007 the news article mentions a "jump" in prices. However, despite indicating there was a positive jump in prices on 3 March 2007, we found that our cojump was negative, although there was also news of how stocks re-

acted badly to news released by the Fed about its concerns in the housing market on that day. Nonetheless, we believe that sources of systematic news other than macroeconomic announcements are responsible for systematic cojumps. Since such a large proportion of systematic cojumps are not associated with macroeconomic announcements, we infer that these alternative sources of systematic news must cause the majority of systematic cojumps.

7.2 Systematic and Idiosyncratic Jump Properties

Jump properties were examined in Section 5, where we found the detected jumps to be, approximately, symmetrically distributed. However, these properties may be different for systematic and idiosyncratic jumps. Asymmetric price responses to macroeconomic news announcements have been documented, with negative news surprises observed to be associated with price decreases that are larger than price increases associated with positive news surprises of an equivalent magnitude (Adams et al., 2002; Conrad et al., 2002; Boyd et al., 2005; Chuliá et al., 2010). Hence, we might expect negative systematic jumps to be more frequent and larger in size.

Table 11 suggests the number and mean sizes of positive and negative systematic, non-singular idiosyncratic and singular idiosyncratic jumps are similar. This is supported by formal Chi-squared and Wilcoxon rank sum tests. In all cases, very few significant differences (p-values <0.05) were found.

Finally, we also compare the magnitudes of systematic, non-singular idiosyncratic and singular idiosyncratic jumps. Intuitively, we might expect the price reaction to systematic news to be larger, on average, and therefore for systematic jumps to be larger in magnitude on average. Using a Kruskall-Wallis test we found a significant difference (p-value <0.05) for only one stock. Therefore, systematic, non-singular idiosyncratic and singular idiosyncratic jumps appear symmetric and there does not appear to be any difference in their sizes.

8 Conclusion

Our main results can be summarised as follows. We show in a Monte Carlo study that our methods for correcting for the intraday volatility pattern and size distortions in the non-parametric jump tests are effective. Bivariate simulations show that the intraday

jump tests are more powerful than the daily BNS test and that the JT test has very low power, at least for the 11-min sampling frequency we use. Empirically, we find that there is a large degree of incongruence between the jumps detected by the different tests. The intraday distribution of detected jumps is also, approximately, consistent with a constant intraday jump intensity, indicative of macroeconomic news announcements not being the main source of (co)jumps. The incongruence observed in the detection of individual jumps extends to the detection of cojumps; aggregating (co)jumps detected using a variety of tests appears to produce more reliable results. Many of the cojumps detected using the BNS test appear to be disjoint cojumps, highlighting the importance of employing detection methods that are robust to disjoint cojumps. On many occasions, only a small fraction of stocks are detected to be involved in systematic cojumps (the median ranges between 3 and 8 stocks). Although this appears to support the claims of Bollerslev et al. (2008), when we compare the results to what would be expected if jump arrivals were independent, the probability of observing cojumps involving the numbers of stocks observed in the majority of systematic cojumps is effectively zero. This contrasts with non-systematic cojumps (which do not involve the market portfolio), where the number of stocks involved in the majority of cases could be explained by independent jump arrivals. Therefore, we claim that there is a *tendency* for a *relatively* large number of stocks to be involved in systematic cojumps, supporting Hypothesis 1. We find only partial support for Hypothesis 2. There appears to be an association between systematic cojumps and the release of the Federal Fund Target Rate. Conditioning on a Federal Fund Target Rate announcement substantially increases the probability of a systematic cojump and the number of stocks detected to be involved in the systematic cojumps is much higher compared to the number observed in systematic cojumps during the same intraday interval on non-announcement days.

Appendix A Data Cleaning

To clean the data we used a procedure similar to Barndorff-Nielsen et al. (2009). We purged all transactions for which the correction indicator (CORR) was not zero and the sale condition indicator (COND) was not empty or equal to either 'E' or 'F' in the TAQ database. Where an identical time stamp was associated with multiple transactions, we used the median price. We removed prices that were more than 50 mean absolute devia-

tions from the median centred on a window of 50 observations.

Appendix B Data Selection

One objective of this study was to obtain a large number of stocks suitable for the application of the jump and cojump tests. However, we also need to be able to accurately estimate BV which, in turn, can only be achieved when the market for the stocks is liquid. That is to say, there must be a sufficient number of transactions observed throughout the trading day for intraday returns to be computed and on which accurate estimates of BV are reliant. To obtain a large sample of liquid stocks, we focused on the constituents of the S&P 500. Specifically, we selected 100 constituent stocks with the highest trading volumes in Jan 2002, where, although not directly proportional to the number of trades, trading volume was used as an indicator of liquidity. From this sample stocks were removed as a consequence of merger activity, delisting or missing data, leaving the 60 stocks used in our sample.

Appendix C Alternative Intraday Volatility Correctors

The intraday volatility pattern corrector of Taylor and Xu (1997) (TX) is given by,

$$\hat{s}^2_{TX,i} = \frac{M \cdot \sum_{t=1}^{T} r^2_{t,i}}{\sum_{t=1}^{T} \sum_{i=1}^{M} r^2_{t,i}}.$$

We also propose a jump robust version based on the Bollerslev et al. (2008),

$$\begin{aligned}
\hat{s}^2_{RobustTX,i} &= \frac{M \cdot \sum_{t=1}^{T} |r_{t,i-1}|^{\frac{1}{2}} |r_{t,i}||r_{t,i+1}|^{\frac{1}{2}}}{\sum_{t=1}^{T} |r_{t,1}||r_{t,2}| + \sum_{t=1}^{T} \sum_{i=2}^{M-1} |r_{t,i-1}|^{\frac{1}{2}} |r_{t,i}||r_{t,i+1}|^{\frac{1}{2}} + \sum_{t=1}^{T} |r_{t,M-1}||r_{t,M}|}, \text{ for } \quad i = 2, \ldots, M \\
\hat{s}^2_{RobustTX,i} &= \frac{M \cdot \sum_{t=1}^{T} |r_{t,i}||r_{t,i+1}|}{\sum_{t=1}^{T} |r_{t,1}||r_{t,2}| + \sum_{t=1}^{T} \sum_{i=2}^{M-1} |r_{t,i-1}|^{\frac{1}{2}} |r_{t,i}||r_{t,i+1}|^{\frac{1}{2}} + \sum_{t=1}^{T} |r_{t,M-1}||r_{t,M}|}, \text{ for } \quad i = 1, \\
\hat{s}^2_{RobustTX,i} &= \frac{M \cdot \sum_{t=1}^{T} |r_{t,i-1}||r_{t,i}|}{\sum_{t=1}^{T} |r_{t,1}||r_{t,2}| + \sum_{t=1}^{T} \sum_{i=2}^{M-1} |r_{t,i-1}|^{\frac{1}{2}} |r_{t,i}||r_{t,i+1}|^{\frac{1}{2}} + \sum_{t=1}^{T} |r_{t,M-1}||r_{t,M}|}, \text{ for } \quad i = M.
\end{aligned}$$

The flexible Fourier function (FFF) intraday volatility corrector of Andersen and Bollerslev (1997, 1998b) is obtained by running the following OLS regression,

$$\log |r_{t,i}| - c = \mathbf{x}_i' \theta + \epsilon_i, \tag{A-1}$$

$$\mathbf{x}_i'\theta = \sum_{q=0}^{Q} \sigma_t^2 \left[\mu_{0,q} + \mu_{1,q}\frac{i}{M_1} + \mu_{2,q}\frac{i^2}{M_2} + \sum_{p=1}^{P} \left(\gamma_{p,q} \cos\left(ip\frac{2\pi}{M} \right) + \eta_{p,q} \sin\left(ip\frac{2\pi}{M} \right) \right) \right],$$

where $M_1 = \frac{(M+1)}{2}$, $M_2 = \frac{(M+1)(M+2)}{6}$ and $\theta = (\mu_{0,q}, \mu_{1,q}, \mu_{2,q}, \gamma_{p,q}, \eta_{p,q})'$. Then,

$$\hat{s}^2_{FFF,i} = \frac{M \cdot \exp\left(2\mathbf{x}_i'\theta\right)}{\sum_{i=1}^{M} \exp\left(2\mathbf{x}_i'\theta\right)}. \tag{A-2}$$

To estimate the intraday volatility correctors of Boudt et al. (2008) we first need to define,

$$\bar{r}_{t,i} = \frac{r_{t,i}}{\frac{1}{M}BV_t}.$$

The shortest half scale (ShortH) intraday volatility corrector is then obtained from,

$$\begin{aligned} ShortH_i &= 0.741 \cdot \min\left\{ \bar{r}_{(h_i),i} - \bar{r}_{(1),i}, \ldots, \bar{r}_{(T_i),i} - \bar{r}_{(T_i-h_i+1),i} \right\} \\ h_i &= \lfloor T_i/2 \rfloor + 1, \end{aligned}$$

where T_i is the total number of observations of intraday interval i, $\lfloor A \rfloor$ rounds A to the lowest integer and $\bar{r}_{(j),i}$ are the order statistics of $\bar{r}_{j,i}$. Then,

$$\hat{s}^2_{ShortH,i} = \frac{M \cdot ShortH_i^2}{\sum_{i=1}^{M} ShortH_i^2}.$$

The weighted standard deviation (WSD) is based on,

$$WSD_i^2 = 1.081 \frac{\sum_{t=1}^{T} w_{t,i}\bar{r}_{t,i}^2}{\sum_{t=1}^{T} w_{t,i}},$$

where $w_{t,i} = w\left(\frac{\bar{r}_{t,i}}{\hat{s}_{ShortH,i}}\right)$ and $w(z) = 1$ if $z^2 \leq 6.635$ and 0 otherwise. Then

$$\hat{s}^2_{WSD,i} = \frac{M \cdot WSD_i^2}{\sum_{i=1}^{M} WSD_i^2}.$$

Finally, the truncated maximum likelihood (TML) intraday volatility corrector is based on the FFF estimator. First, estimates of regression residuals are required from the FFF regression,

$$e_i^{WSD} = \log|r_{t,i}| - c - \log \hat{s}_{WSD,i}.$$

Second, a weighted (negative) likelihood function is computed using,

$$\rho^{ML}(z) \quad = \quad -0.5 \log\left(\frac{2}{\pi}\right) - z - c + (0.5 \times \exp\left(2(z+c)\right)),$$

and

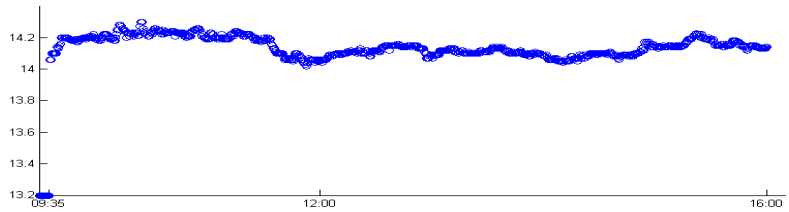
$$w_i \quad = \quad \begin{cases} 1 & \text{if } \rho^{ML}(e_i^{WSD}) \leq 3.36, \\ 0 & \text{otherwise .} \end{cases}$$

The maximum likelihood parameters are then estimated from,

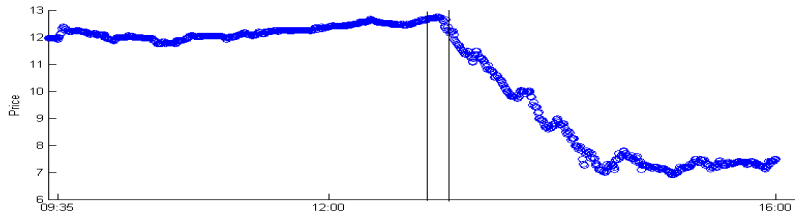
$$\theta^{TML} \quad = \quad \min_{\theta} \frac{1}{\sum_i w_i} \sum_i w_i \rho^{ML}(\epsilon_i),$$

where ϵ_i is from (A-1) and $\hat{s}^2_{TML,i}$ is obtained in an analogous manner to (A-2).

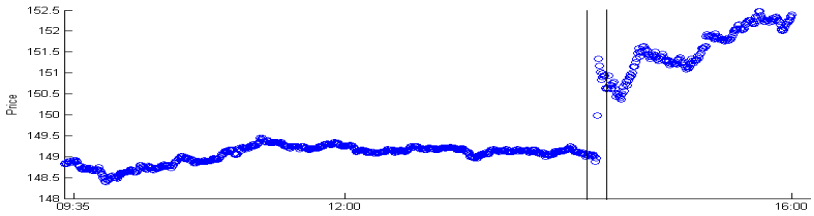
Simulation evidence on the effect the alternative intraday volatility estimators and IV estimators have on the effective size and power of the jump tests is presented in Table 12 and Table 13.



(a)



(b)



(c)

Figure 1: Examples of detected jumps. (a) represents a "large" jump in XRX for the interval 09:35-09:46 on 27/02/2004. (b) represents a "small" jump in EP for the interval 12:53-13:04 on 23/09/2002. (c) represents a jump in our proxy for the market portfolio, SPY, for the interval 14:10-14:21 on 18/09/2007. Vertical lines highlight the location of the detected jump.

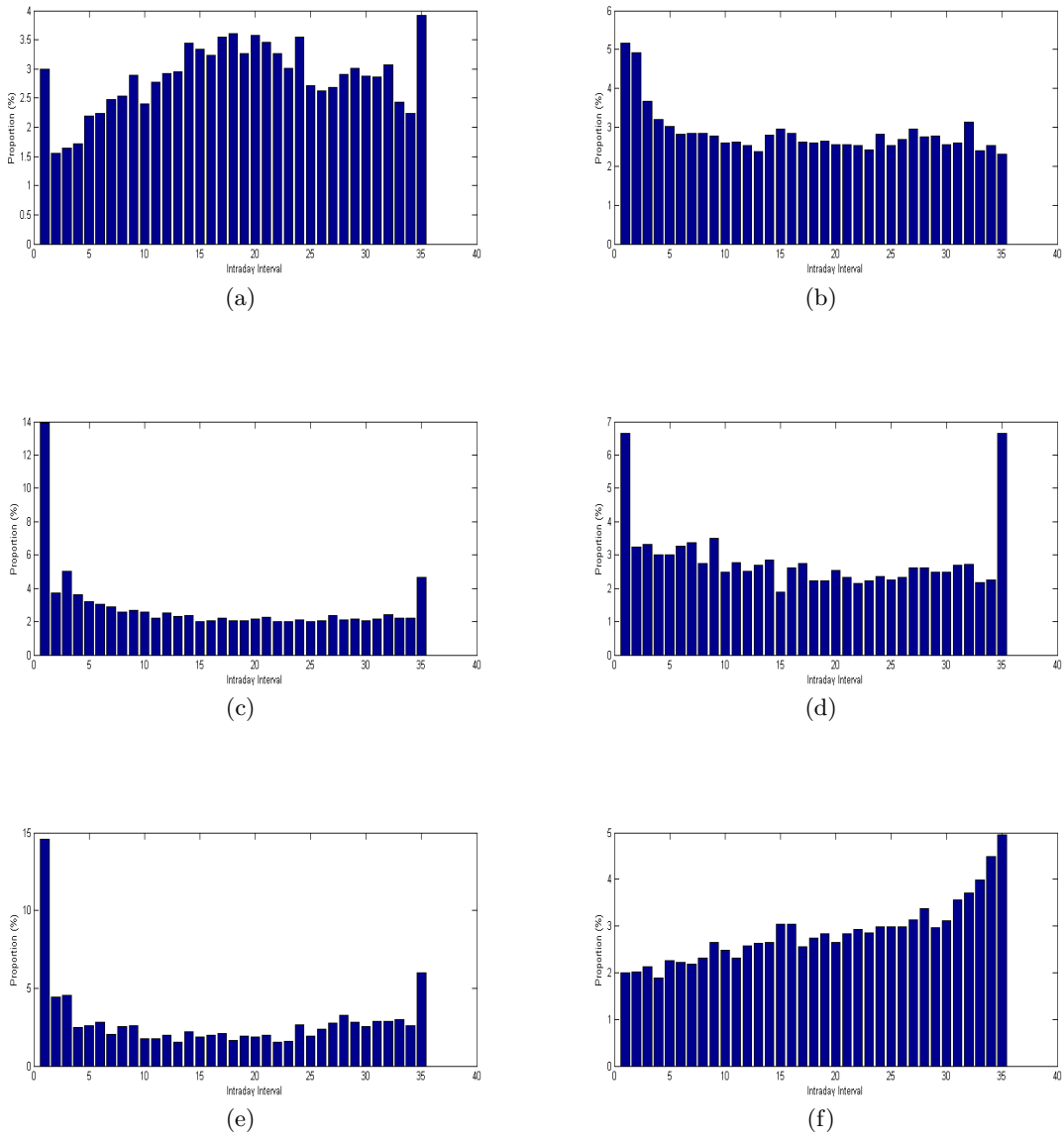


Figure 2: Intraday distribution of detected jumps. The proportion of jumps detected for each intraday interval is shown for each intraday jump test. (a) provides the intraday distribution for the ABD test. (b) provides the intraday distribution for the LM test. (c) provides the intraday distribution for the sBNS test. (d) provides the intraday distribution for the ABD∩s-BNS test. (e) provides the intraday distribution for the LM∩s-BNS test. (f) provides the intraday distribution for the ABD∩LM test. Note, intraday interval 1 corresponds to the interval 09:35-09:46 and so on.

Table 1: Parameter values used in the one factor and two factor models of price dynamics.

One Factor Model		Two Factor Model	
β_0	0	β_0	-1.2
β_1	0.125	β_1	0.04
α_v	-0.1	β_2	1.5
ρ	-0.62	α_{v1}	-1.37E-03
λ	0,0.05,0.1,0.2	α_{v2}	-1.386
σ_J^2	0,6,3,1.5	β_{v1}	0.25
		ρ_1	-0.3
		ρ_2	-0.3

Table 2: Effective size and power of jump tests. Size adjustments have been applied to the ABD and LM tests.

	SV		SVJL		SVJM		SVJS		SV2F	
	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)
ABD	1.2	-	1.1	78.6	1.1	60.4	1.0	24.9	15.4	-
LM	1.2	-	1.0	79.6	1.0	61.4	1.0	26.0	52.4	-
s-BNS	1.7		1.6	68.7	1.6	46.2	1.4	13.2	5.8	
ABD∩s-BNS	0.6	-	0.6	68.6	0.6	46.0	0.5	12.8	4.2	-
LM∩s-BNS	0.2	-	0.2	68.2	0.2	45.5	0.2	12.3	2.4	-
ABD∩LM	0.6	-	0.6	78.6	0.6	59.9	0.6	24.4	11.5	-
BNS	1.6	-	1.6	71.4	1.7	50.7	1.6	17.3	5.7	-

Table 3: Add caption

		SV		SVJL		SVJM		SVJS		SV2F	
		Spurious (%)	True (%)	Spurious (%)	True (%)	Spurious (%)	True (%)	Spurious (%)	True (%)	Spurious (%)	True (%)
Panel A: Intraday Cojumps											
ABD		1.7E-04	-	1.1E-03	53.3	4.6E-04	25.0	4.1E-04	2.2	2.8E-02	-
LM		2.3E-04	-	8.6E-04	55.4	6.9E-04	27.1	5.2E-04	2.4	0.4	-
s-BNS		2.9E-04	-	9.7E-04	37.2	6.3E-04	11.9	4.1E-04	0.4	5.7E-03	-
ABD∩s-BNS		5.7E-05	-	5.7E-04	37.0	2.3E-04	11.7	1.7E-04	0.4	5.0E-03	-
LM∩s-BNS		5.7E-05	-	4.0E-04	36.9	1.7E-04	11.6	2.3E-04	0.3	3.1E-03	-
ABD∩LM		1.1E-04	-	6.9E-04	53.6	3.4E-04	25.4	4.1E-04	2.2	2.7E-02	-
Panel B: Daily Cojumps											
ABD		1.7E-04	-	4.6E-04	55.0	1.7E-04	27.2	5.8E-05	2.8	2.8E-02	-
LM		2.3E-04	-	1.7E-04	56.9	2.3E-04	29.2	2.3E-04	3.0	0.3	-
ABD∩s-BNS		5.7E-05	-	2.3E-04	38.7	5.7E-05	12.8	0	0.5	5.0E-03	-
LM∩s-BNS		5.7E-05	-	5.7E-05	38.5	0	12.7	5.8E-05	0.5	3.1E-03	-
ABD∩LM		1.1E-04	-	5.7E-05	55.3	0	27.5	1.2E-04	2.8	2.7E-02	-
BNS		2.4E-02	-	0.3	38.2	0.2	12.6	3.0E-02	0.5	0.2	-
	Disjoint	-	-	60.0	22.7	55.9	3.9	33.3	0.1	0	-
JT-JD		4.0E-03	-	4.4E-02	10.3	2.8E-02	3.8	0	0.1	1.2E-02	-
	Disjoint	4.0E-03	-	0.5	2.3	0.3	0.6	2.6E-02	0.0	1.2E-02	-
JT-J		4.0E-03	-	5.3E-02	10.4	3.4E-02	3.9	0	0.1	1.4E-02	-
	Disjoint	2.0E-02	-	2.7	18.5	1.6	3.6	0.1	0.1	0.2	-

Table 4: Summary of results from multivariate simulations. Results are reported for small, medium and large cojumps. For each cojump detection method the percentage of spurious and true cojumps detected are reported along with the mean number of stocks detected to be involved in the cojumps.

		BLT	ABD	LM	s-BNS	ABD∩s-BNS	LM∩s-BNS	ABD∩LM	BNS
Small	Spurious	2.2E-02	1.3E-02	5.7E-04	21.6	2.5E-03	5.4E-03	7.8E-02	3.6E-02
	Correct	90.8	1.9	0.5	23.8	0.6	0.6	0.1	1.5
	No. Involved	-	2.0	2.1	2.4	2.1	2.0	2.4	6.8
Medium	Spurious	2.2E-02	1.3E-02	5.7E-04	21.6	2.4E-03	5.5E-03	8.4E-02	3.5E-02
	Correct	90.8	83.3	68.0	63.7	73.9	36.1	14.7	44.9
	No. Involved	-	3.7	3.1	3.0	3.3	2.5	2.3	1.7
Large	Spurious	2.2E-02	1.3E-02	5.7E-04	21.6	2.4E-03	5.6E-03	0.1	3.5E-02
	Correct	90.8	99.8	99.6	99.6	99.6	99.3	99.1	99.2
	No. Involved	-	19.5	20.5	7.7	20.7	7.3	6.9	6.9

Table 5: Summary of jumps detected in our sample of 61 securities. Columns 1-3 provide the mean number of total, positive and negative detected jumps. Columns 4-5 provide the mean size of standardised jumps. In column 6 are the number of stocks for which significant differences (p-value <0.05) in the number of positive and negative jumps are found according to Chi-squared goodness-of-fit tests. In column 7 are the number of stocks for which significant differences (p-value <0.05) in the size of positive and negative standardised jumps are found according to Wilcoxon rank sum tests. Only the mean number of detected jump days is provided for the BNS test.

	Mean no. Jumps			Mean Size		Significant Diff.	
	All	Pos.	Neg.	Pos.	Neg.	No.	Size
ABD	161.2	81.9	79.3	4.4	4.3	8	5
LM	198.2	98.3	99.9	3.6	3.6	5	9
s-BNS	244.5	123.9	120.5	3.4	3.4	3	4
ABD∩s-BNS	59.8	30.7	29	4.7	4.5	4	2
LM∩s-BNS	36.5	19.6	17	4.6	4.4	2	4
ABD∩LM	105.4	53.3	52.2	4.4	4.3	0	5
Intersection	25.7	13.7	12	5.1	4.8	3	7
Union	470.3	235.8	234.5	3.5	3.5	2	5
BNS	186.7						

Table 6: Percentage intersections between jumps detected by alternative jump tests. The numbers correspond to the intersection (%) between the jump tests listed for the row and corresponding column. The intersection is presented as a percentage of the jumps detected by the test listed for the column. Numbers for the BNS test refer to the intersection (%) between jump days.

	ABD	LM	s-BNS	ABD∩s-BNS	LM∩s-BNS	ABD∩LM	BNS
ABD	100	36.2	24.3	100	69.8	80.3	30.3
LM	44.3	100	11.4	35.6	76.3	82.4	14.6
s-BNS	36.4	14.1	100	100	100	26.2	100
ABD∩s-BNS	36.4	10.7	24.3	100	69.8	24.0	30.3
LM∩s-BNS	15.7	14.1	14.9	43.0	100	26.2	18.7
ABD∩LM	52.6	44.0	11.5	43.0	76.3	100	14.6
BNS	36.9	16.7	100	100	100	27.1	100

Table 7: Summary of total, systematic and non-systematic cojumps detected by each cojump detection method. Columns 1-2 list the number of detected cojumps and cojump days. Column 4 lists the median number of stocks detected to be involved in the cojumps. Column 6 provides the mean proportion, across all securities, of jumps detected to be involved in cojumps.

	Cojumps			
	No.	Days	Med. Stks	Jumps (%)
Panel A: Total Cojumps				
ABD	1182	942	2	45.6
LM	1454	858	2	51.6
s-BNS	2353	1467	2	44.7
ABD∩s-BNS	343	323	2	28.4
LM∩s-BNS	189	178	2	26.7
ABD∩LM	714	580	2	47.2
Intersection	134	130	2	28.3
Union	4709	2023	2	57.4
BNS	-	2143	5	98.7
BLT	196	-	-	-
Panel B: Systematic Cojumps				
ABD	129	121	6	12.0
LM	190	160	8	19.2
s-BNS	114	104	4	4.6
ABDnBNS	36	35	4	5.2
LMnBNS	27	26	3	5.9
ABDnLM	94	88	6	14.8
Intersection	23	23	3	6.8
Union	335	290	8	13.2
BNS	-	126	8	10.5
BLT	196	-	-	-
Panel C: Nonsystematic Cojumps				
ABD	1053	855	2	33.6
LM	1264	795	2	32.4
s-BNS	2239	1428	2	40.1
ABDnBNS	307	292	2	23.2
LMnBNS	162	157	2	20.8
ABDnLM	620	512	2	32.4
Intersection	111	110	2	21.5
Union	4374	1972	2	44.2
BNS	-	2017	5	88.1

Table 8: Relative frequencies of detected systematic and non-systematic cojumps involving different numbers of stocks. Expected relative frequencies are given under the assumption that jump arrivals are independent and the probability of a jump is equal to the sample maximum (number of detected jumps/number of intervals). These expectations are provided for both intraday cojumps (Ind. Intra. Jumps) and daily cojumps (Ind. Daily Jumps). The last row in Panel A and B lists the maximum number of stocks detected to be involved in a systematic and non-systematic cojump, respectively.

No. Stocks	ABD	LM	s-BNS	ABD∩s-BNS	LM∩s-BNS	ABD∩LM	Inter.	Union	Ind. Intra. Jumps	BNS	Ind. Daily Jumps
Panel A: Systematic Cojumps											
1	4.4	2.6	23.5	30.8	22.9	1.1	23.3	6.4	50.6	2.3	0
2	11.1	6.7	23.5	15.4	14.3	7.4	16.7	9.8	34.7	0.8	0
3	9.6	8.2	10.1	17.3	25.7	16.8	26.7	8.9	11.7	7.0	0.1
4	12.6	5.6	8.7	15.4	14.3	6.3	13.3	7.3	2.6	6.2	0.3
5	14.1	7.2	8.7	5.8	5.7	9.5	3.3	5.3	0.4	7.8	0.9
6-10	23.0	33.8	18.1	11.5	11.4	25.3	10.0	30.2	0.1	50.4	36.4
11-20	19.3	19.5	6.7	3.8	5.7	25.3	6.7	19.3		22.5	62.0
21-30	3.0	11.3	0.7			3.2		9.5		3.1	0.2
31-40	2.2	2.6	0.0			4.2		1.7			
41-50		1.0				1.1		0.8			
51-61		1.5						0.8			
Max	46	53	21	17	13	48	13	54		30	
Panel B: Non-systematic Cojumps											
1	84.1	82.9	78.8	89.7	91.1	85.1	91.2	74.2	70.2	7.2	0
2	9.9	10.6	14.2	7.5	6.3	8.7	6.1	16.1	23.6	12.8	0.1
3	3.0	3.1	4.1	1.8	1.5	2.6	1.1	5.1	5.2	17.1	0.3
4	1.1	1.3	1.4	0.5	0.4	1.3	0.6	2.0	0.8	16.3	0.9
5	0.6	0.7	0.7	0.2	0.3	0.8	0.4	1.1	0.1	14.4	2.2
6-10	0.9	1.1	0.6	0.4	0.4	1.0	0.6	1.3		29.5	47.6
11-20	0.3	0.3	0.1		0.1	0.3	0.1	0.2		2.8	48.7
21-30											0.1
31-40											
41-50											
51-61											
Max	32	25	12	11	11	25	11	25		20	

Table 9: Relative frequencies of detected systematic and non-systematic cojumps involving different numbers of stocks. Expected relative frequencies are given under the assumption that jump arrivals are independent and the probability of a jump is equal to the sample maximum (number of detected jumps/number of intervals). These expectations are provided for both intraday cojumps (Ind. Intra. Jumps) and daily cojumps (Ind. Daily Jumps). The last row in Panel A and B lists the maximum number of stocks detected to be involved in a systematic and non-systematic cojump, respectively.

No. Stocks	ABD	LM	s-BNS	ABD∩s-BNS	LM∩s-BNS	ABD∩LM	Inter.	Union	Ind. Intra. Jumps	BNS	Ind. Daily Jumps
Panel A: Systematic Cojumps											
1	2.4	0.0	20.5	14.0	20.0	0.0	20.0	4.5	67.3	0.8	0
2	1.6	1.3	16.5	18.0	4.0	2.2	4.0	5.8	26.7	1.7	0
3	9.7	2.5	11.0	22.0	20.0	11.1	20.0	6.1	5.2	4.1	0.1
4	8.9	5.7	11.8	20.0	16.0	6.7	20.0	5.8	0.7	1.7	0.4
5	13.7	6.9	11.8	4.0	12.0	3.3	12.0	5.1	0.1	8.3	1.3
6-10	28.2	34.0	19.7	14.0	20.0	33.3	16.0	31.7		47.9	40.3
11-20	26.6	28.3	7.9	8.0	8.0	34.4	8.0	25.3		32.2	57.7
21-30	4.8	15.1	0.8			3.3		11.9		3.3	0.2
31-40	3.2	3.1				4.4		1.9			
41-50	0.8	1.3				1.1		1.0			
51-61		1.9						1.0			
Max	46	53	21	17	13	48	13	54		30	
Panel B: Non-systematic Cojumps											
1	84.1	82.7	78.9	88.9	91.1	85.1	91.4	74.2	81.7	7.1	0
2	9.9	10.7	14.2	7.9	6.5	8.9	6.2	16.1	16.0	12.9	0.1
3	3.1	3.1	4.1	2.0	1.5	2.7	1.2	5.1	2.1	17.3	0.4
4	1.2	1.4	1.4	0.5	0.3	1.5	0.4	2.0	0.2	16.3	1.3
5	0.6	0.7	0.7	0.2	0.2	0.7	0.2	1.1	0.0	14.2	2.8
6-10	0.8	1.2	0.6	0.4	0.4	0.9	0.6	1.4	0.0	29.7	51.0
11-20	0.2	0.2	0.1	0.0	0.1	0.2	0.1	0.2		2.3	44.3
21-30											0.1
31-40											
41-50											
51-61											
Max	20	16	14	11	11	25	11	16		21	

Table 10: Estimates of the probabilities of (co)jump arrivals associated with macroeconomic news. The first row lists the number of releases of each macroeconomic news announcement. The number, estimated probability and the mean number of stocks involved in all, systematic and non-systematic (co)jumps detected at the times of macroeconomic news announcements are provided. The same information is provided for (co)jumps that occur concomitantly with the release of a macroeconomic news announcement. Note, CS refers to Construction Spending; FO refers to Factory Orders; ISM refers to the ISM Report on Business; NHS refers to New Home Sales; FOMC refers to the Federal Fund Target Rate; and CC refers to Construction Spending.

		News Announcement					
		10:00				14:15	15:00
		CS	FO	ISM	NHS	FOMC	CC
No. Announcements		36	127	85	112	76	114
(Co)Jumps	No.	303				172	174
	Cond. Prob. (%)	12.8				7.3	7.4
	Mean no. Stocks	1.5				2.0	1.8
(Co)JumpsnNews	No.	13	35	31	41	38	26
	Cond. Prob. (%)	36.1	27.6	36.5	36.6	50.0	22.8
	Mean no. Stocks	2.7	1.4	2.6	1.7	9.3	3.0
Systematic (co)jumps	No.	18				18	13
	Cond. Prob. (%)	0.8				0.8	0.5
	Mean no. Stocks	7				18.3	13.4
Systematic (co)jumpsnNews	No.	2	1	3	2	10	2
	Cond. Prob. (%)	5.6	0.8	3.5	1.8	13.2	1.8
	Mean no. Stocks	10	2	12.7	8.5	23.2	18
Non-systematic (co)jumps	No.	296				165	166
	Cond. Prob. (%)	12.5				7.0	7.0
	Mean no. Stocks	1.3				1.5	1.5
Non-systematic (co)jumpsnNews	No.	11	34	28	39	28	24
	Cond. Prob. (%)	30.6	26.8	32.9	34.8	36.8	21.1
	Mean no. Stocks	1.4	1.4	1.6	1.4	4.3	1.7

Table 11: Summary of systematic, non-singular idiosyncratic and singular idiosyncratic jumps detected in our sample of 61 securities. Columns 1-3 provide the mean number of total, positive and negative detected jumps. Columns 4-5 provide the mean size of standardised jumps. In column 6 are the number of stocks for which significant differences (p-value <0.05) in the number of positive and negative jumps are found according to Chi-squared goodness-of-fit tests. In column 7 are the number of stocks for which significant differences (p-value <0.05) in the size of positive and negative standardised jumps are found according to Wilcoxon rank sum tests. Only the mean number of detected jump days is provided for the BNS test.

	Mean no. Jumps			Mean Size		Sig. Diff.	
	All	Pos.	Neg.	Pos.	Neg.	No.	Size
Panel A: Systematic Jumps							
ABD	16.1	8.0	8.1	4.5	4.4	2	3
LM	33.3	13.9	19.5	3.8	3.7	8	2
s-BNS	7.9	4.7	3.2	3.6	3.7	3	1
ABD∩s-BNS	2.3	1.6	0.7	3.9	2.3	1	0
LM∩s-BNS	1.6	0.9	0.7	3.1	2.5	0	0
ABD∩LM	13.4	5.9	7.5	4.5	4.4	1	1
Intersection	1.3	0.9	0.5	2.9	1.9	0	0
Union	53.0	24.8	28.2	3.8	3.7	6	2
Panel B: Non-singular Idiosyncratic Jumps							
ABD	52.7	25.2	27.5	4.4	4.3	4	3
LM	63.0	30.8	32.2	3.6	3.5	6	8
s-BNS	97.5	47.6	49.9	3.4	3.3	3	4
ABD∩s-BNS	13.1	6.0	7.2	4.7	4.5	2	1
LM∩s-BNS	7.1	3.9	3.3	4.6	4.4	0	2
ABD∩LM	33.2	15.6	17.6	4.4	4.3	5	6
Intersection	5.2	2.6	2.6	4.7	4.6	0	1
Union	207.5	101.7	105.9	3.4	3.4	5	6
Panel C: Singular Idiosyncratic Jumps							
ABD	92.5	48.8	43.7	4.4	4.3	7	7
LM	101.8	53.6	48.3	3.6	3.5	11	3
s-BNS	139.1	71.6	67.5	3.4	3.3	4	3
ABD∩s-BNS	44.4	23.2	21.2	4.6	4.5	2	6
LM∩s-BNS	27.8	14.8	13.0	4.5	4.3	4	2
ABD∩LM	58.9	31.8	27.1	4.4	4.3	9	4
Intersection	19.2	10.3	8.9	5.1	4.8	8	2
Union	209.8	109.3	100.5	3.4	3.4	9	3

Table 12: Effective size and power of intraday jump tests for alternative intraday volatility correctors. In all cases, BV was used as the estimator of IV.

	SV		SVJL		SVJM		SVJS		SV2F	
	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)
Panel A: ABD Test										
TX	2.2	-	2.0	79.5	1.9	62.0	1.8	27.2	19.1	-
RobustTX	2.2	-	2.0	79.9	2.0	62.0	1.9	27.5	19.1	-
FFF	2.2	-	2.0	79.8	1.9	62.1	1.8	27.4	19.1	-
ShortH	2.2	-	2.0	79.8	2.0	62.0	1.8	27.5	19.2	-
WSD	2.1	-	1.9	79.6	1.9	62.0	1.8	27.2	19.4	-
TML	2.2	-	2.0	79.7	2.0	62.0	1.8	27.4	18.9	-
Panel B: LM Test										
TX	2.2	-	2.0	80.4	1.9	63.4	1.7	28.7	56.9	-
RobustTX	2.3	-	2.0	80.7	2.0	63.6	1.8	29.0	57.1	-
FFF	2.2	-	2.0	80.7	1.9	63.6	1.8	28.9	57.0	-
ShortH	2.2	-	2.0	80.7	1.9	63.6	1.8	28.9	57.0	-
WSD	2.2	-	1.9	80.6	1.9	63.4	1.7	28.7	57.9	-
TML	2.2	-	2.0	80.7	1.9	63.6	1.8	28.9	57.1	-
Panel C: s-BNS Test										
TX	1.7	-	1.6	68.7	1.6	46.2	1.4	13.2	5.7	-
RobustTX	1.7	-	1.7	68.7	1.7	46.3	1.5	13.2	5.7	-
FFF	1.7	-	1.6	68.7	1.6	46.2	1.5	13.2	5.7	-
ShortH	1.7	-	1.6	68.7	1.6	46.3	1.5	13.2	5.7	-
WSD	1.7	-	1.6	68.7	1.6	46.2	1.4	13.2	5.8	-
TML	1.7	-	1.6	68.7	1.6	46.3	1.5	13.2	5.7	-

Table 13: Effective size and power of the ABD, s-BNS and BNS jump test for alternative IV estimators. The WSD intraday volatility corrector was used when applying the ABD and s-BNS tests.

	SV		SVJL		SVJM		SVJS		SV2F	
	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)	Size (%)	Power (%)
Panel A: ABD										
BV	2.1		1.9	79.6	1.9	62.0	1.8	27.2	19.4	
MedRV	3.9		3.7	81.2	3.7	64.6	3.4	30.6	24.1	
MinRV	5.1		5.0	81.1	5.0	64.7	4.6	30.8	26.8	
Panel B: s-BNS										
BV	1.7		1.6	68.7	1.6	46.2	1.4	13.2	5.8	
MedRV	3.0		3.2	73.0	3.2	52.9	2.9	17.6	7.1	
MinRV	2.4		2.7	66.3	3.1	42.7	2.9	10.6	6.1	
Panel C: BNS										
BV	1.6		1.6	71.4	1.7	50.7	1.6	17.3	5.7	
MedRV	1.3		1.4	73.8	1.4	53.9	1.3	19.8	5.9	
MinRV	0.1		0.1	61.2	0.1	38.1	0.1	8.4	1.3	

References

G. Adams, G. McQueen, and R. Wood. The effects of inflation news on high frequency stock returns. *Journal of Business*, 77(3):547–574, 2002.

T. G. Andersen and T. Bollerslev. Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance*, 4:115–158, 1997.

T. G. Andersen and T. Bollerslev. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, 39(4):885–905, 1998a.

T. G. Andersen and T. Bollerslev. Deutsche mark-dollar volatility Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance*, 53(1):219–265, 1998b.

T. G. Andersen, T. Bollerslev, F. X. Diebold, and P. Labys. Great realisations. *Risk*, 18: 105–108, 2000.

T. G. Andersen, T. Bollerslev, F. X. Diebold, and P. Labys. The distribution of realized exchange rate volatility. *Journal of the American Statistical Association*, 96(453):42–55, 2001.

T. G. Andersen, L. Benzoni, and J. Lund. An empirical investigation of continuous-time equity return models. *Journal of Finance*, 57(3):1239–1284, 2002.

T. G. Andersen, T. Bollerslev, F. X. Diebold, and P. Labys. Modeling and forecasting realized volatility. *Econometrica*, 71:579–625, 2003.

T. G. Andersen, T. Bollerslev, and D. Dobrev. No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. *Journal of Econometrics*, 138(1):125–180, 2007.

T. G. Andersen, T. Bollerslev, and F. X. Diebold. Parametric and nonparametric volatility measurement. In Y. Aït-Sahalia and L. Hansen, editors, *Handbook of Financial Econometrics*, pages 67–139. North-Holland, Amsterdam, 2009a.

T. G. Andersen, D. Dobrev, and E. Schaumburg. Jump robust volatility estimation using nearest neighbour truncation. *Working Paper*, 2009b.

T. G. Andersen, T. Bollerslev, P. H. Frederiksen, and M. Ø. Nielson. Continuous-time models, realized volatilities, and testable distributional implications for daily stock returns. *Journal of Applied Econometrics, volume =*, 2010.

P. Bajgrowicz and O. Scaillet. Jumps in high-frequency data: spurious detections, dynamics, and news. *working Paper*, 2011.

O. E. Barndorff-Nielsen and N. Shephard. Measuring the impact of jumps in multivariate price processes using bipower covariation. *Working Paper, University of Oxford*, 2004b.

O. E. Barndorff-Nielsen and N. Shephard. Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics*, 2(1):1–37, 2004a.

O. E. Barndorff-Nielsen and N. Shephard. Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics*, 4(1):1–30, 2006.

O. E. Barndorff-Nielsen, P. R. Hansen, A. Lunde, and N. Shephard. Realised kernels in practice: Trades and quotes. *Econometrics Journal*, 12(3):1–32, 2009.

T. Bollerslev and V. Todorov. Tails, fears and risk premia. *Working paper*, 2011.

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

T. Bollerslev, V. Todorov, and S. Z. Li. Jump tails, extreme dependencies, and the distribution of stock returns. *Working paper*, 2011.

K. Boudt, C. Croux, and S. Laurent. Robust estimation of intraweek periodicity in volatility and jump detection. *Working Paper*, 2008.

J. H. Boyd, J. Hu, and R. Jagannathan. The stock market's reaction to unemployment news: Why bad news is usually good for stocks. *Journal of Finance*, 60(2):649–672, 2005.

W. H. Chan and J. M. Maheu. Conditional jump dynamics in stock market returns. *Journal of Business & Economic Statistics*, 20(3):377–389, 2002.

M. Chernov, A. R. Gallant, E. Ghysels, and G. Tauchen. Alternative models for stock price dynamics. *Journal of Econometrics*, 116:225–257, 2003.

K. Christensen, R. Oomen, and M. Podolskij. Fact or friction: Jumps at ultra high frequency. *Working Paper*, 2011.

P. Christoffersen, K. Jacobs, and C. Ornthanalai. Exploring time-varying jump intensities: Evidence from S&P 500 returns and options. *Working Paper*, 2008.

H. Chuliá, M. Martens, and D. van Dijk. Asymmetric effects of federal funds target reate changes on s&p100 stock returns, volatilities and correlations. *Journal of Banking and Finance*, 34:834–839, 2010.

J. Conrad, B. Cornell, and W. R. Landsman. When is bad news really bad news? *Journal of Finance*, 57(6):2507–2532, 2002.

F. Corsi, D. Pirino, and R. Renò. Threshold bipower variation and the impact of jumps on volatility forecasting. *Journal of Econometrics*, 159:276–288, 2010.

E. Daal, A. Naka, and J-S. Yu. Volatility clustering, leverage effects, and jump dynamics in the us and emerging asian equity markets. *Journal of Banking & Finance*, 31, 2007.

J-C. Duan, P. Ritchken, and Z. Sun. Approximating garch-jump models, jump-diffusion processes, and option pricing. *Mathematical Finance*, 16(1):21–52, 2006.

A-M Dumitru and G. Urga. Identifying jumps in financial assets: A comparison between nonparametric jump tests. *Working Paper*, 2011.

M. Dungey and L. Hvozdyk. Cojumping: Evidence from the US treasury bond and futures markets. *Working Paper*, 2011.

M. Dungey, M. McKenzie, and V. Smith. Empirical evidence on jumps in the term structure of the US treasury market. *Journal of Empirical Finance*, 16(3):430–445, 2009.

B. Eraker. Do stock prices and volatility jump? reconciling evidence from spot and option prices. *Journal of Finance*, 59(3):1367–1403, 2004.

B. Eraker, M. Johannes, and N. Polson. The impact of jumps in volatility and returns. *Journal of Finance*, 58(3):1269–1300, 2003.

K. P. Evans. Intraday jumps and u.s. macroeconomic news announcements. *forthcoming, Journal of Banking and Finance*, 2011.

F. Gobbi and C. Mancini. Diffusion covariation and co-jumps in bidimensional asset price processes with stochastic volatility and infinite activity lévy jumps. *Working Paper, Universitá di Firenze*, 2007.

P. R. Hansen and A. Lunde. Realized variance and market microstructure noise. *Journal of Business & Economic Statistics*, 24(2):127–161, 2006.

L. Harris. A transaction data study of weekly and intradaily patterns in stock returns. *Journal of Financial Economics*, 16:99–117, 1986.

J. Hasbrouck. The dynamics of discrete bid and ask quotes. *Journal of Finance*, 54(6): 2109–2142, 1999.

X. Huang and G. Tauchen. The relative contribution of jumps to total price variance. *Journal of Financial Econometrics*, 3(4):456–499, 2005.

J. Jacod and T. Todorov. Testing for common arrivals of jumps for discretely observed multidimensional processes. *Annals of Statistics*, 37(4):1792–1838, 2009.

G. J. Jiang and R. C. A. Oomen. A new test for jumps in asset prices. *Journal of Econometrics*, 144(2):352–370, 2008.

G. J. Jiang, I. Lo, and A. Verdelhan. Information shocks, liquidity shocks, jumps, and price discovery: Evidence from the U.S. Treasury market. *Journal of Financial and Quantitative Analysis*, 46:527–511, 2011.

J. Lahaye, S. Laurent, and C. J. Neely. Jumps, cojumps and macro announcements. *Journal of Applied Econometrics, forthcoming*, 2010.

S. S. Lee. Jumps and information flow in financial markets. *Working Paper*, 2009.

S. S. Lee and J. Hannig. Detecting jumps from Lévy jump diffusion processes. *Journal of Financial Economics*, 96(2):271–290, 2010.

S. S. Lee and P. A. Mykland. Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies*, 21(6):2535–2563, 2008.

J. M. Maheu and T. H. McCurdy. New arrival, jump dynamics, and volatility components for individual stock returns. *Journal of Finance*, 59(2):755–793, 2004.

M. McAleer and M. C. Medeiros. Realized volatility: A review. *Econometric Reviews*, 27 (1-3):10–45, 2008.

M. Podolskij and D. Ziggel. New tests for jumps in semimartingale models. *Statistical Inference for Stochastic Processes*, 13(1):15–41, 2010.

M. Schwert. Hop, skip and jump - what are modern "jump" tests finding in stock returns? *Working Paper*, 2011.

S. J. Taylor and X. Xu. The incremental volatility information in one million foreign exchange quotations. *Journal of Empirical Finance*, 4:317–340, 1997.

R A. Wood, T. H. McInish, and J. K. Ord. An investigation of transactions data for nyse stocks. *Journal of Finance*, 40(3):723–739, 1985.