Increased Correlation Among Asset Classes: Are Volatility or Jumps to Blame, or Both?*

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Abstract

We develop estimators and asymptotic theory to decompose the quadratic covariation between two assets into its continuous and jump components, in a manner that is robust to the presence of market microstructure noise. Using high frequency data on different assets classes, we find that the recent financial crisis led to an increase in both the quadratic variations of the assets and their correlations. However, we find little evidence to suggest a change between the relative contributions of the Brownian and jump components, as both comove. Co-jumps stem from surprising news announcements that occur primarily before the opening of the U.S. market, and are also accompanied by an increase in Brownian-driven correlations.

KEYWORDS: Quadratic covariation, continuous and jump components, overnight jumps, news surprises, financial crisis.

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1 Introduction

The recent financial crisis has been accompanied by an across-the-board increase in correlations among asset classes, with obviously unfortunate consequences for portfolio diversification. If we assume that asset prices are represented by semimartingales, there are two possible explanations for this increase: it can be due to an increase in the comovement of the continuous part of the price processes, or to an increase in the comovement of their jumps, or to both together. In times of crisis, one might expect a larger than usual number of information-related shocks to hit all asset classes together, generating jumps that appear nearly simultaneous, and translating mechanically into an increase in realized correlations over the measurement period. Alternatively, one might expect that asset returns exhibit an increased commonality in the common factor sense, which would also translate into an increase in realized correlations, but through the continuous component of the model. The purpose of this paper is to provide methodology and evidence to help distinguish between these two competing, but also possibly complementary, hypotheses. In a portfolio optimization setting, the source of any increased correlation among asset classes, whether continuous or jump-induced, leads to radically different optimal hedging policies (see Aït-Sahalia et al. (2009)), hence the practical interest in the answer to this question.

For this purpose, using high frequency statistics, we decompose the relative contributions of the continuous and discontinuous components of the covariation between two assets’ rates of returns. We establish theoretical asymptotic results that make it possible to separate continuous correlations from co-jumps that are robust to the presence of market microstructure noise in the data. Empirically, we find evidence that the increase in correlation is driven by an increase in the comovements of both components, with the volatility component of prices contributing more to the increase than the co-jumps.

The evidence we provide is compatible with the narrative that has emerged during the
crisis of a “risk-on, risk off” scenario, whereby investors have appeared to alternate between periods where they increase the risk exposure of their portfolios across all asset classes, when the environment is favorable, and periods where they decrease it across-the-board, when the environment turns negative. As these realignments in investment strategy are by nature imperfectly coordinated, the effect from purchases and sales of assets tends to lead to a slow but steady adjustment of prices, over the course of hours or days, rather than to large instantaneous price moves in response to singular news events. High frequency statistics will interpret these price moves, as they should, as volatility-driven rather than jump-driven.

In order to separate the contributions of jumps and volatility to the correlation of asset returns, we therefore need to be able to isolate jumps that happen outside of normal trading hours. Many important macroeconomic news releases or earnings announcements are made outside this period, precisely to mitigate their potential market impact. To the best of our knowledge, prior research employing intraday data focused on jumps occurring during the opening hours of the U.S. market, or aggregated all overnight returns into a single close-to-open return. Using a new 24-hour high-frequency dataset on exchange-traded futures contracts which trade around the clock, we are able to analyze the overnight returns and in particular jumps that occur prior to the spot market opening. We focus on four contracts, representing four asset classes: the S&P 500 eMini futures (as a proxy for U.S. equities), the 10-year Treasury futures (as a proxy for U.S. bonds), crude oil futures (as a proxy for commodities), and the euro/dollar currency futures (as a proxy for foreign currencies). These four contracts are the most actively traded, including outside of normal hours, providing a rich source of data on both trading day and overnight high frequency returns. High frequency overnight data make it possible to identify the immediate market response of a news event, which in fact often leads to a price jump outside of normal trading hours. Empirically, we find that a large proportion of jumps and co-jumps occur at predictable times and that their magnitudes can be explained by the extent of the surprise in scheduled announcements.
relative to the prevailing consensus expectations.

We also find that jumps that occur in the European trading zone before the U.S. market opens tend to have larger magnitudes, except for crude oil. This is potentially due to macroeconomic news announcements which hit the European market prior to the opening of the U.S. market. As to crude oil futures, the most important news relevant to their trading is the crude oil inventory release by the U.S. Energy Information Administration (EIA) on Wednesdays at 10:30 am EST, which explains larger jump magnitudes during U.S. trading hours. Moreover, correlation and volatility are smaller in magnitudes during Asian trading hours, and jumps and co-jumps are fairly rare during this time despite the illiquidity of the market, perhaps reflecting the clearer disconnect between trading activity and news generation between the U.S. and Asian trading hours.

Correlation measurement has attracted attention in the high frequency literature (see Aït-Sahalia and Jacod (2014) for an introduction), with the recent literature focusing on strategies that are robust to microstructure noise and asynchronicity known as the Epps effect, including Hayashi and Yoshida (2005), Aït-Sahalia et al. (2010), Christensen et al. (2010), Zhang (2011), Barndorff-Nielsen et al. (2011), and Bibinger et al. (2014). The presence of price jumps is an accepted fact in the literature.\(^1\) Breaking down the components of the covariation in the presence of price jumps, has not yet been implemented and is the focus of this paper.

The literature has investigated the effect of news announcements, including Andersen

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\(^1\)The literature recognizes that jumps are important sources of risk in asset prices, with evidence on the existence of jumps (see, e.g., the empirical work by Press (1967), Bates (1996), Das (2002), Chernov et al. (2003), Eraker et al. (2003) and Johannes (2004)), the distinction between jumps and volatility (e.g., Aït-Sahalia (2004), Aït-Sahalia and Jacod (2007)), predictive power of jumps (e.g., Tauchen and Zhou (2011)), fear and jump premia (e.g., Todorov (2010), Bollerslev and Todorov (2011)), various methodologies for testing for jumps and co-jumps (e.g., Aït-Sahalia (2002), Huang and Tauchen (2005), Barndorff-Nielsen and Shephard (2006), Lee and Mykland (2008), Jiang and Oomen (2008), Jacod and Todorov (2009), Aït-Sahalia and Jacod (2009), and Jacod and Todorov (2010)), and jump robust inference (e.g., Jacod et al. (2010) and Aït-Sahalia et al. (2012)). Christensen et al. (2011) discuss jumps at ultra high frequency. Bajgrowicz et al. (2014) discuss the multiple testing problem for jump identification.
et al. (2003), Piazzesi (2005), Beechey and Wright (2009), and Faust and Wright (2009), which mainly focus on asset returns and macroeconomic news announcements without focusing on decomposing asset returns. By contrast, this paper is interested in distinguishing between volatility, jumps and co-jumps contribution to asset return risk. Lee (2012) investigates the role of macroeconomic announcements on jumps in individual equities between opening hours.

The effect of policy uncertainty on stock returns and risk premia has been investigated in, e.g., Bernanke and Kuttner (2005), Boutchkova et al. (2012), Pastor and Veronesi (2013), Lucca and Moench (2015). In particular, Bernanke and Kuttner (2005) study stock market reactions to Federal Reserve policy and find that the effects of unanticipated monetary policy actions on expected excess returns account for the largest part of the responses of stock prices. In this paper, we study the informational content of jumps and co-jumps, and point out that they often occur in response to the resolution of policy uncertainty, which affect the prices of different asset classes. We find that while these large shocks affect asset correlations immediately, the persistence of correlation is largely contributed by Brownian shocks, which accumulate at a much slower speed.

The paper is organized as follows. Section 2 develops the statistical theory. Section 3 provides simulation results. Section 4 summarizes the empirical findings. Section 5 concludes. The appendix contains the mathematical proofs.
2 Statistical Theory

2.1 Model Setup and Assumptions

We assume that asset log-prices form a \(d\)-dimensional Itô semimartingale, defined on a filtered space \((\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})\) with the following representation:

\[ X_t = X_0 + \int_0^t b_s ds + \int_0^t \sigma_s dW_s + (\delta 1_{\|\delta\| \leq 1}) \ast (\mu - \nu)_t + (\delta 1_{\|\delta\| > 1}) \ast \mu_t, \quad (1) \]

where \(W\) is a \(d'\)-dimensional Brownian motion and \(\mu\) is a Poisson random measure on \(\mathbb{R}_+ \times \mathbb{R}^d\), with the compensator \(\nu(dt, dx) = dt \otimes \lambda(dx)\), and \(\lambda\) is a \(\sigma\)-finite measure.\(^2\) We further assume:

**Assumption 1.** The drift term \(b_t\) is a \(d\)-dimensional progressively measurable and locally bounded process, and the \(d \times d'\) process \(\sigma_t\) is càdlàg. Moreover, for any \(r \in [0, 1)\), there is a sequence of stopping times \((\tau_n)\) increasing to \(\infty\), and deterministic function \(\gamma_n\) such that

\[ \int_{\mathbb{R}^d} \gamma_n(x)^r \lambda(dx) < \infty \quad \text{and that} \quad \|\delta(\omega, t, x)\| \wedge 1 \leq \gamma_n(x), \quad \text{for all} \ (\omega, t, x) \ \text{with} \ t \leq \tau_n(\omega). \]

In reality, market microstructure noise becomes relevant in asset returns data typically when the sampling interval is below one minute for relatively liquid assets. Using higher frequency data helps improve the efficiency of the estimation. Moreover, jumps become difficult to identify with data sampled too sparsely. For relatively illiquid assets, the noise may matter even for returns sampled every 15 minutes. As a result, the standard realized variance/covariance estimators may become infeasible, and even the standard noise correction approaches, such as subsampling, pre-averaging or various forms of kernel-based averaging, may run into difficulties due to insufficient data to implement them. We model the microstructure noise so as to make use of the entire data. Instead of the efficient price, we...\(^2\)

\(^2\)Throughout the paper, \(\|\cdot\|\) denotes the Euclidean norm. Since we focus on the finite dimensional setting in this paper, all matrix norms are equivalent. We refer to Wang and Zou (2010), Fan et al. (2015), and Aït-Sahalia and Xiu (2015) for studies of high frequency covariance matrices in a diverging dimensionality setting.
Assumption 2. The observed process, polluted by noise, is given by\( Z_t = X_t + \varepsilon_t \). We model the microstructure noise \( \varepsilon_t \) as, conditionally on the whole process \( X \), a family of independent, centered random variables. The conditional second moments of the noise process are denoted as \( \gamma^{ij}_t = E(\varepsilon^i_t \varepsilon^j_t | \mathcal{F}_t) \), which are càdlàg. For each \( q > 0 \), \( E(\|\varepsilon_t\|^q | \mathcal{F}_t) \) is locally bounded.

The “parameters” of interest in this paper are the quadratic covariation of the process \( X \), denoted as \( [X, X]_t \), and its continuous and discontinuous components, namely the first and second terms on the right hand side of

\[
[X, X]_t = [X, X]^c_t + [X, X]^d_t. \tag{2}
\]

With \( c_s = (\sigma \sigma^\top)_s \) where \( ^\top \) denotes transposition, the continuous part of the quadratic covariation is \( [X, X]^c_t = \int_0^t c_s ds \). The jump part, if written explicitly, is \( \sum_{s \leq t} \Delta X_s \Delta X^\top_s \), where \( \Delta X_s \) denotes the jump of \( X \) at time \( s \) (if any).

Using these quantities, we can define two correlation measures, which highlight the continuous and discontinuous contributions respectively:

\[
\text{Corr}_c(X^l, X^m) = \frac{[X^l, X^m]^c}{\sqrt{[X^l, X^l]} \sqrt{[X^m, X^m]}} \quad \text{and} \quad \text{Corr}_d(X^l, X^m) = \frac{[X^l, X^m]^d}{\sqrt{[X^l, X^l]} \sqrt{[X^m, X^m]}}.
\]

When \( X \) is a 1-dimensional process, these measures reduce to

\[
R_c(X, X) = \frac{[X, X]^c}{[X, X]} \quad \text{and} \quad R_d(X, X) = \frac{[X, X]^d}{[X, X]},
\]

which decompose the relative importance of the jumps and continuous part to the quadratic variation.

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\(^3\)For more details on the structure of the filtered probability space on which \( \varepsilon \) and \( X \) are defined, see Section 16.1.1. in Jacod and Protter (2011).
2.2 Estimation and Asymptotic Theory

We now discuss the estimation of \([X, X]\) and its components with intraday data sampled on \([0, t]\) at equal intervals of length \(\Delta_n\), that is at times \(i\Delta_n\) for \(i = 0, \ldots, [t/\Delta_n]\). We choose a sequence \(k_n\) of integers, which satisfies \(k_n\Delta_n^{1/2} = \theta + o(\Delta_n^{1/4})\), for some \(\theta > 0\), and a non-zero real-valued function \(g : \mathbb{R} \to \mathbb{R}\), supported on \([0, 1]\), which is continuous and piecewise \(C^1\) with a piecewise Lipschitz derivative \(g'\) and \(g(0) = g(1) = 0\), and \(\Lambda = \int_0^1 g(s)^2 ds > 0\). Set \(u_n = k_n\Delta_n\). Define the truncation level as

\[
v_n = \alpha u_n^{\omega}, \text{ for some } \alpha > 0, \omega \in \left(0, \frac{1}{2}\right).
\]

Then, for \(l, m = 1, 2, \ldots, d\), we construct the truncated pre-averaging estimators of the covariances between asset \(l\) and asset \(m\), as

\[
[Z^l, Z^m]_t = \frac{1}{k_n\Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} \left( \bar{Z}(g)_i^{n,l} \bar{Z}(g)_i^{n,m} - \frac{1}{2} \hat{Z}(g)_i^{n,lm} \right),
\]

\[
[Z^l, Z^m]_t = \frac{1}{k_n\Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} \left( \bar{Z}(g)_i^{n,l} \bar{Z}(g)_i^{n,m} - \frac{1}{2} \hat{Z}(g)_i^{n,lm} \right) 1\{\|\bar{Z}(g)_i^n\| \leq v_n\},
\]

where, writing \(\Delta^n Z^l = Z^l_{(i+1)\Delta_n} - Z^l_{i\Delta_n}\),

\[
\bar{Z}(g)_i^{n,l} = \sum_{j=1}^{k_n-1} g \left( \frac{j}{k_n} \right) \Delta_i^{n}\Delta^l, \quad \hat{Z}(g)_i^{n,lm} = \sum_{j=1}^{k_n} \left( g \left( \frac{j}{k_n} \right) - g \left( \frac{j-1}{k_n} \right) \right) 2 \Delta_i^{n}\Delta^l \Delta^m.
\]

We can also estimate \(\int_0^t \gamma_s^{lm} ds\), using

\[
\frac{\theta^2}{2k_n\Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} \bar{Z}(g)_i^{n,lm} 1\{\|\bar{Z}(g)_i^n\| \leq v_n\}.
\]
These estimators are natural extensions of Jacod et al. (2009), Christensen et al. (2010) and Hautsch and Podolskij (2010) to the case at hand. To state the asymptotic results, we need more notations. We set for $x, y \in \mathbb{R}^+$,

$$R(x, y, \tilde{x}, \tilde{y}) = 2\theta^{-3}\Lambda^{-2}\int_0^1 \left( x \int_s^1 g(u)g(u - s)du + y \int_s^1 g'(u)g'(u - s)du \right) \times \left( \tilde{x} \int_s^1 g(u)g(u - s)du + \tilde{y} \int_s^1 g'(u)g'(u - s)du \right) ds.$$ 

In addition, we define

$$\Psi_+ = \int_0^1 \left( \int_t^1 g(s)g(s + t)ds \right)^2 dt, \quad \Psi_- = \int_0^1 \left( \int_0^{1-t} g(s)g(s - t)ds \right)^2 dt,$$

$$\Psi'_+ = \int_0^1 \left( \int_t^1 g(s)g'(s + t)ds \right)^2 dt, \quad \Psi'_- = \int_0^1 \left( \int_0^{1-t} g(s)g'(s - t)ds \right)^2 dt.$$ 

We now present asymptotic results for the truncated pre-averaging estimator:

**Theorem 1.** Suppose $1/(4 - 2r) \leq \varpi < 1/2$. Under Assumptions 1 and 2, we have for estimators (4) and (5) the following central limit theorem:

$$\Delta_n^{-1/4} \begin{pmatrix} [\widehat{Z}, Z]_t - [X, X]_t^c \\ [Z, Z]_t - [X, X]_t \end{pmatrix} \overset{L}{\rightarrow} \begin{pmatrix} \widehat{W}_t \\ \widehat{W}_t + \tilde{Z}_t \end{pmatrix},$$

where $\widehat{W}$ is a continuous process defined on an extension of the original probability space, which conditionally on $\mathcal{F}$, is continuous centered Gaussian martingale with covariance given by

$$\mathbb{E}(\widehat{W}^i_t\widehat{W}^j_t|\mathcal{F}) = \int_0^t R(\theta^2 c_s^{ik}, \gamma_s^{ik}, \theta^2 c_s^{jl}, \gamma_s^{jl}) + R(\theta^2 c_s^{il}, \gamma_s^{il}, \theta^2 c_s^{jk}, \gamma_s^{jk}) ds,$$

$\tilde{Z}$ is a purely discontinuous square-integrable Gaussian martingale with independent incre-
ments, zero mean and covariance given by

\[
\mathbb{E}(\tilde{Z}^{i}_{t} \tilde{Z}^{k}_{t} | \mathcal{F}) = \Lambda^{-2} \left( \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} \left( \theta c_{s}^{ij} \Psi_{-} + \theta c_{s}^{jk} \Psi_{+} + \frac{\gamma_{s}^{jl}}{\theta} \Psi_{-} + \frac{\gamma_{s}^{kj}}{\theta} \Psi_{+} \right) \right.
\]
\[
+ \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{j} \left( \theta c_{s}^{ik} \Psi_{-} + \theta c_{s}^{lk} \Psi_{+} + \frac{\gamma_{s}^{jl}}{\theta} \Psi_{-} + \frac{\gamma_{s}^{ik}}{\theta} \Psi_{+} \right) \]
\[
+ \sum_{s \leq t} \Delta X_{s}^{j} \Delta X_{s}^{k} \left( \theta c_{s}^{ik} \Psi_{-} + \theta c_{s}^{lk} \Psi_{+} + \frac{\gamma_{s}^{il}}{\theta} \Psi_{-} + \frac{\gamma_{s}^{jl}}{\theta} \Psi_{+} \right) \]
\[
+ \sum_{s \leq t} \Delta X_{s}^{j} \Delta X_{s}^{l} \left( \theta c_{s}^{ik} \Psi_{-} + \theta c_{s}^{lk} \Psi_{+} + \frac{\gamma_{s}^{il}}{\theta} \Psi_{-} + \frac{\gamma_{s}^{ij}}{\theta} \Psi_{+} \right) \right)
\]

and \(\tilde{W}\) and \(\tilde{Z}\) are independent.

To estimate the asymptotic covariance matrix and build feasible confidence intervals, we construct estimators for

\[
\int_{0}^{t} c_{s}^{ik} c_{s}^{jl} ds, \quad \int_{0}^{t} c_{s}^{ij} \gamma_{s}^{jl} ds, \quad \int_{0}^{t} \gamma_{s}^{ik} \gamma_{s}^{jl} ds, \quad \text{and}
\]
\[
\sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} c_{s}^{jl}, \quad \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} c_{s}^{jl}, \quad \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} \gamma_{s}^{jl}, \quad \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} \gamma_{s}^{jl}.
\]

They can be constructed as,

\[
\frac{\theta^2}{2k_{n}^{2} \Lambda \Lambda_{n}} \sum_{m=1}^{[t/\Delta_{n}]-k_{n}} \tilde{Z}(g)_{m}^{n,i} \tilde{Z}(g)_{m}^{n,k} \tilde{Z}(g)_{m}^{n,jl} = \frac{1}{2} \tilde{Z}(g)_{m}^{n,jl} \rightarrow P \int_{0}^{t} c_{s}^{ik} \gamma_{s}^{jl} ds,
\]
\[
\frac{\theta^4}{4k_{n}^{2} \Lambda^2 \Delta_{n}} \sum_{m=1}^{[t/\Delta_{n}]-k_{n}} \tilde{Z}(g)_{m}^{n,ik} \tilde{Z}(g)_{m}^{n,jl} \rightarrow P \int_{0}^{t} \gamma_{s}^{ik} \gamma_{s}^{jl} ds,
\]
\[
\frac{1}{k_{n} \Lambda} \sum_{m=k_{n}+1}^{[t/\Delta_{n}]-k_{n}} \tilde{Z}(g)_{m}^{n,i} \tilde{Z}(g)_{m}^{n,k} \cdot 1 \{ ||\tilde{Z}(g)_{m}^{n}|| > \nu_{n} \} \tilde{g}_{m,k}^{jl} \rightarrow P \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} c_{s}^{jl},
\]
\[
\frac{1}{k_{n} \Lambda} \sum_{m=k_{n}+k_{n}+1}^{[t/\Delta_{n}]-k_{n}} \tilde{Z}(g)_{m}^{n,i} \tilde{Z}(g)_{m}^{n,k} \cdot 1 \{ ||\tilde{Z}(g)_{m}^{n}|| > \nu_{n} \} \tilde{g}_{m-k_{n}}^{jl} \rightarrow P \sum_{s \leq t} \Delta X_{s}^{i} \Delta X_{s}^{k} \gamma_{s}^{jl},
\]
where $k_n \Delta_n \to 0$, and $k_n \Delta_n^{1/2} \to \theta$, for some $\theta > 0$, $k'_n/k_n \to \infty$, and $k_n \Delta_n \to 0$, writing $\Lambda' = \int_0^1 g'(s)^2 ds$, 

$$c_i^{jl} = \frac{1}{k_n \Delta_n} \sum_{m=1}^{k_n'} \left( Z(g)_{i+m}^n Z(g)_{i+m}^n - \frac{1}{2} \hat{Z}(g)_{i+m}^n \right) \cdot 1\{\|Z(g)_{i+m}^n\| \leq v_n\},$$

$$\tilde{\gamma}_i^{jl} = \frac{\theta^2}{2k_n \Delta_n} \sum_{m=1}^{k_n'} \hat{Z}(g)_{i+m}^n.$$

Finally, we have, with $k_n$ replaced by $k'_n$ in $\hat{Z}(g)$ and $\hat{Z}(g)$:

$$\frac{1}{k_n^2 \Delta_n^2} \sum_{m=1}^{[t/\Delta_n]-k'_n+1} \hat{Z}(g)_m^n \hat{Z}(g)_{m+k'_n}^n \hat{Z}(g)_{m+k'_n}^n \hat{Z}(g)_{m+k'_n}^n \cdot 1\{\|\hat{Z}(g)_m^n\| \leq v_n, \|Z(g)_{m+k'_n}^n\| \leq v_n\} \xrightarrow{P} \int_0^t c_s^i c_s^{jl} ds.$$

They will be proved by extending Theorem 16.4.2, Theorem 16.5.1 and Theorem 16.5.4 in Jacod and Protter (2011) to the multivariate case. These results hold for a general function $g(\cdot)$. Throughout the simulation and the empirical study, we choose $g(x) = \min(x, 1-x)$, as suggested by Jacod et al. (2009).

In the presence of asynchronous observations, we adopt the previous-tick sampling approach, as discussed in Aït-Sahalia et al. (2010) and Zhang (2011). But given the liquidity and sampling frequency considered in this paper (1 minute and below), we can safely ignore the effect of asynchronicity even in finite sample. In the presence of microstructure noise, Bibinger et al. (2014) also point out that the effect of asynchronicity is generally asymptotically negligible.

For clarity of exposition, we use $v_n$ as the threshold for the Euclidean norm of the return vector in order to separate jumps from the continuous component. We can also choose a set of different truncation level parameters $\{\alpha_j, \varpi_j\}$ for each of its component. This will not alter the asymptotic theory of the proposed estimators, yet typically provide better finite
sample performance.

To implement the estimator in practice, we need to settle on the values of tuning parameters. We fix $\varpi_j = 0.47$, so that only $\alpha_j$ needs to be determined. As suggested by the literature, see, e.g., Aït-Sahalia and Jacod (2014), we set $\alpha_0$ to be some number between 2 and 4. We choose $\alpha_j = \alpha_0 \sqrt{\frac{1}{t} \int_0^t c_{jj}^j ds \cdot \Lambda + \frac{1}{t^2} \int_0^t \gamma_{jj}^j ds \cdot \Lambda'}$, because in the absence of jumps, $\tilde{Z}(g)^n_i \sim N(0, (\Lambda c_{jj}^j + \theta^{-2} \Lambda' \gamma_{jj}^j)n^{1/2})$. As to the local window size, $k_n$, the rule of thumb is to select a variety of $k_n$s and find a range of them to which the estimates are insensitive. For daily data sampled every minute, it is typical to choose a local window of size ranging from 20 minutes to an hour or so, i.e., $k_n$ ranges from 20 to 60. We fix $k_n$ at 40 in our empirical analysis.4

3 Simulation Results

We now examine the performance of the proposed estimators in Monte Carlo experiments. We simulate a stochastic volatility model for each individual asset $i$, $i = 1, 2$:

$$dX_{i,t} = \sigma_{i,t}dW_{i,t} + dY_{i,t},$$

where the volatility process follows the dynamics

$$d\sigma_{i,t}^2 = \chi_i(\eta_i - \sigma_{i,t}^2)dt + \xi_i\sigma_{i,t}dB_{i,t} + dJ_{i,t} - \lambda_i\tau_i dt,$$

and $\mathbb{E}(dW_{1,t}dB_{1,t}) = \rho_1 dt$, $\mathbb{E}(dW_{2,t}dB_{2,t}) = \rho_2 dt$, $\mathbb{E}(dW_{1,t}dW_{2,t}) = \rho_B dt$. $J_{i,t}$ is a Poisson process with jump size uniformly distributed on $[0, 2\tau_i]$ and jump intensity $\lambda_i$. To generate

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4It is worth mentioning that almost all noise-robust nonparametric estimators in this setting require a tuning parameter, e.g., the bandwidth in the realized kernel estimator (Barndorff-Nielsen et al. (2008)), the subsample sizes of the two-scales realized volatility estimator (Zhang et al. (2005), Zhang (2011)), etc, except for the quasi-maximum likelihood estimator (Aït-Sahalia et al. (2005), Xiu (2010), Aït-Sahalia et al. (2010), Shephard and Xiu (2012)).
co-jumps in both asset returns, we first simulate $Y_1$ and $Y_0$, which are tempered-stable processes (or CGMY processes) with Lévy measure given by:

$$
\nu_i(x) = \frac{c_i}{|x|^{1+\beta_i}} e^{-\gamma_i-|x|} 1_{\{x<0\}} + \frac{c_i}{x^{1+\beta_i}} e^{-\gamma_i+x} 1_{\{x>0\}}, \quad i = 0, 1,
$$

where $\beta_0, \beta_1 \in (0, 1)$ to ensure finite variation. We set $Y_2 = \rho_YY_1 + \sqrt{1-\rho^2}Y_0$, which leads to co-jumps between $Y_1$ and $Y_2$. We fix $\chi_1 = 5$, $\chi_2 = 4$, $\xi_1 = 0.3$, $\xi_2 = 0.4$, $\eta_1 = 0.25^2$, $\eta_2 = 0.3^2$, $\rho_1 = -0.5$, $\rho_2 = -0.75$, $\tau_1 = 0.05$, $\tau_2 = 0.1$, $\lambda_1 = 5$, $\lambda_2 = 10$, $\gamma_{i+} = 3$, $\gamma_{i-} = 5$, $\rho_B = 0.6$, and $\rho_J = 0.2$.

We pollute the prices by Gaussian microstructure noise $\varepsilon_t$ with standard deviation 0.005 plus rounding level at 1 cent. The sampling frequency is set at $\Delta = 5$ seconds with $T = 1$ day. We estimate the quadratic covariation and its Brownian part between $X_1$ and $X_2$ using the pre-averaging estimator. $\beta_1$ is fixed at 0.5, and $c_1$ is calibrated such that the quadratic variation contributed by jumps in $X_1$ amounts to 15% of the total quadratic variation. $\beta_0$ is selected among 0.25, 0.50, and 0.75. For each $\beta_0$, $c_0$ is calibrated such that the percentages of quadratic variation contributed by jumps in $X_2$ are 5%, 10%, 15%, and 20% respectively. We also consider Poisson jumps, for which the jump size is fixed to be 0.10, and we calibrate the intensity parameter to match the desired percentages of the quadratic variation. The number of Monte Carlo simulations is 1000.

The simulation results are provided in Table 1, in which we report the sample mean and sample standard deviations of $([\widehat{Z}_1, \widehat{Z}_2]_t - [X_1, X_2]_t)/(\text{Avar}([\widehat{Z}_1, \widehat{Z}_2]_t))^{1/2}$ and $([\widehat{Z}_1, \widehat{Z}_2]_t - [X_1, X_2]_t)/(\text{Avar}([\widehat{Z}_1, \widehat{Z}_2]_t))^{1/2}$. We report results based on 3 different values of $k_n$s, 20, 40, and 60, where asymptotic variances are estimated using $k'_n = 3k_n$. All numbers in the table are close to the desired quantities, which verifies Theorem 1 as well as our asymptotic variance estimators. Figure 1 compares the finite sample distribution of the standardized residuals with respect to the continuous components with the standard normal density. The
results show that the finite sample performance is fairly acceptable.

4 Empirical Results

4.1 Data

We now provide evidence on the breakdown of the correlation between asset returns using a diverse panel of futures contracts. High-frequency front-month futures contract prices are obtained from Tick Data Inc., including futures on the eMini-S&P 500 (ES), Crude Oil (CL), Euro/USD FX (EC), and 10-Year Treasury Notes (TY), from January 1 2007 to July 31 2012. During this period, NYMEX and CBOT products are listed on CME Globex, and the electronic Globex volume tends to dominate the pit market’s volume. All contracts are available on a nearly 24-hour schedule via CME Globex. To avoid the potential issue of different market microstructure in the electronic and pit markets, we conduct the analysis using transaction prices from the electronic markets alone.

Trading on the CME Globex platform is generally available Sunday evening through late Friday afternoon with one-hour breaks in between everyday. To mitigate the effect of asynchronicity, we sample each day 1-minute returns from 6:00 p.m. EST the previous day until 5:00 p.m. the next. As is evident from Figure 2 and Table 3, trading volumes for the selected CME products between 3:00 a.m. EST and 5:00 p.m. EST are considerably higher than during the remaining hours when both the European market and U.S. live markets are closed. Also, it is clear that the robustness to microstructure noise is necessary if we use 1-minute returns across the globe. Tick data Inc. computes rolled-over front contracts. The roll-over dates will not affect the results much, as contracts are not rolled-over in the middle

6The roll-over rule for each future contract under consideration can be found on the Tick data Inc.’s website: http://www.tickdata.com/support/futures-data-support/roll-dates/.
of the day, and roll-over returns are eliminated from our analysis.

To understand how jumps are related to news impact, we collect from Bloomberg, Inc., survey data regarding economists’ expectations for 25 influential economic indicators. We then proxy for news shocks or surprises by computing the scaled difference between the actual release and the survey expectations:

\[
\text{News Shock} = \frac{\text{Announced Quantity}_t - \text{Median of Expectations}}{\text{Maximum of Expectations} - \text{Minimum of Expectations}}.
\]  

(6)

We scale the difference by the range of expectations as a proxy for the extent of the disagreement among professional forecasters’ views. Ideally, the standard error would be a better measure than the range, but such data is unfortunately unavailable. Using the range compresses our measurement of news surprises, potentially weakening their effect as explanatory variables. For Federal Open Market Committee (FOMC) and European Central Bank (ECB) meetings, since the target rate rarely changes, and it is the statement from the press release that moves the market, we follow Faust and Wright (2009) and simply construct dummy variables using the pre-announced schedule of meetings.

While most macro announcements occur prior to the opening of the U.S. market, there are two important ones announced within the U.S. trading hours. The FOMC press release is one of them. The other one is the weekly report of crude oil inventory, which is published weekly on Wednesdays around 10:30 a.m. EST by the U.S. Energy Information Administration (EIA). It is considered the most influential announcement in the crude oil futures market.

4.2 Quadratic Variations

We first decompose the quadratic variations of individual future contracts into their continuous and jumps components using the pre-averaging estimators with 1-minute returns on a day-by-day basis. On the top panels of Figures 3 - 6, we plot the time series of the annualized
daily realized volatility, i.e., square roots of the quadratic variation. The percentages due
to the jump component are provided on the top right panels. Interestingly, the percentage
of jump variations does not show a large increase during the crisis period. In contrast with
the results of Santa-Clara and Yan (2010), who find that jumps contribute the major part of
asset price variability during the crisis based on daily data, we find that jumps are not the
dominant effect during the crisis. Large returns are definitely more common during the crisis
than during a normal period, but as volatility is significantly higher too, it means that not
all such returns are due to jumps. The decomposition shows an increase in both Brownian
and jump quadratic variations, with the split between the two remaining surprisingly fairly
stable overall. Asset returns during the crisis evolved like a slow train wreck, rather than a
succession of large disruptions.

We find that jumps are more frequent (measured by the number of days with jumps) but
smaller in relative magnitude on average (measured by the average percentage variations by
jumps in the total variation of the day) during U.S. trading hours than during Europe trading
hours, as shown in the bottom panels of Figures 3 - 6 and Table 3, except that jumps in
crude oil futures have larger magnitudes during the U.S. trading hours. The few jumps that
happen during the European trading hours tend to be large. This is not surprising as the
trading activity in Europe is not as high as in the U.S., yet most macro news announcements
relevant to the ES, EC, and TY futures markets usually occur during the European trading
hours, hence large and infrequent jumps therein are more likely due to the joint effect of
surprising news and illiquidity. As to crude oil, the most important news are regularly
released by the EIA during the U.S. trading hours, leading to larger jump sizes.

These findings fill a gap in the existing literature, in which most jump detection focus
on intraday U.S. returns, without overnight returns. While the Asian trading hours are
relatively quiet with few jumps, trading picks up over the 24-hour day and jumps occur once
European traders are active. Perhaps the most important price discovery occurs right before
the opening of U.S. market, when macro indicators are scheduled to be announced. It is
plausible to expect that jumps during the European and U.S. hours will be highly correlated
with the surprise component of macroeconomic news defined in (6). To look into this, we
regress the part of the quadratic variation due to jumps during the Europe and U.S. trading
hours on the news surprises constructed from the survey data, controlling the continuous
component:

\[ [X, X]_t^d = \alpha + \beta [X, X]_t^c + \sum_{i=1}^{N} \beta_i \cdot |s_{i,t}| + \varepsilon_t, \]

(7)

where \( s_{i,t} \) is the shock defined in (6) for the news \( i \) on day \( t \). If there is no news \( i \) on day \( t \),
\( s_{i,t} = 0 \). The regression results are provided in Table 4.

Not surprisingly, important sources of jumps are the arrival of news surprises. Among
these macro announcements, the news about changes in non-farm payrolls is very influential
to all futures contracts under consideration. These news surprises inevitably contribute to
large overnight returns, which would be otherwise unobservable without 24-hour markets.
The FOMC announcements also have an overwhelming effect on equity and foreign exchange
markets, in addition to the U.S. treasury market. By contrast, unexpected inventory changes
in crude oil affect its future prices dramatically, but the instantaneous spillover effect to other
markets is not as evident.

4.3 Correlations

Next, we further decompose the correlations between the S&P 500 and the other three futures
contracts into their continuous (Corr\(_c\)) and discontinuous (Corr\(_d\)) components in Figures 7,
8, and 9, respectively. These correlations are time-varying over the 2007-2012 period, and
tend to increase in magnitude over the period, consistently with an overall reduction in
diversification benefits. The Brownian correlation (Corr\(_c\)) between the S&P 500 and crude
oil futures shares the same pattern as that between the S&P 500 and euro/dollar futures,
whereas the Brownian correlation between the S&P 500 and U.S. Treasuries is different, consistent with the role of U.S. Treasuries as a safe asset in a crisis.

The correlations contributed by both Brownian motions and co-jumps differ across the pairs. However, for each pair, there is a consistent pattern between the continuous and jumps parts of the correlation. The Brownian correlation between the S&P 500 and crude oil futures switches sign rapidly in the middle of the crisis, right after Lehman Brothers’ September 2008 bankruptcy, and then switches again to a positive and increasing value, reaching levels that are unusually high by historical standards. The overall correlation is mainly driven by Brownian shocks during the crisis, since there are fewer co-jumps between S&P 500 and crude oil during this period. However, post crisis, we find many co-jumps between the S&P 500 and crude oil, which tend to be almost all positive. Co-jumps have a large impact on the correlations with the other two pairs, currencies and Treasuries before, during, and after the crisis. In particular, the vast majority of co-jumps between the S&P 500 and Treasuries after the beginning of 2007 are of opposite signs. As shown from Figures 8 and 9, the magnitudes of correlations driven by Brownian shocks and co-jumps are of the same order, even though the Brownian correlations are highly persistent and co-jumps are fairly infrequent.

These findings agree with the narrative of a “risk-on, risk-off” environment during and immediately after the crisis. At the beginning of the financial crisis, commodities appeared to be a relatively safe hedge against the stock market downturn, resulting in the returns of the two markets being negatively correlated. Shortly after the collapse of Lehman Brothers, during the heightened phase of the crisis, investors switched to a “risk-off” strategy, which initiated a global sell-off across-the-board. As a result, the equity, commodity, and foreign exchange markets started to comove, leading to an increasingly positive correlation among their asset returns although more in the form of an increased correlation of their Brownian components than of their jump components. On the other hand, U.S. Treasuries
retained and in fact increased their position as a safe heaven (similar to German government bonds) in what was effectively a “flight-to-quality” environment. Most other asset classes dropped in value. Therefore, the correlation between many asset classes including equities and Treasuries remained or became increasingly negative. The magnitude of this correlation started to increase (negatively) as early as February 2007, when the Federal Home Loan Mortgage Corporation (Freddie Mac) announced that it would no longer buy the most risky subprime mortgages and mortgage-related securities, which was one of the earliest signals of the impending financial crisis.

As for the value of correlation between U.S. equities and the U.S. dollar, positive returns on the euro-dollar currency futures mean that the U.S. dollar loses value. During the crisis, the correlation turned negative, as the U.S. dollar shifted to a reserve currency role subject to large foreign demand (Japanese yen did as well) despite the heavy losses in U.S. equities and the risks in the U.S. banking sector. During the acute phase of the crisis in 2008-09, most co-jumps are negative. Equities and exchange rate co-jumps during the second part of the crisis (2009-10) were primarily positive. Immediately post-crisis, the Brownian correlation rapidly shifted to a positive value, consistent with S&P 500 stocks foreign profits, hence earnings per share and stock prices, benefitting from a weaker U.S. dollar. Co-jumps tend to be either of the same sign or of opposite sign, consistent with variations in the direction of the Brownian correlation: positive (resp. negative) co-jumps accompanied by an increase (resp. decrease) in Brownian correlation.

Moreover, we find from Figures 7 - 9 that the continuous correlations during the Asian trading hours are much smaller in magnitude than those during the European and U.S. trading hours. Co-jumps are rare during the Asian trading hours, whereas they occur more often during both European and U.S. trading hours. For Treasury and foreign exchange futures, we observe many co-jumps, due to surprising macro announcements that affect both U.S. stocks, U.S. bonds (as a safe asset) and the value of the U.S. dollar (as a reserve
currency) simultaneously. Most co-jumps between the S&P 500 and U.S. Treasuries are of opposite sign. FOMC meetings contribute several co-jumps for U.S. Treasuries and equities during U.S. trading hours.

To relate news surprises to co-jumps, we run the following regression:

\[
[X_1, X_2]_t^d = \alpha + \beta [X_1, X_2]_t^c + \sum_{i=1}^{N} \beta_i \cdot |s_{i,t}| + \varepsilon_t. \tag{8}
\]

The results are provided in Table 5. We find that, even after controlling for the continuous covariation, the co-jumps among equities, Treasuries, and euro/dollar futures are mainly driven by surprising news on employment, consumer price index, and FOMC statements. These are indeed the key economic indicators that affect both monetary and fiscal policies, as well as the other policy responses to address the crisis.

We further investigate the co-jumps that occurred between December 2007 and June 2009, i.e., during the recession period as determined by the National Bureau of Economic Research (NBER), to identify the particular news that may lead to each individual co-jumps. As shown in Table 6, all the identified co-jumps within this period are related to either monetary policy announcements after FOMC meetings or to the surprising macro indicators. It is perhaps worth emphasizing that many of these co-jumps are driven by housing sector related news, although the selected housing-related covariates are not significant across-the-board.

\section{Conclusions}

We develop methodologies to decompose the quadratic covariation of two assets between continuous and discontinuous components. The methods we employ are robust to the presence of market microstructure noise in the data. Analyzing high frequency futures returns on a 24-hour clock, we document that the crisis period of 2007-2010 did indeed result in an
increase in quadratic variation in all the assets we considered, and overall in the covariation between the S&P 500, crude oil, euro/dollar exchange rate and U.S. Treasuries. However, it did not lead to a significant change in the breakdown between their respective Brownian and jump contributions, with both moving consistently with one another. Finally, we document that jumps and co-jumps rarely occur overnight despite the relative illiquidity of the market; rather, most of them are driven by the surprise component in macroeconomic news that are typically announced prior to the opening of U.S. markets, when price discovery occurs and information is incorporated into prices. Overall, the empirical results lend support to the view of the crisis as an across-the-board increase in the commonality of asset returns as much as if not more than as a sequence of nearly instantaneous co-jumps.
References


Appendix A  Proof of Theorem 1

The proof of the multivariate CLT for the quadratic variation is similar to the one-dimensional case given by Theorem 16.6.2 in Jacod and Protter (2011) and Jacod et al. (2010). Then, to obtain the joint convergence between the continuous part and the entire quadratic variation estimator, we need to prove that

$$\Delta_n^{-1/4} \left( \left[ \overline{Z}^i, \overline{Z}^j \right]_t - \left[ \overline{Z}^i, \overline{Z}^j \right]_t^c \right) \to P 0,$$

where $Z' = X' + \varepsilon$, and $X'$ denotes the continuous part of $X$ process, and $X'' = X - X'$. Using the standard localization argument, we can assume that for some constant $A$ and nonnegative deterministic function $\gamma$, we have

$$\|b_t(\omega)\| \leq K, \|\sigma_t(\omega)\| \leq K, \|X_t(\omega)\| \leq K, \|\delta(\omega, t, x)\| \leq \gamma(x) \leq K, \int_{\mathbb{R}^d} \gamma(x)^r \lambda(dx) \leq K.$$

Write $F_u(x) = F(x)1(\|x\| \leq u)$, for some $u > 0$, where $F(x)^{jk} = x^j x^k$. Define

$$\eta^n_i = F_{v_n/\sqrt{u_n}}(\overline{Z}_i^n) - F_{v_n/\sqrt{u_n}}(\overline{Z}_i^n).$$

Hereafter we ignore the dependence of $Z(g)^n_i$ and $\hat{Z}(g)^n_i$ on $g$. Following the argument on page 385 in Jacod and Protter (2011), we can prove for $w_n = v_n/\sqrt{u_n}$,

$$\|F_{w_n}(x + y) - F_{w_n}(x)\| \leq \left( w_n^{-4/2+4} \|x\|^{2+4/2+4} + (1 + \|x\|^2)(\|y\| \wedge 1 + \|y\|^2 \wedge w_n^2) \right).$$

We will plug-in $x = \overline{Z}_i^n/\sqrt{u_n}$, $y = \overline{X}_i^n/\sqrt{u_n}$. According to (16.4.9) in Jacod and Protter (2011), we have

$$\mathbb{E} \left\| \overline{Z}_i^n/\sqrt{u_n} \right\|^{2+4/2+4} \leq K.$$

Also, note that we can write

$$\overline{X}_i^n = \int_{(i-1)\Delta_n + u_n}^{i\Delta_n + u_n} g_n(s - (i-1)\Delta_n)dX'_s$$

where $g_n(t) = \sum_{r=1}^{k_n} g \left( \frac{r}{k_n} \right) 1_{(r-1)\Delta_n, r\Delta_n}$ with $g_n(s) \leq K$. Using (2.1.47) of Corollary 2.1.9 in Jacod and Protter (2011), we have

$$\mathbb{E}\left( \left\| \overline{X}_i^n/\sqrt{u_n} \right\|^2 \wedge 1|\mathcal{F}_{(i-1)\Delta_n}\right) \leq K u_n^{1-r}\phi_n,$$

$$\mathbb{E}(\|\overline{X}_i^n/\sqrt{u_n}\| \wedge 1|\mathcal{F}_{(i-1)\Delta_n}) \leq K u_n^{1-r/2}\phi_n.$$
where \( \phi_n \to 0 \), as \( n \to \infty \). Therefore,

\[
E(||y|| \wedge 1 | F_{(i-1)\Delta_n}) = E(||X_{n,i} || \wedge 1 | F_{(i-1)\Delta_n}) \leq K u_n^{1-r/2} \phi_n;
\]

\[
E(||y||^2 \wedge w_n^2 | F_{(i-1)\Delta_n}) = E(||X_{n,i} ||^2 \wedge w_n^2 | F_{(i-1)\Delta_n}) \leq E(w_n^2 (||X_{n,i} ||^2 \wedge 1)) \leq K u_n^{(2-r)\omega} \phi_n.
\]

Therefore, we obtain

\[
\Delta_n^{-1/4} \frac{1}{k_n \Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} E \left( \left\| \tilde{Z}(g)_{i,n} \tilde{Z}(g)_{i,n} - \tilde{Z}'(g)_{i,n} \tilde{Z}'(g)_{i,n} \right\| \right) \left\{ \left\| Z(g)_{i,n} \right\| \leq v_n \right\} | F_{(i-1)\Delta_n})
\]

\[
\leq K \Delta_n^{-1/4} \frac{1}{k_n \Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} u_n (K u_n^{1-r/2} \phi_n + K u_n^{(2-r)\omega} \phi_n)
\]

\[
= K (\Delta_n^{(1-r)/4} + \Delta_n^{(1-r/2)\omega-1/4}) \phi_n
\]

\[
\to 0.
\]

On the other hand, note that

\[
E(||\Delta_n^{\omega} X || | F_{(i-1)\Delta_n}) \leq K \Delta_n^{1/2}, \quad \left| g \left( \frac{j}{k_n} \right) - g \left( \frac{j-1}{k_n} \right) \right| \leq K/k_n,
\]

then by Hölder’s Inequality, we deduce

\[
\Delta_n^{-1/4} \frac{1}{2k_n \Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} E \left( \left\| \tilde{Z}(g)_{i,n} \tilde{Z}(g)_{i,n} \right\| \right) \left\{ \left\| Z(g)_{i,n} \right\| \leq v_n \right\} | F_{(i-1)\Delta_n})
\]

\[
= \Delta_n^{-1/4} \frac{1}{2k_n \Lambda} \sum_{i=1}^{[t/\Delta_n]-k_n+1} E \left( \left\| \tilde{Z}(g)_{i,n} \tilde{Z}(g)_{i,n} \right\| \right) \left\{ \left\| Z(g)_{i,n} \right\| \leq v_n \right\} | F_{(i-1)\Delta_n})
\]

\[
\leq K \Delta_n^{-1/4+1/2} \sum_{i=1}^{[t/\Delta_n]-k_n+1} u_n \Delta_n
\]

\[
\to 0,
\]

which concludes the proof.
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Table 1: Simulation Results of the 2-D Case

Note: In this table, we report the sample mean (s.mean) and standard deviation (s.stdev) of the statistics $\hat{[Z_1, Z_2]}_t$ and $\hat{[Z_1, Z_2]}_t$ in Columns BV and QV respectively. The percentage of variation by jumps in $X_1$ is fixed at 15%. The results of different panels are based on different values of $k_n$. We fix $k'_n = 3k_n$.  

28
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<td>ADP Employment Change</td>
<td>Employment</td>
<td>Monthly</td>
<td>8:15 am - Two days before Employment situation</td>
</tr>
<tr>
<td>Initial Jobless Claims</td>
<td>Employment</td>
<td>Weekly</td>
<td>8:30 am every Thursday</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>Consumer Spending and Confidence</td>
<td>Monthly</td>
<td>8:30 am 4 weeks after end of reported month</td>
</tr>
<tr>
<td>Advance Retail Sales</td>
<td>Consumer Spending and Confidence</td>
<td>Monthly</td>
<td>8:30 am 2 weeks after end of reported month</td>
</tr>
<tr>
<td>Consumer Confidence</td>
<td>Consumer Spending and Confidence</td>
<td>Monthly</td>
<td>10:00 am - Last Tuesday of month being surveyed</td>
</tr>
<tr>
<td>GDP</td>
<td>National Output and Inventories</td>
<td>Quarterly</td>
<td>8:30 am - Final week of Jan Apr Jul Oct</td>
</tr>
<tr>
<td>Durable Goods Orders</td>
<td>National Output and Inventories</td>
<td>Monthly</td>
<td>8:30 am 3 to 4 weeks after the end of reporting month</td>
</tr>
<tr>
<td>ISM Manufacturing</td>
<td>National Output and Inventories</td>
<td>Monthly</td>
<td>10:00 am First Business day after reporting month</td>
</tr>
<tr>
<td>Chicago PMI</td>
<td>National Output and Inventories</td>
<td>Monthly</td>
<td>10:00 am First Business day of month being covered</td>
</tr>
<tr>
<td>Empire State Manufacturing</td>
<td>National Output and Inventories</td>
<td>Monthly</td>
<td>8:30 am around 15th of month being reported</td>
</tr>
<tr>
<td>Business Inventories</td>
<td>National Output and Inventories</td>
<td>Monthly</td>
<td>10:00 am released six weeks after the month ends</td>
</tr>
<tr>
<td>Production and Utilization</td>
<td>National Output and Inventories</td>
<td>Monthly</td>
<td>9:15 am released the 15th of the following month</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>Housing and Construction</td>
<td>Monthly</td>
<td>8:30 am released 2 to 3 weeks following month being covered</td>
</tr>
<tr>
<td>Existing Home Sales</td>
<td>Housing and Construction</td>
<td>Monthly</td>
<td>8:30 am released 2 to 3 weeks following month being covered</td>
</tr>
<tr>
<td>New Home Sales</td>
<td>Housing and Construction</td>
<td>Monthly</td>
<td>8:30 am released 2 to 3 weeks following month being covered</td>
</tr>
<tr>
<td>FOMC Meeting</td>
<td>Federal Reserve</td>
<td>Eight Times</td>
<td>2:15 pm of day of conclusion of FOMC meeting</td>
</tr>
<tr>
<td>CPI</td>
<td>Prices, Productivity, Wages</td>
<td>Monthly</td>
<td>8:30 am second or third week following month being covered</td>
</tr>
<tr>
<td>PPI</td>
<td>Prices, Productivity, Wages</td>
<td>Monthly</td>
<td>8:30 am two or three weeks after month ends</td>
</tr>
<tr>
<td>Employment Cost Index</td>
<td>Prices, Productivity, Wages</td>
<td>Quarterly</td>
<td>8:30 am - Last Thursday of Jan Apr Jul Oct</td>
</tr>
<tr>
<td>Crude Oil Inventory</td>
<td>Commodity Inventory</td>
<td>Weekly</td>
<td>10:30 am every Wednesday</td>
</tr>
<tr>
<td>ECB Governing Council Meeting</td>
<td>International Economic Indicators</td>
<td>Monthly</td>
<td>8:00 am released first or second week on two months earlier</td>
</tr>
<tr>
<td>German Industrial Production</td>
<td>International Economic Indicators</td>
<td>Monthly</td>
<td>3:30 am - 4:00 am released 2 weeks after the reporting month</td>
</tr>
<tr>
<td>China Industrial Production</td>
<td>International Economic Indicators</td>
<td>Monthly</td>
<td>7:50 am released in the final week of the following month</td>
</tr>
<tr>
<td>Japan Industrial Production</td>
<td>International Economic Indicators</td>
<td>Monthly</td>
<td>8:30 am released in the final week of the following month</td>
</tr>
</tbody>
</table>

Table 2: Economic Indicators

Note: In this table, we report the details of macro news indicators we consider. All times are reported in Eastern Time. For international economic indicators, there may be one-hour difference for the release time between winter and summer due to the US daylight saving times. Source: Bloomberg and “The Secrets of Economic Indicators” by Bernard Baumohl, 2010.
<table>
<thead>
<tr>
<th></th>
<th>CL</th>
<th>EC</th>
<th>ES</th>
<th>TY</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Asia (6:00 pm - 3:00 am EST)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Trading Volume</td>
<td>3.38</td>
<td>10.71</td>
<td>2.78</td>
<td>5.30</td>
</tr>
<tr>
<td>% Bid-Ask Spread</td>
<td>0.0072</td>
<td>0.0018</td>
<td>0.0069</td>
<td>0.0037</td>
</tr>
<tr>
<td>% of 0 returns</td>
<td>21.60</td>
<td>7.87</td>
<td>8.20</td>
<td>32.40</td>
</tr>
<tr>
<td># Days with jumps</td>
<td>3</td>
<td>57</td>
<td>5</td>
<td>8</td>
</tr>
<tr>
<td>% QV due to jumps</td>
<td>18.76</td>
<td>17.45</td>
<td>34.31</td>
<td>26.67</td>
</tr>
<tr>
<td><strong>Europe (3:00 am - 9:00 am EST)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Trading Volume</td>
<td>14.40</td>
<td>28.77</td>
<td>11.58</td>
<td>15.65</td>
</tr>
<tr>
<td>% Bid-Ask Spread</td>
<td>0.0045</td>
<td>0.0015</td>
<td>0.0061</td>
<td>0.0036</td>
</tr>
<tr>
<td>% of 0 returns</td>
<td>2.16</td>
<td>0.40</td>
<td>0.99</td>
<td>5.47</td>
</tr>
<tr>
<td># Days with jumps</td>
<td>99</td>
<td>192</td>
<td>75</td>
<td>182</td>
</tr>
<tr>
<td>% QV due to jumps</td>
<td>19.64</td>
<td>22.72</td>
<td>23.60</td>
<td>29.62</td>
</tr>
<tr>
<td><strong>US (9:00 am - 5:00 pm EST)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Trading Volume</td>
<td>82.22</td>
<td>60.51</td>
<td>85.64</td>
<td>79.05</td>
</tr>
<tr>
<td>% Bid-Ask Spread</td>
<td>0.0020</td>
<td>0.0016</td>
<td>0.0056</td>
<td>0.0035</td>
</tr>
<tr>
<td>% of 0 returns</td>
<td>0.22</td>
<td>0.27</td>
<td>0.05</td>
<td>0.70</td>
</tr>
<tr>
<td># Days with jumps</td>
<td>400</td>
<td>190</td>
<td>322</td>
<td>267</td>
</tr>
<tr>
<td>% QV due to jumps</td>
<td>25.45</td>
<td>22.03</td>
<td>22.49</td>
<td>26.52</td>
</tr>
</tbody>
</table>

**Table 3: Liquidity and Jumps Comparison Across Trading Hours**

Note: In this table, we compare different measures of liquidity and jumps in the four futures contracts across different trading zones, including the percentage daily volume represented by that time zone, the estimated bid-ask spread in percentage using the Roll measure with returns sampled at the highest frequency, the percentage of 0s in 1-min returns, the number of days that have jumps, and the average percentage variation contributed by jumps to the total quadratic variation of the entire day.
<table>
<thead>
<tr>
<th>News</th>
<th>CL</th>
<th>EC</th>
<th>ES</th>
<th>TY</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADP Employment</td>
<td>0.32</td>
<td>(1.02)</td>
<td>0.01</td>
<td>(0.40)</td>
</tr>
<tr>
<td>Advance Retail Sales</td>
<td>−1.85***</td>
<td>(2.73)</td>
<td>0.01</td>
<td>(0.31)</td>
</tr>
<tr>
<td>Business Inventories</td>
<td>2.53***</td>
<td>(3.71)</td>
<td>−0.02</td>
<td>(0.50)</td>
</tr>
<tr>
<td>CPI</td>
<td>2.32*</td>
<td>(1.94)</td>
<td>0.36***</td>
<td>(4.29)</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>−0.01</td>
<td>(0.04)</td>
<td>−0.01</td>
<td>(0.52)</td>
</tr>
<tr>
<td>Change NFP</td>
<td>0.74**</td>
<td>(2.24)</td>
<td>0.06**</td>
<td>(2.46)</td>
</tr>
<tr>
<td>Chicago PMI</td>
<td>0.98**</td>
<td>(2.14)</td>
<td>0.05</td>
<td>(1.44)</td>
</tr>
<tr>
<td>China IP</td>
<td>0.25</td>
<td>(0.42)</td>
<td>−0.06</td>
<td>(1.41)</td>
</tr>
<tr>
<td>Consumer Confidence</td>
<td>−0.33</td>
<td>(0.39)</td>
<td>−0.02</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Durable Goods Orders</td>
<td>−0.14</td>
<td>(0.29)</td>
<td>−0.03</td>
<td>(0.90)</td>
</tr>
<tr>
<td>ECB Rate</td>
<td>−0.04</td>
<td>(0.16)</td>
<td>0.01</td>
<td>(0.73)</td>
</tr>
<tr>
<td>Empire Manufacture</td>
<td>−0.11</td>
<td>(0.27)</td>
<td>−0.04</td>
<td>(1.29)</td>
</tr>
<tr>
<td>Employment Cost</td>
<td>0.13</td>
<td>(0.08)</td>
<td>−0.13</td>
<td>(1.18)</td>
</tr>
<tr>
<td>Existing Home Sales</td>
<td>0.11</td>
<td>(0.68)</td>
<td>−0.01</td>
<td>(0.92)</td>
</tr>
<tr>
<td>Fed Target FOMC</td>
<td>0.09</td>
<td>(0.29)</td>
<td>0.14***</td>
<td>(6.34)</td>
</tr>
<tr>
<td>GDP QoQ</td>
<td>0.00</td>
<td>(0.01)</td>
<td>−0.01</td>
<td>(0.53)</td>
</tr>
<tr>
<td>German IP</td>
<td>0.41</td>
<td>(0.73)</td>
<td>−0.03</td>
<td>(0.87)</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>0.10</td>
<td>(0.20)</td>
<td>−0.02</td>
<td>(0.51)</td>
</tr>
<tr>
<td>ISM PMI</td>
<td>−0.34</td>
<td>(0.58)</td>
<td>0.00</td>
<td>(0.10)</td>
</tr>
<tr>
<td>Initial Jobless Claims</td>
<td>−0.05</td>
<td>(0.18)</td>
<td>0.01</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Japan IP</td>
<td>0.03</td>
<td>(0.30)</td>
<td>0.00</td>
<td>(0.50)</td>
</tr>
<tr>
<td>New Home Sales</td>
<td>−0.23</td>
<td>(0.53)</td>
<td>0.04</td>
<td>(1.29)</td>
</tr>
<tr>
<td>Oil Inventory</td>
<td>0.43**</td>
<td>(2.31)</td>
<td>−0.01</td>
<td>(0.78)</td>
</tr>
<tr>
<td>PPI</td>
<td>−0.02</td>
<td>(0.02)</td>
<td>−0.03</td>
<td>(0.48)</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>0.38</td>
<td>(0.51)</td>
<td>−0.04</td>
<td>(0.69)</td>
</tr>
</tbody>
</table>

Table 4: Jumps Variation Regression

Note: In this table, we report the regression results of jumps variations on news surprises, where *, ** and *** denote 10%, 5% and 1% significant levels, respectively. The t-statistics are provided in parentheses. The quadratic variations are scaled by $10^4$. 

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<table>
<thead>
<tr>
<th>News</th>
<th>ES, CL</th>
<th>ES, EC</th>
<th>ES, TY</th>
</tr>
</thead>
<tbody>
<tr>
<td>ADP Employment</td>
<td>0.02</td>
<td>(1.06)</td>
<td>0.02</td>
</tr>
<tr>
<td>Advance Retail Sales</td>
<td>−0.02</td>
<td>(0.33)</td>
<td>0.00</td>
</tr>
<tr>
<td>Business Inventories</td>
<td>−0.02</td>
<td>(0.35)</td>
<td>−0.02</td>
</tr>
<tr>
<td>CPI</td>
<td>−0.03</td>
<td>(0.31)</td>
<td>0.27***</td>
</tr>
<tr>
<td>Capacity Utilization</td>
<td>−0.01</td>
<td>(0.54)</td>
<td>−0.01</td>
</tr>
<tr>
<td>Change NFP</td>
<td>0.06***</td>
<td>(2.74)</td>
<td>0.03*</td>
</tr>
<tr>
<td>Chicago PMI</td>
<td>0.08**</td>
<td>(2.43)</td>
<td>0.09***</td>
</tr>
<tr>
<td>China IP</td>
<td>0.02</td>
<td>(0.45)</td>
<td>−0.02</td>
</tr>
<tr>
<td>Consumer Confidence</td>
<td>−0.04</td>
<td>(0.69)</td>
<td>0.02</td>
</tr>
<tr>
<td>Durable Goods Orders</td>
<td>−0.01</td>
<td>(0.24)</td>
<td>−0.01</td>
</tr>
<tr>
<td>ECB Rate</td>
<td>0.00</td>
<td>(0.11)</td>
<td>0.00</td>
</tr>
<tr>
<td>Empire Manufacture</td>
<td>0.01</td>
<td>(0.27)</td>
<td>−0.01</td>
</tr>
<tr>
<td>Employment Cost</td>
<td>−0.01</td>
<td>(0.05)</td>
<td>−0.11</td>
</tr>
<tr>
<td>Existing Home Sales</td>
<td>0.00</td>
<td>(0.39)</td>
<td>−0.00</td>
</tr>
<tr>
<td>Fed Target FOMC</td>
<td>0.02</td>
<td>(1.08)</td>
<td>0.12***</td>
</tr>
<tr>
<td>GDPQoQ</td>
<td>−0.00</td>
<td>(0.35)</td>
<td>−0.00</td>
</tr>
<tr>
<td>German IP</td>
<td>−0.01</td>
<td>(0.13)</td>
<td>−0.02</td>
</tr>
<tr>
<td>Housing Starts</td>
<td>−0.02</td>
<td>(0.45)</td>
<td>−0.01</td>
</tr>
<tr>
<td>ISM PMI</td>
<td>0.05</td>
<td>(1.11)</td>
<td>0.03</td>
</tr>
<tr>
<td>Initial Jobless Claims</td>
<td>−0.01</td>
<td>(0.46)</td>
<td>−0.00</td>
</tr>
<tr>
<td>Japan IP</td>
<td>−0.00</td>
<td>(0.18)</td>
<td>−0.00</td>
</tr>
<tr>
<td>New Home Sales</td>
<td>−0.01</td>
<td>(0.41)</td>
<td>−0.01</td>
</tr>
<tr>
<td>Oil Inventory</td>
<td>−0.01</td>
<td>(0.42)</td>
<td>−0.01</td>
</tr>
<tr>
<td>PPI</td>
<td>−0.02</td>
<td>(0.32)</td>
<td>0.05</td>
</tr>
<tr>
<td>Personal Spending</td>
<td>−0.04</td>
<td>(0.70)</td>
<td>0.01</td>
</tr>
</tbody>
</table>

**Table 5: Co-Jumps Variation Regression**

Note: In this table, we report the regression results of co-jumps variations on news surprises, where *, ** and *** denote 10%, 5% and 1% significant levels, respectively. The t-statistics are provided in parentheses. The quadratic covariations are scaled by $10^4$. 

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Date | News
--- | ---
12/11/07 | FOMC decided to lower its target for the federal funds rate 25 basis points to 4-1/4 percent.
12/12/07 | Fed announced a plan to inject billions of dollars into the financial system.
12/27/07 | Stocks slumped as investors mulled geopolitical concerns and reports on oil inventories, consumer confidence and factory orders.
01/04/08 | Employers add fewer to payrolls than forecast, and the jobless rate hits 5%.
01/10/08 | Retailers reported deep declines in their December sales.
01/22/08 | Fed slashes key rate to 3.5%, following an unscheduled meeting.
01/30/08 | Fed delivers another rate cut to 3.0% after the scheduled FOMC meeting.
02/05/08 | The stock selloff quickened after a surprisingly weak service sector reading exacerbated bets that the economy is in a recession.
02/27/08 | A big decline in Chinese stocks, weakness in durable goods orders in US fueled the selling on Wall Street.
03/04/08 | Ben Bernanke said Mortgage delinquencies and foreclosures would continue to rise for a while longer.
03/07/08 | Payrolls sink in February according to Labor Department Report.
03/11/08 | Fed announced today an expansion of its securities lending program following the FOMC meeting.
03/14/08 | In conjunction with the Fed New York, JPMorgan Chase would provide temporary funding for the Bear Stearns.
03/18/08 | Fed cuts rates by 3/4 of a point to 2.25%.
03/24/08 | Home sales rise on biggest-ever price drop.
04/11/08 | General Electric - widely viewed as a proxy for the U.S. economy - posted a surprising first-quarter earnings miss Friday.
04/30/08 | Fed cut a key short-term interest rate and signaled it may not cut rates again anytime soon.
05/02/08 | Single-family home prices dropped 7.7% in the first quarter in the largest year-over-year decline since 1982.
05/21/08 | Oil futures surge after a government report shows a surprise drop in crude and gasoline stockpiles.
07/29/08 | Consumer confidence posts surprise increase.
07/31/08 | The GDP grew at an annual rate of 1.9% in the three months ended in June.
09/18/08 | Dow gains 410 on talk of a long-term government solution to absorbing bad debt.
12/16/08 | Fed cut its key interest rate to a range of between zero percent and 0.25%.
03/18/09 | FOMC decided to maintain the rate at 0 to 1/4 percent and likely for an extended period.
04/03/09 | Unemployment rate spikes to 8.5%, a 25-year high.
05/26/09 | Home prices show record decline according to the S&P/Case-Shiller national home price index.

Table 6: Co-Jumps and News

Note: In this table, we report the potential news that cause co-jumps among eMini S&P 500, 10-year treasury, euro/dollar, and crude oil futures between December 1, 2007 and June 1, 2009.
Figure 1: Histogram of the Feasible CLT

Note: In this figure, we verify Theorem 1 by plotting the histograms of the standardized statistics with feasible asymptotic variances. The parameters are $\beta_1 = 0.5$, $\beta_0 = 0.25$, $\theta_1 = 1.7$, $\theta_0 = 1.8$, $\omega_i = 0.47$, and $\alpha_i = 3$. Jumps in $X_1$ account for 15% of total quadratic variation, whereas jumps in $X_2$ account for 10%.
Figure 2: Average Minute-by-Minute Trading Volumes of Front Contracts

Note: In this figure, we plot the average minute-by-minute trading volumes of the contracts across the day. The red dashed lines mark the beginning and the end of the U.S. open-outcry market hours in Eastern Time.
Figure 3: Quadratic Variation of eMini S&P 500 Futures

Note: In the top left panel, we plot the annualized daily total volatility (y-axis) across the sample. The top right panel plots the time series of the weekly average percentage total variance that are due to jumps. The bottom panels plot the time series of continuous and jump quadratic variations over Asian, European, and U.S. trading hours respectively.
Figure 4: Quadratic Variation of Crude Oil Futures

Note: In the top left panel, we plot the annualized daily total volatility (y-axis) across the sample. The top right panel plots the time series of the weekly average percentage total variance that are due to jumps. The bottom panels plot the time series of continuous and jump quadratic variations over Asian, European, and U.S. trading hours respectively.
Figure 5: Quadratic Variation of Euro/USD Foreign Exchange Futures

Note: In the top left panel, we plot the annualized daily total volatility (y-axis) across the sample. The top right panel plots the time series of the weekly average percentage total variance that are due to jumps. The bottom panels plot the time series of continuous and jump quadratic variations over Asian, European, and U.S. trading hours respectively.
Figure 6: Quadratic Variation of 10-Year Treasury Notes Futures

Note: In the top left panel, we plot the annualized daily total volatility (y-axis) across the sample. The top right panel plots the time series of the weekly average percentage total variance that are due to jumps. The bottom panels plot the time series of continuous and jump quadratic variations over Asian, European, and U.S. trading hours respectively.
Figure 7: Correlation Between eMini S&P 500 and Crude Oil Futures

Note: In this figure, we decompose the quadratic covariation into its continuous and jump parts. The top panels plot the estimates based on the entire day. The following three panels are estimates using Asian, European, and U.S. trading hours, respectively. The red dots mark the estimates, and the blue line plots the 21-day moving average of the estimates. The three vertical black dashed lines mark the days of Bear Stern’s Bail-out, Lehman Brothers’ Bankruptcy, and Libyan Civil War. The grey area corresponds to the NBER classification of the recession.
Figure 8: Correlation Between eMini S&P 500 and Euro/USD Futures

Note: In this figure, we decompose the quadratic covariation into the continuous part and the jump part. The top panels plot the estimates based on the entire day. The following three panels are estimates using Asian, European, and U.S. trading hours, respectively. The red dots mark the estimates, and the blue line plots the 21-day moving average of the estimates. The grey area corresponds to the NBER classification of the recession.
Figure 9: Correlation Between eMini S&P 500 and 10-Year Notes Futures

Note: In this figure, we decompose the quadratic covariation into the continuous part and the jump part. The top panels plot the estimates based on the entire day. The following three panels are estimates using Asian, European, and U.S. trading hours, respectively. The red dots mark the estimates, and the blue line plots the 21-day moving average of the estimates. The first vertical black dash line marks the date when the Freddie Mac announced that it would no longer buy the most risky subprime mortgages and mortgage-related securities. The next two vertical black dash lines mark the announcement dates of the first two rounds of Quantitative Easing by the Federal Reserve. The grey area corresponds to the NBER classification of the recession.