Econometric modeling of exchange rate volatility and jumps

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Section 1

Introduction

Volatility measures the dispersion of asset price returns. Recognizing the importance of foreign exchange volatility for risk management and policy evaluation, academics, policymakers, regulators, and market practitioners have long studied and estimated models of foreign exchange volatility and jumps.

Financial economists have long sought to understand and characterize foreign exchange volatility, because the volatility process tells us about how news affects asset prices, what information is important, and how markets process that information.

Policymakers are interested in measuring asset price volatility to learn about market expectations and uncertainty about policy. For example, one might think that a clear understanding of policy objectives and tools would tend to reduce market volatility, other things equal.

More practically, understanding and estimating asset price volatility is important for asset pricing, portfolio allocation, and risk management. Traders and regulators must consider not only to the expected return from their trading activity but also the trading strategy's exposure to risk during periods of high volatility. Traders' risk-adjusted performance depends upon the accuracy of their volatility predictions. Therefore, both traders and regulators use volatility predictions as inputs to models of risk management, such as Value-at-Risk (VaR).

The goal for volatility modelers has been to simultaneously account for the most prominent features of foreign exchange volatility: (i) it tends to be autocorrelated; (ii) it is periodic, displaying intraday and intraweek patterns; and (iii) it includes discontinuities (jumps) in prices.

To account for these characteristics, researchers started modeling weekly and daily volatility with parametric ARCH/GARCH models in the 1980s. Practitioners often use the RiskMetrics statistical model, which is a member of the large ARCH/GARCH family. These models effectively described the autocorrelation in daily and weekly volatility. At intraday horizons, however, institutional features—that is, market openings/closings and news announcements—create strong intraday patterns, including discontinuities in prices. Much research on intraday data sorted out the factors behind these periodic patterns and discontinuities. The use of intraday data enabled the next big advance in volatility modeling: "realized volatility," which is the use of very high frequency returns to calculate volatility at every instant. A few years later, researchers began to develop increasingly sophisticated models that estimate jumps and that combine autoregressive volatility and jumps.

In short, academic researchers have improved volatility estimation remarkably quickly in the last 30 years, and policymakers, traders and regulators have benefitted from these advances. This chapter reviews those advances and provides some suggestions for further research.

The next section begins with parametric methods before Section 3 describes non-parametric models. Section 4 describes how researchers have modeled intraday periodicity. Section 5 introduces the subject of testing for jumps or discontinuities in foreign exchange data. Section 6 evaluates the important literature on how news, including central bank intervention, affects volatility and jumps in foreign exchange rates. Section 7 concludes.

Exchange rate data

We start our review of the foreign exchange volatility literature by illustrating some stylized facts of currency markets with intradaily data for the EUR/USD and USD/JPY exchange rates over a period from 3 January 1995 to 30 December 2009.[1] Olsen and Associates provides the last mid-quotes (average of the logarithms of bid and ask quotes) of 5-minute intervals throughout the global 24-hour trading day. Following Andersen and Bollerslev (1998a), one trading day extends from 21:00 GMT on day $t-1$ to 21:00 GMT on day t. Let us denote $P_{t,i}$ the i-th price of day t. The i-th return (in per cent) of day t, denoted $(y_{t,i})$, is computed as $100(p_{t,i} - p_{t,i-1})$ where $p_{t,i} = \log P_{t,i}$ and by convention $p_{t,0} = p_{t-1,M}$.

We omit trading days that display either too many missing values or low trading activity because they will provide poor estimates of volatility. Similarly, we deleted week-ends plus certain fixed and irregular holidays, trading days for which there are more than 57 missing values at the 5-minute frequency (corresponding to more than 20 per cent of the data), and trading days with too many empty intervals and consecutive prices.[2] These criteria leave 3716 and 3720 days, respectively, for the EUR/USD and the USD/JPY exchange rates. We obtain return series of lower frequencies by summing 5-minute returns at 30-minute, 1-hour, daily, weekly and monthly horizons.

Stylized facts

The top-left panels of Figures 1 and 2 show that nominal exchange rates have stochastic trends, that is, they are nonstationary. The top-right panels of Figures 1 and 2 plot daily returns in (per cent). Those returns clearly exhibit volatility clustering, that is periods of low volatility mingle with periods of high volatility. The bottom-left panels of Figures 1 and 2 illustrate another stylized facts of daily exchange rate return series: returns are not normally distributed. The empirical distribution is more peaked than the normal density and it has fatter tails or excess kurtosis.[3]

[Insert Figures 1 and 2 about here]

The bottom-right panels of the figures plot the autocorrelogram (with 100 lags) of the squared returns and the upper bound of the 95 per cent Bartlett's confidence interval for the null hypothesis of no autocorrelation. These graphs illustrate that exchange rates exhibit volatility clustering (that is, volatility shows positive autocorrelation) and the shocks to volatility take several months to die out. In addition, both exchange rates exhibit autocorrelation at much longer horizons than one would expect.

Statistical properties of exchange rates

Tables 1 and 2 confirm that exchange rate returns are not normally distributed (last column of Table 1 and JB test in Table 2), and exhibit autocorrelation in squared returns or "ARCH effects" (see the LM-test and the Q-test on the squared returns in Table 2). The last column of Table 2 suggests that the exchange rate returns do not have a unit root at any sampling frequency.

[Insert Tables 1 and 2 about here]

We calculate Ljung-Box test statistics with 20 lags, denoted $LB(20)$, to diagnose serial correlation in the returns.[4] While the $LB(20)$ statistic fails to reject the null hypothesis of no serial correlation for daily and lower frequencies, the robust test does reject that hypothesis for intradaily frequencies except for the 1-hour EUR/USD returns.

These characteristics in Figures 1 and 2 and Tables 1 and 2 suggest that a good model for exchange rate series should capture i) serial correlation, ii) time-varying variance, iii) long-memory iv) peakedness as well as v) fat tails. The next section presents that attempt to capture those features with parametric models.

Section 2

Parametric volatility models

Conditional mean

To correctly model the conditional variance of exchange rates, one must model the conditional mean. If Ω_{t-1} is the information set at time $t-1$, the exchange rate return, y_t, is usually modeled as follows:

$$y_t = E(y_t|\Omega_{t-1}) + \varepsilon_t, \tag{2.1}$$

where $E(.|.)$ denotes the conditional expectation operator and ε_t is the disturbance term, with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_s) = 0, \forall\ t \neq s$.[5]

Researchers have often modeled the conditional mean $E(y_t|\Omega_{t-1})$ with Autoregressive (AR) and Moving Average (MA) terms, as well as explanatory variables. Using such specification, we obtain the ARMAX(n, s) process

$$\begin{aligned} &\Psi(L)(y_t - \mu_t) = \Theta(L)\varepsilon_t \\ &\mu_t = \mu + \sum_{i=1}^{n_1} \delta_i x_{i,t}, \end{aligned} \tag{2.2}$$

where L is the lag operator, that is $L^k y_t = y_{t-k}$, $\Psi(L) = 1 - \sum_{i=1}^{n} \psi_i L^i$ and $\Theta(L) = 1 + \sum_{j=1}^{s} \theta_j L^j$.

The ARCH model

In order to model the volatility clustering in economic variables, Engle (1982) developed the Autoregressive Conditional Heteroscedastic (ARCH) model. An ARCH process of order q can be written as follows:

$$\begin{aligned} \varepsilon_t &= z_t \sigma_t \\ \sigma_t^2 &= \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2, \end{aligned} \tag{2.3}$$

where z_t is an independently and identically distributed (*i.i.d.*) process with $E(z_t) = 0$ and

$Var(z_t) = 1$. The model assumes that ε_t is serially uncorrelated, and mean zero, with time varying conditional variance, σ_t^2. To ensure that σ_t^2 is positive for all t, it is sufficient to impose $\omega > 0$ and $\alpha_i \geq 0$.[6]

The ARCH model can describe volatility clustering because the conditional variance of ε_t is an increasing function of ε_{t-1}^2. Consequently, if ε_{t-1} was large in absolute value, σ_t^2 and thus ε_t is expected to be large (in absolute value) as well. The unconditional variance of ε_t exists if $\omega > 0$ and $\sum_{i=1}^{q} \alpha_i < 1$, and is given by

$$\sigma^2 \equiv E[E(\varepsilon_t^2|\Omega_{t-1})] = \frac{\omega}{1 - \sum_{i=1}^{q} \alpha_i}. \tag{2.4}$$

Explanatory variables (for example macro-news announcements, central bank interventions, and so on) can be introduced in the conditional variance equation.

The GARCH model

Bollerslev (1986) usefully generalized the simple ARCH model with the parsimonious and frequently used Generalized ARCH (GARCH) model, which models current conditional variance with geometrically declining weights on lagged squared residuals. The GARCH (p, q) model can be expressed as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2. \tag{2.5}$$

Using the lag (or backshift) operator L, the GARCH (p, q) model becomes:

$$\sigma_t^2 = \omega + \alpha(L)\varepsilon_t^2 + \beta(L)\sigma_t^2,$$

with $\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \ldots + \alpha_q L^q$ and $\beta(L) = \beta_1 L + \beta_2 L^2 + \ldots + \beta_p L^p$. As in the ARCH case, some restrictions are needed to ensure σ_t^2 to be positive for all t. For example, one can impose $\omega > 0$, $\alpha_i \geq 0$ and $\beta_j \geq 0$ as proposed by Bollerslev (1986).

Leverage effect

Stocks exhibit a "leverage effect" in which large negative returns are more likely to predict high volatility than large positive returns. To account for the leverage effect, Glosten, Jagannathan, and Runkle (1993) have proposed a simple model, the eponymous GJR model, which can be expressed as

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i \varepsilon_{t-i}^2 + \gamma_i S_{t-i}^- \varepsilon_{t-i}^2) + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{2.6}$$

where $S_t^- = 1$ when $\varepsilon_t < 0$ and 0 otherwise.[7]

In contrast to results in equity markets, foreign exchange returns usually exhibit symmetric volatility, that is past positive and negative shocks have similar effects on future volatility (Diebold and Nerlove, 1989; Andersen, Bollerslev, Diebold, and Labys, 2001; Hansen and Lunde, 2005a and Laurent, Rombouts, and Violante, 2011). For instance, Bollerslev, Chou, and Kroner (1992) argue that "whereas stock returns have been found to exhibit some degree of asymmetry in their conditional variances, the two-sided nature of foreign exchange markets makes such asymmetries less likely".[8]

FIGARCH

Section 1 illustrated the long-range dependence in squared foreign exchange returns. That is, the effects of a volatility shock can take a considerable time to fully decay. Ding, Granger, and Engle (1993) find that the squared S&P500 daily returns series has positive autocorrelations over more than 2,500 lags (or more than 10 years!). Therefore, neither an I(0) process with exponential decay in autocorrelations nor an I(1) volatility process with no decay in autocorrelations can easily explain this phenomenon.[9]

To mimic the behavior of the correlogram of the observed volatility, Baillie, Bollerslev, and Mikkelsen (1996) (hereafter BBM) introduce the Fractionally Integrated GARCH (FIGARCH) model. The conditional variance of the FIGARCH (p, d, q) is given by:

$$\sigma_t^2 = \underbrace{\omega[1-\beta(L)]^{-1}}_{\omega^*} + \underbrace{\left\{1-[1-\beta(L)]^{-1}\phi(L)(1-L)^d\right\}}_{\lambda(L)}\varepsilon_t^2, \tag{2.7}$$

or $\sigma_t^2 = \omega^* + \sum_{i=1}^{\infty} \lambda_i L^i \varepsilon_t^2 = \omega^* + \lambda(L)\varepsilon_t^2$, with $0 \leq d \leq 1$ and $\phi(L)$ is a polynomial of order q. It is fairly easy to show that $\omega > 0, \beta_1 - d \leq \phi_1 \leq \frac{2-d}{3}$ and $d\left(\phi_1 - \frac{1-d}{2}\right) \leq \beta_1\left(\phi_1 - \beta_1 + d\right)$ are sufficient to ensure that the conditional variance of the FIGARCH $(1, d, 1)$ is positive almost surely for all t.[10] Setting $\phi_1 = 0$ gives the condition for the FIGARCH $(1, d, 0)$.

Estimation

Researchers commonly estimate ARCH-type models by maximum likelihood, which requires that they specify the distribution of the innovation process z_t. Weiss (1986) and Bollerslev and Wooldridge (1992) show that under the normality assumption, the quasi-maximum likelihood (QML) estimator is consistent if the conditional mean and the conditional variance are correctly specified. The log-likelihood function of the standard normal distribution is given by:

$$L_{Gauss} = -\frac{1}{2}\sum_{t=1}^{T}\left[\log(2\pi) + \log\left(\sigma_t^2\right) + z_t^2\right], \tag{2.8}$$

where T is the number of observations, $z_t = \varepsilon_t/\sigma_t$ and $\varepsilon_t = y_t - E(y_t|\Omega_{t-1})$.

The normal distribution cannot account for the pronounced "fat tails" of exchange rate returns, however—see Figure 1 and Table 1. To account for this characteristic, researchers widely use fat-tailed distributions, such as the Student-t distribution and the Generalized Error distribution (GED) (see Palm, 1996; Pagan, 1996 and Bollerslev, Chou, and Kroner, 1992). The log-likelihood for a Student-t distribution is:

$$\begin{aligned} L_{Stud} &= T\left\{\log\Gamma\left(\frac{\upsilon+1}{2}\right) - \log\Gamma\left(\frac{\upsilon}{2}\right) - \frac{1}{2}\log\left[\pi(\upsilon-2)\right]\right\} \\ &- \frac{1}{2}\sum_{t=1}^{T}\left[\log(\sigma_t^2) + (1+\upsilon)\log\left(1+\frac{z_t^2}{\upsilon-2}\right)\right], \end{aligned} \tag{2.9}$$

where υ is the degrees of freedom, $2 < \upsilon \leq \infty$ and $\Gamma(.)$ is the gamma function. The GED log-likelihood function is given by:

$$L_{GED} = \sum_{t=1}^{T}\left[\log\left(\frac{\upsilon}{\lambda_\upsilon}\right) - 0.5\left|\frac{z_t}{\lambda_\upsilon}\right|^{\upsilon} - (1+\upsilon^{-1})\log(2) - \log\Gamma\left(\frac{1}{\upsilon}\right) - 0.5\log(\sigma_t^2)\right], \tag{2.10}$$

where $0 < \upsilon < \infty$ and

$$\lambda_\upsilon \equiv \sqrt{\frac{\Gamma(1/\upsilon)\,2^{(-2/\upsilon)}}{\Gamma(3/\upsilon)}}.$$

These densities account for fat tails but not asymmetry. Both skewness and kurtosis, however, are important in financial applications, such as in asset pricing models, portfolio selection, option pricing theory and Value-at-Risk. To properly model skewness, Lambert and Laurent (2000, 2001) and Bauwens and Laurent (2005) apply and extend the skewed-Student density proposed by Fernández and Steel (1998) to the GARCH framework. The log-likelihood of the standardized (zero mean and unit variance) skewed-Student is:

$$\begin{aligned} L_{SkSt} &= T\left\{\log\Gamma\left(\frac{\upsilon+1}{2}\right) - \log\Gamma\left(\frac{\upsilon}{2}\right) - 0.5\log\left[\pi\left(\upsilon-2\right)\right] + \log\left(\frac{2}{\xi+\frac{1}{\xi}}\right) + \log\left(s\right)\right\} \\ &- 0.5\sum_{t=1}^{T}\left\{\log\sigma_t^2 + (1+\upsilon)\log\left[1+\frac{\left(sz_t+m\right)^2}{\upsilon-2}\xi^{-2I_t}\right]\right\}, \end{aligned} \tag{2.11}$$

where

$$I_t = \begin{cases} 1 \text{ if } z_t \geq -\frac{m}{s} \\ -1 \text{ if } z_t < -\frac{m}{s} \end{cases},$$

ξ is the asymmetry parameter, υ is the degree of freedom of the distribution,

$$m = \frac{\Gamma\left(\frac{\upsilon+1}{2}\right)\sqrt{\upsilon-2}}{\sqrt{\pi}\Gamma\left(\frac{\upsilon}{2}\right)}\left(\xi - \frac{1}{\xi}\right),$$

and

$$s = \sqrt{\left(\xi^2 + \frac{1}{\xi^2} - 1\right) - m^2}.$$

There are other definitions of skewed-Student distribution (see for example Hansen, 1994; Mittnik and Paolella, 2000; Aas and Haff, 2006; Dark, 2010; Deschamps, 2011). For instance, Aas and Haff (2006) extend the skewed-Student distribution to the Generalized Hyperbolic skewed-Student distribution (GHSST), while Deschamps (2011) proposes a Bayesian estimation of GARCH models with GHSST errors. Forsberg and Bollerslev (2002) use a GARCH model with Normal Inverse Gaussion (NIG) error distributions on exchange rate data.

Application

How do the models described above compare? Tables 3 and 4 report model estimates for the EUR/USD and USD/JPY return series, respectively.[11]

[Insert Tables 3 and 4 about here]

The first columns of those tables report the quasi-maximum likelihood estimation of an ARCH (1) model. The Box-Pierce statistics on squared standardized returns are way to high suggesting that the model is misspecified for both series. The GARCH $(1, 1)$ clearly improves upon the ARCH (1) model because it has a much higher log likelihood and no serial correlation.

We then ask whether the EUR/USD and USD/JPY return series display asymmetric volatility or leverage effects. The GJR model (column 3) does not significantly improve on the fit of the GARCH $(1, 1)$ model and so provides no evidence of leverage effect for either exchange rate. This result implies that the news impact curve is likely to be symmetric, that is past positive shocks have the same effect on today's volatility as past negative shocks.

To account for the potential presence of long-memory in volatility (as suggested by Figures 1 and 2), we also estimate a FIGARCH $(1, d, 1)$ model. The data do not reject the additional flexibility of the FIGARCH model. This might be due to breaks in the volatility process, however, rather than genuine long memory. Furthermore, the last three columns of Tables 3 and 4 report parameter estimates of the FIGARCH model with Student, skewed-Student and GED distributions, respectively. As expected, the normal distribution is rejected. For the EUR/USD data, the estimated $\log(\xi)$ parameter is not statistically different from 0, which allows us to conclude that the conditional distribution of the daily returns is likely to be well described as symmetric but has fatter tails than the normal.[12]

To investigate the stability of the parameters, we split the EUR/USD sample into two sub-periods, that is before and during the subprime mortgage crisis. The results suggest that the d parameter of the FIGARCH model was smaller than 0.5 during the pre-crisis period and about 0.9 during the crisis. This result may suggest that volatility shocks display much higher persistence during the turbulent periods than in normal times.[13]

In summary, our empirical results show that FIGARCH models with fat-tailed distributions are capable of capturing serial correlation, time-varying variance, long-memory, peakedness as well as fat tails. In line with the literature, we find no evidence of leverage effect for the EUR/USD and USD/JPY exchange rates.

Section 3

Non-parametric volatility estimators

Realized volatility

The models described in the previous section are parametric and usually designed to estimate the daily, weekly or monthly volatility using data sampled at the same frequency. The recent widespread availability of intradaily asset prices have permitted econometricians to use high-frequency data to compute ex-post measures of volatility at a lower frequency (see French, Schwert, and Stambaugh, 1987). This method is known as the "realized volatility" approach. The popular continuous-time diffusion provides the most commonly used framework to model realized volatility:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t), t \geq 0, \tag{3.1}$$

where $dp(t)$ denotes the logarithmic price increment, $\mu(t)$ is a continuous locally bounded variation process, $\sigma(t)$ is a strictly positive and càdlàg (right-continuous with left limits) stochastic volatility process and $W(t)$ is a standard Brownian motion. Security prices evolve in a nearly continuous fashion throughout the trading day and so it is natural to think of the price and return series of financial assets as arising through discrete observations from an underlying continuous-time process.

Assuming that the time length of one day is one, what does Equation (3.1) imply for the one-period daily return? It follows immediately that

$$r_t \equiv p(t) - p(t-1) = \int_{t-1}^{t} \mu(s)ds + \int_{t-1}^{t} \sigma(s)dW(s). \tag{3.2}$$

The volatility for the continuous-time process over $[t-1, t]$ is therefore linked to the evolution of the spot volatility $\sigma(t)$. Furthermore, returns are normally distributed, conditional on the sample path of the drift and the spot volatility processes,

$$r_t \sim N\left(\int_{t-1}^{t} \mu(s)ds, IV_t\right), \tag{3.3}$$

where IV_t denotes the so-called integrated variance (which converges also to the quadratic variation in this case), and is defined as follows:

$$IV_t \equiv \int_{t-1}^{t} \sigma^2(s)ds. \tag{3.4}$$

IV_t is latent because $\sigma^2(s)$ is not directly observable. The daily squared return y_t^2 provides a simple unbiased non-parametric estimate of IV_t in this framework.

Andersen and Bollerslev (1998a) were the first to point-out that a much more precise ex-post estimator than y_t^2 can be obtained by simply summing up intraday squared returns. They called this estimator realized volatility.[14] This estimator is defined as follows:

$$RV_t = \sum_{i=1}^{M} y_{t,i}^2. \tag{3.5}$$

The sum of the high-frequency squared returns is an "error free/model free" measure of the daily volatility that is relatively insensitive to sampling frequency. The literature finds that under Model (3.1) and some suitable conditions (like the absence of serial correlation in the intraday returns) RV_t consistently estimates the integrated volatility in the sense that when $\Delta \to 0$, it measures the latent integrated volatility IV_t perfectly. However, in practice, at very high frequencies, returns are polluted by microstructure noise (bid-ask bounce, unevenly spaced observations, discreteness,...). This "errors-in-variables" problem produces autocorrelation in the high-frequency returns (see Table 2). Researchers have proposed several solutions, such as sparse sampling (for example Bandi and Russell, 2008, 2005), subsampling and two time-scale estimators (for example Zhang, Mykland, and Aït-Sahalia, 2005), and kernel-based estimators (for example Hansen and Lunde, 2004, 2005b, 2006; Barndorff-Nielsen, Hansen, Lunde, and Shephard, 2008), to tackle these microstructure problems. McAleer and Medeiros (2008) compare these methods and provide a practical guide to estimate integrated variance under microstructure noise.

[Insert Figure 3 about here]

The left-block graphs of Figure 3 illustrate the similarity of RV measures using 5-minute, 30-minute, and 1-hour EUR/USD returns.

Bi-power variation

Empirical studies have shown that a continuous diffusion model as in Equation (3.1) fails to explain some characteristics of asset returns such as sudden spikes or jumps. The inadequacy of the standard stochastic diffusion model has led to developments of continuous time jump-diffusion and stochastic volatility models.

One class of these models is known as the "Brownian SemiMartingale with Finite Activity Jumps" (hereafter denoted BSMFAJ) model. This model has two main components: i) a diffusion component to capture the smooth variation of the price process, and ii) a jump component to account for the discontinuities in the observed prices. Intuitively, a jump process is defined to be of finite activity if the number of jumps in *any* interval of time is finite.[15] Andersen, Bollerslev, and Dobrev (2007) cite several authors who found that this is a realistic model for the price series of many financial assets. A BSMFAJ log-price diffusion admits the representation

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), t \geq 0, \tag{3.6}$$

where $dq(t)$ is a counting process with $dq(t) = 1$ corresponding to a jump at time t and $dq(t) = 0$ otherwise. The (possibly time-varying) jump intensity is $l(t)$ and $\kappa(t)$ is the size of the corresponding jump. Model (3.6) implies that realized volatility converges in probability to the sum of integrated diffusion variance and the sum of squared jumps:

$$RV_t \to \int_{t-1}^{t} \sigma^2(s)ds + \sum_{t-1<s\leq t} \kappa^2(s), \tag{3.7}$$

when $\Delta \to 0$.

In other words, in the absence of jumps, the realized volatility consistently estimates the integrated volatility, but does not do so in the presence of jumps. Barndorff-Nielsen and Shephard (2004) showed that under Model (3.6), the normalized sum of products of the absolute value of contiguous returns (that is bi-power variation) is a consistent estimator for IV_t (see Equation (3.4).

The bi-power variation is defined as:

$$BV_t \equiv \mu_1^{-2} \frac{M}{M-1} \sum_{i=2}^{M} |y_{t,i}||y_{t,i-1}|, \tag{3.8}$$

where $\mu_1 \equiv \sqrt{2/\pi} \simeq 0.79788$.

Unlike RV_t, BV_t is designed to be robust to jumps because its building block is the product between two consecutive returns instead of the squared return. If one of the returns corresponds to a jump and the next one follows the BSM diffusion process, then the product has a small impact on BV_t, being the sum of many of these building blocks. If the jump process has finite activity then "almost surely" jumps cannot affect two contiguous returns for $\Delta \to 0$ (or equivalently $M \to \infty$) and the jump process has a negligible impact on the probability limit of BV_t, which coincides with the IVar. Under the BSMFAJ model, bipower variation converges in probability to diffusion variance as the sampling frequency increases to infinity.

$$\text{plim}_{\Delta \to 0} BV_t = \int_{t-1}^{t} \sigma^2(s) ds. \tag{3.9}$$

The middle graphs of Figure 3 show that there are less spikes in BV_t than in RV_t, suggesting that BV_t is indeed more robust to jumps.

Realized outlyingness weighted variance

One of the disadvantages of the BV_t is that it is downward biased in the presence of "zero" measured returns in the sample. Moreover, jump might significantly affect BV_t when returns are computed over longer time intervals such as 5 or 30 minutes. For these reasons, Boudt, Croux, and Laurent (2011a) have proposed a robust-to-jumps alternative to BV_t. The realized outlyingness weighted variance ($ROWVar_t$) is defined as:

$$\text{ROWVar}_t = c_w \frac{\sum_{i=1}^{M} w(d_{t,i}) y_{t,i}^2}{\frac{1}{M} \sum_{i=1}^{M} w(d_{t,i})}, \tag{3.10}$$

where $w(.)$ is the weight function, $d_{t,i}$ is an outlyingness, and the c_w is a correction factor to ensure that the $ROWVar_t$ is consistent for the IV_t under the BSM and BSMFAJ models.[16] To compute $ROWVar_t$, one should measure the outlyingness $d_{t,i}$ of return $y_{t,i}$ as the square of the robustly standardized return. That is,

$$d_{t,i} = \left(\frac{y_{t,i}}{\hat{\sigma}_{t,i}} \right)^2, \tag{3.11}$$

where $\hat{\sigma}_{t,i}$ is a robust estimate of the instantaneous volatility computed from all the returns belonging to the same local window as $y_{t,i}$.[17] Because of the presence of intraday periodicity in volatility, Boudt, Croux, and Laurent (2011a) propose to compute $d_{t,i}$ on returns that have their intraday periodicity filtered out instead of raw returns.[18] Further, Boudt, Croux, and Laurent (2011b) chose a weight function that maintains a compromise between robustness and efficiency. They recommend using the Soft-rejection (SR) weight function with 95 per cent quantile of the χ_1^2 distribution function. The SR weight function is defined as:

$$w_{\mathrm{SR}(z)} = \min\{1, k/z\}, \tag{3.12}$$

where k a tuning parameter to be selected. The right graphs of Figure 3 show that the $ROWVar_t$ is less affected by jumps than RV_t or BV_t.

MinRV and MedRV

Andersen, Dobrev, and Schaumburg (2008) propose two estimators of IV_t, $MinRV_t$ and $MedRV_t$, that are consistent in the presence of jumps and are less sensitive to zero returns than BV_t. These estimators are defined as follows:

$$MinRV_t \equiv M\frac{M}{M-1}\mu_2\sum_{i=2}^{M} min(|y_{t,i}|, |y_{t,i-1}|)^2 \tag{3.13}$$

$$MedRV_t \equiv M\frac{M}{M-2}\mu_3\sum_{i=3}^{M} med(|y_{t,i}|, |y_{t,i-1}|, |y_{t,i-2}|)^2, \tag{3.14}$$

where $\mu_2 \equiv \pi/(\pi-2)$ and $\mu_3 \equiv 3\pi/(6-4\sqrt{3}+\pi)$, "$Min$" stands for minimum and "Med" for median.

[Insert Figure 4 about here]

Figure 4 plots $MinRV_t$ and $MedRV_t$ for the three sampling frequencies. It is hard to conclude which measure is superior at the considered sampling frequencies.

Truncated power variation

We have reviewed several robust-to-jumps estimaters—that is, BV_t, $ROWVar_t$, $MinRV_t$ and $MedRV_t$—of integrated volatility, which have been proved robust for BSMFAJ models. Indeed, Aït-Sahalia (2004), Barndorff-Nielsen, Shephard, and Winkel (2006), and Lee and Hannig (2010) show the presence of other types of jumps in the evolution of prices. These type of jumps are called *infinite activity* Lévy type jumps. That is, if the jumps are type of infinite activity, then the number of jumps (the intensity) in any interval of time is infinite. In this regard, several estimations of IV_t have been also designed to be immune to jumps with infinite activity (hereafter denoted IA).

We now consider log-price processes that belong to the Brownian SemiMartingale with *Infinite* Activity Jumps (BSMIAJ) family of models. Under the BSMIAJ model, the diffusion component captures the smooth variation of the price process as before, while the jump component accounts for both rare, large discontinuities and frequent, small jumps in the prices. A BSMIAJ log-price diffusion admits the representation

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \underbrace{\kappa(t)dq(t)}_{\text{finite activity}} + \underbrace{h(t)dL(t),}_{\text{infinite activity}} \quad t \geq 0, \tag{3.15}$$

where $q(t)$ is a counting process (possibly a Poisson process) as in Model (3.6), and $L(t)$ represents either an α-stable process or a Cauchy process as in Lee and Hannig (2010). $\kappa(t)$ and $h(t)$ further denote the jump sizes of the corresponding jump processes, respectively. The jump component of Model (3.15) captures both finite and infinite activity price jumps as in the studies of Aït-Sahalia and Jacod (2009a, 2009b, 2010, 2011), Todorov and Tauchen (2006) and Carr and Wu (2003), among others.

Under the BSMIAJ, Mancini (2009) and Bollerslev and Todorov (2011) suggest using the truncated power variation TV_t to consistently estimate IV_t. The truncated power variation TV_t is defined as:

$$TV_t(\Delta) \equiv \sum_{i=1}^{M} (y_{t,i})^2 1_{|y_{t,i}| \leq g(\Delta)^{\tilde{\omega}}} \xrightarrow{\mathbb{P}} \int_{t-1}^{t} \sigma^2(s)ds, \tag{3.16}$$

where $g > 0$, and $\tilde{\omega} \in (0,\, 1/2)$ are the thresholds to truncate the returns. TV_t eliminates the large returns and retains the ones that are lower than the specified thresholds. To estimate TV_t, we use the parameter values of $g = 0.3 \times 9$, and $\tilde{\omega} = 0.47$, following Aït-Sahalia and Jacod (2009b).

The block-graphs on the right of Figure 4 plot the truncated power variation for the EUR/USD, constructed from the 5-minute, 30-minute and 1-hour intraday returns. The graphs show that the TV_t is highly robust to jumps in that it exhibits fewer spikes than $MinRV_t$ and $MedRV_t$.

[Insert Table 5 and Figure 5 about here]

As an alternative comparison, Figure 5 plots the first 50 lags of the autocorrelation function of RV_t, BV_t and TV_t constructed from 5-minute, 30-minute and 1-hour returns. This figure clearly suggests the presence of long-memory in volatility. The estimated long-memory parameters given by the log-periodogram regression method of Geweke and Porter-Hudak (1983) are about 0.30, 0.35 and 0.45 for RV_t, BV_t and TV_t, respectively (see the last column in Table 5). These coefficient estimates suggest that the more robust-to-jumps estimators also imply more evidence of long-memory persistence in volatility.[19]

Section 4

Intraday periodicity

A time series is periodic if it shows a regular, time-dependent structure. Foreign exchange volatility shows strong intraday periodic effects caused by regular trading patterns, such as openings and closings of the three major markets, Asia, Europe and North America, as well as effects from regularly scheduled macroeconomic announcement effects.

Andersen and Bollerslev (1997) show that failure to account for this intra-daily periodicity is likely to result in misleading statistical analyses because intraday returns do not conform at all to the theoretical aggregation results for the GARCH models.

This section documents the intraday periodicity found in foreign exchange volatility and discusses methods of modeling it.

[Insert Figure 6 about here]

Figure 6 displays a distinct U-shaped patterns in the ACF for the 5-minute, 30-minute and 1-hour absolute returns $|y_{t,i}|$. Standard ARCH models imply a geometric decay in the absolute return autocorrelation structure and simply cannot accommodate strong regular cyclical patterns of the sort displayed in Figure 6.

[Insert Figure 7 about here]

Figure 7 depicts the mean absolute EUR/USD returns over the (288) five-minute intervals. This intraday pattern is quite similar across all days of the week with discrete changes in quoting activity marking the opening and closing of business hours in the three major regional centres, all of which have their own activity pattern.

In illustrating the properties of intraday foreign exchange volatility, we use the following hours of active trading: the Far East is open from 16:00 EST (21:00 GMT) to 1:00 EST (6:00 GMT), Europe trades between 2:00 EST (7:00 GMT) and 11:00 EST (16:00 GMT) and trading in North America occurs from 7:00 EST (12:00 GMT) to 16:00 EST (21:00 GMT). Using the discussion of market opening and closures presented above, we explain the intraday periodic volatility as follows. At 19:00 EST, the Far Eastern market has already been trading for around three hours and market activity is high. From 19:00 EST until about 22:00 EST, activity levels and volatility remain high. The lunchtime in Tokyo (22:00 EST- 23:45 EST) is the point of the day corresponding to the most prominent feature of the series. Volatility drops sharply and regains its former value at about 0:00 EST. Generally, there is a small peak in volatility as Europe begins to contribute to activity at around 2:00 EST and the Far Eastern market activity begins to wane. During European lunch hours (starting around 6:30 EST), both activity and volatility show a slight lull. The most active period of the day is clearly when both the European and North American markets are open (between 7:00 EST and 11:00 EST). Volatility starts to decline as first the European and then US markets wind down. At around 16:00 EST, the Asian market begins to trade again and the daily cycle is repeated after midnight. This intraday pattern is consistent with previous evidence reported in the literature, see Andersen and Bollerslev (1998b) among others.

Classical and robust estimation of intraday periodicity

Recall that we use T days of $\lfloor 1/\Delta \rfloor \equiv M$ equally-spaced and continuously compounded intraday returns and that $y_{t,i}$ is the i-th return of day t. Assume first that the log-price follows a Brownian SemiMartingale (BSM) diffusion as in Equation (3.1). If Δ is sufficiently small, returns are conditionally normally distributed with mean zero and variance $\sigma^2_{t,i} = \int_{t+(i-1)\Delta}^{t+i\Delta} \sigma^2(s)ds$, that is $y_{t,i} \approx \sigma_{t,i} z_{t,i}$, where $z_{t,i} \sim N(0,1)$. Due to the daily/weekly cycle of opening and closing times of the financial centers around the world, the high-frequency return variance $\sigma^2_{t,i}$ has a periodic component $f^2_{t,i}$.

At daily frequencies, the intraday periodic component accounts for almost all variation in variance. Andersen and Bollerslev (1997, 1998b), Andersen, Bollerslev, and Dobrev (2007) and Lee and Mykland (2008) use local windows of one day. It is therefore realistic to assume that $\sigma^2_{t,i} = s_{t,i} f_{t,i}$, where $s_{t,i}$ is the stochastic part of the intradaily volatility that is assumed to be constant over the day but varies from one day to another.

Andersen and Bollerslev (1997, 1998b) suggest estimating $s_{t,i}$ by $\hat{s}_t = \sqrt{\frac{1}{M} h_t}$ $\forall i = 1, \ldots, M$, where h_t is the conditional variance of day t obtained by estimating a GARCH model on daily returns. Under the BSM model, a more efficient estimator for $s_{t,i}$ is $\hat{s}_t = \sqrt{\frac{1}{M} RV_t}$.

As explained above, under the BSMFAJ model, the daily integrated volatility is better estimated using Barndorff-Nielsen and Shephard (2004)'s realized bi-power variation, that is, $\hat{s}_{t,i} = \sqrt{\frac{1}{M-1} BV_t}$, where BV_t is the bi-power variation computed on all the intraday returns of day t (see Equation (3.8)). In the presence of infinite activity Lévy jumps—Model (3.15)—the truncated power variation TV_t—Equation (3.16)—would be a better choice for estimating daily integrated volatility. In this case, $\hat{s}_{t,i} = \sqrt{\frac{1}{M-1} TV_t}$, where TV_t is the truncated power variation computed on all the intraday returns of day t.[20]

Under this model, the standardized high-frequency return $\overline{y}_{t,i} = y_{t,i}/\hat{s}_{t,i} \sim N(0, f_{t,i}^2)$ as $\Delta \to 0$. This result suggests estimating the periodicity factor using either a non-parametric or parametric estimator of the scale of the standardized returns.

Non-parametric estimation of periodicity

The non-parametric estimates of intraday volatility patterns are all based on average variation in volatility across different periods of the week. In other words, the non-parametric estimates for the volatility periodicity factor on Wednesdays at 10:00 AM are some sort of weighted average of the magnitude of the returns on all Wednesdays at 10:00 AM. The non-parametric estimators differ in whether or how they compensate for the presence of jumps, which should be excluded from the estimation of the periodic diffusion volatility factor.

The classical periodicity estimator is based on the standard deviation

$$\hat{f}_{t,i}^{\text{SD}} = \frac{\text{SD}_{t,i}}{\sqrt{\frac{1}{M} \sum_{j=1}^{M} \text{SD}_{t,j}^2}}, \tag{4.1}$$

where $\text{SD}_{t,i} = \sqrt{\frac{1}{n_{t,i}} \sum_{j=1}^{n_{t,i}} \overline{y}_{j;t,i}^2}$. This estimator is similar to Taylor and Xu (1997)'s periodicity estimate based on averages of squared returns. In absence of jumps, $\hat{f}_{t,i}^{\text{SD}}$ efficiently estimates $f_{t,i}^{\text{SD}}$ if the standardized returns are normally distributed. In the presence of jumps, this estimator is useless, since it suffices that one observation in the sample is affected by a jump to make the periodicity estimate arbitrarily large.

Because $\hat{f}_{t,i}^{\text{SD}}$ does not robustly estimate its population counterpart in the presence of jumps, Boudt, Croux, and Laurent (2011b) propose replacing the standard deviation in (4.1) by a robust non-parametric estimator. One candidate is the median absolute deviation (MAD), which is proportional to the size of the median deviation from the median of a series. The MAD of a sequence of observations $y_1, \ldots, y_n$ is defined as

$$1.486 \cdot \text{median}_i |y_i - \text{median}_j y_j|, \tag{4.2}$$

where 1.486 is a correction factor to guarantee that the MAD is a consistent scale estimator at the normal distribution. The MAD estimator for the periodicity factor of $y_{t,i}$ equals

$$\hat{f}_{t,i}^{\text{MAD}} = \frac{\text{MAD}_{t,i}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M} \text{MAD}_{t,j}^2}}. \tag{4.3}$$

Among the large number of robust-scale estimators available in the literature (see Maronna, Martin, and Yohai, 2006, for an overview), Boudt, Croux, and Laurent (2011b) also recommend the use of the Shortest Half scale estimator proposed by Rousseeuw and Leroy (1988), because it remains consistent in the presence of infinitesimal contaminations by jumps in the data. Importantly, the Shortest Half Scale estimator has the smallest jump-induced bias among a wide class of estimators. Under normality, the Shortest Half scale estimator is as efficient as the MAD and the interquartile range. It is also computationally convenient and does not need any location estimation.

To define the Shortest Half scale estimator, we denote the corresponding order statistics $\overline{y}_{(1);t,i}, \ldots, \overline{y}_{(n_{t,i});t,i}$ such that $\overline{y}_{(1);t,i} \leq \overline{y}_{(2);t,i} \leq \ldots \leq \overline{y}_{(n_{t,i});t,i}$. The shortest half scale is the smallest length of all "halves" consisting of $h_{t,i} = \lfloor n_{t,i}/2 \rfloor + 1$ contiguous order observations. These halves equal $\{\overline{y}_{(1);t,i}, \ldots, \overline{y}_{(h_{t,i});t,i}\}$, …, $\{\overline{y}_{(n_{t,i}-h_{t,i}+1);t,i}, \ldots, \overline{y}_{(n_{t,i});t,i}\}$, and their length is $\overline{y}_{(h_{t,i});t,i} - \overline{y}_{(1);t,i}$, …, $\overline{y}_{(n_{t,i});t,i} - \overline{y}_{(h_{t,i});t,i}$, respectively. The corresponding scale estimator (corrected for consistency under normality) equals the minimum of these lengths:

$$\text{ShortH}_{t,i} = 0.741 \cdot \min\{\overline{y}_{(h_{t,i});t,i} - \overline{y}_{(1);t,i}, \ldots, \overline{y}_{(n_{t,i});t,i} - \overline{y}_{(n_{t,i}-h_{t,i}+1);t,i}\}. \tag{4.4}$$

The Shortest Half estimator for the periodicity factor of $y_{t,i}$ equals

$$\hat{f}_{t,i}^{\text{ShortH}} = \frac{\text{ShortH}_{t,i}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M} \text{ShortH}_{t,j}^2}}. \tag{4.5}$$

The shortest half dispersion is highly robust to jumps, but it has only a 37 per cent relative efficiency under normality of the $\overline{y}_{t,i}$'s. Boudt, Croux, and Laurent (2011b) show that the standard deviation applied to the returns weighted by their outlyingness under the ShortH estimate offers a better trade-off between the efficiency of the standard deviation under normality and robustness to jumps, that is

$$\hat{f}_{t,i}^{\text{WSD}} = \frac{\text{WSD}_{t,i}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M} \text{WSD}_{t,j}^2}}, \tag{4.6}$$

where

$$\text{WSD}_{t,j} = \sqrt{1.081 \cdot \frac{\sum_{l=1}^{n_{t,j}} w[(\overline{y}_{l;t,j}/\hat{f}_{t,j}^{\text{ShortH}})^2]\overline{y}_{l;t,j}^2}{\sum_{l=1}^{n_{t,j}} w[(\overline{y}_{l;t,j}/\hat{f}_{t,j}^{\text{ShortH}})^2]}}.$$

Because the weighting is applied to the squared standardized returns, which are extremely large in the presence of jumps, Boudt, Croux, and Laurent (2011b) recommend the use of the hard rejection with threshold equal to the 99 per cent quantile of the χ^2 distribution with one degree of freedom, that is

$$w(z) = \begin{cases} 1 & \text{if } z \leq 6.635 \\ 0 & \text{else.} \end{cases} \tag{4.7}$$

The factor 1.081 ensures the consistency of the estimator under normality. The Weighted Standard Deviation (WSD) in (4.6) has a 69 per cent efficiency under normality of the $\overline{y}_{t,i}$'s.

Parametric estimation of periodicity

The non-parametric periodicity estimators use the standardized returns that have the same periodicity factor. This means that if we are interested in the impact of calender effects, the non-parametric estimators take the returns that are observed on the same time of the day, and same day of the week. Alternatively, Andersen and Bollerslev (1997) show that one can efficiently estimate the periodicity process with trigonometric functions of time. These trigonometric functions implicitly constrain the periodicity to be "smooth" over time in ways that the non-parametric techniques, which estimate the periodicity factor independently during each time period, do not. Under the assumption that returns are not affected by jumps, Andersen and Bollerslev (1997) show that $\log(\frac{|y_{t,i}|}{s_{t,i}}) \approx \log f_{t,i} + \log|z_{t,i}|$, which isolates $f_{t,i}$ as follows,

$$\log(|y_{t,i}/s_{t,i}|) - c = \log f_{t,i} + u_{t,i}, \tag{4.8}$$

where the error term $u_{t,i}$ is i.i.d. distributed with mean zero and has the density function of the centered absolute value of the log of a standard normal random variable, that is

$$g(z) = \sqrt{2/\pi}\exp[z + c - 0.5\exp(2(z + c))]. \tag{4.9}$$

The parameter $c = -0.63518$ equals the mean of the log of the absolute value of a standard normal random variable. Andersen and Bollerslev (1997) then propose modeling $\log f_{t,i}$ as a function h of a vector of variables x (such as sinusoid and polynomial transformations of the time of the day) that is linear in the parameter vector θ

$$\log f_{t,i} = h(x_{t,i};\theta) = x'_{t,i}\theta. \tag{4.10}$$

Combining (4.8) with (4.10), we obtain the following regression equation

$$\log(|\overline{y}_{t,i}|) - c = x'_{t,i}\theta + u_{t,i}. \tag{4.11}$$

Researchers commonly estimate the parameter θ in (4.11) by OLS. This approach is neither efficient nor robust, because the error terms are not normally distributed. Denote the loss functions of the OLS and Maximum Likelihood (ML) estimators by $\rho^{\text{OLS}}(z) = z^2$ and by

$$\rho^{\text{ML}}(z) = -0.5\log(2/\pi) - z - c + 0.5\exp(2(z+c)),$$

respectively. The OLS and ML estimates equal

$$\hat{\theta}^{\text{OLS}} = \text{argmin}\frac{1}{MT}\sum_{t=1}^{T}\sum_{i=1}^{M}\rho^{\text{OLS}}(u_{t,i}) \text{ and } \hat{\theta}^{\text{ML}} = \text{argmin}\frac{1}{MT}\sum_{t=1}^{T}\sum_{i=1}^{M}\rho^{\text{ML}}(u_{t,i}), \tag{4.12}$$

where $u_{t,i}$ is a function of θ.

As an alternative to the OLS and ML estimators, Boudt, Croux, and Laurent (2011b) propose using the *Truncated Maximum Likelihood* (TML) estimator introduced by Marazzi and Yohai (2004). This estimator gives a zero weight to outliers, as defined by the value of the ML loss function evaluated at the corresponding residual computed under the robust non-parametric estimator $\hat{f}^{\text{WSD}}$ in (4.6). Let

$$u_{t,i}^{\text{WSD}} = \log\overline{y}_{t,i} - c - \log\hat{f}_{t,i}^{\text{WSD}}. \tag{4.13}$$

Observations for which $\rho^{\text{ML}}(u_{t,i}^{\text{WSD}})$ is large, have a low likelihood and are therefore likely to be outliers (Marazzi and Yohai, 2004). Denote q an extreme upper quantile of the distribution of $u_{t,i}$. The TML estimator is defined as

$$\hat{\theta}^{\text{TML}} = \frac{1}{\sum_{t=1}^{T}\sum_{i=1}^{M} w_{t,i}}\sum_{t=1}^{T}\sum_{i=1}^{M} w_{t,i}\rho(u_{t,i}), \tag{4.14}$$

with

$$w_{t,i} = \begin{cases} 1 & \text{if } \rho^{\text{ML}}(u_{t,i}^{\text{WSD}}) \leq \rho^{\text{ML}}(q) \\ 0 & \text{else.} \end{cases}$$

The parametric estimate for the periodicity factor equals

$$\hat{f}_{t,i}^{\text{TML}} = \frac{\exp x'_{t,i}\hat{\theta}^{\text{TML}}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M}(\exp x'_{t,j}\hat{\theta}^{\text{TML}})^2}}, \tag{4.15}$$

and similarly for $\hat{f}_{t,i}^{\text{OLS}}$ and $\hat{f}_{t,i}^{\text{ML}}$. Boudt, Croux, and Laurent (2011b) show that parametric methods are generally much more efficient than non-parametric ones. They also show that in the presence of jumps, the TML estimator is the most robust method. However, the main weakness of this approach is that little is known about the asymptotic distribution of the TML estimates in the presence of jumps, which makes the statistical inference based on this method challenging.

[Insert Figures 8 and 9 about here]

Figures 8 and 9 depict the non-parametric and parametric periodicity estimates of the EUR/USD and USD/JPY series. In Figure 8, we see that the SD method (that is Taylor and Xu, 1997 filter) is indeed more sensitive to jumps than the other non-parametric estimators. Among the parametric candidates given in Figures 9, TML periodicity estimates seem to be smoother than the OLS and ML estimates.

Are the periodic volatility patterns common to several time series? To investigate this issue, Hecq, Laurent, and Palm (2011) propose a reduced rank method to examine the presence of such commonalities in the intraday cyclical movements. This approach, along with a multivariate information criteria, further allows to determine the variables that explain the common periodic features. In an application to thirty US stocks, their empirical results suggest using three common sources to describe the periodic patterns, whereas they find no evidence of common factors in the intradaily periodic volatility of the major exchange rates.

Section 5

Jumps

Researchers have noted jumps (that is, discontinuities) in asset prices for some time. The efficient markets hypothesis easily explains many jumps because it predicts very rapid systematic price reactions to news surprises to prevent risk-adjusted profit opportunities. Decomposing volatility into jumps and time-varying diffusion volatility is important because these two components have different implications for modeling, forecasting, and hedging. For example, persistent time-varying diffusion volatility would help forecast future volatility, while jumps might contain no predictive information or even distort volatility forecasts (Neely, 1997 and Andersen, Bollerslev, and Diebold, 2007). Therefore, it makes sense to detect jumps and either model them separately or clean them from the data. This section describes recent tests for jumps in foreign exchange rates.

Daily non-parametric tests for large jumps

The difference between RV_t and any robust-to-jumps estimator of IV_t, denoted $\hat{IV}_t$, estimates the jump contribution or realized jumps under the BSMFAJ model. That is, the realized jump measure equals a realized volatility measure less a robust-to-jumps measure of diffusion volatility.

$$RJ_t \equiv RV_t - \hat{IV}_t \to \sum_{t-1<s\leq t} \kappa^2(s), \tag{5.1}$$

where $\hat{IV}_t$ is for instance BV_t or $ROWVar_t$. We will review several statistics that estimate jumps using the difference between RV and robust-to-jumps estimates of IV.

Based on the theoretical results of Barndorff-Nielsen and Shephard (2006) that

$$\sqrt{\Delta}\begin{pmatrix} RV_t - IV_t \\ \hat{IV}_t - IV_t \end{pmatrix} \xrightarrow{d} MN\left(0, \begin{pmatrix} 2 & 2 \\ 2 & \theta \end{pmatrix} IQ_t\right) \text{ if } \Delta \to 0, \tag{5.2}$$

where $IQ_t \equiv \int_{t-1}^{t} \sigma^4(s)ds$ is the integrated quarticity. Andersen, Bollerslev, and Diebold (2007) have developed a formal test for (daily) jumps, that is

$$Z_t \equiv \frac{RV_t - \hat{IV}_t}{\sqrt{(\theta - 2)\frac{1}{M}\hat{IQ}_t}}, \tag{5.3}$$

where $\hat{IQ}_t$ is a robust-to-jumps estimate of the integrated quarticity, IQ_t. Andersen, Bollerslev, and Diebold (2007) estimate integrated variance with bipower variation and use the Tri-power quarticity TQ_t to estimate IQ_t, where

$$TQ_t \equiv M\frac{M}{M-2}\mu_{4/3}^{-3}\sum_{i=3}^{M}|y_{t,i}|^{4/3}|y_{t,i-1}|^{4/3}|y_{t,i-2}|^{4/3}, \tag{5.4}$$

with $\mu_{4/3} \equiv 2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1}$.

Another popular estimator for IQ_t, in the spirit of the bi-power (or multi-power) variation, is the Quad-power quarticity QQ_t, that is

$$QQ_t \equiv M\frac{M}{M-3}\mu_1^{-4}\sum_{i=4}^{M}|y_{t,i}||y_{t,i-1}||y_{t,i-2}||y_{t,i-3}|. \tag{5.5}$$

When $\hat{IV}_t = BV_t$, $\theta = \mu_1^{-4} + 2\mu_1^{-2} - 3 \approx 2.609$. The main drawback of TQ_t and QQ_t is that like BV_t they are downward biased in the presence of zero returns. To overcome this problem, Boudt, Croux, and Laurent (2011a) have proposed replacing $\hat{IV}_t$ in Equation (5.3) by $ROWVar_t$ and $\hat{IQ}_t$

by the Realized Outlyigness Weighted Quarticity

$$\text{ROWQuarticity}_t = d_w \frac{\sum_{i=1}^{M} w(d_{t,i}) y_{t,i}^4}{\sum_{i=1}^{M} w(d_{t,i})}, \tag{5.6}$$

where $w(.)$ is the hard rejection weight function. Table 6 reports the correction factor d_w and the asymptotic variance of the ROWVar θ for several choices of the critical level β (used to get the outlyingness threshold k).

[Insert Table 6 about here]

In the spirit of their MinRV and MedRV estimators, Andersen, Dobrev, and Schaumburg (2008) propose two alternative robust estimators of the integrated quarticity, namely the MinRQ and MedRQ. The formulas are given herebelow:

$$MinRQ_t \equiv M \frac{M}{M-1} \mu_4 \sum_{i=2}^{M} min(|y_{t,i}|, |y_{t,i-1}|)^4 \tag{5.7}$$

$$MedRQ_t \equiv M \frac{M}{M-2} \mu_5 \sum_{i=3}^{M} med(|y_{t,i}|, |y_{t,i-1}|, |y_{t,i-2}|)^4, \tag{5.8}$$

where $\mu_4 \equiv \pi/(3\pi - 8)$ and $\mu_5 = 3\pi/(9\pi + 72 - 52\sqrt{3})$. Note also that Andersen, Dobrev, and Schaumburg (2008) show that both the MinRV and MedRV satisfy (5.2), where θ equals 3.81 for the former and 2.96 for the latter (the MedRV being asymptotically more efficient than the MinRV in absence of jumps).

Barndorff-Nielsen and Shephard (2006) advocated the use of a log version of the Z_t statistics. According to them, the following statistic

$$logZ_t \equiv \frac{\log(RV_t) - \log(I\hat{V}_t)}{\sqrt{(\theta - 2)\frac{1}{M} I\hat{Q}_t I\hat{V}_t^{-2}}}, \tag{5.9}$$

has better finite sample properties.

They also proposed another version of this statistic, denoted $maxlogZ_t$, where

$$maxlogZ_t \equiv \frac{\log(RV_t) - \log(I\hat{V}_t)}{\sqrt{(\theta - 2)\frac{1}{M} max\{1, I\hat{Q}_t I\hat{V}_t^{-2}\}}}. \tag{5.10}$$

Under the null of no jump on day t, Z_t, $logZ_t$ and $maxlogZ_t$ are asymptotically (as $\Delta \to 0$) standard normal. The sequences $\{Z_t\}_{t=1}^T$, $\{logZ_t\}_{t=1}^T$ and $\{maxlogZ_t\}_{t=1}^T$ provide estimates of the daily occurrence of jumps in the price process.

Intradaily non-parametric tests for large jumps

The tests presented in the previous section rely on intraday returns to test for jumps at a lower frequency, for example, over one day. This section describes the tests that examine whether any given intra-day return $y_{t,i}$ is from a purely continuous diffusion or is due to a jump in the price process. Lee and Mykland (2008) propose detecting intraday jumps by comparing returns to a local volatility measure. However, what constitutes an abnormally big return depends on the prevailing level of volatility. That is, in times of high volatility, an abnormal return is expected to be bigger than an abnormal return in times of low volatility. Hence, Lee and Mykland (2008) study the properties of the ratio of the tested return over a measure of local volatility. They propose a powerful and parsimonious methodology that allows to test whether any return contains a jump component.

Their jump statistic, denoted as $J_{t,i}$, is defined as the absolute return divided by an estimate of the local standard deviation $\hat{\sigma}_{t,i}$, that is

$$J_{t,i} = \frac{|y_{t,i}|}{\hat{\sigma}_{t,i}}. \tag{5.11}$$

Under the null of no jump in the ith return, that the process belongs to the family of BSMFAJ models described in Equation (3.6), and a suitable choice of the window size for local volatility, $\frac{y_{t,i}}{\hat{\sigma}_{t,i}}$ asymptotically follows a standard normal distribution.

Lee and Mykland (2008) recommend replacing $\hat{\sigma}_{t,i}$ by $\hat{s}_t = \sqrt{\frac{1}{M-1} BV_t}$ where BV_t is the bi-power variation computed on all the intraday returns of day t. Boudt, Croux, and Laurent (2011b) propose to account for the strong periodicity in volatility and show that replacing $\hat{\sigma}_{t,i}$ by either $\hat{f}^{\mathrm{WSD}}_{t,i}\hat{s}_t$ or $\hat{f}^{\mathrm{TML}}_{t,i}\hat{s}_t$ is more appropriate. They show that ignoring periodic volatility patterns leads to spurious jump identification. Indeed, the original Lee/Mykland statistic, which neglects the periodicity, tends to overdetect (underdetect) jumps in periods of high (low) intraday periodic volatility.

Under the null of no jump and a consistent estimate $\hat{\sigma}_{t,i}$, $J_{t,i}$ follows the same distribution as the absolute value of a standard normal variable. Brownlees and Gallo (2006) propose comparing $J_{t,i}$ with the $1-\alpha/2$ quantile of the standard normal distribution. This rule might spuriously detect many jumps, however. Andersen, Bollerslev, and Dobrev (2007) use a Bonferroni correction to minimize spurious jump detection. To minimize the risk of falsely finding jumps, Lee and Mykland (2008) propose inferring jumps from a conservative critical value, which they obtain from the distribution of the statistic's maximum over the sample size. If the statistic exceeds a plausible maximum, one rejects the null of no jump. Under the stated assumptions and no jump in the interval $i-1, i$ of day t, then when $\Delta \to 0$, the sample maximum of the absolute value of a standard normal variable (that is the jump statistic $J_{t,i}$) follows a Gumbel distribution. We reject the null of no jump if

$$J_{t,i} > G^{-1}(1-\alpha)S_n + C_n, \tag{5.12}$$

where $G^{-1}(1-\alpha)$ is the $1-\alpha$ quantile function of the standard Gumbel distribution, $C_n = (2\log n)^{0.5} - \frac{\log(\pi)+\log(\log n)}{2(2\log n)^{0.5}}$ and $S_n = \frac{1}{(2\log n)^{0.5}}$. When $n = 1$, the test is similar to the one of Brownlees and Gallo (2006) in the sense that the expected number of spurious detected jumps (under the null) can be extremely large, that is αMT. When $n = M$ (that is number of observations per day) and $n = MT$ (that is total number of observations), this number equals respectively αT and α (that is ≈ 0). So if we choose a significance level of $\alpha = 0.0001$, then we reject the null of no jump at testing time if $J_{t,i} > S_n\beta^* + C_n$ with β^* such that $P(\psi \leq \beta^*) = exp(-e^{-\beta^*}) = 0.9999$, that is $\beta^* = -log(-log(0.9999)) = 9.21$.

Lee and Hannig (2010) propose a method to decompose jump risk into *big* jump risk and *small* jump risk. To identify big jump arrivals, they propose using the following statistic:

$$J^{\text{LH}}_{t,i} = \frac{|y_{t,i}|}{\hat{\sigma}_{t,i}}, \tag{5.13}$$

where $\hat{\sigma}_{t,i}$ is now replaced by $\hat{s}_t = \sqrt{\frac{1}{M-1}TV_t}$, where TV_t is the truncated power variation given in Equation (3.16), and computed on all the intraday returns of day t. The test detects the arrival times of the *big* jumps when data follows a BSMIAJ model as in Equation (3.15).[21] The detection method for the big jumps is same as the Lee and Mykland test, and thus given by the rule (5.12).

[Insert Figure 10 about here]

Like the Lee/Mykland statistic, $J^{\text{LH}}_{t,i}$ neglects periodic volatility. To account for such cyclical patterns in volatility, one can replace $\hat{\sigma}_{t,i}$ by $\hat{f}_{t,i}\hat{s}_t$, which is a periodicity-robust volatility measure. Indeed, the left-block graphs of Figure 10 show that ignoring periodicity leads to spurious jump identification.[22] Like the Lee/Mykland test, the original Lee/Hannig test (without periodicity filtration) tends to overdetect (underdetect) jumps in periods of high (low) intraday periodic volatility. The figure also suggests that filtered Lee/Hannig test (by either $\hat{f}^{\text{WSD}}_{t,i}\hat{s}_t$ or $\hat{f}^{\text{TML}}_{t,i}\hat{s}_t$) leads to a more uniform distribution of the number of spurious jumps over a day (see middle and right-block graphs in Figure 10).

Application

This section applies the daily and intradaily jump tests described in the previous sections to 5-minute returns.

[Insert Table 7 and Figure 11 about here]

Table 7 reports the number of detected daily jumps and their proportions to all sample days. The table clearly shows the presence of jumps in the exchange rates. The tests using BV_t, $MinRV_t$ and $MedRV_t$ as integrated volatility measures detect about 300-400 daily jumps. Furthermore, Figure 11 illustrates the time series of these detected jumps. Jumps occur more frequently during the financial crisis period, 2007-2009, particularly for the USD/JPY exchange rate.

[Insert Table 8 and Figure 12 about here]

We now turn our attention to intraday jumps. Table 8 reports the results of the Lee/Mykland-test and the Lee/Hannig-test, as well as their periodicity-free versions. The table indicates that there are about 2000 intraday jumps detected in both exchange rates. Nevertheless, the intraday jumps do not occur very often. For instance, the likelihood of observing an intraday return as a jump (that is $p(jumps)$ in the second column) is less than 1 per cent in general.

How does periodicity in volatility affect intraday jump identification? Figure 12 plots the number of jumps per intraday interval. The fact that the filtered and unfiltered tests detect different returns as jumps (see the right and left-block graphs in Figure 12) suggests that one should account for intraday periodicity in jumps. The unfiltered tests tend to underdetect jumps at times of low periodicity and overdetect jumps at high periodicity times, in line with our simulation results. Accounting for periodicity leads to a more uniform distribution for intraday jump occurrences (see right-block graphs in Figure 12).

Section 6

Macro news and central bank interventions

Because asset prices react to news about discount rates or future earnings, researchers have long recognized that announcements affect foreign exchange volatility. Scheduled announcements can help explain two important properties of foreign exchange volatility: periodicity and discontinuities in prices.

The study of announcement effects on volatility grew out of an earlier literature on autocorrelation, intraday and intraweek patterns in volatility. Researchers sought to distinguish patterns caused by market opening/closing from those caused by regular macro announcements. Links between announcements and volatility have implications for policy: a strong relation between volatility and news argues against taxing foreign exchange transactions to reduce allegedly meaningless churning that creates "excess" volatility (Melvin and Yin, 2000). Recent research has clearly linked macro announcements to price discontinuities (jumps), which have implications for volatility forecasting (Neely, 1999 and Andersen, Bollerslev, and Diebold, 2007). Finally, microstructure theory has motivated studies that show that the prolonged impact of news announcements on volatility occurs through the persistent release of private information through order flow.

Research methods

The literature has devoted disproportionate attention to U.S. announcements because U.S. announcements are scheduled and expectations of those announcements and accompanying exchange rate data have been widely available for a long time.[23] Tables 9 and 10 show commonly used U.S. announcements, their source and the delay in their release.

[Insert Tables 9 and 10 about here]

Researchers have commonly used three measures of volatility to study announcement effects: implied volatility, realized volatility and variants of GARCH models (Engle, 1982, and Bollerslev, 1986).[24] Implied volatility is strongly forward looking and often insensitive to short-lived volatility effects from macro announcements. GARCH models fitted to daily data predict daily volatility through essentially autoregressive processes, but such models cannot estimate intraday effects. In contrast, high-frequency data—which can be used with parametric models such as GARCH—are well suited to measuring short-lived, intraday effects.

Researchers also study the extent to which a scheduled announcement itself—rather than the surprise component—could be expected to change volatility. To separate the effects of the announcement itself from the effects of the surprise component, researchers generally estimate the expectation of the announcement with the median response from the Money Market Services (MMS) Friday survey of 40 money managers on their expectations of coming economic releases.[25] Grossman (1981), Engel and Frankel (1984), Pearce and Roley (1985), and McQueen and Roley (1993) showed that the MMS survey data provide approximately unbiased and informationally efficient estimates of news announcements that outperform time series models.[26]

To compare coefficients on announcement surprise series with different magnitudes, researchers have typically followed Balduzzi, Elton, and Green (2001) in standardizing surprises by subtracting the MMS expectation from the release and dividing those differences by the SD of the series of differences. For example, the standardized surprise for announcement j is as follows:

$$S_t^j = \frac{R_t^j - E_t^j}{\hat{\sigma}_j}, \tag{6.1}$$

where R_t^j is the realization of announcement j at day t, E_t^j is the MMS market expectation, and $\hat{\sigma}_j$ is the estimated SD of the series of the differences. Thus, announcement surprises are close to mean zero and have a unit SD.

Early study of volatility patterns

Early studies of volatility patterns by Engle, Ito, and Lin (1990) and Harvey and Huang (1991) motivated specific study of announcement effects on volatility, despite the fact that the latter paper did not explicitly incorporate macro announcements.

Harvey and Huang (1991) discover an intraday U-shaped volatility pattern in hourly foreign exchange returns as well as intraweek effects. The authors speculate that important news announcements at the end of the week raise volatility on Thursday and Friday. Volatility is highest during the traded currency's own domestic business hours, particularly so for non-USD (United States dollar) cross rates. Engle, Ito, and Lin (1990) extend this research in intraday volatility patterns by introducing the concepts of *heat waves* and *meteor showers* in the foreign exchange market. Heat waves refer to the idea that volatility is geographically determined—that is, a heat wave might raise volatility in New York on Monday and Tuesday but not in London on Tuesday morning. Heat waves might occur if most or all important news that affects volatility occurs during a particular country's business day and there is little price discovery when that country's markets are closed. In contrast, meteor showers refer to the tendency of volatility to spill over from market to market, from Asian to European to North American markets, for example. Therefore, meteor showers imply volatility clusters in time, not by geography. Using a GARCH model with intraday data, Engle, Ito, and Lin (1990) find that the meteor shower hypothesis better characterizes foreign exchange volatility engendered by balance of trade announcements. Baillie and Bollerslev (1991) confirm the meteor shower effect but also find some evidence of heat wave behavior. In retrospect, it seems unsurprising that meteor showers should predominate over heat waves in a world of global trading and a high degree of autocorrelated common shocks across countries: News tends to cluster in time and will surely affect volatility across the globe.

Decomposing announcements and periodic volatility patterns

Ederington and Lee (1993, 1994, and 1995) argued that announcements explain most of the daily and intraweek volatility patterns, leaving little residual explained by a periodic pattern. Because announcements and periodicity are correlated, however, one must jointly model them to consistently estimate and compare their impact (Payne, 1996 and Andersen and Bollerslev, 1998b). In doing so, Andersen and Bollerslev (1998b) affirm the importance of macro releases as addressed by Ederington and Lee (1993), but argue that these are secondary to the intraday pattern; periodic patterns and autoregressive volatility forecasts explain more of intraday and daily volatility than do announcements. The debate on the relative importance of announcement versus periodic effects continued in Han, Kling, and Sell (1999) and Ederington and Lee (2001).

Announcements and intraday patterns are not the whole story, however, Andersen and Bollerslev (1998b) find that—after accounting for the intraday volatility pattern—including ARCH terms still significantly improves forecasting power, even in a high-frequency volatility process.

To illustrate the issues involved in disentangling announcements, other periodic effects and autocorrelation, one can regress absolute hourly foreign exchange returns—24 hours a day, 5 days a week—on announcement variables and periodic components. The following equation describes such a regression for hourly returns:

$$\log(|y_{t,i}|/\hat{s}_{t,i}) - c = \alpha_0 + \beta_0^{(US)} D_{t,i}^{(US)} + \beta_1^{(For)} D_{t,i}^{(For)} + \sum_{j=1}^{N} \beta_{2,j} |Surprise_{t,i}^{(j)}| + \sum_{q=1}^{4} \beta_{3,q} \cos\left(\frac{i2\pi q}{24}\right) \\ + \sum_{q=1}^{4} \beta_{4,(4+q)} \sin\left(\frac{i2\pi q}{24}\right) + \sum_{l=1}^{5} \beta_{5,l} |y_{t,i-1}| + \sum_{h=19}^{23} \beta_{6,h} D_{t,i}^{(Friday_h)} + \varepsilon_{t,i}, \tag{6.2}$$

where $\log(|y_{t,i}|/\hat{s}_{t,i})$ is the standardized log return (annualized) from period i to $i+1$; c is as defined in Section 4; $D_{t,i}^{(US)}$ and $D_{t,i}^{(For)}$ are dummy variables that take the value 1 if there is any U.S. or foreign announcement, respectively, during i to $i+1$, and 0 otherwise; $Surprise_{t,i}^{(j)}$ is the standardized surprise of announcement j at period i on day t; $\cos\left(\frac{i2\pi q}{24}\right)$ and $\sin\left(\frac{i2\pi q}{24}\right)$ are trigonometric functions that allow parsimonious estimation of an intraday periodic component.[27] Finally, $D_{t,i}^{(Friday_h)}$ takes the value 1 if the observation i coincides with hour h of a Friday, and 0 otherwise.

We estimate Equation (6.2) by ordinary least squares on 1-hour log changes in the EUR/USD exchange rate over the period 5 November 2001 to 12 March 2010, after first removing weekends and the following holidays from the sample: New Year's Day (December 31 - January 2), Good Friday, Easter Monday, Memorial Day, Fourth of July (July 3 or 5 when the Fourth falls on a Saturday or Sunday), Labor Day, Thanksgiving (and the Friday after), and Christmas (December 24 - 26). We use daily annualized GARCH $(1,1)$ volatility (that is σ_t), and also RV_t to estimate

$s_{t,i}$ for Equation (6.2).

[Insert Table 11 about here]

Table 11 shows the relative explanatory power of the various components of Equation (6.2) for absolute returns. When we use RV_t to compute endogenous variable (that is SYSTEM-II), the full regression has a substantial R^2 of 0.1828, with the greatest explanatory power coming from lagged absolute returns, with a partial R^2 of 0.0644, and the intraday periodicity (0.0457). The announcement dummies provide a very low partial R^2 of 0.0002 and the absolute announcement surprises provide a statistic of only 0.0044. Thus, the announcement surprises are fairly important but not as important as some other features of the data, confirming the views of Andersen and Bollerslev (1998b).

[Insert Tables 12 and 13 about here]

Tables 12 and 13 show the estimated regression coefficients and the robust t-statistics from Equation (6.2). Most—but not all—of the news surprise coefficients are positive, indicating that larger surprises increase volatility. Some of the news surprise coefficients are perverse (negative), which often results from their correlation with the periodic components and/or the announcement indicators. Of all the German/euro announcements, German real GDP growth, Euro area producer price index, and Euro area industrial production indicators are significant and positive (see the columns of SYSTEM-II). Germany preliminary cost of living indicator is slightly significant and negative. The U.S. announcement indicator is significant, whereas the German/euro indicator is essentially zero—that is, U.S. announcements raise volatility but German announcements do not. The significance of the U.S. announcement indicator confirms the results of Andersen, Bollerslev, Diebold, and Vega (2003), who use high-frequency (5-minute) data from 1992 through 1998 to study the effects of a large set of U.S. and German announcements on the conditional mean and the conditional volatility of DEM/USD, USD/GBP (British pound sterling), JPY/USD, CHF (Swiss franc)/USD, and USD/EUR (euro) exchange rates. The authors find that both the magnitude of the surprise and the pure announcement effect are significant.

In summary, the results in Table 11 indicate that Andersen and Bollerslev (1998b) were correct to argue that announcements are important explanatory variables for volatility, though not as important as intraday periodicity. Likewise, Tables 12 and 13 confirm the findings of Ederington and Lee (1993) that U.S. nonfarm payroll and U.S. trade balance surprises are among the most important for volatility.

Volatility and news arrival

Although the first studies of news volatility effects used U.S. news reports and USD exchange rates, later studies branched out to study the effect of foreign news and broader definitions of news. Most such work has found that U.S. news has stronger effects on foreign exchange volatility than does foreign news (Cai, Joo, and Zhang, 2009; Evans and Speight, 2010; Harada and Watanabe, 2009).

Not all news consists of macro announcements. Information about the international economy and politics arrives continuously in financial markets via newswire reports. Although most papers documenting the impact of information arrival measure that variable by the frequency of headlines from wire service news agencies, DeGennaro and Shrieves (1997) use unexpected quote arrival instead. The most common theme in this literature is that information arrival typically increases volatility (DeGennaro and Shrieves, 1997; Eddelbüttel and McCurdy, 1998; Joines, Kendall, and Kretzmer, 1998; Melvin and Yin, 2000; Chang and Taylor, 2003). Melvin and Yin (2000) interpret this result as casting doubt on proposals to apply "sand-in-the-wheels" transaction taxes that would reduce allegedly self-generated foreign exchange volatility.

Although news arrival usually boosts volatility, DeGennaro and Shrieves (1997) find that unscheduled announcements actually reduce volatility for 20 minutes, perhaps inducing traders to pause to consider unexpected information.

Eddelbüttel and McCurdy (1998) confirm that use of Reuters' news headlines as a proxy for news arrival renders the GARCH-implied variance process much less persistent. This fact appears to confirm the intuitively attractive proposition that persistence in news arrival drives part of the volatility persistence captured by GARCH models. The literature also shows, however, that public information arrival cannot explain the entire increase in volatility.

Joines, Kendall, and Kretzmer (1998) and Chang and Taylor (2003) argue that trading must also release private information that hikes volatility. Researchers working with order flow data would further explore this point.

Announcements and jumps

Researchers have long noted that asset prices display jumps or discontinuities. Such jumps are consistent with the efficient markets hypothesis, which predicts very rapid systematic price reactions to news surprises to prevent risk-adjusted profit opportunities. Jumps and time-varying diffusion volatility have different implications for modeling, forecasting, and hedging and therefore jumps should be identified and distinguished. For example, persistent time-varying diffusion volatility would help forecast future volatility, while jumps might contain no predictive information or even distort volatility forecasts (Neely, 1999 and Andersen, Bollerslev, and Diebold, 2007). Therefore, it makes sense to investigate the effect of announcements on jumps.

Goodhart, Hall, Henry, and Pesaran (1993) first suggested the importance of accounting for news-induced discontinuities in exchange rates. The authors claim that including news indicators in the conditional mean and variance equations of a GARCH-in-mean (GARCH-M) model renders both of these processes stationary (Perron, 1990). The short (3-month) span of their data would seem to preclude useful inference about the degree of persistence in the processes.

To link daily jumps in the JPY, GBP, and DEM exchange rates to four announcements from U.S., British, German, and Japanese sources, Johnson and Schneeweis (1994) introduce an announcement effect parameter to Jorion's (1988) jump-diffusion model, permitting the conditional variance to depend on an announcement indicator. Real announcements—U.S. trade balance and industrial production news—cause larger volatility movements than do money supply and inflation news and U.S. news influences currency market variance more than does foreign news. Using data from 1982 to 2000, Fair (2003) relates the largest changes in U.S. foreign exchange (and stock and bond) futures tick prices to changes to monetary, price level, employment, and trade balance news.

Advances in econometric jump modeling enabled later researchers to better examine the relation between announcements and jumps. Barndorff-Nielsen and Shephard (2004) used their method of bipower variation to pinpoint jump dates and to observe that they often correspond to days of macroeconomic releases, which is consistent with Andersen, Bollerslev, Diebold, and Vega (2003) and Andersen, Bollerslev, Diebold, and Vega (2007) (see for example Equations (5.9) and(5.10)).[28]

The Barndorff-Nielsen and Shephard (2004) bipower procedure estimates the sum of jumps during a period, usually a day but does not pin down the precise times of those jumps, which precludes linking jumps to specific news releases. Lahaye, Laurent, and Neely (2011) use the Lee and Mykland (2008) technique—which more precisely identifies jump times and sizes—to determine that U.S. macro announcements explain jumps and cojumps—simultaneous jumps in multiple markets—across equity, bond, and foreign exchange markets. Nonfarm payroll and federal funds target announcements are the most important news across asset classes, while trade balance shocks are also important for foreign exchange jumps (see Equation (5.11)).

[Insert Figure 13 about here]

Figure 13 illustrates the intraday frequency and size of jumps in the USD/EUR market (Lahaye, Laurent, and Neely, 2011). Exchange rate jumps are more frequent around the times of major U.S. macro news announcements, at 8:30 a.m., and during periods of low liquidity, that is, the gap between the U.S. and the Asian business day, 4 p.m. to 8 p.m., and the Tokyo lunch, 10 p.m. to 2 a.m. U.S. ET.

[Insert Tables 14 and 15 about here]

Lahaye, Laurent, and Neely (2011) use tobit-GARCH and probit models to formally confirm the relation between U.S. news and a variety of asset price jumps and cojumps, respectively. Table 14 shows that the tobit-GARCH results: nonfarm payroll (NFP), federal funds target announcements, trade balance reports, preliminary GDP, government fiscal announcements, and consumer confidence surprises explain to foreign exchange jumps. Table 15 likewise shows that a probit model consistently and strongly links cojumps to macro surprises, such as those to the federal funds rate target, NFP, and preliminary GDP. Federal funds target surprises significantly explain cojumps in every currency pair.

Order flows and foreign exchange volatility

News might create order flows—signed transaction flows—that transmit private information to the foreign exchange market. Private agents combine public news releases with their own private information, and their publicly observable decisions may convey that private information. For example, a business might revise its estimates of future demand from a positive industrial production surprise and decide to build a new plant—but only if the firm's privately known cost structures would make it expect to profit from that decision. The release of private information creates a channel by which news can affect volatility over a prolonged period.

Obtaining order flow data is difficult and/or expensive, prompting some researchers to use proxies for order flow, while others have used relative short spans from electronic brokers such as Reuters D2000-1 or Electronic Brokerage Services or proprietary datasets from commercial banks. The limited length and market coverage of order flow data has hindered clear inference about the effect of specific announcements on order flow.

The main finding from the literature on order flow and announcements is that news releases public information, which immediately affects prices and volatility and—after a delay—volume through release of private information through order flow (Evans and Lyons, 2005). The delayed effects of order flow can contribute to volatility for hours after announcements, particularly if the announcement is important and unscheduled, as in Carlson and Lo (2006).

Berger, Chaboud, and Hjalmarsson (2009) conclude that both persistence in order flow and persistence in sensitivity to that order flow contribute to the persistence of volatility. In other words, the *type* of order flow matters for volatility transmission: Financial customers are thought to be "informed traders," to have better information on asset prices than commercial firms, which trade currency to import/export. Frömmel, Mende, and Menkhoff (2008) find that only order flow from banks and financial customers (that is, informed order flow) is linked to higher foreign exchange volatility.[29] Savaser (2011) finds that informed traders substantially increase their use of limit orders prior to news releases and that accounting for this surge substantially improves the ability to explain exchange rate jumps that follow news.

Summary

The research on announcements and volatility highlights the role of announcements in contributing to two of the main characteristics of volatility: periodicity and jumps. Trading and volatility typically increase for about an hour after certain announcements: nonfarm payrolls, trade balance, advance GDP, and interest rate changes (Ederington and Lee, 1993).

Early researchers disentangled the contributions of macroeconomic news from those of other periodic market effects—such as market openings and closings, showing that both had significant effects on volatility (Payne, 1996 and Andersen and Bollerslev, 1998b). Further studies showed that news flow (that is, headline counts) influence volume and volatility (Ederington and Lee, 2001; Melvin and Yin, 2000; Chang and Taylor, 2003). More generally, researchers have established that news has a prolonged effect on order flow, which channels private information to market prices and produces sustained increases in volatility (Cai, Cheung, Lee, and Melvin, 2001; Evans, 2002; Evans and Lyons, 2005; Frömmel, Mende, and Menkhoff, 2008).

The development of better tests for price discontinuities has aided more recent studies to connect jumps to macro announcements and other news (Goodhart, Hall, Henry, and Pesaran, 1993; Fair, 2003; Andersen, Bollerslev, Diebold, and Vega, 2003; Lahaye, Laurent, and Neely, 2011). Removing such jumps from the volatility process improves autoregressive volatility forecasts (Neely, 1999 and Andersen, Bollerslev, and Diebold, 2007).

Central Bank Intervention, Foreign Exchange Volatility and Jumps

Foreign exchange intervention is the practice by monetary authorities or finance ministries of buying or selling foreign currency to influence exchange rates. From 1985 through 2004, the U.S., Japanese and German (European) central banks intervened more than 600 times—about 3 times per month, on average—in either the DEM-dollar (DEM/USD or EUR/USD after the introduction of the euro) or the yen-dollar (JPY/USD) market.[30]

The importance of foreign exchange markets for international trade and finance makes it unsurprising that central banks should frequently intervene in markets that are of crucial importance for international trade and finance. Specifically, central banks often motivate intervention with a desire to respond to “disorderly markets,” an ill-defined term that could include excess volatility.

The International Monetary Fund's (IMF) document: "Surveillance over Exchange Rate Policies," for example, states that "*A member should intervene in the exchange market if necessary to counter disorderly conditions, which may be characterized inter alia by disruptive short-term movements in the exchange value of its currency.*"[31] In practice, authorities have often referred to market volatility in justifying intervention: On 17 March 2011, for example, the G-7 announced a coordinated intervention to sell the yen in response to unwanted appreciation after the Japanese earthquake of the previous week. The G-7 press release contained the following text:

> "*[A]t the request of the Japanese authorities, the authorities of the United States, the United Kingdom, Canada, and the European Central Bank will join with Japan, on 18 March 2011, in concerted intervention in exchange markets. As we have long stated, excess volatility and disorderly movements in exchange rates have adverse implications for economic and financial stability. (G-7, 2011).*"

Foreign exchange intervention is a type of unscheduled news; market participants generally quickly find out about such transactions. Many researchers have studied the relation between intervention and foreign exchange volatility and, more recently, with jumps.

Although intervention is often motivated by a desire to counter volatility, research has usually found that interventions generally increase foreign exchange volatility. This result is robust to the use of any of the three main measures of asset price volatility: univariate GARCH models (Baillie and Osterberg, 1997; Dominguez, 1998; Beine, Bénassy-Quéré, and Lecourt, 2002); implied volatilities extracted from option prices (Bonser-Neal and Tanner, 1996; Dominguez, 1998; Galati and Melick, 1999); and realized volatility (Beine, Laurent, and Palm, 2009; Dominguez, 2006). Hung (1997) says that results could be sample dependent: Intervention reduced both JPY/USD and DEM/USD volatilities during 1985-1986, but increased them during 1987-1989. Fratzscher (2008) finds that oral—not actual—interventions tend to reduce exchange rate volatility. Using bipower variation to determine days of jumps, Beine, Lahaye, Laurent, Neely, and Palm (2007) likewise find that although jumps are not more likely to occur on days of intervention, the jumps that do occur are larger than average. Their analysis strongly suggests that intervention normally generates the jumps, rather than reacting to them. The only period in which intervention appears to respond to jumps is that of the "Louvre Accords," when central banks were very keen to dampen volatility by leaning against the wind. In addition, coordinated operations statistically explain an increase in the persistent (continuous) part of exchange rate volatility. This correlation is even stronger on days with jumps.

While most studies find that intervention raises uncertainty, the literature is not unanimous on this point. Failure to correctly resolve the difficult issues of simultaneity/identification of the cross-effects of volatility and intervention might explain the finding that intervention raises volatility.

That is, intervention responds to volatility, so these variables will be positively correlated. Volatility does tend to decline in the hours and days following intervention, but it is difficult to ascertain whether the decline is the result of intervention or simply the natural tendency of very volatile markets to return to normal volatility levels over time. That is, Figure 14, excerpted from Neely (2011), shows that both realized and implied volatility drop remarkably after the March 18, 2011 G-7 intervention. After the intervention, short-horizon implied volatility dropped much more than long-horizon volatility, which suggests that the unexpected intervention did calm markets.

[Insert Figure 14 about here]

Although high frequency data or more sophisticated econometric techniques might account for simultaneity, another method would be to ask market participants—who observe very high frequency data—about the effect of intervention on volatility. Cheung and Clement (2000) report that traders believe that intervention increases volatility, though they also believe that it helps restore equilibrium. Neely (2008) reports that central bankers who are directly involved with intervention generally do not believe that it raises volatility.

In summary, intervention and volatility are clearly correlated. The effect of intervention on volatility likely depends on the intervention reaction function and market conditions at the time of intervention.

Section 7

Conclusion

This chapter reviewed the recent developments in modeling exchange rate volatility and jumps. Volatility models of foreign exchange inform a variety of agents, including academic researchers, policymakers, regulators, and traders. A good volatility model fits the three characteristics of volatility: intraday periodicity, autocorrelation and allowance for discontinuities in prices.

Early research focused on ARCH/GARCH modeling of the autocorrelation in daily and weekly squared residuals. We show that a FIGARCH model with a fat-tailed distribution describes daily exchange rate volatility dynamics quite well. Researchers soon discovered the value of high frequency data for better volatility and jump estimation, however. Using high-frequency exchange rate data, we presented several methods to estimate the quadratic variation, integrated volatility, jumps and intraday periodicity in a continuous-time framework. In doing so, we illustrate the prevalence of jumps in the data and show that one must account for intraday periodicity in detecting jumps. We concluded our chapter by discussing the effects of macro news announcements and central bank interventions on exchange rate volatility and jump dynamics. Macro news affects volatility but not as much as periodicity caused by market openings and closings. The effect of interventions on volatility depends on market conditions.

More recently, researchers have investigated the impact of central bank communication on exchange rates. Does communication calm foreign exchange markets? How and when do markets process communication news? A future research may shed more light on these issues.

Notes

[1]We splice DEM/USD returns with EUR/USD returns on 1 January 1999, and call the resulting series EUR/USD for simplicity.

[2]These holidays include New Year (December 31 - January 2), Martin Luther King Day, Washington's Birthday or Presidents' Day, Good Friday, Easter Monday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day and Christmas (December 24 - 26).

[3]See also Table 1.

[4]The weakness of the Ljung-Box test is that its asymptotic distribution is known under the very restrictive assumption that errors are *i.i.d.* Francq, Roy, and Zakoïan (2005) propose a robust version of that test whose distribution is derived under the weaker assumption of a martingale difference sequence. This test is therefore robust to ARCH effects. See also Francq and Zakoïan (2009).

[5]For the sake of simplicity, we present the parametric volatility models for the daily frequency only.

[6]However, these conditions are not necessary as shown by Nelson and Cao (1992).

[7]Researchers have proposed other specifications accounting for this leverage effect. See the EGARCH of Nelson (1991), the TARCH of Zakoïan (1994) and the APARCH of Ding, Granger, and Engle (1993), among others.

[8]Nevertheless, some empirical studies do find evidence of asymmetry for some exchange rates (Oh and Lee, 2004 and McKenzie and Mitchell, 2002).

[9]Granger (1980) and Granger and Joyeux (1980) initially developed the ARFIMA process to model long memory in time series processes. An ARFIMA specification fills the gap between short and complete persistence, so that the ARMA parameters capture the short-run behavior of the time-series and the fractional differencing parameter models the long-run dependence. Baillie (1996) surveys this topic. ARFIMA models have been combined with an ARCH-type specification by Baillie, Chung, and Tieslau (1996), Tschernig (1995), Teyssière (1997), Lecourt (2000) and Beine, Laurent, and Lecourt (2002). However, among these studies, Tschernig (1995), Beine, Laurent, and Lecourt (2002) find evidence of only weak long-memory in the conditional mean of some exchange rate returns. To check this result using our dataset, we estimated an ARFIMA$(1, d, 1)$ model for the EUR/USD exchange rate. We found that the long-memory parameter d in the conditional mean equation is not statistically different from zero, which is consistent with the main body of the literature. For brevity, we do not report these results but they are available upon request.

[10]Conrad and Haag (2006) further derive necessary and sufficient positivity constraints for FIGARCH models.

[11]We first estimated an ARFIMA-GARCH model to test for the long-memory in the conditional mean. We did not find any evidence of long-range dependence and therefore only reported short-memory models for the conditional mean.

[12]The Student-t and GED distribution are not nested and hence one cannot rely a standard likelihood ratio test to discriminate between the two distributions.

[13]For brevity, these results are not reported yet they are available upon request. Note that pre-crisis sample covers the periods 2004-01-05 to 2006-12-29, and the crisis sample spans 2007-01-03 to 2009-12-30.

[14]The origin of realized volatility is not as recent as it would seem at first sight. Merton (1980) already mentioned that, provided data sampled at a high frequency are available, the sum of squared realizations can be used to estimate the variance of an *i.i.d.* random variable.

[15]In other words, a counting process (such as Poisson process) is defined to be of finite activity if the change in the counting process over any time interval is finite with probability one.

[16]Even in absence of jumps, some squared returns are down-weighted and therefore $c_w > 1$ is intended to compensate for this, to make the weighted sum of squared returns consistently estimate IV_t.

[17]The length of the local window is usually set to one day.

[18]We discuss the periodicity estimations methods in Section 4.

[19]One can also compare the non-parametric volatility estimators based on their volatility forecasting performance. One candidate model is an ARFIMA. As an alternative to ARFIMA model, Corsi (2009) proposed a simple AR-type model that considers volatilities realized over different horizons (typically three, that is daily, weekly and monthly). This model is called Heterogeneous Auto-Regressive (HAR) model.

[20]Note that it is standard practice to normalize the integral of the periodicity factor (or its square) to equal one over the day.

[21]Lee and Hannig (2010) also propose a detection rule to identify *small* jumps in the data. In our study, we only focus on the big jump detection test.

[22]Unreported simulation results. The underlying DGP is a continuous-time GARCH model. There are no jumps in the process. These results are available upon request.

[23]MMS expectations have been available for other countries for some time.

[24]Neely (2005) discusses the measurement and uses of implied volatility estimated from options prices. Engle (1982) developed the autoregressive conditionally heteroskedastic (ARCH) model that Bollerslev (1986) extended to the GARCH formulation. GARCH models usefully account for the time-varying volatility and fat-tailed distributions of daily and intraday financial returns.

[25]The number of survey participants and the dates of the survey have changed over time. Hakkio and Pearce (1985) report that MMS surveyed about 60 money market participants during the early 1980s. MMS conducted the surveys on both Tuesdays and Thursdays before February 8, 1980 and on Tuesday after that date.

[26]Rigobon and Sack (2008) discuss two methods to compensate for the error inherent in estimating market expectations with survey data. Bartolini, Goldberg, and Sacarny (2008) apply this methodology.

[27]Equation (6.2) could be altered to take into account a host of effects, including asymmetry or business cycle dependence, for example.

[28]Beine, Lahaye, Laurent, Neely, and Palm (2007) use macro announcements as control variables in a study of the effects of U.S., German, and Japanese foreign exchange intervention on the continuous and discontinuous components of DEM-EUR/USD and JPY/USD exchange rate volatility. They estimate exchange rate jumps with bipower variation.

[29]*Informed* order flow would be order flow that is generated by private information and speculates on a change in asset prices. In contrast, *uninformed* order flow would be generated by demands for commercial or hedging purposes

and would not be predicated on private information that informs expectations of changes in asset prices.

[30]The central banks of major economies have tended to intervene far less frequently since 1995. See Savaser (2011).

[31]See http://www.imf.org/external/pubs/ft/sd/2011/123110.pdf.

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APPENDIX: Tables and Figures

Table 1: Summary statistics for exchange rate returns

	#Obs	Mean	Min	Max	Std	Skew	Kurt
5-min returns							
EUR/USD	1070208	0.00	-1.43	2.79	0.04	0.49	59.85
USD/JPY	1071360	0.00	-2.89	1.98	0.05	-0.49	65.59
30-min returns							
EUR/USD	178368	0.00	-2.28	2.64	0.10	0.16	23.95
USD/JPY	178560	0.00	-3.39	3.54	0.11	-0.19	41.34
1-hour returns							
EUR/USD	89184	0.00	-2.36	2.19	0.14	0.08	17.00
USD/JPY	89280	0.00	-3.36	4.05	0.16	-0.30	30.64
daily returns							
EUR/USD	3716	0.00	-3.59	3.53	0.66	0.03	4.89
USD/JPY	3720	0.00	-7.91	3.90	0.74	-0.62	9.36
weekly returns							
EUR/USD	743	0.02	-6.72	8.60	1.47	0.14	5.54
USD/JPY	744	-0.01	-12.72	5.65	1.58	-0.99	9.25
monthly returns							
EUR/USD	185	0.09	-10.71	10.63	3.06	0.08	4.06
USD/JPY	186	-0.04	-12.67	9.97	3.21	-0.42	4.06

Note: The sample covers the periods from 3 January 1995 to 30 December 2009.

Table 2: Time series properties and preliminary tests for exchange rate returns

	#Obs	JB	$Q(20)$	$LB(20)$	$Q^2(20)$	$LM(5)$	$ADF(2)$
5-min returns							
EUR/USD	1070208	1.4×10^8**	4311.82**	816.12**	24883.30**	2329.20**	-625.59**
USD/JPY	1071360	1.7×10^8**	5236.13**	627.58**	66991.10**	6405.30**	-627.85**
30-min returns							
EUR/USD	178368	3.3×10^6**	127.32**	58.14**	6566.12**	692.48**	-243.64**
USD/JPY	178560	1.1×10^7**	285.11**	45.28**	30157.90**	2173.5**	-245.09**
1-hour returns							
EUR/USD	89184	7.3×10^5**	44.27**	25.76	4082.98**	354.94**	-173.06**
USD/JPY	89280	2.8×10^6**	156.52**	42.39**	20007.80**	1846.90**	-176.52**
daily returns							
EUR/USD	3716	554.67**	23.65	16.50	778.59**	24.14**	-35.93**
USD/JPY	3720	6517.3**	43.64**	28.73	356.83**	21.41**	-35.63**
weekly returns							
EUR/USD	743	202.55**	22.98	17.39	165.81**	6.68**	-14.85**
USD/JPY	744	1329.80**	23.67	16.99	43.37**	3.51**	-14.94**
monthly returns							
EUR/USD	185	8.93**	19.25	15.02	39.21**	4.84**	-7.32**
USD/JPY	186	13.99**	21.67	14.96	21.91	3.32**	-7.55**

Note: The sample covers the periods from 3 January 1995 to 30 December 2009. *#Obs* corresponds to the total number of observations. JB is the statistic of the Jarque-Bera normality test. $Q(20)$ and $Q^2(20)$ correspond respectively to the Box-Pierce test of serial correlation in the raw and squared returns with 20 lags. $LB(20)$ is the robust Ljung-Box statistic on raw returns with 20 lags and $LM(5)$ is the statistic of the ARCH-LM test for 5 lags. $ADF(2)$ denotes the Augmented Dickey-Fuller unit root test statistics with two lags, without intercept and time trend. Davidson and MacKinnon (1993) provide asymptotic critical values for the ADF tests. **: Indicates significance at the 1% level.

Table 3: Estimation results of parametric volatility models for daily EUR/USD returns

	ARCH	*GARCH*	*GJR*	*FIGARCH*	*FIGARCH-t*	*FIGARCH-St*	*FIGARCH-GED*
μ	0.002	0.009	0.009	0.008	0.006	0.008	0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.009)
ω	0.392	0.002	0.002	0.001	0.001	0.001	0.001
	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α_1	0.087	0.030	0.030	.	.	.	.
	(0.026)	(0.004)	(0.006)	.	.	.	.
β_1	.	0.966	0.966	0.944	0.943	0.943	0.944
	.	(0.004)	(0.004)	(0.016)	(0.013)	(0.013)	(0.014)
γ_1	.	.	-0.001	.	.	.	.
	.	.	(0.008)	.	.	.	.
d	.	.	.	0.883	0.902	0.905	0.896
	.	.	.	(0.056)	(0.044)	(0.044)	(0.048)
ϕ_1	.	.	.	0.074	0.042	0.040	0.055
	.	.	.	(0.048)	(0.037)	(0.037)	(0.041)
υ	.	.	.	.	8.406	8.412	1.464
	.	.	.	.	(1.132)	(1.133)	(0.053)
$log(\xi)$	.	.	.	.	.	0.018	.
	.	.	.	.	.	(0.021)	.
log-l	-3684.11	-3488.06	-3488.05	-3485.57	-3444.75	-3444.42	-3441.84
$Q(20)$	22.64	20.24	20.20	20.03	19.99	19.98	20.03
$Q^2(20)$	524.15**	20.03	20.14	14.47	15.39	15.44	14.71

Note: Parameter estimation of ARCH (1), GARCH $(1, 1)$, GJR $(1, 1)$ and FIGARCH $(1, d, 1)$ models. Robust standard errors are reported in parenthesis. The first four models are estimated by quasi-maximum likelihood. A Student-t, skewed Student-t and GED distribution is chosen respectively for the last three models. $Q(20)$ and $Q^2(20)$ correspond respectively to the Box-Pierce statistics on standardized and squared standardized residuals with 20 lags. **: Indicates significance at the 1% level.

Table 4: Estimation results of parametric volatility models for daily USD/JPY returns

	ARCH	*GARCH*	*GJR*	*FIGARCH*	*FIGARCH-t*	*FIGARCH-St*	*FIGARCH-GED*
μ	0.009	0.006	0.002	0.009	0.019	0.009	0.016
	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)
ω	0.442	0.005	0.006	0.021	0.030	0.029	0.026
	(0.021)	(0.002)	(0.003)	(0.010)	(0.012)	(0.012)	(0.011)
α_1	0.197	0.042	0.031	.	.	.	.
	(0.046)	(0.011)	(0.010)	.	.	.	.
β_1	.	0.950	0.948	0.686	0.583	0.591	0.608
	.	(0.013)	(0.016)	(0.098)	(0.092)	(0.087)	(0.094)
γ_1	.	.	0.019	.	.	.	.
	.	.	(0.013)	.	.	.	.
d	.	.	.	0.342	0.337	0.333	0.328
	.	.	.	(0.067)	(0.066)	(0.064)	(0.060)
ϕ_1	.	.	.	0.453	0.301	0.313	0.355
	.	.	.	(0.104)	(0.068)	(0.066)	(0.085)
υ	.	.	.	.	5.654	5.823	1.315
	.	.	.	.	(0.494)	(0.516)	(0.044)
$log(\xi)$	.	.	.	.	.	-0.062	.
	.	.	.	.	.	(0.023)	.
log-l	-4072.13	-3905.84	-3902.60	-3903.72	-3787.18	-3783.56	-3802.27
$Q(20)$	33.99	27.46	27.38	25.88	26.29	26.50	25.92
$Q^2(20)$	282.10**	12.61	12.53	11.43	13.16	13.05	11.37

Note: Parameter estimation of ARCH (1), GARCH $(1, 1)$, GJR $(1, 1)$ and FIGARCH $(1, d, 1)$ models. Robust standard errors are reported in parenthesis. The first four models are estimated by quasi-maximum likelihood. A Student-t, skewed Student-t and GED distribution is chosen respectively for the last three models. $Q(20)$ and $Q^2(20)$ correspond respectively to the Box-Pierce statistics on standardized and squared standardized residuals with 20 lags. **: Indicates significance at the 1% level.

Table 5: Distributions of the non-parametric volatility measures for exchange rates

		mean	min	max	std	skew	kurt	$Q(20)$	d
EUR/USD									
	$RV_{(5-min)}$	0.52	0.05	10.95	0.49	5.82	75.69	13946.60**	0.34**
	$RV_{(30-min)}$	0.45	0.04	9.18	0.49	5.79	62.98	9999.38**	0.31**
	$RV_{(1-hour)}$	0.44	0.03	8.42	0.52	5.34	48.96	8393.41**	0.29**
	$BV_{(5-min)}$	0.46	0.04	5.65	0.41	4.37	34.81	19510.50**	0.41**
	$BV_{(30-min)}$	0.39	0.03	6.25	0.41	4.79	40.12	13446.60**	0.35**
	$BV_{(1-hour)}$	0.38	0.02	7.59	0.44	5.79	61.00	11624.10**	0.33**
	$TV_{(5-min)}$	0.41	0.05	1.85	0.24	1.83	8.22	35104.10**	0.54**
	$TV_{(30-min)}$	0.36	0.04	2.38	0.25	2.11	9.87	22706.70**	0.42**
	$TV_{(1-hour)}$	0.35	0.02	2.54	0.26	2.11	10.24	16969.00**	0.34**
USD/JPY									
	$RV_{(5-min)}$	0.70	0.03	32.90	0.96	13.73	371.52	6859.34**	0.42**
	$RV_{(30-min)}$	0.59	0.02	49.42	1.13	24.29	959.81	2617.29**	0.34**
	$RV_{(1-hour)}$	0.58	0.02	48.57	1.17	21.90	796.02	2381.10**	0.34**
	$BV_{(5-min)}$	0.62	0.03	27.06	0.82	12.85	327.95	8542.60**	0.45**
	$BV_{(30-min)}$	0.52	0.02	41.00	0.94	24.25	953.58	3262.92**	0.35**
	$BV_{(1-hour)}$	0.51	0.02	58.08	1.21	31.27	1388.60	1696.90**	0.30**
	$TV_{(5-min)}$	0.50	0.03	2.09	0.29	1.57	6.13	30602.20**	0.57**
	$TV_{(30-min)}$	0.43	0.02	2.24	0.30	1.83	7.44	19417.80**	0.45**
	$TV_{(1-hour)}$	0.42	0.02	2.42	0.32	1.93	8.00	14471.00**	0.37**

Note: Descriptive statistics on the non-parametric volatility measures of the EUR/USD and USD/JPY exchange rates. The sample cover is from 3 January 1995 to 30 December 2009. Realized volatilities, bipower variations and truncated power variations are constructed from *5-min*, *30-min* and *1-hour* returns. $Q(20)$ corresponds to the Box-Pierce statistic for serial correlation with 20 lags. The last column reports the log-periodogram regression estimates of the long memory parameter, based on the method of Geweke and Porter-Hudak (1983). **: Indicates significance at the 1% level.

Table 6: The correction factor d_w and the asymptotic variance of the ROWVar θ

β	1	0.99	0.975	0.95	0.925	0.90	0.85	0.80
c_w HR	1	1.081	1.175	1.318	1.459	1.605	1.921	2.285
c_w SR	1	1.017	1.041	1.081	1.122	1.165	1.257	1.358
θ HR	2	2.897	3.707	4.674	5.406	5.998	6.917	7.592
θ SR	2	2.072	2.184	2.367	2.539	2.699	2.989	3.245
d_w HR	0.333	0.440	0.554	0.741	0.945	1.177	1.760	2.566

Note: c_w, θ and d_w for different critical levels β (such that the threshold $k = \chi^2_1(\beta)$, with $\chi^2_1(\beta)$ the β quantile of the χ^2_1)

Table 7: Daily jump tests

	Statistic	BV_t	$MinRV_t$	$MedRV_t$
EUR/USD				
	Z_t	475 [0.13]	373 [0.10]	516 [0.14]
	$logZ_t$	366 [0.10]	243 [0.07]	374 [0.10]
	$maxlogZ_t$	364 [0.10]	243 [0.07]	374 [0.10]
USD/JPY				
	Z_t	441 [0.12]	360 [0.10]	500 [0.13]
	$logZ_t$	366 [0.10]	224 [0.06]	381 [0.10]
	$maxlogZ_t$	365 [0.10]	224 [0.06]	381 [0.10]

Note: Results of the daily jump tests. The sample covers the periods from 3 January 1995 to 30 December 2009. The table reports the number of detected daily jumps and the jump proportion in brackets (p(jumps)=100×#jumps/#days). The significance level of the tests is 0.0001. IV_t is computed by BV_t, $MinRV_t$, and $MedRV_t$.

Table 8: Intraday jump tests: LM-test and LH-test

	Statistic	$\#jumps$	$p(jumps)$	$\#jumpdays$	$p(jumpdays)$
EUR/USD					
	Lee/Mykland	2105	0.20%	1580	42.52%
	Lee/Hannig	2589	0.24%	1619	43.57%
	Lee/Mykland(filt)	1863	0.17%	1345	36.19%
	Lee/Hannig(filt)	2254	0.21%	1411	37.97%
USD/JPY					
	Lee/Mykland	1866	0.17%	1456	39.14%
	Lee/Hannig	2738	0.26%	1576	42.37%
	Lee/Mykland(filt)	1838	0.17%	1341	36.04%
	Lee/Hannig(filt)	2640	0.25%	1480	39.78%

Note: Results of the intraday jump tests. The sample covers the periods from 3 January 1995 to 30 December 2009. Equation (5.11) and Equation (5.13) give the jump detection statistics of the tests. "(filt)" implies that the corresponding test accounts for the periodicity based on the estimator WSD. $\#jumps$ is the number of detected intradaily jumps, $p(jumps)$ is the jump proportion (that is p(jumps)=100×#jumps/#obs), $\#jumpdays$ is the number of days with at least one intraday jump and $p(jumpdays)$ denotes the jump-day proportion (that is p(jumpdays)=100×#jumpdays/#days). The significance level of the tests is 0.1.

Table 9: U.S. Macroeconomic Announcements

Name of announcement	Units of announcement	Frequency	Release lag	Source	Release time
Average Hourly Earnings	$ per hour	Monthly	Almost none	BLS	8:30 AM
Beige Book		8 times per year		FRB	2:15 PM
Business Inventories		Monthly	$\sim$ 6 weeks	CB	10:00 AM
Capacity Utilization Rate	Index (2002 = 100), % m-m	Monthly	$\sim$ 2 weeks	FRB	9:15 AM
Construction Spending	% m-m	Monthly	$\sim$ 5 weeks	CB	10:00 AM
Consumer Confidence Index	Index (1985 = 100)	Monthly	None	Conf. Board	10:00 AM
Consumer Credit Report	% m-m	Monthly	$\sim$ 5 weeks	FRB	3:00 PM
Consumer Installment Credit	% m-m, % q-q, No.	Monthly	$\sim$ 5 weeks	FRB	3:00 PM
Consumer Price Index	% m-m (1982 = 100)	Monthly	$\sim$ 2 weeks	BLS	8:30 AM
Domestic Vehicle Sales	Millions of vehicles	Monthly	Almost none	BEA	3:00 PM
Durable Goods Orders	% m-m	Monthly	$\sim$ 3-4 weeks	CB	8:30 AM
Employment Cost Index	% q-q (2005 = 100)	Quarterly	$\sim$ 2-3 weeks	BLS	8:30 AM
Existing Home Sales	No. of sales	Monthly	$\sim$ 4 weeks	NAR	10:00 AM
Factory Inventories	$ billion change	Monthly	$\sim$ 4 weeks	CB	10:00 AM
Factory Orders	$ billion change	Monthly	$\sim$ 4 weeks	CB	10:00 AM
Federal Budget/Deficit	$ Trillions	Monthly		CBO	2:00 PM
FOMC Minutes		8 times per year	$\sim$ 2-3 weeks	FRB	2:00 PM
GDP	% q/q	Quarterly		BEA	8:30 AM
GDP-Advance	% q/q	Quarterly	1 month lag	BEA	8:30 AM
GDP-Deflator	% q/q	Quarterly		BEA	8:30 AM
GDP-Final	% q/q	Quarterly	3 month lag	BEA	8:30 AM
GDP-Preliminary	% q/q	Quarterly	2 month lag	BEA	8:30 AM
Housing Starts	No. of units, % m-m	Monthly	$\sim$ 3 weeks	CB	8:30 AM
Humphrey-Hawkins Testimony		Semiannual		FRB Chairman	10:00 AM
Index of Coincident Indicators	m-m	Monthly	$\sim$ 3 weeks	Conf. Board	10:00 AM
Industrial Production	Index (2002 = 100), % m-m	Monthly	$\sim$ 2 weeks	FRB	9:15 AM
Initial Unemployment Claims	No. of claims	Weekly	$\sim$ 5 days	ETA	8:30 AM
International Trade in Goods and Services	$ Billions	Monthly	$\sim$ 6 weeks	Commerce	8:30 AM
Inventories and Sales Ratio		Monthly	$\sim$ 6 weeks	CB	10:00 AM

Note: See Table 10.

Table 10: U.S. Macroeconomic Announcements (cont'd)

Name of announcement	**Units of announcement**	**Frequency**	**Release lag**	**Source**	**Release time**
ISM Index (formerly the NAPM Survey)	Index	Monthly	Almost none	ISM	10:00 AM
Lagging Indicators	m-m	Monthly	$\sim$ 3 weeks	Conf. Board	10:00 AM
Leading Indicators	m-m	Monthly	$\sim$ 3 weeks	Conf. Board	10:00 AM
M1	Change in $ billions	Weekly		FRB	4:30 PM
M2	Change in $ billions	Weekly		FRB	4:30 PM
Merchandise Trade Balance				CB	8:30 AM
New Home Sales	Thousands	Monthly	$\sim$ 3-4 weeks	CB	10:00 AM
Nonfarm Payrolls	Thousands	Monthly	A few days	BLS	8:30 AM
Personal Consumption Expenditure Index (PCE)	% m-m	Monthly	$\sim$ 4 weeks	BEA	8:30 AM
Personal Income	% m-m	Monthly	$\sim$ 4 weeks	BEA	8:30 AM
Personal Spending	% m-m	Monthly	$\sim$ 4 weeks	BEA	8:30 AM
Producer Price Index	% m-m	Monthly	$\sim$ 2 weeks	BLS	8:30 AM
	Index (1982 = 100)				
Productivity Costs	Index of output/ index of hours worked	Quarterly	Several months	BLS	8:30 AM
Retail Sales (Advance)	% m-m	Monthly	$\sim$ 2 weeks	CB	8:30 AM
Retail Trade	$ Millions	Monthly	$\sim$ 6 weeks	CB	8:45 (Sales)
					10:15 (Inventories)
Target Federal Funds Rate	%	8 times a year		FRB	2:15 PM
Trade Balance	$ Billions	Monthly	$\sim$ 6-7 weeks	BEA	8:30 AM
Treasury Auction Results		Weekly		Treasury	11:00 AM
Unemployment rate	% of labor force	Monthly	A few days	BLS	8:30 AM
U.S. Exports	% m-m	Monthly	$\sim$ 5-6 weeks	CB	8:30 AM
	(2000 = 100)				
U.S. Imports	% m-m	Monthly	$\sim$ 5-6 weeks	CB	8:30 AM
	(2000 = 100)				
Value of New Constr. put in place	$ Millions	Monthly	$\sim$ 5 weeks	CB	10:00 AM
	% m-m				

Note: CPI, consumer price index; GDP, gross domestic product; M1, M2, NAPM, National Association of Purchasing Managers; NFP, nonfarm payroll; PCE, personal consumption expenditures; PMI, Purchasing Managers' Index; PPI, producer price index. The following abbreviations are used for announcements: BEA, Bureau of Economic Analysis; BLS, Bureau of Labor Statistics; CB, U.S. Census Bureau; Conf. Board, Conference Board; CBO, Congressional Budget Office; Commerce, U.S. Department of Commerce; ETA, Department of Labor's Employment and Training Administration; FRB, Federal Reserve Board; ISM, Institute for Supply Management; NAR, National Association of Realtors; Treasury, U.S. Department of the Treasury. % m-m, Percent change from month to month; % q/q, percent change quarter over quarter; % q-q, percent change quarter to quarter. Descriptions of the announcements are available upon request.

Table 11: R^2 and partial R^2s

Independent variable(s)	SYSTEM-I $\log(\lvert y_{t,i}\rvert/\sigma_{t,i})$	SYSTEM-II $\log(\lvert y_{t,i}\rvert/RV_{t,i})$
Full regression (adjusted)	0.1175	0.1828
Announcement dummies	0.0009	0.0002
Absolute announcement surprises	0.0035	0.0044
Seasonal effect	0.0659	0.0457
Lags of absolute returns	0.0134	0.0644
Friday night dummies	0.1036	0.0008

Note: The table displays the R^2 and partial R^2s from regression (6.2) and various combinations of its regressors: the announcement dummies, $\beta_0^{(US)} D_{t,i}^{(US)}$ and $\beta_1^{(For)} D_{t,i}^{(For)}$; the absolute announcement surprises, $\sum_{j=1}^{N} \beta_{2,j} |Surprise_{t,i}^{(j)}|$; the periodic component, $\sum_{q=1}^{4} \beta_{3,q} \cos\left(\frac{i2\pi q}{24}\right)$ and $\sum_{q=1}^{4} \beta_{4,(4+q)} \sin\left(\frac{i2\pi q}{24}\right)$; five lags of absolute returns, $\sum_{l=1}^{5} \beta_{5,l} |y_{t,i-1}|$; and the Friday night indicators, $\sum_{h=19}^{23} \beta_{6,h} D_{t,i}^{(Friday_h)}$. Endogenous variables are $\log(|y_{t,i}|/\sigma_{t,i})$ in SYSTEM-I, and $\log(|y_{t,i}|/RV_{t,i})$ in SYSTEM-II.

Table 12: Regression coefficients

Independent variable	SYSTEM-I Coefficient	SYSTEM-I t-HACSE	SYSTEM-I Impact	SYSTEM-II Coefficient	SYSTEM-II t-HACSE	SYSTEM-II Impact
Constant	-0.777	-85.100	(−)	-5.149	-287.000	(−)
US Announcement Dummy	0.240	6.360	(+)	0.114	2.560	(+)
German/Euro Announcement Dummy	-0.054	-1.380	.	-0.065	-1.290	.
U.S.: Real GDP: Advance	0.417	2.890	(+)	0.478	2.020	(+)
U.S.: Real GDP: Preliminary	-0.138	-0.779	.	-0.238	-1.090	.
U.S.: Real GDP: Final	0.158	1.810	(+)	0.135	1.320	.
U.S.: Business Inventories	-0.041	-0.396	.	-0.062	-0.399	.
U.S.: Capacity Utilization Rate: Total Industry	-0.409	-2.840	(−)	-0.439	-2.480	(−)
U.S.: Consumer Confidence	0.222	2.050	(+)	0.355	3.000	(+)
U.S.: Construction Spending	0.265	2.670	(+)	0.434	4.390	(+)
U.S.: Consumer Price Index	0.040	0.386	.	0.154	1.160	.
U.S.: Consumer Credit	-0.287	-2.930	(−)	-0.068	-0.568	.
U.S.: New Orders: Advance Durable Goods	0.128	1.320	.	0.211	1.890	.
U.S.: New Orders	-0.284	-2.430	(−)	-0.306	-1.970	(−)
U.S.: Housing Starts	-0.019	-0.223	.	0.035	0.316	.
U.S.: Industrial Production	0.307	2.110	(+)	0.544	3.860	(+)
U.S.: Composite Index of Leading Indicators	-0.107	-1.050	.	-0.016	-0.137	.
U.S.: ISM: Mfg Composite Index	0.345	3.080	(+)	0.519	4.310	(+)
U.S.: Employees on Nonfarm Payrolls	0.842	5.490	(+)	1.688	7.030	(+)
U.S.: New Home Sales	0.061	0.585	.	0.070	0.630	.
U.S.: PCE	-0.041	-0.461	.	-0.013	-0.106	.
U.S.: Personal Income	-0.181	-1.490	.	-0.115	-0.511	.
U.S.: Producer Price Index	-0.034	-0.344	.	-0.010	-0.084	.
U.S.: Retail Sales	0.170	1.300	.	0.151	1.330	.
U.S.: Retail Sales ex Motor Vehicles	0.127	0.922	.	0.193	1.290	.
U.S.: Trade Balance: Goods & Services [BOP]	0.350	3.720	(+)	0.499	4.540	(+)
U.S.: Government Surplus/Deficit	-0.049	-0.588	.	0.038	0.443	.
U.S.: Initial Claims	-0.004	-0.075	.	0.072	1.260	.
Euro area: CPI Flash Estimate Y/Y %Chg	0.121	1.630	.	0.277	1.060	.
Euro area: Industrial Production Y/Y %Chg WDA	0.236	2.750	(+)	0.298	2.370	(+)
Euro area: Money Supply M3 Y/Y %Chg	-0.051	-0.574	.	-0.010	-0.082	.
Euro area: Harmonised CPI Y/Y %Chg	-0.019	-0.175	.	-0.046	-0.337	.
Euro area: Unemployment Rate	0.109	1.310	.	0.110	1.070	.
Euro area: Producer Price Index Y/Y %Chg	0.130	1.670	.	0.196	2.210	(+)
Euro area: Retail Sales WDA Y/Y %Chg	-0.183	-1.650	.	-0.171	-1.340	.
Euro area: Trade Balance Eurostat	0.005	0.047	.	-0.061	-0.380	.
Euro area: Preliminary Real GDP Y/Y %Chg	-0.287	-1.420	.	-0.012	-0.044	.
Euro area: Final Real GDP Y/Y %Chg	0.039	0.303	.	-0.215	-0.649	.

Note: See Table 13.

Table 13: Regression coefficients (cont'd)

	SYSTEM-I			SYSTEM-II		
Independent variable	Coefficient	t-HACSE	Impact	Coefficient	t-HACSE	Impact
Germany: Current Account Balance	-0.089	-0.660	.	-0.016	-0.083	.
Germany: Final Cost of Living	0.066	0.466	.	-0.033	-0.232	.
Germany: Prelim Cost of Living	-0.137	-1.720	(−)	-0.310	-1.870	(−)
Germany: IP: Total Industry M/M %Chg	-0.028	-0.279	.	0.067	0.565	.
Germany: Producer Price Index: Mfg Y/Y %Chg	-0.001	-0.014	.	0.053	0.374	.
Germany: Real Retail Sales Y/Y %Chg	0.075	0.627	.	0.151	1.030	.
Germany: Current Account: Trade Balance	0.138	1.180	.	0.058	0.322	.
Germany: Real GDP Q/Q %Chg	0.447	4.570	(+)	0.445	2.970	(+)
Cos_q1	-0.136	-19.200	(−)	0.013	1.250	
Cos_q2	0.021	3.400	(+)	0.012	1.620	
Cos_q3	-0.157	-24.200	(−)	-0.171	-21.800	(−)
Cos_q4	-0.120	-18.400	(−)	-0.140	-18.300	(−)
Sin_q1	0.248	39.700	(+)	0.249	28.400	(+)
Sin_q2	-0.021	-3.210	(−)	-0.015	-1.840	(−)
Sin_q3	0.027	4.060	(+)	0.058	6.920	(+)
Sin_q4	-0.074	-11.600	(−)	-0.072	-9.540	(−)
Abs Return Lag1	1.124	17.300	(+)	2.465	30.900	(+)
Abs Return Lag2	0.714	10.700	(+)	1.811	21.100	(+)
Abs Return Lag3	0.566	8.280	(+)	1.765	18.600	(+)
Abs Return Lag4	0.582	8.790	(+)	1.764	19.600	(+)
Abs Return Lag5	0.450	6.940	(+)	1.642	18.900	(+)
Friday_1900	-0.494	-3.510	(−)	-1.050	-5.310	(−)
Friday_2000	-0.269	-1.520	.	-0.624	-1.620	.
Friday_2100	-0.056	-0.178	.	0.041	0.500	.
Friday_2200	-0.375	-1.760	(−)	.	.	.
Friday_2300	-1.039	-72.000	(−)	.	.	.

Note: The table shows the regression coefficients from estimating Equation (6.2) on $\log(|y_{t,i}|/\hat{s}_t)$, over the sample period November 5, 2001, to March 12, 2010. Endogenous variables are $\log(|y_{t,i}|/\sigma_{t,i})$ in SYSTEM-I, and $\log(|y_{t,i}|/RV_{t,i})$ in SYSTEM-II. BOP, balance of payments; CPI, consumer price index; GDP, gross domestic product; IP, industrial production; ISM, Institute for Supply Management; PCE, personal consumption expenditures; PPI, producer price index; WDA, work days adjusted. t-HACSE: Heteroskedasticity and autocorrelation corrected robust t-statistics. (+): Indicates statistically significant positive coefficient. (−): Indicates statistically significant negative coefficient.

Table 14: Tobit-GARCH models for jumps

	S&P futures		Nasdaq futures		Dow jones futures		U.S. bond futures		USD/EUR		JPY/USD		USD/GBP		CHF/USD	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$
CONSCONF	-	-	-	-	0.71	0.88	-	-	-	-	0.74	0.00	0.38	0.08	0.43	0.02
CONSCONF (-1)	-	-	-	-	-	-	0.96	0.01	-	-	-	-	-	-	-	-
CONSCRED	-	-	-	-	0.98	0.10	-	-	-	-	-	-	0.06	0.99	-0.13	0.99
CPI	2.13	0.00	1.90	0.59	0.81	0.68	1.20	0.00	0.01	1.00	0.09	0.99	-	-	-0.06	0.99
FFRTARGET	1.06	0.49	1.39	0.63	1.65	0.00	0.74	0.05	0.88	0.00	0.72	0.00	0.66	0.00	0.57	0.00
FFRTARGET (-1)	-	-	-	-	-	-	0.66	0.02	-	-	-	-	-	-	-	-
GDPADV	2.19	0.01	3.47	0.01	2.09	0.00	-	-	-	-	-	-	0.40	0.83	0.48	0.81
GDPPRE	-	-	-	-	1.17	0.51	-	-	0.81	0.00	0.84	0.01	-	-	0.58	0.04
GVFISCDEF	0.97	0.69	-	-	-	-	0.30	0.88	-0.55	0.17	-0.72	0.08	-0.32	0.66	-0.62	0.08
MFGIND	-	-	-	-	2.61	0.00	1.69	0.74	0.24	0.81	-0.21	1.00	-0.04	1.00	0.54	0.12
NFPAYROL	2.28	0.00	4.75	0.00	1.78	0.00	1.52	0.00	0.98	0.00	0.35	0.25	0.16	0.94	0.43	0.00
PPI	1.05	0.14	-0.12	0.96	0.49	0.70	0.55	0.10	-0.70	0.99	-0.82	0.99	-0.15	0.58	-1.02	0.67
RETSALES	0.78	0.04	1.37	0.05	0.59	0.27	0.41	0.27	-0.21	0.99	-	-	-	-	-1.18	0.99
TRADEBAL	-10.09	0.79	-	-	0.10	0.92	-3.99	0.81	0.43	0.05	0.02	1.00	0.17	0.89	0.47	0.02
ω	1.65	0.03	11.58	0.00	0.90	0.10	0.69	0.06	0.30	0.00	0.26	0.00	0.25	0.00	0.52	0.00
α_1	0.27	0.02	0.34	0.00	0.11	0.01	0.19	0.02	0.19	0.00	0.18	0.00	0.28	0.00	0.26	0.00
α_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.09	0.00
β_1	0.46	0.01	-	-	0.72	0.00	0.46	0.04	0.49	0.00	0.60	0.00	0.28	0.00	-	-
Function value	-877.44	0.00	-1204.57	0.00	-924.59	0.00	-917.35	0.00	-7090.68		-7542.77		-7727.96		-7331.87	
# obs	49135.00	0.00	49662.00	0.00	53909.00	0.00	40559.00	0.00	352127.00		351359.00		352799.00		352319.00	

Note: The latent Tobit jump variable is given by $Jump^*_{t,i} = \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i}$, where $|Jump_{t,i}| = Jump^*_{t,i}$ if $Jump^*_{t,i} > 0$ and $|Jump_{t,i}| = 0$ if $Jump^*_{t,i} \leq 0$, $\varepsilon_{t,i}|\mathcal{I}_{t,i-1}$ is $N(0, \sigma_t^2)$. The variance σ_t^2 is assumed to follow an ARCH or GARCH process. $|Jump_{t,i}|$ represents significant jumps ($\alpha = 0.1$) as defined in the theoretical part. $\eta_{t,i}$ controls for day of the week effects (not reported) and $\mu_{t,i}$ includes surprises concerning macro announcements. For each series, we regress jumps in absolute value on surprises in absolute value. $\xi_{t,i}$ controls for intradaily periodicity (not reported). Estimates and robust p-values ($2 \times (1 - Prob(X < |tstat|))$, X being a $t-$distributed random variable with $N - K$ (# obs. - #parameters) degrees of freedom, and $tstat$ being the estimated coefficient over its std. error) are reported for surprise coefficient (if it is significant at 10% in at leats one series), as well as the ARCH and GARCH coefficients. Regressors with no contemporaneous match with significant jumps are excluded from the model. See Lahaye, Laurent, and Neely (2011) for the sample periods.

Table 15: Probit models for cojumps

	USD/EUR - USD/GBP		USD/EUR - JPY/USD		USD/EUR - CHF/USD		USD/GBP - JPY/USD		USD/GBP - CHF/USD		JPY/USD - CHF/USD	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$		
CNSTRSPEND	-	-	-	-	-7.41	0.00	-	-	-	-	-	-
CONSCONF	-	-	-	-	-	-	-	-	-	-	0.73	0.00
FFRTARGET	1.08	0.00	0.86	0.00	0.83	0.00	0.90	0.00	0.89	0.00	0.74	0.01
GDPPRE	-	-	0.87	0.00	0.60	0.02	-	-	-	-	0.83	0.00
GVFISCDEF	-	-	0.23	0.07	0.17	0.18	-	-	-	-	0.25	0.05
MFGIND	-	-	-	-	1.50	0.00	-	-	-	-	-	-
NFPAYROL	-	-	0.65	0.00	0.79	0.00	-	-	-	-	0.61	0.00
TRADEBAL	-	-	-	-	0.76	0.02	-	-	-	-	-	-
Function value	-1842.90		-1181.87		-3130.59		-742.60		-1610.76		-933.24	
Pseudo R^2	0.04		0.04		0.03		0.05		0.04		0.05	
# obs	349355		348967		349557		348593		349542		348619	

Note: The latent probit cojump variable is given by $COJump^*_{t,i} = \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i}$, where $COJump_{t,i} = 1$ if $COJump^*_{t,i} > 0$ and $COJump_{t,i} = 0$ if $COJump^*_{t,i} \leq 0$. $\varepsilon_{t,i}$ is $NID(0,1)$. $COJump_{t,i}$ is the cojump indicator). $\eta_{t,i}$ controls for day of the week effects (not reported) and $\mu_{t,i}$ includes surprises concerning macro announcements. For each series, we regress cojumps on surprises in absolute value. $\xi_{t,i}$ controls for intradaily seasonality (not reported). Estimates and robust p-values ($2 \times (1 - Prob(X < |tstat|))$, X being a $t-$distributed random variable with $N - K$ (# obs. - #parameters) degrees of freedom, and $tstat$ being the estimated coefficient over its std. error) are reported for each surprise coefficient. Regressors with no contemporaneous match with significant cojumps are excluded from the model. We further report the maximized log-likelihood function value, and the McFadden R^2 (defined as $1 - \frac{LogLik_1}{LogLik_0}$, i.e. 1 minus the ratio of the log likelihood function value of the full model to the constant only model one). See Lahaye, Laurent, and Neely (2011) for the sample periods.

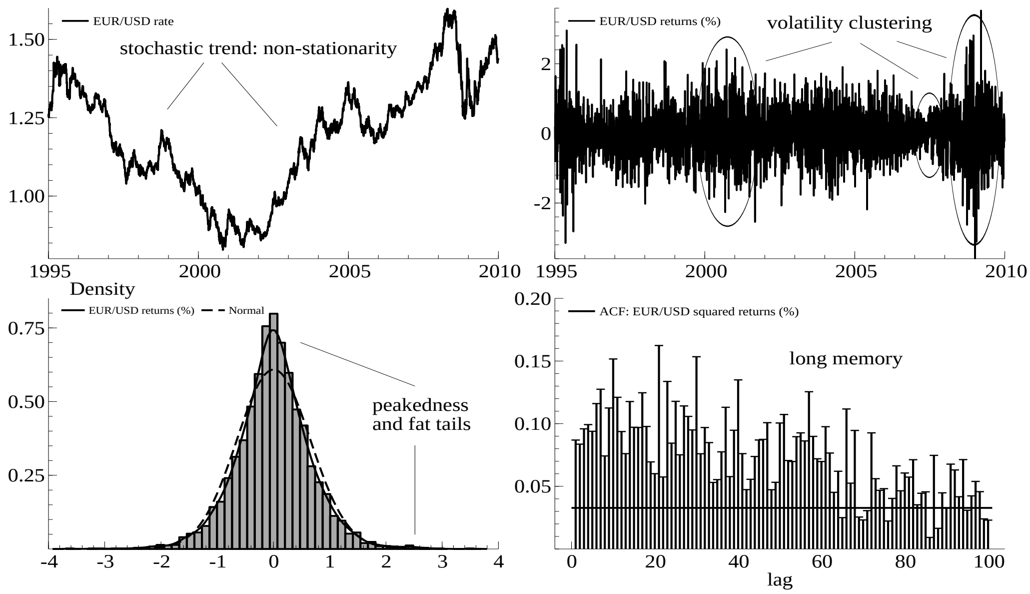

Figure 1: *Stylized facts of the daily EUR/USD exchange rate.*

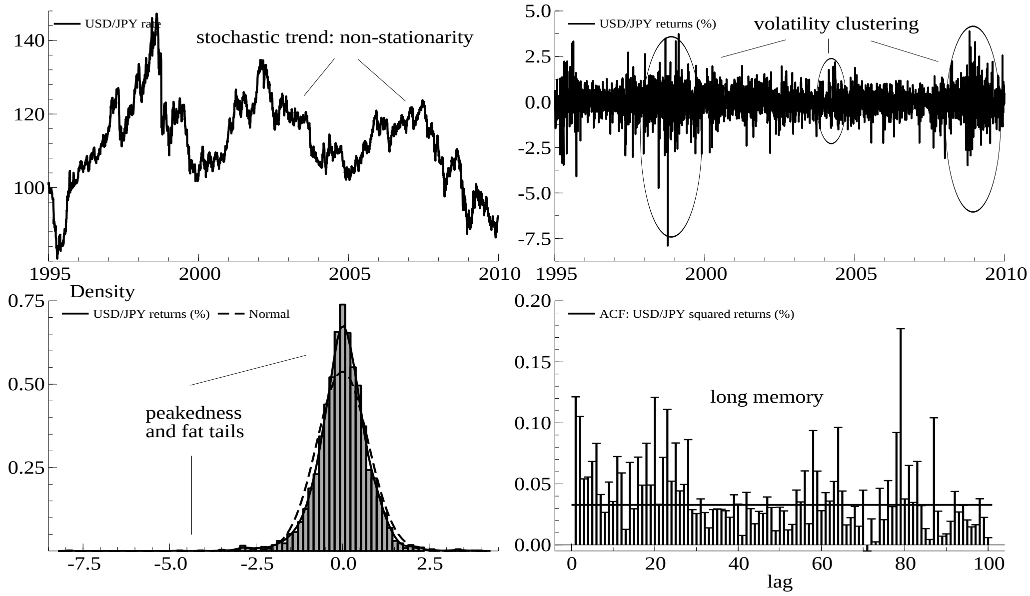

Figure 2: *Stylized facts of the daily USD/JPY exchange rate.*

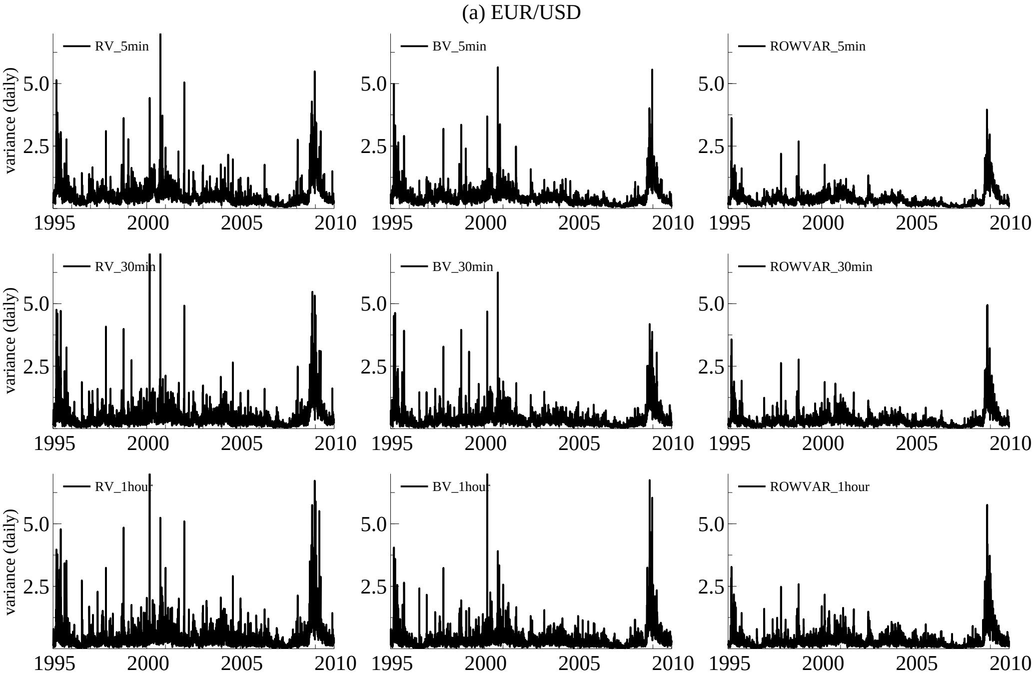

Figure 3: *RV_t, BV_t and $ROWVar_t$ constructed from 5-min, 30-min and 1-hour intraday returns for the EUR/USD series.*

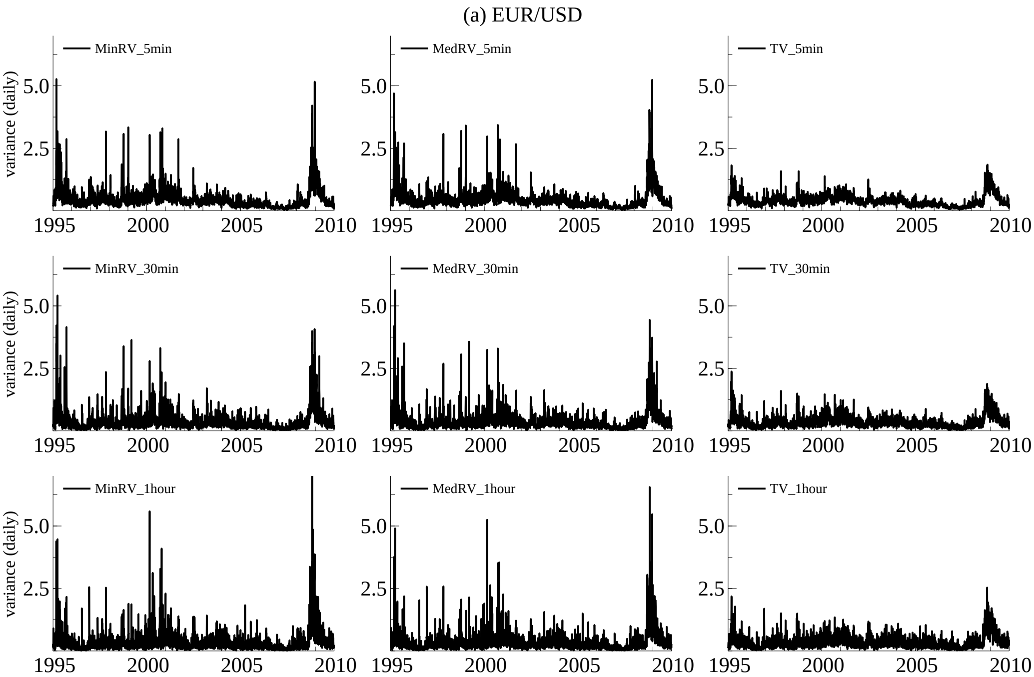

Figure 4: *$MinRV_t$, $MedRV_t$ and TV_t constructed from 5-min, 30-min and 1-hour intraday returns for the EUR/USD series. We set $g = 0.3 \times 9$ and $\tilde{\omega} = 0.47$ as thresholds for TV_t.*

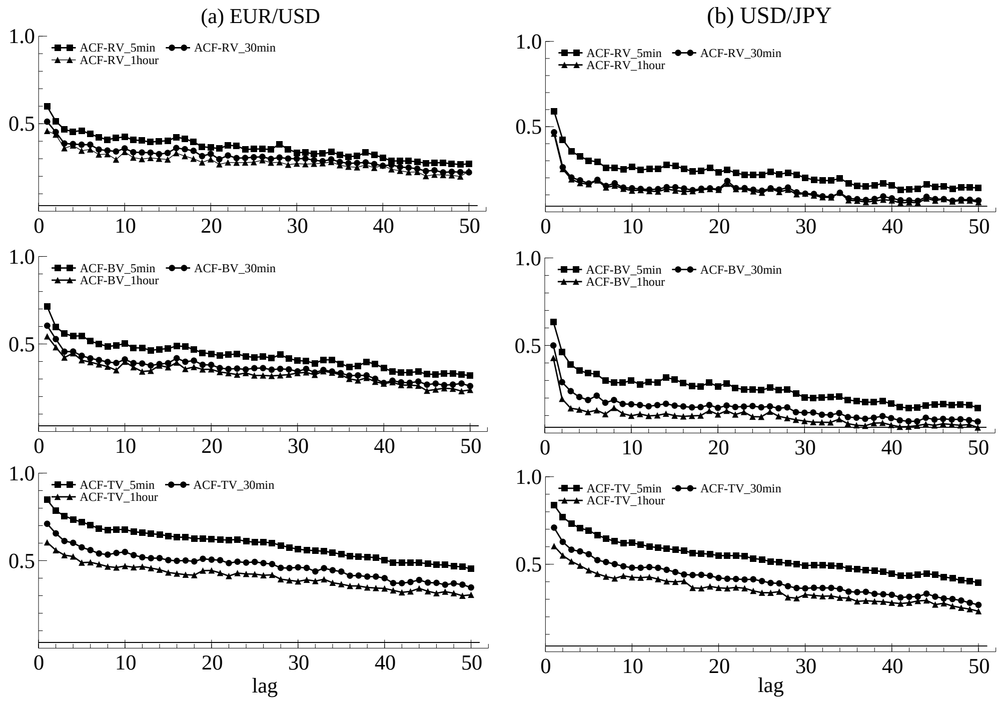

Figure 5: *ACFs of the realized volatility (RV_t), bipower variation (BV_t) and truncated power variation (TV_t) constructed from 5-min, 30-min and 1-hour intraday returns.*

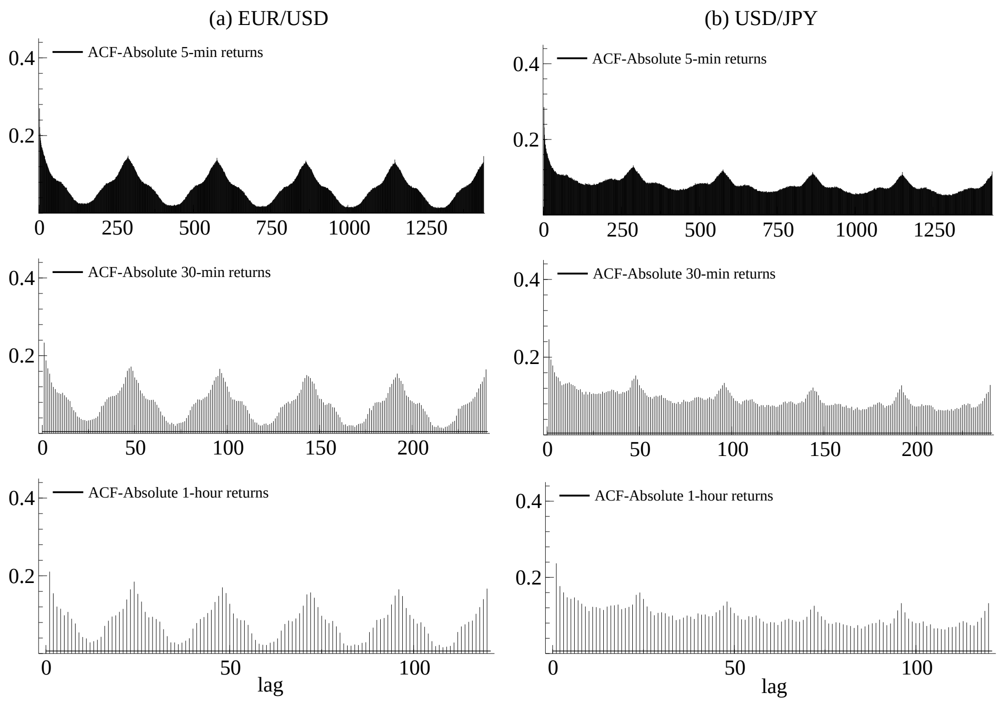

Figure 6: *ACF of the absolute EUR/USD and USD/JPY returns at 5-min, 30-min and 1-hour sampling frequencies. The number of lags corresponds to 5 days.*

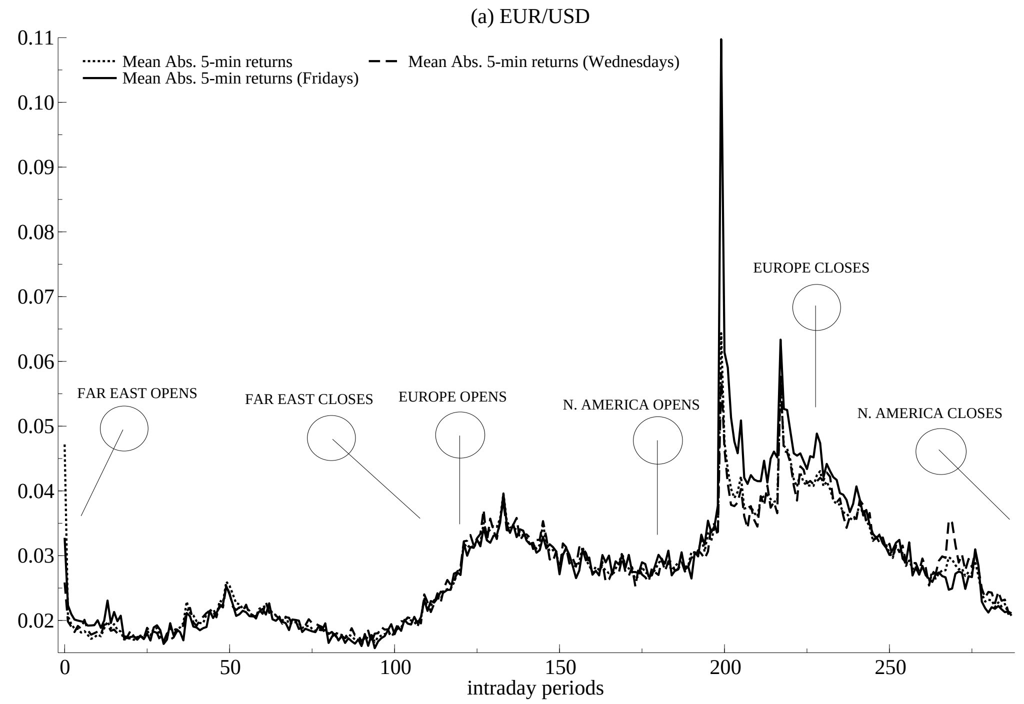

Figure 7: *Mean absolute 5-min EUR/USD returns on whole sample, Wednesdays, and Fridays. The X-axis represents the intraday periods in GMT, from 21:00 GMT of day $t-1$ to 21:00 GMT of day t.*

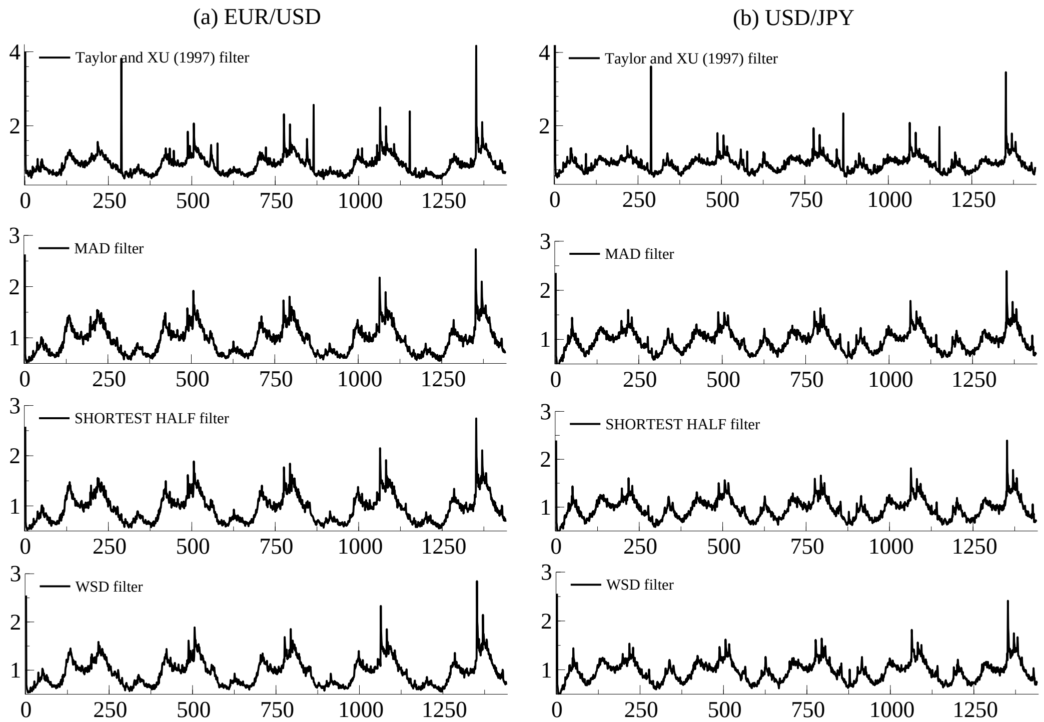

Figure 8: *Estimates of the non-parametric periodicity filters for the 5-min EUR/USD and USD/JPY exchange rates.*

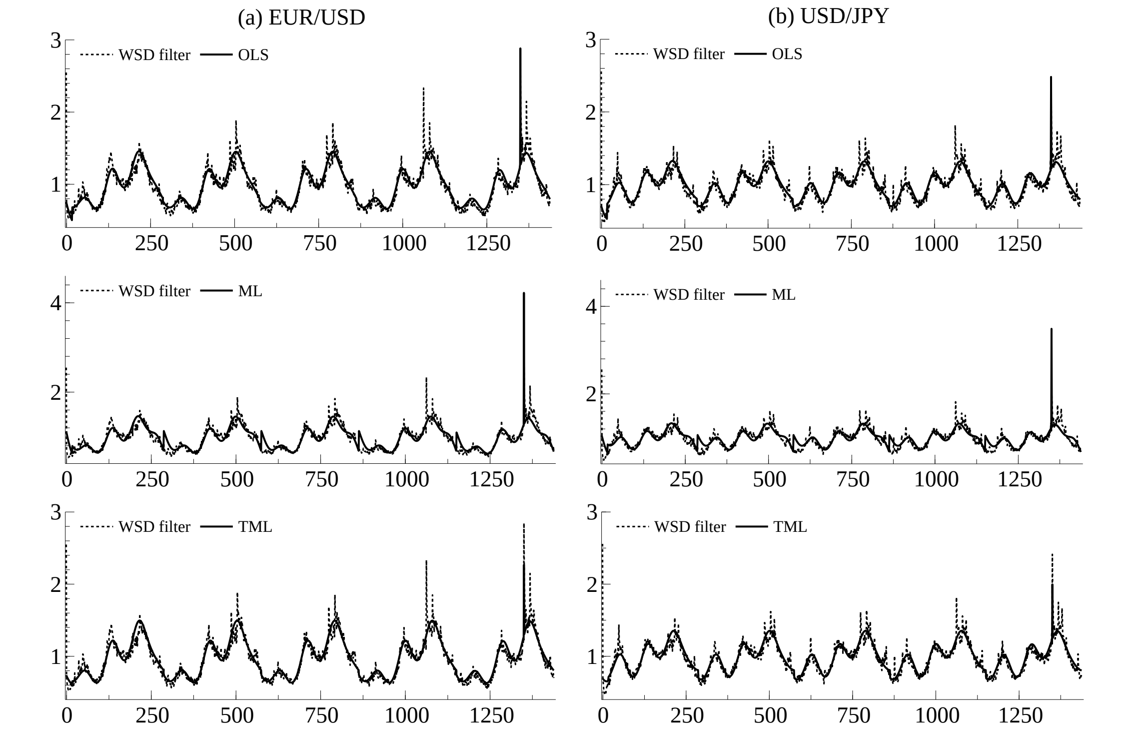

Figure 9: *Estimates of the parametric periodicity filters for the 5-min EUR/USD and USD/JPY exchange rates.*

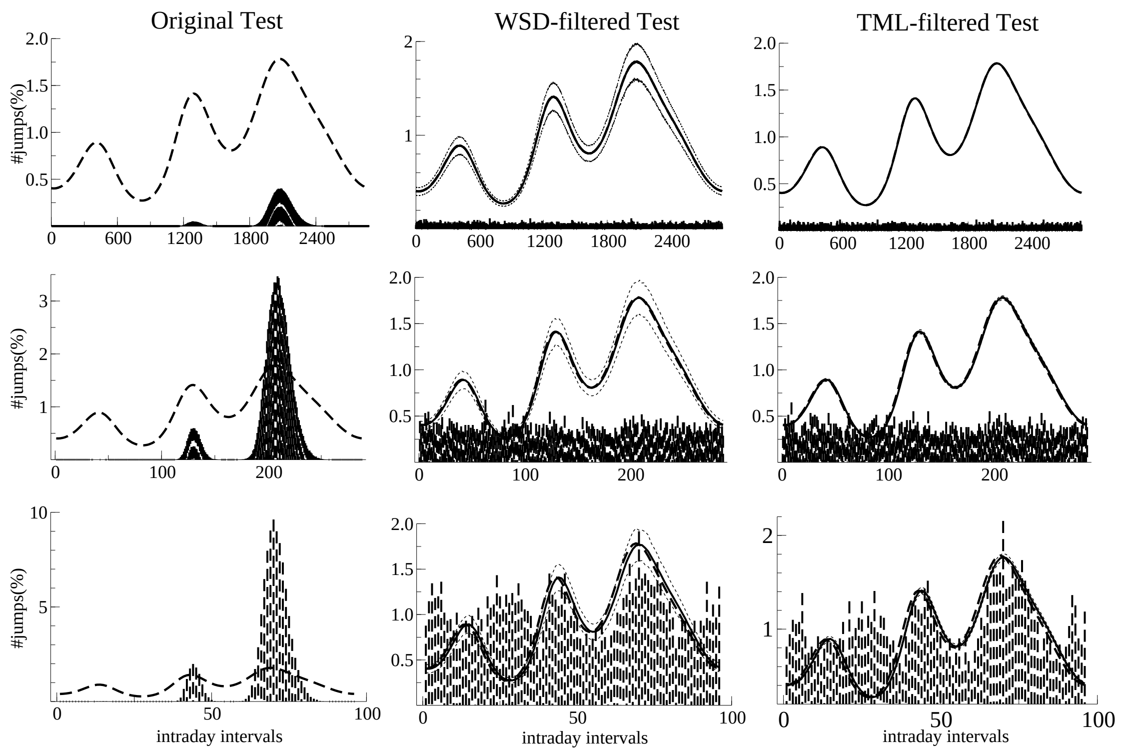

Figure 10: *Proportion of intraday returns affected by spurious jumps according to the original and the filtered Lee/Hannig tests. The periodicity estimators are WSD and TML. DGP: Continuous-time GARCH diffusion model. Number of days: 250. Number of replications: 1000. Sampling frequencies: 30-seconds (top-row panels), 5-minutes (middle-row panels), 15-minutes (bottom-row panels).* $n = M$ *and* $\alpha = 0.1$. *Rejection thresholds: 4.74 (for 30-seconds) , 4.30 (for 5-minutes), and 4.10 (for 15-minutes).*

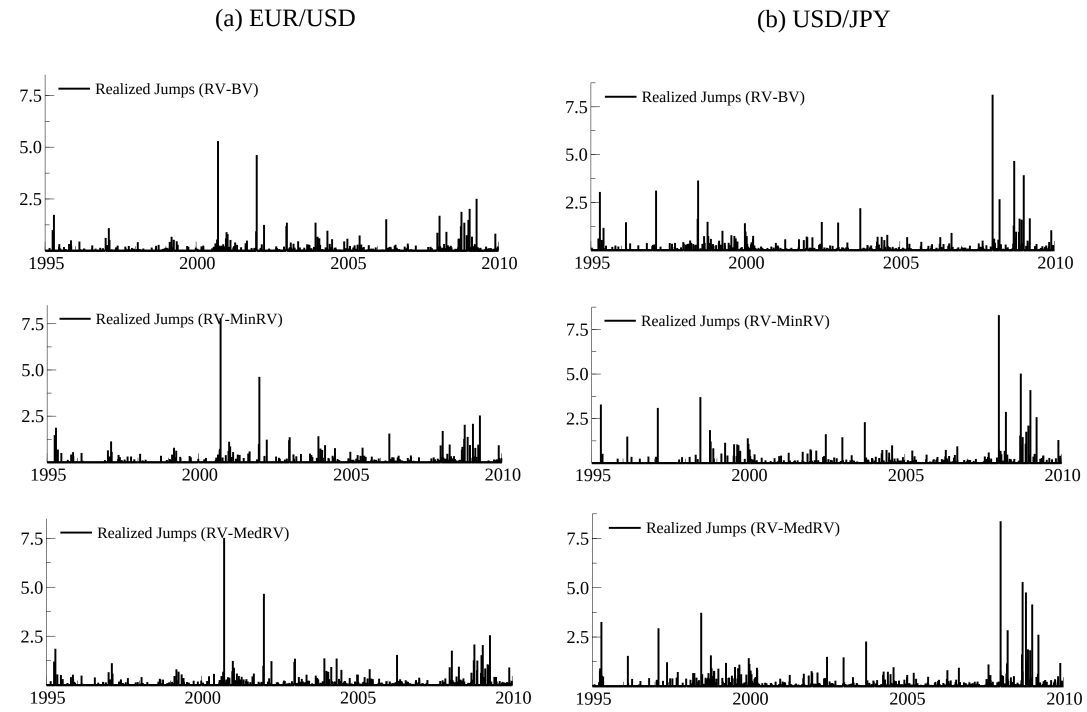

Figure 11: *EUR/USD and USD/JPY daily realized jumps. The test statistics are based on $maxlogZ_t$. The significance level of the tests is 0.0001.*

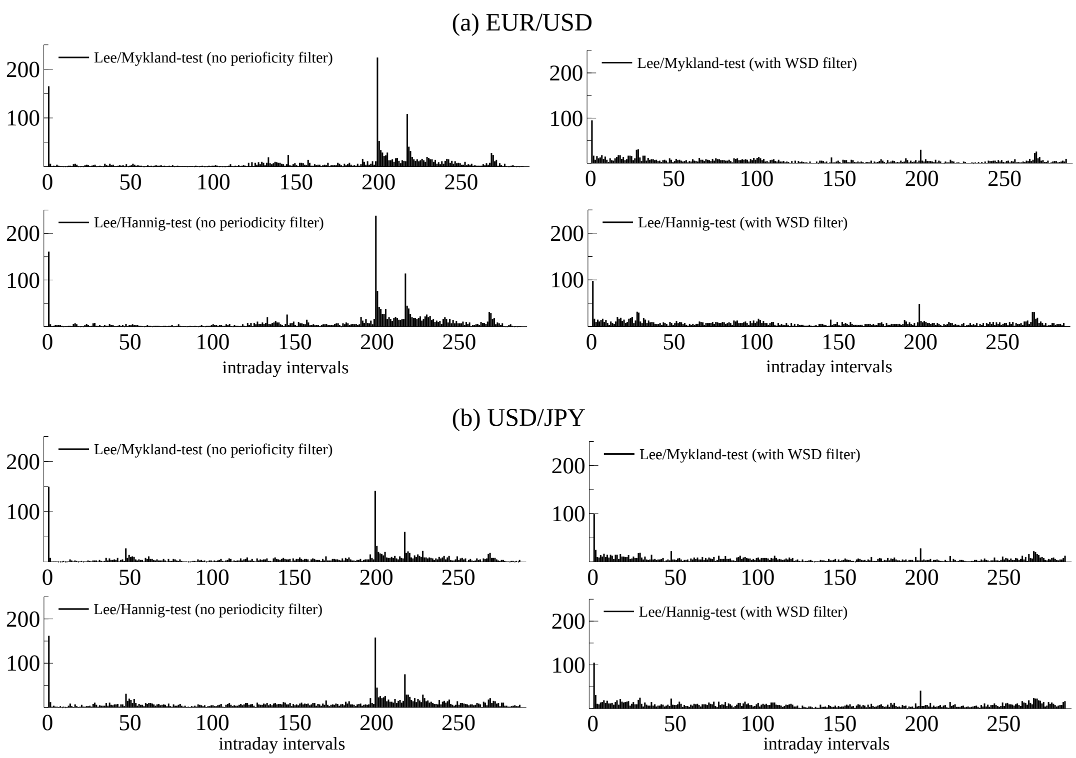

Figure 12: *Number of EUR/USD and USD/JPY jumps per intraday period of time.*

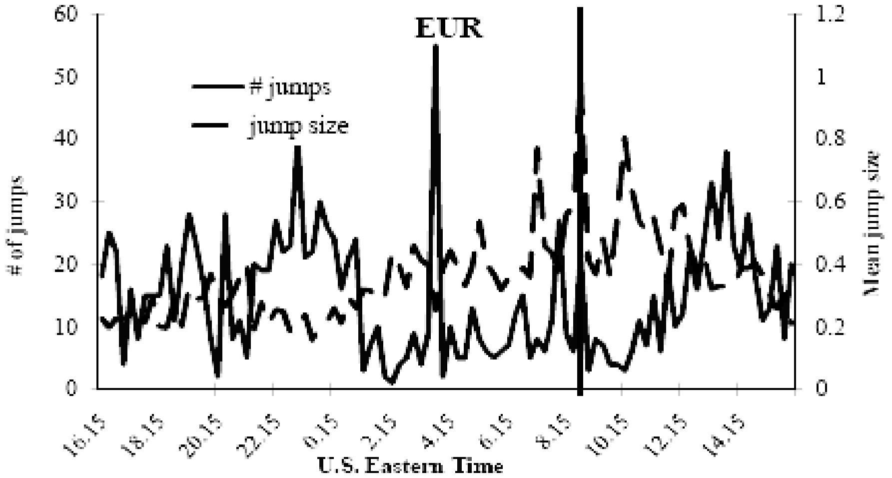

Figure 13: *The X-axis represents intraday time (U.S. ET). The left Y-axis displays the number of significant jumps ($\alpha = 0.1$), while the right Y-axis shows the mean of absolute values of significant jumps. Solid lines denote the number of jumps and dashed lines denote mean jump size. The vertical lines denote the interval containing 8:30 a.m., the time of most news arrivals. The sample period is 1987-2004. SOURCE: From Figure 2 in Lahaye, Laurent, and Neely (2011).*

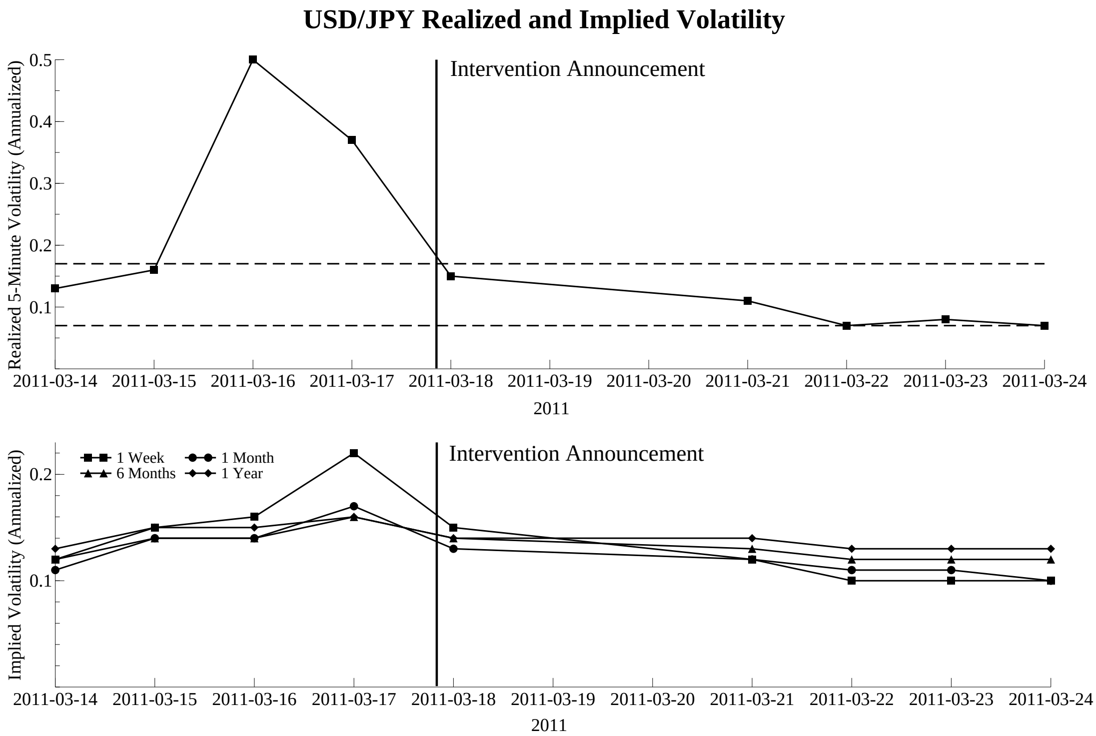

Figure 14: *Top panel shows the annualized realized volatility, computed from 5-minute squared returns, for the JPY/USD market from March 14 to March 24, 2011. The horizontal lines show the 10th and 90th percentiles of volatility for the USD/JPY over the March 26, 1998-March 31, 2011, period. Bottom panel shows option-implied volatility over four horizons for the same market during the same period in March 2011.*