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The role of jumps in volatility spillovers in foreign exchange markets: meteor shower and heat waves revisited*

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Abstract

This paper extends the previous literature on geographic (heat waves) and intertemporal (meteor showers) foreign exchange volatility transmission to characterize the role of jumps and cross-rate propagation. We employ heterogeneous autoregressive (HAR) models to capture the quasi-long-memory properties of volatility and the Shapley-Owen R2 measure to quantify the contributions of components. We conclude that meteor showers are more influential than heat waves, that jumps play a modest but significant role in volatility transmission and that significant, bidirectional cross-rate volatility transmission exists. Finally, we illustrate what types of news weaken or strengthen heat wave and meteor shower effects with sensitivity analysis.

Keywords: realized, volatility, jumps, transmission, periodicity, intraday, meteor shower, heat wave, exchange rate, euro, yen, dollar

JEL Codes: C13, C14, C32, C58, F31, F37, F65, G15

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1 Introduction

What drives exchange rate volatility? Several studies have addressed whether exchange rate volatility transmission is better described by meteor showers or heat waves. Heat waves refer to the idea that geography determines volatility. A heat wave might raise volatility in New York trading on Monday and Tuesday but not in London on Tuesday morning. In contrast, meteor showers refer to the tendency of volatility to be temporally correlated, with volatility spilling over from Asian to European to North American markets in the same day, for example. Intuitively, heat waves are more likely to occur if most or all important news that affects volatility occurs during a particular country's business day. Similarly, it seems that meteor showers will tend to predominate if autocorrelated international news is more important.

Engle, Ito and Lin (1990 and 1992) introduced the concepts of meteor showers and heat waves, studying the issue with generalized autoregressive heteroskedastic (GARCH) models. Baillie and Bollerslev (1991) and Hogan and Melvin (1994) extended this early research. Melvin and Peiers Melvin (2003) reinvestigated the question with a vector autoregression (VAR) model for realized volatilities. Whereas Engle, Ito, and Lin (1990) found that meteor showers predominated, Melvin and Peiers Melvin (2003) argued that heat waves were more important. Thus, different approaches to volatility measurement and modeling led to different conclusions. The GARCH approach (using one observation per trading segment) pointed to the importance of meteor showers, whereas the realized volatility / VAR approach pointed to heat waves. More recently, Cai, Howorka, and Wongswan (2008) reinvestigated the issue with a new dataset: firm quotes from the Electronic Broking Services (EBS) trading platform, rather than indicative Reuters quotes used by Melvin and Peiers Melvin (2003).[1] Cai, Howorka, and Wongswan (2008) confirm Melvin and Peiers Melvin's (2003) result that heat waves dominate the volatility transmission mechanism. Furthermore, they find that trading activity and volatility exhibit similar dynamics.

Our investigation introduces both substantive and methodological advances to the literature that together provide a more complete and accurate picture of volatility transmission.

Substantively, we characterize the role of jumps in volatility transmission and we permit cross-market meteor shower and heat wave effects. That is, we estimate the effects of lagged volatility

[1] Indicative Reuter quotes have the advantages of widespread availability and good informational content (Phylaktis and Chen 2009).

and jumps from the Japanese yen (JPY) market on the euro (EUR) market and vice versa. We connect the time series model with economic ideas by using sensitivity analysis to illustrate how different types of news influence the strength of meteor shower / heat wave mechanisms.

Our methods provide a new and more accurate understanding of volatility transmission. Specifically, we combine the Lee and Mykland (2008) and Andersen, Bollerslev, and Dobrev (2007) procedures with the threshold bipower variation of Corsi, Pirino, and Reno (2010) to detect jumps at intraday frequencies. We use heterogeneous autoregressive (HAR) models to capture the quasi-long-memory dynamics of foreign exchange volatility and we establish the structural stability of these regressions with Andrews's (1993) tests for breaks at an unknown point. Finally, we use the Shapley-Owen measure of explanatory power to quantify the contributions of groups of variables – heat waves, meteor showers, volatility and jumps – to the total explanatory power of the system.

These methods provide new insights into the issue of meteor shower and heat waves in volatility transmission, including cross-rate transmission. Specifically, the Shapley-Owen R^2 implies that meteor showers contribute 60 percent of explanatory power for realized volatility versus 40 percent for heat waves. This challenges the conclusions in Cai, Howorka, and Wongswan (2008) and Melvin and Peiers Melvin (2003) that heat wave effects dominate. We also find that jumps have modest but positive explanatory power, accounting for about 10 percent of total predictive power versus the 90 percent due to lagged integrated volatility.

The cross-rate HAR system implies that volatility propagates across exchange rates to a significant degree, with approximately 25% of total explanatory power for both exchange rates coming from the other exchange rate. The relative importance of meteor showers versus heat waves is approximately the same for cross-market effects as for own-market effects. Our cross-rate results contrast with those of Soucek and Todorova (2014) who found no role for jumps in spillovers between foreign exchange, the S&P500 and commodity markets. Sensitivity analysis shows that particularly large shocks tend to weaken the fit of both the heat wave and meteor shower relations while smaller and more frequent shocks tend to strengthen the fit of the model.

The remainder of the paper proceeds as follows: Section 2 describes the volatility and jump estimators used in this study, Section 3 presents data and the proposed HAR model. Section 4 presents empirical findings: results on volatility transmission within exchange rates and spillovers across markets, as well as a study of the causes of meteor shower and heat waves. Section 5 concludes.

2 Volatility and jump estimation

Erdemlioglu, Laurent, and Neely (2015) provide evidence supporting a Brownian semimartingale process with jumps for foreign exchange data. We use this framework and the associated realized estimators for jumps and volatility. We use a 5-minute sampling frequency because Liu, Patton, and Sheppard (2015) show that it provides a good tradeoff between accurately measuring volatility and minimizing microstructure noise. Following Lahaye, Laurent, and Neely (2011), we identify jumps with the Lee and Mykland (2008)/Andersen, Bollerslev, and Dobrev (2007) method. Dumitru and Urga (2012) show that this test is the best among a broad set of alternatives.[2]

2.1 Jumps

Define high-frequency 5-minute log-returns, for $n = 288$ intervals over a 24-hour trading day t, as

$$\Delta_{j,t}X = X_{j,t} - X_{j-1,t}, j = 1...n, \tag{2.1}$$

where X_j is the last log-price of the interval j.

We must remove deterministic intraday volatility patterns in returns in order to identify intraday jumps. If the local volatility estimator does not account for the circadian pattern, the jump test will identify too many (few) jumps during periods of high (low) intraday periodic volatility (Boudt, Croux, and Laurent 2011). Therefore, we adjust returns for intraday periodicity before estimating integrated volatility or jumps and we denote these periodicity-corrected returns as $\tilde{\Delta_{j,t}}X$. Appendix A-1 details our approach to correcting for periodicity, which follows Boudt, Croux, and Laurent (2011) and Lahaye, Laurent, and Neely (2011).

The jump test statistic (Lee and Mykland 2008, Andersen, Bollerslev, and Dobrev 2007) is defined as:

$$\widetilde{J_{j,t}} = \frac{|\tilde{\Delta_{j,t}}X|}{\sqrt{\hat{IV}_{j,t}/n}}, \tag{2.2}$$

where $\sqrt{\hat{IV}_{j,t}/n}$ is the estimated integrated volatility during period j of day t. The test statistic is half-normally distributed under the hypothesis of a Brownian semimartingale and no jumps.

[2] We choose to measure jumps with the LM method because it appears to be the best method for measuring jumps and despite the fact that it is not completely consistent with our measure of integrated variance.

To reduce false jump detection, Lee and Mykland (2008) propose comparing the test statistic to critical values from the distribution of the maximum value of the statistic. We consider the maximum over the course of a day and choose a size $\alpha = 0.001$. The test detects a jump when $\widetilde{J_{j,t}} > G^{-1}(1-\alpha)S_n + C_n$, where $G^{-1}(1-\alpha)$ is the $1-\alpha$ quantile function of the standard Gumbel distribution, $S_n = \frac{1}{(2\log n)^{0.5}}$ and $C_n = (2\log n)^{0.5} - \frac{\log(\pi)+\log(\log n)}{2(2\log n)^{0.5}}$, n being the number of observations per day. With these parameters, we would expect to spuriously identify one jump in a 1000-day sample.

We use Corsi, Pirino, and Reno's (2010) corrected threshold bipower variation (CTBPV) to compute $\sqrt{I\hat{V}_{j,t}/n}$, rather than Lee and Mykland's (2008) bipower variation approach because threshold bipower variation is robust to successive jumps (Appendix A-1.2 provides details about these power variation estimators). Unreported results actually show that the core of our results are insensitive to that choice.[3] We denote the jump time series as $J_{j,t} = \tilde{\Delta_{j,t}}X$ when $\widetilde{J_{j,t}}$ rejects the null and $J_{j,t} = 0$ otherwise.

2.2 Segment decomposition

To study the dynamic patterns in intraday volatility and jumps, we follow the literature in considering 5 trading segments in the following order: Asia (AS), Asia-Europe overlap (AE), Europe (EU), Europe-US overlap (ES) and the US (US) segment. We define segments as in Cai, Howorka, and Wongswan (2008), who rely on volume data, in addition to price. Their hours differ slightly from those of Melvin and Peiers Melvin (2003). For each intraday segment in our sample, we define RV and jumps over the segment.

Realized volatility is defined for a segment $S_i \in S = \{AS, AE, EU, ES, US\}$ as the root mean squared 5-minute return in the segment:

$$RV_{S_i,t} = \sqrt{\sum_{j \in S_i} \Delta_{j,t}X^2/n_{S_i}}, \tag{2.3}$$

where n_{S_i} is the number of 5-minute returns in segment S_i.

Within each segment, we define Corsi, Pirino, and Reno's (2010) corrected threshold bipower

[3] We use the Lee and Mykland (2008) / Andersen, Bollerslev, and Dobrev (2007) test, that identifies when intraday jumps occur. On the other hand, Corsi, Pirino, and Reno (2010) propose an aggregated jump tests (i.e. the difference between realized volatility CTBPV) that do not provide jump time information as such. Therefore, our results are not directly comparable to those of Corsi, Pirino, and Reno (2010).

variation measure, $CTBPV_{S_i,t}$, equivalently. That is, we compute the jump-robust measure defined in Appendix A-1.2 using returns belonging to segment S_i and rescaling per intra-day period (dividing by n_{S_i}).

We identify 5-minute jumps as described in Section 2.1. We aggregate jumps for each intraday segment as follows:

$$J_{S_i,t} = \sqrt{\sum_{j \in S_i} J_{j,t}^2 / n_{S_i}}. \tag{2.4}$$

That is, a segment's jump contribution is the root mean squared jump during that segment.

The next section presents data and the HAR model.

3 HAR with meteor shower/heat waves

3.1 Data and descriptive statistics

We construct volatility and jump measures on the EUR/USD and USD/JPY using 5-minute returns, provided by Disktrading. We clean the exchange rate data in standard ways to remove holidays, weekends and other days with too many missing values. Lahaye, Laurent, and Neely (2011) describe the procedures. The cleaned EUR/USD and USD/JPY series cover 3573 and 3509 trading days respectively, from January 5, 1999 to April 26, 2013. As described in Section 2, we compute all scale measures in standard deviation form per intraday interval, to compare them across segments.[4]

Table 1 presents descriptive statistics for volatility (Eq. 2.3) and jumps (Eq. 2.4) in each segment. The varying means across segments are in line with the literature. Average volatility and the volatility of volatility are highest during the Europe/US overlap. Average jump frequency, on the other hand, is highest during the Asian segment, but the largest jump magnitudes are found during the Asian-European overlap and the European segment.

3.2 The HAR model

This section introduces the HAR model that evaluates how integrated variance and jumps predict realized volatility through heat waves and meteor showers. The slowly decaying autocorrelation exhibited by foreign exchange realized volatility has prompted researchers to consider models, such

[4] Our results are robust to using variances or their log transformation.

as autoregressive, fractionally integrated, moving average (ARFIMA) and HAR models (see Corsi (2009)), that can fit this prominent feature of the data. We choose to use the HAR model to capture meteor shower and heat wave dynamics because it is tractable, flexible and can parsimoniously reproduce the slowly decaying autocorrelation in foreign exchange realized volatility.

Recent research has also established the importance of jumps (discontinuities) in asset prices, including their impact on volatility (see e.g. Soucek and Todorova (2014)). Because jumps are important features of volatility with different characteristics than the continuous components of volatility, it is important to integrate them into a volatility spillover model in order to accurately and fully characterize the process. Therefore, we follow Andersen, Bollerslev, and Diebold (2007) in including jump components in the HAR model.

Before describing the HAR system, we first note that – as theoretical constructs – quadratic variation equals the sum of integrated volatility and the sum of squared jumps over a given period. Therefore, regressions of realized volatility (RV_t) on either lagged integrated volatility estimators ($\hat{IV}_{t-1}$) and lagged jump estimators (J_{t-1}), or rather on RV_{t-1} and J_{t-1}, are equivalent in information content. The only difference in the systems would be the magnitude and interpretation of the estimates. In other words, a functional form with $\hat{IV}$ on the right-hand side, that is, $RV_t = a\hat{IV}_{t-1} + bJ_{t-1} + \epsilon_t$, can be rewritten as $RV_t = c(\hat{IV}_{t-1} + J_{t-1}) + dJ_{t-1} + \epsilon_t$, where the coefficients are related as follows: $a = c$, and $b = c + d$. Using that relation, one can convert the HAR equation in RV_t, $\hat{IV}_{t-1}$ and J_{t-1} to an equivalent relation in RV_t, RV_{t-1} and J_{t-1} with which one can calculate impulse responses. An advantage of using $\hat{IV}$ as a regressor, rather than RV, is that the interpretation of the coefficient on $\hat{IV}$ is more straightforward. On the other hand HAR regressions of RV on lagged RV and lagged jumps are convenient for constructing impulse response functions and testing structural stability. Therefore, we will use the most adequate specification for each purpose. We present the model using only RV regressors in the interest of brevity.

Previous studies of heat wave and meteor showers used purely short-term specifications: Melvin and Peiers Melvin (2003) used 2 daily lags for the DEM and 2 daily lags for the JPY. Cai, Howorka, and Wongswan (2008) do not report their lag lengths but it is likely to be similar to the Melvin and Peiers Melvin (2003) choice as they used the AIC to choose it for an unrestricted VAR. Such short specifications probably omitted important and correlated regressors at longer lags and probably did not match the slowly decaying autocorrelation in RV. In estimating the HAR model, we permit 4 days of free coefficients, as well as HAR heat wave and meteor shower variables for weekly, monthly and quarterly data. Likelihood ratio tests rejected restricting the model further.

Equation 3.1 describes the model that predicts RV for segment $S_i \in S = \{AS, AE, EU, ES, US\}$. The set of trading segments excluding S_i, i.e. $NS = S \setminus S_i$, has elements NS_i. Moreover, recall that $RV_{S_i,t}$ denotes realized volatility for segment S_i (first subscript) and day t (second subscript). The model using RV and jumps as regressors can be written as follows:

$$\begin{aligned} RV_{S_i,t} = \alpha^{S_i} + \sum_{d=1}^{4} \alpha_d^{S_i} \mathbb{1}(t=d) + & \overbrace{\sum_{j \in HW_{S_i}} \beta_j^{S_i} RV_{S_i,j}}^{heat\quad wave\quad effects} + \overbrace{\sum_{\substack{j \in MS_{S_i} \\ NS_i \in NS}} \beta_j^{S_i,NS_i} RV_{NS_i,j}}^{meteor\quad shower\quad effects} \\ + & \sum_{j \in HW_{S_i}} \delta_j^{S_i} J_{S_i,j} + \sum_{\substack{j \in MS_{S_i} \\ NS_i \in NS}} \delta_j^{S_i,NS_i} J_{NS_i,j} \\ + & \sum_{h \in \{w,m,q\}} \theta_h^{S_i} \overline{RV_{S_i}}^h + \sum_{h \in \{w,m,q\}} \kappa_h^{S_i} \overline{RV_{NS}}^h \\ + & \sum_{h \in \{w,m,q\}} \lambda_h^{S_i} \overline{J_{S_i}}^h + \sum_{h \in \{w,m,q\}} \mu_h^{S_i} \overline{J_{NS}}^h + \epsilon_{S_i,t}. \end{aligned} \tag{3.1}$$

The first term (α^{S_i}) is the constant in segment S_i equation. The second term ($\sum_{d=1}^{4} \alpha_d^{S_i} \mathbb{1}(t=d)$) allows different constants for each day of the week, with the indicator function $\mathbb{1}(t=d)$ returning 1 when day t is day of the week d, and $d = 1, ..., 4$, for Monday to Thursday. The column of terms adjacent to the constants consists of heat wave regressors, while the right column displays meteor shower regressors.

The first two lines include meteor shower and heat wave effects (of RV and jumps) for the first 4 lagged days. For daily heat wave effects, the sum subscript j takes values in the set HW_{S_i} that selects appropriate days for heat wave effects with respect to segment S_i. For example, in the equation for the US segment, i.e. $S_i = US$, the set HW_{S_i} will contain lags of the US segment. On the other hand, the sum subscript j takes values in the set MS_{S_i} that selects appropriate days for segment S_i's meteor shower effects, while the sum subscript NS_i selects segments other than S_i. For example, the subscripts NS_i and j select non-US segments on day t for the US segment equation, and non-US segments on previous days.

The last two lines contain longer term effects of jumps and realized volatility aggregated over the week, month or quarter (i.e. the lower frequency effects from our HAR approach). For example, $\overline{RV_{S_i}}^w$ is the past week's heat wave RV effects, that is, the average RV over the past week of segment S_i data. $\overline{RV_{S_i}}^m$ and $\overline{RV_{S_i}}^q$ similarly represent heat wave RV effects over a month and a quarter of data, respectively. $\overline{RV_{NS}}^h$ is constructed equivalently for $h \in \{w, m, q\}$, but using segments other than S_i in the set NS. Note that, for parsimony, HAR meteor shower (weekly, monthly and quarterly) effects aggregate segments in NS. That is, for the US equation ($S_i = US$), we group the segments ES, EU, AE and AS in NS as one "meteor shower" segment.

For each equation, we have 4 days of free lags of heat wave and meteor shower RV, which produces 20 coefficients, plus 3 (weekly, monthly and quarterly) heat wave and 3 meteor shower HAR coefficients. That is, there are 26 coefficients on lagged volatility, plus another 26 coefficients on lagged jumps with an identical structure, plus 5 deterministic variables to model the weekly volatility cycle, for a total of $(2 * 26 + 5 =)$ 57 coefficients per equation.

4 Predictability

4.1 How to measure of predictability?

We seek to evaluate the importance of heat wave and meteor shower effects in models that include jumps and (possibly) cross-rate propagation. There are potentially several ways to evaluate the importance of these effects. First, we could show coefficient estimates–perhaps standardized–and the statistical significance of those coefficients. This strategy, however, does not lend itself easily to evaluating the effect of groups of coefficients and the individual coefficient estimates will be conditional marginal effects that depend on the effects of correlated regressors, not unconditional effects. Second, we could compute partial and/or semi-partial R^2s for groups of regressors but neither of these measures effectively apportions the total explanatory power among groups of correlated regressors. Third, forecast error decompositions are also inappropriate as they would show that contemporaneous shocks to any series explains most of its own error variance rather than attributing total forecast power to heat wave and meteor shower effects. Thus, that procedure fails to attribute forecast value to current and past data.

We choose two complementary strategies to evaluate the relative importance of heat waves versus meteor showers. First, we follow the existing literature in displaying the dynamic impacts of shocks with impulse response functions. Such functions do not quantify relative contributions to predictability, however. Second, to quantify the relative importance of meteor showers and heat waves, we use the Shapley-Owen R^2 measure, sometimes called the LMG measure (Lindeman, Merenda, and Gold 1980) after its first appearance in econometrics. See also Chevan and Sutherland (1991) and Grömping (2007). Appendix A-2 describes the construction of the Shapley-Owen R^2 in a simple example.

The Shapley-Owen (or LMG) R^2 measure has origins in game theory and was developed to evaluate the relative importance of correlated regressors. Shapley (1953) proposed a way to apportion the gains from a cooperative game among cooperating players; Owen (1977) extended this concept to coalitions of players. Lindeman, Merenda, and Gold (1980) subsequently used essentially the same concept to decompose goodness-of-fit among regressors and coalitions of regressors. The Shapley-Owen measure of the R^2s of a group of regressors is the average improvement in R^2s for each regressor (or coalition) over all possible permutations of regressors or coalitions of regressors. Young (1985) shows that the Shapley Value is unique in having a set of several desirable properties.[5] Shapley-Owen values are *efficient* in that the total R^2s is distributed among the regressors or coalitions of regressors. The method treats regressors/coalitions *symmetrically* and *apportions contributions linearly* in that a coalition gets exactly the sum of the gains due its members. Variables with no predictive value receive a Shapley-Owen R^2 value of zero.

4.2 Predictability in a single exchange rate

4.2.1 Impulse-responses

For continuity with the literature, we will begin by evaluating the propagation of volatility and jumps in a single exchange rate before assessing the propagation across exchange rates. The baseline model is the system of five HAR equations 3.1, one for each intraday segment.

We assume that jumps are essentially unpredictable and so enter the HAR system as exogenous variables but that the RV variables are endogenous. To construct impulse responses, one can convert the HAR coefficients on lagged RV variables into the implied VAR coefficients on lagged RV variables and then invert the VAR coeffcients in order to obtain the moving average representation (MAR) and implied impulse responses, shown in Figures 1 and 2. We note that starting the 24-hour global "day" with the Asia market is arbitrary; changing the starting period for a "day" would have no substantive effect on the impulse responses, though it would shift some of them on the x-axis. For example, if we started the day with the US market, the initial impact of the US shock

[5]Neither the partial nor semi-partial R^2s exhibit the desirable properties shown by the Shapley-Owen measure.

on the Asia market would be contemporaneous, instead of at lag 1 and the dynamic impact would be identically shaped but shifted to the left by one unit.

Figures 1 and 2 show the HAR-implied impulse responses for the EUR and JPY, respectively, with 95 percent pointwise confidence intervals.[6] The (i, j) plot shows the impact of a one unit shock to the ith market on volatility in the jth market from 0 to 10 calendar days. Heat wave shocks–i.e., "own-effects"– are displayed along the diagonal in highlighted boxes. Meteor shower effects are on the off-diagonals. Note that impulse responses above the diagonal have zeros as the first element because a shock to the jth market affects the ith market volatility only on the next calendar day if $j > i$. For example, the top row of each figure depicts each intraday period's volatility reactions to a one unit shock to US volatility. Because the US trading session is the last session of the calendar day, all non-US markets respond to the US shock with a one-day lag.

The figures illustrate that heat wave effects appear to be large compared to the individual meteor shower effects and that the largest of the meteor shower effects tend to be first-lag effects e.g., AS effects on AE in box (5,4) or US effects on AS in box (1,5). The similar prominence of heat wave effects in their impulse responses led Melvin and Peiers Melvin (2003) and Cai, Howorka, and Wongswan (2008) to conclude that heat wave effects were dominant. "More important in the present paper is the finding that own-region volatility spillovers are more significant economically (larger in magnitude) than interregional spillovers. In terms coined by Engle et al. (1990), heat waves are more important than meteor showers." – Melvin and Peiers Melvin (2003, p. 678-679). The dynamic impacts of heat wave shocks remain significant for at least 4 to 10+ business days while the impact of meteor shower shocks tend to be significant for 2 to 10+ days. The panels in the last row of each figure illustrate that in both the EUR and JPY markets, shocks to Asian volatility appear to have particularly large effects while the first column of each figure suggests that US volatility may respond less to shocks in other markets.

4.2.2 Relative importance

The visual prominence of heat wave effects in the impulse responses could be an artifact of the construction of impulse responses. By construction, initial own-market impulse responses are very

[6]Bootstrapped confidence intervals were reasonably similar to those implied by the delta method constructed with Newey-West covariance matrices with automatic lag selection, which are shown.

large compared to contemporaneous responses of other variables. In order to better quantify the information content in heat waves and meteor showers, we compute Shapley-Owen R^2s for groups of coefficients in the HAR model. We also compute Wald tests for the null hypotheses that the coefficients in each of these groups of are jointly zero.[7] Such a test is also a test of whether the Shapley-Owen R^2 is statistically significantly different from zero because the population Shapley-Owen R^2 would be zero if and only if the set of population coefficients is zero. In other words, under the null of no predictability in a group, the S-O R^2 should converge in probability to zero.

Though we focus on Shapley-Owen decompositions to discuss relative importance, we report coefficient estimates in Appendix A-3 for completeness. As explained in Section 3.2, using $\hat{IV}$ as a regressor, rather than RV, implies more straightforward coefficient interpretation. Therefore, Appendix A-3 and related relative importance results in this section (and Section 4.4) use estimates obtained with $CTBPV_{S_i,t}$, rather than $RV_{S_i,t}$, on the right-hand side of Equation 3.1.

Table 2 shows the Shapley-Owen proportions of the total R^2s, as well as p-values in parentheses, for groups of coefficients in the HAR model. There are 6 groups of coefficients: The initial heat wave contribution, which includes the first 4 heat wave (own) lags of RV, the heat wave HAR contribution, consisting of the average heat wave effects over the past week, month and quarter, the heat wave jump contribution (all heat wave jump variables) and the 3 meteor shower counterparts to those three heat wave variables. The groups have no intersection and include all non-deterministic regressors, so the proportions of explanatory power for each intraday period sum to 100. The final column of the table shows the average Shapley-Owen contribution for each set of coefficients across the 5 equations. The bottom row in each panel – labeled "R Squared (p-value)" – shows the R^2s for each trading segment, as well as the average R^2 across segments. The upper panel of the table shows results for the euro while the lower panel shows results for the yen.

The broadest conclusion from Table 2 is that both heat waves and meteor shower volatility contribute substantially to the R squared. Volatility contributes about 90% of explanatory power for future realized volatility, much more than do the squared jumps. For example, if we add the average contributions of the four volatility variables in the final column (i.e., "Average") of the top panel of Table 2, we obtain a volatility contribution of $0.21 + 0.21 + 0.29 + 0.21 = 0.92$ for the

[7] For brevity and clarity, we do not discuss coefficient estimates, which we consign to an appendix. As discussed earlier, coefficients are difficult to directly interpret for purposes of assessing heat waves and meteor showers.

EUR. The contribution of jumps is much smaller but not trivial. Squared jumps account for 8 and 11% of the total average explanatory power for the euro and the yen systems, respectively.

The upper panel of Table 2 (the EUR results) shows that when one averages across the five intraday periods, the heat wave volatility contributions of the four initial days and the HAR coefficients are each 21%, with heat wave jumps contributing 2% more, for a heat wave total of 44%. Meteor showers have a somewhat larger contribution, with the four initial days and the HAR volatility and jump coefficients explaining 29, 21 and 6% of the total R^2, respectively, for a sum of 56%. The lower panel shows that heat waves are slightly less important for the yen system, jointly contributing 35% of the total explanatory power.

In summary, heat waves in volatility and jumps contribute 44 and 35% of the total explanatory power for the EUR and JPY, respectively, while meteor showers in volatility and jumps contribute the rest. Volatility has significantly more explanatory power than jumps but jumps still contribute approximately 10% of the total explanatory power. Reassuringly, these statistics are generally fairly stable across the five equations for intraday periods and also across the two exchange rates.

4.3 Structural stability tests

Structural instability is common in time-series regressions. Therefore, we test for structural instability at an unknown point with the Andrews (1993) procedures. This provides a flexible way to search for breaks without specifying the exact nature of the break. See Appendix A-4 for details about the test.

The Andrews test initially calculates the Wald test statistics for a structural break in the HAR coefficients at each observation in the middle 70% of each sample. An automatic lag length selection (Newey and West 1994) provides lag orders for the Newey-West covariance matrices. The supremum of this time series of Wald test statistics identifies a possible structural break in the series but will have a nonstandard distribution (Andrews 1993). To find the distribution of this supremum under the null of no break, we follow the advice implicit in Chen and Diebold (1996), who show that the bootstrap approximation to the critical values is much more consistently accurate than the asymptotic approximation. Therefore, we simulate the data generating process, i.e., the HAR, 1000 times with a moving block bootstrap with a window of length 10, calculating the supremum of the break statistics for each of the simulated series. If the supremum of the break statistics for the real data exceeds the critical value implied by the distribution of the simulated suprema at a given significance level, then the test rejects the null of stability.

Figures 3 and 4 plot the Andrews (1993) unknown-point structural break statistics for the null hypotheses that the HAR parameters are stable over time, along with bootstrapped 1, 5, and 10 percent critical values. The top left panel in each figure illustrates the break statistics for the system as a whole while the five other panels illustrate the statistics for each of the individual equations. The structural break statistics never exceed the bootstrapped 10 percent critical value in any panel; one fails to reject the null that the HAR systems are stable.

4.4 Predictability across exchange rates

Previous studies of meteor showers and heat waves have focused exclusively on single market studies but foreign exchange volatility is strongly correlated across exchange rates. Therefore, this paper also characterizes meteor showers and heat waves across the EUR and JPY markets. To study cross-rate effects we include the other markets' regressors in the HAR predictive equation. That is, we take the EUR regressors and include them in the JPY predictive equations and vice versa. This doubles the number of regressors and coefficients for each equation.[8]

To characterize cross market effects, we again compute Shapley-Owen R^2s for groups of cross-market regressors. That is, we can now not only compute own-market heat wave and meteor shower effects but also such effects from volatility and jumps in the other market. Table 3 shows the Shapley-Owen R^2s for these cross-market effects. The own-market effects are grossly similar to those computed for the own-market regressions in Table 2. That is, summing the first four rows of the "average" column of Table 3 shows that the average own-market predictive capacity is about 73% of the total predictive effect and that is split between heat waves and meteor showers, with meteor showers having a modest majority of that effect. For example, in the euro regression, the top panel of Table 3 shows that, on average, heat-wave-own-market volatility shocks contribute 30% of the explanatory power and meteor-shower-own-market volatility shocks contribute 36% of

[8]cross-market coefficients reported for in Appendix A-3. Own-market coefficients are grossly similar to those for the univariate case. The co-linearity between the many correlated regressors in each equation results in relatively few statistically significant coefficients for other-market effects. That is EUR and JPY QV are fairly highly contemporaneously correlated and each are autocorrelated over time, as well. Nevertheless, there are some statistically significant and positive cross-market meteor shower coefficients, particularly in the first four days.

the explanatory power while own-market heat-wave and meteor-shower jumps contribute 2 and 5%, respectively. JPY regressors, however, do contribute a substantial amount of predictability in the EUR equation, with JPY heat wave variables – volatility plus jumps – contributing 11% and JPY meteor shower variables – volatility plus jumps – contributing 17% of the total explanatory power in the regression.[9] Figure 5 illustrates the proportions of of cross-market predictability for own-market and cross-market lagged volatility and jump components.

The lower panels of Table 3 and Figure 5 show that the results in the JPY market are similar to those in the EUR market. Own-market effects contributing 74% of predictive power for JPY RV and other-market effects contribute the remaining 26%. Of these effects, IV contributes 86% and jumps 14%. About 2/3 of both domestic and cross-market effects are from meteor showers.

In summary, while own-market effects contribute about 75 percent of the explanatory power, other-market effects are substantial, at about 25 percent. In contrast, to conclusions in Melvin and Peiers Melvin (2003) and Cai, Howorka, and Wongswan (2008), meteor showers are collectively more important than heat waves, contributing about 60 percent and 40 percent of explanatory power, respectively. Given that there are four times as many meteor shower periods than heat wave periods, each heat wave period is much more important than a typical meteor shower period. Collectively, volatility regressors have 8 to 10 times the predictive power of jumps for RV but jumps still contribute substantially.

4.5 Causes of heat waves and meteor showers

We wish to investigate the source of shocks that might increase or decrease the heat wave and/or meteor shower effects. One might hypothesize that temporally clustered national news–released within a country's particular working hours– creates heat wave effects. In contrast, temporally clustered international news or news that releases private information in the form of delayed trading creates meteor shower effects.

To investigate this question, we perform a variation of regression sensitivity analysis. Sensitivity analysis (a.k.a., influence analysis) is usually performed on a regression to determine if the results

[9]Particularly observant readers might note that the R^2s in the cross-rate regression results displayed in Table 3 are not much larger than the single-rate regressions in Table 2. Because the regressions are run on slightly different samples, the R^2s from the cross-rate regression need not exceed the R^2s from the single-rate regressions.

are heavily influenced by particular observations. One estimates the regression, removing one observation at a time, to see if removing any particular observations cause the coefficients – or other statistics – to change substantially.

In our case, we remove one observation at a time and then compute the Shapley-Owen R^2s (not just proportions) for each of 4 groups: 1) the heat-wave variables for the RV regressors; 2) the meteor shower variables for the RV regressors; 3) the heat-wave variables for the jump regressors; 4) the meteor shower variables for the jump regressors. We will refer to these time series as Shapley-Owen R^2 sensitivity series and denote them as $R^2_{i,t}(SO)$. We then examine whether news and time trends explain the time series of these Shapley-Owen R^2 sensitivity series. Specifically, we regressed the standardized change in the Shapley-Owen R^2s when day t is removed on a time series of the absolute value of standardized news releases and a quartic time trend.[10] If a particular type of news event–say FOMC announcements –increases heat-wave effects in volatility, one would expect that removing those events would reduce the Shapley-Owen R^2s for the heat-wave volatility coefficients, resulting in a negative coefficient on FOMC shocks in the following regression:

$$\tilde{R}^2_{i,t}(SO) = \frac{R^2_{i,t}(SO) - \overline{R}^2_i(SO)}{\sigma_{R^2_{i,t}}} = \sum_{j=1}^{N} \beta_j \mid \frac{A_{j,t} - E(A_{j,t})}{\sigma_{A_i}} \mid + \sum_{j=1}^{4} \beta_{N+j} t^j + \varepsilon_{i,t}, \qquad (4.1)$$

where $\mid \frac{A_{j,t}-E(A_{j,t})}{\sigma_{A_i}} \mid$ is the absolute value of the standardized jth announcement on day t and $\sum_{j=1}^{4} \beta_{N+j} t^j$ is the quartic time trend.

Because we have much better data on US news and announcements than on non-US news, the estimated regressions produce much more significant results for the US and ES segments than the other three (AS, AE, and EU). Therefore, in the interests of clarity and brevity, we report results for only those equations. We expect that the results for the US and ES segments would provide inference representative of that from the three other periods, if we had access to long samples of high-quality announcement and expectations data from Europe and Japan.

We examine 8 major US announcements that have been previously shown to have substantial effects on asset price volatility (Neely 2011). Most of these announcements are standard, including advance real Gross Domestic Product (GDP), the implicit GDP deflator, the consumer price index (CPI), the producer price index (PPI), unemployment and nonfarm payrolls (NFP). In addition, we include measures of conventional monetary policy, MP1 and ED12, developed by Kuttner (2001),

[10]We considered other specifications, including an announcement indicator instead of the absolute value of the shock and day-of-the-week indicators but these alternatives did not improve the fit of the relations.

Gürkaynak, Sack, and Swanson (2005) and Hausman and Wongswan (2011) and an unconventional policy measure due to Wright (2012). Fawley and Neely (2014) detail these monetary policy measures.

Tables 4 and 5 show the results of the exercise for the US and ES equations, respectively. First, we observe that removing days of US monetary shocks (Table 4) and NFP (Table 5) has the largest effects on the Shapley-Owen sensitivity series. This is consistent with their importance in other foreign-exchange-announcement-effect studies (Lahaye, Laurent, and Neely 2011, Neely 2015). Second, the signs and significance of coefficients within each table show some consistency.

Let us first consider shocks with positive coefficients. Positive coefficients indicate that these shocks actually reduce estimated heat wave and meteor shower effects, presumably by producing atypical volatility patterns that weaken the estimated fit. It is well known that particularly large shocks present problems for volatility models that rely on autocorrelation in volatility because the very large shocks die out much too quickly for typical models (Neely 1999, Andersen, Bollerslev, and Diebold 2007).

Both the very large unconventional policy (Wright) shocks and the very important NFP shocks have positive coefficients in the heat wave and meteor shower volatility equations for both the EUR and JPY markets. The Wright shocks have their larger effects in the US trading period (Table 4), which is the period when almost all of the US unconventional policy announcements were made, while the NFP shocks have all their significant effects in the ES period (i.e., the Europe-US overlap, Table 5), which is the period when the Labor Department releases NFP news. The Wright shocks weakened all the volatility predictive power for the US market but strengthened the heat wave-jump predictive power. The top row of Table 4 shows that the coefficient on heat-wave volatility is 0.56, in the Euro market / US period, meaning that a one-standard deviation Wright shock reduces the Shapley-Owen R^2 sensitivity series for heat-wave volatility by 0.56 of a standard deviation in the US market. Wright shocks also tend to decrease the meteor shower effect of jumps in both the EUR and JPY markets during the US period (”Wright” column, Table 4). That is, large and unusual unconventional monetary shocks decrease the fit of the autocorrelation model of jumps.

The coefficients on NFP shocks are positive in both the EUR and JPY markets for both heat wave and meteor shower volatility effects. That is, NFP shocks are probably large but expected. They are more easily interpretable and do not set off serially correlated releases of private information that would produce meteor shower or heat wave volatility effects. Therefore they tend to weaken the usual predictive patterns.

The coefficients on conventional monetary policy shocks – MP1 and ED12 – are negative for the heat wave and meteor shower volatility equations during the US period (Table 4), which is when conventional monetary announcements were made. The largest such negative coefficient, at -0.23, is that on the ED12 shock for the EUR exchange rate for the US volatility heat wave equation. Conventional monetary policy shocks increase the estimated heat wave and meteor shower effects, presumably because they stimulate the release of private US-specific and international information that increases volatility in the following periods in a manner consistent with the rest of the data.

Interestingly, the coefficients on the Wright shocks are significantly negative (-0.16 and -0.19) for the heat wave jump equation for both exchange rates during the US segment, increasing the heat-wave effect of jumps (Table 5). That is, unconventional policy shocks create jumps that predict future volatility in the US market.

In summary, unconventional policy and NFP shocks are probably so influential that they actually reduce the predictive effect of heat wave and meteor shower in volatility equations. In contrast, the more frequent and smaller conventional policy shocks increase both heat wave and meteor shower effects because they presumably reinforce patterns in the volatility data from other types of news. Not surprisingly, news has its most significant effects on heat wave and meteor shower patterns in the intraday trading periods in which it is announced.[11]

5 Conclusion

This paper has extended the study of meteor showers and heat waves in foreign exchange markets by integrating data on jumps into the study, by evaluating effects with the Shapley-Owen R^2, and by characterizing cross-rate predictability in such studies.

To maintain continuity with the literature, we initially study systems with data from a single exchange rate. We find that jumps contribute modestly to explanatory power; integrated variance contributes 90% of explanatory power; jumps add about 10%. In contrast to the previous literature,

[11] The PPI appears to be an exception to this for the JPY market. Its releases appear consistently effect the heat wave and meteor shower volatility patterns in the US segment, which occurs several hours after the PPI's 8:30 AM release.

we find that meteor showers contribute more (60%) predictive power than heat waves (40%), although individual heat wave periods are more informative than typical meteor shower periods. Andrews (1993) tests fail to reject the hypothesis that the one-exchange rate HAR systems are structurally stable over time.

Our cross-rate HAR systems show that volatility propagates across FX markets. Own-market patterns explain about 75% of variation while other-market effects explain 25%. The heat-wave-meteor-shower breakdown is similar to that in the single-rate systems. Meteor showers contribute 60-65% of the predictability while heat waves are responsible for the rest.

The impulse response functions suggest that shocks to Asian volatility have particularly important effects on volatility in other periods. At the same time, US volatility appears to be relatively insensitive to shocks in other regions.

Finally, sensitivity analysis suggests that certain very large shocks – unconventional monetary policy and NFP – decrease heat wave and meteor shower effects in volatility while more frequent, smaller but still important shocks – i.e., conventional monetary policy shocks – strengthen both of these relations. This is consistent with studies by Neely (1999) and Andersen, Bollerslev, and Diebold (2007), in which very large shocks reduced the fit of volatility models while smaller shocks improved it by reinforcing patterns created by other news. Shocks tend to have their greatest effects on predictive patterns during the intraday period in which they are announced.

References

ANDERSEN, T., T. BOLLERSLEV, AND D. DOBREV (2007): "No-arbitrage Semi-martingale Restrictions for Continous-time Volatility Models Subject to Leverage Effects, Jumps and i.i.d. noise: Theory and Testable Distributional Implications," *Journal of Econometrics*, 138, 125–180.

ANDERSEN, T. G., T. BOLLERSLEV, AND F. X. DIEBOLD (2007): "Roughing It Up: Including Jump Components in the Measurement, Modelling and Forecasting of Return Volatility," *Review of Economics and Statistics*, 89, 701–720.

ANDREWS, D. (1993): "Tests for Parameter Instability and Structural Change with Unknown Change Point," *Econometrica*, 61, 821–856.

BAILLIE, R. T., AND T. BOLLERSLEV (1991): "Intra Day and Inter Market Volatility in Foreign Exchange Rates," *Review of Economic Studies*, 58, 565–585.

BARNDORFF-NIELSEN, O., AND N. SHEPHARD (2006): "Econometrics of testing for jumps in financial economics using bipower variation," *Journal of Financial Econometrics*, 4, 1–30.

BOUDT, K., C. CROUX, AND S. LAURENT (2011): "Robust estimation of intraweek periodicity in volatility and jump detection," *Journal of Empirical Finance*, 18, 353–367.

CAI, F., E. HOWORKA, AND J. WONGSWAN (2008): "Informational Linkages Across Trading Regions: Evidence from Foreign Exchange Markets," *Journal of International Money and Finance*, 27, 1215–1243.

CHEN, C., AND F. X. DIEBOLD (1996): "Testing structural stability with endogenous breakpoint: A size comparison of analytic and bootstrap procedures," *Journal of Econometrics*, 70, 221–241.

CHEVAN, A., AND M. SUTHERLAND (1991): "Hierarchical Partitioning," *The American Statistician*, 45, 90–96.

CORSI, F. (2009): "A Simple Approximate Long-Memory Model of Realized Volatility," *Journal of Financial Econometrics*, 7, 174–196, doi:10.1093/jjfinec/nbp001.

CORSI, F., D. PIRINO, AND R. RENO (2010): "Threshold bipower variation and and the impact of jumps on volatility forecasting," *Journal of Econometrics*, 159, 276–288.

Dumitru, A. M., and G. Urga (2012): "Identifying jumps in financial assets: a comparison between non-parametric jump tests," *Journal of Business and Economic Statistics*, 30, 242–255.

Engle, R. F., T. Ito, and W. L. Lin (1990): "Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market," *Econometrica*, 58, 525–542.

——— (1992): "Where does the meteor shower come from? The role of stochastic policy coordination," *Journal of International Economics*, 32, 221–240.

Erdemlioglu, D., S. Laurent, and C. J. Neely (2015): "Which continuous-time model is most appropriate for exchange rates," *Journal of Banking and Finance*, 61, S256–S268.

Fan, J., and Q. Yao (2003): *Nonlinear Time Series*. Springer-Verlag, New York.

Fawley, B., and C. J. Neely (2014): "The Evolution Of Federal Reserve Policy And The Impact Of Monetary Policy Surprises On Asset Prices," *Federal Reserve Bank of St. Louis Review*, 96, 73–109.

Grömping, U. (2007): "Estimators of relative importance in linear regression based on variance decomposition," *The American Statistician*, 61, 139–147.

Gürkaynak, R. S., B. P. Sack, and E. T. Swanson (2005): "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1, 55–93.

Hamilton, J. D. (1994): *Time Series Analysis*. Princeton University Press, Princeton.

Hausman, J., and J. Wongswan (2011): "Global Asset Prices and FOMC Announcements," *Journal of International Money and Finance*, 30, 547–71.

Hogan, K., and M. Melvin (1994): "Sources of meteor showers and heat waves in the foreign exchange market," *Journal of International Economics*, 37, 239–247.

Holzinger, K. J., and F. Swineford (1939): "A study in factor analysis: the stability of a bi-factor solution," *Supplementary Educational Monographs*, 48.

Kuttner, K. N. (2001): "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47, 523–44.

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

Lee, S. S., and P. A. Mykland (2008): "Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics," *Review of Financial Studies*, doi: 10.1093/rfs/hhm056.

Lindeman, R., P. Merenda, and R. Gold (1980): *Introduction to Bivariate and Multivariate Analysis*. Scott Foresman, Glenview, IL.

Liu, L., A. Patton, and K. Sheppard (2015): "Does Anything Beat 5-Minute RV? A Comparison of Realized Measures Across Multiple Asset Classes," *Journal of Econometrics*, 187, 293–311.

Mancini, C. (2009): "Non-parametric threshold estimation for models with stochastic diffusion coefficient and jumps," *Scandinavian Journal of Statistics*, 36, 270–296.

Melvin, M., and B. Peiers Melvin (2003): "The global transmission of volatility in the foreign exchange market," *The Review of Economics and Statistics*, 85, 670–679.

Nathans, L. L., L. O. Frederick, and K. Nimon (2012): "Interpreting multiple linear regression: A guidebook of variable importance," *Practical Assessment, Research & Evaluation*, 17.

Neely, C. J. (1999): "Target Zones and Conditional Volatility: the Role of Realignments," *Journal of Empirical Finance*, 6, 177–192.

——— (2011): "A Survey Of Announcement Effects On Foreign Exchange Volatility And Jumps," *Federal Reserve Bank of St. Louis Review*, 93, 361–385.

——— (2015): "Unconventional Monetary Policy Had Large International Effects," *Journal of Banking and Finance*, 52, 101–111.

Newey, W. K., and K. D. West (1994): "Automatic Lag Selection in Covariance matrix Estimation," *Review of Economic Studies*, 61, 631–653.

Owen, G. (1977): "Values of games with a priori unions," in *Essays in Mathematical Economics and Game Theory*, ed. by R. Henn, and O. Moeschlin, pp. 76–88. Springer, Berlin.

Phylaktis, K., and L. Chen (2009): "Price Discovery in Foreign Exchange Markets: A Comparison of Indicative and Actual Transaction Prices," *Journal of Empirical Finance*, 16, 640–654.

Rousseeuw, P., and A. Leroy (1988): "A robust scale estimator based on the shortest half," *Statistica Neerlandica*, 42, 103–116.

Shapley, L. (1953): "A Value for n-Person Games," reprinted in *The Shapley Value: Essays in Honor of Lloyd S. Shapley*, ed. A. Roth, Cambridge: Cambridge University Press.

Soucek, M., and N. Todorova (2014): "Realized volatility transmission: The role of jumps and leverage effects," *Economics Letters*, 122, 111–115.

Taylor, S. J., and X. Xu (1997): "The Incremental Volatility Information in One Million Foreign Exchange Quotations," *Journal of Empirical Finance*, 4, 317–340.

Wright, J. H. (2012): "What Does Monetary Policy Do to Long-Term Interest Rates at the Zero Lower Bound?," *The Economic Journal*, 122, 447–66.

Young, H. P. (1985): "Monotonic solutions of cooperative games," *International Journal of Game Theory*, 14 (2), 65–72.

Table 1: Descriptive statistics on segments' RV and jumps

		AS	AE	EU	ES	US
RV	Mean	2.98	4.67	4.07	5.38	3.50
	Median	2.77	4.34	3.76	5.03	3.15
	Std. dev.	1.18	1.95	1.71	2.04	1.62
Jump	Freq.	0.08	0.01	0.02	0.04	0.05
	Mean	3.43	6.95	5.45	4.15	4.78
	Std. dev.	2.34	5.16	4.74	1.81	2.43

Note: The table provides descriptive statistics for each trading segment's volatility (Eq. 2.3) and jumps (Eq. 2.4): mean, median and standard deviation, as well as frequency of jump days.

Table 2: Shapley-Owen R^2s for the EUR and JPY

EUR	**AS**		**AE**		**EU**		**ES**		**US**		**Average**
HW initial vol contribution (p-value)	0.25	(0.00)	0.20	(0.00)	0.18	(0.16)	0.21	(0.00)	0.22	(0.00)	0.21
HW HAR vol contribution (p-value)	0.24	(0.00)	0.19	(0.00)	0.19	(0.00)	0.22	(0.00)	0.23	(0.00)	0.21
MS initial vol contribution (p-value)	0.27	(0.00)	0.30	(0.00)	0.34	(0.00)	0.27	(0.00)	0.29	(0.00)	0.29
MS HAR vol contribution (p-value)	0.20	(0.06)	0.19	(0.02)	0.23	(0.02)	0.21	(0.12)	0.23	(0.47)	0.21
HW jump contribution (p-value)	0.03	(0.07)	0.01	(0.15)	0.01	(0.03)	0.01	(0.61)	0.02	(0.74)	0.02
MS jump contribution (p-value)	0.02	(0.16)	0.10	(0.03)	0.05	(0.01)	0.08	(0.00)	0.03	(0.31)	0.06
R Squared (p-value)	0.56	(0.00)	0.47	(0.00)	0.47	(0.00)	0.45	(0.00)	0.49	(0.00)	0.49
JPY	**AS**		**AE**		**EU**		**ES**		**US**		**Average**
HW initial vol contribution (p-value)	0.21	(0.00)	0.14	(0.15)	0.13	(0.97)	0.17	(0.06)	0.19	(0.00)	0.17
HW HAR vol contribution (p-value)	0.17	(0.00)	0.15	(0.18)	0.14	(0.03)	0.18	(0.00)	0.19	(0.00)	0.16
MS initial vol contribution (p-value)	0.30	(0.00)	0.42	(0.00)	0.46	(0.00)	0.35	(0.00)	0.32	(0.00)	0.37
MS HAR vol contribution (p-value)	0.17	(0.00)	0.17	(0.42)	0.19	(0.06)	0.19	(0.22)	0.20	(0.12)	0.19
HW jump contribution (p-value)	0.04	(0.40)	0.02	(0.58)	0.02	(0.25)	0.02	(0.64)	0.03	(0.16)	0.02
MS jump contribution (p-value)	0.12	(0.00)	0.10	(0.00)	0.06	(0.01)	0.09	(0.00)	0.07	(0.00)	0.09
R Squared (p-value)	0.47	(0.00)	0.43	(0.00)	0.45	(0.00)	0.42	(0.00)	0.41	(0.00)	0.44

Note: The table shows the Shapley-Owen proportion of the total R^2s, as well as p-values in parentheses, for groups of coefficients in the HAR model in which RV is predicted by lagged IV and lagged jumps (Equation 3.1). There are 6 groups of coefficients: The initial heat wave (HW) contribution, which includes the first 4 heat wave (own) lags of RV, the heat wave HAR contribution, consisting of the average heat wave effects over the past week, month and quarter, the heat wave jump contribution (all heat wave jumps variables) and the 3 meteor shower (MS) counterparts to those three heat wave variables. The groups have no intersection and include all non-deterministic regressors, so the proportions for each intraday period sum to 100. The final column of the table shows the average Shapley-Owen contribution for each set of coefficients across the 5 equations. Statistics in parentheses are p-values from Wald tests that the coefficients within each group are jointly zero.

Table 3: Shapley-Owen R^2s for cross-market prediction of the EUR and JPY RV

Dependent variable: EUR RV	**AS**		**AE**		**EU**		**ES**		**US**		**Average**
HW own vol contribution (p-value)	0.33	(0.00)	0.30	(0.00)	0.27	(0.00)	0.31	(0.00)	0.31	(0.00)	0.30
MS own vol contribution (p-value)	0.30	(0.00)	0.39	(0.00)	0.42	(0.00)	0.34	(0.00)	0.36	(0.00)	0.36
HW own jump contribution (p-value)	0.03	(0.00)	0.02	(0.11)	0.02	(0.04)	0.01	(0.29)	0.01	(0.48)	0.02
MS own jump contribution (p-value)	0.02	(0.03)	0.05	(0.05)	0.05	(0.06)	0.08	(0.00)	0.03	(0.20)	0.05
HW other vol contribution (p-value)	0.12	(0.91)	0.08	(0.89)	0.08	(0.15)	0.09	(0.04)	0.12	(0.13)	0.10
MS other vol contribution (p-value)	0.15	(0.06)	0.12	(0.22)	0.12	(0.24)	0.12	(0.08)	0.13	(0.09)	0.13
HW other jump contribution (p-value)	0.01	(0.01)	0.01	(0.12)	0.02	(0.30)	0.01	(0.03)	0.02	(0.87)	0.01
MS other jump contribution (p-value)	0.03	(0.27)	0.04	(0.68)	0.03	(0.21)	0.05	(0.00)	0.03	(0.04)	0.04
R Squared (p-value)	0.61	(0.00)	0.45	(0.00)	0.48	(0.00)	0.47	(0.00)	0.51	(0.00)	0.50
Dependent variable: JPY RV	**AS**		**AE**		**EU**		**ES**		**US**		**Average**
HW own vol contribution (p-value)	0.27	(0.00)	0.20	(0.16)	0.19	(0.00)	0.25	(0.00)	0.27	(0.00)	0.24
MS own vol contribution (p-value)	0.34	(0.00)	0.44	(0.00)	0.46	(0.00)	0.40	(0.00)	0.37	(0.00)	0.40
HW own jump contribution (p-value)	0.03	(0.43)	0.02	(0.90)	0.02	(0.16)	0.02	(0.67)	0.02	(0.26)	0.02
MS own jump contribution (p-value)	0.12	(0.00)	0.09	(0.01)	0.06	(0.01)	0.08	(0.00)	0.07	(0.00)	0.08
HW other vol contribution (p-value)	0.11	(0.11)	0.07	(0.01)	0.06	(0.43)	0.08	(0.12)	0.09	(0.24)	0.08
MS other vol contribution (p-value)	0.10	(0.33)	0.14	(0.07)	0.17	(0.00)	0.14	(0.68)	0.16	(0.03)	0.14
HW other jump contribution (p-value)	0.02	(0.02)	0.01	(0.07)	0.00	(0.61)	0.01	(0.84)	0.01	(0.39)	0.01
MS other jump contribution (p-value)	0.01	(0.12)	0.02	(0.09)	0.04	(0.03)	0.02	(0.04)	0.02	(0.57)	0.02
R Squared (p-value)	0.48	(0.00)	0.44	(0.00)	0.46	(0.00)	0.42	(0.00)	0.42	(0.00)	0.44

Note: The table shows the Shapley-Owen proportion of the total R^2s, as well as p-values in parentheses, for groups of coefficients in the cross-market HAR model in which each period's RV is predicted by both its own lagged IV and jumps, as well as lagged IV and jump from the other foreign exchange rate. The top (bottom) panel shows results for EUR (JPY) RV as the dependent variables. The final column of the table shows the average Shapley-Owen contribution for each set of coefficients across the 5 equations. Statistics in parentheses are p-values from Wald tests that the coefficients within each group are jointly zero.

Table 4: The effect of standardized absolute announcement shocks on Shapley-Owen R^2s – US equation

Market		GDP	GDP Defl.	CPI	PPI	Unemp.	NFP	Wright	MP1	ED12
EUR	RV heat-wave	-0.01	-0.01	0.01	0.02	0.02	-0.03	0.56	-0.02	-0.23
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
EUR	RV meteor shower	-0.01	0.00	0.06	0.01	0.00	-0.01	0.42	0.01	-0.12
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
EUR	Jump heat-wave	0.01	-0.02	-0.11	0.04	-0.02	0.01	-0.19	-0.05	0.06
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
EUR	Jump meteor shower	0.00	0.00	0.00	0.00	0.02	0.03	0.05	0.01	-0.04
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	RV heat-wave	0.00	0.00	-0.01	0.12	0.00	-0.01	0.25	-0.04	-0.12
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	RV meteor shower	0.00	0.00	0.02	0.13	-0.01	0.00	0.31	-0.04	-0.13
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	Jump heat-wave	0.00	0.00	-0.07	0.13	0.03	-0.03	-0.16	0.02	0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	Jump meteor shower	0.00	0.01	0.01	0.01	-0.01	0.03	0.13	-0.01	-0.09
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)

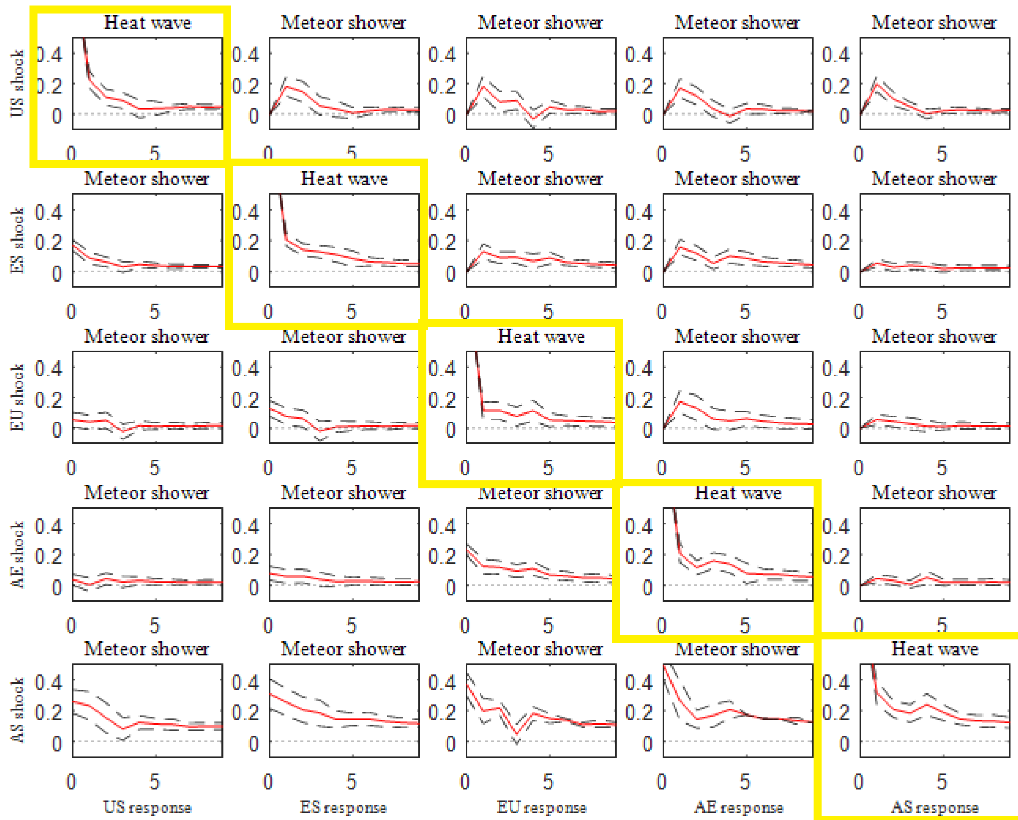
Note: The table shows the results of regressions of standardized Shapley-Owen R^2s for four groups of regressors on the absolute value of standardized news announcement shocks. The table presents results for the US equation in the EUR market (upper panel) and the JPY market (lower panel). The time series of Shapley-Owen R^2s were created by removing one observation at a time from the sample and therefore represents the change in R^2 for the four respective groups on each of the days in the sample. Each row represents the results for the Shapley-Owen R^2 for one group of regressors. For example, the first row shows the results for the regression of the series of the sensitivity Shapley-Owen R^2s for the heat-wave, volatility variables, in the Euro market (US equation), on absolute standardized shocks. Highlighted cells denote coefficients that are statistically significant at the 5 percent level and standard errors are in parentheses below the coefficient estimates.

Table 5: The effect of standardized absolute announcement shocks on Shapley-Owen R^2s – ES equation

Market		GDP	GDP Defl.	CPI	PPI	Unemp.	NFP	Wright	MP1	ED12
EUR	RV heat-wave	-0.01	-0.01	0.02	-0.01	-0.01	0.13	0.08	0.05	-0.05
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
EUR	RV meteor shower	-0.01	0.00	-0.01	0.00	-0.03	0.19	0.13	0.00	-0.09
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
EUR	Jump heat-wave	0.02	-0.01	0.01	0.01	-0.10	0.13	0.00	0.00	0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
EUR	Jump meteor shower	0.01	0.01	-0.02	0.01	-0.02	0.08	-0.16	0.04	0.04
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	RV heat-wave	-0.02	0.01	0.00	-0.02	-0.05	0.09	0.07	-0.04	-0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	RV meteor shower	-0.01	0.01	-0.01	0.00	0.02	0.14	0.04	-0.11	-0.02
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	Jump heat-wave	0.03	-0.01	0.01	0.01	0.02	0.03	0.02	-0.04	-0.01
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
JPY	Jump meteor shower	0.00	0.01	-0.03	0.02	0.03	0.00	-0.15	0.03	0.05
		(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)

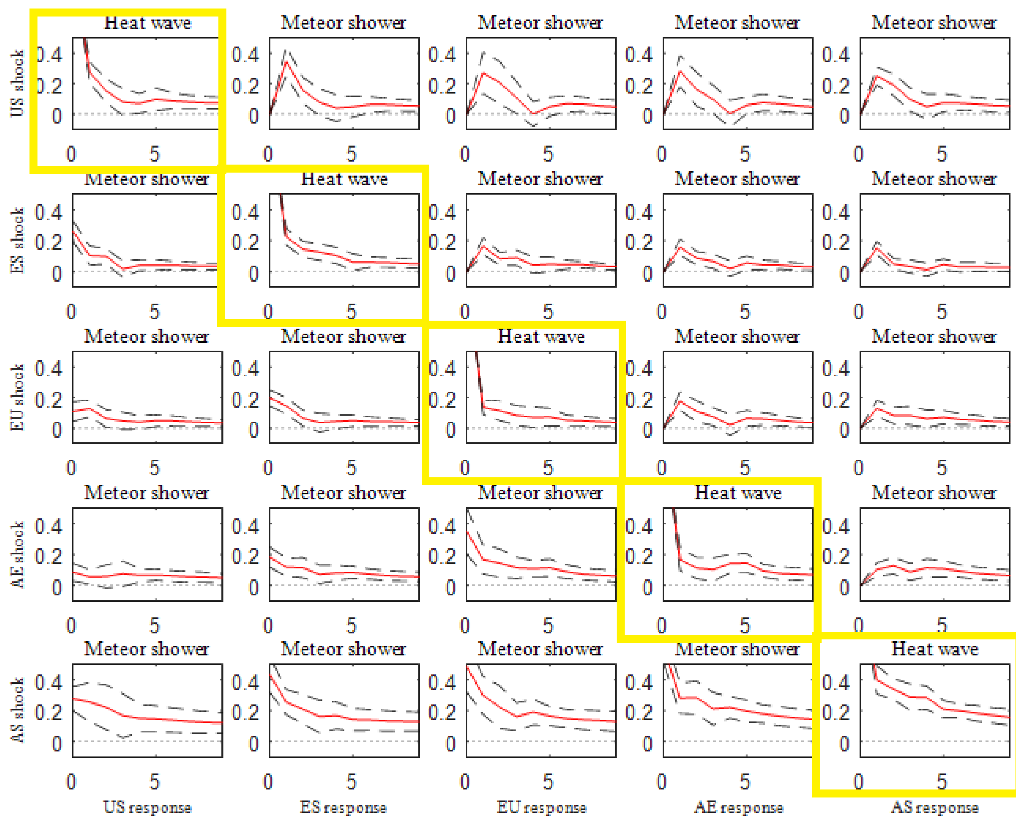
Note: The table shows the results of regressions of standardized Shapley-Owen R^2s for four groups of regressors on the absolute value of standardized news announcement shocks. The table presents results for the ES equation in the EUR market (upper panel) and the JPY market (lower panel). The time series of Shapley-Owen R^2s were created by removing one observation at a time from the sample and therefore represents the change in R^2 for the four respective groups on each of the days in the sample. Each row represents the results for the Shapley-Owen R^2 for one group of regressors in one market. For example, the first row shows the results for the regression of the series of the sensitivity Shapley-Owen R^2s for the heat-wave, volatility variables, in the Euro market (ES equation), on absolute standardized shocks. Highlighted cells denote coefficients that are statistically significant at the 5 percent level and standard errors are in parentheses below the coefficient estimates

Figure 1: Impulse responses implied by the HAR model for the EUR



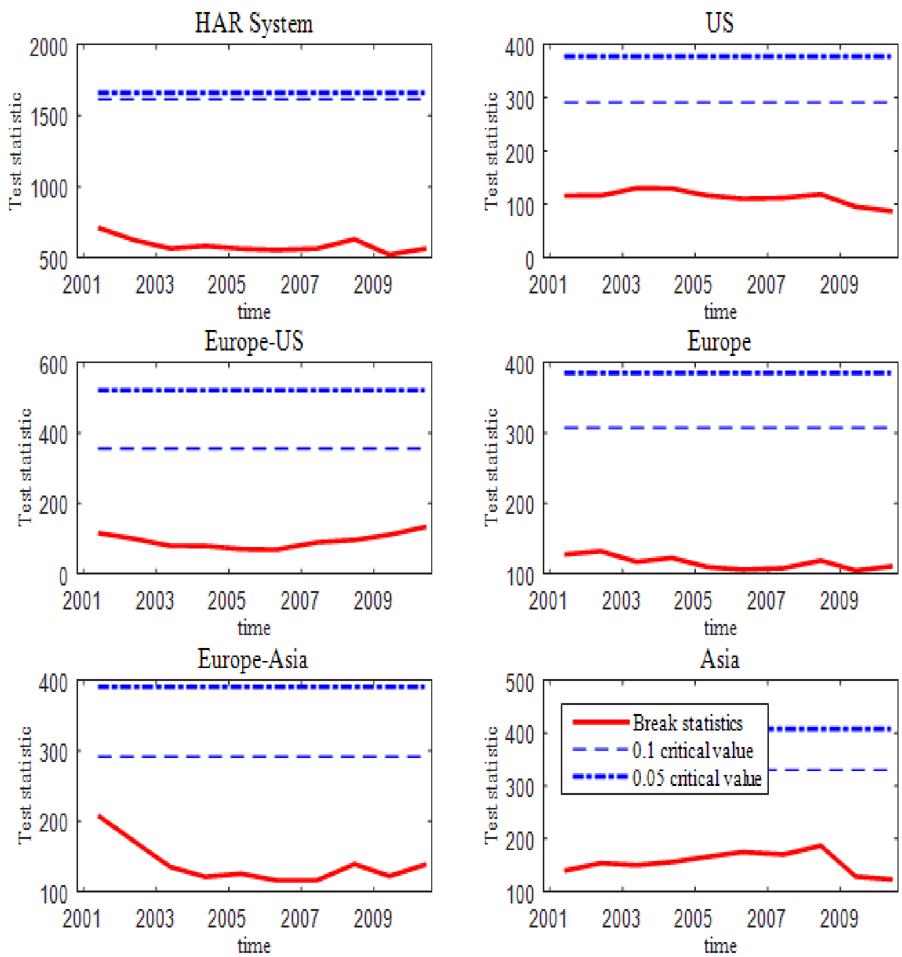
Notes: The figure displays the point estimate for the impulse response functions in red and a 95 percent confidence interval – with median – in black.

Figure 2: Impulse responses implied by the HAR model for the JPY



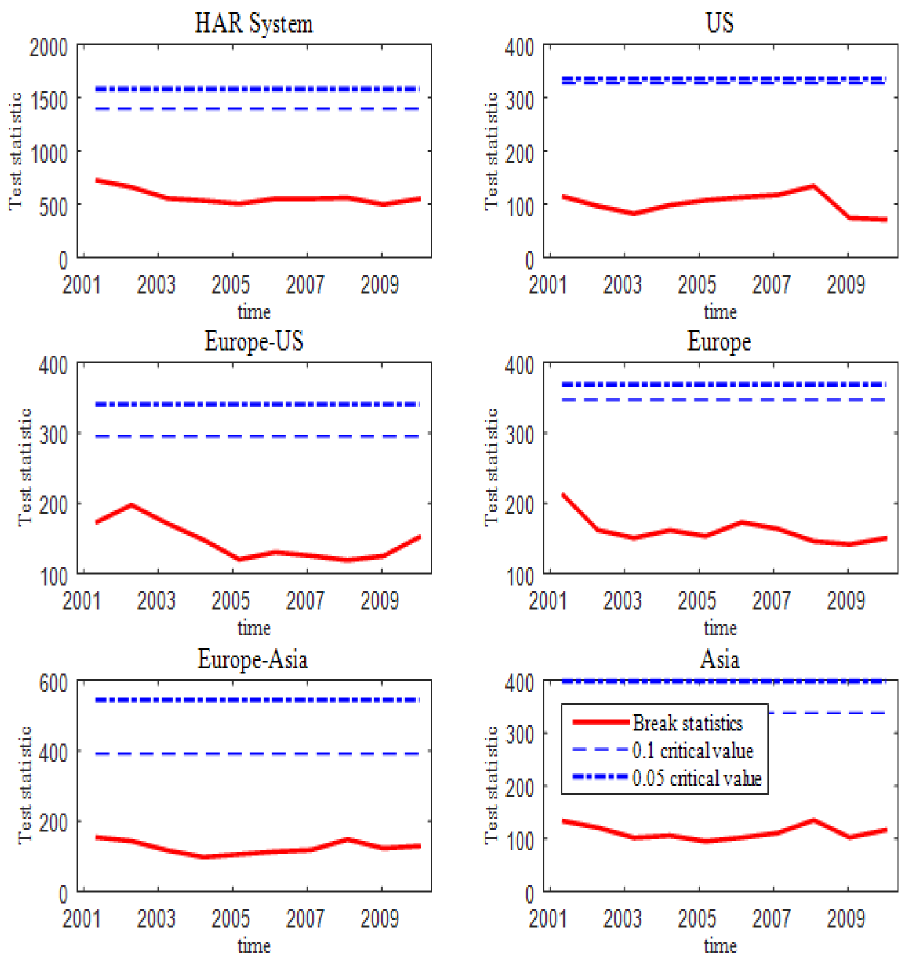
Notes: The figure displays the point estimate for the impulse response functions in red and a 95 percent confidence interval – with median – in black.

Figure 3: Andrews break statistics for the EUR HAR System and individual equations



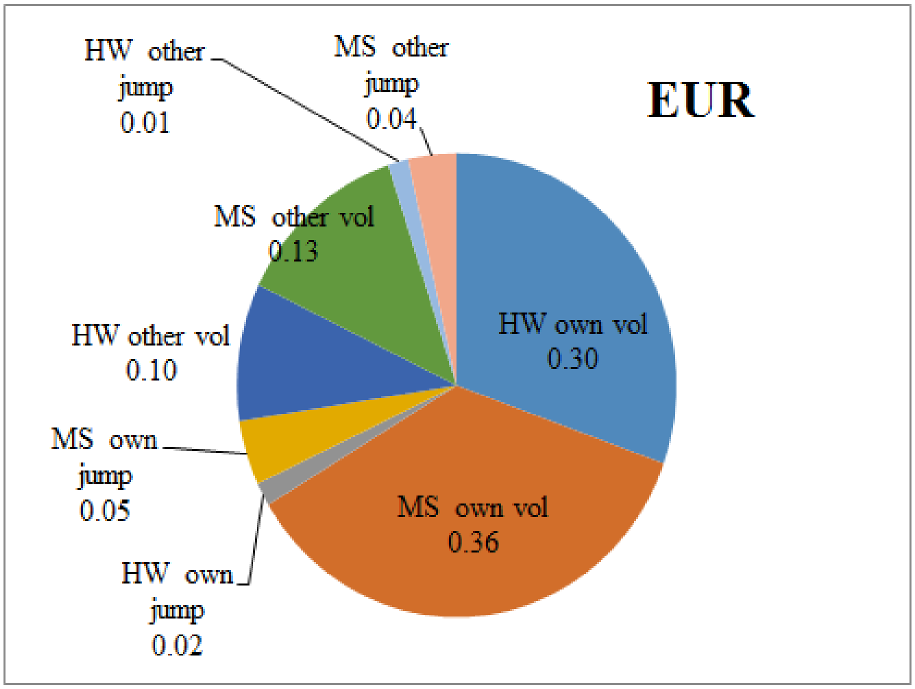
Notes: The six panels of the figure plot the Andrews test statistics and the bootstrapped 1, 5, and 10 percent critical values from the 15th to the 85th percentile of the samples, for a structural break in the EUR HAR system and each of the 5 individual HAR equations. Critical values were obtained by simulating the HAR system under the null of stability with a moving block bootstrap with a 10-day block.

Figure 4: Andrews break statistics for the JPY HAR System and individual equations

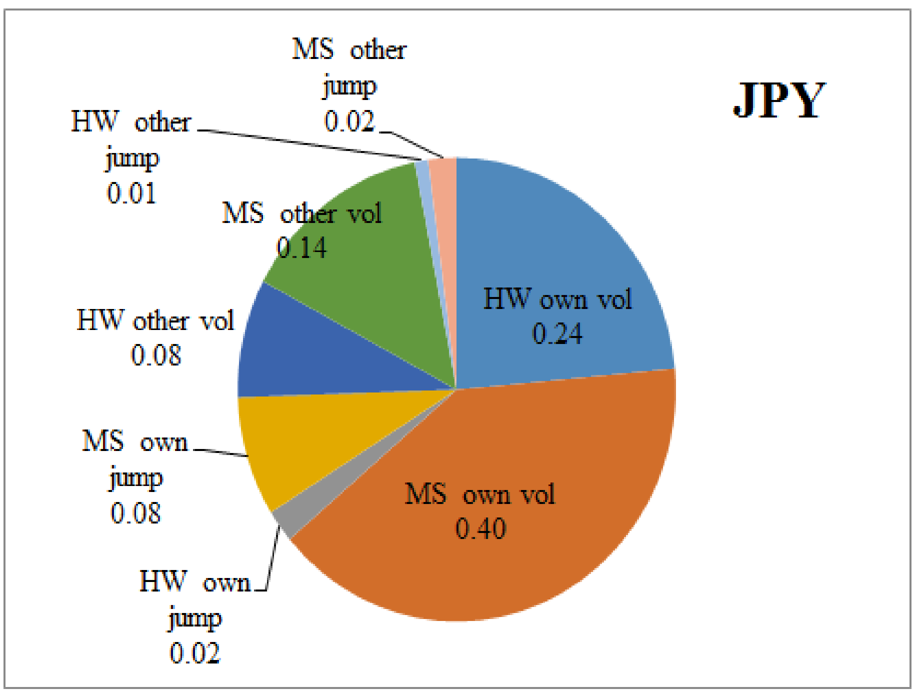


Notes: The six panels of the figure plot the Andrews test statistics and the bootstrapped 1, 5, and 10 percent critical values from the 15th to the 85th percentile of the samples, for a structural break in the JPY HAR system and each of the 5 individual HAR equations. Critical values were obtained by simulating the HAR system under the null of stability with a moving block bootstrap with a 10-day block.

Figure 5: Shapley-Owen R^2s for cross-market prediction



(a) EUR/USD



(b) USD/JPY

Note: The figure displays the proportion of cross-market predictability for own-market and cross-market lagged volatility and jump components.

A-1 APPENDIX (not-for-publication): robust periodicity and integrated volatility estimators

A-1.1 Periodicity estimation

Following Boudt, Croux, and Laurent (2011), we assume a multiplicative periodic component. First, we normalize each intraday return $\Delta_{j,t}X$ with its corresponding daily volatility estimate scaled to the intraday interval length, $\sqrt{I\hat{V}_t/n}$. For intraday period j of day t, assuming D sample days:

$$\overline{\Delta_{j,t}X} = \frac{\Delta_{j,t}X}{\sqrt{I\hat{V}_t/n}}, \quad j = 1...n, \quad t = 1, ...D, \tag{A-1}$$

The periodic volatility component for period j is a scale estimate obtained using the standardized returns for period j (from Equation A-1) from all days in the sample:[12]

$$\overline{\sigma_j} = scale_j(\overline{\Delta_{j,1}X}, \overline{\Delta_{j,2}X}, ..., \overline{\Delta_{j,D}X}), \quad j = 1...n. \tag{A-2}$$

Following Boudt, Croux, and Laurent (2011) and Lahaye, Laurent, and Neely (2011), we choose the weighted standard deviation (WSD) as the scale measure.

The WSD first involves the shortest half scale (SHS) (Rousseeuw and Leroy 1988). To compute SHS_j, the SHS for intraday period j, take all sample interval j returns (across D sample days) and rank them such that $\overline{\Delta_{j,t^1}X} < \ldots < \overline{\Delta_{j,t^D}X}$. $\overline{\Delta_{j,t^1}X}$ is the smallest sample return for intraday period j, and $\overline{\Delta_{j,t^D}X}$ is the largest. The SHS is the minimum value of halves length. Halves are subsets of $\lfloor \frac{D}{2} \rfloor + 1 = h$ contiguous returns in the ranked set $\overline{\Delta_{j,t^1}X} < \ldots < \overline{\Delta_{j,t^D}X}$. A half length is the difference between its maximum and minimum values. We define

$$SHS_j = 0.741 \min\{\overline{\Delta_{j,t^h}X} - \overline{\Delta_{j,t^1}X}, \ldots, \overline{\Delta_{j,t^d}X} - \overline{\Delta_{j,t^{D-h+1}}X}\}. \tag{A-3}$$

The SHS estimator for the periodicity factor of period j is

$$\widehat{f}_j^{SHS} = \frac{SHS_j}{\sqrt{\frac{1}{n}\sum_{j=1}^{n} SHS_j^2}}. \tag{A-4}$$

Boudt, Croux, and Laurent (2011) show that the standard deviation, applied to the returns weighted in function of their outlyingness under the SHS estimate, offers a better trade-off between

[12] The scale estimate is normalized such that it sums to one over the periodic cycle.

the efficiency of the standard deviation under normality and the high robustness to jumps of the shortest half dispersion. The WSD is obtained as follows:

$$\widehat{f}_j^{WSD} = \frac{WSD_j}{\sqrt{\frac{1}{n}\sum_{j=1}^{n} WSD_j^2}}, \tag{A-5}$$

where

$$WSD_j = \sqrt{1.081 \frac{\sum_{j=1}^{D} w[\overline{\Delta_{j,t}X}/\widehat{f}_j^{SHS}]\overline{\Delta_{j,t}X}^2}{\sum_{j=1}^{D} w[\overline{\Delta_{j,t}X}/\widehat{f}_j^{SHS}]}}. \tag{A-6}$$

The function $w(z)$ is an indicator function equal to one when $z \leq 6.635$, the $\chi^2(1)$ 99% quantile, and 0 otherwise. The function w selects jump free returns, based on a first approximation of periodicity with the shortest half scale, to evaluate a Taylor and Xu (1997) type of periodicity.

Intraday standardized returns are defined as

$$\tilde{\Delta_{j,t}}X = \frac{\Delta_{j,t}X}{\overline{\hat{\sigma}_j}}, \tag{A-7}$$

with $\overline{\hat{\sigma}_j} = \widehat{f}_j^{WSD}$. These standardized returns, which have no intraday periodicity patterns in volatility, permit us to estimate IV and identify jumps.

A-1.2 APPENDIX (not-for-publication): integrated volatility

This appendix describes volatility estimators used in this paper. We assume a Brownian semi-martingale with jumps for the log-price $(X_t)_{t\in[0,T]}$:

$$dX_t = \mu_t dt + \sigma_t dW_t + dJ_t, \tag{A-8}$$

where $dJ_t = c_t dN_t$, c_t being the jump size, dN_t the increment of a Poisson process. W_t is a Wiener process, σ_t is the spot stochastic volatility, and μ_t is the drift process. Quadratic variation (QV) decomposes into diffusion variation (integrated variance) and the sum of squared jumps:

$$[X]_0^T = \underbrace{[X^c]_0^T}_{=\int_0^T \sigma_s^2 ds} + \underbrace{[X^d]_0^T}_{=\sum_{j=1}^{N_T} c_j^2}, \tag{A-9}$$

where N_T is the number of jumps over the interval. Redefine[13] returns sampled over small intervals δ, assuming n intervals over T:

$$\Delta_j X = X_{j\delta} - X_{(j-1)\delta}, j = 1...n. \tag{A-10}$$

[13] A daily subscript t is not needed and ignored, unlike in the remainder of the text.

Barndorff-Nielsen and Shephard (2006) have introduced the following multipower variation statistic:

$$MPV_\delta(X)_t^{[\gamma_1,\ldots,\gamma_M]} = \delta^{1-\frac{1}{2}(\gamma_1+\ldots+\gamma_M)} \sum_{j=M}^{n} \prod_{k=1}^{M} |\Delta_{j-k+1}X|^{\gamma_k}, \tag{A-11}$$

that consistently estimates IV or integrated quarticity ($\int_t^{t+T} \sigma_s^2 ds$ or $\int_t^{t+T} \sigma_s^4 ds$), in the presence of jumps, for appropriate choices of M and γ_k.

Realized variance is a particular case of multipower variation for $M = 1$ and $\gamma_1 = 2$:

$$RV_\delta(X)_t = MPV_\delta(X)_t^{[2]} = \sum_{j=1}^{n} \Delta_j X^2. \tag{A-12}$$

This estimator of integrated variance is not robust to jumps, however. In the presence of jumps, RV estimates QV, i.e. integrated variance plus the sum of squared jumps (see Eq. A-9).

Setting $M = 2$ and $\gamma_1 = \gamma_2 = 1$ yields the bipower variation estimator:

$$BPV_\delta(X)_t = \mu_1^{-2} MPV_\delta(X)_t^{[1,1]} = \mu_1^{-2} \sum_{j=2}^{n} |\Delta_{j-1}X||\Delta_j X| \tag{A-13}$$

that consistently estimates IV ($\int_t^{t+T} \sigma_s^2 ds$) in the presence of jumps.[14] Bipower variation eliminates the influence of jumps on estimates of diffusion variance by estimating that variance with the product of adjacent absolute returns. Jumps are downweighted because the probability of successive Poisson jumps tends to zero as the sampling frequency tends to zero. Nevertheless, successive jumps are still possible with discrete sampling frequency and these can bias BPV estimates of IV. To solve that problem, the generalized threshold multipower variation (TMPV) combines Mancini's (2009) threshold approach with Barndorff-Nielsen and Shephard's (2006) multipower variation. It is defined as:

$$TMPV_\delta(X)_t^{[\gamma_1,\ldots,\gamma_M]} = \delta^{1-\frac{1}{2}(\gamma_1+\ldots+\gamma_M)} \sum_{j=M}^{n} \prod_{k=1}^{M} |\Delta_{j-k+1}X|^{\gamma_k} I_{\{|\Delta_j X|^2 \le \vartheta_{j-k+1}\}}, \tag{A-14}$$

of which threshold bipower variation is a special case for $M = 2$ and $\gamma_k = 1$:

$$TBPV_\delta(X)_t = \mu_1^{-2} TMPV_\delta(X)_t^{[1,1]} = \mu_1^{-2} \sum_{j=2}^{n} |\Delta_{j-1}X||\Delta_j X| I_{\{|\Delta_{j-1}X|^2 \le \vartheta_{j-1}\}} I_{\{|\Delta_j X|^2 \le \vartheta_j\}}. \tag{A-15}$$

In practice, the threshold is set to a multiple of the local spot variance:

$$\vartheta_t = c_\vartheta^2 \hat{V}_t \tag{A-16}$$

[14]The constant $\mu_1 \simeq 0.7979$ ensures the proper convergence of bipower variation towards integrated variance.

where $\hat{V}_t$ estimates σ_t^2, and c_ϑ^2 is set at 3.

We follow Corsi, Pirino, and Reno (2010) in estimating $\hat{V}_t$ with a non-parametric filter (Fan and Yao 2003) (see Corsi, Pirino, and Reno (2010), Appendix B). Moreover, following Corsi, Pirino, and Reno (2010), we correct the downward bias in the TBPV estimator that exists because the threshold approach can incorrectly remove returns that are not jumps. This corrected estimator is named CTBPV.

A-2 APPENDIX (not-for-publication): The Shapley-Owen R^2

This appendix briefly describes the construction of the Shapley-Owen R^2 with a simple example following an exercise in Nathans, Frederick, and Nimon (2012). Consider a regression using the Holzinger and Swineford (1939) dataset of test results from a test administered to 301 pupils. The test contained 26 subtests and one can use the scores from subtests to predict a student's deductive mathematical reasoning score. That is, one can regress deductive mathematical reasoning scores on scores from the numeric, arithmetic, and addition subsections. The estimated regression can be written as follows:

$$reasoning = -2.92 + 1.43 * numeric + 0.89 * arithmetic - 0.12 * addition + error \qquad \text{(A-1)}$$

This appendix describes the computation of the Shapley-Owen contribution of the "numeric" regressor. Note that there are 6 possible permutations of the 3 regressors. Each row in the table below shows one of the six permutations. Let us show the contribution of numeric for each permutation.

- Permutation 1: The first permutation is {Numeric, Arithmetic, Addition} and the R^2 for these three regressors is 0.207. "Numeric" is the first variable so it is removed first and the remaining regressors {Arithmetic, Addition} provide an R^2 of 0.115. The contribution of numeric in this permutation is $0.207 - 0.115 = 0.092$.

- Permutation 2: The second permutation is {Numeric, Addition, Arithmetic}. Again, "numeric" is the first variable removed and the contribution of numeric in this permutation is $0.207 - 0.115 = 0.092$.

- Permutation 3: The third permutation is {Arithmetic, Numeric, Addition}. "Numeric" is the second variable removed and the marginal contribution of numeric (over Addition) in this permutation is $0.169 - 0.002 = 0.167$.

- Permutation 4: The fourth permutation is {Arithmetic, Addition, Numeric}. "Numeric" is the last variable to be removed its marginal contribution is $0.158 - 0.000 = 0.158$.

- Permutation 5: The fifth permutation is {Addition, Numeric, Arithmetic}. "Numeric" is the second variable removed and the marginal contribution of numeric (over Arithmetic) in this permutation is $0.185 - 0.108 = 0.077$.

- Permutation 6: The sixth permutation is {Addition, Arithmetic, Numeric}. "Numeric" is the last variable to be removed its marginal contribution is $0.158 - 0.000 = 0.158$.

The Shapley-Owen R^2 for numeric is the average marginal contribution of numeric over the 6 permutations, which is $(0.092 + 0.092 + 0.167 + 0.158 + 0.077 + 0.158)/6 = 0.124$. The analogous statistics for the other regressors or groups of regressors can be computed similarly.

Table A1: Shapely-Owen R^2 illustration

	Regressor Permutations	R^2	Regressors	R^2	Regressor	R^2	Improvement		Value of "numeric"
1	Numeric, Arithmetic, Addition	**0.207**	Arithmetic, Addition	**0.115**	Addition	0.002	0.207 - 0.115	**=**	**0.092**
2	Numeric, Addition, Arithmetic	**0.207**	Addition, Arithmetic	**0.115**	Arithmetic	0.108	0.207 - 0.115	**=**	**0.092**
3	Arithmetic, Numeric, Addition	0.207	Numeric, Addition	**0.169**	Addition	**0.002**	0.169 - 0.002	**=**	**0.167**
4	Arithmetic, Addition, Numeric	0.207	Addition, Numeric	0.169	Numeric	**0.158**	0.158 - 0.000	**=**	**0.158**
5	Addition, Numeric, Arithmetic	0.207	Numeric, Arithmetic	**0.185**	Arithmetic	**0.108**	0.185 - 0.108	**=**	**0.077**
6	Addition, Arithmetic, Numeric	0.207	Arithmetic, Numeric	0.185	Numeric	**0.158**	0.158 - 0.000	**=**	**0.158**
							Shapley Value	=	**0.124**

A-3 APPENDIX (not-for-publication): HAR estimates

Table A2: HAR estimates - EUR/USD

		AS		AE		EU		ES		US	
		coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
Integrated volatility											
$\beta_j^{S_i}$	HW lag 1	0.190	0.044	0.254	0.056	0.060	0.058	0.228	0.064	0.190	0.054
	HW lag 2	0.019	0.038	0.063	0.063	0.069	0.045	0.069	0.059	0.000	0.047
	HW lag 3	0.034	0.051	0.195	0.063	0.017	0.057	0.061	0.057	0.027	0.057
	HW lag 4	0.086	0.047	0.075	0.056	0.121	0.072	0.032	0.067	0.001	0.060
$\theta_h^{S_i}$	lagged weekly HW	0.187	0.126	-0.086	0.186	-0.029	0.142	0.131	0.183	-0.013	0.144
	lagged monthly HW	0.101	0.108	0.167	0.127	0.102	0.127	0.178	0.128	0.347	0.115
	lagged trimester HW	0.119	0.071	0.255	0.147	0.293	0.147	0.248	0.150	0.103	0.112
$\beta_j^{NS_i}$	MS lag 1 - 1st preceding segment	0.310	0.045	0.513	0.054	0.383	0.036	0.227	0.042	0.301	0.037
	MS lag 1 - 2nd preceding segment	0.071	0.027	0.089	0.052	0.256	0.040	0.124	0.042	0.036	0.035
	MS lag 1 - 3rd preceding segment	0.089	0.028	0.202	0.054	0.108	0.039	0.275	0.054	0.013	0.035
	MS lag 1 - 4th preceding segment	0.075	0.026	0.173	0.058	0.089	0.058	0.180	0.043	0.187	0.039
	MS lag 2 - 1st preceding segment	0.014	0.024	-0.080	0.063	0.052	0.044	0.057	0.047	0.000	0.038
	MS lag 2 - 2nd preceding segment	0.004	0.025	-0.018	0.044	-0.044	0.059	0.044	0.048	-0.015	0.038
	MS lag 2 - 3rd preceding segment	0.045	0.028	0.053	0.049	-0.045	0.049	0.088	0.050	-0.064	0.044
	MS lag 2 - 4th preceding segment	0.040	0.029	0.072	0.046	0.019	0.042	0.089	0.050	0.087	0.049
$\kappa_h^{S_i}$	lagged weekly MS	-0.418	0.199	0.309	0.315	0.425	0.346	-0.501	0.259	0.191	0.199
	lagged monthly MS	0.114	0.103	-0.227	0.158	-0.154	0.154	0.184	0.153	0.136	0.120
	lagged trimester MS	-0.140	0.077	-0.146	0.171	-0.186	0.169	-0.235	0.160	-0.117	0.119
Jumps											
$\delta_j^{S_i}$	HW lag 1	0.009	0.025	-0.023	0.026	-0.001	0.042	0.035	0.037	0.026	0.032
	HW lag 2	0.028	0.027	-0.058	0.025	0.022	0.031	0.019	0.045	0.038	0.039
	HW lag 3	0.022	0.022	-0.051	0.020	-0.001	0.032	0.042	0.042	0.015	0.030
	HW lag 4	-0.008	0.022	-0.014	0.022	-0.050	0.038	0.008	0.037	-0.016	0.028
$\lambda_h^{S_i}$	lagged weekly HW	0.037	0.041	0.073	0.035	-0.016	0.063	-0.042	0.070	-0.033	0.049
	lagged monthly HW	0.010	0.018	-0.022	0.035	-0.033	0.040	0.064	0.041	-0.018	0.029
	lagged trimester HW	-0.048	0.017	0.041	0.043	0.008	0.050	-0.035	0.037	0.003	0.025
$\delta_j^{NS_i}$	MS lag 1 - 1st preceding segment	0.054	0.017	0.124	0.042	0.072	0.033	0.175	0.052	-0.012	0.021
	MS lag 1 - 2nd preceding segment	0.000	0.013	0.107	0.044	0.014	0.027	-0.025	0.026	-0.006	0.026
	MS lag 1 - 3rd preceding segment	0.013	0.012	0.039	0.024	0.040	0.038	-0.040	0.036	-0.042	0.019
	MS lag 1 - 4th preceding segment	0.015	0.016	0.122	0.059	0.002	0.018	-0.034	0.040	-0.027	0.026
	MS lag 2 - 1st preceding segment	0.001	0.017	0.302	0.198	-0.036	0.021	-0.037	0.028	0.005	0.022
	MS lag 2 - 2nd preceding segment	-0.013	0.013	0.040	0.032	-0.033	0.028	-0.035	0.022	-0.005	0.016
	MS lag 2 - 3rd preceding segment	0.004	0.014	0.004	0.024	0.115	0.034	-0.029	0.030	0.002	0.022
	MS lag 2 - 4th preceding segment	0.032	0.024	0.006	0.024	0.012	0.024	-0.011	0.040	0.012	0.030
$\mu_h^{S_i}$	lagged weekly MS	-0.030	0.031	-0.079	0.054	-0.025	0.071	0.173	0.089	0.069	0.060
	lagged monthly MS	-0.015	0.019	-0.114	0.046	0.049	0.052	-0.036	0.039	0.001	0.031
	lagged trimester MS	0.003	0.016	0.094	0.036	0.023	0.035	0.076	0.043	0.034	0.031
	LB stat 5 lags (p-value)	0.630	0.987	1.055	0.958	0.572	0.989	0.274	0.998	1.016	0.961
	LB stat 35 lags (p-value)	28.203	0.785	18.067	0.992	104.414	0.000	58.557	0.008	49.200	0.056

Note: OLS estimates from the model described in Section 3.2 for the EUR/USD market. Day-of-the-week constants, and the 3rd and 4th lags of meteor shower effects, are omitted to save space. The last 2 lines report Ljung-Box statistics with 5 and 35 lags (with their respective p-values in the "p-val." column). Columns report parameter estimates and associated p-values (based on robust standard errors) for each segment equation in the system. The Greek letters in the first column refer to Equation 3.1.

Table A3: HAR estimates - USD/JPY

		AS		AE		EU		ES		US	
		coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
Integrated volatility											
$\beta_j^{S_i}$	HW lag 1	0.334	0.081	0.019	0.072	-0.006	0.056	0.157	0.067	0.123	0.073
	HW lag 2	0.172	0.068	-0.095	0.065	-0.011	0.050	0.147	0.056	-0.053	0.075
	HW lag 3	0.131	0.067	-0.048	0.062	-0.029	0.057	0.119	0.062	-0.100	0.067
	HW lag 4	0.126	0.066	0.013	0.052	0.014	0.048	0.124	0.063	-0.027	0.070
$\theta_h^{S_i}$	lagged weekly HW	-0.208	0.202	0.308	0.157	0.133	0.142	-0.075	0.160	0.205	0.186
	lagged monthly HW	0.149	0.108	0.084	0.137	-0.124	0.127	0.124	0.145	0.241	0.121
	lagged trimester HW	0.249	0.124	-0.057	0.133	0.425	0.175	0.367	0.161	0.383	0.159
$\beta_j^{NS_i}$	MS lag 1 - 1st preceding segment	0.367	0.048	0.802	0.065	0.638	0.145	0.344	0.048	0.505	0.074
	MS lag 1 - 2nd preceding segment	0.150	0.044	0.182	0.070	0.363	0.054	0.224	0.050	0.099	0.059
	MS lag 1 - 3rd preceding segment	0.126	0.047	0.044	0.058	0.161	0.067	0.370	0.075	0.040	0.057
	MS lag 1 - 4th preceding segment	0.047	0.036	0.115	0.045	0.084	0.057	0.309	0.065	0.169	0.058
	MS lag 2 - 1st preceding segment	-0.010	0.043	-0.125	0.058	0.110	0.064	0.063	0.046	-0.032	0.063
	MS lag 2 - 2nd preceding segment	-0.113	0.039	-0.035	0.079	0.006	0.055	0.015	0.045	0.093	0.060
	MS lag 2 - 3rd preceding segment	-0.013	0.049	0.047	0.045	0.058	0.075	-0.042	0.057	-0.042	0.036
	MS lag 2 - 4th preceding segment	0.107	0.046	0.027	0.055	0.003	0.046	-0.031	0.050	0.111	0.070
$\kappa_h^{S_i}$	lagged weekly MS	0.281	0.224	0.162	0.259	-0.112	0.287	-0.282	0.236	-0.058	0.279
	lagged monthly MS	-0.136	0.125	-0.106	0.185	0.212	0.147	0.179	0.155	0.038	0.121
	lagged trimester MS	-0.312	0.139	0.243	0.161	-0.444	0.169	-0.293	0.162	-0.339	0.147
Jumps											
$\delta_j^{S_i}$	HW lag 1	-0.030	0.049	0.031	0.035	-0.024	0.038	0.033	0.039	0.008	0.035
	HW lag 2	0.026	0.050	-0.021	0.036	-0.014	0.037	0.066	0.040	-0.035	0.032
	HW lag 3	-0.003	0.042	0.111	0.084	-0.072	0.039	0.011	0.038	0.008	0.032
	HW lag 4	-0.066	0.038	0.076	0.055	-0.086	0.037	0.038	0.043	0.001	0.027
$\lambda_h^{S_i}$	lagged weekly HW	0.046	0.081	-0.025	0.060	0.051	0.058	-0.089	0.067	-0.004	0.052
	lagged monthly HW	0.029	0.039	0.038	0.040	-0.025	0.039	0.064	0.046	-0.041	0.035
	lagged trimester HW	0.020	0.037	0.005	0.046	0.024	0.040	-0.038	0.046	-0.008	0.033
$\delta_j^{NS_i}$	MS lag 1 - 1st preceding segment	0.082	0.028	0.172	0.049	0.093	0.040	0.179	0.057	0.128	0.041
	MS lag 1 - 2nd preceding segment	0.023	0.026	0.053	0.046	-0.059	0.041	-0.032	0.033	0.086	0.062
	MS lag 1 - 3rd preceding segment	0.125	0.041	0.064	0.039	-0.012	0.047	-0.125	0.047	-0.009	0.019
	MS lag 1 - 4th preceding segment	-0.004	0.023	0.073	0.053	-0.051	0.029	-0.015	0.047	-0.011	0.029
	MS lag 2 - 1st preceding segment	0.073	0.088	0.012	0.042	-0.037	0.032	-0.099	0.040	0.060	0.043
	MS lag 2 - 2nd preceding segment	0.028	0.027	0.073	0.036	-0.018	0.040	-0.107	0.030	0.023	0.023
	MS lag 2 - 3rd preceding segment	0.035	0.033	0.039	0.036	-0.006	0.035	-0.090	0.039	-0.010	0.015
	MS lag 2 - 4th preceding segment	0.062	0.072	-0.095	0.064	0.069	0.083	-0.088	0.043	0.043	0.031
$\mu_h^{S_i}$	lagged weekly MS	0.018	0.061	-0.142	0.079	0.108	0.080	0.295	0.162	-0.124	0.066
	lagged monthly MS	0.003	0.034	0.036	0.052	-0.025	0.051	-0.046	0.053	-0.027	0.042
	lagged trimester MS	0.058	0.036	-0.044	0.051	0.051	0.038	0.004	0.051	0.027	0.045
	LB stat 5 lags (p-value)	1.305	0.934	0.779	0.978	1.040	0.959	0.360	0.996	0.666	0.985
	LB stat 35 lags (p-value)	29.121	0.747	52.726	0.028	48.831	0.060	60.751	0.004	36.795	0.386

Note: OLS estimates from the model described in Section 3.2 for the USD/YEN market. Day-of-the-week constants, and the 3rd and 4th lags of meteor shower effects, are omitted to save space. The last 2 lines report Ljung-Box statistics with 5 and 35 lags (with their respective p-values in the "p-val." column). Columns report parameter estimates and associated p-values (based on robust standard errors) for each segment equation in the system. The Greek letters in the first column refer to Equation 3.1.

Table A4: HAR cross rates estimates - EUR/USD (own market effects)

	AS		AE		EU		ES		US	
	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
Integrated volatility										
HW lag 1	0.185	0.045	0.230	0.058	0.073	0.063	0.260	0.069	0.198	0.059
HW lag 2	0.027	0.041	0.168	0.060	0.079	0.047	0.110	0.066	-0.061	0.065
HW lag 3	0.043	0.046	0.171	0.061	0.006	0.069	0.045	0.067	0.059	0.064
HW lag 4	0.112	0.045	0.150	0.083	0.134	0.083	-0.057	0.089	0.015	0.067
lagged weekly HW	0.135	0.130	-0.225	0.157	-0.093	0.174	0.173	0.212	0.017	0.178
lagged monthly HW	0.148	0.105	0.221	0.157	0.139	0.154	0.101	0.159	0.302	0.132
lagged trimester HW	0.115	0.087	0.267	0.149	0.238	0.153	0.425	0.192	0.027	0.132
MS lag 1 - 1st preceding segment	0.235	0.030	0.532	0.083	0.336	0.044	0.187	0.047	0.298	0.048
MS lag 1 - 2nd preceding segment	0.051	0.030	0.137	0.072	0.240	0.047	0.065	0.048	0.033	0.037
MS lag 1 - 3rd preceding segment	0.060	0.024	0.257	0.075	0.115	0.051	0.221	0.060	0.005	0.041
MS lag 1 - 4th preceding segment	0.060	0.028	0.183	0.074	0.076	0.066	0.154	0.051	0.195	0.044
MS lag 2 - 1st preceding segment	0.010	0.027	-0.076	0.058	0.078	0.055	0.048	0.048	0.011	0.047
MS lag 2 - 2nd preceding segment	0.013	0.030	-0.039	0.051	-0.065	0.065	0.060	0.053	-0.005	0.042
MS lag 2 - 3rd preceding segment	0.040	0.024	0.090	0.058	-0.034	0.065	0.098	0.060	-0.059	0.044
MS lag 2 - 4th preceding segment	0.019	0.024	0.124	0.065	0.014	0.052	0.073	0.056	0.090	0.054
lagged weekly MS	-0.286	0.153	-0.158	0.533	0.426	0.475	-0.253	0.304	0.108	0.259
lagged monthly MS	0.071	0.105	-0.055	0.230	0.069	0.176	0.317	0.188	0.276	0.140
lagged trimester MS	-0.106	0.089	-0.301	0.162	-0.282	0.191	-0.490	0.208	-0.081	0.138
Jumps										
HW lag 1	-0.001	0.024	-0.025	0.024	0.014	0.044	0.028	0.040	0.019	0.035
HW lag 2	0.010	0.025	-0.033	0.024	0.028	0.031	0.014	0.051	0.049	0.037
HW lag 3	0.008	0.020	-0.068	0.024	0.000	0.033	0.040	0.047	0.008	0.030
HW lag 4	-0.001	0.020	-0.023	0.020	-0.043	0.043	-0.047	0.041	0.019	0.027
lagged weekly HW	0.068	0.038	0.082	0.038	-0.027	0.066	-0.006	0.075	-0.063	0.054
lagged monthly HW	0.033	0.021	-0.015	0.035	-0.058	0.044	0.052	0.044	-0.007	0.034
lagged trimester HW	-0.049	0.018	0.047	0.039	0.012	0.054	-0.016	0.040	-0.030	0.029
MS lag 1 - 1st preceding segment	0.036	0.019	0.070	0.031	0.066	0.032	0.176	0.052	-0.023	0.024
MS lag 1 - 2nd preceding segment	0.000	0.016	0.089	0.052	-0.011	0.020	-0.014	0.028	-0.017	0.026
MS lag 1 - 3rd preceding segment	0.014	0.012	0.018	0.027	0.034	0.033	-0.065	0.028	-0.035	0.015
MS lag 1 - 4th preceding segment	0.042	0.016	0.118	0.060	0.000	0.022	-0.037	0.039	-0.024	0.027
MS lag 2 - 1st preceding segment	-0.002	0.019	0.038	0.031	-0.006	0.017	-0.041	0.027	0.006	0.027
MS lag 2 - 2nd preceding segment	-0.016	0.014	0.051	0.034	-0.007	0.024	-0.027	0.019	-0.004	0.019
MS lag 2 - 3rd preceding segment	-0.001	0.013	0.017	0.027	0.101	0.035	-0.038	0.028	0.015	0.020
MS lag 2 - 4th preceding segment	0.045	0.020	0.004	0.023	-0.004	0.027	-0.014	0.042	0.012	0.032
lagged weekly MS	-0.039	0.034	-0.057	0.056	-0.043	0.067	0.162	0.072	0.066	0.058
lagged monthly MS	-0.007	0.021	-0.150	0.046	0.088	0.056	-0.047	0.046	0.006	0.034
lagged trimester MS	-0.005	0.018	0.107	0.039	0.019	0.041	0.048	0.047	0.016	0.032

Note: First part (own-market effects) of OLS estimates from the model described in Section 4.4 for the EUR/USD market. The 3rd and 4th lags of meteor shower effects are omitted to save space. Columns report parameter estimates and associated p-values for each segment equation in the system.

Table A5: HAR cross rates estimates - EUR/USD (other market effects)

	AS		AE		EU		ES		US	
	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
Integrated volatility										
HW lag 1	-0.038	0.036	0.016	0.063	-0.046	0.047	-0.077	0.063	-0.020	0.060
HW lag 2	-0.047	0.037	-0.016	0.059	-0.065	0.048	-0.042	0.066	0.079	0.065
HW lag 3	-0.019	0.041	0.043	0.054	0.076	0.053	0.051	0.065	-0.043	0.056
HW lag 4	-0.019	0.039	0.049	0.053	-0.035	0.053	0.146	0.076	-0.054	0.069
lagged weekly HW	0.134	0.106	-0.093	0.168	0.074	0.130	-0.039	0.177	0.031	0.184
lagged monthly HW	-0.064	0.080	0.062	0.138	-0.161	0.139	-0.013	0.132	0.017	0.129
lagged trimester HW	0.019	0.081	-0.085	0.166	0.050	0.154	-0.143	0.157	-0.193	0.120
MS lag 1 - 1st preceding segment	0.095	0.032	0.104	0.051	0.093	0.047	0.049	0.041	0.042	0.049
MS lag 1 - 2nd preceding segment	0.006	0.035	0.049	0.057	-0.028	0.041	0.061	0.045	0.019	0.046
MS lag 1 - 3rd preceding segment	-0.001	0.026	-0.081	0.060	0.018	0.049	0.142	0.054	0.020	0.043
MS lag 1 - 4th preceding segment	0.045	0.024	-0.004	0.050	0.013	0.041	0.051	0.045	-0.064	0.048
MS lag 2 - 1st preceding segment	0.002	0.032	-0.053	0.051	-0.043	0.052	0.044	0.044	-0.041	0.062
MS lag 2 - 2nd preceding segment	-0.040	0.031	0.045	0.050	0.080	0.048	0.023	0.040	0.000	0.044
MS lag 2 - 3rd preceding segment	-0.013	0.025	-0.009	0.050	-0.026	0.043	-0.038	0.056	-0.069	0.036
MS lag 2 - 4th preceding segment	0.038	0.023	-0.045	0.042	0.001	0.045	0.031	0.046	0.039	0.050
lagged weekly MS	0.010	0.146	0.212	0.278	-0.107	0.316	-0.355	0.246	0.158	0.257
lagged monthly MS	-0.013	0.095	-0.302	0.170	-0.018	0.128	0.064	0.150	-0.114	0.125
lagged trimester MS	-0.011	0.098	0.240	0.200	0.019	0.155	0.172	0.171	0.248	0.107
Jumps										
HW lag 1	-0.033	0.024	0.036	0.032	-0.031	0.033	0.034	0.032	0.006	0.040
HW lag 2	-0.005	0.026	-0.040	0.030	-0.014	0.028	0.028	0.034	-0.028	0.030
HW lag 3	-0.006	0.020	0.041	0.028	-0.008	0.034	-0.028	0.034	-0.010	0.026
HW lag 4	-0.068	0.023	-0.018	0.027	-0.053	0.031	0.083	0.039	-0.002	0.032
lagged weekly HW	0.000	0.038	0.011	0.044	0.045	0.049	-0.056	0.055	0.010	0.050
lagged monthly HW	0.007	0.022	-0.040	0.046	-0.054	0.037	-0.040	0.040	-0.024	0.035
lagged trimester HW	-0.005	0.020	0.017	0.047	0.036	0.037	-0.033	0.040	0.031	0.034
MS lag 1 - 1st preceding segment	0.012	0.023	-0.025	0.034	0.036	0.022	-0.017	0.031	0.027	0.021
MS lag 1 - 2nd preceding segment	-0.002	0.015	-0.011	0.047	-0.026	0.026	0.001	0.028	0.023	0.024
MS lag 1 - 3rd preceding segment	0.023	0.016	0.025	0.028	-0.008	0.046	-0.076	0.033	-0.006	0.019
MS lag 1 - 4th preceding segment	-0.005	0.013	0.023	0.032	-0.027	0.023	-0.081	0.030	0.028	0.030
MS lag 2 - 1st preceding segment	0.022	0.027	-0.014	0.031	-0.026	0.018	-0.046	0.030	0.017	0.028
MS lag 2 - 2nd preceding segment	0.023	0.016	-0.023	0.027	-0.037	0.023	-0.070	0.026	0.009	0.024
MS lag 2 - 3rd preceding segment	-0.004	0.016	-0.025	0.035	-0.020	0.029	0.036	0.035	0.026	0.021
MS lag 2 - 4th preceding segment	-0.007	0.013	-0.049	0.034	0.022	0.039	-0.070	0.038	0.012	0.030
lagged weekly MS	0.007	0.036	-0.015	0.070	0.095	0.068	0.210	0.097	-0.054	0.064
lagged monthly MS	0.000	0.025	0.065	0.057	-0.038	0.037	-0.042	0.051	0.054	0.039
lagged trimester MS	0.005	0.024	0.001	0.074	0.005	0.042	0.013	0.050	-0.041	0.035
LB stat 5 lags (p-value)	0.755	0.980	0.634	0.986	0.765	0.979	0.105	1.000	0.438	0.994
LB stat 35 lags (p-value)	27.341	0.819	21.359	0.966	94.512	0.000	62.415	0.003	56.999	0.011

Note: Second part (other-market effects) of OLS estimates from the model described in Section 4.4 for the EUR/USD market. Day-of-the-week constants, and the 3rd and 4th lags of meteor shower effects, are omitted to save space. The last 2 lines report Ljung-Box statistics with 5 and 35 lags (with their respective p-values in the "p-val." column). Columns report parameter estimates and associated p-values for each segment equation in the system.

Table A6: HAR cross rates estimates - USD/JPY (own market effects)

	AS		AE		EU		ES		US	
	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
Integrated volatility										
HW lag 1	0.259	0.081	-0.015	0.077	0.028	0.058	0.099	0.070	0.067	0.086
HW lag 2	0.155	0.075	-0.123	0.070	-0.018	0.060	0.080	0.066	-0.055	0.081
HW lag 3	0.115	0.081	-0.064	0.065	-0.008	0.058	0.059	0.072	-0.149	0.078
HW lag 4	0.082	0.074	-0.019	0.056	0.026	0.055	0.103	0.079	-0.063	0.082
lagged weekly HW	-0.208	0.231	0.309	0.172	0.099	0.154	-0.045	0.187	0.281	0.211
lagged monthly HW	0.105	0.131	0.036	0.157	-0.059	0.150	0.204	0.167	0.279	0.130
lagged trimester HW	0.438	0.165	-0.153	0.157	0.483	0.185	0.410	0.182	0.300	0.170
MS lag 1 - 1st preceding segment	0.349	0.052	0.789	0.069	0.556	0.127	0.346	0.054	0.504	0.088
MS lag 1 - 2nd preceding segment	0.188	0.052	0.167	0.074	0.295	0.056	0.225	0.051	0.088	0.063
MS lag 1 - 3rd preceding segment	0.101	0.049	0.020	0.065	0.113	0.078	0.380	0.086	0.041	0.061
MS lag 1 - 4th preceding segment	0.041	0.037	0.117	0.047	0.086	0.063	0.300	0.073	0.112	0.069
MS lag 2 - 1st preceding segment	-0.024	0.055	-0.093	0.061	0.110	0.067	0.078	0.053	-0.070	0.073
MS lag 2 - 2nd preceding segment	-0.115	0.047	-0.029	0.083	0.029	0.059	0.016	0.047	0.103	0.069
MS lag 2 - 3rd preceding segment	-0.038	0.053	0.066	0.054	0.074	0.083	-0.056	0.064	-0.035	0.038
MS lag 2 - 4th preceding segment	0.106	0.049	0.008	0.059	-0.024	0.052	-0.042	0.055	0.082	0.073
lagged weekly MS	0.513	0.267	0.112	0.300	0.014	0.296	-0.181	0.278	0.057	0.338
lagged monthly MS	-0.129	0.149	0.017	0.199	0.207	0.173	-0.041	0.171	-0.176	0.149
lagged trimester MS	-0.508	0.165	0.371	0.181	-0.542	0.202	-0.190	0.196	-0.142	0.153
Jumps										
HW lag 1	-0.040	0.048	0.025	0.034	-0.038	0.041	0.038	0.044	0.022	0.043
HW lag 2	0.032	0.050	-0.020	0.038	-0.021	0.035	0.071	0.043	-0.049	0.042
HW lag 3	0.017	0.039	0.101	0.085	-0.075	0.037	0.015	0.043	0.011	0.036
HW lag 4	-0.056	0.033	0.064	0.056	-0.087	0.039	0.057	0.048	-0.003	0.029
lagged weekly HW	0.017	0.066	-0.005	0.063	0.052	0.057	-0.105	0.073	-0.001	0.063
lagged monthly HW	0.013	0.040	0.006	0.038	-0.049	0.039	0.047	0.049	-0.010	0.040
lagged trimester HW	0.021	0.038	0.012	0.044	0.028	0.048	-0.045	0.048	-0.031	0.036
MS lag 1 - 1st preceding segment	0.090	0.030	0.156	0.052	0.099	0.040	0.171	0.058	0.131	0.046
MS lag 1 - 2nd preceding segment	0.038	0.027	0.049	0.048	-0.049	0.038	-0.025	0.035	0.074	0.067
MS lag 1 - 3rd preceding segment	0.117	0.041	0.065	0.043	-0.021	0.048	-0.121	0.049	-0.008	0.021
MS lag 1 - 4th preceding segment	0.001	0.023	0.081	0.049	-0.016	0.031	0.002	0.055	-0.030	0.032
MS lag 2 - 1st preceding segment	0.074	0.095	-0.010	0.043	-0.030	0.032	-0.100	0.041	0.050	0.047
MS lag 2 - 2nd preceding segment	0.043	0.028	0.058	0.043	-0.023	0.041	-0.097	0.030	0.011	0.023
MS lag 2 - 3rd preceding segment	0.031	0.031	0.026	0.040	-0.029	0.035	-0.089	0.041	-0.008	0.018
MS lag 2 - 4th preceding segment	0.064	0.070	-0.097	0.063	0.086	0.092	-0.073	0.043	0.018	0.030
lagged weekly MS	0.029	0.065	-0.097	0.084	0.067	0.080	0.273	0.163	-0.068	0.073
lagged monthly MS	0.011	0.037	0.062	0.053	-0.021	0.052	-0.016	0.052	-0.031	0.044
lagged trimester MS	0.053	0.037	-0.080	0.048	0.069	0.042	-0.002	0.055	0.023	0.045

Note: First part (own-market effects) of OLS estimates from the model described in Section 4.4 for the USD/JPY market. The 3rd and 4th lags of meteor shower effects are omitted to save space. Columns report parameter estimates and associated p-values for each segment equation in the system.

Table A7: HAR cross rates estimates - USD/JPY (other market effects)

	AS		AE		EU		ES		US	
	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.	coeff.	p-val.
Integrated volatility										
HW lag 1	0.145	0.078	0.069	0.065	-0.081	0.062	0.139	0.079	0.055	0.063
HW lag 2	-0.007	0.068	0.128	0.065	-0.020	0.073	0.123	0.075	-0.046	0.071
HW lag 3	-0.041	0.067	0.093	0.060	-0.064	0.056	0.115	0.075	0.038	0.072
HW lag 4	0.089	0.071	0.023	0.065	-0.010	0.063	0.100	0.099	0.040	0.057
lagged weekly HW	0.029	0.187	-0.207	0.169	0.084	0.188	-0.148	0.216	-0.043	0.180
lagged monthly HW	-0.060	0.141	0.290	0.124	-0.184	0.164	-0.098	0.159	-0.110	0.149
lagged trimester HW	-0.140	0.165	-0.011	0.143	-0.044	0.161	-0.190	0.195	-0.230	0.148
MS lag 1 - 1st preceding segment	0.037	0.050	0.111	0.069	0.182	0.039	0.000	0.053	-0.008	0.052
MS lag 1 - 2nd preceding segment	-0.067	0.049	-0.018	0.055	0.098	0.077	0.014	0.052	0.041	0.039
MS lag 1 - 3rd preceding segment	0.025	0.042	0.049	0.055	0.031	0.050	0.011	0.065	-0.048	0.041
MS lag 1 - 4th preceding segment	-0.011	0.038	-0.008	0.046	-0.006	0.060	0.014	0.060	0.144	0.053
MS lag 2 - 1st preceding segment	-0.015	0.063	-0.046	0.056	-0.030	0.050	-0.034	0.052	0.094	0.051
MS lag 2 - 2nd preceding segment	0.036	0.041	0.012	0.069	-0.041	0.050	-0.018	0.049	0.042	0.046
MS lag 2 - 3rd preceding segment	0.082	0.040	-0.058	0.062	-0.058	0.055	0.055	0.068	-0.073	0.044
MS lag 2 - 4th preceding segment	0.003	0.039	0.024	0.053	0.030	0.058	0.036	0.066	0.082	0.065
lagged weekly MS	-0.492	0.251	0.022	0.325	-0.122	0.297	-0.346	0.328	-0.322	0.264
lagged monthly MS	0.147	0.160	-0.409	0.169	0.028	0.202	0.366	0.219	0.417	0.146
lagged trimester MS	0.228	0.137	0.024	0.156	0.098	0.196	-0.093	0.241	0.039	0.156
Jumps										
HW lag 1	-0.007	0.033	-0.024	0.023	0.041	0.025	-0.012	0.044	-0.028	0.043
HW lag 2	-0.019	0.036	-0.035	0.029	0.018	0.025	-0.028	0.055	0.026	0.048
HW lag 3	-0.022	0.031	0.034	0.026	0.046	0.030	-0.026	0.043	0.010	0.039
HW lag 4	-0.029	0.030	0.100	0.041	0.038	0.034	-0.053	0.045	-0.020	0.032
lagged weekly HW	0.078	0.058	-0.001	0.036	-0.060	0.044	0.041	0.075	-0.007	0.071
lagged monthly HW	0.093	0.041	-0.051	0.036	0.040	0.033	-0.029	0.040	-0.067	0.040
lagged trimester HW	-0.106	0.031	0.063	0.043	-0.038	0.035	0.009	0.035	0.033	0.031
MS lag 1 - 1st preceding segment	-0.039	0.023	0.000	0.033	0.010	0.027	0.013	0.037	-0.041	0.028
MS lag 1 - 2nd preceding segment	-0.058	0.023	0.027	0.037	0.001	0.036	-0.037	0.026	-0.026	0.020
MS lag 1 - 3rd preceding segment	-0.006	0.017	-0.028	0.030	0.043	0.037	-0.043	0.038	0.008	0.026
MS lag 1 - 4th preceding segment	0.012	0.021	0.006	0.026	-0.047	0.023	-0.020	0.049	0.006	0.027
MS lag 2 - 1st preceding segment	-0.009	0.028	0.073	0.058	-0.044	0.018	-0.025	0.030	-0.013	0.025
MS lag 2 - 2nd preceding segment	-0.042	0.023	0.024	0.040	0.036	0.054	0.045	0.052	0.000	0.029
MS lag 2 - 3rd preceding segment	-0.023	0.019	0.002	0.029	0.048	0.039	0.000	0.030	-0.025	0.016
MS lag 2 - 4th preceding segment	-0.027	0.016	-0.002	0.022	-0.011	0.041	-0.034	0.034	0.041	0.047
lagged weekly MS	0.003	0.049	-0.075	0.064	0.056	0.059	0.039	0.079	0.013	0.055
lagged monthly MS	0.025	0.034	-0.069	0.037	-0.004	0.038	-0.076	0.046	-0.013	0.037
lagged trimester MS	-0.010	0.032	0.032	0.036	-0.010	0.043	0.052	0.041	-0.011	0.032
LB stat 5 lags (p-value)	1.090	0.955	0.651	0.986	1.216	0.943	0.459	0.994	0.650	0.986
LB stat 35 lags (p-value)	23.502	0.931	42.405	0.182	44.281	0.135	48.204	0.068	35.123	0.462

Note: Second part (other-market effects) of OLS estimates from the model described in Section 4.4 for the USD/JPY market. Day-of-the-week constants, and the 3rd and 4th lags of meteor shower effects, are omitted to save space. The last 2 lines report Ljung-Box statistics with 5 and 35 lags (with their respective p-values in the "p-val." column). Columns report parameter estimates and associated p-values for each segment equation in the system.

A-4 APPENDIX (not-for-publication): Testing for a structural break at an unknown break point

We test for an unknown break point in the middle third of the sample by first constructing a series of statistics for each observation in the subsample. The statistic at a given point, T_0, in a sample running from time zero to T, is calculated by estimating the HAR from time zero to T_0, and from T_0 to T, obtaining two sets of coefficient estimates, $\hat{\theta_1}$ and $\hat{\theta_2}$. If $\pi = T_0/T$ denotes the fraction of the total observations which are from the first part of the sample, then

$$\sqrt{T}(\hat{\theta_1} - \theta_1) \sim N(0, V_1/\pi) \quad and \quad \sqrt{T}(\hat{\theta_2} - \theta_2) \sim N(0, V_2/\pi) \tag{A-1}$$

where $V_1 = \Omega_1 \otimes Q_1^{-1}$, $V_2 = \Omega_2 \otimes Q_2^{-1}$, $Q_1 = \frac{1}{T_0}\sum_{t=1}^{T_0} y_{t-1}y_{t-1}^{'}$, $Q_2 = \frac{1}{T-T_0}\sum_{t=T_0+1}^{T} y_{t-1}y_{t-1}^{'}$, $\Omega_1 = \frac{1}{T_0}\sum_{t=1}^{T_0} u_t u_t^{'}$ and $\Omega_2 = \frac{1}{T-T_0}\sum_{t=T_0+1}^{T} u_t u_{t-1}^{'}$ (Hamilton 1994). The test statistic for a break at T_0 is given by the quadratic function of the difference between the parameter estimates weighted by the inverse of their covariance matrix.

$$\lambda = T(\hat{\theta_1} - \hat{\theta_2})'[(\Omega_1 \otimes Q_1^{-1})/\pi + (\Omega_2 \otimes Q_2^{-1})/(1-\pi)]^{-1}(\hat{\theta_1} - \hat{\theta_2}) \tag{A-2}$$

The null of no structural break within a given subsample is rejected for sufficiently high values of the supremum of λ over the subsample. For tests of structural breaks in one equation or in an individual coefficient, statistics similar to that denoted by λ can be calculated using the appropriate coefficient estimate(s) and the variance-covariance matrix of those estimate(s). We calculate the 1% critical values from the following Monte Carlo experiment:

1. We estimate the HAR over the whole sample, saving coefficients and the covariance matrix.

2. Using the initial conditions, estimated coefficients and covariance matrix we create 1000 new data sets of length T, where T is the length of the whole sample.

3. We compute 1000 time series of structural break statistics from 0.15T to 0.85T of each of the simulated data sets, one series for each generated data set.

4. The ninety-ninth percentile of the distribution of suprema over these 1000 time series is the one per cent critical value used in Figures 3 and 4.