Information Spillover, Volatility and the Currency Markets

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ABSTRACT

We use an impulse response methodology to analyse the effects of U.S. macroeconomic news announcements on the volatilities of three major exchange rates (Euro, Pound Sterling and Yen). Our data consist of 5 minute returns on exchange rates as well as the times of news announcements. In the definition of impulse responses, we allow for different types of news, and consider two categories in the application: those considered positive or negative for the U.S. economy. Using a multivariate GARCH model with exogenous news effects, we find that the initial impact of positive news on the volatility of the Pound is higher than that of the Euro, whereas the persistence of shocks is highest for the Yen. For negative news, we find that an important part of the impact on the Yen and Pound is induced by volatility spillover from the Euro.

Key words: *Information, Volatility, Impulse Response Function, Foreign Exchange*
JEL Classifications: C32, C53, F31

1. INTRODUCTION

The impact of news announcements on foreign exchange (FX) volatility has been studied in several papers, e.g. Degennaro and Shrieves (1997), Andersen and Bollerslev (1998), Cai, Cheung et al. (2001) and Bauwens et al. (2005). Each study has focused on the effect of some news announcements on volatility corresponding to the one of the most active currency markets (Euro/US Dollar (EUR/USD), Great Britain Pound/US Dollar (GBP/USD) and Japanese Yen/US Dollar (JPY/USD)). All find that some categories of public information, and more specifically their unexpected component, have a significant positive effect on FX volatility. Their methodology consists of implementing univariate ARCH-type or realized volatility models, considering news announcements through lagged dummies as exogenous variables.

The above studies have, however, limited their investigation to the discrete shock of public information on one currency volatility without studying its persistency through time. Beine (2004) has analysed the effect of central bank interventions on multivariate volatilities and correlations, but to the best of our knowledge, no previous study has investigated the simultaneous effect of public news announcements taking into account the dependence between the currencies. Thus, the aim of this paper is twofold. Firstly, we analyze the impact

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of the most important news announcement, involving the US macro-economic figures, simultaneously on high frequency EUR/USD, GBP/USD and JPY/USD volatilities. The idea is to assess the instantaneous impact of news related to the dollar on currencies quoted against USD. Secondly, we infer the persistence of the estimated news effects through an impulse response analysis.

Since its introduction by Sims (1980), impulse response analysis has evolved into an important tool for analyzing the dynamics of macroeconomic and financial systems . It has been mainly designed for the conditional mean of linear systems, e.g. VARMA models, but recently interest has focused on generalizations to nonlinear systems and, in particular, to the volatility in conditionally heteroskedastic models. For example, Gallant et al. (1993) define conditional moment profiles in nonlinear models, Koop et al. (1996) propose a general simulation-based approach to nonlinear impulse response analysis, Lin (1997) proposes a particular approach to volatility impulse response analysis as a special case of Gallant et al. (1993), and Hafner and Herwartz (2006) use the notion of independence to identify endogenous news or innovations to the system. These approaches analyze the effect of ***endogenous*** news, i.e. news events that are not explicitly observed but have to be estimated within the econometric system, on volatility.

In practice one may have observations of news events, for example those appearing on Reuters screens etc., which can be considered as exogenous to the variables of interest. In those cases one can use that information to estimate the impact of particular types of news on volatility. In this paper we use an impulse response methodology to analyze the effect of ***exogenous news*** on volatility in a multivariate system. We allow for different types of news to take into account different effects on exchange rates as documented by Cheung and Chinn (2001). In the empirical application we distinguish between positive and negative announcements for the U.S. economy. Our results suggest that in the very short term, positive macroeconomic news announcements in the US increase the GBP/USD volatility stronger than that of EUR/USD, whereas the JPY/USD volatility is only mildly affected. On the other hand, in the longer term (more than two hours), the effect of a shock on JPY/USD volatility is relatively more important than that of GBP/USD and EUR/USD. In other words, positive shocks are more persistent in JPY/USD volatility than they are in the two other rates. For negative news, on the other hand, the volatility of EUR/USD is affected the most, both in the short term and long term.

Using a decomposition of the news effects in one FX rate according to volatility spillover from other FX rates, we find that more than 60 percent of the long run impact of positive news can be attributed to an instantaneous shock in JPY/USD, while the long run impact of negative news is dominated by the EUR/USD rate. The EUR/USD rate also has an important impact on the ***cumulated*** effect of both cross-rates in the case of negative news.

The remainder of the paper is organised as follows. Section 2 introduces the impulse response methodology and Section 3 provides the empirical application to the exchange rates. Section 4 concludes.

2. METHODOLOGY

Consider a system of returns to exchange rates $R_t = (r_{1t},\ldots, r_{Nt})$. We use the following model

$$R_t = \mu_t + \varepsilon_t \tag{2.1}$$

$$\varepsilon_t = H_t^{1/2} z_t \tag{2.2}$$

The vector μ_t is a function of past returns and therefore the mean of returns conditional on the past. Likewise, the $N \times N$ matrix H_t is a function of past returns and therefore the conditional variance-covariance matrix of returns. The error term z_t is identically and independently distributed (i.i.d.) with mean zero and variance-covariance the identity matrix.

For H_t we specify a constant conditional correlation (CCC) model as proposed by Bollerslev (1990). Thus, $H_t = S_t R S_t$, where R is a constant correlation matrix and S_t is a diagonal matrix containing the conditional standard deviations on the diagonal. We specify these as an extension of the univariate GARCH model to the multivariate case as in Jeantheau (1998) and Ling and McAleer (2003):

$$h_t = \omega + A\eta_{t-1} + Bh_{t-1} + \sum_{l=1}^{L} \gamma_l D_{lt} \tag{2.3}$$

where[1] h_t = dg(H_t) is the $N \times 1$ vector containing the diagonal elements of H_t, $\eta_t = (\varepsilon_{1t}^2, \ldots, \varepsilon_{Nt}^2)'$ and D_{lt} are dummy variables that take the value 1 if there were news of type l at time t, and zero otherwise. We assume that the arrival of news of any type is independent of the past, such that D_{lt} is independent of $D_{l's}$ for all $s \neq t$ and all l'. There are L types of news, for example originating in different markets or indicating good or bad news.

Parameters of the model (2.3) are the ($N \times N$) matrices A and B and the ($N \times 1$) vectors ω, $\gamma_1, \ldots, \gamma_L$. This model has the advantage of being sufficiently flexible such that volatility spillover between the exchange rates can be taken into account with non-zero off-diagonal elements in A or B. On the other hand, it is very easy to estimate since univariate GARCH estimation tools can be used by adding lagged cross-returns as observed variables in the volatility equation.

We now define the volatility impulse response function of exogenous shocks of type l at time horizon k as

$$V_{kl} = E[h_{t+k} \mid \Im_t, D_{lt} = 1] - E[h_{t+k} \mid \Im_t, D_{lt} = 0] \tag{2.4}$$

where $\Im_t$ is the information set at time t. By direct calculation we obtain $V_{1l} = \gamma_l$, $V_{2l} = (A+B)\gamma_l$, …, $V_{kl} = (A+B)^{k-1}\gamma_l$. If the process is covariance stationary, then all eigenvalues of $A+B$ are smaller than one in modulus and V_{kl} tends to zero as $k \to \infty$, that is, the impact of shocks on volatility will eventually die out.

Rather than calculating the news effect at a given time horizon k, one may be interested in the accumulated effect after k periods, $\Sigma_{i=1}^{N} V_{il}$. Given the form of V_{kl}, this accumulated effect converges to $(I_N - \mathrm{A} - \mathrm{B})^{-1}$ as $k \to \infty$, where I_N is the identity matrix of dimension N.

For inference on V_{kl} we first refer to results of Jeantheau (1998) and Ling and McAleer (2003) on the consistency and asymptotic normality, respectively, of quasi maximum likelihood (QML) parameter estimators. Under regularity conditions, they show that $\sqrt{n}(\hat{\theta} - \theta) \xrightarrow{L} N(0, \Sigma_{\hat{\theta}})$, where θ is the vector containing all model parameters and n is the number of observations. Analytical formulae for the asymptotic covariance matrix $\Sigma_{\hat{\theta}}$ are provided by Hafner and Herwartz (2008). For V_{kl} denote an estimator based on QML parameter estimators by $\hat{V}_{kl}$. We can then use the delta method to show that

[1] The operator dg stacks the diagonal of a matrix into a column vector.

$$\sqrt{n}(\hat{V}_{kl} - V_{kl}) \xrightarrow{L} N(0, \frac{\partial V_{kl}}{\partial \theta'} \Sigma_{\hat{\theta}} \frac{\partial V'_{kl}}{\partial \theta}) \tag{2.5}$$

where $\partial V_{kl}/\partial\theta'$ is evaluated at the true parameter values. Analytical expressions are given by $\partial V_{kl}/\partial\omega' = 0$, $\partial V_{kl}/\partial\gamma_l' = (A+B)^{k-1}$, $\partial V_{kl}/\partial\gamma_r' = 0$, $r \neq l$

$$\frac{\partial V_{kl}}{\partial \text{vec}(A)'} = \frac{\partial V_{kl}}{\partial \text{vec}(B)'} = (\gamma_l' \otimes I_N) \sum_{i=1}^{k} (A+B)^i \otimes (A+B)^{k-i}$$

and where $\otimes$ is the Kronecker product operator. These results can be used to construct point-wise confidence bands for the estimated volatility impulse response functions.

One may further be interested in the proportion of the total effect of type l news in one exchange rate that is explained by volatility spillover from some other rate. Let us define the relative type l news spillover effect from the j-th to the i-th exchange rate at time horizon k as

$$\delta_{ijkl} = \frac{\Gamma_{k,ij}\gamma_{lj}}{\sum_{r=1}^{N}\Gamma_{k,ir}\gamma_{lr}}, \; i,j = 1,\ldots,N \tag{2.6}$$

where $\Gamma_k = (A+B)^{k-1}$, $\Gamma_{k,ij}$ is the ij-element of Γ_k and γ_{lr} is the r-th element of γ_l. The denominator of (2.6) is just the i-th component of V_{kl} and thus gives the total effect for the i-th exchange rate after k periods for news of type l. The numerator of (2.6), $\Gamma_{k,ij}\gamma_{lj}$, is the contribution of the j-th exchange rate to this total effect. If the instantaneous news effect in the j-th exchange rate is not zero ($\gamma_{lj} \neq 0$) and there is volatility spillover (A and/or B are not diagonal), then this contribution will not be zero for $k > 1$. The ratio δ_{ijkl} now gives the relative contribution of individual exchange rates' instantaneous news effects to the total news effects of other exchange rates in subsequent periods due to volatility spillover. Note that δ_{ijkl} converges to the same proportion, δ_{jl} say, for $k \to \infty$ irrespective of i. This is due to the fact that $\Gamma_k/||\Gamma_k||$ converges to a rank one matrix, see e.g. Friedland (2004), which implies that $\lim_{k\to\infty} \Gamma_{k,ij}/\Sigma_{r=1}^{N} \Gamma_{k,ir}$ is the same for all i. Thus, for very long horizons the contributions of the j-th exchange rate news effect to that of the i-th exchange rates is the same irrespective of i and given by δ_{jl}.

A similar analysis of relative contributions can be performed with the *accumulated* volatility impulse responses, i.e. $\Sigma_{i=1}^{N} V_{il}$. In an analogous way, we can define the accumulated relative news spillover effect from the j-th to the i-th exchange rate after k periods as

$$\Delta_{ijkl} = \frac{\sum_{m=1}^{k}\Gamma_{m,ij}\gamma_{lj}}{\sum_{m=1}^{k}\sum_{r=1}^{N}\Gamma_{m,ir}\gamma_{lr}}, \; i,j = 1,\ldots,N \tag{2.7}$$

The coefficient Δ_{ijkl} represents the proportion of the total accumulated type l news effect of exchange rate i that can be attributed to the accumulated news effect of exchange rate j. Unlike the relative contribution at a given horizon k, the relative contribution of the accumulated volatility impulse responses converges as $k \to \infty$ to a proportion that depends on i.

3. DATA AND EMPIRICAL RESULTS

The database (provided by Olsen and Associates) consists of five-minute quotes for the EUR/USD, GBP/USD, and JPY/USD over the period ranging from May 15 to November 14, 2001 i.e. 6 months. These currency quotes are market makers' quotes and not transaction prices, as would be preferable. Since Danielsson and Payne (2002) showed that the statistical properties of five-minute US dollar/Deutsche Mark quotes are similar to those of transaction quotes, and transaction quotes are not widely available, we have resorted to using five minute quotes. The database also contains the date, the time-of-day stamped to the five minutes in Greenwich mean time (GMT), and the mid-quotes.

The return at time t is computed as the difference between the logarithms of the mid-quotes[2] at times t and $t - 1$, multiplied by 100 to get percentage returns. Because of scarce trading activity during the week-end, we excluded all returns computed between Friday 22h05 and Sunday 24h. In addition, we took into account the daylight saving time and we excluded the first return of each Monday to avoid possible biases due to the lack of activity during the week-end. The total number of returns is 37,653. The final data transformation consists of adjusting the returns for the intradaily seasonality component of volatility The seasonally adjusted returns are obtained by dividing each return by the standard deviation of all returns belonging to the corresponding intra-day five minute interval. An average value of volatility is computed and attributed to the endpoint of every 5 minute interval. The time series of these values constitutes an intradaily 'seasonal index' of volatility. This can be done by considering all days of the week as similar (an overall index), or by computing a specific index for each day of the week[3]. In the appendix we explain the details of the procedure we adopted to compute these indices and to adjust the returns. For example, the return of May 16, 2001, 9h05, is divided by the standard deviation of those returns over the whole sample that are recorded at 9h05. By construction, the average volatility for all adjusted series is one.

Furthermore, our news announcements database includes the news headlines related to US macro-economic figures that were released on the Reuters news-alert screens over the May 15 to November 14, 2001 period. These events are time stamped to the minute and are a key feature of our news announcements analysis. A total of 142 news events are identified in our sample period. As in Bauwens et al. (2005), we classify the news into two categories, i.e. news that are considered positive or negative for the U.S. economy. Thus, we define two news dummy variables D_{1t} and D_{2t} corresponding to positive or negative news, respectively. To distinguish positive from negative news, we consider the difference between expected and realized values: if the realization is larger than the expectation and is a figure which corresponds to economic growth, the news is classified as positive; if the actual figure implies instead higher-than-expected inflation or a slowdown of the economy, it is regarded as negative. The expected values are given on Reuters screens a few days before the news announcements. Note that by assessing the effects of news announcements on the de-seasonalized volatility, we consider only the unexpected components of news, see Bauwens et al. (2005).

For the conditional mean μ_t in model (2.1) we specify an MA(2) model based on standard model selection criteria. To simplify the conditional variances in model (2.2) but still allow for volatility spillover, we let A be a full 3×3 parameter matrix but restrict B to be diagonal, thus containing only three parameters. We have tried additional lagged dummies in model (2.2), but none of them were significant. Thus, news events appear to be incorporated almost instantaneously (within five minutes) into exchange rate volatility. Our impulse response methodology permits us to analyse how these instantaneous effects are propagated through the system over time.

[2] Where the mid-quote is the average of the bid and ask prices.
[3] Since Bauwens et al. (2005) showed that each day of the week has its own seasonal profile, we have considered a specific index for each day of the week.

	EUR/USD (i=1)	*GBP/USD* (i=2)	*JPY/USD* (i=3)
c_0	0.0007	0.003	-0.003
	(0.86)	(0.45)	(0.50)
c_1	-0.166	-0.137	-0.093
	(0.00)	(0.00)	(0.00)
c_2	-0.026	-0.032	-0.024
	(0.00)	(0.00)	(0.00)
ω_i	0.061	0.109	0.042
	(0.00)	(0.00)	(0.00)
A_{i1}	0.079	0.016	0.008
	(0.00)	(0.00)	(0.00)
A_{i2}	0.011	0.090	0.005
	(0.00)	(0.00)	(0.00)
A_{i3}	0.019	0.024	0.068
	(0.00)	(0.00)	(0.00)
B_{ii}	0.826	0.756	0.875
	(0.00)	(0.00)	(0.00)
γ_{1i}	0.215	0.316	0.107
	(0.00)	(0.00)	(0.01)
γ_{2i}	0.201	0.096	0.013
	(0.00)	(0.22)	(0.82)

Table 3.1 Estimation results for equations (2.1) to (2.3). P-values are in parentheses. For the conditional mean equations, c_0 is the intercept, c_1 the MA(1) coefficient and c_2 the MA(2) coefficient. The maximum eigenvalue of the matrix A+B is 0.949. The estimated constant conditional correlation between EUR/USD and GBP/USD is 0.3500, between EUR/USD and JPY/USD 0.1560 and between GBP/USD and JPY/USD 0.0922. The sample involves 37653 observations from May 15 to November 14, 2001.

Estimation results of model (2.1)-(2.2) are given in Table 3.1. All first order MA coefficients are negative and highly significant, reflecting the bid-ask bounce effect. The diagonal elements of A tend to be higher than those off-diagonal, showing that the own lagged squared returns of an exchange rate have a higher impact on its volatility than those of other rates. However, there is significant spillover in volatilities, as all off-diagonal elements of A are significantly different from zero. Note that the estimator of B is substantially smaller than in typical GARCH estimates without exogenous news dummies, i.e. the estimated persistence is smaller. For example, for the full sample, the maximum eigenvalue of the matrix $A + B$ is given by 0.949 as opposed to values typically much closer to one for GARCH (1,1) models applied to high-frequency FX rates. The reason is that some of the persistence is absorbed by the exogenous news.

The estimated γ_1 coefficients corresponding to positive news, which represents the instantaneous effect of positive news on volatility, is highest for GBP/USD (31.6 percent of average volatility), followed by EUR/USD (21.5 percent), and JPY/USD (10.7 percent). This is surprising as one would expect the highest effect in the largest and most liquid exchange rate, the EUR/USD. This latter is the largest FX market in terms of volume, liquidity and number of participants. Indeed, we see the largest instantaneous impact in the EUR/USD for negative news (γ_2): 20.1 %, compared with 9.6 % of GBP/USD and 1.3 % for JPY/USD. There is an asymmetry of the amplitude of news effects on GBP/USD and JPY/USD volatility with respect to events of positive or negative news.

k	Δt	*EUR/USD*		*GBP/USD*		*JPY/USD*	
		+	–	+	–	+	–
1	5 min	0.2154	0.2014	0.3164	0.0958	0.1073	0.0131
		(0.0569)	(0.0689)	(0.0713)	(0.0538)	(0.0504)	(0.0422)
3	15 min	0.1766	0.1651	0.2271	0.0688	0.0954	0.0116
		(0.0457)	(0.0554)	(0.0501)	(0.0374)	(0.0445)	(0.0372)
6	30 min	0.1314	0.1229	0.1386	0.0419	0.0803	0.0098
		(0.0331)	(0.0467)	(0.0296)	(0.0216)	(0.0371)	(0.0310)
12	1 hour	0.0736	0.0688	0.0526	0.0159	0.0572	0.0070
		(0.0181)	(0.0215)	(0.0110)	(0.0077)	(0.0262)	(0.0217)
24	2 hours	0.0242	0.0226	0.0087	0.0027	0.0296	0.0036
		(0.0068)	(0.0071)	(0.0035)	(0.0028)	(0.0138)	(0.0111)
72	6 hours	0.0006	0.0006	0.0002	5.19e–005	0.0023	0.0003
		(0.0006)	(0.0004)	(0.0004)	(0.0003)	(0.0015)	(0.0010)
144	12 hours	1.16e–005	1.09e–005	3.79e–006	1.14e–006	5.31e–005	6.47e–006
		(2.27e–005)	(1.31e–005)	(1.62e–005)	(8.89e–006)	(6.06e–005)	(3.18e–005)
288	24 hours	6.13e–008	5.73e–009	2.02e–009	6.10e–010	2.83e–008	3.44e–009
		(2.66e–008)	(1.28e–008)	(1.79e–008)	(8.56e–009)	(6.23e–008)	(2.96e–008)

Table 3.2 Estimates of volatility impulse responses $\hat{V}_k$. Standard errors (in parentheses) are calculated using (2.5). The symbol (+) indicates positive news (l = 1) and (–) negative news (l = 2).

In Table 3.2 we report estimates of volatility impulse responses $\hat{V}_k$ and standard errors calculated using (2.5). These could be used to construct confidence bands for V_k. Until roughly six hours, estimated V_k are significantly different from zero for all three FX rates.

Table 3.3 shows the relative contributions δ_{ijkl}, defined by (2.6) as the contribution of exchange rate j to the volatility impulse response V_{kl} of the i-th exchange rate, divided by the corresponding total value of V_{kl}. As shown in Section 2, all proportions converge to the same distribution δ_{jl}. For positive news (l = 1), these proportions are given by 26 percent explained by the Euro, 13.7 percent by the Pound, and 60.3 percent by the Yen. Thus, more than sixty percent of the long run impact of positive news can be attributed to an instantaneous shock in JPY/USD and its persistence over time. For a fixed k of one hour, for example, 77 percent of the news effect on the Euro after one hour is attributed to the initial effect on the Euro, 12 percent are attributed to the Pound, and 11 percent to the Yen. For negative news (l = 2), the asymptotic proportions are given by 68 percent explained by the Euro, 12 percent by the Pound, and 20 percent by the Yen. Thus, more than two thirds of the long run impact of negative news can be attributed to an instantaneous shock in EUR/USD and its persistence over time.

	k	Δt	*EUR/USD* (j=1)		*GBP/USD* (j=2)		*JPY/USD* (j=3)	
			+	–	+	–	+	–
EUR/USD	1	5min	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000
(i=1)	3	15min	0.9468	0.9861	0.0332	0.0112	0.0199	0.0027
	6	30min	0.8787	0.9674	0.0712	0.0254	0.0501	0.0072
	12	1hour	0.7699	0.9358	0.1181	0.0465	0.1120	0.0177
	24	2hours	0.6090	0.8834	0.1524	0.0716	0.2385	0.0450
	72	6hours	0.3093	0.7247	0.1424	0.1081	0.5483	0.1673
	144	12hours	0.2612	0.6804	0.1372	0.1157	0.6016	0.2040
	288	24hours	0.2598	0.6788	0.1370	0.1160	0.6032	0.2052
GBP/USD	1	5min	0.0000	0.0000	1.0000	1.0000	0.0000	0.0000
(i=2)	3	15min	0.0260	0.0772	0.9546	0.9153	0.0193	0.0075
	6	30min	0.0678	0.1887	0.8784	0.7918	0.0538	0.0195
	12	1hour	0.1538	0.3840	0.7060	0.5705	0.1402	0.0456
	24	2hours	0.2794	0.6237	0.3863	0.2792	0.3342	0.0971
	72	6hours	0.2753	0.6939	0.1400	0.1143	0.5846	0.1918
	144	12hours	0.2602	0.6793	0.1371	0.1159	0.6026	0.2048
	288	24hours	0.2598	0.6788	0.1370	0.1160	0.6032	0.2052
JPY/USD	1	5min	0.0000	0.0000	0.0000	0.0000	1.0000	1.0000
(i=3)	3	15min	0.0320	0.1953	0.0307	0.0606	0.9373	0.7442
	6	30min	0.0706	0.3469	0.0626	0.0994	0.8668	0.5537
	12	1hour	0.1261	0.4873	0.0980	0.1225	0.7759	0.3902
	24	2hours	0.1898	0.5946	0.1239	0.1256	0.6863	0.2798
	72	6hours	0.2536	0.6724	0.1363	0.1170	0.6100	0.2105
	144	12hours	0.2596	0.6787	0.1370	0.1160	0.6034	0.2054
	288	24hours	0.2598	0.6788	0.1370	0.1160	0.6032	0.2052

Table 3.3 Relative contributions δ_{ijkl}, defined by (2.6) as the contribution of exchange rate j (in the columns) to the volatility impulse reponse V_{kl} of the i-th exchange rate, divided by the corresponding total value of V_{kl}. The symbol (+) indicates positive news (l = 1) and (–) negative news (l = 2).

Table 3.4 shows the relative contributions Δ_{ijkl}, defined by (2.7) as the contribution of exchange rate j to the cumulated volatility impulse response $\Sigma_{m=1}^{k} V_{ml}$ of the i-th exchange rate, divided by the corresponding total value of $\Sigma_{m=1}^{k} V_{ml}$. For positive news (γ_1), in all three cases, most of the cumulated effect is explained by the own initial effect. For example, for the Yen the cumulated effect after one day attributed to the Euro is only 13.8 percent of the total cumulated effect. For negative news, however, the EUR/USD rate has a substantial impact after one day on the cumulated effect in both GBP/JPY (29.7%) and JPY/USD (52.2%). Thus, an important part of the effect of negative news on the Yen and the Pound is induced by volatility spillover from the Euro. The cumulated news effect of the Pound and the Yen on the Euro is only 3.8 and 2.2 percent, respectively, which indicates that the cumulated news effect on the Euro is absorbed mainly by its own initial news effect.

	k	Δt	*EUR/USD* (j=1)		*GBP/USD* (j=2)		*JPY/USD* (j=3)	
			+	−	+	−	+	−
EUR/USD	1	5min	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000
(i=1)	3	15min	0.9744	0.9934	0.0162	0.0053	0.0095	0.0013
	6	30min	0.9420	0.9850	0.0352	0.0119	0.0228	0.0031
	12	1hour	0.8930	0.9721	0.0603	0.0213	0.0466	0.0066
	24	2hours	0.8338	0.9567	0.0832	0.0309	0.0830	0.0124
	72	6hours	0.7711	0.9410	0.0959	0.0379	0.1330	0.0211
	144	12hours	0.7655	0.9396	0.0964	0.0383	0.1381	0.0221
	288	24hours	0.7653	0.9396	0.0964	0.0383	0.1382	0.0221
GBP/USD	1	5min	0.0000	0.0000	1.0000	1.0000	0.0000	0.0000
(i=2)	3	15min	0.0117	0.0355	0.9796	0.9610	0.0086	0.0034
	6	30min	0.0279	0.0824	0.9507	0.9094	0.0214	0.0082
	12	1hour	0.0544	0.1545	0.9007	0.8288	0.0450	0.0166
	24	2hours	0.0861	0.2351	0.8333	0.7363	0.0806	0.0286
	72	6hours	0.1098	0.2935	0.7676	0.6639	0.1226	0.0426
	144	12hours	0.1111	0.2967	0.7627	0.6594	0.1263	0.0439
	288	24hours	0.1111	0.2968	0.7625	0.6593	0.1263	0.0439
JPY/USD	1	5min	0.0000	0.0000	0.0000	0.0000	1.0000	1.0000
(i=3)	3	15min	0.0160	0.1087	0.0155	0.0340	0.9686	0.8572
	6	30min	0.0362	0.2152	0.0333	0.0640	0.9305	0.7207
	12	1hour	0.0666	0.3345	0.0564	0.0917	0.8770	0.5737
	24	2hours	0.1029	0.4381	0.0783	0.1079	0.8189	0.4540
	72	6hours	0.1394	0.5168	0.0944	0.1133	0.7663	0.3699
	144	12hours	0.1425	0.5227	0.0955	0.1134	0.7620	0.3639
	288	24hours	0.1426	0.5228	0.0955	0.1134	0.7619	0.3638

Table 3.4 Relative contributions Δ_{ijkl}, defined by (2.7) as the contribution of exchange rate j (in the columns) to the cumulated volatility impulse response $\sum_{m=1}^{k} V_{ml}$ of the i-th exchange rate, divided by the corresponding total value of $\sum_{m=1}^{k} V_{ml}$. The symbol (+) indicates positive news (l = 1) and (−) negative news (l = 2).

Figure 3.1 illustrates the impulse response functions for positive news. Clearly, the persistence in the JPY/USD is higher than that of the other rates, even though the initial effect is much smaller. After three and a half hours, the cumulated effect on the EUR/USD reaches

95% of the total cumulated effect, while this takes three hours for the GBP/USD and five hours for the JPY/USD. Figure 3.2 shows the corresponding functions for negative news. Clearly, the EUR/USD dominates in this case while having a similar form as that for positive news.

Figure 3.1 Positive US macroeconomic figures: Volatility impulse response functions V_k, k = 1,...,50 for the full sample, May 15 to November 14, 2001.

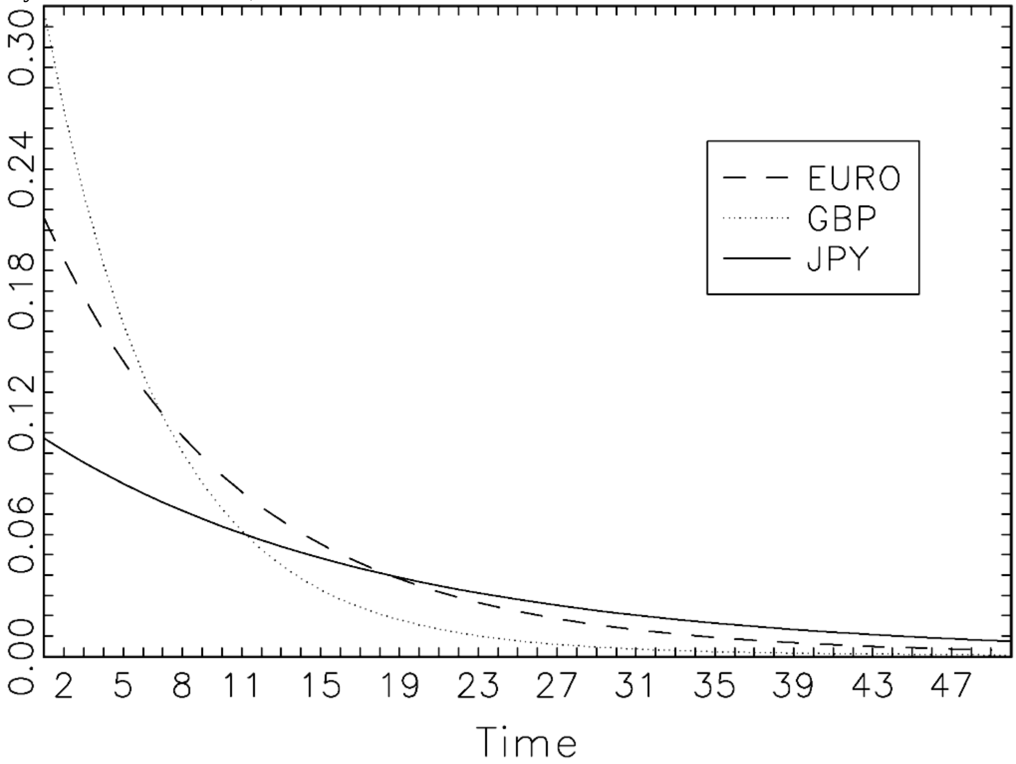
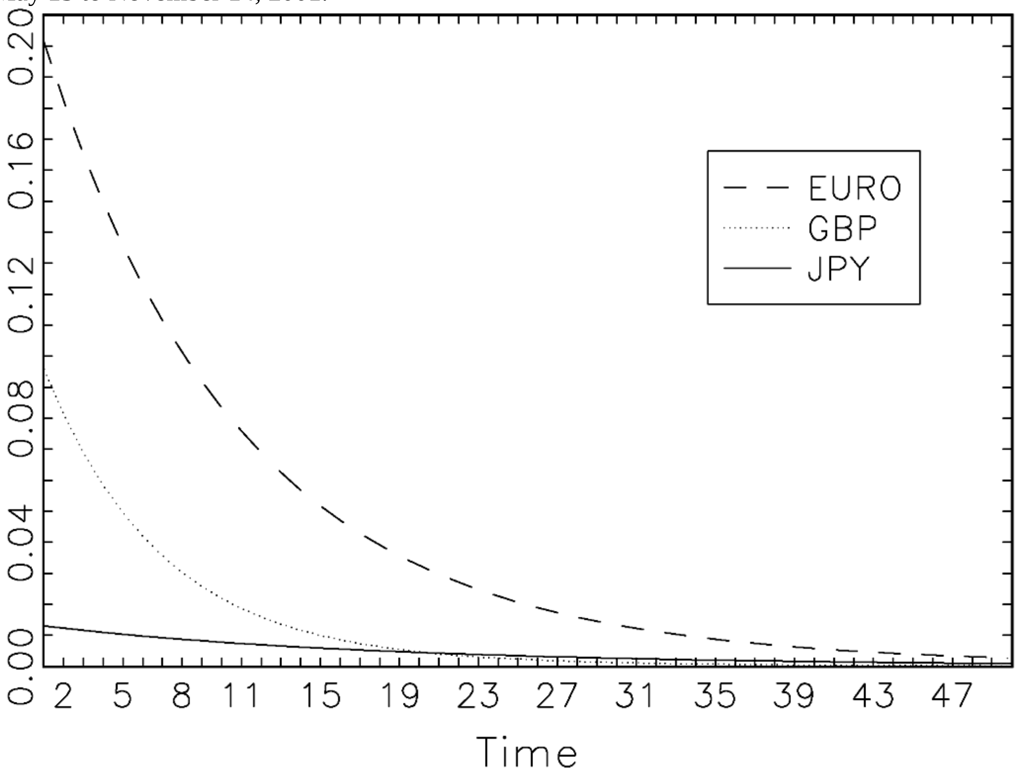


Figure 3.2 Negative US macroeconomic figures: Volatility impulse response functions V_k, k = 1,...,50 for the full sample, May 15 to November 14, 2001.



4. CONCLUSION

We have introduced a new concept of assessing the importance of news effects on volatility of exchange rates through an impulse response analysis. The news events in our case are observed headlines from Reuters screens, and therefore can be modelled explicitly as exogenous news in a multivariate GARCH model framework. We deal with three intra-day dollar exchange rates and consider news related to U.S. macroeconomic figures. Our results suggest that the Yen has the smallest initial impact of positive news, but with the highest persistence. Conversely to what one would expect, the Pound has a higher initial impact than the Euro. Due to volatility spillover, a considerable proportion of cumulated news effects in one FX rate can be attributed to other currencies. This holds in particular for the impact of EUR/USD on the two cross-rates in case of negative news. We believe that our detailed impulse response analysis sheds light on the structural dissemination of macroeconomic news in a multivariate FX rate system.

APPENDIX

To compute the intradaily average volatility at time n_k of day k (called mv_{n_k}), we divide each day into 288 five-minute intervals. We assume for simplicity that we have exactly S weeks of data. For each interval endpoint per day of the week over the S week period, we have one euro/dollar return. We thus compute in principle 288 values mv_{n_k} for each day of the week. Actually, as explained in Section 3, we delete the first interval of Monday and the intervals from 22h05 to 24h of Friday. Hence, we have 287 points on Monday and 264 on Friday. That makes a total of 1415 values over a week.

Each value mv_{n_k} is the square root of the average of the S squared returns at time n_k of day k (k=1 is for Monday, k=5 for Friday). For example, the value of mv_{n_k} on Thursday at 12h (k=4 and n_4 = 144) is the square root of the average of the squared returns observed every Thursday at 12h during the S week period. Formally,

$$mv_{n_k} = \left(\frac{1}{S} \sum_{s=1}^{S} r^2_{f(s,k,n_k)} \right)^{0.5} \tag{A.8}$$

where

$$f(s, k, n_k) = 1415(s-1) + \sum_{j=1}^{k} N_j + n_k \tag{A.9}$$

for s=1,...,S; k=1,...,5; N_1=0; N_2=287; N_3=N_4=N_5= 288; n_1=2,...,288; n_2=1,...,288; n_3 and n_4 likewise, and n_5=1,...,264 as stated above. Notice that when s varies from 1 to S=26 for example, the function $f(s,k,n_k)$ takes the values from 1 to 36,790. Actually, in our database, we have 37,654 price observations (hence one return less), corresponding to 26 full weeks starting a Tuesday and three more days of the twenty-seventh week.

To adjust the returns for seasonality, we divide the return at the endpoint of each five minute interval by the corresponding value of the intradaily average volatility (using the day-specific volatility). That means, for example, that all returns at 12h on Thursday in the sample are divided by the same value (the average volatility at 12h on Thursday).

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