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Information arrivals and intraday exchange rate volatility

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Abstract

This paper investigates the link between information arrivals and intraday DEM/$ volatility. Information arrivals are measured by the numbers of news items that appeared in the Reuters News Service. We separate news stories into different categories and find that total headline news counts, US and German macroeconomic news and German Bundesbank monetary policy news all have a significant impact on intraday DEM/$ volatility. The larger quantitative effects of the German Bundesbank monetary policy news and US macroeconomic news at 15-min intervals are consistent with the findings of a two-stage adjustment process of public information arrivals [Fleming and Remolona, J. Finance (1999) 1901]. Our results suggest that the persistent of intraday exchange rate volatility set off by public information is extended by traders' private information about 15 min later. The conclusions are obtained from ARCH models that incorporate intraday seasonal volatility terms.

Keywords: Intraday exchange rates; Information arrivals; GARCH

JEL classifications: G14; E58

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1. Introduction

The link between information arrivals and the variation of asset prices is an important issue in finance. Mitchell and Mulherin (1994) use daily news numbers, reported by Dow Jones on the Broadtape, to examine the link between news arrivals and stock prices. Their results show that there is a significant relationship between information arrivals and trading volumes, but only a weak link with stock returns. Berry and Howe (1994) count the numbers of news items released by Reuters News Service as their information proxies, which include not only political but also economic announcements circulated by major news vendors. They find a positive relationship between information arrival and trading volume, but an insignificant relationship with stock price volatility.

This paper contributes to the accumulating empirical literature addressing similar issues using exchange rate data. There is already an extensive literature that focuses on currency volatility using ARCH related models (Hsieh, 1988; Gallant et al., 1991; Bollerslev et al., 1992). These studies show that ARCH models can capture the clustering of volatility seen in time series of exchange rates. One explanation for time-varying conditional variance is that returns are generated by a mixture of distributions, in which information arrivals are the mixing variables (Diebold, 1986; Taylor, 1986; Lamoureux and Lastrapes, 1990; Gallant et al., 1991; Goodhart et al., 1993; Bollerslev and Domowitz, 1993). These studies have suggested that auto-correlation in information arrivals leads to the serial dependency in conditional volatility that is captured by the ARCH model.

Since mixing variables are generally unobservable, proxies of information arrivals have been used in the literature. Lamoureux and Lastrapes (1990) choose transaction volume as their information proxy. Locke and Sayers (1993) test a series of information proxies such as volume, floor transactions, number of price changes and executed order imbalance on S&P-500 futures contracts. They find some evidence of remaining variance persistence regardless of the definition of the rate of information proxy. Goodhart et al. (1993) use dummy variables to test the effect of US trade figure and UK base rate changes on tick by tick Dollar–Sterling exchange rates. They find these news variables have a significant effect on volatility changes and including them in the conditional variance equation reduces the variance persistence. Bollerslev and Domowitz (1993) test other intraday information proxies such as quote frequency and changes in the bid-ask spread. Their results show that conditional volatility is increasing in the size of the spread, but quote frequency has a negligible effect on conditional volatility. Moreover, including an information proxy did not change many of the other parameters of the GARCH (1, 1) specification.

Our interpretation of information arrivals parallels that used in independent work by Low and Muthuswamy (1995), Melvin and Yin (2000). Low and Muthuswamy use the number of news items reported in Reuters News pages as information proxies and discuss the relationship between these variables and DEM/$ and JPY/$ intraday volatility. However, they do not adjust for intraday volatility seasonality which could influence their results. Melvin and Yin (2000) study the relationship between news and exchange rate volatility from December 1993 to April 1995. Their results show that the volatility of the DEM/$ exchange rate varies positively with the total number of news items reported in Reuters News Service. They use a similar seasonal adjustment process to that employed in this paper and their results are based on estimating GARCH models with conditional normal distributions from hourly data. In this paper, we also consider fat-tailed distributions, the impact of different categories of information, higher data frequencies and the adjustment of GMT times during daylight saving periods.

DeGennaro and Shrieves (1997) use key words concerning the status of US–Japan trade negotiations, interest rate changes, and economic policy to investigate the impact of information arrivals on JPY/$ volatility. They use hourly return data and adjust for intraday seasonality by including the rate of quote arrivals in the conditional variance equation. Ederington and Lee (1993, 1995) use intraday futures exchange rate data to show the significant impact of macroeconomic news on intraday exchange rate volatility. Payne (1996) discusses the impact of US macroeconomic news announcement on the DEM/$ exchange rate using a stochastic volatility model. Fleming and Remolona (1999) uncover a two-stage adjustment process in the US. Treasury market around the release times of major US macroeconomic announcements. They find that the first stage is marked by a sharp and nearly instantaneous price change to public information. In a prolonged second stage, price volatility persists as investors trade to reconcile residual differences in their private views based on the knowledge of their customer order flows.

Given the intraday exchange rate data and news items supplied to us by Olsen and Associates (O&A), it is of interest to assess the impact of various categories of economic news on intraday DEM/$ exchange rates. The most comprehensive information proxy, we have used is the total number of news items reported per period by the Reuters News Service. In addition, we also consider four subsets of the report to assess their individual impact on intraday DEM/$ exchange rate volatility. They are news related to US macroeconomic variables, news related to German macroeconomic variables, and news related to the monetary policy instruments of the US Federal Reserve and the German Bundesbank.

The remainder of the paper is arranged as follows, Section 2 describes the data and intraday seasonal multipliers. Section 3 discusses the categories of news arrivals and Section 4 describes the ARCH methodology. Section 5 provides results. Conclusions are summarized in Section 6.

2. Data and intraday seasonal multipliers

2.1. Relevance of the data and characteristics of the intraday foreign exchange rate

The data used in this study was obtained from O&A Research Institute. It consists of a complete record of Reuters' interbank DEM/$ quotations and news headlines from 1 October 1992 to 30 September 1993. There were 1.4 million quotations in this year with almost four quotes a minute on average during weekdays. The relevance of the data and sample period stems from the fact that European currency markets were in turmoil during this period, which resulted in a major restructuring of the European Exchange Rate Mechanism (ERM). This turmoil was sparked by the Deutsche Bundesbank and its interest rate policy[2]. Therefore, our paper provides important documentation of the relationship between public information arrivals and exchange rate volatility. More importantly, we are using the one and only year of Reuters information that is available to all researchers. Until more recent data are widely available, our analysis provides the most comprehensive investigation that highlights the different impacts of major categories of public information on DEM/$ volatility.

Returns are defined as the logarithms of quotation price changes, $r_t = \ln(p_t) - \ln(p_{t-1})$, and can be interpreted as compounded rates. Returns are here measured at intervals of 1 h, 30, 15, 10 and 5 min. To reduce the influence of the slow-trading pattern over the weekend, we follow the adjustment process of Andersen and Bollerslev (1997) by excluding returns from Friday 21:00 GMT through Sunday 21:00 GMT. A detailed description of this weekend definition can be found in Bollerslev and Domowitz (1993). For our data, there are, respectively, 6,263, 12,527, 25,055, 37,583, and 75,167 returns for hourly, 30, 15, 10 and 5-min intervals after the adjustment for the weekend periods. We use the averages of the bid and ask quotes recorded at the end of fixed time intervals to calculate returns. Intervals that have no quotes are assigned zero returns. The percentage of intervals without quotations is, respectively, 1.2, 1.9, 3.1, 4.3 and 7.0% for hourly, 30, 15, 10 and 5-min data.

Summary statistics of the return series are presented in Table 1. The sample means of the DEM/$ return series are all close to zero. The hourly sample skewness and kurtosis show that the return series are not normally distributed. The first-lag correlation for the hourly return series (−0.018) is almost zero but the first-lag correlations of both the absolute and squared returns are much higher (0.196 and 0.183). The autocorrelation structures for the other data frequencies show a similar pattern to the hourly series. The slow declining autocorrelations for absolute and squared returns indicate serial dependent conditional heteroskedasticity of the return series. This can also be seen from the highly significant Ljung and Box (1978) statistics, $Q_1(12)$ and $Q_2(12)$, that test for up to 12th order serial correlation in the absolute and squared return series.

Reuters' news and price data are recorded in Greenwich mean time (GMT). Analysis of the impact of news without a suitable adjustment to GMT could be

[2] Prior to the 1992–1993 currency crisis, there had been no ERM exchange rate realignments since 1987. Following the withdrawal from the ERM of the British pound and Italian lire in September 1992, the Bundesbank cut its discount and Lombard rate on 4 Feburary, 1993. This rate cut was followed by four subsequent discount/Lombard rate reductions in the spring of 1993. Then, the French franc came under heavy selling pressure in the middle of July 1993. On 29 July, the Bundesbank cut its Lombard rate but not the discount rate, which was interpreted by the currency market as merely making a gesture to placate other ERM countries and there being no intention to further lower the discount rate. On 1 August, 1993, a crisis meeting held by European foreign ministers decided to widen the obligatory marginal intervention thresholds of the participants in the ERM from ±2.5 to 15% around the central rates.

Table 1
Return series summary statistics

Intervals	Hourly	30 min	15 min	10 min	5 min
Mean $\times 10^3$	0.016	0.008	0.005	0.003	0.002
Variance $\times 10^4$	0.022	0.011	0.006	0.004	0.002
Skewness	0.171	0.112	0.063	0.035	0.030
Kurtosis	5.178	5.696	5.640	5.683	5.659
Minimum	−0.007	−0.006	−0.005	−0.004	−0.003
Maximum	0.008	0.007	0.005	0.004	0.003
$\rho(1)$	−0.018	−0.066	−0.085	−0.093	−0.108
$\rho(2)$	0.006	0.008	−0.018	−0.030	−0.019
$\rho(3)$	−0.018	0.024	0.006	−0.002	−0.011
$\rho_1(1)$	0.196	0.189	0.218	0.225	0.238
$\rho_1(2)$	0.109	0.145	0.157	0.168	0.170
$\rho_1(3)$	0.074	0.110	0.132	0.145	0.164
$\rho_2(1)$	0.183	0.142	0.196	0.197	0.221
$\rho_2(2)$	0.098	0.137	0.123	0.134	0.146
$\rho_2(3)$	0.052	0.111	0.098	0.109	0.136
$Q(12)$	22.7	71.9	203.9	377.3	949.4
$Q_1(12)$	735.4	1019.1	5066.5	8015.8	18 351.4
$Q_2(12)$	571.7	1026.0	3676.5	5488.9	13 352.7
$T \times R^2$	213.4	253.9	966.5	1456.5	3665.8
Sample size	6263	12 527	25 055	37 583	75 167

$\rho(j)$, $\rho_1(j)$, $\rho_2(j)$, respectively, denote the jth order autocorrelations of returns, their absolute values and their squares, i.e. r, $|r|$ and r^2. $Q(12)$, $Q_1(12)$, and $Q_2(12)$ are the respective Ljung and Box (1978) test statistics for no serial correlation up to lag 12. TR^2 is Engle (1982) test for heteroskedasticity based on one lag.

misleading because GMT is 1 h different from London time during daylight saving periods. We adjust GMT during the American daylight saving period, which is in effect from the first Sunday in April until the last Sunday in October. For our data, it is from 1 October 1992 to 25 October 1992, and from 4 April 1993 to 30 September 1993. The adjustment procedure is to add 1 h to GMT during the American daylight saving time and to leave other times unchanged[3]. We denote this adjusted clock by GMT_{adj} The rest of the analysis is based on this GMT_{adj} clock. US Eastern time can be obtained by subtracting 5 h from GMT_{adj}.

2.2. Tests of variations in volatility during different trading intervals

The interbank foreign exchange market is a global market and it operates 24 h a day and 7 days a week. A systematic, although not necessarily regular, intraday

[3] The daylight saving periods in European countries are slightly different from that of the US. For example, the UK starts daylight saving on the third Sunday of March and finishes it on the fourth Sunday in October. These are minor differences, which we ignore in this paper by adjusting using American daylight saving time. The absence of time changes in Japan is probably not important because we only consider the DEM/$ rate.

volatility pattern has been reported by Dacorogna et al. (1993), Bollerslev and Domowitz (1993), Andersen and Bollerslev (1997) among others. This could be the result of changing information flows to the foreign exchange market. Harvey and Huang (1991), Ederington and Lee (1993, 1995) show significant day of the week volatility patterns that are in part the result of US macroeconomic news releases.

We report two simple tests of the equality of DEM/$ intraday volatility across hours based on data sampled at 30-min intervals. Our first method involves multiple t-tests. We calculate the fraction of the day t realized variance that occurs in each 30-min interval j, $W_{t,j}$, $(=r_{t,j}^2/\Sigma_{i=0}^{47} r_{t,i}^2)$, and the average $W_{t,j}$ across days t for each j, $\bar{W}_j$. If the variances are equal on average for all 30-min intervals, then $(\bar{W}_j - 1/48)$ divided by the standard error of $\bar{W}_j$ gives us 48 t-statistics that can be used for simple tests of variance equality. In addition, we separate the data into the 5 days of the week and test the equality of average variance by weekdays.

The average proportions $\bar{W}_j$ are presented[4] in Table 2. The average during $\mathrm{GMT_{adj}}$ 00:00–02:30 h on Monday is higher than on other weekdays, the second peak on Monday appears during $\mathrm{GMT_{adj}}$ 08:00–08:30 h with the major peak on Monday during $\mathrm{GMT_{adj}}$ 15:00–17:30 h. The average proportion on Tuesday is highest during $\mathrm{GMT_{adj}}$ 15:00–15:30 h, which is about twice the average in the same period on Wednesday and Thursday. The average proportions on Wednesday and Thursday are high during $\mathrm{GMT_{adj}}$ 13:30–14:00 h. On Friday the average proportion during $\mathrm{GMT_{adj}}$ 13:30–14:00 h is the highest (0.1205) among all intervals, which corresponds to the time when most US macroeconomic news is released (Harvey and Huang, 1991; Ederington and Lee, 1993, 1995). The overall pattern of the multiple t-tests can be seen from the last column in Table 2. The average volatility between $\mathrm{GMT_{adj}}$ 03:00 and 05:00 h is significantly lower than average. The lowest level happens between $\mathrm{GMT_{adj}}$ 04:00 and 04:30 h, which is the Asian lunch time. The volatility between $\mathrm{GMT_{adj}}$ 13:00 and 15:00 h is significantly higher than average when the European market overlaps the American market and it declines significantly from $\mathrm{GMT_{adj}}$ 19:30 h onwards when the activity in the American market slows down.

A χ^2-goodness of fit test has also been used to test the equality of variance across all 30-min intervals. We count the number of days that 30-min i gives the maximum realized variance, and compare this count with the expected number under the null hypothesis $(=261/48)$. The test statistic is distributed as χ^2_{47} under the null hypothesis of equal variance across 30-min intervals. The χ^2 test statistic is 367.96 which is significant at low levels, such as 0.1%, and rejects the null hypothesis of equal variance for all 30-min intervals during weekdays. Results from χ^2-statistics confirm the results of multiple t-tests that the volatility patterns are different at 30-min intervals for each day of the week. Therefore, it is essential to take into account both the intraday and the day of the week effects when modeling the intraday volatility process. We use a set of seasonal multipliers described in the next section to incorporate these characteristics.

[4] Returns in this table are calculated using bid quotes rather than the averages of bid and ask quotes.

Table 2
Proportions of daily DEM/$ average realized variance in 30-min intervals

GMT_{adj}	Monday	Tuesday	Wednesday	Thursday	Friday	All days
0:00–0:30	0.0201	0.0144	0.0142	0.0083*	0.0330	0.0181
0:30–1:00	0.0309	0.0082*	0.0124*	0.0120*	0.0196	0.0166
1:00–1:30	0.0239	0.0107*	0.0146	0.0110*	0.0118*	0.0144*
1:30–2:00	0.0176	0.0125*	0.0073*	0.0116*	0.0099*	0.0118*
2:00–2:30	0.0149	0.0102*	0.0132	0.0149	0.0105*	0.0128*
2:30–3:00	0.0144	0.0104*	0.0101*	0.0195	0.0122	0.0133*
3:00–3:30	0.0081*	0.0068*	0.0047*	0.0087*	0.0111	0.0079*
3:30–4:00	0.0101*	0.0082*	0.0075*	0.0118*	0.0069*	0.0089*
4:00–4:30	0.0043*	0.0039*	0.0028*	0.0035*	0.0031*	0.0035*
4:30–5:00	0.0080*	0.0076*	0.0080*	0.0074*	0.0046*	0.0071*
5:00–5:30	0.0051*	0.0090*	0.0057*	0.0044*	0.0083*	0.0065*
5:30–6:00	0.0198	0.0117*	0.0141*	0.0089*	0.0092*	0.0127*
6:00–6:30	0.0126*	0.0147*	0.0136*	0.0113*	0.0144	0.0133*
6:30–7:00	0.0251	0.0149	0.0148	0.0158	0.0091*	0.0159*
7:00–7:30	0.0260	0.0122*	0.0223	0.0195	0.0209	0.0202
7:30–8:00	0.0253	0.0348	0.0280	0.0190	0.0317	0.0277*
8:00–8:30	0.0404*	0.0218	0.0295	0.0263	0.0273	0.0290*
8:30–9:00	0.0165	0.0304	0.0332	0.0143*	0.0162	0.0221
9:00–9:30	0.0213	0.0249	0.0239	0.0166	0.0386	0.0250
9:30–10:00	0.0142*	0.0165	0.0261	0.0276	0.0112*	0.0192
10:00–10:30	0.0187	0.0158	0.0182	0.0229	0.0137*	0.0179
10:30–11:00	0.0163	0.0191	0.0024	0.0190	0.0125*	0.0182
11:00–11:30	0.0182	0.0150	0.0188	0.0081*	0.0167	0.0153*
11:30–12:00	0.0189	0.0162	0.0164	0.0233	0.0127*	0.0175
12:00–12:30	0.0164	0.0199	0.0160	0.0263	0.0116*	0.0180
12:30–13:00	0.0166	0.0107*	0.0117*	0.0395	0.0153	0.0188
13:00–13:30	0.0211	0.0197	0.0179	0.0436	0.0169	0.0239
13:30–14:00	0.0298	0.0550*	0.0682*	0.0721*	0.1205*	0.0691*
14:00–14:30	0.0384*	0.0396*	0.0457*	0.0531*	0.0515*	0.0457*
14:30–15:00	0.0306	0.0437*	0.0526*	0.0332	0.0570*	0.0434*
15:00–15:30	0.0593*	0.0809*	0.0464*	0.0418*	0.0551*	0.0567*
15:30–16:00	0.0502*	0.0583*	0.0741*	0.0565*	0.0475*	0.0573*
16:00–16:30	0.0229	0.0462*	0.0421*	0.0359*	0.0464*	0.0387*
16:30–17:00	0.0341	0.0363*	0.0324	0.0341	0.0349	0.0343*
17:00–17:30	0.0532*	0.0312	0.0225	0.0320	0.0202	0.0318*
17:30–18:00	0.0250	0.0219	0.0221	0.0238	0.0202	0.0226
18:00–18:30	0.0231	0.0289	0.0256	0.0337	0.0167	0.0256
18:30–19:00	0.0169	0.0314	0.0198	0.0244	0.0175	0.0220
19:00–19:30	0.0224	0.0203	0.0210	0.0218	0.0095*	0.0190
19:30–20:00	0.0156	0.0195	0.0188	0.0131*	0.0112*	0.0156*
20:00–20:30	0.0152*	0.0144*	0.0182	0.0089*	0.0064*	0.0126*
20:30–21:00	0.0128	0.0136*	0.0093*	0.0063*	0.0051*	0.0094*
21:00–21:30	0.0126*	0.0129*	0.0138	0.0075*	0.0128*	0.0119*
21:30–22:00	0.0125*	0.0121*	0.0077*	0.0112*	0.0280	0.0143
22:00–22:30	0.0156	0.0095*	0.0113*	0.0110*	0.0088*	0.0112*
22:30–23:00	0.0130*	0.0041*	0.0106*	0.0063*	0.0200	0.0108*
23:00–23:30	0.0058*	0.0113*	0.0045*	0.0073*	0.0077*	0.0073*
23:30–0:00	0.0064*	0.0084*	0.0046*	0.0112*	0.0124*	0.0086*

Numbers represent $\bar{W}_j$, the proportion of daily realized variance in the 30-min period j. * indicates a significant difference from 1/48 at the 5% level.

2.3. Intraday seasonal multipliers

Andersen and Bollerslev (1997), using the same data, compare certain intraday ARCH model estimates with theoretical results and conclude that parameter estimates for ARCH models can suffer from a serious bias if the seasonal factor is not taken into account. They suggest filtering procedures that can eliminate the seasonal component found in high frequency financial data. Bollerslev and Ghysels (1996) propose another method to capture the repetitive seasonal variations in the volatility changes by allowing periodic varying coefficients in the conditional variance equation.

Taylor and Xu (1997) model the intraday seasonality by a set of multiplicative factors. They estimate seasonal multipliers after averaging sums of squared returns across similar time periods and a deseasonalized return series is calculated by dividing each return by its seasonal multiplier. We adopt a similar method to adjust for intraday volatility seasonality. To take account of day-of-the-week effects, we estimate 120 h multiplicative factors that average one over a complete week. A detailed description of this adjustment process is given in Chang and Taylor (1998).

There are 240, 480, 720, and 1440 seasonal multipliers, respectively, for 30, 15, 10 and 5-min intervals. Plots of the logarithms of the seasonal multipliers at 30-min intervals are given on Fig. 1. Results for the other frequencies are similar and are available upon request. A general pattern in the seasonal multipliers can be seen from Fig. 1. The multipliers pick up around GMT_{adj} 00:00–03:00 h as the Sydney, Tokyo, Hong Kong, and Singapore markets open and decline about GMT_{adj} 04:00 h corresponding to lunch time in the Asian markets. They bounce back near GMT_{adj} 08:00–09:00 h when the Asian markets overlap the European markets, and reach their peak around GMT_{adj} 13:00–14:00 h when the North American markets join in with the European markets. These multipliers decline thereafter until the Asian markets open again.

The patterns of seasonal multipliers vary across the days of the week as shown on Fig. 1. There is a sharp increase in the multipliers during the Asian trading hours on Monday but this pattern is not repeated in the European and American markets on

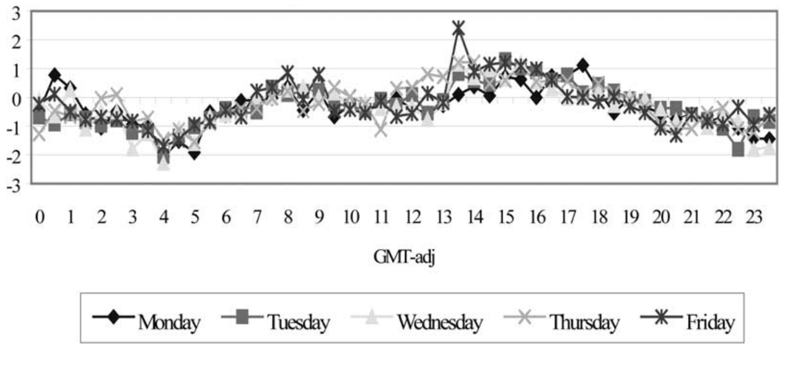

Fig. 1. DEM/$ 30-min log-scaled seasonal multipliers.

Monday. The pattern of the multipliers is similar on Tuesday with the peak of activity around 15:00 h GMT_{adj}. The activity on Wednesday is distinct in that the first peak is about 13:30 h GMT_{adj} in the European market and declines slowly before the second peak near 15:30 h GMT_{adj} is reached in the American market. It is easy to spot a spike on Friday at 13:30 h GMT_{adj} (US EST 08:30 h), which corresponds to the time of major US macroeconomic news releases noted by Ederington and Lee (1993, 1995). The multiplier is highest during the 30-min that includes these releases. These patterns highlight the intraday and day of the week effects of foreign exchange volatility.

After estimating seasonal multipliers for each interval, we divide each return by its own seasonal multiplier to obtain the deseasonalized returns from which the deseasonalized volatilities are calculated in Section 5. To examine the effect on the intraday periodic patterns of the volatility process after applying these seasonal multipliers, we plot the correlograms of the absolute return series, $|R_{t,j}|$, and the deseasonalized absolute return series, $|R_{t,j}|/S_{t,j}$, on Fig. 2 for 30-min returns. A clear periodic pattern can be seen for absolute returns. The autocorrelations reach a peak every 48, 30-min intervals which corresponds to a 1 day cycle. However, this periodic pattern is eliminated after applying the seasonal multipliers.

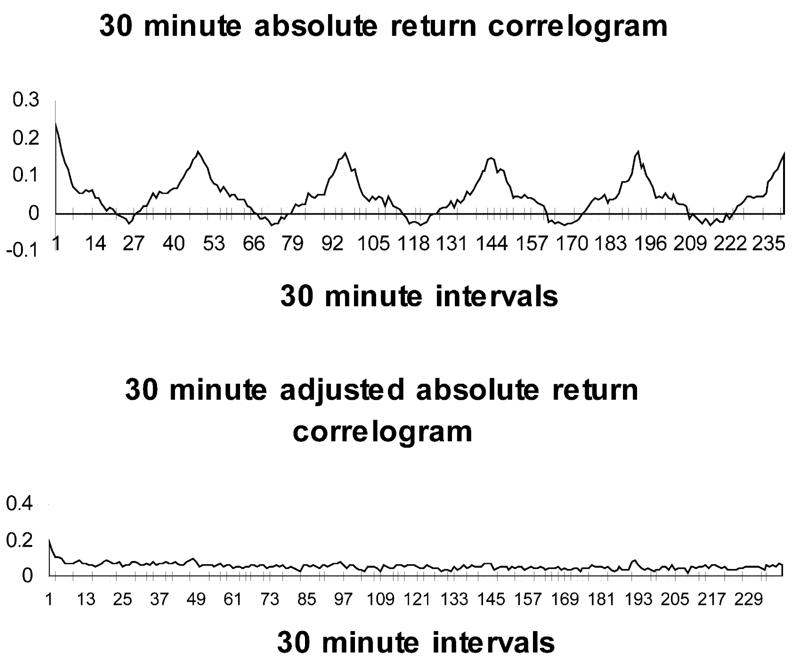

Fig. 2. DEM/$ 30 min absolute return and seasonality adjusted correlograms.

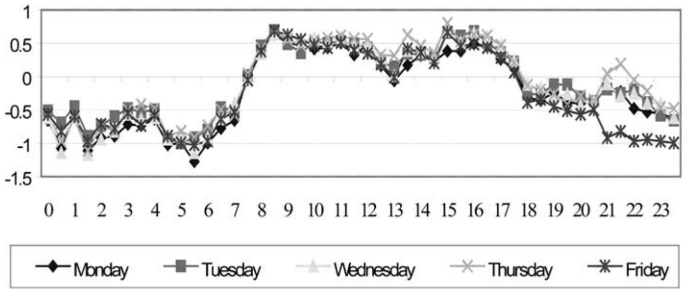

Fig. 3. Total news counts 30-min log-scaled seasonality.

3. Categories of information arrivals

The purpose of this paper is to examine the impact of news arrivals on intraday exchange rate volatility. This leads to the question of how we might measure news arrivals. Although the information content of news is difficult to quantify, we can construct a dummy variable proxy for news which is equal to 1 as the news occurs and 0 everywhere else. The Reuters news pages are very diverse and include not only economic but also political news around the world. Samples from the news pages are given in Appendix A. To enhance our understanding of the impact of major economic announcements, we also extract major economic news items from these headlines using different key words. A list of these key words is in Appendix B.

We divide the news into five groups according to their nature. First, we count the number of headlines reported by Reuters within a fixed interval. This is called the total news count variable. It can be seen from Fig. 3 that the total news counts have their own intraday seasonal pattern due to the changing presence of major financial markets. A news seasonal multiplier is calculated according to the formulae of Chang and Taylor (1998) with squared returns $r_{t,j}^2$ simply replaced by information counts $I_{t,j}$. A deseasonalized news variable ($I_{t,j}^*$) is calculated by dividing the news count by its news seasonal multiplier. We test the impact of total news arrivals with this adjustment for intraday news seasonality.

Second, we extract US scheduled macroeconomic news following Ederington and Lee (1993, 1995). Seventeen out of 18 news items are the same as described in their papers. The only exception is the unemployment data. We include weekly as well as monthly unemployment announcements in our analysis. Industrial production and the capacity utilization are reported together in the Reuters news page, so they are treated as one announcement. There are a few cases when these macroeconomic news announcements are not reported in the Reuters news pages[5] and they are not included in this news data. Third, we extract the counterpart of the German macroeconomic news using key words provided in Appendix B.

[5] There is no December 1992 budget deficit announcement and the industrial output and capacity use in March, April and May are not reported in the news pages.

Fourth, as noted by Kaen et al. (1997), information about German Bundesbank monetary policy has a significant impact on the German equity market, and market participants closely monitor the Bundesbank's security repurchase operations to forecast its monetary policies. A subset of news related to Bundesbank's monetary policy instruments was extracted to investigate its effect on DEM/$ volatility changes. Fifth, we examine the impact of news related to the US Federal Reserve's monetary policy instruments. The contents of the last two proxies include the German Bundesbank and US Federal Reserves' open market operations via customer or fixed date repurchase agreements, and the changes of German or US discount and/or Lombard rates. We extract these last four categories of news when they are announced or occurred and test the impact of these news arrivals after adjustment for intraday news seasonality.

Summary statistics for each group of news counts are presented in Table 3. Panel A shows the summary statistics of the total news variable after the news seasonality adjustment. There are on average 16, 8, 4, 3, and 1 total news items in hourly, 30, 15, 10 and 5-min intervals. The minimum number of total news items in all intervals is zero. The standard deviation and serial correlation of total news counts become smaller after the news seasonality adjustment. The first order serial correlation for hourly intervals after the news seasonality adjustment is 0.27.

Panels B and C contain summary statistics of the other four categories of news variables. The average numbers in each of these four groups are all less than 0.1. It can be seen from panel B that the average numbers of US macroeconomic news counts are similar to those for German macroeconomic news. Panel C shows that the average numbers of US Federal Reserve news items are higher than those for the German Bundesbank news.

4. ARCH methodology

We model the pervasive conditional heteroskedasticity of DEM/$ volatility using GARCH models and discuss the impact of news arrivals within this framework. A generalization of the GARCH model was estimated by incorporating news variables in the conditional variance equation. This specification involves returns $r_{t,j}$ with day index t and interval index j, seasonal return multipliers $\hat{s}^2_{t,j}$, seasonal news multipliers $\tilde{s}^2_{t,j}$, conditional variances $h_{t,j}$, deseasonalized conditional variances $h^*_{t,j}$, contemporaneous information counts $I_{t,j}$ and deseasonalized contemporaneous information counts $I^*_{t,j}$. The most general GARCH model that has been estimated is:

$$r_{t,j} = \ln(p_{t,j}) - \ln(p_{t,j-1}) = \lambda - \gamma\varepsilon_{t,j-1} + \varepsilon_{t,j}$$

$$r_{t,j}|\phi_{t,j-1} \sim D(0,\ h_{t,j})$$

$$h_{t,j} = \hat{s}^2_{t,j} \times h^*_{t,j}$$

Table 3
News series summary statistics

News types	Total news (seasonality adjusted)									
Intervals	Hourly	30 min	15 min	10 min	5 min					
Panel A: total news counts										
Mean	15.95	7.98	3.99	2.66	1.33					
S.D.	5.78	3.71	2.48	1.99	1.38					
Minimum	0	0	0	0	0					
Maximum	64	39	22	28	25					
$\rho(1)$	0.27	0.22	0.14	0.09	0.06					
$\rho(2)$	0.20	0.16	0.12	0.09	0.04					
$\rho(3)$	0.22	0.15	0.11	0.08	0.05					
	US macroeconomic News					German macroeconomic news				
Intervals	Hourly	30 min	15 min	10 min	5 min	Hourly	30 min	15 min	10 min	5 min
Panel B: US and German macroeconomic news										
Mean $\times$ 10	0.38	0.19	0.09	0.06	0.03	0.40	0.20	0.10	0.07	0.03
S.D.	0.23	0.17	0.12	0.09	0.06	0.23	0.15	0.11	0.09	0.06
Minimum	0	0	0	0	0	0	0	0	0	0
Maximum	3	3	3	3	3	4	3	2	2	2
$\rho(1)$	0.02	0.02	0.01	0.02	0.02	0.02	0.06	0.05	0.05	0.04
$\rho(2)$	0.08	−0.01	−0.00	−0.01	0.02	0.08	0.01	0.03	0.02	0.03
$\rho(3)$	−0.03	0.09	0.03	−0.00	0.00	0.02	0.02	0.01	0.03	0.01

Intervals	US Federal Reserve news: Hourly	30 min	15 min	10 min	5 min	German Bundesbank news: Hourly	30 min	15 min	10 min	5 min
Panel C: US Federal Reserve and German Bundesbank news										
Mean × 10	0.33	0.17	0.08	0.05	0.03	0.12	0.06	0.03	0.02	0.01
S.D.	0.18	0.13	0.09	0.08	0.05	0.11	0.08	0.05	0.04	0.03
Minimum	0	0	0	0	0	0	0	0	0	0
Maximum	2	2	2	2	2	1	1	1	1	1
$\rho(1)$	−0.03	−0.01	−0.00	−0.00	0.07	0.00	0.01	0.00	0.00	−0.00
$\rho(2)$	−0.03	−002	−0.00	−0.00	0.02	−0.01	−0.01	0.01	−0.00	−0.00
$\rho(3)$	−0.03	−0.02	−0.01	−0.01	−0.03	−0.01	−0.01	−0.00	−0.00	−0.00

$\rho(j)$ denotes jth order autocorrelation.

$$I_{t,j} = \hat{s}_{t,j}^2 \times I_{t,j}^*$$

$$h_{t,j}^* = c + \alpha \times \frac{r_{t,j-1}^2}{\hat{s}_{t,j-1}^2} + \beta \times h_{t,j-1}^* + \vartheta \times I_{t,j}^*$$

Here $D(0,\ h_{t,j})$ is the generalized error distribution with thickness parameter v, mean zero and variance $h_{t,j}$. When ϑ is equal to zero and the seasonal multipliers $\hat{s}_{t,j-1}^2$ are equal to 1, this specification simplifies to a GARCH(1,1) model. When $v = 2$ the conditional distributions are normal, whilst for $v < 2$ they have excess kurtosis and fat tails (Nelson, 1991). The term $I_{t,j}$ counts either total news or reports in one of the four categories mentioned in Section 3.

We use contemporaneous news proxies in the variance equation because this specification is based on the hypothesis of the conditional mixture model. The simplest version of the mixture model implies that $r_{t,j} = \sigma \times I_{t,j}^{1/2}$, where $U_{t,j}$ is N (0,1) and independent of $I_{t,j}$. Conditional on $I_{t,j}$, $r_{t,j}$ is normally distributed with mean zero and variance $\sigma^2 \times I_{t,j}$. Taylor (1994), following Clark (1973), Tauchen and Pitts (1983), describes an information counting model that assumes returns can be modeled by a stochastic number of intraperiod price revisions. If the intraperiod price revisions are independent of their number, then the conditional volatility at time t is proportional to the amount of price information at time t. Gallant et al. (1991) point out that the magnitude of past price changes will convey information about the magnitude of subsequent price changes whenever there is predictability in the rate of flow of new information to the market.

5. Results for ARCH models and the impact of information arrivals

We discuss the parameter estimates of ARCH models without incorporating news variables in Section 5.1. The impact of different categories of news is examined for normal and GED distributions, respectively, in Sections 5.2 and 5.3. Residual diagnostic tests for all the ARCH model specifications are discussed in Section 5.4.

5.1. ARCH models, without news variables

The results of maximum likelihood estimation of the GARCH models are summarized in Tables 4–8. Table 4 contains the parameter estimates of GARCH(1,1) models without news variables[6]. These models are used as benchmarks to compare with models using different categories of information proxies in the conditional variance equations. The GARCH-normal models are estimated at hourly, 30, 15, 10 and 5-min intervals, and the GARCH–GED models are estimated at hourly, 30 and 15-min intervals. The sums of the variance parameters, $\alpha + \beta$, are

[6] The constant terms in the mean equations are small and insignificantly different from zero, so they are omitted from the results in Tables.

Table 4
GARCH(1,1) parameter estimates without news variables

Parameter	Hourly	30 min	15 min	10 min	5 min
Panel A: normal distributions					
γ	0.0163	0.0726	0.0958	0.1104	0.1336
	(1.12)	(7.44)	(12.20)	(16.28)	(29.95)
α	0.0447	0.0348	0.0984	0.0979	0.0999
	(3.83)	(4.36)	(8.32)	(8.26)	(13.82)
β	0.9322	0.9533	0.8527	0.8586	0.8643
	(48.33)	(79.74)	(38.53)	(42.83)	(75.89)
$10^6 \times c$	0.0500	0.0134	0.0308	0.0198	0.0091
	(2.61)	(2.58)	(4.31)	(4.74)	(7.07)
v	2	2	2	2	2
	(0)	(0)	(0)	(0)	(0)
Max. $\ln(L)$	321 36.1	68 501.7	145 083.2	224 182.1	471 867.1
Std_residual Sk	0.0837	0.0562	0.0164	0.0089	0.0179
Std_residual Ku	4.9673	5.6075	5.4972	5.7224	5.8572
Std_resid $Q(12)$	19.92	19.56	22.44	38.93	17.48
Std_resid $Q_2(12)$	37.20	61.06	28.37	56.42	32.09
Panel B: GED distributions					
γ	0.0430	0.0896	0.1144		
	(3.54)	(8.14)	(17.25)		
α	0.0529	0.0543	0.1055		
	(5.07)	(4.86)	(4.97)		
β	0.9296	0.9359	0.8780		
	(59.91)	(66.01)	(26.64)		
$10^6 \times c$	0.0400	0.0135	0.0151		
	(2.66)	(2.78)	(1.82)		
v	1.1725	1.1231	1.1280		
	(41.71)	(52.14)	(58.82)		
Max. $\ln(L)$	32 383.0	69 096.8	146 180.2		
Std_residual Sk	0.0732	0.0670	0.0379		
Std_residual Ku	5.0858	5.8846	6.1289		
Std_resid $Q(12)$	27.18	26.48	38.50		
Std_resid $Q_2(12)$	38.73	46.09	54.21		

The numbers in parentheses are robust t-statistics calculated using the formulae in Bollerslev and Wooldridge (1992). Std_residual Sk and Ku are skewness and kurtosis of standardized residuals. Std_resid $Q(12)$ and $Q_2(12)$ are the respective Ljung and Box (1978) test statistics for no serial correlation up to lag 12 of standardized residuals. The numbers in parentheses are t-statistics calculated from numerical second derivatives.

persistence estimates that exceed 0.95 for normal distributions and are close to 0.99 when we estimate GARCH–GED. The GED thickness parameters are 1.17, 1.12 and 1.13, which suggests the underlying distribution is close to a double exponential distribution.

The maximum likelihoods show that the GED distribution is superior to the normal distribution for describing DEM/$ returns. The maximum log-likelihoods are much higher, typically by about 200, 500, and 1000, for GARCH–GED than for GARCH-normal at intervals of 1 h, 30 and 15 min. Comparing twice these numbers

Table 5
GARCH(1,1) parameter estimates assuming normal distributions

Parameter	Hourly	30 min	15 min	10 min	5 min
Panel A: with total news (seasonally adjusted)					
γ	0.0161	0.0728	0.0961	0.1104	0.1339
	(1.14)	(6.21)	(12.24)	(17.25)	(31.61)
α	0.0457	0.0373	0.0985	0.0989	0.1019
	(4.38)	(3.17)	(7.08)	(8.02)	(13.33)
β	0.9274	0.9473	0.8483	0.8562	0.8571
	(49.01)	(48.06)	(32.40)	(40.81)	(67.03)
$10^6 \times c$	0.0277	0.0096	0.0257	0.0187	0.0078
	(1.68)	(1.69)	(2.49)	(4.21)	(4.29)
v	2	2	2	2	2
	(0)	(0)	(0)	(0)	(0)
$10^6 \times \vartheta$	0.0020	0.0010	0.0020	0.0004	0.0011
	(1.55)	(0.99)	(1.39)	(1.23)	(2.80)
Max. ln(L)	32 140.1	68 506.7	145 092.4	224 187.6	471 900.4
Std_residual Sk	0.0985	0.0718	0.0282	0.0133	0.0295
Std_residual Ku	4.9176	5.6186	5.6155	5.7620	6.1593
Std_resid $Q(12)$	19.31	19.22	22.56	38.81	17.00
Std_resid $Q_2(12)$	37.59	56.12	25.70	55.23	26.99
Panel B: with US macroeconomic news					
γ	0.0168	0.0727	0.0955	0.1107	0.1340
	(1.26)	(6.10)	(10.13)	(14.78)	(29.04)
α	0.0449	0.0341	0.0100	0.0991	0.1005
	(4.76)	(4.22)	(7.23)	(7.90)	(12.87)
β	0.9311	0.9538	0.8492	0.8558	0.8630
	(57.17)	(77.96)	(33.91)	(40.27)	(68.35)
$10^6 \times c$	0.0463	0.0123	0.0313	0.0200	0.0091
	(2.72)	(2.37)	(4.01)	(4.57)	(6.49)
v	2	2	2	2	2
	(0)	(0)	(0)	(0)	(0)
$10^6 \times \vartheta$	0.4418	0.2947	0.4429	0.3495	0.2048
	(1.58)	(1.86)	(2.17)	(2.48)	(3.07)
Max. ln(L)	32 139.6	68 507.0	145 091.0	224 192.4	471 885.9
Std_residual Sk	0.0921	0.0610	0.0157	0.0127	0.0172
Std_residual Ku	4.9447	5.5981	5.5137	5.7367	5.8668
Std_resid $Q(12)$	19.64	19.11	22.01	38.07	17.14
Std_resid $Q_2(12)$	36.28	59.87	26.74	54.74	31.42
Panel C: with German macroeconomic news					
γ	0.0169	0.0729	0.0958	0.1104	0.1337
	(1.10)	(7.11)	(12.14)	(19.19)	(27.17)
α	0.0465	0.0352	0.0980	0.0979	0.0999
	(3.92)	(3.96)	(7.39)	(8.27)	(12.83)
β	0.9292	0.9528	0.8533	0.8586	0.8640
	(45.76)	(74.05)	(36.01)	(42.68)	(69.14)
$10^6 \times c$	0.0477	0.0129	0.0305	0.0198	0.0090
	(2.37)	(2.48)	(4.23)	(4.71)	(6.39)
v	2	2	2	2	2
	(0)	(0)	(0)	(0)	(0)
$10^6 \times \vartheta$	0.2370	0.0745	0.0515	0.0084	0.0322

Table 5 (*Continued*)

Parameter	Hourly	30 min	15 min	10 min	5 min
	(1.33)	(0.81)	(0.74)	(0.15)	(1.32)
Max. ln(L)	32 138.6	68 503.1	145 083.9	224 182.2	471 869.8
Std_residual Sk	0.0802	0.0568	0.0166	0.0089	0.0176
Std_residual Ku	4.9586	5.5975	5.4988	5.7229	5.8610
Std_resid $Q(12)$	20.25	19.65	22.44	38.93	17.47
Std_resid $Q_2(12)$	36.88	61.03	28.73	56.41	32.09
Panel D: with Federal Reserve monetary policy news					
γ	0.0163	0.0728	0.0958	0.1106	0.1336
	(1.18)	(7.24)	(11.38)	(16.80)	(29.09)
α	0.0451	0.0346	0.0974	0.0974	0.0998
	(4.40)	(4.10)	(8.61)	(6.87)	(16.23)
β	0.9313	0.9537	0.8550	0.8599	0.8644
	(52.81)	(75.87)	(42.06)	(34.97)	(84.73)
$10^6 \times c$	0.0495	0.0136	0.0304	0.0196	0.0090
	(2.79)	(2.64)	(5.21)	(3.86)	(7.78)
v	2	2	2	2	2
	(0)	(0)	(0)	(0)	(0)
$10^6 \times \vartheta$	0.1984	−0.1590	−0.2447	−0.1947	−0.0143
	(0.45)	(−0.81)	(−2.89)	(−2.02)	(−0.26)
Max. ln(L)	32 136.5	68 502.7	145 085.7	224 185.3	471 867.2
Std_residual Sk	0.0878	0.0521	0.0163	0.0088	0.0180
Std_residual Ku	4.9473	5.6286	5.4882	5.7154	5.8565
Std_resid $Q(12)$	16.66	19.46	22.52	38.99	17.49
Std_resid $Q_2(12)$	36.92	61.22	28.94	56.51	32.14
Panel E: with German Bundesbank monetary policy news					
γ	0.0166	0.0728	0.0967	0.1104	0.1337
	(1.27)	(6.79)	(15.14)	(16.13)	(30.65)
α	0.0469	0.0363	0.1001	0.1015	0.1001
	(4.62)	(4.07)	(9.41)	(9.11)	(12.91)
β	0.9282	0.9508	0.8486	0.8519	0.8631
	(53.54)	(68.75)	(42.34)	(44.16)	(68.25)
$10^6 \times c$	0.0513	0.0139	0.0316	0.0207	0.0091
	(2.77)	(2.31)	(4.81)	(5.02)	(6.46)
v	2	2	2	2	2
	(0)	(0)	(0)	(0)	(0)
$10^6 \times \vartheta$	0.7858	0.4874	1.1417	0.9754	0.4321
	(1.42)	(1.54)	(2.66)	(2.90)	(1.79)
Max. ln(L)	32 138.6	68 505.3	145 100.1	224 217.7	471 894.1
Std_residual Sk	0.0905	0.0624	0.0247	0.0080	0.0223
Std_residual Ku	4.9621	5.6028	5.4545	5.6313	5.8090
Std_resid $Q(12)$	19.47	18.91	22.71	39.27	17.35
Std_resid $Q_2(12)$	37.43	60.93	25.53	51.72	31.31

The numbers in parentheses are robust t-statistics calculated using the formulae in Bollerslev and Wooldridge (1992). Std_residual Sk and Ku are skewness and kurtosis of standardized residuals. Std_resid $Q(12)$ and $Q_2(12)$ are the respective Ljung and Box (1978) test statistics for no serial correlation up to lag 12 of standardized residuals.

Table 6
Summary of news parameter estimates assuming normal distributions

News types ($10^6 \times \vartheta$)	Hourly	30 min	15 min	10 min	5 min
Total news	0.0020	0.0010	0.0020	0.0004	0.0011*
	(1.55)	(0.99)	(1.39)	(1.23)	(2.80)
US macroeconomic news	0.4418	0.2947*	0.4429*	0.3495*	0.2048*
	(1.58)	(1.86)	(2.17)	(2.48)	(3.07)
German macroeconomic news	0.2370	0.0745	0.0515	0.0084	0.0322
	(1.33)	(0.81)	(0.74)	(0.15)	(1.32)
US Federal Reserve news	0.1984	−0.1590	−0.2447*	−0.1947*	−0.0143
	(0.45)	(−0.81)	(−2.89)	(−2.02)	(−0.26)
German Bundesbank news	0.7858	0.4874	1.1417*	0.9754*	0.4321*
	(1.42)	(1.54)	(2.66)	(2.90)	(1.79)

*, Indicates significant at the 5% level, two tail test.

with χ_1^2, the large increases of the log-likelihood indicate that a nonnormal conditional distribution is more suitable for the intraday DEM/$ exchange rate.

5.2. Impact of news variables assuming normal distributions

We examine the impact of news variables separately for conditional normal and GED distributions. We discuss the results for normal distributions first as hypothesis tests are then robust and subsequently results for GED distributions are discussed in Section 5.3. Following Bollerslev and Wooldridge (1992), parameter estimates under normal distributions are consistent and their standard errors are consistent if we calculate covariances as $A^{-1}BA^{-1}$, from the inverse hessian (A^{-1}) and the outer product matrix (B). We can also perform robust tests of the null hypothesis that a news variable parameter equals zero, that are not affected by mis-specification of the conditional distributions.

Results for the GARCH-normal specification with the five news variables are presented in Table 5. Panel A shows parameter estimates when total news is seasonally adjusted. The robust t-statistics for the news parameter are insignificant for hourly, 30, 15 and 10-min intervals, but are significant for 5-min intervals at the 5% level. Panel B contains parameter estimates when US macroeconomic news is used as the information proxy. We see that US macroeconomic news is significant for 30, 15, 10 and 5-min intervals at the 5% level. As the intervals become shorter, the impact of the news variables is more significant, as should be expected. However, we also find that the largest quantitative effects occur at 15-min intervals. These results are consistent with the findings of a two-stage adjustment process of public information arrivals (Fleming and Remolona, 1999). The persistence set off by US macroeconomic news is extended by traders' private information in a prolonged second stage. Panel C provides parameter estimates when German macroeconomic news is used as the information proxy. We see that the German macroeconomic news variable is insignificant at all frequencies at the 5% level.

Table 7
GARCH(1,1) parameter estimates assuming GED distributions

Parameter	Hourly	30 min	15 min
Panel A: with total news (seasonally adjusted)			
γ	0.0432	0.0944	0.0987
	(2.21)	(7.26)	(6.14)
α	0.0587	0.0686	0.1507
	(4.56)	(2.11)	(21.58)
β	0.9160	0.9002	0.7723
	(42.39)	(15.25)	(97.23)
$10^6 \times c$	0.0115	−0.0005	0.0043
	(0.80)	(−0.18)	(0.00)
v	1.1671	1.0899	1.0732
	(38.85)	(27.95)	(9.78)
$10^6 \times \vartheta$	0.0031	0.0053	0.0139
	(1.91)	(1.17)	(2.57)
Max. ln(L)	32 388.1	69 138.1	146 266.2
Std_residual Sk	0.1113	0.6154	0.5639
Std_residual Ku	5.0766	14.6857	19.2473
Std_resid $Q(12)$	26.57	25.79	0.49
Std_resid $Q_2(12)$	39.27	11.09	5.69
Panel B: with US macroeconomic news			
γ	0.0431	0.0896	0.1146
	(4.08)	(7.05)	(14.21)
α	0.0534	0.0558	0.1091
	(4.66)	(3.71)	(5.50)
β	0.9282	0.9331	0.8716
	(53.91)	(49.80)	(27.67)
$10^6 \times c$	0.0390	0.0138	0.0161
	(2.57)	(2.08)	(1.89)
v	1.1748	1.1243	1.1289
	(41.10)	(63.38)	(82.80)
$10^6 \times \vartheta$	0.3040	0.2736	0.5348
	(1.05)	(1.00)	(2.24)
Max. ln(L)	32 384.0	69 098.7	146 187.6
Std_residual Sk	0.0801	0.0710	0.0350
Std_residual Ku	5.0623	5.8902	6.1478
Std_resid $Q(12)$	26.78	25.85	38.13
Std_resid $Q_2(12)$	38.25	44.51	52.86
Panel C: with German macroeconomic news			
γ	0.0431	0.0897	0.1144
	(2.20)	(9.19)	(13.09)
α	0.0545	0.0549	0.1023
	(4.65)	(4.84)	(4.78)
β	0.9274	0.9355	0.8828
	(54.19)	(57.27)	(26.28)
$10^6 \times c$	0.0370	0.0123	0.0135
	(2.44)	(1.82)	(1.51)
v	1.1729	1.1224	1.1266
	(39.49)	(64.37)	(87.45)
$10^6 \times \vartheta$	0.2520	0.1190	0.1131

Table 7 (*Continued*)

Parameter	Hourly	30 min	15 min
	(1.44)	(1.34)	(1.99)
Max. ln(L)	32 384.7	69 098.4	146 182.6
Std_residual Sk	0.0688	0.0687	0.0423
Std_residual Ku	5.0723	5.8797	6.2074
Std_resid $Q(12)$	27.34	26.56	38.17
Std_resid $Q_2(12)$	38.59	46.75	54.06
Panel D: with Federal Reserve monetary policy news			
γ	0.0430	0.0898	0.1145
	(3.96)	(9.03)	(11.88)
α	0.0531	0.0527	0.1046
	(5.72)	(3.64)	(5.15)
β	0.9293	0.9381	0.8795
	(69.94)	(49.90)	(28.26)
$10^6 \times c$	0.0400	0.0131	0.0149
	(3.41)	(2.00)	(1.89)
v	1.1726	1.1236	1.1282
	(42.88)	(57.31)	(74.98)
$10^6 \times \vartheta$	0.0730	−0.1749	−0.1068
	(0.28)	(−1.28)	(−1.08)
Max. ln(L)	32 383.0	69 097.5	146 180.6
Std_residual Sk	0.0750	0.0625	0.0383
Std_residual Ku	5.0761	5.8904	6.1281
Std_resid $Q(12)$	27.07	26.56	38.61
Std_resid $Q_2(12)$	38.74	46.49	54.18
Panel E: with German Bundesbank monetary policy news			
γ	0.0432	0.0894	0.1146
	(4.95)	(7.44)	(88.21)
α	0.0554	0.0564	0.1046
	(4.37)	(3.29)	(4.85)
β	0.9256	0.9328	0.8785
	(49.96)	(44.31)	(27.20)
$10^6 \times c$	0.0410	0.0138	0.0147
	(2.49)	(2.02)	(1.78)
V	1.1731	1.1234	1.1289
	(36.95)	(65.67)	(67.97)
$10^6 \times \vartheta$	0.8430	0.6570	0.9578
	(1.53)	(1.40)	(2.74)
Max. ln(L)	32 384.6	69 099.5	146 187.8
Std_residual Sk	0.0815	0.0744	0.0500
Std_residual Ku	5.0750	5.8810	6.1083
Std_resid $Q(12)$	26.62	25.33	38.17
Std_resid $Q_2(12)$	39.26	46.86	52.12

The numbers in parentheses are t-statistics calculated from numerical second derivatives. Std_residual Sk and Ku are skewness and kurtosis of standardized residuals. Std_resid $Q(12)$ and $Q_2(12)$ are the respective Ljung and Box (1978) test statistics for no serial correlation up to lag 12 of standardized residuals.

Table 8
Summary of news parameter estimates assuming GED distributions

News types ($10^6 \times \vartheta$)	Hourly	30 min	15 min
Total news, seasonality adjusted	0.0031	0.0053	0.0139*
	(1.91)	(1.17)	(2.57)
US macroeconomic news	0.3040	0.2736	0.5348*
	(1.05)	(1.00)	(2.24)
German macroeconomic news	0.2520	0.1190	0.1131*
	(1.44)	(1.34)	(1.99)
US Federal reserve news	0.0730	−0.1749	−0.1068
	(0.28)	(−1.28)	(−1.08)
German Bundesbank news	0.8430	0.6570	0.9578*
	(1.53)	(1.40)	(2.74)

*, Indicates significant at the 5% level, two tail test.

Panel D shows parameter estimates when US Federal Reserve news is used as the information proxy. US Federal Reserve news has a negative and significant effect on the DEM/$ volatility at 15 and 10-min intervals at the 5% level but it is insignificant at the 5-min interval. A close look at Reuters' news file shows that there were no US discount rate changes because the Federal Reserve adopted a steady monetary policy during the sample period. News related to the US Federal Reserve seems to gradually confirm its steady monetary policy so perhaps this can explain the decrease in the DEM/$ volatility when these reports appeared on Reuters' screen.

Panel E contains parameter estimates when German Bundesbank news is used as the information proxy. We see that German Bundesbank news is significant for 15, 10 and 5-min intervals at the 5% level. The parameter estimates for this news variable are much larger than for the other news categories. They show that the impact of German Bundesbank news on the DEM/$ volatility is the largest because the focus of the foreign exchange market is on the Deutsche Bundesbank and its interest rate policy during the sample period. We also find that the largest quantitative effects occur at 15-min intervals. This indicates that volatility was increased by traders' private information in a prolonged second stage adjustment to German Bundesbank news.

Parameter estimates for the news variables and their robust t-statistics are summarized in Table 6. We see that total news has a statistical significant impact on volatility at 5-min intervals, but the parameter estimates of the news variable are much smaller than those of the German Bundesbank news, US macroeconomic and German macroeconomic news. This indicates that the quantitative impact of the total news counts on DEM/$ volatility are less than these news categories and it is essential to extract major economic news items from these headlines to evaluate their economic importance during the sample period.

5.3. Impact of news variables assuming GED distributions

The impact of the news variables when returns are modelled by conditional GED distributions is presented in Table 7. Panel A shows GARCH–GED parameter estimates when total news is seasonally adjusted. The t-statistics, calculated using standard errors derived from numerical second derivatives of the log-likelihood function, are significant for 15-min intervals at the 5% level. Results for the US macroeconomic news as the information proxy are in Panel B. We see that US macroeconomic news is also significant in 15-min intervals at the 5% level.

Estimates of t-statistics for the other three categories of news are provided in Panels C–E. We observe that German macroeconomic news has a significant impact in 15-min intervals at the 5% level. The US Federal Reserve news has insignificant effects in all intervals at the 5% level. News related to the monetary policies of the German Bundesbank has a significant impact for 15-min intervals at the 5% level. Similar to the results in Section 5.2, we find that the largest quantitative effects occur at 15-min intervals for US macroeconomic news and German Bundesbank news.

The results for news arrivals assuming returns have conditional GED distributions support some of the effects found by assuming normal distributions. The reason why some GED t-statistics are more significant than robust normal t-statistics is that the relevant news parameter estimates under GED distributions are larger, and their standard errors are smaller than those of the normal cases. This could be the result of a better description of the data by the GED distribution so that the news parameter estimates are more efficient.

5.4. Residual diagnostic tests and statistics

To assess the specification of our GARCH (1,1) models, we obtain time series of standardized residuals, $z_{t,j} = r_{t,j}/h_{t,j}^{1/2}$. If the GARCH model is correctly specified, we would expect the $z_{t,j}$ to be close to having an i.i.d. distribution. Summary statistics of the standardized residuals are presented in Tables 4, 5 and 7.

The results assuming normal distributions without news variables are provided in Panel A of Table 4. We see that the small autocorrelations of $z_{t,j}$ are of a similar magnitude to those of $r_{t,j}$ as shown by the Ljung–Box Q-statistics. The autocorrelations of $z_{t,j}^2$ are much smaller than those of $r_{t,j}^2$, although some deviations from the i.i.d. assumption are indicated by the Ljung–Box test statistics. These results are similar to those obtained by Andersen and Bollerslev (1997), who examine the specification of GARCH(1,1) models for high frequency exchange rates and find there are some short-run dynamics not captured by this model. The results assuming normal distributions with news variables are similar to those in Panel A of Table 4.

Summary statistics of the standardized residuals of the GARCH–GED model without news variables are presented in Panel B of Table 4. The skewness is 0.07 for the hourly data and is sensitive to extreme outliers. We find the kurtosis for hourly intervals is 5.08 which is smaller than the value for the GED distribution with thickness parameter one (kurtosis = 6), but it is slightly higher when we estimate the models from 15-min intervals. The autocorrelations of $z_{t,j}^2$ again show some deviations from the i.i.d. assumption.

Histograms of the standardized residuals show a sharp peak near zero and they become more pronounced when we estimate at high frequencies. Given that the standardized residuals have an obvious peak at the origin, a mixed discrete and GED distribution might fit the data more effectively.

6. Conclusions

The purpose of this paper is to improve our understanding of the relationship between news arrivals and intraday exchange rate volatility. The relevance of the sample period stems from the fact that European currency markets were in turmoil during this period. Therefore, our paper provides important documentation of the relationship between public information arrivals and exchange rate volatility during the 1992–1993 currency crisis. Our analysis is closely related to that of Berry and Howe (1994), Mitchell and Mulherin (1994). We extend their studies by considering the impact of public information on the exchange rate market. Further, we put events into categories by countries and types of news, and discuss their individual impact on volatility. ARCH models show that total headline news counts have a significant impact on exchange rate volatility at 5-min intervals. However, including the total news counts in the variance equation only changed the other parameters of the GARCH model by small amounts. This indicates that total news counts alone can not explain the volatility clustering of DEM/$ intraday exchange rates. This is consistent with the results of Melvin and Yin (2000). The total news counts, although it measures some less relevant reports, is the most comprehensive news variable available. The results show that the quantitative impacts of the total news counts are less than those of US and German economic news; therefore, it is essential to extract major economic news items from these headlines to evaluate their individual economic importance.

It has been shown that both US and German macroeconomic news also have a significant impact on DEM/$ volatility at high frequencies and this can be compared with the related studies of Ederington and Lee (1993, 1995) that investigate volatility and the timing of macroeconomic announcements. Our results suggest that DEM/$ volatility has a symmetric response to macroeconomic announcements from the US and Germany. The impact of the monetary policy news of the German Bundesbank and the US Federal Reserve are different during the sample period. It is seen that German Bundesbank news is significant for 15, 10 and 5-min intervals at the 5% level and its parameter estimates are much larger than those of the other news categories. Thus, the economic impact on the DEM/$ volatility of German Bundesbank news is the largest which indicates that the focus of the exchange rate market was on the monetary policies of the German Bundesbank during the sample period.

There is an interesting question of market efficiency related to the times of information arrival. Though our sample frequencies do not allow us to investigate the instantaneous price reactions to public information, we find that the largest quantitative effects of the German Bundesbank monetary policy news and US macroeconomic news occur at 15-min intervals. These results are consistent with the findings of a two-stage adjustment process of public information arrivals (Fleming and Remolona, 1999). The persistence of intraday exchange rate volatility set off by public information is extended by traders' private information about 15 min later.

US Federal Reserve news has a negative and significant effect on the DEM/$ volatility at 15 and 10-min intervals. There were news reports that the Federal Reserve adopted a steady monetary policy during the sample period. News related to the US Federal Reserve seems to gradually confirm its steady monetary policy so that the DEM/$ volatility decreased when these reports appeared on Reuters' screen. It would be interesting to compare the impact of Federal Reserve news over different sample periods.

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Appendix A

Samples of the total news from Reuters News
1992-10-01 15:48:48 'DOLLAR RALLIES FROM LOWS DESPITE DISMAL US DATA'
1992-10-01 15:49:16 'ECU BONDS DRIFT SLIGHTLY HIGHER BUT SENTIMENT WEAK'
1992-10-01 15:49:36 'KAZAKHSTAN GRAIN HARVEST REACHES 25 MLN TONNE MARK'
1992-10-01 15:54:30 'CZECH PARLIAMENT REJECTS DRAFT ON FEDERATION SPLIT'
1992-10-01 15:57:06 'MAJOR CALLS FOR END TO WAR OF WORDS WITH GERMANY'
1992-10-01 16:01:28 'US SENATE BACKS BUSH ON CHINA TRADE SANCTIONS VETO'
1992-10-01 16:03:06 'EC TRIES TO UNDERSTAND MONEY FLOWS THAT HIT ERM'
1992-10-01 16:05:12 'US TREASURIES SHARPLY HIGHER MIDDAY AFTER DATA'

Samples of the US macroeconomic news from Reuters News
1992-10-16 12:30:26 'US AUG TRADE DEFICIT $9.00 BILLION'
1992-11-18 13:30:48 'US SEPT TRADE DEFICIT $8.31 BILLION'
1992-12-17 13:31:18 'US OCT. TRADE DEFICIT $7.03 BILLION'
1993-01-15 13:32:04 'US NOV TRADE DEFICIT $7.59 BILLION'
1993-02-18 13:32:52 'US DEC TRADE DEFICIT $6.95 BILLION'
1993-03-18 13:32:38 'US JAN TRADE DEFICIT $7.30 BILLION'
1993-04-16 12:31:00 'US FEB TRADE DEFICIT $7.20 BILLION'
1993-05-19 12:31:32 'US MARCH TRADE DEFICIT $10.21 BILLION'

Samples of the German macroeconomic news from Reuters News

1993-07-29 08:14:26 'W.GERMAN JUNE IMPORT PRICES RISE 0.3 PCT'
1993-08-04 10:45:42 'W.GERMAN JUNE INDUSTRIAL ORDERS FALL 1.6 PCT'
1993-08-06 08:07:52 'W.GERMAN JULY ADJUSTED UNEMPLOYMENT RISES'
1993-08-06 08:08:30 'E.GERMAN JULY UNADJUSTED UNEMPLOYMENT RISES'
1993-08-10 11:55:32 'E.GERMAN JULY COST OF LIVING UNCHANGED FROM JUNE'
1993-08-11 12:04:40 'W.GERMAN JUNE RETAIL SALES FALL REAL 2.8 PCT'
1993-08-12 06:36:56 'W.GERMAN JULY WHOLESALE PRICES FALL 0.2 PCT'
1993-08-20 06:37:02 'W.GERMAN JULY PRODUCER PRICES RISE 0.1 PCT'

Samples of the US Federal Reserve news from Reuters News

1993-09-22 15:35:18 'FED ADDS RESERVES WITH OVERNIGHT SYSTEM RPS'
1993-09-23 15:36:20 'FED ADDS RESERVES VIA 4-DAY SYSTEM RPS'
1993-09-24 15:35:32 'FED ADDS RESERVES WITH 6-DAY SYSTEM RPS'
1993-09-27 15:38:54 'FED ADDS RESERVES VIA $1.5 BLN CUSTOMER RPS'
1993-09-28 15:44:04 'FED ADDS TEMPORARY RESERVES VIA 2-DAY SYSTEM RPS'
1993-09-29 15:42:04 'FED ADDS RESERVES VIA OVERNIGHT SYSTEM RPS'
1993-09-30 15:14:30 'FED ADDS TEMPORARY RESERVES VIA OVERNIGHT RPS'
1992-10-02 15:49:06 'FED REFRAINS FROM RESERVES ADD, NO EASING SEEN'

Samples of the German Bundesbank news from Reuters News

1992-10-21 09:04:18 'LOWEST RATE ON BUBA REPO FALLS TO 8.75 PCT'
1993-01-27 08:56:58 'BUBA REPO ADDS 3.7 BLN MARKS, LOWEST RATE 8.58 PCT'
1993-02-03 09:12:18 'BUBA REPO ADDS 1.2 BLN MARKS, LOWEST RATE 8.57 PCT'
1993-02-17 09:11:52 'BUBA ADDS FUNDS,LOWEST REPO RATE SLIPS TO 8.49 PCT'
1993-03-05 08:22:24 'BUBA CUTS REPO RATE TO 8.25 FROM 8.49 PCT'
1993-04-14 07:47:58 'BUBA REPO ADDS 6.7 BLN MARKS, LOWEST RATE 8.11 PCT'
1993-04-21 07:49:54 'LOWEST RATE ON BUBA REPO FALLS TO 8.09 PCT VS. 8.11'
1993-04-28 07:58:34 'BUBA LOWEST REPO RATE CUT TO 7.75 PCT,DRAINS FUNDS'

Appendix B

Key words for US macroeconomic news:

'US JOBLESS CLAIMS'
'US BUDGET DEFICIT'
'US BUSINESS INVENTORIES'
'US CONSTRUCTION SPENDING'
'US CONSUMER PRICES'
'US DURABLE GOODS ORDERS'
'US FACTORY ORDERS'
'US REAL GDP'

'US HOUSING STARTS'
'US INDUSTRIAL OUTPUT, CAPACITY USE'
'US JOBLESS RATE'
'US LEADING INDICATORS'
'US PERSONAL INCOME'
'US PRODUCER PRICE INDEX'
'US PURCHASING MANAGERS'INDEX'
'US RETAIL SALES'
'US SINGLE FAMILY HOME SALES'
'US TRADE DEFICIT'

Key words for German macroeconomic news:
'GERMAN WHOLE SALE/TURNOVER'
'GERMAN INDUSTRIAL OUTPUT/PRODUCTION/ORDER'
'GERMAN IMPORT/PRODUCER/WHOLESALE/CONSUMER PRICE'
'GERMAN JOBLESS/UNEMPLOYMENT'
'GERMAN CURRENT/TRADE SURPLUS'
'GERMAN RETAIL SALES/TURNOVER'
'GERMAN COST OF LIVING'
'GERMAN ENGINEERING ORDER'
'GERMAN M3'
'GERMAN GDP/GNP'
'GERMAN BUSINESS INSOLVENCIES'
'GERMAN INFLATION'

Key words for US Federal Reserve news:
'FED ADDS RESERVES'
'FED REFRAINS FROM MONEY-MARKET ACTION'

Key words for German Bundesbank news:
'BUBA REPO'
'BUNDESBANK REPO RATE'
'BUNDESBANK CUTS LOMBARD/DISCOUNT RATE'
'BUNDESBANK LEAVES INTEREST RATES UNCHANGED'

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