A Survey of Announcement Effects on Foreign Exchange Volatility and Jumps

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This article reviews, evaluates, and links research that studies foreign exchange volatility reaction to macro announcements. Scheduled and unscheduled news typically raises volatility for about an hour and often causes price discontinuities or jumps. News contributes substantially to volatility but other factors contribute even more to periodic volatility. The same types of news that affect returns—payrolls, trade balance, and interest rate shocks—are also the most likely to affect volatility, and U.S. news tends to produce more volatility than foreign news. Recent research has linked news to volatility through the former’s effect on order flow. Empirical research has confirmed the predictions of microstructure theory on how volatility might depend on a number of factors: the precision of the information in the news, the state of the business cycle, and the heterogeneity of traders’ beliefs. (JEL F31, E01, E44)


Researchers have long sought to understand how announcements of various sorts affect foreign exchange volatility, which is the magnitude of changes in foreign exchange rates. Unfortunately, such studies are frequently disconnected from each other, making it difficult for casual observers to see the big picture. To remedy this situation, this paper surveys and draws together the literature on announcements and foreign exchange volatility. 1

The literature on announcements and foreign exchange volatility is part of a larger literature that seeks to characterize patterns in conditional variance or conditional standard deviations (SDs). People and firms do not like volatile asset prices because they are risk averse; loss of wealth puts their desired consumption at risk. Similarly, traders must quantify the volatility of their positions because excessive losses put their jobs at risk. Understanding and estimating asset price volatility is therefore important for asset pricing, portfolio allocation, and risk management.

Asset price volatility can change for a variety of reasons: the opening or closing of markets, a changing rate of news arrival, or a change in the rate of how agents act on information. Together, these factors produce three prominent characteristics in foreign exchange volatility: (i) It tends to be autocorrelated; (ii) it is periodic, displaying intraday and intraweek patterns; and (iii) it includes discontinuities (jumps) in prices.

Characterizing asset price volatility is an important goal for financial economists. Scheduled macroeconomic announcements are useful natural experiments through which to study how the release of public information affects prices and volatility. Because survey expectations permit researchers to measure the surprise component...
of an announcement, researchers can distinguish the reaction of volatility to the magnitude of surprises from the reaction of volatility to the existence of the announcement itself.

Prior to the formal study of announcement effects on volatility, researchers found that volatility is autocorrelated and displays intraday and intraweek patterns. In addition, many regularly scheduled announcements—especially those that affected returns—also influenced volatility. Researchers sought to distinguish patterns caused by market opening/closing from those caused by regular macro announcements. Although Ederington and Lee (1993) argue that announcements account for most intraday and intraweek volatility patterns, Andersen and Bollerslev (1998) demur; they stress that it is important to jointly model the contributions of announcements, other intraday patterns, and the persistent component of volatility.

The study of announcements and volatility also has direct implications for policy. For example, some policy analysts have proposed taxing foreign exchange transactions to reduce allegedly meaningless churning that creates “excess” volatility. Melvin and Yin (2000), however, establish a strong link between news arrival and volatility, which argues against proposals to reduce trading volume through regulation.

Much of the literature on volatility patterns and news is only loosely linked to microstructure theory; it seeks mainly to characterize which announcements are important influences on volatility and how long the effects last. At times, however, microstructure theory has influenced the study of announcement effects on volatility, volume, and spreads. For example, microstructure theory motivates the study of how market conditions—heterogeneity of interpretation or the presence of conflicting information or the state of the business cycle, or the quality of information—influence reactions to announcements (Baillie and Bollerslev, 1991, and Laakkonen and Lanne, 2009). More recently, researchers have considered the relative importance of public and private information releases in creating price volatility through order flow (Cai et al., 2001; Evans, 2002; Evans and Lyons, 2005).

This survey considers the impact of announcements on price discontinuities (jumps) because jumps are defined by their magnitude and have implications for volatility forecasting. Specifically, Neely (1999) and Andersen, Bollerslev, and Diebold (2007) show that removing jumps from current and lagged volatility estimates improves the accuracy of volatility forecasts.

The next section begins with a discussion of the methodological considerations involved in studying the effect of announcements on volatility. This is followed by a review of the major areas of research on the effect of announcements on foreign exchange market volatility. The final section includes a discussion of the results and conclusions.2

METHODS OF STUDYING ANNOUNCEMENT EFFECTS ON FOREIGN EXCHANGE VOLATILITY

Methodology

Two methodological questions arise in the study of the effects of announcements on foreign exchange volatility: How should volatility be measured, and what information about announcements influences volatility? Researchers have used three measures of volatility to study announcement effects: implied volatility, which is an estimate of future volatility derived from option prices; high-frequency squared returns, a nonparametric method that Andersen and Bollerslev (1998) later formalized as realized volatility; and volatility estimated parametrically by some variant of generalized autoregressive conditionally heteroskedastic (GARCH) models (Engle, 1982, and Bollerslev, 1986).3

Volatility measures respond differently to macro announcements because they approach

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2 Neely and Dey (2010) describe the most commonly studied U.S. announcements.
3 Neely (2005) discusses the measurement and uses of implied volatility estimated from options prices. Engle (1982) developed the autoregressive conditionally heteroskedastic (ARCH) model that Bollerslev (1986) extended to the GARCH formulation. GARCH models usefully account for the time-varying volatility and fat-tailed distributions of daily and intraday financial returns.
volatility in different ways. Implied volatility, for instance, approximates average volatility until the expiry of the option, which could be in weeks or months. Therefore, it is strongly forward looking and often insensitive to short-lived volatility effects from macro announcements. Likewise, GARCH models fit to daily data predict daily volatility through essentially autoregressive processes, but such models cannot estimate intraday effects. In contrast to implied volatility or daily GARCH estimates, high-frequency data—which can be used with parametric models such as GARCH—are well suited to measuring short-lived, intraday effects.

The second issue is what type of information about announcements influences volatility. A scheduled announcement itself—regardless of content—could be expected to change volatility either before or after the announcement. In addition, surprising information in the announcement might influence volatility by precipitating additional trading from revised expectations. In practice, researchers have used both announcement indicators and surprises, sometimes finding different effects.

An announcement is “surprising” to the extent that it deviates from market expectations. To construct announcement surprises, researchers generally use the median response from the Money Market Services (MMS) survey to estimate the expected announcement. Each Friday, MMS surveys 40 (formerly 30) money managers on their expectations of forthcoming economic releases.4 Cornell (1982) and Engel and Frankel (1984) first used these survey data in the literature on announcement effects in the foreign exchange market, though other researchers (e.g., Grossman, 1981) had used them in other contexts. Grossman (1981), Engel and Frankel (1984), Pearce and Roley (1985), and McQueen and Roley (1993) show that the MMS survey data estimate news announcements in an approximately unbiased and informationally efficient fashion, outperforming time-series models.5

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

$$S_j^t = \frac{R_j^t - E_j^t}{\hat{\sigma}_j}$$

where $R_j^t$ is the realization of announcement $j$ on day $t$, $E_j^t$ is the MMS market expectation, and $\hat{\sigma}_j$ is the estimated SD of the series of the differences.6 Thus, announcement surprises are close to mean zero and have a unit SD.

**THE LITERATURE ON ANNOUNCEMENTS AND FOREIGN EXCHANGE VOLATILITY**

*Early Study of Volatility Patterns*

The earliest studies of announcement effects on the foreign exchange market considered only the reaction of prices/returns, but researchers added focus on volatility in the 1990s. Early studies of volatility patterns by Engle, Ito, and Lin (1990) and Harvey and Huang (1991) motivated this work, although the latter paper did not explicitly incorporate macro announcements.

Harvey and Huang (1991) discover an intraday U-shaped volatility pattern in hourly foreign exchange returns as well as intraweek effects. Volatility is higher on Thursday and Friday but

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4 The number of survey participants and the dates of the survey have changed over time. Hakko and Pearce (1985) report that MMS surveyed about 60 money market participants during that era and that they conducted the surveys on both Tuesdays and Thursdays before February 8, 1980, and on Tuesdays after that date.

5 Although the MMS survey expectations exhibit fairly good properties compared with alternatives, they still surely measure market expectations with some error, both because they are at least a couple days old and because they reflect the views of a small group of money managers. More subtly, any macroeconomic release will surely contain some error about the true state of the economy because it is estimated with finite resources and limited information. Therefore, the macroeconomic surprise will be estimated with error and this error will generally attenuate the estimated market response toward zero. Rigobon and Sack (2008) discuss two methods to compensate for this error. Bartolini, Goldberg, and Sacarny (2008) discuss the application of this methodology.

6 In a personal communication, Mike McCracken raises the interesting question of whether it would be better to normalize with the conditional SD.
volatility on Monday is no different from volatility on Tuesday. The authors speculate that important news announcements at the end of the week raise volatility on Thursday and Friday. Finally, volatility is highest during the traded currency’s own domestic business hours, particularly so for non-USD (U.S. dollar) cross rates. For example, USD volatilities peak during U.S. trading hours, implying the potential importance of U.S. macroeconomic announcements (Ito and Roley, 1987).

Engle, Ito, and Lin (1990) extend this research in intraday volatility patterns by introducing the concepts of heat waves and meteor showers in the foreign exchange market. Heat waves refer to the idea that volatility is geographically determined—that is, a heat wave might raise volatility in New York on Monday and Tuesday but not in London on Tuesday morning. Heat waves might occur if most or all important news that affects volatility occurs during a particular country’s business day and there is little price discovery when that country’s markets are closed. In contrast, meteor showers refer to the tendency of volatility to spill over from market to market, from Asian to European to North American markets, for example. Therefore, meteor showers imply volatility clusters in time, not by geography. Using a GARCH model with intraday data, Engle, Ito, and Lin (1990) find that the meteor shower hypothesis better characterizes foreign exchange volatility engendered by balance of trade announcements.  

Motivated by the microstructure theory of Epps and Epps (1976) and Tauchen and Pitts (1983), Hogan and Melvin (1994) follow up on the meteor shower/heat wave literature by exploring the role of heterogeneous expectations in volatility persistence across markets. Using the SD of MMS responses to measure heterogeneity of market expectations in a four-observations-per-day GARCH model, Hogan and Melvin (1994) find support for the idea that heterogeneous expectations do increase volatility persistence in the wake of a U.S. trade balance announcement. In retrospect, it seems unsurprising that meteor showers should predominate over heat waves in a world of global trading and a high degree of autocorrelated common shocks across countries: News tends to cluster in time and will surely affect volatility across the globe.

Early Research on Announcements and Volatility

Harvey and Huang (1991) and the meteor shower/heat wave literature found intraday and intraweek patterns that indicated that macro announcements were potentially important sources of volatility. Later studies extended this research by directly studying the effect of announcements on various measures of foreign exchange volatility.

In the late 1980s and early 1990s, U.S. trade deficit news was considered very important, especially for the USD/JPY (Japanese yen) exchange rate. Two of the earliest papers examine volatility responses to these releases. Madura and Tucker (1992) analyze the effect of trade balance surprises on the change in average implied SDs (volatilities) of currency options from the day before the announcement to the day of the announcement. They argue that studying implied volatility permits researchers to observe how announcements change the market’s (long-run) ex-ante volatility forecast. Although unexpected news—good or bad—increases implied volatilities, the announcement itself tends to reduce them. This probably reflects the fact that implied volatilities look forward over several months. While announcements generally increase volatility over the very short term, resolving the uncertainty associated with the announcement should reduce expected volatility over longer horizons.

Using a bivariate GARCH model to study spot and futures market responses to U.S. trade deficit announcements, Sultan (1994) finds two types of asymmetry in daily volatility responses: The USD/JPY is much more responsive to trade

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7 The appendix describes the key features of the papers studying announcement effects on volatility.

8 Curiously, Hogan and Melvin (1994) find that news has no impact on conditional volatility. This is almost certainly due to a misspecification; the authors specify conditional volatility as a function of signed news surprises rather than absolute news surprises.
deficit news than other exchange rates, and larger-than-expected U.S. trade deficits provoke much stronger volatility responses than smaller-than-expected ones, presumably because larger trade deficits are much more likely to provoke a policy response than smaller deficits.

In contrast to the work with implied volatility and daily GARCH modeling, Ederington and Lee (1993, 1994) investigate how U.S. macroeconomic release indicators affect very short-run volatility: absolute 5-minute USD/DEM (German deutsche mark) and USD/JPY returns, respectively. The merchandise trade deficit, employment report, producer price index (PPI), durable goods orders, gross national product (GNP), and retail sales all affect USD/DEM volatility significantly. Volatility is not particularly high at the opening of the market (8:20 a.m. ET) but increases 10 minutes later at 8:30 a.m., which is the time of many major announcements. It remains very high for 15 minutes and higher than normal for several hours following a news release. After controlling for announcement effects, the authors find that average volatility is flat over both the trading day and week—that is, news “mainly” explains both intraday and weekly patterns. Using 10-second data, Ederington and Lee (1995) observe high USD/DEM futures volatility immediately preceding a news announcement but find no evidence of information leakage. Volatility might anticipate news surprises.

**Decomposing Announcements and Periodic Volatility Patterns**

The very early literature on announcements and volatility noted the periodicity in volatility and speculated that announcements might be responsible. The work of Ederington and Lee (1993, 1994, and 1995) illustrated the importance of announcements for volatility and considered whether there was any residual, unexplained periodicity: “We find these [macro] announcements are responsible for most of the observed time-of-day and day-of-the-week volatility patterns in these [foreign exchange] markets” (Ederington and Lee, 1993, p. 1161).

Because announcements and periodicity are correlated, however, one must jointly model them to consistently estimate and compare their impact (Payne, 1996, and Andersen and Bollerslev, 1998). In particular, Andersen and Bollerslev (1998) use 5-minute USD/DEM currency returns to integrate prior research on daily volatility persistence, intraday and intraweek periodicity, and announcement effects. They affirm the importance of macro releases as addressed by Ederington and Lee (1993), but argue that these are secondary to the intraday pattern; periodic patterns and autoregressive volatility forecasts explain more of intraday and daily volatility than do announcements.

Presaging the literature on the effect of announcements on order flow, Andersen and Bollerslev (1998) conjecture that the intraday volatility pattern alters daily trading patterns. Further, they find that—after accounting for the intraday volatility pattern—including ARCH terms significantly improves forecasting power, even in a high-frequency volatility process. Real U.S. announcements—employment, gross domestic product (GDP), trade balance, and durable goods orders—are the most influential U.S. announcements in explaining volatility movements, while monetary policy news is most significant among German announcements. This finding is consistent with the conventional wisdom that the Bundesbank was relatively more concerned with monetary measures than the Federal Reserve.

The debate on the relative importance of pure periodicity versus announcement effects continued after publication of the paper by Andersen and Bollerslev (1998). To compare periodicity to announcement effects on foreign exchange volatility, Han, Kling, and Sell (1999) and Ederington and Lee (2001) both examine USD futures data, finding similar results but interpreting them differently. Using high-frequency futures data for four currencies from 1990 to 1997, Han, Kling, and Sell (1999) show that the DEM and JPY exhibit strong day-of-the-week volatility effects, even after controlling for indicators of 18 U.S. announcements. These authors speculate that differences in their testing procedures—testing

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9 Leng (1996) notes that major announcements have longer-lived effects on volatility than minor announcements.

10 Andersen and Bollerslev (1998) argue that the intraday volatility pattern obscures ARCH effects in intraday data.
by interval, rather than over pooled intervals—might account for the disparity in their conclusions with those of Ederington and Lee (1993). Ederington and Lee (2001) compare the power of seasonal effects, macro announcement indicators, and past volatility to predict volatility in 10-minute futures data on the DEM/USD from July 1989 through May 1993. Confirming their 1993 research but disputing the inference of Andersen and Bollerslev (1998), Ederington and Lee (2001) argue that macro announcements create most of the time-of-day and day-of-week effects and greatly reduce persistence in ARCH models. Unscheduled announcements create volatility that persists longer than that of scheduled announcements.

The appearance of contradictory results is at least partly due to a difference in emphasis: Ederington and Lee (2001) argue that announcements are more important than day-of-the-week effects, but Han, Kling, and Sell (1999) take the null hypothesis to be no day-of-the-week effects after controlling for announcements. The use of futures data by both studies, however, is likely to bias the results in favor of the importance of announcements, as the futures markets are open for U.S. announcements but not for important periodic shifts in volatility during non-U.S. business hours.

How can we resolve the disparate conclusions of Andersen and Bollerslev (1998) and Ederington and Lee (2001) about the relative importance of announcement effects and other periodic factors? To illustrate the issues involved in disentangling announcement and other periodic effects, one can regress absolute hourly foreign exchange returns—24 hours a day, 5 days a week—on announcement variables and periodic components. The following equation describes such a regression for hourly returns:

\[
|r_t| = \alpha + \beta_{US} Dum_{USann,t} + \beta_{for} Dum_{forann,t} + \sum_{j=1}^{N} \beta_{s,j} s_{j,t} + \sum_{q=1}^{4} \left( \beta_{1,q} \cos \left( \frac{q \pi t}{24} \right) + \beta_{2,q} \sin \left( \frac{q \pi t}{24} \right) \right) + \sum_{i=1}^{5} \beta_{i,t} r_{t-i} + \beta_{d} \frac{\sigma_{d(t)}}{\sqrt{24}} + \sum_{h=19}^{23} \beta_{h,j} Dum_{FRI_{t-h}} + \epsilon_t,
\]

where \( r_t \) is the annualized log return from period \( t \) to \( t+1 \); \( Dum_{USann,t} \) and \( Dum_{forann,t} \) are dummy variables that take the value 1 if there is any U.S. or foreign announcement, respectively, during \( t \) to \( t+1 \), and 0 otherwise; \( s_{j,t} \) is the standardized surprise of announcement \( j \) at period \( t \);

\[
\cos \left( \frac{q \pi t}{24} \right) \text{ and } \sin \left( \frac{q \pi t}{24} \right)
\]

are trigonometric functions that allow parsimonious estimation of an intraday periodic component; and

\[\sigma_{d(t)}\]

is the square root of the 1-day-ahead annualized GARCH(1,1) daily volatility forecast for day \( d(t) \). Finally, \( Dum_{FRI,t} \) takes the value 1 if period \( t \) coincides with hour \( h \) of a Friday, and 0 otherwise.

The treatment of periodicity in equation (2) differs from that of either Han, Kling, and Sell (1999) or Ederington and Lee (2001), who both used less parsimonious combinations of indicator variables for times of the day. Equation (2) is closer in spirit to the work of Andersen and Bollerslev (1998).

I estimate equation (2) by ordinary least squares on 1-hour log changes in the USD/EUR (euro) exchange rate over the period November 5, 2001, to March 12, 2010, after first removing weekends and the following holidays from the sample: New Year’s Day (December 31–January 2), Good Friday, Easter Monday, Memorial Day, Fourth of July (July 3 or 5 when the Fourth falls on a Saturday or Sunday, respectively), Labor Day, Thanksgiving (and the Friday after), and Christmas (December 24-26).

Table 1 shows the relative explanatory power of the various components of equation (2) for absolute returns. The full regression has a substantial \( R^2 \) of 0.2211, with the greatest explanatory power coming from the intraday periodicity with a partial \( R^2 \) of 0.0514, and the GARCH daily volatility forecast (0.0429). The announcement dummies provide a partial \( R^2 \) of 0.0020 and the
absolute announcement surprises provide a statistic of 0.0199. Thus, the announcement surprises are fairly important but not as important as some other features of the data, confirming the views of Andersen and Bollerslev (1998).

Figure 1 illustrates the predictive power of various components of regression (2) by showing the average actual volatility over various hours of the week along with average predicted volatility for those hours. The periodic component shows the greatest covariation with actual volatility but the announcement predictors and the lagged returns also help explain the average actual volatility.

Table 2 shows the estimated regression coefficients and the t-statistics from equation (2). Most—but not all—of the news surprise coefficients are positive, indicating that larger surprises increase volatility. Some of the news surprise coefficients are perverse (negative), which often results from their correlation with the periodic components and/or the announcement indicators. Of all the German/euro announcements, only German real GDP growth is significant and positive. The U.S. announcement indicator is significant, whereas the German/euro indicator is essentially zero—that is, U.S. announcements raise volatility but German announcements do not. The significance of the U.S. announcement indicator confirms the results of Andersen et al. (2003), who use high-frequency (5-minute) data from 1992 through 1998 to study the effects of a large set of U.S. and German announcements on the conditional mean and the conditional volatility of DEM/USD, USD/GBP (British pound sterling), JPY/USD, CHF (Swiss franc)/USD, and USD/EUR exchange rates. The authors find that
### Table 2
Regression Coefficients from Equation (2)

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Coefficient</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. announcement dummy</td>
<td>0.025</td>
<td>10.016*</td>
</tr>
<tr>
<td>German/Euro announcement dummy</td>
<td>0.000</td>
<td>0.039</td>
</tr>
<tr>
<td>U.S.: Real GDP: Advance</td>
<td>0.050</td>
<td>4.161*</td>
</tr>
<tr>
<td>U.S.: Real GDP: Preliminary</td>
<td>-0.014</td>
<td>-1.178</td>
</tr>
<tr>
<td>U.S.: Real GDP: Final</td>
<td>0.011</td>
<td>0.963</td>
</tr>
<tr>
<td>U.S.: Business inventories</td>
<td>-0.002</td>
<td>-0.287</td>
</tr>
<tr>
<td>U.S.: Capacity utilization rate: Total industry</td>
<td>-0.036</td>
<td>-3.051†</td>
</tr>
<tr>
<td>U.S.: Consumer confidence</td>
<td>0.036</td>
<td>5.175*</td>
</tr>
<tr>
<td>U.S.: Construction spending</td>
<td>0.047</td>
<td>5.675*</td>
</tr>
<tr>
<td>U.S.: CPI</td>
<td>0.004</td>
<td>0.554</td>
</tr>
<tr>
<td>U.S.: Consumer credit</td>
<td>-0.027</td>
<td>-3.843†</td>
</tr>
<tr>
<td>U.S.: New orders: Advance durable goods</td>
<td>0.006</td>
<td>0.829</td>
</tr>
<tr>
<td>U.S.: New orders</td>
<td>-0.017</td>
<td>-2.439†</td>
</tr>
<tr>
<td>U.S.: Housing starts</td>
<td>-0.014</td>
<td>-1.935</td>
</tr>
<tr>
<td>U.S.: Industrial production</td>
<td>0.032</td>
<td>2.736*</td>
</tr>
<tr>
<td>U.S.: Composite Index of Leading Indicators</td>
<td>-0.012</td>
<td>-1.776</td>
</tr>
<tr>
<td>U.S.: ISM: Manufacturing Composite Index</td>
<td>0.045</td>
<td>5.117*</td>
</tr>
<tr>
<td>U.S.: Employees on nonfarm payrolls</td>
<td>0.173</td>
<td>25.862*</td>
</tr>
<tr>
<td>U.S.: New home sales</td>
<td>0.004</td>
<td>0.608</td>
</tr>
<tr>
<td>U.S.: PCE</td>
<td>-0.016</td>
<td>-2.123†</td>
</tr>
<tr>
<td>U.S.: Personal income</td>
<td>-0.014</td>
<td>-1.930</td>
</tr>
<tr>
<td>U.S.: PPI</td>
<td>-0.009</td>
<td>-1.199</td>
</tr>
<tr>
<td>U.S.: Retail sales</td>
<td>0.021</td>
<td>2.208*</td>
</tr>
<tr>
<td>U.S.: Retail sales ex motor vehicles</td>
<td>0.015</td>
<td>1.497</td>
</tr>
<tr>
<td>U.S.: Trade balance: Goods &amp; services (BOP)</td>
<td>0.050</td>
<td>7.132*</td>
</tr>
<tr>
<td>U.S.: Government surplus/deficit</td>
<td>-0.010</td>
<td>-1.366</td>
</tr>
<tr>
<td>U.S.: Initial unemployment claims</td>
<td>0.001</td>
<td>0.281</td>
</tr>
<tr>
<td>Euro area: CPI flash estimate Yr/Yr %Chg</td>
<td>0.005</td>
<td>0.755</td>
</tr>
<tr>
<td>Euro area: IP WDA Yr/Yr %Chg</td>
<td>0.013</td>
<td>1.846</td>
</tr>
<tr>
<td>Euro area: Money supply M3 Yr/Yr %Chg</td>
<td>-0.012</td>
<td>-1.615</td>
</tr>
<tr>
<td>Euro area: Harmonized CPI Yr/Yr %Chg</td>
<td>0.002</td>
<td>0.329</td>
</tr>
<tr>
<td>Euro area: Unemployment rate</td>
<td>0.006</td>
<td>0.845</td>
</tr>
<tr>
<td>Euro area: PPI Yr/Yr %Chg</td>
<td>0.006</td>
<td>0.799</td>
</tr>
<tr>
<td>Euro area: Retail sales WDA Yr/Yr %Chg</td>
<td>-0.010</td>
<td>-1.453</td>
</tr>
<tr>
<td>Euro area: Trade balance</td>
<td>-0.005</td>
<td>-0.675</td>
</tr>
<tr>
<td>Euro area: Preliminary real GDP Yr/Yr %Chg</td>
<td>-0.018</td>
<td>-1.539</td>
</tr>
<tr>
<td>Euro area: Final real GDP Yr/Yr %Chg</td>
<td>-0.003</td>
<td>-0.282</td>
</tr>
</tbody>
</table>
### Table 2, cont’d

#### Regression Coefficients from Equation (2)

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Coefficient</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Germany: Current account balance</td>
<td>-0.014</td>
<td>-1.392</td>
</tr>
<tr>
<td>Germany: Final cost of living</td>
<td>-0.002</td>
<td>-0.342</td>
</tr>
<tr>
<td>Germany: Preliminary cost of living</td>
<td>-0.018</td>
<td>-2.432†</td>
</tr>
<tr>
<td>Germany: IP: Total industry Mo/Mo %Chg</td>
<td>-0.007</td>
<td>-1.095</td>
</tr>
<tr>
<td>Germany: Total Mfg. New Orders Mo/Mo %Chg</td>
<td>0.002</td>
<td>0.333</td>
</tr>
<tr>
<td>Germany: PPI: Mfg. Yr/Yr %Chg</td>
<td>0.002</td>
<td>0.300</td>
</tr>
<tr>
<td>Germany: Real retail sales Yr/Yr %Chg</td>
<td>0.001</td>
<td>0.134</td>
</tr>
<tr>
<td>Germany: Current account: Trade balance</td>
<td>0.016</td>
<td>1.732</td>
</tr>
<tr>
<td>Germany: Real GDP Qtr/Qtr %Chg</td>
<td>0.042</td>
<td>3.483*</td>
</tr>
<tr>
<td>Cos_q1</td>
<td>-0.011</td>
<td>-22.020†</td>
</tr>
<tr>
<td>Cos_q2</td>
<td>0.004</td>
<td>8.152*</td>
</tr>
<tr>
<td>Cos_q3</td>
<td>-0.009</td>
<td>-20.885†</td>
</tr>
<tr>
<td>Cos_q4</td>
<td>-0.007</td>
<td>-15.361†</td>
</tr>
<tr>
<td>Sin_q1</td>
<td>0.016</td>
<td>35.468*</td>
</tr>
<tr>
<td>Sin_q2</td>
<td>-0.001</td>
<td>-3.293†</td>
</tr>
<tr>
<td>Sin_q3</td>
<td>0.003</td>
<td>6.115*</td>
</tr>
<tr>
<td>Sin_q4</td>
<td>-0.007</td>
<td>-14.929†</td>
</tr>
<tr>
<td>Absolute return lag1</td>
<td>0.095</td>
<td>21.436*</td>
</tr>
<tr>
<td>Absolute return lag2</td>
<td>0.043</td>
<td>9.630*</td>
</tr>
<tr>
<td>Absolute return lag3</td>
<td>0.024</td>
<td>5.420*</td>
</tr>
<tr>
<td>Absolute return lag4</td>
<td>0.031</td>
<td>6.921*</td>
</tr>
<tr>
<td>Absolute return lag5</td>
<td>0.022</td>
<td>5.020*</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.009</td>
<td>-8.008†</td>
</tr>
<tr>
<td>GARCH daily volatility</td>
<td>3.010</td>
<td>47.127*</td>
</tr>
<tr>
<td>Friday_7 p.m.</td>
<td>-0.039</td>
<td>-11.171†</td>
</tr>
<tr>
<td>Friday_6 p.m.</td>
<td>-0.045</td>
<td>-12.959†</td>
</tr>
<tr>
<td>Friday_9 p.m.</td>
<td>-0.043</td>
<td>-12.432†</td>
</tr>
<tr>
<td>Friday_10 p.m.</td>
<td>-0.033</td>
<td>-9.409†</td>
</tr>
<tr>
<td>Friday_11 p.m.</td>
<td>-0.026</td>
<td>-7.411†</td>
</tr>
</tbody>
</table>

NOTE: The table shows the regression coefficients from estimating equation (2) (below) on absolute USD/EUR log changes, over the sample period November 5, 2001, to March 12, 2010. BOP, balance of payments; CPI, consumer price index; GDP, gross domestic product; IP, industrial production; ISM, Institute for Supply Management; PCE, personal consumption expenditures; PPI, producer price index; WDA, work days adjusted. *Statistically significant positive coefficients; †, statistically significant negative coefficients.

\[
|r_t| = \alpha + \beta_{1,US} Dum_{US,t} + \beta_{1,FR} Dum_{FR,t} + \sum_{j=1}^{N} \beta_{2,j} |r_{t-j}| + \sum_{q=1}^{4} \left( \beta_{3,q} \cos \left( \frac{q \pi t}{24} \right) + \beta_{4,q} \sin \left( \frac{q \pi t}{24} \right) \right) + \sum_{j=1}^{5} \beta_{5,j} |r_{t-j}| + \beta_{6,0} \frac{\sigma(t)}{\sqrt{24}} + \sum_{h=0}^{24} \beta_{6,h} Dum_{FR,h,t} + \epsilon_t.
\]
both the magnitude of the surprise and the pure announcement effect are significant.\(^\text{13}\)

In summary, the results in Table 1 indicate that Andersen and Bollerslev (1998) were correct to argue that announcements are important explanatory variables for volatility, though not as important as intraday periodicity and daily volatility. Likewise, Table 2 confirms the findings of Ederington and Lee (1993) that U.S. nonfarm payroll and U.S. trade balance surprises are among the most important for volatility.

**Volatility and News Arrival**

Not all news consists of macro announcements. Information about the international economy and politics arrives continuously in financial markets via newswire reports. The literature on the impact of information on stock trading and volatility (i.e., Berry and Howe, 1994, and Mitchell and Mulherin, 1994) helped motivate research in the foreign exchange market on whether such events create asset price jumps in all markets. They also use macro release indicators to model conditional volatility but do not focus on those results.

\(^{13}\) Andersen et al. (2007) use a similar model to study the effects of macroeconomic news releases on asset returns across countries and over the business cycle. They find evidence that news creates asset price jumps in all markets. They also use macro release indicators to model conditional volatility but do not focus on those results.
public information flow affects market volume and volatility.\textsuperscript{14} Most papers documenting the impact of information arrival use some measure of the frequency of headlines from wire service news agencies such as Reuters. DeGennaro and Shrieves (1997), however, incorporate unexpected quote arrival as a proxy for information arrival.\textsuperscript{15} This strategy is implicitly endorsed by Melvin and Yin (2000), who show that public information arrival influences both quote frequency and GARCH volatility of high-frequency JPY/USD and DEM/USD data.

The most common theme in this literature is that information arrival typically \emph{does} increase volatility (DeGennaro and Shrieves, 1997; Eddelbüttel and McCurdy, 1998; Joines, Kendall, and Kretzmer, 1998; Melvin and Yin, 2000; Chang and Taylor, 2003). Melvin and Yin (2000) interpret this result as casting doubt on proposals to apply “sand-in-the-wheels” transaction taxes that would reduce allegedly self-generated foreign exchange volatility.

There are exceptions to the rule that news arrival boosts volatility, however. DeGennaro and Shrieves (1997) find that unscheduled announcements actually reduce volatility for 20 minutes, perhaps inducing traders to pause to consider unexpected information. And not all news is created equal. Chang and Taylor (2003) find that Bundesbank news is most significant for DEM/USD volatility, and major U.S. and German announcements are more significant than simple headline counts.

Eddelbüttel and McCurdy (1998) use Reuters’ news headlines as a proxy for news arrival and confirm that the addition of such a news variable renders the GARCH-implied variance process much less persistent. This fact appears to confirm the intuitively attractive proposition that persistence in news arrival drives part of the volatility persistence captured by GARCH models.

The literature also shows, however, that public information arrival cannot explain the entire increase in volatility. Joines, Kendall, and Kretzmer (1998) and Chang and Taylor (2003) argue that trading must also release private information that hikes volatility. Researchers working with order flow data would further explore this point.

\textbf{Volatility and Non-U.S. Announcements}

The earliest papers on announcement effects studied the effects of U.S. announcements almost exclusively, but researchers soon began to consider how announcements from a variety of countries influence foreign exchange volatility. Many of these studies used variations on the popular GARCH model, including the EGARCH-in-mean (exponential GARCH-in-mean) model (Kim, 1998, 1999), trivariate GARCH to compare announcement effects on foreign exchange rates and Italian bond markets (Fornari et al., 2002), and FIGARCH (fractionally integrated GARCH) to account for possible long memory (Han, 2004). Other studies look at the effect of the announcement itself versus the information content (Kim, McKenzie, and Faff, 2004), the effect of conflicting information (Laakkonen, 2004) or heterogeneous information (Hashimoto and Ito, 2009), and asymmetric responses to news (Han, 2004).

These papers frequently contain two themes. First, most studies find that U.S. news has a greater impact on volatility than foreign news (e.g., Cai, Joo, and Zhang, 2009; Evans and Speight, 2010; Harada and Watanabe, 2009); however, Kopecký (2004) is an exception in finding that Czech announcements raise CZK (Czech crown [koruna])/USD volatility but—very curiously—U.S. announcements do not. The second common theme is that the volatility effect of announcements potentially depends on many factors: heterogeneous expectations, conflicting information, the source of the shocks, the sign of the shock, and whether the announcement is scheduled or unscheduled.

\textsuperscript{14} Public information flow is effectively synonymous with \textit{news arrival}, which refers to the rate at which news headlines or quotes are observed rather than the outcome of specific announcements. Chaboud, Chernenko, and Wright (2008) introduce a new dataset of volume in foreign exchange markets from the Swiss Electronic Bourse system. Although they do not study volatility specifically, they find that volume increases after U.S. macroeconomic announcements regardless of whether the announcement is expected or unexpected. For unexpected news, a price jump precedes the increase in volume.

\textsuperscript{15} Financial traders receive electronic feeds that allow them to see quotes on asset prices. \textit{Quote arrival} is the rate at which such quotes are updated. \textit{Unexpected quote arrival} is the surprise component of this measure.
Announcements and Jumps

Researchers have noted jumps—discontinuities in asset prices—for some time. The efficient markets hypothesis easily explains many jumps because it predicts very rapid systematic price reactions to news surprises to prevent risk-adjusted profit opportunities. Decomposing volatility into jumps and time-varying diffusion volatility is important because these two components have different implications for modeling, forecasting, and hedging. For example, persistent time-varying diffusion volatility would help forecast future volatility, while jumps might contain no predictive information or even distort volatility forecasts (Neely, 1999, and Andersen, Bollerslev, and Diebold, 2007). Therefore, it makes sense to investigate the effect of announcements on jumps.

Goodhart et al. (1993) first suggested the importance of accounting for news-induced discontinuities in modeling exchange rates. The authors study the effect of announcements on the time-series properties of exchange rates using a 3-month sample (April 9 to July 3, 1989) of high-frequency USD/GBP data from Reuters. The authors make strong claims that including news indicators in the conditional mean and variance equations of a GARCH-in-mean (GARCH-M) model renders both of these processes stationary. This is similar to the well-known phenomenon that discontinuities in macro series lead to spurious findings of non-stationarity (Perron, 1990). At high frequencies, conditional volatility appears to be very persistent; accounting for shocks to conditional volatility greatly reduces this persistence.

To link jumps to economic news, Johnson and Schneeweis (1994) introduce an announcement effect parameter to Jorion’s (1988) jump-diffusion model, permitting the conditional variance to depend on an announcement indicator. Using daily data between 1988 and 1990, the authors relate jumps in the JPY, GBP, and DEM exchange rates to four announcements from U.S., British, German, and Japanese sources. They find that certain real announcements—U.S. trade balance and industrial production news—cause larger volatility movements than do money supply and inflation news. U.S. news influences currency market variance more than does foreign news, and covariances between the exchange rates were highest on U.S. announcement days. Conditional variance and jump-diffusion models outperform simple diffusion and homoskedastic models. Incorporating news indicators in a diffusion model fits the conditional variance process better than estimating a jump process.

Fair (2003) turns the usual procedure for examining the relation between announcements and large exchange rate changes on its head. Instead of estimating a jump model of exchange rates that incorporates macro surprises, Fair looks for the largest changes in U.S. foreign exchange (and stock and bond) futures tick prices from 1982 to 2000 and then relates those changes to contemporaneous news. Monetary, price level, employment, and trade balance news are often associated with large changes in U.S. foreign exchange futures prices.

Advances in econometric jump modeling enabled later researchers to better examine the relation between announcements and jumps. Specifically, Barndorff-Nielsen and Shephard’s (2004) bipower procedure enabled researchers to pinpoint the dates and magnitudes of exchange rate jumps without needing to specify a likelihood function. Barndorff-Nielsen and Shephard (2004) observe that many jumps appear to correspond to macroeconomic releases, which is consistent with Andersen et al. (2003, 2007).

The Barndorff-Nielsen and Shephard (2004) bipower procedure estimates the sum of jumps during a period, usually a day. It does not pin down the precise times of those jumps, however, which makes it difficult to precisely link jumps to events such as news releases. Lee and Mykland (2008) developed another jump-detection method that compares each return, standardized by local volatility, with the distribution of the maximal diffusion return over the sample. The Lee and

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16 While it is plausible that accounting for discontinuities would render the conditional variance much less persistent, a broader view of the data indicates that nominal exchange rates are very unlikely to be stationary—and one cannot draw conclusions about such behavior from three months of data in any case.

17 Andersen and Bollerslev (1998) perform a similar exercise, examining whether any obvious political or economic events could explain the 25 largest 5-minute returns in their sample.
Mykland (2008) method permits one to more precisely time jumps than does bipower variation.

Lahaye, Laurent, and Neely (2010) use the Lee and Mykland (2008) technique to determine that U.S. macro announcements explain jumps and cojumps—simultaneous jumps in multiple markets—across equity, bond, and foreign exchange markets.18 Nonfarm payroll and federal funds target announcements are the most important news across asset classes, while trade balance shocks are also important for foreign exchange jumps.

Figure 2 illustrates the frequency and size of shocks in the USD/EUR market by time of day. Exchange rate jumps are more frequent around 8:30 a.m., 4 p.m. to 8 p.m., and 10 p.m. to 2 a.m. U.S. ET. The largest jumps occur at the times of major macro news; smaller liquidity jumps are associated with periods of low volatility (i.e., Tokyo lunch and early Asian trading).

Lahaye, Laurent, and Neely (2010) use tobit-GARCH and probit models to formally examine the relation between U.S. news and a variety of asset price jumps and cojumps, respectively. Table 3 shows that the tobit-GARCH regression formally confirms that nonfarm payroll (NFP), federal funds target announcements, trade balance reports, preliminary GDP, government fiscal announcements, and consumer confidence

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Figure 2

Number of Significant Jumps and Mean of Absolute Jumps Conditional on the Intraday Period

NOTE: The x-axis represents intraday time (U.S. ET). The left y-axis displays the number of significant jumps ($\alpha = 0.1$), while the right y-axis shows the mean absolute value of significant jumps in the USD/EUR exchange rate. The solid line denotes the number of jumps and the dashed line denotes mean jump size. The vertical gray line denotes the interval containing 8:30 a.m., the time of most news arrivals. The sample period is 1987-2004.

SOURCE: From Figure 2 in Lehaye, Laurent, and Neely (2010).

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18 Beine et al. (2007) use macro announcements as control variables in a study of the effects of U.S., German, and Japanese foreign exchange intervention on the continuous and discontinuous components of DEM-EUR/USD and JPY/USD exchange rate volatility. They estimate exchange rate jumps with bipower variation.
### Table 3

**Tobit-GARCH Models for Jumps**

<table>
<thead>
<tr>
<th>Variable</th>
<th>USD/EUR coefficient</th>
<th>JPY/USD coefficient</th>
<th>USD/GBP coefficient</th>
<th>CHF/USD coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer confidence</td>
<td>0.74</td>
<td>0.00</td>
<td>0.38</td>
<td>0.06</td>
</tr>
<tr>
<td>Consumer credit</td>
<td>0.06</td>
<td>0.99</td>
<td>–0.13</td>
<td>0.99</td>
</tr>
<tr>
<td>CPI</td>
<td>0.09</td>
<td>0.99</td>
<td>0.03</td>
<td>0.99</td>
</tr>
<tr>
<td>Federal funds target</td>
<td>0.72</td>
<td>0.00</td>
<td>0.66</td>
<td>0.00</td>
</tr>
<tr>
<td>Advanced GDP</td>
<td>0.81</td>
<td>0.00</td>
<td>0.40</td>
<td>0.83</td>
</tr>
<tr>
<td>Preliminary GDP</td>
<td>–0.55</td>
<td>0.17</td>
<td>–0.32</td>
<td>0.66</td>
</tr>
<tr>
<td>Government fiscal surplus/deficit</td>
<td>–0.21</td>
<td>0.99</td>
<td>–1.02</td>
<td>0.67</td>
</tr>
<tr>
<td>Manufacturing index</td>
<td>0.24</td>
<td>0.81</td>
<td>0.54</td>
<td>0.12</td>
</tr>
<tr>
<td>Nonfarm payroll</td>
<td>0.98</td>
<td>0.00</td>
<td>0.43</td>
<td>0.00</td>
</tr>
<tr>
<td>PPI</td>
<td>–0.70</td>
<td>0.99</td>
<td>–1.18</td>
<td>0.99</td>
</tr>
<tr>
<td>Retail sales</td>
<td>0.43</td>
<td>0.05</td>
<td>0.05</td>
<td>0.47</td>
</tr>
<tr>
<td>Trade balance</td>
<td>0.30</td>
<td>0.00</td>
<td>0.30</td>
<td>0.00</td>
</tr>
<tr>
<td>Omega</td>
<td>0.19</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Alpha1</td>
<td>0.49</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Alpha2</td>
<td>–0.60</td>
<td>0.00</td>
<td>–7542.77</td>
<td>–7727.96</td>
</tr>
<tr>
<td>Function value</td>
<td>–7090.68</td>
<td>–7542.77</td>
<td>–7727.96</td>
<td>–7331.87</td>
</tr>
<tr>
<td>No. of observations</td>
<td>352,127</td>
<td>351,359</td>
<td>352,799</td>
<td>352,319</td>
</tr>
</tbody>
</table>

**NOTE:** The latent tobit jump variable is denoted by $\text{Jump}_t^* = \mu + \eta_{ij} + \mu_{ij} + \xi_{ij} + \epsilon_t$, where $|\text{Jump}_{ij}| = \text{Jump}_t^*$ if $\text{Jump}_{ij} > 0$ and $|\text{Jump}_{ij}| = 0$ if $\text{Jump}_{ij} \leq 0$; $\epsilon_{ij}$ controls for day of the week effects (not reported) and $\mu_{ij}$ includes absolute surprises concerning macro announcements. $\eta_{ij}$ controls for intradaily periodicity (not reported). Estimates and robust $p$-values ($2x(1 - \text{Prob}(X < |\text{stat}||)))$ are reported for surprise coefficients that are significant at the 10 percent level in at least one series, as well as the ARCH and GARCH coefficients, where $X$ is a $t$-distributed random variable with $N-K$ (no. of observations – no. of parameters) degrees of freedom under the null and $\text{stat}$ is the estimated coefficient over its standard error. Regressors with no contemporaneous match with significant jumps are excluded from the model. Function value is the maximized log-likelihood function value. The exchange rate samples start in January 1990 and end on October 1, 2004. CHF, Swiss franc; CPI, consumer price index; EUR, euro; GBP, British pound sterling; GDP, gross domestic product; JPY, Japanese yen; PPI, producer price index; USD, U.S. dollar.

**SOURCE:** From Table 6 in Lahaye, Laurent, and Neely (2010).
### Table 4
Probit Models for Cojumps

<table>
<thead>
<tr>
<th>Variable</th>
<th>USD/EUR-USD/GBP coefficient</th>
<th>USD/EUR-JPY/USD coefficient</th>
<th>USD/EUR-CHF/USD coefficient</th>
<th>USD/GBP-JPY/USD coefficient</th>
<th>USD/GBP-CHF/USD coefficient</th>
<th>JPY/USD-CHF/USD coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$p &gt;</td>
<td>t</td>
<td>$</td>
<td>$p &gt;</td>
<td>t</td>
<td>$</td>
</tr>
<tr>
<td>Construction spending</td>
<td>$-7.41$</td>
<td>$0$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer confidence</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$0.74$</td>
</tr>
<tr>
<td>Federal funds target</td>
<td>$1.08$</td>
<td>$0$</td>
<td>$0.86$</td>
<td>$0$</td>
<td>$0.83$</td>
<td>$0.90$</td>
</tr>
<tr>
<td>Preliminary GDP</td>
<td>$0.87$</td>
<td>$0$</td>
<td>$0.6$</td>
<td>$0.02$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Government fiscal surplus/deficit</td>
<td>$0.23$</td>
<td>$0.07$</td>
<td>$0.17$</td>
<td>$0.18$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufacturing index</td>
<td></td>
<td>$1.50$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonfarm payroll</td>
<td>$0.65$</td>
<td>$0$</td>
<td>$0.79$</td>
<td>$0$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trade balance</td>
<td></td>
<td>$0.76$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Function value</td>
<td>$-1842.90$</td>
<td>$-1181.87$</td>
<td>$-3130.59$</td>
<td>$-742.60$</td>
<td>$-1610.76$</td>
<td>$-933.24$</td>
</tr>
<tr>
<td>Pseudo-$R^2$</td>
<td>$0.04$</td>
<td>$0.04$</td>
<td>$0.03$</td>
<td>$0.05$</td>
<td>$0.04$</td>
<td>$0.04$</td>
</tr>
<tr>
<td>No. of observations</td>
<td>$349,355$</td>
<td>$348,967$</td>
<td>$349,557$</td>
<td>$348,593$</td>
<td>$349,542$</td>
<td>$348,619$</td>
</tr>
</tbody>
</table>

NOTE: The latent probit cojump variable is denoted by $CO\text{ Jump}_{t,i} = \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \epsilon_{t,i}$, where $CO\text{ Jump}_{t,i} = 1$ if $CO\text{ Jump}_{t,i} > 0$ and $CO\text{ Jump}_{t,i} = 0$ if $CO\text{ Jump}_{t,i} \leq 0$. $\epsilon_{t,i}$ is $NID(0,1)$. $CO\text{ Jump}_{t,i}$ is the cojump (simultaneous significant jumps) indicator. $\eta_{t,i}$ controls for day of the week effects (not reported) and $\mu_{t,i}$ includes absolute surprises concerning macro announcements. $\xi_{t,i}$ controls for intraday seasonality (not reported). Estimates and robust $p$-values ($2x(1 - \text{Prob}(X < |tstat|))$) are reported for surprise coefficients that are significant at the 10 percent level in at least one series, as well as the ARCH and GARCH coefficients, where $X$ is a t-distributed random variable with N–K (no. of observations – no. of parameters) degrees of freedom under the null and $tstat$ is the estimated coefficient over its standard error. Regressors with no contemporaneous match with significant cojumps are excluded from the model. We further report the maximized log likelihood function value, and the McFadden $R^2$, which is $1 - (\text{LogLik}_{1}/\text{LogLik}_{0})$ (i.e., 1 minus the ratio of the log-likelihood function value of the full model to the constant-only model). The exchange rate samples start in January 1990 and end on October 1, 2004. CHF, Swiss franc; EUR, euro; GBP, British pound sterling; GDP, gross domestic product; JPY, Japanese yen; USD, U.S. dollar.

SOURCE: From Table 7 in Lahaye, Laurent, and Neely (2010).
surprises contribute to foreign exchange jumps. Table 4 likewise shows that a probit model consistently and strongly links cojumps to macro surprises, such as those to the federal funds rate target, NFP, and preliminary GDP. It is noteworthy that federal funds target surprises significantly explain cojumps in every currency pair. In summary, research has shown that many announcements cause jumps and cojumps and that a substantial proportion of jumps are associated with announcements.

**Order Flows and Foreign Exchange Volatility**

News might create order flows—signed transaction flows—that transmit private information to the foreign exchange market. Private agents combine public news releases with their own private information, and their publicly observable decisions may convey that private information. For example, a business might observe an uptick in industrial production, revise its estimates of future demand accordingly, and decide to build a new plant—but only if the firm’s privately known cost structures would make it expect to profit from that decision. If news announcements cause the release of private information that generates conflicting trades, then this provides a channel through which news can affect volatility over a prolonged period.

Because obtaining order flow data is expensive and/or difficult, some researchers have used proxies for order flow: Cai et al. (2001) use yen positions held by major market participants, and Bawens, Ben Omrane, and Giot (2005) use quote frequency. Most researchers have used data from electronic brokers such as Reuters D2000-1 (Evans, 2002), Reuters D2000-2 (Domínguez and Panthaki, 2006, and Carlson and Lo, 2006), or Electronic Brokerage Systems (Berger, Chaboud, and Hjalmarsson, 2009). Others have used proprietary datasets from commercial banks (Savaser, 2006, and Frömmel, Mende, and Menkhoff, 2008). Unfortunately, the difficulty of obtaining long spans of order flow data has left many of the studies of announcements and order flow with samples only a few months long. This limitation has prevented those studies from drawing clear conclusions about the effect of specific announcements on order flow.

The main finding from the literature on order flow and announcements is that news releases public information that immediately impacts prices and volatility and impacts volume through order flow with a delay. The release of public information causes an immediate “average” effect on prices, as well as delayed trading based on both the news and private information (Evans and Lyons, 2005). This delayed trading produces the protracted volatility found in the literature. In fact, the indirect impact of news on volatility through order flow is more important than the direct impact of the news itself (Cai et al., 2001). Likewise, Evans (2002) estimates some fairly complex microstructure models that decompose macro news (and other shocks) into common knowledge and non-common knowledge shocks. Evans (2002) argues that non-common knowledge shocks are of greater importance than textbook models emphasize.

The delayed effects of order flow can contribute to volatility for hours after announcements, particularly if the announcement is important and unscheduled. Carlson and Lo (2006) examine the reaction of the Reuters D2000-2 electronic order book on foreign exchange transactions to a single announcement—an October 9, 1997, surprise interest rate hike by the Bundesbank, aimed at heading off inflation pressures. Volatility remained high for about 2 hours after this unscheduled and surprising news. There were also price jumps after the announcement: 14 of the 19 largest price changes in a 4-day window occurred within 2 hours after the release.

It is possible, of course, that volatility persists after news is released either because of persistence...
in news/order flow or persistence in sensitivity to news/order flow. Berger, Chaboud, and Hjalmarsson (2009) tackle the difficult problem of disentangling the importance of these two effects. Using six years of high-frequency exchange rate data, Electronic Broking Services (EBS) order flows, and news, they conclude that both factors contribute to the persistence of volatility.

The theoretical and empirical microstructure literature has found that much of the effect of order flow consists of transmitting private information to markets. The amount of information depends on the type of order flow. Financial customers are thought to have better information on asset prices from their own trading and research, whereas commercial firms are considered to be price takers that trade to import or export goods rather than because the firms’ agents think that they have superior information about future asset prices. That is, the type of order flow matters. Frömmel, Mende, and Menkhoff (2008) find that only order flow from banks and financial customers (i.e., informed order flow) is linked to higher foreign exchange volatility.20 Savaser (2006) finds that investors—probably informed traders—substantially increase their use of limit orders—stop-loss and take-profit orders—prior to news releases and that accounting for this surge substantially improves the ability to explain the exchange rate jumps that follow news.

Perhaps more surprising than the post-announcement increase in volatility is the fact that informed trading can apparently increase volatility before announcements as the informed traders take speculative positions based on their private information (Bauwens, Ben Omrane, and Giot, 2005).

Not only does the type of order flow matter, but the definition of “news” matters as well. Domínguez and Panthaki (2006) argue for expanding the definition of news to include both “fundamental” and “non-fundamental” news.

Non-fundamental news includes technical analysis indicators, political news, and important private sector changes, such as mergers and acquisitions. The authors suggest taking a broader view of relevant variables in models of exchange rate determination.

In summary, the literature has found that (i) orders and order flow often respond to news, (ii) informed order flow has greater effects, and (iii) persistence in order flow and persistence in sensitivity to order flow both produce persistence in volatility in the wake of many announcements.

Recent Research on Monetary Policy Announcements and Exchange Rate Volatility

Several developments in central banking led researchers to renew attention to the effects of monetary policy announcements in the late 1990s. First, the Bank of England gained operational independence in the conduct of monetary policy from the government of the United Kingdom in 1998.21 Second, the European Central Bank (ECB) began to conduct a common monetary policy for the European Monetary Union as of January 1, 1999.22 Third, policymakers and researchers began to seriously reconsider the importance of communication in the 1990s and central banks responded by publicly explaining their policy actions.23 These policies prompted economists to begin to reconsider the effects of monetary structure, policy actions, and communications on asset prices and volatility.

The two most common themes of research on the effects of monetary policy news are as fol-

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20 Informed order flow would be order flow that is generated by private information and speculates on a change in asset prices. In contrast, uninformed order flow would be generated by demands for commercial or hedging purposes and would not be predicated on private information that informs expectations of changes in asset prices.


22 The original members of the European Monetary Union were Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal, and Spain.

23 For example, the Federal Open Market Committee (FOMC) began to contemporaneously announce policy actions in 1994 and adopted this as formal policy in 1995. Starting in August 1997, each FOMC policy directive has included the quantitative value of the “intended federal funds rate.” And since 1999, the FOMC has issued a press release after each meeting with the value for the “intended federal funds rate” and, in most cases, an assessment of the balance of risks (Poole, Rasche, and Thornton, 2002).
allows: (i) that surprising policy actions, such as changes in interest rates or currency parities, increase volatility and (ii) that clarification of longer-term policy reduces volatility. This seems to be true of the ECB, the Bank of England, and the Bank of Canada. Using a Markov-switching model, Sager and Taylor (2004) find that volatility tends to increase after an ECB interest rate announcement, peaking 15 minutes later but remaining elevated for an hour. Conrad and Lamla (2010) likewise show that the ECB’s interest rate decision and press conference strongly affect EUR/USD volatility but its later question and answer session produces no substantial effect. Using data from 1997 to 2007, Melvin et al. (2009) find that the USD/GBP Markov volatility-generating process changes entirely after surprising Bank of England interest rate announcements. Hayo and Neuenkirch (2009) use daily GARCH-M models to determine that Canadian interest rate changes raise CAD/EUR volatility. The close relationship between monetary policy and exchange rate policy means that a change in exchange rate parities implies a change in monetary policy analogous to a change in the expected interest rate path. So it should not be surprising that Chelley-Steeley and Tsorakidis (2009) find that the devaluation of the Greek drachma increased exchange rate volatility. Interest rate changes and changes in currency parity are not the only central bank actions that can change foreign exchange volatility. Jansen and De Haan (2005) find that indicators of statements from ECB and national central bank officials raise USD/EUR EGARCH volatility.

Central bank actions that fix expectations about future policy without changing current policy often reduce volatility, however. Bank of Canada communications lower CAD/EUR volatility (Hayo and Neuenkirch, 2009), and Greece’s announcements that it would be joining the European Exchange Rate Mechanism and its commitment to the euro zone reduced exchange rate volatility (Chelley-Steeley and Tsorakidis, 2009).

**Recent Research on State-Dependent Reactions**

Economists have considered how the response of volatility to news announcements might depend on the nature of the economy or the nature of the news. Pearce and Solakoglu (2007) reject asymmetry and nonlinearity in DEM/USD and JPY/USD volatility reactions but find some evidence of changes across the state of the business cycle.

Motivated by the idea that investors should react more strongly to high-quality information, Laakkonen and Lanne (2009) use 6 years of high-frequency USD/EUR data and 20 announcements to find that “precise” U.S. news announcements affect volatility more than imprecise announcements. The authors measure precision as the degree to which the previous month’s news announcements are not revised.

**DISCUSSION AND CONCLUSION**

This article has reviewed the literature on how news affects foreign exchange volatility. The ability to understand and quantify asset price uncertainty is crucial to managing risk and choosing portfolio composition.

The research on announcements and volatility has been particularly useful because it highlights the role of announcements in contributing to two of the main characteristics of volatility: periodicity and jumps. The most basic result of the literature is that trading and volatility typically increase for about an hour after an announcement. The same announcements that strongly affect foreign exchange returns—nonfarm payrolls, trade balance, advance GDP, and interest rate changes—also tend to increase volatility (Ederington and Lee, 1993).

Disentangling the contributions of macroeconomic news from those of other periodic market effects—such as market openings and closings—challenged the early authors in this literature (Payne, 1996, and Andersen and Bollerslev, 1998). Indeed, studies of intraday and intraweek periodicity in volatility motivated researchers to consider announcement effects on volatility.

Scheduled macroeconomic announcements shed light on market microstructure because they provide a natural experiment through which to study the release of public information on volatility. A series of studies established that public...
information flow affects market volume and volatility (Ederington and Lee, 2001; Melvin and Yin, 2000; Chang and Taylor, 2003). Other studies have used microstructure theory to motivate investigations into how volatility might depend on the precision of the information in the news, the state of the business cycle, and/or the heterogeneity of beliefs (Baillie and Bollerslev, 1991, and Kim, 1998).

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

Announcements frequently cause jumps, which are an important part of foreign exchange volatility (Goodhart et al., 1993; Fair, 2003; Andersen et al., 2003; Lahaye, Laurent, and Neely, 2010). The development of better tests for price discontinuities has aided the more recent jump studies. Removing such jumps from the volatility process improves autoregressive volatility forecasts (Neely, 1999, and Andersen, Bollerslev, and Diebold, 2007).

More recently, researchers have established that news has a prolonged effect on order flow, releasing private information, which leads to sustained increases in volatility (Cai et al., 2001; Evans, 2002; Evans and Lyons, 2005; Frömmel, Mende, and Menkhoff, 2008). Berger, Chaboud, and Hjalmarsson (2009) show that time variation in sensitivity to order flow contributes to the persistence of volatility. And the definition of “news” has expanded over time (see Domínguez and Panthaki, 2006).

Monetary policy communications can raise foreign exchange volatility when they describe a surprising change in current interest rates, but they tend to lower volatility when the communications anchor longer-term expectations of policy (Sager and Taylor, 2004; Melvin et al., 2009; Conrad and Lämla, 2010).

REFERENCES


