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Abstract

We study whether the accuracy of news announcements matters for the impact of news on exchange rate volatility. We use high-frequency EUR/USD returns and releases of 20 US macroeconomic indicators, and measure the precision of news in three different ways. When the precision is defined by the size of the first revision of the previous month's figure, we find that precise news increases volatility significantly more than imprecise news. Also, news on indicators that are in general more precise increase volatility more than news on typically imprecise indicators. Finally, we use real time data to measure the 'true' precision of news and find that the size of the first revision of the previous month's figure is a reasonable signal of 'true' precision.

JEL Classification: C22, F31, G00, E44

Keywords: volatility, exchange rates, macroeconomic announcements, high frequency data

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1 Introduction

According to theories concentrating on the quality of information (e.g. Veronesi, 2000), investors' reaction to new information does not only depend on the amount of unanticipated information, i.e., the difference between the announced figure and investors' personal expectations of the figure, but also on what they think about the quality of information. Despite this, the extensive literature on the effects of news announcements on financial markets has mostly ignored such quality aspects. To the best of our knowledge, only two previous empirical studies (Krueger and Fortson (2003) and Hautsch and Hess (2007)), discussed in more detail below, have specifically addressed this issue.

The scheduled releases of macroeconomic indicators comprise an important part of new information in the markets. The extensive empirical literature (De Gennaro and Schrieves, 1997; Andersen et al., 2003; Bauwens et al., 2005; Dominquez and Panthaki, 2006; Laakkonen, 2007a among others) has shown that announcements of macroeconomic figures typically cause a jump in asset prices and significantly increase volatility right after the announcement. The issue of news accuracy is of particular importance for macroeconomic news because it is widely known that the first released estimate of a macroeconomic indicator, such as the gross domestic product (GDP) often deviates considerably from the 'final' estimate. The figures can be revised for years and the difference between the first and final estimates can be substantial. For example, according to Swanson and van Dijk (2001) it takes at least 12 months for the seasonally adjusted US producer price index and industrial production figures to reach the 'correct' value. Also, there is a large literature confirming that the revisions of macroeconomic figures are somewhat predictable (e.g. Swanson and van Dijk, 2001).

While the literature on the effects of news announcements on financial returns and their volatility is voluminous, there appears to be very little research addressing the consequences of the precision of news announcements. Krueger and Fortson (2003) measured information precision by a linear time trend, which was assumed to capture the increasing precision of news releases over time, and found only limited evidence in favour of the relevance of US employment news accuracy for daily Treasury bond prices. On the other hand, the results of Hautsch and Hess (2007) suggest that more precise news on the US nonfarm payroll has a stronger impact on the intraday prices of Treasury bond futures than less precise news. Hautsch and Hess (2007) state that because the first revision of the previous month's figure (released at the same time as the present month's figure) reveals the measurement error in the previous period, it may help traders to assess the accuracy of the currently released news. Therefore, they measure the precision of an announcement by using the one-step-ahead conditional variance forecast of an ARMA-GARCH model fitted to the time series of revisions of US nonfarm payroll. In particular, the reliability of the announced figure is expected to decrease when the expected revision variance increases. They also study the asymmetries between positive and negative news, and find that the Treasury bond futures market reacts significantly more strongly to negative than positive news, and more strongly to precise 'bad' news than to imprecise 'bad' news.

In this paper, we study the relevance of the precision of news announcements concerning 20 macroeconomic indicators for the effect on the volatility of the euro against United States dollar (EUR/USD) exchange rate returns. We consider three ways of defining the precision of news. First, because the revision of the previous month's figure is always announced at the same time as the first estimate of the present month's figure, we follow Hautsch and Hess (2007) and assume that the size of this revision is a signal to investors of the accuracy of the present month's figure. We study whether investors react differently to standardized news surprises, when the standardized absolute revision of the previous month's figure is lower or higher than the sample mean of the standardized absolute revisions of all 20 indicators over the entire sample period. In other words, our first measure of precision is conditional on the previous revision.

The different macroeconomic indicators deviate considerably by the magnitude of revisions. Some indicators are often revised quite considerably (e.g. nonfarm payroll) while others undergo hardly any revision at all (e.g. confidence figures). These differences allow us to study the importance of the overall accuracy of news announcements on volatility. We study this issue by comparing investors' reactions to standardized news on macro indicators, whose mean standardized absolute revision (the first revision of the previous month's figure) is lower or higher than the sample mean of the standardized absolute revisions of all 20 indicators over the entire sample period. Hence, our second measure of precision is unconditional. We also analyze the conditional and unconditional measures jointly to see whether there are differences in investors' reactions to precise and imprecise announcements of indicators that are usually precise or imprecise.

Ex ante, investors do not actually know which announcements are accurate, and they try to resolve this issue by using prior information. Whether they are successful in predicting the accuracy of the announcements can be determined by means of the 'final correct' figures that become available after several revisions. Specifically with such data, we can compute ex post news surprises that should yield similar results as the ex ante measures if investors' signals of news accuracy are efficient. Moreover, by comparing the two precision measures, we can infer whether investors are trying to predict the first release or final figures.

In the previous literature, the paper that comes closest to ours, is Hautsch and Hess (2007). However, while Hautsch and Hess (2007) argue that investors' reaction to news depends on the relative precision of the announced data compared to the precision of the investors' beliefs, we study if the precision of announcements have direct effects on investors' reactions to news. Also, as mentioned above, we study the issue from several different viewpoints, while they only concentrate on the similar ex ante conditional measure of precision as we do. To our knowledge, neither the ex ante unconditional nor the ex post measures have been used earlier in the literature. Finally, while Hautsch and Hess (2007) only use the news on US nonfarm payroll, our data contains 20 US macroeconomic indicators, and the results are therefore more general, albeit the US nonfarm payroll is probably the most important macro indicator. Our paper also differs from the previous literature in that we study the relevance of news accuracy on exchange rate volatility, while the two earlier papers consider Treasury bond returns.

The results show that when using the revision of the previous month's figure in defining the accuracy of the news releases, the announcements that are more precise, increase volatility significantly more than imprecise ones. Also, the macro indicators that are usually more precise increase volatility significantly more than those usually imprecise. When considering the conditional and unconditional measures of accuracy simultaneously, we find that investors are reacting to both measures of precision. The conditional measure of precision seems to be relevant for investors, since news on the high-precision indicators increase volatility significantly more than news on low-precision indicators only when the announcement is also conditionally precise. On the other hand, among the unconditionally precise or imprecise news, the conditional precision does not cause asymmetric reaction to news, as it does when the indicators are not classified to precise and imprecise by using the unconditional measure. This indicates that the size of the revision of the previous month's figure is not the only signal the investors are using, but that investors react to both, conditional and unconditional measure of precision.

We also find that announcements that ex post turned out to be more precise, increase volatility more than those that turned out to be imprecise. Thus the precision of the previous revision seems to provide an efficient signal of current precision. Moreover, the results suggest that investors try to predict the first-release rather than final figures.

The plan of the paper is as follows. Section 2 describes the data and the Flexible Fourier Form method, which is used to filter the intraday seasonality from the data. Section 3 presents the different measures of precision and the estimation results. Section 4 concludes.

2 Data

2.1 Exchange Rate Data

The original data set contains the five-minute quotes[1] of the EUR/USD exchange rate from 1 January 1999 to 31 December 2004, and it was obtained from Olsen and Associates. The prices are formed by taking the average of the bid and ask quotes, and the returns are computed as the differences of logarithmic prices.

As the foreign exchange market activity slows down decidedly during weekends and certain holiday non-trading periods, it is standard in the literature to explicitly

[1] According to many studies, five-minute returns strike the best balance between the disadvantages of microstructure noise (when sampling too frequently) and the loss of important information (when sampling too infrequently). For a discussion, see Andersen et al. (2007).

exclude a number of days from the raw five-minute return series. Following Andersen and Bollerslev (1998), we exclude the weekends and certain holidays by always leaving out the returns from 21:05 GMT the night before to 21:00 GMT that evening. Andersen and Bollerslev (1998) state that this definition of a "day" retains intact the intraday periodic volatility structure. The following holidays are excluded from the data: Christmas, New Year, Good Friday and Easter Monday. Besides these holidays, three days are left out from the data because of lack of observations (10 May 1999, 21 Dec 2000, 24 Dec 2000). Daylight savings time is also taken into account, as is standard in the literature.

The five-minute returns exhibit strong intraday periodicity because of the different trading times in the global 24-hour foreign exchange markets. This has to be taken into account in modeling news effects, and one way of doing this is to use a filtered return series. Of the alternative filtering methods proposed in the literature, we choose the Flexible Fourier Form (FFF) model of Andersen and Bollerslev (1997) that uses different frequencies of sine and cosine functions to capture the periodicity. This choice is motivated by Laakkonen (2007b), who studied the consequences of data filtering on the results obtained by using filtered returns. She concluded that for the purpose of studying the impact of news on volatility, the FFF method performs the best among a number of commonly employed filtering methods because it produces the smallest bias in the estimated news coefficients compared to other filtering methods.

The FFF method is based on the following decomposition:

$$R_{t,n} - \bar{R}_{t,n} = \sigma_t \cdot s_{t,n} \cdot Z_{t,n} \qquad (1)$$

where $R_{t,n}$ denotes the five-minute returns, $\bar{R}_{t,n}$ is the expected five-minute returns and $Z_{t,n}$ is an i.i.d (with mean zero and unit variance) innovations, σ_t represents daily volatility and $s_{t,n}$ is intraday volatility[2].

Squaring both sides of (1), taking logs, approximating $\bar{R}_{t,n}$ with the sample mean $\bar{R}$ and eliminating the daily volatility component σ_t from the return process, we end up with the following expression,

[2]In the equations t denotes the day and n the five-minute interval.

$$2\log\frac{|R_{t,n}-\bar{R}|}{\hat{\sigma}_t/N^{1/2}} = 2\log(s_{t,n}) + 2\log|Z_{t,n}| \quad (2)$$

where following Andersen and Bollerslev (1997), we replace σ_t by $\hat{\sigma}_t$ predicted by a GARCH(1,1) model for the daily volatility. N denotes the number of five-minute intervals in one day (288 in a 24-hour market). Andersen and Bollerslev (1997) suggest a parametric representation of the intraday volatility $s_{t,n}$ and estimate the smooth cyclical volatility pattern by using trigonometric functions. The FFF regression model is the following,

$$\begin{aligned} f_{t,n} &= \alpha + \delta_1 n + \delta_2 n^2 + \sum_{k=1}^{D} \lambda_k I_k(t,n) \quad (3) \\ &+ \sum_{p=1}^{P}\left(\delta_{c,p}\cos\left(\frac{p2\pi}{N}n\right) + \delta_{s,p}\sin\left(\frac{p2\pi}{N}n\right)\right) + \varepsilon_{t,n}, \end{aligned}$$

where $f_{t,n} = 2\log\frac{|R_{t,n}-\bar{R}|}{\hat{\sigma}_t/N^{1/2}}$. Besides the sinusoids[3], a second order polynomial in the intraday interval, n, and the error term of the model $\varepsilon_{t,n}$, the model also contains indicator variables $I_k(t,n)$, which are used to control for weekday effects and outliers. The estimate of intraday volatility $\hat{s}_{t,n}$ is obtained as $\hat{s}_{t,n} = \exp(\hat{f}_{t,n}/2)$, where $\hat{f}_{t,n}$ are the fitted values from model (3). This estimate $\hat{s}_{t,n}$ is normalized so that the mean of the normalized periodicity estimate $\tilde{s}_{t,n}$ equals one: $\tilde{s}_{t,n} = \frac{T\cdot\hat{s}_{t,n}}{\sum_{t=1}^{T/N}\sum_{n=1}^{N}\hat{s}_{t,n}}$ where T is the number of observations in the entire sample and T/N denotes the number of days in the data. To get the filtered returns, the original returns $R_{t,n}$ are divided by the normalized estimate $\tilde{s}_{t,n}$, i.e., $\tilde{R}_{t,n} = \frac{R_{t,n}}{\tilde{s}_{t,n}}$. See Andersen and Bollerslev (1997, 1998) for further details of the method.

If the intraday periodicity pattern could be assumed to remain constant over the sample period, the FFF model would be estimated for the entire data set. Unfortunately this in not likely to be the case. For example, the trading hours of European markets were much more volatile in the first years after the introduction of euro than they do nowadays (Laakkonen 2007b). Therefore, to be able to filter out all the intraday periodicity in volatility, we need to filter the data in subsets. In the empirical analysis, filtering is done for each week separately.

[3]The value $P=9$ was selected by using the Schwarz information criteria.

The autocorrelation coefficients of absolute filtered and original returns for 1500 five-minute lags, i.e., the autocorrelogram for five days, is depicted in Figure 1. It is seen that there is still some autocorrelation left in the filtered absolute returns, although much of the intraday periodicity has been filtered out. In the empirical analysis of Section 3, the remaining autocorrelation will have to be taken into account in computing the covariance matrix of the errors of the regression models.

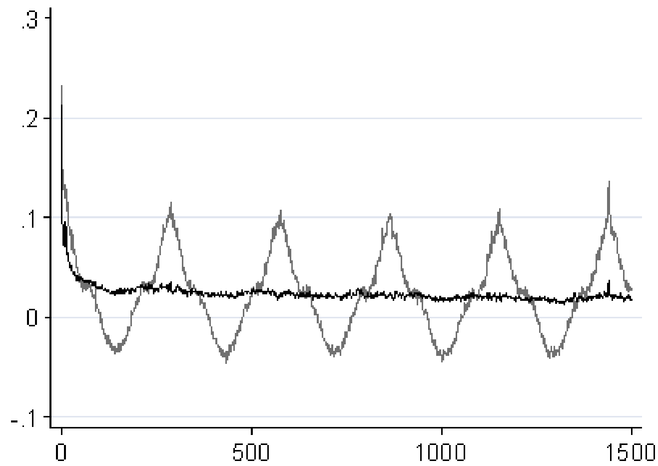

Figure 1 Autocorrelation coefficients of absolute returns

The figure shows the five day autocorrelogram of the filtered five-minute absolute EUR/USD returns (black line) compared to original absolute returns (grey line). The intraday periodicity was filtered by using the Flexible Fourier Form method.

Some descriptive statistics of the original and filtered return series are presented in Table 1. Mean and standard deviation of the return series are not effected dramatically by filtering. However, filtering does have an effect on skewness and kurtosis. The distribution of financial return series is usually very leptokurtic compared to the normal distribution, which indicates the overabundance of great returns compared to the normal distribution. The distribution of the EUR/USD returns is also positively skewed, which suggests that there are more great positive than negative returns. The distribution of the filtered returns is almost symmetric: due to filtering, skewness falls from 0.78 to 0.06. Also, the extra kurtosis of the distribution falls from 66 to 29. Although the distribution of the returns seems to be closer to the normal distribution after filtering, because of the excess kurtosis, neither the original nor filtered returns are normally distributed.

Table 1 Key statistical figures

Table presents the key statistical figures for the original and for the filtered returns. The returns were filtered with the Flexible Fourier Form method.

	Returns	**Filtered returns**
Mean	$5.0E-05$	$6.6E-05$
Standard Deviation	0.0432	0.0434
Skewness	0.781	-0.154
Kurtosis	65.94	40.92
Minimum	-1.35	-1.69
Maximum	2.79	1.68

2.2 Macroeconomic Announcement Data

The macroeconomic news data set includes the scheduled releases of 20 US macroeconomic indicators from the years 1999-2004 published in the Bloomberg World Economic Calendar (WECO). Table 2 presents the number of the releases of different macro indicators in our data set. Most of the indicators are released once a month, but some of them more often than monthly.

The data comprise the announcement date and time to an accuracy of one minute, the released estimate of the present month's figure of a macro indicator k ($k = 1, 2, ..., 20$), henceforth denoted $A_{t,n;k}$, the market forecast for the figure[4], henceforth denoted $F_{t,n;k}$ and the first revised estimate for the previous month's figure of indicator k , henceforth denoted $A^1_{t,n;k}$.

Besides the Bloomberg announcement data, we use the real time data set of the Federal Reserve Bank of Philadelphia for five macro indicators: nonfarm payroll, consumer price index, housing starts, industrial production and capacity utilization. The data set contains all the revised figures beginning from the first-release figure $A_{t,n;k}$ up to the 'final correct' estimate released m months after the first release, denoted as $A^m_{t+m,n;k}$.

[4]The market forecast is the median of the survey forecasts that Bloomberg collects from the market agents.

Table 2 Number of announcements

Indicator	**Announcements**
Capacity Utilization	70
Change in Nonfarm Payroll	71
Chicago Purchasing Manager Index	71
Consumer Confidence Index	71
Consumer Price Index	72
Durable Goods Orders	71
Factory Orders	71
Gross Domestic Product	71
Housing Starts	71
Import Price Index	69
Industrial production	71
Initial Jobless Claims	307
ISM Manufacturing Index	71
Leading Indicators Index	71
New Home Sales	72
Philadelphia Fed Index	71
Producer Price Index	73
Trade Balance	71
University of Michigan Consumer Confidence Index	133
Wholesale Inventories	71

3 Empirical Results

In this section, we present the empirical results on the relevance of the precision of macroeconomic indicators on the impact of macro news on EUR/USD volatility. As discussed in the Introduction, we consider three different ways of defining the accuracy of news. In subsection 3.1, we concentrate on two ex ante measures. First, *conditional* precision is determined in terms of the extent of the previous month's revision which can be considered a signal that investors use to assess the accuracy of the current announcement. Second, we compare the volatility effects of news announcements of indicators that are usually precise and imprecise. We call this the *unconditional* measure of precision. Moreover, we examine whether the volatility effects of the typically precise and imprecise indicators depend on the accuracy of the previous month's announcement. In subsection 3.2, we present the results based on an ex post measure of accuracy. All the regression models considered below are linear, and they are estimated by ordinary least squares (OLS). Following Andersen and Bollerslev (1998), the autocorrelation in the errors is accounted for by Newey-West heteroskedasticity and autocorrelation consistent covariance matrix estimator with 288 lags.

3.1 Ex ante measure of precision

Because the revision of the previous month's macro figure is always announced along with the present month's figure, we assume that investors use the size of the revision as a signal of the accuracy of the news announcement. Similar assumption was also made by Hautsch and Hess (2007) when studying the Treasury bond markets. Following their approach, we relate accuracy to absolute revisions. In particular, we study whether investors react differently to announced macro figures, when the standardized absolute revision of the previous month's figure is smaller or grater than the sample mean of the standardized absolute revisions of all indicators over the entire sample period. To examine the announcement effects, we consider the following model,

$$y_{t,n} = c + \phi^h \left[S_{t,n} \times D_{t,n}^{high} \right] + \phi^l \left[S_{t,n} \times D_{t,n}^{low} \right] + \varepsilon_{t,n} \qquad (4)$$

where $y_{t,n} = \log \dfrac{\left|\tilde{R}_{t,n} - \bar{R}\right|}{\hat{\sigma}_t / N^{1/2}}$ is our measure of exchange rate volatility. The dependent variable is of the same form as in the FFF regression (3), but now the raw returns, $R_{t,n}$, are replaced by the filtered returns, $\tilde{R}_{t,n}$. This notation is used throughout this section. Apart from the intercept, c, the explanatory variables include the news variables, $S_{t,n} \times D_{t,n}^{high}$ and $S_{t,n} \times D_{t,n}^{low}$. As usual in the literature, news is defined as standardized absolute surprise $S_{t,n;k} = |A_{t,n;k} - F_{t,n;k}| / \hat{\sigma}_k$, where $A_{t,n;k}$ is a released macro figure of indicator k announced at day t and intraday interval n, $F_{t,n;k}$ is the survey forecast of this figure reported by Bloomberg, and $\hat{\sigma}_k$ is the standard deviation of the absolute surprise of indicator k estimated from the entire sample period. In the empirical analysis, we consider 20 different indicators and combine them into one variable $S_{t,n}$, which takes on a nonzero value whenever there is a news announcement.

The standardized absolute news surprise $S_{t,n}$ interacts with the dummy variables $D_{t,n}^{high}$ and $D_{t,n}^{low}$, which take on value 1 if the first standardized absolute revision $REV_{t,n;k}$ of the previous month's figure is smaller or grater than its sample mean $\overline{REV}$ over all 20 indicators and entire sample period, respectively, and 0 otherwise. $REV_{t,n;k}$ is computed as $REV_{t,n;k} = \left|A_{t,n;k}^1 - A_{t-1,n;k}\right| / \hat{\sigma}_k^{REV}$, where $A_{t-1,n;k}$ is the previous month's announcement of indicator k, $A_{t,n;k}^1$ is its revised estimate released at the same time as $A_{t,n;k}$. The absolute difference is standardized by the standard deviation of the absolute first revisions of indicator k, $\hat{\sigma}_k^{REV}$. A macroeconomic announcement $A_{t,n;k}$ is classified as precise or imprecise if $REV_{t,n;k}$ is smaller ($D_{t,n}^{high} = 1$) or greater ($D_{t,n}^{low} = 1$) than $\overline{REV}$, respectively.

Note that when there are multiple simultaneous announcements, it is possible that both precise and imprecise news are announced at the same time. This happens, e.g., if news of two indicators k_1 and k_2 are announced simultaneously, and $REV_{t,n;k_1} < \overline{REV}$ but $REV_{t,n;k_2} > \overline{REV}$. In this case, $D_{t,n}^{high}$ and $D_{t,n}^{low}$ both take on value 1, and while $D_{t,n}^{high}$ interacts with the standardized surprise of the precise news $S_{t,n} = S_{t,n;k_1}$, $D_{t,n}^{low}$ interacts with the standardized surprise of the imprecise news $S_{t,n} = S_{t,n;k_2}$. On the other hand, if there are multiple precise (or imprecise) news released simultaneously, $S_{t,n}$ is computed as an average of the standardized surprises of different indicators k in the same category of precision (i.e., when there are for instance four simultaneous releases, two precise news announcements $S_{t,n;k_1}$ and $S_{t,n;k_2}$

and two imprecise releases $S_{t,n;k_3}$ and $S_{t,n;k_4}$, $D_{t,n}^{high}$ interacts with $S_{t,n} = \frac{1}{2}\sum_{k=1}^{2} S_{t,n;k}$ and $D_{t,n}^{low}$ interacts with $S_{t,n} = \frac{1}{2}\sum_{k=3}^{4} S_{t,n;k}$).

News announcements have been reported to have long-lasting effects on volatility. For instance, according to Andersen and Bollerslev (1998), the impact lasts from one to two hours. To allow for such prolonged effects, we have to modify model (4) to some extent. Specifically, following Andersen and Bollerslev (1998), the impact of an announcement is assumed to diminish gradually and go to zero after two hours. We first estimate the average news impact pattern by computing the average absolute returns at each five-minute interval following the news announcement minus the average absolute return over the entire sample period. All the news announcements are pooled in computing this average. We then estimate the decay structure of the volatility response pattern of news by fitting a third order polynomial to the average news impact pattern. OLS estimation yields the following equation for the average absolute returns following the news announcements,

$$\lambda_m = 0.054\left(1 - (m/25)^3\right) - 0.009\left(1 - (m/25)^2\right)m + 0.0007\left(1 - (m/25)\right)m^2 \quad (5)$$

where $m = 1, 2, ...25$ denotes the five-minute interval after the news announcement.

The estimated decay structure captures the average news impact pattern quite well and forces the impact to zero after two hours, as depicted in Figure 2. In the empirical models, the explanatory variables are hence not the news variables as such, but whenever there is an announcement, i.e., $S_{t,n} \neq 0$, in the 25 subsequent 5-minute intervals the corresponding regressor equals $\lambda_1 \times S_{t,n}$, $\lambda_2 \times S_{t,n}$, ..., $\lambda_{25} \times S_{t,n}$ and zero otherwise.

The third column of Table 3 presents the results of model (4). In general, both precise and imprecise news announcements increase volatility significantly. All the coefficients are positive and significant, as expected. Moreover, the news announcements that are more precise, increase volatility significantly more than imprecise ones (p-value of the Wald test for the equality of the coefficients is $2.53E-04$).

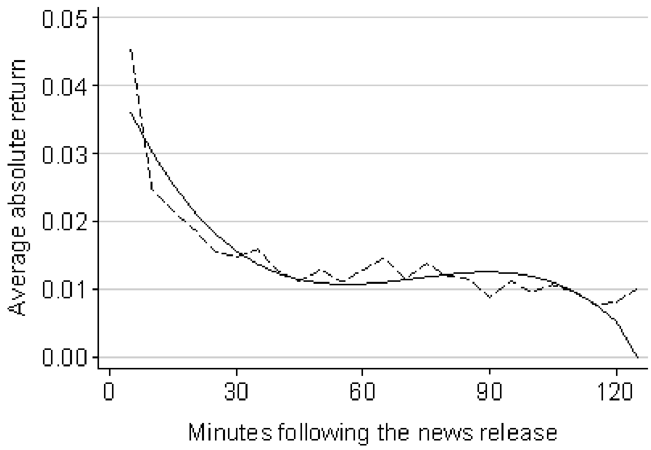

Figure 2 Decay structure of volatility response pattern after news

The figure presents the mean absolute returns from 5 to 125 minutes after news announcements (dashed line) and the estimated news impact decay structure (solid line).

Because some indicators are typically revised a lot (e.g. nonfarm payroll) and some only a little or not at all (e.g. confidence figures), investors might take this into account and react differently to those indicators that are generally more precise than others. We study this issue by comparing investors' reactions to news on indicators for which the mean absolute revision (the first revision of the previous month's figure) over the entire sample period is smaller or greater than that of all the indicators[5]. Specifically, we consider the following model,

$$y_{t,n} = c + \phi^{h\_i} \left[S_{t,n} \times D_{t,n}^{high\_ind} \right] + \phi^{l\_i} \left[S_{t,n} \times D_{t,n}^{low\_ind} \right] + \varepsilon_{t,n} \tag{6}$$

where with the exception of the dummy variable, the notation is the same as in model (4). Dummy variables $D_{t,n}^{high\_ind}$ and $D_{t,n}^{low\_ind}$ take on value of 1 if the sample mean $\overline{REV}_k$ of the first standardized absolute revisions of indicator k is smaller or greater than the sample mean $\overline{REV}$ over all the 20 indicators, respectively, and 0 otherwise. In other words, if $\overline{REV}_k$ is smaller than $\overline{REV}$, indicator k is deemed a high-precision indicator ($D_{t,n}^{high\_ind} = 1$), and otherwise low-precision indicator ($D_{t,n}^{low\_ind} = 1$).

[5]University of Michigan Consumer Confidence Index, ISM Manufacturing Index, Philadelphia Fed Index, Consumer Price Index, Producer Price Index, Chicago Purchasing Manager Index and Gross Domestic Product are the indicators that are on average more precise than the others.

The results of model (6) are reported in the fourth column of Table 3. The results are very similar to those of model (4). Also, the releases of the macro indicators that are usually more precise increase volatility significantly more than those usually imprecise (p-value of the Wald test equals 0.006). Thus news items that are more accurate, conditionally or unconditionally, increase volatility more than inaccurate news items. This indicates that investors pay attention to the quality of news, and act more upon precise news announcements.

It is possible that both the conditional and unconditional measures of precision simultaneously affect investors' confidence in the news. To allow for both effects, we let the dummy variables interact as follows,

$$\begin{aligned} y_{t,n} &= c + \phi^{h\_i,h}\left[S_{t,n} \times D_{t,n}^{high\_ind} \times D_{t,n}^{high}\right] + \phi^{h\_i,l}\left[S_{t,n} \times D_{t,n}^{high\_ind} \times D_{t,n}^{low}\right] \quad (7) \\ &+\phi^{l\_i,h}\left[S_{t,n} \times D_{t,n}^{low\_ind} \times D_{t,n}^{high}\right] + \phi^{l\_i,l}\left[S_{t,n;k} \times D_{t,n}^{low\_ind} \times D_{t,n}^{low}\right] + \varepsilon_{t,n} \end{aligned}$$

Here, for instance, $\phi^{h\_i,l}$ gives the effect of news of a high-precision indicator k ($D_{t,n}^{high\_ind} = 1$) whose previous announcement turned out to be imprecise ($D_{t,n}^{low} = 1$). The difference between $\phi^{h\_i,h}$ and $\phi^{h\_i,l}$, on the other hand, tells us the volatility impact of the accuracy of the previous announcement for high-precision indicators, whereas $\phi^{l\_i,l} - \phi^{l\_i,h}$ is the corresponding figure for news on low-precision indicators. Hence, this model allows us to examine the interactions of conditional and unconditional precision in different ways.

The estimation results of model (7) and the p-values of Wald tests of some hypotheses of interest are presented in the last column of Table 3. The results suggest that investors take both conditional and unconditional precision simultaneously into account. In particular, while in model (4) we saw that the conditional measure of precision is relevant to investors such that they react significantly more strongly to conditionally precise news than imprecise news, this holds no more when the unconditional measure of precision is taken into account. When considering the high-precision and low-precision indicators separately, we see that investors do not react differently to conditionally precise and imprecise news (the p-values of the Wald tests of $\phi^{h\_i,h} = \phi^{h\_i,l}$ and $\phi^{l\_i,h} = \phi^{l\_i,l}$ equal 0.188 and 0.205, respectively). This might suggest that the unconditional measure of precision is more relevant to investors than the conditional measure. However, when we compare the investors' reactions to unconditionally precise and imprecise news among the conditionally precise and imprecise news, we see that also the conditional precision measure is relevant. In particular, the news on high-precision indicators increase volatility significantly more than news on low-precision indicators only when the news are conditionally precise (the p-values of the Wald tests of $\phi^{h\_i,h} = \phi^{l\_i,h}$ and $\phi^{h\_i,l} = \phi^{l\_i,l}$ equal 0.014, and 0.398, respectively.

All in all, our findings hence indicate that investors not only use the latest revision as a signal of news precision but also simultaneously take the overall accuracy of the different indicators into account. The latter effect was not considered by Hautsch and Hess (2007).

3.2 Ex post measure of precision

Investors' assessment of the precision of a news announcement is based on information available when the announcement is made. This information may include past and present revision and a measure of the overall precision of a macro indicator, as discussed above. However, investors' assessment may not be precise as a typical macroeconomic figure converges to its 'final correct' value only after a number of revisions. Therefore, it would be interesting to see whether the volatility effects differ between news announcements that are truly accurate and inaccurate. Significant differences would indicate that investors are successful in predicting the accuracy of news. Moreover, considering both ex ante and ex post accuracy simultaneously would allow for judging whether it is the first-release or 'final' values that they are trying to predict. Due to the presence of predictability of revisions documented in the previous literature (see, e.g., Swanson and Dijk (2001) and the references therein), significant volatility effects of news surprises defined by the first-release instead of 'final' figures would indicate investors' inability to take the revision process into account.

To measure ex post accuracy, we use the Philadelphia Fed data for five macro indicators: nonfarm payroll, consumer price index, housing starts, industrial production and capacity utilization, discussed in Section 2.2. To divide the news into accurate or inaccurate, we have to decide which is the proper number of revisions after which the figure has reached the 'final correct' value. According to Swanson

Table 3 Estimation results

Table presents the parameter estimates of models (4), (6) and (7). The explanatory news variables are the standardized absolute surprises of 20 different macro indicators k. The news surprises interact with dummy variables which divide news to precise and imprecise. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively.

		(4)	(6)	(7)
$S_{t,n}\times D_{t,n}^{high}$	ϕ^{h}	19.42** (1.14)	–	–
$S_{t,n}\times D_{t,n}^{low}$	ϕ^{l}	12.43** (1.43)	–	–
$S_{t,n}\times D_{t,n}^{high\_ind}$	ϕ^{h_i}	–	20.24** (1.21)	–
$S_{t,n}\times D_{t,n}^{low\_ind}$	ϕ^{l_i}	–	15.40** (1.21)	–
$S_{t,n}\times D_{t,n}^{high\_ind}\times D_{t,n}^{high}$	$\phi^{h\_i,h}$	–	–	20.41** (1.30)
$S_{t,n}\times D_{t,n}^{high\_ind}\times D_{t,n}^{low}$	$\phi^{h\_i,l}$	–	–	15.38** (3.52)
$S_{t,n}\times D_{t,n}^{low\_ind}\times D_{t,n}^{high}$	$\phi^{l\_i,h}$	–	–	15.11** (1.72)
$S_{t,n}\times D_{t,n}^{low\_ind}\times D_{t,n}^{low}$	$\phi^{l\_i,l}$	–	–	12.15** (1.49)
Wald test, p-value				
$\phi^{h}= \phi^{l}$		$2.5E-04$	–	–
$\phi^{h\_i}= \phi^{l\_i}$		–	0.006	–
$\phi^{h\_i,h}= \phi^{h\_i,l}$		–	–	0.188
$\phi^{h\_i,h}= \phi^{l\_i,h}$		–	–	0.014
$\phi^{h\_i,h}= \phi^{l\_i,l}$		–	–	$4.06E-05$
$\phi^{h\_i,l}= \phi^{l\_i,h}$		–	–	0.946
$\phi^{h\_i,l}= \phi^{l\_i,l}$		–	–	0.398
$\phi^{l\_i,h}= \phi^{l\_i,l}$		–	–	0.205

and Dijk (2001), it takes at least 12 months for US industrial production and produces prices to reach the correct values. We define the 'final correct' value to be the one released 24 months after the first release, i.e. $A^{24}_{t+24,n;k}$.

We consider models analogous to those in Section 3.1. First, to study the differences in the volatility impact of ex post precise and imprecise news, we estimate the following model

$$y_{t,n} = c + \phi^h \left[S_{t,n} \times D^{high\_expost}_{t,n} \right] + \phi^l \left[S_{t,n} \times D^{low\_expost}_{t,n} \right] + \varepsilon_{t,n} \tag{8}$$

where, as in the ex ante analysis, $S_{t,n}$ combines the surprises on news of all five indicators. The dummy variables $D^{high\_expost}_{t,n}$ and $D^{low\_expost}_{t,n}$ divide the news into precise and imprecise (high and low precision), respectively. An announcement $A_{t,n;k}$ is deemed precise, if its standardized absolute 'final' revision $REV^{24}_{t,n;k}$ is smaller than the sample mean of all the 'final' revisions over all five indicators and the entire sample period, denoted by $\overline{REV}^{24}$, and imprecise otherwise. $REV^{24}_{t,n;k}$ is given by $REV^{24}_{t,n;k} = \left| A^{24}_{t+24,n;k} - A_{t,n;k} \right| / \hat{\sigma}^{24}_k$, where $A^{24}_{t+24,n;k}$ is the 'final correct' value of macro figure $A_{t,n;k}$, released 24 months after the first release. $\hat{\sigma}^{24}_k$ is the standard deviation of the absolute 'final' revisions of indicator k. If $REV^{24}_{t,n;k}$ is smaller than the sample mean $\overline{REV}^{24}$ ($D^{high\_expost}_{t,n} = 1$), news is classified precise, and otherwise ($D^{low\_expost}_{t,n} = 1$) imprecise[6]. Hence, model (8) facilitates studying whether truly accurate news has an impact different from that of inaccurate news. If also ex post more precise news announcements turn out to have a greater impact on volatility, it indicates that the signals investors use to infer the accuracy of news indeed are useful.

The model (8) is corresponding to model (4) in the previous subsection, and by comparing the results of these two models we can see whether the ex ante and ex post measures of precision yield different results. The coefficient estimates and some test results are presented in the third column of Table 4. As can be seen from the results of model (8), the coefficient estimates are very similar when using the different definitions of the precision. The estimated coefficient of the precise news in greater than that of the imprecise news in each case, although the difference is not

[6]Note that similarly to ex ante analysis, the dummy variables may take on a value of 1 simultaneously if there are multiple announcements at the same time of both precise and imprecise indicators.

statistically significant.

As pointed out above, the results in Table 4 are based on only five macro indicators, while the data set used in Subsection 3.1 contains 20 indicators. As a robustness check, we estimated also model (4) with the same subset of macro indicators that is used in estimating model (8). We found that also in that case the coefficient of precise news is greater than the coefficient of imprecise news, but the difference is not statistically significant (p-value = 0.600). It seems that ignoring the majority of the news announcements leads to greater standard errors, causing nonrejection in the Wald test. This suggests that had we estimated model (8) with the data set containing the 20 indicators, we could have found significant differences also with the ex post measures of precision.

So far, we have implicitly assumed that investors try to predict the (potentially false) first release of a macroeconomic indicator, as the news surprise has been defined in terms of that figure and the market forecast. However, another possibility is that they are actually predicting the 'final' value, taking the revision process into account. To find out about the investors' expectations formation, let us consider new surprises defined in terms of the 'final' value instead of the first release. In other words, we define the news surprise as the standardized absolute difference between the 'final' figure $A^{24}_{t+24,n;k}$ and the market expectation $F_{t,n;k}$, i.e. $\tilde{S}_{t,n;k} = \left|A^{24}_{t+24,n;k} - F_{t,n;k}\right| / \hat{\sigma}^{\tilde{S}}_{k}$, where $\hat{\sigma}^{\tilde{S}}_{k}$ is the standard deviation of the absolute surprise of indicator k. As in the previous analysis, $\tilde{S}_{t,n}$ combine the surprises of news of all five indicators. As a first step, we estimate the following model,

$$y_{t,n} = c + \phi^{h\_\tilde{S}} \left[\tilde{S}_{t,n} \times D^{high\_expost}_{t,n}\right] + \phi^{l\_\tilde{S}} \left[\tilde{S}_{t,n} \times D^{low\_expost}_{t,n}\right] + \varepsilon_{t,n}, \tag{9}$$

where regardless of the news surprise $\tilde{S}_{t,n}$, everything else is the same as in model (8). The estimation results can be compared to those of model (8) to see whether the news effects are similar irrespective of the definition of the news surprise. The results of the model (9) are reported in the fourth column of Table 4. As can be seen from the results of models (8) and (9), the coefficient estimates are very similar when using the different definitions for the news surprise.

Next, to examine the relative importance of the first release and the 'final' figure to investors, we include news variables based on both in the following model,

$$\begin{aligned} y_{t,n} &= c + \phi^{h}\left[S_{t,n} \times D_{t,n}^{high\_expost}\right] + \phi^{l}\left[S_{t,n} \times D_{t,n}^{low\_expost}\right] \\ &\quad +\phi^{h\_\tilde{S}}\left[\tilde{S}_{t,n} \times D_{t,n}^{high\_expost}\right] + \phi^{l\_\tilde{S}}\left[\tilde{S}_{t,n} \times D_{t,n}^{low\_expost}\right] + \varepsilon_{t,n} \end{aligned} \tag{10}$$

The significance of ϕ^{h} and ϕ^{l} and insignificance of $\phi^{h\_\tilde{S}}$ and $\phi^{l\_\tilde{S}}$ would indicate that investors attempt to predict the first release instead of the final figures, and vice versa. The results of model (10) are presented if the last column of Table 4, and they suggest that investors are trying to predict the first release rather than the 'final' figure. Here, only the coefficients of the news variables based on surprise $S_{t,n;k}$ are statistically significant. This suggests that rather than the difference between the 'final correct' value $A^{24}_{t+24,n;k}$ and the forecast $F_{t,n;k}$, the unanticipated information that investors react to, is the difference between the first release of the figure $A_{t,n;k}$ and the forecast $F_{t,n;k}$.

As discussed above, if the ex ante measure provides a good signal of the actual accuracy of a news released that is revealed only later, this could explain the similarity of the results based on ex ante and ex post measure. To study this, we examined whether the ex ante and ex post measures of revision indeed produce similar categories of precise and imprecise news. With the ex post measure of precision, 170 news announcements were classified as precise and 146 announcements as imprecise. Out of the 170 precise announcements, 106 were classified as precise by the ex ante measure of precision. The same ratio of imprecise news was 64 out of 146. So, roughly 60% percent of the precise news and 45% of the imprecise news were classified to the same category regardless of the precision measure. Thus, the ex ante measure of precision gives quite a good approximation to the "true" precision of news.

4 Conclusion

In this paper, we study the relevance of the accuracy of news announcements for their impact on the volatility of the EUR/USD exchange rate returns. The sample comprises the five-minute returns from 1999 until 2004, and the news data consists of the announcements of 20 different US macroeconomic indicators.

Table 4 Estimation Results

Table presents the parameter estimates of models (8), (9) and (10). We assume that the estimate of a macro figure has reach to its 'correct' value $A^{24}_{t+24,n;k}$ after revising it 24 months. Two alternative definitions for the news surprise is considered. In model (8) it is assumed that investors try to forecast the first estimate of a macro figure $A_{t,n;k}$, while in model (9) investors try to estimate the 'correct' figure $A^{24}_{t+24,n;k}$. The news surprises interact with dummy variables, which divide the news to precise and imprecise expost. In model (10) both definitions of news surprises are included to model to see for which one of them the investors react to. Table presents the values of the coefficients for the explanatory variables and the Newey-West standard errors (288 lags) in the parentheses. * and ** denote the 5% and 1% significance levels, respectively.

		(8)	(9)	(10)
$S_{t,n} \times D^{expost\_high}_{t,n}$	ϕ^h	18.88** (2.95)	–	15.83** (6.06)
$S_{t,n} \times D^{expost\_low}_{t,n}$	ϕ^l	12.76** (3.03)	–	8.48* (3.89)
$\tilde{S}_{t,n} \times D^{expost\_high}_{t,n}$	$\phi^{h\_\tilde{S}}$	–	18.68** (3.31)	2.67 (6.81)
$\tilde{S}_{t,n} \times D^{expost\_low}_{t,n}$	$\phi^{l\_\tilde{S}}$	–	12.41** (2.79)	6.09 (3.76)
Wald test, p-value				
$\phi^h = \phi^l$		0.194	–	0.340
$\phi^{h\_\tilde{S}} = \phi^{l\_\tilde{S}}$		–	0.183	0.672
$\phi^h = \phi^l = 0$		–	–	$2.59E-04$
$\phi^{h\_\tilde{S}} = \phi^{l\_\tilde{S}} = 0$		–	–	0.241

We define the accuracy of news by both conditional and unconditional measures. Following Hautsch and Hess (2007), in the conditional analysis, we assume that investors use the size of the revision of the previous month's figure as a signal of the precision of the current announcement. More precise news announcements turn out to increase exchange rate volatility significantly more than imprecise announcements. In the unconditional analysis, we examine whether the volatility impact of a news announcement depends on the overall accuracy of an indicator, defined in terms of the average size of its revisions. We find that the announcements of high-precision indicators increase volatility significantly more than those of low-precision indicators.

Finally, when considering the conditional and unconditional measures of accuracy simultaneously, we find that both measures are to some extent relevant in terms of the impact of news on volatility. News on the high-precision indicators increase volatility significantly more than news on low-precision indicators only when the announcement is also conditionally precise. Hence, the conditional measure of precision seems relevant. On the other hand, when considering the high-precision and low-precision indicators separately, we find no difference in the reactions to conditionally precise and imprecise news. This indicates that the size of the revision of the previous month's figure is not the only signal the investors are using.

We complement the ex ante analysis by measuring the precision of news in terms of the 'final correct' figure that only became available after a great number of revisions. To this end, we use the real time data set of the Federal Reserve Bank of Philadelphia, which contains all the revisions of a subset of five macroeconomic indicators. This data set allows us to define an ex post measure of precision as the absolute standardized difference between the final and first-release figures. Our results suggest that the news precise ex post increases volatility more than imprecise news, but the difference is not statistically significant at conventional significance levels. This may be due to fact that because of data limitations, only five indicators are included in the ex post analysis. The real-time data is also used for examining whether investors are capable of taking the revision process into account. When news surprises defined in terms of both first-release and the 'final' figures are included in the same regression model, only the former turn out to have significant volatility effects. This suggests that investors are actually attempting to predict the first-release figures instead of the correct final figures.

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