The impact of macroeconomic news on quote adjustments, noise, and informational volatility

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\begin{abstract}
We study the impact of the arrival of macroeconomic news on the informational and noise-driven components in high-frequency quote processes and their conditional variances. We decompose bid and ask returns into a common ("efficient return") factor and two market-side-specific components capturing market microstructure effects. The corresponding variance components reflect information-driven and noise-induced volatilities. We find that all volatility components reveal distinct dynamics and are positively influenced by news. The proportion of noise-induced volatilities is highest before announcements and significantly declines thereafter. Moreover, news-affected responses in all volatility components are influenced by order flow imbalances.
\end{abstract}

\section{1. Introduction}

The arrival of news and the processing of (non-anticipated) information is a major driving force of asset price volatility. Though the availability of financial high-frequency data allows researchers to study the impact of news on the price process at the micro level, the ultimate effect on volatility is still unclear. In fact, the measurement of high-frequency volatility is a non-trivial issue, as it is overshadowed by noise stemming from market frictions – so-called market microstructure effects. Therefore, it is unclear how much of a news-implied increase in asset price volatility is ultimately due to larger fluctuations of the underlying "efficient" return and how much is due to "microstructure noise" inducing a higher instability of bid and ask quotes. Disentangling both components is necessary to estimate the ultimate effect of announcements on the efficient asset return volatility and to produce a more complete picture of high-frequency price discovery.

The objective of this paper is to address this fundamental question and to analyze what proportion of volatility changes around the arrival of macroeconomic news is due to so-called "informational" volatility (i.e., the volatility of the efficient price) and how much is due to noise volatility (induced by quote fluctuations around the efficient price). We develop a structural model decomposing bid and ask quote returns into three conditionally heteroscedastic and news-dependent components: a common efficient return component and two market-side-specific noise components capturing noise-driven deviations between observed and efficient returns.

Using this methodological framework, we analyze the following major research questions: (i) how strong is the impact of news on the information and noise components of volatility, and how much does this effect depend on the magnitude and the precision of surprises? (ii) How large is the relative share of noise in conditional quote return volatilities, and how does it change around announcements? (iii) Can trading volume and net order flow (partly) explain the impact of news on informational and noise volatility?

We propose a state-space model decomposing bid and ask quote returns into a common efficient return component and two market-side-specific factors capturing deviations from efficient returns. The three unobserved return components follow a VAR (1) model with conditionally heteroscedastic errors. To capture the impact of news announcements and the state of the market, the conditional means and variances are augmented by corresponding regressors. We estimate the model by quasi maximum likelihood using the Kalman filter. To reduce the computational complexity due to the need of highly parameterized conditional variances,
The literature on heterogeneous beliefs presents the data concludes.

The analysis of macroeconomic news' effects on asset return volatility is a central area of research in empirical finance. One of the early studies examining the effect of macroeconomic news on volatility is that of Ederington and Lee (1993), who analyze 5-min sample variances across announcement days and find that volatility is significantly higher in the interval immediately following an announcement but rapidly declines afterwards. Christie-David and Chaudhry (1999) show that volatility seems to be more persistent if the underlying asset is more liquid. Hautsch and Hess (2002) and Andersen et al. (2003) stress the importance of disentangling the impact of news on both the first and the second conditional moments of the return process. Both studies document a strong and persistent increase in the conditional volatility following an announcement while controlling for shifts in prices.

However, in both theoretical and empirical literature, the effects of news on efficient and noise-driven volatility components are widely unexplored. The literature on heterogeneous beliefs suggests that uncertainty about the equilibrium price level is created by disagreement among traders about the precision of the news or about its interpretation (e.g., Harris and Raviv (1993), Kandel and Pearson (1995), and Kandel and Zilberfarb (1999)). According to this literature, greater disagreement among traders leads to higher trading activity. As long as this induces a higher liquidity supply, we expect that market microstructure frictions become less important resulting in a reduction of the relative importance of noise volatility. A related argument is provided by the literature on speculative trading suggesting that volatility and trading volume results primarily from heterogeneous information among market participants (e.g., Kyle (1985) or Foster and Viswanathan (1996)). According to Pasquariello and Vega (2007), more diverse information among traders allows them to trade more cautiously on their own private information. If, however, a public signal is announced, it becomes more difficult to exploit private (prior) information cautiously. Consequently, traders trade more aggressively, market liquidity increases, and the noise volatility component should decline. The volatility component contributes to the literature on modeling quote processes on financial markets. In a seminal paper, Hasbrouck (1991) studies the price impact of trades by proposing a VAR model for returns and signed trades. Hasbrouck (1993) proposes decomposing security transaction prices into a random walk component and stationary error components. Engle and Patton (2004) and Escribano and Pascual (2006) extend the framework by Hasbrouck (1991) and propose a vector error correction model for bid and ask quotes with the spread acting as the co-integrating vector.


The spirit of Madhavan et al. (1997) by decomposing quotes into a common stochastic trend—the efficient price—and transitory noisy components. Zhang et al. (2008) propose a similar decomposition inducing an asymmetric rounding mechanism generating discrete bid and ask quotes from a latent continuous process.

Finally, our study also contributes to the literature on volatility estimation using high-frequency data. An important issue in this literature is to address the impact of market microstructure frictions occurring on high sampling frequencies (see Hansen and Lunde (2006), or Barndorff-Nielsen et al. (2010), among others). Indeed, the estimates of our structural model for quote returns provide additional insights into the dependence structure of market microstructure noise and the variances thereof.

Our empirical analysis employs monthly announcements on non-farm payrolls and unemployment rates issued by the US labor market report. It is well documented that these figures are among the most influential scheduled releases. To quantify the magnitude of non-anticipated information (so-called “surprises”), we use consensus analyst forecasts. The impacts of news on prices are quantified based on minute-by-minute quotes of the German Bund futures traded on Eurex. Being closely related to long-term interest rates, Bund futures react very sensitively to macroeconomic announcements. Though the home market of these futures is in Germany, several studies clearly document that US labor market figures are the most important announcements (Andersen et al., 2003, Andersen et al., 2007, or Andersson et al., 2009). Furthermore, Eurex is an electronic system providing precise and detailed data not only on trade prices but also on quotes, volumes, and market depth.

The most important findings of our analysis are as follows: first, news announcements have a highly positive impact on both efficient and noise volatility. Instantly after the announcement, both volatility components reveal significant jumps followed by a gradual decline. The relationship between efficient volatility and the magnitude of surprises is concave. Conversely, for noise volatility, a convex relationship is found. This supports the hypothesis that very large surprises are interpreted to be less reliable and thus induce smaller (or even negative) marginal increases in prices and efficient volatility and a relatively higher share of noise volatility. Second, noise and efficient volatility show around news announcements different patterns resulting in a higher proportion of noise before the release. This share significantly drops instantly after the announcement and reaches a minimum approximately 30 min later. Third, the net order flow has a significantly positive effect on both volatility components. This impact becomes even stronger directly after news arrival. Fourth, the noise components reveal distinct serial dependencies confirming results for stock markets shown by, e.g., Hansen and Lunde (2006). Finally, our results show that apart from news-induced variations, noise variances reflect distinct GARCH effects. The overall share of noise volatility in total volatility is approximately 3%, reflecting comparably low spread variations in Bund futures trading.

The remainder of the paper is structured as follows. In Section 2, we introduce the econometric model. Section 3 presents the data and the construction of underlying variables. Empirical results are presented and discussed in Section 4. Section 5 analyzes the impact of news on the proportion of the efficient variance in the total quote variances. Section 6 concludes.

2. A state-space model for bid and ask returns

In this section, we introduce a new type of structural microstructure model for bid and ask quote returns. Define \( a_t \) and \( b_t \) as the log best ask and best bid quotes, respectively, at time \( t = 1, \ldots, T \). Then, \( a_t \) and \( b_t \) denote the corresponding ask and bid returns. We assume that \( r_t = (r_a, r_b) \) is...
driven by the sum of a common return component $m_t$, market-side-specific components $S_{a,t}$ and $S_{b,t}$ as well as $k_1$ announcement-related regressors $x^1_t$ and $k_2$ market liquidity variables $z^1_t$ capturing the state of the market. The bivariate process $r_t$ is described by

$$r_t = H_t z^1_t + B^1 x^1_t + D^1 z^1_t,$$

where $H = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \end{pmatrix}$ and $z^1_t := \begin{pmatrix} S_{a,t} \\ S_{b,t} \end{pmatrix}$. Here, $B^1 = \begin{pmatrix} \beta_{a} \\ \beta_{b} \end{pmatrix}$ is a $k_1 \times 2$ matrix of coefficients capturing the effect of news on returns and $D^1 = \begin{pmatrix} \delta_{a} \delta_{b} \end{pmatrix}$ is a $k_2 \times 2$ matrix of coefficients associated with the state of the market around announcements.

We assume the common component $m_t$ to capture the underlying (unobservable) efficient return driving both ask and bid returns. By contrast, $S_{a,t}$ and $S_{b,t}$ are associated with time-variations in market-side-specific spread variations and capture deviations between $m_t$ and $r_t$. Following the terminology in the literature, we refer to $S_{a,t}$ and $S_{b,t}$ as ask and bid noise returns, respectively.

The underlying framework is similar to the model by Pascual and Veredas (2010), who decompose bid and ask prices in a common random walk component and idiosyncratic noise factors. However, here we directly model returns. This approach is more natural and sensible in the given context, as it removes the need to account for stochastic trends in prices and allows focussing the analysis on event windows around the announcements.

The dynamics of the unobservable return components are assumed to be driven by a vector autoregressive (VAR) process of order one, i.e.,

$$z^1_t = \mu + F z^1_{t-1} + \varepsilon^1_t,$$

where $\mu = \begin{pmatrix} \phi_0 \\ 0 \\ 0 \end{pmatrix}$ is a $3 \times 1$ vector, and $F$ is a $3 \times 3$ matrix of the form

$$F = \begin{pmatrix} \phi_0 & 0 & 0 \\ 0 & \phi_0 & 0 \\ 0 & 0 & \phi_m \end{pmatrix}.$$

According to traditional structural microstructure models of price formation, efficient returns should follow a white noise process implying $\phi_0$ and $c$ to be zero. Conversely, noise returns have a zero mean and show mean-reverting behavior resulting in negative coefficients $\phi_0$ and $\phi_m$. The diagonal specification of $F$ rules out dynamic spill-overs between the latent components. Preliminary analyses based on more flexible specifications of $F$ show that this restriction is widely confirmed by the data. As we observe that the off-diagonal elements are rather small and difficult to identify, we consider the diagonal specification as being sufficiently flexible while being computationally tractable.

Note that we include the regressors $x^1_t$ and $z^1_t$ directly in (1). This implies that the effect of $x^1_t$ and $z^1_t$ on $r_{a,t}$ and $r_{b,t}$ is present only in period $t$. Because the regressors contain period-specific variables, this specification is most appropriate and eases the interpretation of regressor effects. Alternatively, or additionally, we could include components $C x^1_t$ and $E z^1_t$ in (2), with $C$ and $D$ denoting corresponding parameter matrices. The regressors would then be included in the autoregression and would enter the model in terms of an infinite lag structure, making interpretation more difficult.\(^2\)

\(^2\) Moreover, factor-specific effects of $x^1_t$ and $z^1_t$ in (2) are only individually identifiable as long as either $\phi_{x} \neq 0$ or $\phi_{z} \neq 0$ and $\phi_{x} \neq 0$. In the case of a joint identification of $B$ and $C$ as well as of $D$ and $E$, it is even required that $\phi_{x} \neq 0$ and $\phi_{z} \neq 0$. Otherwise, because of the linearity of (1), $r_{a,t}$ and $r_{b,t}$ are effectively driven by the same set of regressors twice.

The $3 \times 1$ vector of innovations $\varepsilon^1_t = (\varepsilon^a_{t}, \varepsilon^b_{t}, \varepsilon^m_{t})^T$ is conditionally normally distributed, i.e.,

$$\varepsilon^1_t | F_{t-1} \sim N(0, \Sigma^1),$$

where $\Sigma^1 = \text{diag}(\sigma^a_{t}, \sigma^b_{t}, \sigma^m_{t})$ and $F_{t}$ denotes the information set up to $t$. This notation does not necessarily mean that we impose (and need) an assumption on the diagonality of the covariance matrix. It rather means that only the conditional variance elements are explicitly modeled while the off-diagonal elements are left unspecified.\(^3\) We refer the components $h_{a,t} h_{b,t} h_{m,t}$ to as (conditional) ask and bid noise variances as well as the efficient variance, respectively. Each variance component is specified in terms of a multiplicative error specification (see, among others, Engle, 2002b; Engle and Rangel, 2008; or Hautsch, 2008):

$$h_i = \text{dyn}_i \cdot \text{ton}_i \cdot \text{liq}_i \cdot \text{news}_i, \quad i = (a, b, m),$$

where

$$\text{dyn}_i := \exp \left[ \omega + \theta_i \ln \text{dyn}_{i,t-1} + \varepsilon_{i,t-1} \left( \frac{\text{dyn}_{i,t-1}}{\text{dyn}_{i,T}} - \frac{2}{\theta_i} \right) \right],$$

$$\text{ton}_i := \exp \left[ \sum_{j=1}^{4} \psi_{i,j} \sin(2\pi j t) + \psi_{i,j} \cos(2\pi j t) \right],$$

$$\text{liq}_i := \exp \left( \gamma_i z^1_{i,t} \right),$$

$$\text{news}_i := \exp \left( \delta_i x^1_{i,t} \right).$$

The first component, $\text{dyn}_i$, captures dynamics in the variance processes according to an EGBARCH structure (Nelson, 1991). The second component, $\text{ton}_i$, is associated with deterministic volatility patterns around the announcement dates. We refer them to ‘time-of-news’ (ton) effects and model them using a flexible Fourier form (Gallant, 1981) of order three.\(^4\) Here $\tau = t/T \in [0,1]$ is the standardized time during the event window, where $T$ denotes the number of (1-minute) time intervals around the announcement. The third component, $\text{liq}_i$, contains regressors $z^1_{i,t}$ capturing market activity and liquidity with corresponding parameters $\gamma_i$. Finally, $\text{news}_i$ consists of news-specific regressors $x^1_{i,t}$ with parameters $\delta_i$.

Eqs. (1)–(3) form a linear state-space system (which can be estimated with the Kalman filter. An (efficient) one-step estimation of the model is numerically and computationally expensive when the number of variance regressors ($x^1_t$ and $z^1_t$) and the number of Fourier terms are high. To reduce the computational complexity, we suggest a two-step estimation procedure. Two-step estimations in volatility modeling are quite common and are performed in Schwert (1989), Andersen et al. (2005), Beine et al. (2007) and Engle and Rangel (2008), among others. Pascual and Veredas (2010) also suggest proceeding in two-steps in a state-space setting similar to ours.\(^5\)

In the first-step, we consistently estimate the model using a state-space system with constant variances (denoted by $\Sigma$ with diagonal elements $\Sigma_{ij} = a_i b_j m_j$). The exponential function ensures positivity and avoids numerical problems if the variances take very small values. Normality allows us to estimate the factors

\(^3\) Note that this restriction does not affect the estimates of the conditional variances as long as we rule out that conditional variances are driven by (lagged) conditional correlations themselves. An explicit modeling of (conditional) correlations, for instance, in terms of Engle’s (2002a) dynamic conditional correlation model, is beyond the scope of the present paper and is left for future research.

\(^4\) This is mostly supported by information criteria. To check the robustness, we also estimated other orders of the Fourier series. The results, available under request, barely change.

\(^5\) Alternatively, the model might be estimated using Monte Carlo Markov Chain techniques as used in a similar context by Zhang et al. (2008). However, given our highly parameterized conditional variances this would also be computationally very demanding.
using the Kalman filter as well as the parameters using the corresponding error prediction decomposition (see Harvey, 1989). Using pseudo-maximum likelihood (PML) arguments in an exponential family setting, the estimates are consistent, though not efficient, under distributional misspecification as long as the conditional means are correctly specified (see Gourieroux et al., 1984). In the second step, we estimate (univariate) EGARCH models based on the updated Kalman filter residuals,

\[ e_{it} = \mathbb{E}[\epsilon_i | \mathcal{F}_t], i = \{a, b, m\}. \]

The model (1)-(3) can be written in reduced form as

\[ r_{at} = \frac{c}{1 - \phi_a} + \beta_a \frac{x_{it}}{C_0} + \delta_a \frac{z_i}{C_0} + e_{at} + e_{mt} + \sum_{j=1}^{\infty} \phi_j e_{a,t-j} + \sum_{j=1}^{\infty} \phi_{aj} e_{a,m,t-j}, \]

(5)

\[ r_{bt} = \frac{c}{1 - \phi_b} + \beta_b \frac{x_{it}}{C_0} + \delta_b \frac{z_i}{C_0} + e_{bt} + e_{mt} + \sum_{j=1}^{\infty} \phi_j e_{b,t-j} + \sum_{j=1}^{\infty} \phi_{bj} e_{b,m,t-j}, \]

(6)

which is a Vector MA (\(\infty\)) model with exogenous regressors and a common error term induced by the efficient return. If efficient returns have a zero mean and are uncorrelated, the unique source of serial dependence in (5) and (6) are the noise terms. Thus the equations simplify to

\[ r_{at} = \beta_a \frac{x_{it}}{C_0} + \delta_a \frac{z_i}{C_0} + e_{at} + e_{mt} + \sum_{j=1}^{\infty} \phi_j e_{a,t-j}. \]

(7)

\[ r_{bt} = \beta_b \frac{x_{it}}{C_0} + \delta_b \frac{z_i}{C_0} + e_{bt} + e_{mt} + \sum_{j=1}^{\infty} \phi_j e_{b,t-j}. \]

(8)

Conditioning on past information, (contemporaneous) news arrival and the state of the market, the conditional (co-)variances are given by

\[ \sigma_{it}^2 = \mathbb{V}[r_{it} | \mathcal{F}_{t-1}, x_{it}, z_i, x_{i,t}'], \quad \sigma_{it} = \mathbb{V}[\epsilon_{it} | \mathcal{F}_{t-1}, x_{it}, z_i, x_{i,t}'], \]

(9)

(10)

Following Engle and Patton (2004), a parameterization of \(r_{at}\) and \(r_{bt}\) also implies a parameterization of changes in the log spread \(s_{at} = a_t - b_t\) and the log mid-quote \(mq_{it} = 0.5(a_t + b_t)\). Pre-multiplying (1) by the matrix \((1:1,0.5:0.5)\) yields the reduced form

\[ \Delta s_{at} = \beta_a \frac{x_{it}}{C_0} + \delta_a \frac{z_i}{C_0} + e_{at} + e_{mt} + \sum_{j=1}^{\infty} \phi_j e_{a,t-j}. \]

(12)

\[ \Delta mq_{it} = c + 0.5(S_{at} + S_{bt}) + \mu_t + 0.5(\beta_a - \beta_b) \frac{x_{it}}{C_0} + 0.5(\delta_a - \delta_b) \frac{z_i}{C_0}. \]

(13)

where \(\Delta\) denotes the first-difference operator. Correspondingly, the conditional variances of \(\Delta s_{at}\) and \(\Delta mq_{it}\) are given by

\[ \sigma_{at}^2 = \mathbb{V}[\Delta s_{at} | \mathcal{F}_{t-1}, x_{it}, z_i, x_{i,t}'], \quad \sigma_{mq_{it}}^2 = \mathbb{V}[\Delta mq_{it} | \mathcal{F}_{t-1}, x_{it}, z_i, x_{i,t}'] = 0.5(h_{at} + h_{bt}) + h_{mt}. \]

The conditional variance of spread changes thus equals the sum of the noise variances. Consequently, if the noise variances are zero, the spread is constant, and quote returns and efficient returns coincide corresponding to the mid-quote return. As a result, its conditional variance simply equals \(h_{mq_{it}}\).

3. Data

We estimate the model using intraday data of the German Bund futures traded on Eurex. We extract data from Eurex’s time and sales records including prices as well as best bid and ask quotes. Because the data directly stem from a computerized matching system, the information provided is very precise, including time stamps up to the second. Trade data are available since the inception of the Bund futures contract in 1989, but we focus exclusively on data from 1995 onwards, when liquidity in the Bund futures reached a significant level (see Franke and Hess, 2000). The sample ends in December 2005, at a time when Bund futures had been the most liquid government bond futures around the world, attracting even more trading volume than the CBOT T-bond futures. For instance, in 1995, we observe on an announcement day of the US employment report roughly four trades per minute with an average trade size of 21 contracts. This figure steadily rises and reaches 17 trades per minute with an average trade size of 77 contracts in 2005.

We extract 1-min log bid and log ask returns from the front month contract, i.e., the most actively traded contract at a given day. In the Bund future, prices are denoted in basis points of the face value (EUR 100,000). As a result, approximately 99% of all (absolute) quote changes are between zero and seven basis points. Nevertheless, while this is true for simple returns, the corresponding log returns are virtually continuous and thus in line with our model assumptions. We focus on an interval of ±80 min around the announcement time of the US employment report. This report is typically released at 2:30 pm Frankfurt time on the first Friday after the end of the month. We use only those employment announcement days on which no other US macroeconomic report is released at the same time. Covering a sample period of 11 years from January 1995 to December 2005, we obtain 123 employment report days after excluding a few days due to overlapping releases as well as one day due to an inadvertently early release of the employment report (see Fleming and Remolona, 1999b). Note that German or European macroeconomic announcements may have an important influence on Bund future trading, too (see, e.g., Andersson et al., 2009). However, these releases are typically made during the morning, i.e., well in advance of the US employment release at 14:30 CET. Likewise we do not control for actions of the Federal Reserve or the European Central Bank since usually they do not coincide with employment announcements. Linking together the event window results in a time series of minute-by-minute returns observed over the concatenated series of ±80 min around the employment announcement, yielding 25,600 observations.

In accordance with a wide range of previous studies of the employment report, we focus our analysis on the non-farm payrolls figure, which is shown to be the most influential macroeconomic news announcement. Nevertheless, unemployment rate news being released within the same report is used as well. We measure non-anticipated information in these two headline figures on the basis of survey data on analysts’ forecasts, provided by Stan-

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6 Theoretically, the second step estimators should account for the estimation error involving \(e_{mt}\). However, due to the large number of observations, we do not expect that this uncertainty qualitatively affects our results.

7 Due to different dates of daylight savings time switches in Europe and the US, the employment report is released on a few occasions at 1:30 pm or 3:30 pm Frankfurt time.

8 Note that we refrain from re-initializing the process in every announcement period. Though it is obviously not legitimate to treat the series as being continuous, this procedure effectively only affects the very first observations in each interval but has virtually no impact on all announcement-related effects. In particular, given the estimated persistence in the processes, the influence of past information basically vanishes after approximately 20 (1-min) periods. Consequently, period-specific initialization effects are irrelevant for effects caused by news events occurring after 80 periods (in the middle of the event window). Moreover, re-running a model with re-initializations in each period provides virtually identical parameter estimates.
dard and Poors Global Markets (MMS) and its successor, Informa Global Markets. Initially released non-revised figures are extracted from the original monthly releases. We define surprises as the difference between initially announced figures and the median of analyst forecasts. Following Hautsch and Hess (2007), we exploit the fact that both figures are closely related and measure surprises in both figures in terms of percentage changes, which facilitates a direct comparison of the price impact across headline figures. That is, non-farm payroll surprises are defined as the deviation of the announced number of new non-farm payrolls from the median of analyst forecasts divided by the total non-farm payrolls in the previous-month (times 100). The unemployment rate figure is already given in percentage points (i.e., the month-to-month difference in the overall unemployment rate). To capture the impact of news at specific time points during the event window, we interact the surprise variables with dummy variables indicating the periods around the announcement.

To quantify the release-specific precision of a monthly employment release, Hautsch and Hess (2007) suggest quantifying the so-called "price-response coefficient" \( \pi_m := \rho_{AM}(\rho_{AN} + \rho_{PM}) \). This coefficient is derived in a standard Bayesian learning model and is based on the precision (i.e., the inverse of the variance) of the estimation error of a monthly announcement, \( \rho_{AM} \), and the precision of analysts' forecasts of a figure, \( \rho_{PM} \), with \( m \) indexing the monthly time series. A natural estimator for \( \rho_P \) is the cross-sectional standard deviation of analysts' forecasts for a particular month. However, as typically no release-specific precision measure for macroeconomic announcements is available, Hautsch and Hess (2007) propose exploiting information on revisions of previous-month non-farm payroll figures. Interpreting the magnitude of a revision as a natural indicator for the (im)precision of the previous-month's figure, a 1-month-ahead forecast of squared revision variance, \( \rho_{AM} \), and the precision of (analysts') forecasts of a figure, \( \rho_{PM} \) with \( m \) indexing the monthly time series. A natural estimator for \( \rho_P \) is the cross-sectional standard deviation of analysts' forecasts for a particular month. Finally, we include two sets of additional regressors. First, we include the net order flow of (analysts') forecasts of a figure divided by the total non-farm payrolls in the previous-month (times 100). The unemployment rate figure is already given in percentage points (i.e., the month-to-month difference in the overall unemployment rate). To capture the impact of news at specific time points during the event window, we interact the surprise variables with dummy variables indicating the periods around the announcement.

4. Estimation results

4.1. Conditional mean effects

Table 2 provides the estimation results based on six different specifications, starting with a simple baseline model (A) capturing news effects in reduced form that is subsequently augmented by variables accounting for asymmetries, the news' precision as well as market liquidity. We summarize the following findings: first, we find highly significant negative estimates for \( \phi_0 \) and \( \phi_\delta \) indicating reversal effects in the noise components of the ask and bid log returns: an upward movement of \( S_A \) and \( S_B \) tends to be followed by a downward movement. This effect essentially reflects dynamics in spread changes. As shown, for example, by Hautsch and Huang (2009), a widening of the spread induced by a transaction removing a part of the pending order volume and thus shifting the best quotes induces an increase in the liquidity supply as well as a dynamically re-balancing of the spread. We observe converse effects after the arrival of aggressive limit orders narrowing the spread. Given the estimates of \( \phi_0 \) and \( \phi_\delta \), the coefficients of the resulting MA polynomials in (5) and (6) converge to zero relatively quickly. After few lags, they are negligible, implying that the reduced-form model can be approximated by a VMA of order two or three. This is consistent with the literature that has found returns to behave like a MA process (see, e.g., Art-Sahalia et al., 2005). For the efficient return itself, we find a weakly negative (but clearly significant) serial dependence reflecting slight evidence for mean-reversion effects in efficient prices.

Second, we observe strong and instantaneous effects of announcement surprises. Negative (positive) reactions on positive (negative) surprises in non-farm payrolls (unemployment rates) is well in accordance with economic theory. These results are consistent with previous findings based on returns of US T-bond futures and show that US labor market announcements do have a significant impact on Eurex Bund futures trading. It turns out that the price adjustment to non-farm payroll surprises is completed within the first 1-min interval after the announcement. The adjustment to unemployment news takes slightly more time, i.e., 2 min (2:29–2:31 pm). Note that for both non-farm payrolls and unemployment the corresponding coefficients take on almost identical values for both bid and ask quotes. We identify no significant effects (coefficients omitted) after the second minute for both headlines. This indicates that the market processes new information very quickly. Moreover, we observe slight evidence of significant quote reactions in the interval preceding the announcement, i.e., 2:29–2:30 pm. On first glance this might suggest leakage effects. However, given the very strict lock-up conditions guiding Bureau of Labor Statistics releases (see, for example, Edelington and Lee (1993) or Fleming and Remolona (1999c), Fleming and Remolona (1999a)) information leakages are quite unlikely.

Third, we obtain strong evidence for asymmetric price reactions due to large vs. small surprises. In line with the notion of Bayesian learning the significantly negative coefficient associated with \( h_{f,1} \)

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9 Most previous studies scrutinizing the efficiency of these forecasts could not detect systematic biases in MMS survey forecasts. For a recent survey see Hess and Orbe (2011).

10 See, e.g., Green (2004), Andersen et al. (2003), or Pasquariello and Vega (2007).
indicates that (too) large surprises are indeed interpreted as being “too large to be true”. However, the revision-based precision measure turns out to be insignificant. This is in contrast to the findings by Hautsch et al. (2008) based on US T-bond futures. Bund futures traders – in contrast to traders on the T-bond ‘home market’ – seem to account for the size of surprises as a proxy for reliability but disregard additional information such as revisions of past figures.
Fourth, we find a remarkably strong influence of imbalances in the order flow. It turns out that standardized net order flow \( (nof_t) \) drives both bid and ask quote revisions during the whole 160-min event window. The interactions with time dummies show that the impact of order flow imbalances peaks in the first minute after the announcement and is about two times as high as usual. Still, over the following 4 min, the impact is increased by about three quarters and over the next 10 min is increased by about one quarter. This suggests that net order flow may help traders to better interpret the news, particularly, by learning about other traders’ news-driven post-announcement reversals, as depicted by Panels (C) and (D). We therefore observe a concave relationship between efficient volatility and the magnitude and thus the reliability of surprises. Conversely, for noise volatilities, this relationship is convex. That is, a lower reliability of news as indicated by large surprises is reflected in noise-driven volatility rather than in efficient volatility. The former effects are obviously not distinctly attributable to single 1-min intervals but are rather spread over the complete 5-min interval following the news arrival. As in the mean function, we do not observe significant impacts of the revision-driven precision variable.

Third, efficient and noise volatility react in different ways around news announcements. While efficient volatility reveals a distinct jump at the announcement that decays relatively quickly thereafter, noise volatility is particularly high shortly before and after the announcement (see Panels (a) of Figs. 1 and 2). This is induced by more pronounced baseline patterns of the noise volatilities around the announcement (see Figs. 1d and 2d) compared to that of the efficient volatility. Additionally, it is enforced by news-driven post-announcement reversals, as depicted by Panels (c) in Figs. 1 and 2. In the case of large surprises, noise volatility is significantly and instantaneously pushed up at the time of news arrival, significantly drops in subsequent trading minutes and reverts after approximately 10 min. We associate this pattern with an overshooting of noise-driven volatility at the time of news arrival and a corresponding re-balancing thereafter. These effects are particularly driven by news in non-farm payrolls and to a lesser extent by unemployment rate figures.

Fourth, all volatilities reveal distinct dynamics. The parameters of the dynamic components \( dyn_t \) are significant and take values in the range of what is usually found in the volatility literature. Obviously, efficient volatility is more affected by informational shocks and shows a higher impact of innovations and a lower persistence than do noise volatilities. Figs. 1b and 2b depict the median values of the estimated E-GARCH components, \( dyn_t \). It turns out that the dynamic components strongly increase instantaneously after the announcement. This indicates that news effects not only are captured by the components \( ton_t \) and \( news_t \) but also cause high innovations in the E-GARCH process inducing persistent upward shifts of the component \( dyn_t \). These effects obviously enforce the impact of news on overall ask and bid return volatility.

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**4.2. Conditional variance effects**

Table 4 gives the estimation results of individual E-GARCH models based on the updated Kalman filter residuals stemming from the first-step estimates of model F shown in Table 2. Again, we estimate different specifications, starting with a simple baseline specification (A) and successively including the individual variance components. Ultimately, model (F) is most flexible, containing all underlying components. All specifications account for deterministic volatility patterns through the event window according to the specification of \( ton_t \) in (4). Accordingly, Figs. 1 and 2 show the median patterns of the estimated volatilities and their components during the event periods across all announcements based on the model (D) and (F). For the sake of brevity, we refrain from reporting the estimates of the component \( ton_t \) in the tables, instead depicting them graphically in Panel (d) of Figs. 1 and 2. Recall that \( ton_t \) is an average deterministic volatility pattern that is (multiplicatively) scaled upwards or downwards by the other components. Consequently, the mean values of the components \( news_t \) and \( ton_t \) are by construction equal to one and cannot be interpreted on an absolute scale.

We can identify the following major findings. First, large surprises in news have an instantaneous and strongly positive impact on both efficient and noise volatility. Overall, surprises in non-farm payrolls induce significantly stronger and more distinct reactions in volatility than does news regarding unemployment rates (see Panels A and B). As captured by the interactions of absolute surprises with corresponding time dummies, we observe the strongest effects in volatility in the minute following the arrival of the announcement. In subsequent minutes, these effects generally become smaller, less distinct and less significant.\(^\text{13}\) Moreover, the negative impact of unemployment (on noise volatilities) after the first 1-min interval indicates that noise volatilities reverse (more) quickly to normal levels.

Second, in the case of large (non-farm payroll) surprises (i.e., those greater than the 75%-quantile), the efficient volatility is marginally negatively affected, whereas the noise volatility is marginally positively affected (Panels (C) and (D)). We therefore observe a concave relationship between efficient volatility and the magnitude and thus the reliability of surprises. Conversely, for noise volatilities, this relationship is convex. That is, a lower reliability of news as indicated by large surprises is reflected in noise-driven volatility rather than in efficient volatility. The former effects are obviously not distinctly attributable to single 1-min intervals but are rather spread over the complete 5-min interval following the news arrival. As in the mean function, we do not observe significant impacts of the revision-driven precision variable.

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\(^{13}\) We also tested for asymmetries with respect to the sign of the news but did not find any significant results.
Fifth, the estimates in Table 2 reveal that the unconditional ask volatility is significantly higher than the bid volatility, providing hints for asymmetries in market-side-specific quoting activities. Conversely, it turns out that the news-implied effects on ask and bid noise volatilities are relatively similar. In fact, we provide some evidence for slightly stronger reactions of the bid noise volatility. Though the ask noise volatility is overall on a higher level and, correspondingly, is (absolutely) more strongly upward driven noise-driven components. This is naturally explained by the strong link between volatility and trading volume, which is not only found on a daily level but also on an intraday level (see, e.g., Hautsch, 2008). Panel (e) in Fig. 2 shows the median pattern of the liquidity components $liq_{m}$ around the announcement. We observe that $liq_{m}$ is strongly shifted upwards at the time of news arrivals. Hence, efficient volatility is increased not only due to news arrivals but also due to a rising net order flow and trading volume. This additional effect is also reflected in a higher median peak of the efficient volatility component $h_{m}$ (Panel (a)) compared to the effects shown in Fig. 1. After the announcement, the liquidity-induced component $liq_{m}$ remains at a high level and decays only slowly. Conversely, the median pattern of $liq_{m}$ and $liq_{m}$ decay prior to the announcement, shift upward at the event period and fluctuate around this level in subsequent periods. Interestingly, the liquidity-induced noise components reach a minimum directly after news arrivals. Hence, in this period, market activity declines and the market is seemingly awaiting information.

Finally, likelihood-ratio tests (Panel II of Table 3) suggest that the most general model (F) including both precision and liquidity effects dominate the more reduced models (A) to (E). This indicates the importance of accounting for market liquidity and asymmetric volatility effects when responses in volatility to news announcements are analyzed. This is particularly true for efficient volatility.

5. Variance ratios and marginal effects

To provide insights whether news announcements have an impact on the relative proportion of the conditional efficient variance

![Table 4](image)

Estimation results for E-GARCH models for Eq. (4) based on updated Kalman filter residuals stemming from the estimates of specification (F) in Table 2.

<table>
<thead>
<tr>
<th></th>
<th>(A) ask</th>
<th>(B) ask</th>
<th>(C) ask</th>
<th>(D) bid</th>
<th>(E) bid</th>
<th>(F) bid</th>
</tr>
</thead>
<tbody>
<tr>
<td>dyn_{t}</td>
<td>X</td>
<td>0.057***</td>
<td>0.332***</td>
<td>0.524***</td>
<td>-0.384***</td>
<td>0.363***</td>
</tr>
<tr>
<td>phi</td>
<td>X</td>
<td>0.995**</td>
<td>0.952**</td>
<td>0.873**</td>
<td>0.939***</td>
<td>0.951***</td>
</tr>
<tr>
<td>x</td>
<td>X</td>
<td>0.060***</td>
<td>0.208**</td>
<td>0.321***</td>
<td>0.248***</td>
<td>0.230***</td>
</tr>
<tr>
<td>news_{t}</td>
<td>lnf</td>
<td>16.370***</td>
<td>17.885***</td>
<td>38.107***</td>
<td>16.355***</td>
<td>17.283***</td>
</tr>
<tr>
<td></td>
<td>lnf</td>
<td>-0.136</td>
<td>-2.336</td>
<td>10.217***</td>
<td>-2.020</td>
<td>-2.501</td>
</tr>
<tr>
<td></td>
<td>lnf</td>
<td>0.247***</td>
<td>0.208***</td>
<td>0.325***</td>
<td>0.245***</td>
<td>0.230***</td>
</tr>
<tr>
<td>liq_{m}</td>
<td>trdvol</td>
<td>20.915</td>
<td>-0.868</td>
<td>0.997</td>
<td>0.949</td>
<td>0.243</td>
</tr>
<tr>
<td></td>
<td>trdvol</td>
<td>0.325</td>
<td>0.935</td>
<td>0.214</td>
<td>0.208***</td>
<td>0.325***</td>
</tr>
</tbody>
</table>

Columns (X.ask), (X.bid) and (X.eff) refer to the volatility equations for $h_{m}$, $h_{b}$, and $h_{m}$, respectively. (A) and (B): inclusion of news 1 min. and 2–5 min. after the announcements (e.g. $lnf_{t}$ and $lnf_{t-5}$). (C) and (D): inclusion of news and precision effects 1 min. and 2–5 min. after the announcements (i.e. $lnf_{t}$ and $lnf_{t-5}$). (E) and (F): inclusion of news, precision effects and market variables 1 min. and 2–5 min. after the announcements (trading volume $trdvol_{t}$ and absolute net order flow $lnf_{t}$). Sample: 1/1993–12/2005, resulting in 159 (non-overlapping) employment observations. 160-min windows around announcements (-80 to +80 min.) resulting in 25.440 1-min return observations. Standard errors are computed based on QML estimates.

* Indicates significance at the 10% level.

** Indicates significance at the 5% level.

*** Indicates significance at the 1% level.
in the total conditional ask and bid return variance, we define the ask and bid Information Variance Ratios:

\[
IVR_a^t := \frac{h_{a,t}}{h_{a,t} + h_{b,t}},
\]

\[
IVR_b^t := \frac{h_{b,t}}{h_{a,t} + h_{b,t}}.
\]

As these ratios approach one, the observed bid and ask returns are close to the (unobserved) efficient return, and the share of noise in returns thus decreases. If, in the limit, the bid-ask spread is constant, \( h_{a,t} = h_{b,t} = 0 \), we have \( IVR_a^t = IVR_b^t = 1 \).

Accordingly, the proportion of noise in (conditional) variances of spreads and mid-quotes are given by

\[
IVR_{spr}^{i,t} := \frac{h_{i,t}}{h_{a,t} + h_{b,t}}, \quad i \in \{a,b\},
\]

\[
IVR_{mq}^{t} := \frac{h_{m,t}}{0.5(h_{a,t} + h_{b,t}) + h_{m,t}}.
\]

Obviously, \( IVR_{spr}^{a,t} + IVR_{spr}^{b,t} = 1 \). If, for instance, \( IVR_{spr}^{a,t} > IVR_{spr}^{b,t} \), more than 50% of the variability in spread changes stems from the ask side.

Figs. 3 and 4 show the median values of \( IVR_{spr}^{a,t}, IVR_{spr}^{b,t}, IVR_{mq}^{t} \) and \( IVR_{spr}^{b,t} \) around all announcements based on models (D) and (F). Several conclusions can be drawn: on average the information variance ratios \( IVR_{spr}^{a,t}, IVR_{mq}^{t} \), and \( IVR_{spr}^{b,t} \) are very high, mostly above 95%. Though noise volatility is surprisingly small, the ratios are not constant during the event period but reflect a distinct pattern around the announcement. Information variance ratios start decreasing approximately 40-min prior to the announcement, reaching a minimum roughly 10-min before news arrival. This indicates that market liquidity tends to “dry out” prior to the announcement, inducing a significantly higher proportion of noise-induced quote fluctuations. Instantaneously after the announcement, the relative share of informational volatility sharply increases. This is obviously induced by a jump in efficient return volatility, which is dominating during this period. However, during the first minutes after the announcement, uncertainty in the interpretation of news induces again an increase in quoting activity and consequently a drop in information shares. After approximately 10-min, market uncertainty seems to be widely resolved, yielding rising information variance ratios, which reach their maximum approximately 30-min after the announcement.

Furthermore, we find distinct differences between \( IVR_{spr}^{a,t} \) and \( IVR_{spr}^{b,t} \). Supporting the findings of the previous subsection, the share of noise in quote volatilities is systematically higher on the ask side than on the bid side. This difference is most distinct in the period

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prior to the announcement and becomes significantly smaller after market uncertainty is widely resolved. This asymmetry is particularly striking in \( IVR_{spr}^a \) and \( IVR_{spr}^b \). As shown by Figs. 3b and 4b, the proportion of ask noise volatility in the total spread volatility is approximately 75%. This ratio is widely constant during the announcement window, indicating that news barely has an effect on \( IVR_{spr}^a \) and \( IVR_{spr}^b \).

This finding relates to several studies that have found asymmetries in the incorporation of information into bid and ask quotes. Engle and Patton (2004) and Escribano and Pascual (2006) find buys to have a greater impact on the ask quote than on the bid quote, and sells to have a greater impact on the bid than on the ask. Furthermore, Pascual and Pascual-Fuster (2009) observe the ask quote to incorporate information faster than the bid quote on days with...
positive daily returns. Opposite effects are prevalent on days with negative returns. In order to provide evidence to which extent our findings are related to such effects we regress $IVR_{t}^{pr,a}$ and $IVR_{t}^{pr,b}$ on the sign of the ask and bid returns yielding the following estimates:

$$IVR_{t}^{pr,a} = -0.046 \text{sgn}(\epsilon_{at}) + 0.068 \text{sgn}(\epsilon_{at}) + \epsilon_{at},$$

$$IVR_{t}^{pr,b} = -0.005 \text{sgn}(\epsilon_{bt}) + 0.006 \text{sgn}(\epsilon_{bt}) + \epsilon_{bt},$$

with all estimates being highly significant. Therefore, the sign of underlying returns explain, at least partly, the bid-ask asymmetry in the share of noise. If the ask (bid) return is positive (negative) indicating a buy (sell), the ask (bid) proportion of noise in conditional variances of spreads decreases (increases). More importantly, ask-induced effects are clearly higher than bid-induced effects. In this sense, our findings confirm the results reported in the aforementioned literature.

To analyze the effects of news on the resulting volatilities of bid and ask quotes, mid-quotes and bid-ask spreads, we compute the corresponding marginal effects. In general, marginal changes in $\sigma_{\epsilon t}^a$ and $\sigma_{\epsilon t}^b$ induced by changes in the news-related variables $\theta_{i}$, $i \in \{a,b,m\}$ are given by

$$\frac{\partial \sigma_{\epsilon t}^a}{\partial \theta_{i}} = 2(\theta_{a}\epsilon_{a}^2 + \theta_{m}\epsilon_{m}^2),$$

$$\frac{\partial \sigma_{\epsilon t}^b}{\partial \theta_{i}} = 2(\theta_{b}\epsilon_{b}^2 + \theta_{m}\epsilon_{m}^2).$$

where $\theta_{a} = (\theta_{a0}\theta_{an})$ and $\theta_{b} = (\theta_{b0}\theta_{bn})$. Correspondingly, we have for the marginal impacts on $\sigma_{\epsilon t}^{mq}$ and $\sigma_{\epsilon t}^{mq}$,

$$\frac{\partial \sigma_{\epsilon t}^{mq}}{\partial \theta_{i}} = 2(\theta_{a}\epsilon_{a}^2 + \theta_{b}\epsilon_{b}^2 + 2\theta_{m}\epsilon_{m}^2),$$

$$\frac{\partial \sigma_{\epsilon t}^{mq}}{\partial \theta_{i}} = 2(\theta_{a}\epsilon_{a}^2 + \theta_{b}\epsilon_{b}^2) + 2\theta_{m}\epsilon_{m}^2).$$

Then, for instance, the marginal effects at the minute of the announcement of a surprise in non-farm payrolls (for simplicity denoted by $nf_{1,t}$) in $\sigma_{\epsilon t}^a$ and $\sigma_{\epsilon t}^b$ are given by

$$\frac{\partial \sigma_{\epsilon t}^a}{\partial nf_{1,t}} = 2(\theta_{a1}\epsilon_{a1}^2 + \theta_{m1}\epsilon_{m1}^2),$$

$$\frac{\partial \sigma_{\epsilon t}^b}{\partial nf_{1,t}} = 2(\theta_{b1}\epsilon_{b1}^2 + \theta_{m1}\epsilon_{m1}^2),$$

where $\theta_{a1}, \theta_{b1}$ and $\theta_{m1}$ are the associated coefficients of $nf_{1,t}$ in $\epsilon_{a1}, \epsilon_{b1}$ and $\epsilon_{m1}$, respectively.

The marginal impact of a large surprise in non-farm payrolls on $\sigma_{\epsilon t}^a$ and $\sigma_{\epsilon t}^b$ at the minute after the announcement is given by

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As shown above, opinions regarding the "true" efficient return. Accordingly, the efficient return around its conditional expectation. The latter is interpreted as an indicator for unreliable news in the spirit of information volatility, reflecting that traders tend to disagree about the "true" reaction of the efficient price. Third, we identified by informational volatility, reflecting that traders tend to disagree about the "true" reaction of the efficient price. Accordingly, the efficient return around its conditional expectation. The latter is interpreted as an indicator for unreliable news in the spirit of information volatility, reflecting that traders tend to disagree about the "true" reaction of the efficient price. Moreover, the marginal effects confirm the major relationships discussed above. The largest effects are induced by surprises in non-farm payroll figures – induce severe jumps in all volatility patterns after news announcements are clearly dominant by a large strong and significant increase in both efficient and noise volatility. The relative proportion of noise volatility in conditional return variances yields an easily interpretable measure of the relative noise proportion.

We allow the latent return components to follow a VAR (1) structure with errors driven by EGARCH models. To capture the characteristics of arriving news, we augment both the conditional mean and noise volatility with corresponding regressors. We apply the model to study the impact of monthly announcements of US headline figures for non-farm payrolls and unemployment rates on 1-min ask and bid quote returns in the German Bund futures traded on Eurex. By focusing exclusively on announcement days, we analyze the impact of surprises (computed as the difference between the announced figure and the corresponding publicly announced consensus analyst forecast) in the individual figures on the conditional means of quote returns as well as on the informational and noise volatility components. Confirming previous results, we find that quotes adjust to their new levels very quickly, where the size of the price jump significantly depends on the magnitude of the surprise component in announcements.

We summarize the following main findings: first, we observe a strong and significant increase in both efficient and noise volatilities when new information arrives in the market. Besides an (average) baseline volatility pattern revealing relatively symmetric peaks around the announcements, large surprises – particularly those in non-farm payroll figures – induce severe jumps in all volatility components during the minute after news arrival. This is followed by a gradual decline lasting approximately 30 min thereafter. Second, noise volatility reacts relatively more strongly to news than does efficient volatility. The relative proportion of noise volatility in conditional return variances is highest before and at the announcement. While the average noise ratio prior to news arrivals is approximately 5%, this proportion peaks slightly before the announcement, revealing evidence of an overshooting of noise-driven volatility, which is re-balanced and reaches its minimum of approximately 1% half an hour later. This indicates that volatility patterns after news announcements are clearly dominated by informational volatility, reflecting that traders tend to disagree about the "true" reaction of the efficient price. Third, we
observe a concave (convex) relationship between efficient (noise-driven) volatility and the magnitude of surprises indicating that large surprises are interpreted to be “too large to be reliable”. Fourth, net order flow has a significantly positive impact on both efficient and noise-driven volatility and amplifies news-driven effects. Fifth, we observe an ask volatility that is systematically higher than the bid volatility. This is also reflected in the relative noise shares in the ask volatility and spread volatility. However, we observe that the arrival of news tends to dissolve such asymmetries.

Overall, we find that the relative share of the noise variance is around 3%, which is relatively low and indicates the high liquidity as well as the low degree of market friction in BUND futures trading. Nevertheless, our model and analysis provide insights into the impact of (non-anticipated) information on the noise component. The corresponding changes of the relative noise proportion dependent on the timing of announcements and the characteristics of news shed some light on the informational efficiency of the market, how market participants interpret information and how this is translated into prices. Applying the proposed framework to other announcements and markets represents a clear agenda for future research.

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