FACULTEIT ECONOMIE
EN BEDRIJFSKUNDE

TWEEKERKENSTRAAT 2
B-9000 GENT
Tel. : 32 - (0)9 – 264.34.61
Fax. : 32 - (0)9 – 264.35.92

WORKING PAPER

Order Flows, News, and Exchange Rate Volatility

Michael Frömmel

Alexander Mende

Lukas Menkhoff

July 2007

2007/474

D/2007/7012/45

Order Flows, News, and Exchange Rate Volatility*

Michael Frömmel, Ghent University, Belgium, and Leibniz Universität Hannover, Germany[a],
Alexander Mende, Risk and Portfolio Management AB, Sweden[b],
and Leibniz Universität Hannover, Germany,
Lukas Menkhoff, Leibniz Universität Hannover, Germany[c]

Abstract:
This paper examines the roles of order flow (reflecting private information) and news (reflecting public information) in explaining exchange rate volatility. Analyzing four months of a bank's high frequency US dollar-euro trading, three different kinds of order flow are used in addition to seasonal patterns in explaining volatility. We find that only larger sized order flows from financial customers and banks – indicating informed trading – contribute to explaining volatility, whereas flows from commercial customers do not. The result is robust when we control for news and other measures of market activity. This strengthens the view that exchange rate volatility reflects information processing.

JEL-Classification: F 31, G15
Keywords: exchange rate, market microstructure, order flow, financial customer orders, volatility patterns

April 4, 2007

* We are deeply indebted to the bankers who provided the data and discussed findings with us. We would like to thank Weiwei Cong, Ekaterina Gracheva, Sandra Schniedermeier and Maik Schmeling for their research assistance and an anonymous referee for valuable suggestions.

[a] corresponding author: Department of Economics, Leibniz Universität Hannover, D-30167 Hannover, GERMANY, froemmel@gif.uni-hannover.de
[b] RPM Risk & Portfolio Management AB, Norrmalmstorg 16, SE 111 46 Stockholm, SWEDEN, alexander.mende@rpm.se
[c] Department of Economics, Leibniz Universität Hannover, D-30167 Hannover, GERMANY, menkhoff@gif.uni-hannover.de

Order Flows, News, and Exchange Rate Volatility

1 Introduction

Volatility of exchange rates is positively linked to the arrival of public information to the market, a stylized fact which has been well documented (Sarno and Taylor, 2002). The main body of evidence in this line of research examines public information flows, such as Melvin and Yin (2000) or Andersen et al. (2003) to name just two. There is increasing evidence, however, that foreign exchange markets may be characterized by an important role of private information, too. The prominent empirical measure for the revelation of private information is order flow, i.e. signed transaction volume (Lyons, 2001). So, does the flow of private information into markets – proxied by order flow – create volatility as the flow of public information does? This study is the first, to the best of our knowledge, to directly provide evidence on this issue. We find, indeed, that the arrival of order flow from informed parties is positively linked to exchange rate volatility. This result holds controlling for the usual determinants of volatility in a high frequency setting, i.e. news, calendar effects and intraday activity pattern (Andersen and Bollerslev, 1998).

Our research is motivated by the recent attention given to order flow as a measure to better understand exchange rate dynamics and we are going to examine its potential role in explaining exchange rate volatility. We know from surveys that professionals regard order flow as an important means to understand foreign exchange markets (Goodhart, 1988, Cheung and Chinn, 2001, Gehrig and Menkhoff, 2004). We know that cumulative order flow is related to exchange rate changes (e.g. Evans and Lyons, 2002), we know from high frequency analyses that order flow has permanent price impact (Payne, 2003), and we know that order flow is also related to news (Evans and Lyons, 2004, Dominguez and Panthaki, 2006). All this indicates very clearly that order flow may carry private information into prices and, thus, raises the question whether order flow might also play a significant role in determining exchange rate volatility.

A high frequency analysis of this question should consider that exchange rate volatility is influenced by two further groups of determinants, i.e. institutional forces and the flow of public information. As a flexible and powerful framework to examine volatility we use Andersen and Bollerslev (1998) which is also applied by Cai et al. (2001) or Dominguez and

Panthaki (2006). This framework was developed to examine the effect of news on exchange rate volatility, controlling for systematic intraday and interday patterns in volatility. We use this approach and complement it by also considering order flow as a measure of private information.

The joint analysis of public and private information arrival on exchange rate volatility has been conducted in a few papers before, i.e. DeGennaro and Shrieves (1997), Cai et al. (2001) and Bauwens et al. (2005), which we introduce in detail in the following Section 2 below. The main innovation of our approach is the fact that we proxy private information by high frequency order flows whereas earlier papers had to rely on different – less advantageous – measures. The reliance on order flows helps to address the identification problem, i.e. the distinction between uninformed liquidity trading and informed trading. Liquidity trading will be more equally distributed on buying and selling, whereas informed trading will be more often on one side of the market only. As Bauwens et al. (2005, p.1121) write: "Market activity would be ideally measured by the flow of orders between traders and their customers."

Accordingly, the order flow data we can use is the limiting resource which determines the period of investigation. Our data covers four months dollar/euro trading in 2001 of a bank in Germany. As a particularly interesting feature we have information on interbank as well as financial customers (mutual funds, hedge funds, and insurance companies) and commercial customer (ex- and importers) transactions. The breakdown of order flow into the order flows of several groups has shown that only the order flow of financial institutions and dealers seems to be informative at short-term horizons whereas order flow of non-financial firms is not (Lyons, 2001, Marsh and O'Rourke, 2005, Osler et al., 2006). Accordingly, we reach beyond earlier studies and hypothesize that informed order flow will be a stronger determinant of volatility than order flow from uninformed participants.

Our evidence is consistent with the view that private information is a significant determinant of exchange rate volatility. In order to derive this main result we model and empirically confirm the intraday volatility pattern found by Andersen and Bollerslev (1998) for our data. Adding various categories of news shows that some of them contribute systematically to explaining exchange rate volatility, in particular US macroeconomic announcements. This asymmetry between the US and Europe is found by Andersen et al. (2003) and Ehrmann and Fratzscher (2005), too. We then add three order flows. We find that only informed flows, i.e. order flow from banks and from financial customers, help to explain volatility.

The remainder of this paper discusses literature on information and volatility in Section 2. Section 3 describes data used. Section 4 explains the coherent framework of volatility measurement introduced by Andersen and Bollerslev (1998). Section 5 presents results, and Section 6 concludes.

2 Information and volatility

This section shortly reviews the impact of information revelation on exchange rate volatility, in particular the contribution and measurement of public as well as private information. Then we introduce the most important studies in this respect and finally we discuss the contribution that a consideration of order flow can make.

Financial market models since the 1980s have concentrated on the mechanisms by which information that is dispersed among asymmetrically informed agents is compounded in prices. It follows from these models that information processing causes volatility. By contrast, only in frictionless markets information would be compounded instantaneously and without dispute, so that price change just once, from the old to a new equilibrium.

The empirical literature on the relation between information arrival and price changes in foreign exchange has focused in the beginning on the analysis of important economic announcements, such as measuring the price change around the publication of a trade balance figure. It is consistently found that surprising realizations of fundamentals do indeed change exchange rates and thus contribute to volatility. A comprehensive recent study in this respect is Andersen et al. (2003) who show the impact of announcements on exchange rate returns and volatility. Another strand of literature has not studied announcements of certain fundamentals but more aggregated news, in particular classified headline news from newswire agencies (e.g. Melvin and Yin, 2000). Again, volatility goes up with the arrival of news. The limitation of these studies is, however, that they cover – due to their design – publicly available information only and neglect the possible role of private information (see Bauwens et al., 2006, also for an overview of studies).

The existence of private information in foreign exchange has sometimes been questioned because it is not obvious what kind the private information should be in this market. Of course, central banks possess a systematic information advantage as they set interest rates and conduct foreign exchange interventions but this does not spill over to private market participants. When we ask foreign exchange traders, however, they themselves mention information differences and ascribe systematic advantages to larger traders (Cheung and Chinn, 2001; see Bjønnes et al., 2005a). Moreover, there is mounting evidence that information is also asymmetrically distributed over space, so that information may differ in foreign exchange according to the location of a participant (Goodhart and Figliuoli, 1992, Covrig and Melvin, 2002, Menkhoff and Schmeling, 2006). Finally, financial customers seem to be better informed than commercial customers, as mentioned above. Lyons (2001) has generalized these observations in the way that information about exchange rates is dispersed and that the trading process can be seen as a search mechanism to identify information, i.e. to distinguish it from noise, and to reveal the market's opinion about its implication on the price (see also Evans and Lyons, 2002, Osler, 2006). This raises the question how to identify such private information which cannot be as easily observed as fundamental announcements.

According to our knowledge, there are three papers which examine the role of public *and* private information in explaining exchange rate volatility. The first paper in this direction is DeGennaro and Shrieves (1997), who model volatility in a GARCH specification including hourly dummies to capture the intraday pattern. News is covered by Reuters headline news. Moreover, in order to measure private information flow they decompose the ten-minute quote arrival rate into the expected and the unexpected component. The unexpected part serves as their measure of private information. The second paper is Cai et al. (2001). They take the Andersen and Bollerslev (1998) approach to model volatility and complement it by considering day of the week effects. News is 65 regular items of macroeconomic announcements. Regarding their measure of private information they rely on the weekly foreign exchange position changes of large US investors. The most recent paper is Bauwens et al. (2005) who analyze the euro/dollar rate whereas the earlier studies focus on yen/dollar. Bauwens et al. (2005) calculate volatility by an EGARCH model on a five-minute basis. News headlines are taken from the Reuters news-alert screens. Private information is calculated as unexpected market activity in a similar way as in DeGennaro and Shrieves (1997). A focus of Bauwens et al. (2005) is to document the pattern in market activity before, at, and after news announcements.

All of these papers share their main conclusion: exchange rate volatility is determined by strong seasonal patterns, by the occasion of news and by the revelation of private information. However, the private information measures are necessarily imprecise either because the frequency is weekly (Cai et al., 2001) or because the measure implies in fact a joint hypothesis (DeGennaro and Shrieves, 1997, Bauwens et al., 2005). Joint hypothesis means here that the measure of unexpected activity is assumed to capture informed trading, a hypothesis being derived from the Admati and Pfleiderer (1988) model that informed traders prefer to place their trades in the crowd of uninformed liquidity trading; then unusually high trading is informative because informed traders place their orders when uninformed trade much. However, the same paper discusses the opposite possibility that uninformed traders prefer to cluster their trades, which might increase the role of informed traders in periods of thin trading (when uninformed traders are absent). So, theory does not provide an unambiguous ex ante-expectation on the share of informed trading in unexpected activity: either the share is high because informed traders hide among the large amount of uninformed trading or the share is low because the uninformed traders prefer to trade with each other and thus avoid trading with informed traders.[1] If the second alternative applies, then the correlation of unexpected activity and volatility – as observed in some studies – may be caused in a high frequency setting by the immediate price impact of large uninformed trades.

Bauwens et al. (2005) have thus mentioned the advantage of analyzing customer order flow data. Order flow measures signed transactions, i.e. it measures for example buying of a currency as positive and selling as negative and then calculates the accumulated net activity. An overweight of buy-initiated trades is interpreted as revealed appreciation expectation of participants. The problem with any order flow analysis is, however, that the relation between positive order flow in the above given sense – i.e. net buying – and currency appreciation is not necessarily due to information. Instead, this relation may be also caused by illiquidity (see Osler, 2006). It is thus comforting that we can divide customer order flow into two groups, i.e. commercial customers who will be rather liquidity traders at the short horizons of our analysis and financial customer whose motivation of trading is much more influenced by informed expectations on shorter-term returns. So, the order flow – net buying – of both groups will dry up liquidity but only financial customers can be regarded as informed, whereas commercial customers are rather uninformed (see Osler, 2006).

In fact, we also have the order flow of a third group, i.e. other foreign exchange dealers. This interbank trading may be caused either by information of banks, generating own account trading, or may be induced by customer trading. Regarding the dealers' reaction on customers we know that they treat them according to their expected level of information: if they trade with a financial customer they will faster and more intensively cover their own position, i.e. they transmit this trade into the interbank market and thereby the information of this customer (Osler et al., 2006). By contrast, if the counterparty is a commercial customer, bank traders react much less. As a consequence, interbank order flow tends to be similar to financial customer order flow with respect to the information contained.

[1] The empirical contribution by Lyons (1996) led to an ambiguous result, as he found some support for both views, however, on a basis of five trading days.

3 Data

The analysis is based on established data sets which cover the period from July 11 to November 9, 2001. Data is compiled from three different sources. The calculation of high frequency volatility is based on minute-by-minute data provided by Olsen Financial Technologies. News is taken from the Factiva data base, containing Reuters headline news. Finally, transaction data are from a bank and is the only source used that is of private property.

The latter data set consists of the complete USD/EUR trading record of a bank in Germany. The record covers 87 trading days, with business hours from 8:00 to 18:00 (MET).[2] For each trade, we obtain the following information: (1) the exact date and time; (2) the initiator and the direction of each trade (bank buys or sells); (3) the quantity traded; and (4) the type of counterparty: bank, financial customer, commercial customer.[3] Table 1 displays descriptive statistics for the aggregated and disaggregated order flow series. Our ability to distinguish among customer types is almost unique in currency research using transactions data: Lyons (1995) only uses data on interbank trading; Yao (1998) has customer trade data but does not generally distinguish among customer types; Bjønnes and Rime (2005) have insufficient customer transactions to perform a detailed analysis; finally, Lyons (2001), Evans and Lyons (2004) and Marsh and O'Rourke (2005) can distinguish among customer groups but only in daily data.

The trading volume of this bank is small compared to market leaders (such as documented in Lyons, 1995) but it is large enough to serve big customers and it is professional enough to serve the full range of derivatives and other currencies, too (see Mende and Menkhoff, 2006). Moreover, trading pattern of this bank is similar to those of the few large banks where information has been published (Osler et al., 2006). Finally, the foreign exchange market is so competitive and conventions are so important that relevant banks cannot afford to behave differently, which has been confirmed to us by market participants.

Whereas this part of the data set covers actual FX transactions of a single bank, the second data set consists of market-wide, quoted FX data. Olsen's USD/EUR spot data records all last bid and ask quotes within one-minute intervals. From these we calculate a minute-by-

2 Compared to other microstructure data sets such as Lyons (1995), Yao (1998), and Bjønnes and Rime (2005) this is possibly the longest observation period for transactions from an individual currency dealer up to date.

3 *Bank* incorporates other FX dealers (thus: interbank trading), *financial customers* are institutional investors, such as asset managers, hedge or mutual funds, and insurance companies, *commercial customers* are non-financial corporations, such as ex- and importers.

minute exchange rate as their midpoint and the returns at a 5-minute frequency as 100 times their log difference. Figure 1 shows the USD/EUR exchange rate for the whole sample period.

The third data set used covers news and is provided by Factiva, a Dow Jones & Reuters company. We collected all headlines available on the Reuters newswires between July and November 2001 from the categories 'finance', 'macro', 'politics' and 'others', counted them (we use "event of news" as a variable), and assigned them to five categories: (1a) US macro news, (1b) Euro macro news and (1c) other countries' macro news, such as news related to GDP, (2) financial markets news, such as market developments, and technical indicators, and finally (3) other news, mainly including political news. Due to the highly integrated financial markets the news categories (2) and (3) are not further assigned to currency areas (US dollar, euro) as we do for the macro news. Table 2 provides information about our classification scheme and Table 3 gives a brief overview about descriptive statistics. In total there are 6,348 news ticks in our sample.

Counting newswire headlines is common in the recent literature (see for instance Bauwens et al., 2005, Dominguez and Panthaki, 2006). However, the exact coverage of news differs between studies. First, our analysis is particular because it primarily relies on order flows; this has the "price" of a limited sample length. Due to the four months period typical scheduled news, which is published once per month, can be observed only a few times and can thus not be usefully analyzed. Accordingly, we do not focus on single kinds of macroeconomic news as many other studies do (Andersen et al., 2003). Second, we use a slightly different classification of news. While it is common to use macro news as one category, the above mentioned studies do not consider financial market news as an category by its own. They are either neglected (Bauwens et al., 2005) or put together with political and other news (Dominguez and Panthaki, 2006). Third, different from e.g. Dominguez and Panthaki (2006) we do not exclude re-published news, as this corresponds strongly with the importance of the news headline[4]. So we get some kind of an implicit weighting scheme for the importance of news.

4 Framework of volatility measurement

Before we analyze the effects of news and order flow on exchange rate volatility, we need to adjust the returns for daily and intraday volatility patterns, which empirical research

[4] For instance regularly re-published news are those on GDP or unemployment figures, which are usually repeated several times within a couple of minutes due to their economic relevance.

has proven to be a characteristic feature of exchange rate data (see the seminal paper by Andersen and Bollerslev, 1998).

For comparing the different data sets the bank data has to be transformed from unevenly recorded tick-by-tick-data to evenly-spaced intervals as given in the market-wide data. Our analysis is based on commonly used 5-minute intervals, because higher frequencies may lead to distortions due to microstructure noise, caused by differences between observed and true prices, bid-ask spreads and rounding errors (Hansen and Lunde, 2004, Andersen et al., 2001). Hence, order flows are summed up within each interval. We define the 5-minute return for the exchange rate $e_{t,n}$ as

$$R_{t,n} = log(e_{t,n}) - log(e_{t,n-1}), \text{ for } 1 < n \leq m, \tag{1}$$

where n is the respective 5-minute interval on day t and m is the total number of 5-minute intervals per day.

Assume then that the demeaned return process takes the following form,

$$R_{t,n} - \mu = \sigma_t \cdot \sigma_{t,n} \cdot z_t \tag{2}$$

where the $R_{t,n}$ is the five minute return over the 5-minute interval n on day t, μ is the expected return of the exchange rate[5], σ_t is the daily volatility level, whereas $\sigma_{t,n}$ represents the remaining intraday movements in exchange rate volatility including the deterministic pattern and other determinants. Both, σ_t and $\sigma_{t,n}$ take only positive values and z_t is an error term, which is i.i.d. with zero mean and unit variance. Equation (2) allows analyzing intraday and daily volatility separately, but within a common framework. Furthermore, it takes into account that the level of daily volatility also affects high-frequency volatility by shifting the intraday pattern (Andersen and Bollerslev, 1998).

By squaring and taking logs equation (2) takes the following form

$$2 \cdot log\left(\frac{|R_{t,n} - \mu|}{\sigma_t}\right) = \underbrace{E\left[log(Z_{t,n}^2)\right]}_{=:c} + 2 \cdot log\left(\sigma_{t,n}\right) + \underbrace{log(Z_{t,n}^2) - E\left[log(Z_{t,n}^2)\right]}_{=:u_{t,n}}, \tag{3}$$

which allows linear estimation of the components. The intraday volatility term $log(\sigma_{t,n})$ may then be further decomposed into a deterministic intraday pattern and the impact of further determinants[6]:

$$h_{t,n} := 2 \cdot log\left(\frac{|R_{t,n} - \mu|}{\sigma_t}\right) = c + \alpha p(n) + \beta \cdot |OF_{t,n}| + \sum_{j=1}^{5} \gamma_j \cdot news_{j,t,n} + \sum_{k=1}^{4} \delta_k \cdot day_k + u_{t,n} \tag{4}$$

[5] Following Andersen and Bollerslev (1998) we choose the sample mean of the returns as a proxy for μ.

[6] These will be specified in more detail in Section 5.

where $p(n)$ is the deterministic intraday pattern, as a function of the current 5-minute interval n, $OF_{t,n}$ represents the order flow in the respective 5-minute interval n on day t and $news_{j,t,n}$ the amount of news ticks in category j and interval n on day t.

Furthermore we add dummies for capturing potential day of the week effects, as in e.g. Melvin and Yin (2000). The equation includes four dummies for Monday, Tuesday, Thursday and Friday. Following Andersen and Bollerslev (1997) we also estimated the news impact in terms of a decay function. We did however not find any significant contribution of past news as soon as we include the intraday pattern to the equation. Therefore we do not present these results in the paper. They are, however, available on request.

If one considers the order flow not as a whole, but dependent on the counterparty group, equation (4) simply emerges to

$$h_{t,n} = c + \alpha p(n) + \sum_{i=1}^{3} \beta_i \cdot |OF_{i,t,n}| + \sum_{j=1}^{5} \gamma_j \cdot news_{j,t,n} + \sum_{k=1}^{4} \delta_k \cdot day_k + u_{t,n} \tag{5}$$

with variables for the order flows for commercial customers ($OF_1=OF_{CC}$), financial customers ($OF_2=OF_{FC}$) and from the interbank market ($OF_3=OF_{IB}$) and their respective coefficients $\beta_1=\beta_{CC}$, $\beta_2=\beta_{FC}$ and $\beta_3=\beta_{IB}$.

According to equations (2) and (3) the first step is to estimate the daily volatility levels. We do this by applying a standard GARCH(1,1) model based on daily exchange rate data[7], which is commonly accepted to describe the exchange rate dynamics well (Bollerslev et al., 1992). Figure 2a depicts the GARCH volatility estimation for the sample under investigation. The peak on September 11 and afterwards impressively shows the importance of controlling for daily volatility levels Next, we model the deterministic intraday volatility pattern $p(n)$. Figure 2b plots the average logarithmic-squared, normalized, and demeaned 5-minute return across the trading hours over the whole sample period (that is the left-hand side of equations (4) and (5)). Indeed, a distinct intraday periodicity of volatility appears. Andersen and Bollerslev (1998) suggest to describe $p(n)$ by applying a set of trigonometric functions. As our data set, however, is restricted to the time between 8:00 and 18:00 (MET), a simpler pattern evolves. Hence, a 4[th] order polynomial turns out to track the data sufficiently well and provides a more parsimonious specification[8].

---

[7] The series was achieved from the Federal Reserve System's H.10 database. In accordance with Andersen and Bollerslev (1998) we base our estimation on a longer period of time, i.e. January 1, 2001, to June 28, 2002, to obtain a sufficiently large sample.

[8] As Melvin and Yin (2000) point out, there is no need to work with the more complex flexible Fourier form if the intraday pattern is simple and sufficiently well described by a parsimonious function.

After these necessary prearrangements, we have now generated a high-frequency volatility series adjusted for the expected return, the daily volatility level and the deterministic intraday periodicity. This series allows for a direct assessment of the impact of order flows and news on intraday volatility.

5 Results

Estimating the impact of news – representing public information – and order flow – representing private information – on exchange rate volatility, we find that it is indeed informed trade only that is significantly related to volatility. As a side-effect we reproduce major results of the literature for our data, such as the well-known intraday volatility pattern or the positive correlation between volatility and news. This section proceeds in three steps from the use of aggregated to disaggregated order flow data and closes with some robustness calculations. All regressions have been performed as GMM estimations with Newey-West heteroskedastic and autocorrelation consistent covariance estimates.

5.1 Results with aggregated order flow

We start by estimating equation (4), i.e. the version of our volatility decomposition with aggregated order flow. Results are given in Table 4 for four specifications, providing separate estimations for each kind of information as well as for the fully specified equation (4). Independent of the specification, the variable "intraday pattern" is always highly significant, indicating its importance as control when analyzing information flows. In contrast to this, we do not find any significant relation between the total order flow and high frequency exchange rate volatility (specification 1), although the positive sign of the coefficient is intuitive: the higher the absolute value of the order flow, the higher is the volatility of the exchange rate. A plausible reason for this result is that data are noisy as informed as well as uninformed order flow is aggregated here into a single variable. We confirm this argument in the next subsection (5.2) when we disaggregate order flow and find that some flows are indeed related to volatility.[9]

Specification (2) shows that the number of news headlines is significant for the category which has been identified as most important, i.e. the number of macro news on the US economy (see Andersen et al., 2003, Ehrmann and Fratzscher, 2005). Further news categories do

[9] Alternatively, one might argue that our data may be inappropriate because order flow is bank-specific, whereas the volatility is measured as market volatility. However, this does not explain why some order flow, i.e. the theoretically expected one, is related to volatility.

not significantly explain volatility, although they are signed as expected. Only the news on the Euro economy has an unexpected negative sign, so that this news dampened volatility – a result that is achieved in Dominguez and Panthaki (2006) too.

Furthermore, specification (3) reveals a weekly pattern of exchange rate volatility. From Monday to Friday there is a continuous increase in volatility, although only the coefficient for Friday is significant. This day of the week effect is in line with Cai et al. (2001), who report increased volatility during the second half of the week for the yen/dollar.

It is reassuring that results of specifications (1) to (3) reported above hold in the full specification (4). We conclude from this sub-section that our data reproduce core findings of the literature as we find a complex intraday pattern, a significant relation between headline news and exchange rate volatility and finally a significant day of the week effect. The less expected finding is, however, that our measure of private information flow – aggregated order flow at the bank level – is not significantly related to volatility. To further explore this relation we disaggregate the total order flow.

5.2 Results with disaggregated order flow

Results differ substantially from above when we proceed to estimating equation (5), i.e. an explanation of exchange rate volatility with disaggregated order flow series. Table 5 gives results for four specifications that mirror the ones from Table 4, plus a fifth specification which we motivate later. The regression results show that the substitution of total order flow by three distinct categories – order flow of commercial customers, financial customers and incoming interbank orders – does *not* affect the other variables: results remain stable for the intraday pattern, news and calendar effects.

However, there is now a remarkable change in the relation between volatility and order flow. All specifications indicate that the source of the order flow, i.e. the bank's counterpart, is of crucial importance. Accordingly, the order flow from commercial customers is least important, the coefficient is positive albeit not significant. The results fit quite well to their role as uninformed liquidity traders as which they may be regarded (see Bjønnes et al., 2005). In contrast, both, the order flow from financial customers as well as incoming order flow from banks, show a significant and positive relation with exchange rate volatility. Interestingly the coefficient for incoming interbank trades exceeds the one for orders from financial customers in size and significance. The latter, however, may be due to the higher number of interbank trades as shown in Table 1. As both, financial customers and banks may be regarded as better informed than commercial customers, results indicate nicely that it is indeed the information flow of informed parties – transported via their order flow – that is related to volatility (see also Bjønnes et al., 2005a, in a different setting).

Nevertheless, as we regress order flow at a single bank on volatility of market-wide quotes the question may arise on the transmission mechanism. Most important in this respect is possibbly order splitting (Sager and Taylor, 2006).[10] If financial institutions reallocate their international investments they easily move hundreds of millions or billions of US dollars. The direct price impact of outright transactions would be considerable and at the disadvantage of the customer. It is thus common practice to split large orders into smaller lots, i.e. for example that one bank orchestrates the distribution of a single order into smaller orders that are placed at one time with different other dealing banks (and possibly through various channels, i.e. through electronic trading, direct trading and conventional brokers). So single banks which are active interbank dealers become part of an international network and relevant order flow shocks will be felt everywhere – although to different degrees – within this system.[11]

The disaggregation of order flows also provides an answer to the questions raised at the end of Sub-section 5.1: the missing relation between total order flow and exchange rate volatility may stem from the noise generated by commercial customer trading in our sample due to its limited number of observations.

In order to test reliability of our core finding, we further disaggregate the order flow according to size. Smaller sized orders, i.e. orders below a volume of 1 million euro,[12] are often regarded as less informed than larger sized orders (see Osler et al., 2006). The reason is twofold: larger traders, relying more often on larger trades, are seen as better informed and any trader with information wants to capitalize on it and will, thus, use a considerable order size to profit from the information advantage. Our analysis with respect to volatility, given as specification (5) in Table 5, conforms to this line of reasoning: it is only the large order flow of financial customers and other banks that matters, whereas smaller orders of both counterparty types are unrelated to volatility. Interestingly, larger orders of commercial customers keep

[10] Lyons (2001) argues that there is another channel which causes a clustering of informed trades, i.e. the reaction on news whose price impact is ex ante unclear. To quote Lyons (2001, p.21) who imagines the reasoning of a foreign exchange dealer in such situations: “If I do not know how you [i.e. another dealer] will interpret the announcement’s price implications, then I need to watch your trade to learn about your interpretation.”

[11] Unfortunately we cannot model the volatility of bank’s quotes for comparison. One may imagine the volatility of bank’s quotes, which we can observe, as a compounded process of volatility multiplied by an binary process indicating whether there is a quote or not. We are only able to observe the compound process, but not the single components.

[12] The median value of all kinds of order flow is close to one million euro.

their insignificant relation, further strengthening the finding that volatility is driven by information and not by liquidity shocks.

To check robustness of findings from a more technical point of view, we have split the sample and receive tentatively the same results, although the small number of financial customer trades becomes a problem. Moreover, we have excluded September 11, 2001 from the sample, again without new insights. Further robustness tests which use modified sets of variables are reported in the following sub-section.

5.3 Further robustness results

Our main concern here is to carve out the relation of interest – order flows to volatility – by considering further possible influences and methods: first, we take account of the fact that order flow is also a means to transport public information (Evans and Lyons, 2004), second, we include more variables into the regression which are linked to volatility to control for omitted variables, and third, we test robustness by applying an EGARCH model and a vector autoregression.

Regarding the decomposition of order flow, Evans and Lyons (2004) find that order flow serves a double role in transmitting information: on the one hand order flow reacts to news and, thus, adjusts prices to information. On the other order flow contains further information – private information – that is independent from news. Accordingly, we control for this double role by retrieving that component of order flow that is not explained by its reaction to news, i.e. the residuals.

The justification for this argument can be directly seen from Table 6 which documents the regression of various news components on the three order flows distinguished here. As hypothesized earlier, order flow from *commercial customers* is basically uninformed (or: liquidity-motivated) because no significant relation between these flows and news items can be detected. In contrast, order flow from *financial customers* shows significant relations to US and Euro macro news. The sign of these coefficients may be surprising at first sight. However, the inaction of German based financial customers on US data may well reflect a rational response, assuming that they are less informed than participants from the US.[13] The negative sign on Euro news cannot be explained this way. It is, thus, revealing to compare financial customer flows with the order flow from other banks: this flow has a positive sign on US

[13] There is evidence that information sets may differ between locations (see Section 2). This is reflected by the fact that many Germany-based financial institutions focus their research on Europe whereas they may cooperate with an US-institution to cover those areas.

macro news, indicating that the order flow arriving from the interbank market includes information from "specialists" on the US market. As these informed professionals do not react on Euro news, our sample seems to contain rather Euro non-news. This fits to the result that this item is also negatively related to volatility, indicating that it does not contain "news" but possibly anticipated "news".

As order flows are indeed related to news it will be interesting to see whether the residuals – order flow that is not explained by news – still influence volatility, indicating that they transport private information. Taking the residuals from the regression underlying Table 6 and using them in the estimation for eq. (5) instead of the order flow, we receive the result given as specification (1) in Table 7. We show only the significant variables in this table as we basically find the same result as before (full specification 4 in Table 5). Results also hold for partial estimations (not shown here).

As an additional exercise we control for possibly omitted variables by including further variables that are known being related to volatility: first, we approximate market activity by the number of price quotations per interval (see e.g. Payne, 2003) and, second, we include the prevailing spread at each 5-minute interval, making use of a stylized relationship between spread and volatility (Sarno and Taylor, 2002).[14] Specifications (2) to (4) in Table 7 show that both enlarged regressions, as well as including both variables simultaneously, help to increase the typically low R^2 of such estimations but that they do not reduce the significance of order flows.

As a further check, we test whether order flow may capture turnover and thus non-directed, i.e. uninformed, trading. However, specification (5) in Table 7 shows that turnover is unrelated to volatility.

A possible alternative method to capture the impact of information on volatility is applying models from the GARCH family. Following Bauwens et al. (2005) we therefore additionally estimate an EGARCH model:

$$r_{t,n} = const. + a \cdot r_{t,n-1} + u_t\,,\; u_t \sim N(0,\sigma_t^2)$$

$$ln(\sigma_{t,n}^2) = \omega + \alpha ln(\sigma_{t,n-1}^2) + \beta\left|\frac{\varepsilon_{t,n-1}}{\sigma_{t,n-1}} - E\left[\frac{\varepsilon_{t,n-1}}{\sigma_{t,n-1}}\right]\right| + \gamma\frac{\varepsilon_{t,n-1}}{\sigma_{t,n-1}} + \sum_{l=1}^{3}\delta_{OF}OF_{t,n,l} + \sum_{m=1}^{5}\delta_{news}news_m + \sum_{n=1}^{4}\delta_{day}day_n \quad (6)$$

where $r_{t,n}$ is the five-minute return adjusted for an intraday pattern. The estimation output is given in Table 8 and confirms our previous results. While there are some differences in the

[14] The number of price quotations is taken from the Olsen data base. As these quotations reflect the older Reuters dealing system Reuters Dealing 2000 which has dramatically lost importance at the end of the 1990s, this variable may be seen as imprecise measure. The spread variable is calculated as the last bid-ask difference in each five minutes interval.

impact of news on volatility – there are more significant coefficients for the news variables, what may be due to adjusting for daily volatility levels in our previous analysis – the relations between the different kinds of order flow and volatility seem to be robust with respect to the particular approach chosen. First, we again find no significant impact of commercial customers' order flow on volatility. Second, order flow from financial customers and the interbank market are highly significant and third, the disaggregation into order flows of small, i.e. up to one million euro, and large trades confirms the picture from the previous estimations: it is mainly the order flow from the large deals that is closely related to volatility.

One might argue that volatility, the exchange rate and news form an interdependent economic system rather than isolated single equation relations. As a final exercise, we therefore apply a vector autoregression[15] of the form

$$
\begin{aligned}
h_{t,n} &= c + \alpha p(n) + \sum_{cp=1}^{3} \beta_0^{cp} \left| OF_{t,n}^{cp} \right| + \sum_{cp=1}^{3}\sum_{h=1}^{2} \beta_h^{cp} \left| OF_{t,n-h}^{cp} \right| + \sum_{i=1}^{2} \gamma_i h_{t,n-i} + \sum_{j=1}^{4} \zeta_j day_j + \sum_{k=1}^{K}\sum_{l=-m}^{m} \delta_{k,l} news_{k,t,n-l} + u_{t,n} \\
OF_{t,n}^{CC} &= c^{CC} + \sum_{cp=1}^{3}\sum_{h=1}^{2} \beta_h^{cp} OF_{t,n-h}^{cp} + \sum_{i=1}^{2} \gamma_i^{CC} h_{t,n-i} + \sum_{k=1}^{K}\sum_{l=-m}^{m} \delta_{k,l}^{CC} news_{k,t,n+l} + \eta_{t,n}^{CC} \\
OF_{t,n}^{FC} &= c^{FC} + \sum_{cp=1}^{3}\sum_{h=1}^{2} \beta_h^{cp} OF_{t,n-h}^{cp} + \sum_{i=1}^{2} \gamma_i^{FC} h_{t,n-i} + \sum_{k=1}^{K}\sum_{l=-m}^{m} \delta_{k,l}^{FC} news_{k,t,n+l} + \eta_{t,n}^{FC} \qquad (7) \\
OF_{t,n}^{IB} &= c^{IB} + \sum_{cp=1}^{3}\sum_{h=1}^{2} \beta_h^{cp} OF_{t,n-h}^{cp} + \sum_{i=1}^{2} \gamma_i^{IB} h_{t,n-i} + \sum_{k=1}^{K}\sum_{l=-m}^{m} \delta_{k,l}^{IB} news_{k,t,n+l} + \eta_{t,n}^{IB}
\end{aligned}
$$

where the volatility $h_{t,n}$ and the three kinds of order flow ($cp=CC, FC, IB$) are treated as endogenous variables. Note that volatility is allowed to depend contemporaneously on order flow, whereas order flows will react only to lagged endogenous variables (similar to Love and Payne 2003, Dominguez and Panthaki 2006). The results do not differ too much, the relation between volatility and order flow of interbank trades remains stable. Furthermore, a noticeable reaction of interbank order flow to the other sources of order flow can be found.

We conclude that order flows from financial customers and other banks – indicating informed trading – are positively related to volatility in a very robust way, whereas order flow from commercial customers is not – indicating liquidity trading.

[15] As the additional insights from the VAR are limited, we do not present the results here. They are available from the authors on request.

6 Conclusion

Exchange rate volatility is an important issue being debated in academia as well as by policy makers. "Why are exchange rates so volatile …?" Obstfeld and Rogoff (2000, p.339) ask when motivating the exchange-rate disconnect puzzle. At the same time (excessive) exchange rate volatility is of high policy relevance because it is often seen as an impediment to trade and to welfare in the last instance (e.g. Rose, 2000).

Our study provides a new piece of evidence in the discussion of this important issue by complementing and extending earlier papers. Our innovation is based on the use of a rare data set that provides high frequency transaction data of a bank with three different kinds of counterparties: other banks, financial customers and commercial customers. We conduct the analysis in a standard framework which was suggested by Andersen and Bollerslev (1998).

We *complement* earlier studies by analyzing the determinants of volatility on the basis of order flow data. This data has two advantages, first, it consists of effective trades and not just indications, and, second, order flow nets out accidental arrival of liquidity motivated transactions (and relies on the clustering of orders on the same side in the market instead). We *extend* earlier studies in the sense that we use disaggregated measures of market activity. By splitting-up order flow into the order flows of three kinds of participants we can conduct differential analysis and do indeed find that the origin of the order flow is important. As one might expect from a theoretical point of view it is only order flow from other banks and financial customers – indicating informed trading – that is positively related to exchange rate volatility. This finding is strengthened by the fact that some order flow is not related to volatility and this flow stems from commercial customers that are expected to be less informed.

Overall, our study supports the notion that exchange rate volatility is a consequence of information aggregation in the foreign exchange market. Nevertheless, the limited sample being available for study here calls for more research.

References

Admati, Anat R. and Paul Pfleiderer, 1988. A theory of intraday patterns: volume and price variability. *Review of Financial Studies* 1, 3-40.

Andersen, Torben G. and Tim Bollerslev, 1997. Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance* 4, 115-158.

Andersen, Torben G. and Tim Bollerslev, 1998. Deutsche Mark-Dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies. *Journal of Finance* 53 (1), 219-265.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, und Paul Labys, 2001. The distribution of realized exchange rate volatility. *Journal of the American Statistical Association* 96, 42-55.

Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Clara Vega, 2003. Micro effects of macro announcements: real-time price discovery in foreign exchange. *American Economic Review* 93, 38-62.

Bauwens, Luc, Walid Ben Omrane and Pierre Giot, 2005. News announcements, market activity and volatility in the euro/dollar foreign exchange market. *Journal of International Money and Finance* 24, 1421-1443.

Bauwens, Luc, Dagfinn Rime and Genaro Succarat, 2006. Exchange rate volatility and the mixture of distribution hypothesis. *Empirical Economics* 30, 889-911.

Bjønnes, Geir Høidal and Dagfinn Rime, 2005. Dealer behavior and trading systems in foreign exchange markets. *Journal of Financial Economics* 75, 571-605.

Bjønnes, Geir Høidal, Dagfinn Rime and Haakon O.Aa. Solheim, 2005. Liquidity provision in the overnight foreign exchange market. *Journal of International Money and Finance* 24, 175-196.

Bjønnes, Geir Høidal, Dagfinn Rime and Haakon O.Aa. Solheim, 2005a. Volume and volatility in the FX market: does it matter who you are?, in: Paul De Grauwe (ed.), *Exchange Rate Economics: Where Do We Stand?*, MIT Press, Cambridge et al. 2005, 39-62.

Bollerslev, Tim, Ray Y. Chou and Kenneth F. Kroner, 1992. ARCH modeling in finance: A review of the theory and empirical evidence. *Journal of Econometrics*, 52, 5-59.

Cai, Jun, Yan-Leung Cheung, Raymond S.K. Lee and Michael Melvin, 2001. Once-in-a-generation volatility in 1998: fundamentals, intervention, and order flow. *Journal of International Money and Finance* 20, 327-347.

Cheung, Yin-Wong and Menzie D. Chinn, 2001. Currency traders and exchange rate dynamics: a survey of the U.S. market. *Journal of International Money and Finance* 20, 439-471.

Covrig, Vicentiu and Michael Melvin, 2002. Asymmetric information and price discovery in the FX market: does Tokyo know more about the yen?. *Journal of Empirical Finance* 9, 271-285.

DeGennaro, Ramon P. and Ronald E. Shrieves, 1997. Public information releases, private information arrival and volatility in the foreign exchange market. *Journal of Empirical Finance* 4, 295-315.

Dominguez, Kathryn M.E. and Freyan Panthaki, 2006. What defines 'news' in foreign exchange markets? *Journal of International Money and Finance* 25, 168-198.

Ehrmann, Michael and Marcel Fratzscher, 2005. Exchange rates and fundamentals: new evidence from real-time data. *Journal of International Money and Finance* 24, 317-341.

Evans, Martin D.D. and Richard K. Lyons, 2002. Order flow and exchange rate dynamics. *Journal of Political Economy* 110, 170-180.

Evans, Martin D.D. and Richard K. Lyons, 2004. Do markets learn about fundamentals from order flow? Working Paper, UC Berkeley.

Gehrig, Thomas and Lukas Menkhoff, 2004. The use of flow analysis in foreign exchange: exploratory evidence. *Journal of International Money and Finance* 23, 573-594.

Goodhart, Charles A.E., 1988. The foreign exchange market: a random walk with a dragging anchor. *Economica* 55, 437-460.

Goodhart, Charles A.E. and Lorenzo Figliuoli, 1992. The geographical location of the foreign exchange market: a test of an "islands" hypothesis. *Journal of International and Comparative Economics* 1, 13-27.

Hansen, Peter R. and Asger Lunde, 2004. An unbiased measure of realized variance. Working Paper, (March 31, 2004). http://ssrn.com/abstract=524602

Love, Ryan and Richard Payne (2003), Macroeconomic news, order flows and exchange rates, *London School of Economics FMG Discussion Paper* dp475.

Lyons, Richard K., 1995. Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics* 39, 321-351.

Lyons, Richard K, 1996. Foreign exchange volume: sound and fury signifying nothing? In: Jeffrey A. Frankel, Gianpaolo Galli and Alberto Giovannini (eds.), *The microstructure of foreign exchange markets*. Chicago et al.: University of Chicago Press, 183-201.

Lyons, Richard K., 2001. *The microstructure approach to exchange rates*. Cambridge: MIT Press.

Melvin, Michael and Xixi Yin, 2000. Public information arrival, exchange rate volatility, and quote frequency. *Economic Journal* 110, 644-661

Mende, Alexander and Lukas Menkhoff, 2006. Profits and speculation in intra-day foreign exchange trading. *Journal of Financial Markets* 9, 223-245.

Menkhoff, Lukas and Maik Schmeling, 2006. Local information in foreign exchange. University of Hannover working paper.

Obstfeld, Maurice and Kenneth Rogoff, 2000. The six major puzzles in international macroeconomics: is there a common cause?, *NBER Macroeconomics Annual* 15, 339-390.

Osler, Carol L., 2006. Macro lessons from microstructure. *International Journal of Finance and Economics* 11, 55-80.

Osler, Carol, Alexander Mende and Lukas Menkhoff, 2006. Price discovery in currency markets, Brandeis University working paper.

Payne, Richard, 2003. Informed trade in spot foreign exchange markets: an empirical investigation. *Journal of International Economics* 61:2, 307-329.

Rose, Andrew, 2000. One money, one market: estimating the effect of common currencies on trade. *Economic Policy* 30, 7-45.

Sager, Michael J. and Mark P. Taylor, 2006. Under the microscope: The structure of the foreign exchange market. *International Journal of Finance and Economics* 11:1, 81-95.

Sarno, Lucio and Mark P. Taylor, 2002. *The economics of exchange rates*. Cambridge et al.: Cambridge University.

Yao, Jian M., 1998. Market making in the interbank foreign exchange market. Working paper S-98-3, Stern School of Business, New York University.

TABLE 1. Descriptive Statistics of Order Flows

	FX order flow[a)]	CC trades[a), b)]	FC trades[a), b)]	(incoming) IB trades[a), b)]
Mean	0.2497	0.0929	0.0356	0.1212
Median	0.0000	0.0000	0.0000	0.0000
Maximum	76.49	76.49	41.68	15.42
Minimum	0.00	0.00	0.00	0.00
Number of intervals with OF	1,859 (17.8 %)	909 (8.7 %)	136 (1.3 %)	951 (9.1 %)
Std. Dev.	1.79	1.46	0.75	0.61
Observations	10,438	10,438	10,438	10,438
Correlations:				
CC Trades[b)]		1.000		
FC Trades[b)]		0.006	1.000	
IB Trades[b)]		0.049	0.048	1.000

Based on the complete EUR/USD trading record of a small bank in Germany between July 11 and November 9, 2001.
[a)] All numbers in millions of EUR;
[b)] CC: commercial customers, FC: financial customers, IB: interbank trades, OF: order flow

TABLE 2. Definition of News Categories

US, Euro and other macro news categories (1a)-(1c)	Financial markets news category (2)	Other news news category (3)
• data and forecasts on.. ..GDP ..employment ..prices ..sales numbers ..orders ..international trade • macroeconomic indicators • consumer confidence • statements of central banks and other institutions on the whole economy	• news from the stock market, FX market and bond market • interest rate decisions by central banks • statements of central banks and other institutions on financial markets • technical indicators	• news from politics and society

News achieved from Reuters newswire headlines via Factiva.

TABLE 3. Descriptive Statistics of News Data

	US macro (1a)	Euro area macro (1b)	Other macro (1c)	Financial markets (2)	Other news (3)
Number of news ticks	738	164	323	1020	4103
Number of intervals with news ticks	595 (5.70 %)	159 (1.52 %)	296 (2.84 %)	773 (7.41 %)	2776 (26.60 %)
Max. number of news ticks per interval	5	2	4	5	12
Mean	0.071	0.016	0.309	0.098	0.393
Standard deviation	0.319	0.128	0.192	0.382	0.810
Correlations:					
US macro	1.000				
Euro area macro	0.036	1.000			
Other macro	0.019	0.058	1.000		
Financial markets	0.129	0.076	0.035	1.000	
Other news	0.080	0.042	0.116	0.190	1.000

For a description of the news categories see table 2.

Table 4. Estimations with Aggregrated Order Flow

Variable	Only OF (1)	Only news (2)	Only days (3)	Full specification (4)
Constant	0.011	-0.610	-0.071	-0.616
	(0.993)	(0.624)	(0.953)	(0.617)
Intraday pattern	**1.002******	**0.951******	**0.999******	**0.957******
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Total OF	0.041			0.039
	(0.146)			(0.156)
News (1a)		**0.202****		**0.189****
(US macro)		**(0.031)**		**(0.044)**
News (1b)		-0.353		-0.333
(Euro macro)		(0.178)		(0.206)
News (1c)		0.184		0.190
(oth. macro)		(0.179)		(0.165)
News (2)		0.092		0.088
(fin. markets)		(0.309)		(0.333)
News (3)		0.019		0.020
(others)		(0.660)		(0.641)
Monday			-0.094	-0.075
			(0.413)	(0.511)
Tuesday			-0.018	-0.007
			(0.869)	(0.948)
Thursday			0.140	0.145
			(0.187)	(0.172)
Friday			**0.226****	**0.232****
			(0.028)	**(0.024)**
adj. R^2	0.013	0.013	0.013	0.014
D-W	1.887	1.888	1.889	1.891

All regressions have been performed as GMM estimations. Dependent variable: volatility per five-minute-interval as described in eq. (4); Newey-West standard errors, significance is given in parentheses. Asterisks refer to level of significance, *: ten per cent, **: five per cent, ***: one per cent. D-W: Durbin-Watson statistic for residuals.

Table 5. Estimations with Disaggregated Order Flow

Variable	Only OF (1)	OF and news (2)	OF and days (3)	Full specification (4)	Full specification disaggregated by counterparty and size (5)	
Constant	0.501	-0.175	0.021	-0.610	-0.612	
	(0.698)	(0.895)	(0.987)	(0.647)	(0.653)	
Intraday pattern	**1.044*** **	**0.990*** **	**1.009*** **	**0.959*** **	**0.958*** **	
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	
					<1 million €	≥1 million €
OF_{CC}	0.010	0.012	0.007	0.010	-0.086	0.009
	(0.722)	(0.681)	(0.773)	(0.712)	(0.808)	(0.729)
OF_{FC}	**0.055** **	**0.054** **	**0.053* **	**0.052* **	-0.151	**0.053* **
	(0.041)	**(0.044)**	**(0.052)**	**(0.058)**	(0.878)	**(0.055)**
OF_{IB}	**0.182*** **	**0.181*** **	**0.165*** **	**0.165*** **	-0.000	**0.168*** **
	(0.000)	**(0.000)**	**(0.001)**	**(0.001)**	(0.506)	**(0.001)**
News (1a)		**0.169* **		**0.182** **	**0.183** **	
(US macro)		**(0.064)**		**(0.047)**	**(0.045)**	
Friday			**0.215* **	**0.229** **	**0.230* **	
			(0.058)	**(0.043)**	**(0.052)**	
adj. R^2	0.013	0.014	0.014	0.014	0.016	
D-W	1.890	1.892	1.892	1.894	1.894	

All regressions have been performed as GMM estimations. Rows without any significant coefficient are not displayed. Dependent variable: volatility per five-minute-interval as described in eq. (5); Newey-West standard errors, significance is given in parentheses. Asterisks refer to level of significance, *: ten per cent, **: five per cent, ***: one per cent. D-W: Durbin-Watson statistic for residuals.

Table 6. Order Flow - News Relation

Variable	OF_{CC}	OF_{FC}	OF_{IB}
Constant	**0.083*** **	**0.038*** **	**0.120*** **
	(0.000)	**(0.000)**	**(0.000)**
News (1a)	0.033	**-0.017*** **	**0.063** **
(US macro)	(0.629)	**(0.007)**	**(0.018)**
News (1b)	-0.045	**-0.022* **	**-0.062** **
(Euro macro)	(0.220)	**(0.0533)**	**(0.010)**
News (1c)	-0.031	0.004	-0.006
(oth. macro)	(0.338)	(0.893)	(0.793)
News (2)	0.077	-0.004	0.018
(fin. markets)	(0.366)	(0.683)	(0.489)
News (3)	0.005	-0.002	**-0.010* **
(others)	(0.550)	(0.779)	**(0.085)**
adj. R^2	0.000	0.000	0.001
D-W	1.420	1.981	1.651

Regression of the respective order flow on news headlines. All regressions have been performed as GMM estimations. Newey-West standard errors, significance is given in parentheses. Asterisks refer to level of significance, *: ten per cent, **:five per cent, ***: one per cent. D-W: Durbin-Watson statistic for residuals.

Table 7. Robustness Checks

Variable	eq(5) with residuals (1)	eq (5) +quotes (2)	eq (5) +spread (3)	eq (5) +quotes, +spread (4)	eq (5) with turnover (5)
Constant	-0.636	**-3.986*** **	**-2.201***	**-4.641*** **	-0.679
	(0.633)	**(0.003)**	**(0.085)**	**(0.000)**	(0.617)
Intraday pattern	**0.958*** **	**0.744*** **	**0.856*** **	**0.701*** **	**0.951*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
OF_{CC}	0.011	0.012	0.008	0.010	-4.61E-06
(turnover CC)	(0.719)	(0.636)	(0.757)	(0.678)	(0.144)
OF_{FC}	**0.051***	**0.055***	0.040	**0.046***	5.37E-06
(turnover FC)	**(0.063)**	**(0.040)**	(0.134)	**(0.076)**	(0.141)
OF_{IB}	**0.183*** **	**0.133*** **	**0.165*** **	**0.137*** **	2.98E-08
(turnover IB)	**(0.001)**	**(0.003)**	**(0.001)**	**(0.002)**	(0.444)
News (1a)	**0.181***	**0.148***	**0.180***	**0.151***	**0.193***
(US macro)	**(0.048)**	**(0.094)**	**(0.048)**	**(0.087)**	**(0.035)**
News (1c)	0.192	0.196	0.214	**0.212***	0.186
(oth. macro)	(0.142)	(0.125)	(0.101)	**(0.097)**	(0.154)
Friday	**0.229***	**0.241***	**0.234***	**0.243***	**0.227***
	(0.043)	**(0.030)**	**(0.031)**	**(0.025)**	**(0.052)**
Ticks		**0.031*** **		**0.027*** **	
		(0.000)		**(0.000)**	
Spread			**1.188*** **	**0.821*** **	
			(0.000)	**(0.000)**	
adj. R^2	0.014	0.034	0.025	0.039	0.013
D-W	1.894	1.904	1.911	1.913	1.890

All regressions have been performed as GMM estimations. Rows without any significant coefficient are not displayed. Dependent variable: volatility per five-minute-interval as described in eq. (5). Column 1 with residuals instead of order flow, columns 2-4 with additional variables; Ticks: price quotes per five-minute-interval, spread: 1000 times the difference between the last log ask rate and the last log bid rate per five-minute-interval. Column 5: equation (5) with turnover of commercial customers (CC), financial customers (FC) and interbank trades (IB) respectively instead of order flow; Newey-West standard errors, significance is given in parentheses. Asterisks refer to level of significance, *: ten per cent, **:five per cent, ***: one per cent. D-W: Durbin-Watson statistic for residuals.

Table 8. Estimations from an EGARCH model

Variable	Order flow by counterpart	Order flow by counterpart and size	
	-1.359* **	**-1.322*** **	
ω	**(0.000)**	**(0.000)**	
	0.922* **	**0.925*** **	
α	**(0.000)**	**(0.000)**	
	-0.026* **	**-0.027*** **	
β	**(0.000)**	**(0.000)**	
	0.203* **	**0.120*** **	
γ	**(0.000)**	**(0.000)**	
		<1 million €	≥1 million €
	-3.60E-09	6.65E-08	-4.11E-09
OF_{CC}	(0.397)	(0.150)	(0.328)
	2.73E-08* **	**-3.21E-07** **	**2.78E-08*** **
OF_{FC}	**(0.000)**	**(0.018)**	**(0.000)**
	1.79E-08* **	2.15E-10	**1.47E-08** **
OF_{IB}	**(0.0039)**	(0.647)	**(0.017)**
News (1a)	**0.086*** **	**0.086*** **	
(US macro)	**(0.000)**	**(0.000)**	
News (1b)	**0.179*** **	**0.177*** **	
(Euro macro)	**(0.000)**	**(0.000)**	
News (1c)	**-0.074*** **	**-0.074*** **	
(oth. macro)	**(0.002)**	**(0.002)**	
News (2)	**0.072*** **	**0.071*** **	
(fin. markets)	**(0.000)**	**(0.000)**	
News (3)	0.000	4.49E-05	
(others)	(0.933)	(0.991)	
	-0.020* **	**-0.020*** **	
Monday	**(0.000)**	**(0.000)**	
	-0.011 **	**-0.011*** **	
Tuesday	**(0.010)**	**(0.010)**	
	0.005	0.004	
Thursday	(0.248)	(0.290)	
	0.004	0.005	
Friday	(0.298)	(0.246)	

Estimates from the variance equation of the EGARCH model in eq. (6) (as suggested by Bauwens et al. (2005):

$$ln(\sigma_{t,n}^{2}) = \omega + \alpha\, ln(\sigma_{t,n-1}^{2}) + \beta \left| \frac{\varepsilon_{t,n-1}}{\sigma_{t,n-1}} - E\left[\frac{\varepsilon_{t,n-1}}{\sigma_{t,n-1}}\right] \right| + \gamma \frac{\varepsilon_{t,n-1}}{\sigma_{t,n-1}} + \sum_{l=1}^{3} \delta_{OF}\, OF_{t,n,l} + \sum_{m=1}^{5} \delta_{news}\, news_{m} + \sum_{n=1}^{4} \delta_{day}\, day_{n}$$