Exchange Rate Forecasting, Order Flow and Macroeconomic Information*

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Abstract

This paper investigates empirically the ability of simple microstructure models based on order flow to overturn the stylized fact that empirical exchange rate models cannot outperform a naive random walk benchmark. Using one year of data for three major exchange rates obtained from Reuters on special order, we find evidence that order flow is a powerful predictor of future movements in daily exchange rates in an out-of-sample exercise where an investor carries out allocation decisions based on order flow information. The economic value of order flow, measured in terms of Sharpe ratios, is generally above unity and substantially higher than the ones delivered by alternative models, including the random walk benchmark. We also document that the information in order flow is intimately related to a broad set of economic fundamentals of the kind suggested by exchange rate theories, as well as to expectational errors about these fundamentals. In turn, our interpretation is that order flow is the vehicle via which fundamentals information impacts on current and future prices, consistent with Evans-Lyons (2002a, 2005a) microstructure theories.

Keywords: Exchange Rates; Microstructure; Order Flow; Forecasting; Fundamental News; Macroeconomic Information.
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1 Introduction

Following decades of failures to explain and forecast exchange rates using traditional exchange rate determination models (Meese and Rogoff, 1983; Cheung, Chinn and Garcia-Pascual, 2005), the recent microstructure literature has provided rays of hope, pioneered by a series of papers by Evans and Lyons (2002a,b; 2005a,b; 2006a). These papers have established that there exists a close contemporaneous link at the daily frequency between exchange rates movements and order flow (Evans and Lyons, 2002a) and the importance of order flow for one exchange rate on another in the context of a currency portfolio allocation problem (Evans and Lyons, 2002b).

In this literature, order flow is taken to be a variant of the more familiar concept of 'net demand' and measures the net of buyer-initiated orders and seller-initiated orders.[1] The landmark piece of Evans and Lyons (2002a) provides a model which sheds light on the role of order flow in determining exchange rates. In their model, order flow is a proximate determinant of prices since it aggregates disperse information that currency markets need to aggregate–anything pertaining to the realization of uncertain demands (differential interpretation of news, shocks to hedging demands and to liquidity demands, etc.). Evans and Lyons provide evidence that order flow is a significant determinant of two major bilateral exchange rates at the daily frequency, obtaining coefficients of determination substantially larger than the ones usually obtained using standard macroeconomic models of nominal exchange rates.[2]

In a simplistic micro-macro dichotomy, one may view the standard macro approach to exchange rates as based on the assumption that only public macroeconomic information matters for exchange rates, and the micro approach as based on the view that private information is key to understanding exchange rates. However, neither of these extreme perspectives is likely to be correct, whereas a hybrid view seems much more plausible. The finding that order flow has more explanatory power than macro variables in explaining exchange rate behavior is interesting and has a fairly clear interpretation in terms of expectations formation mechanisms (Engel and West, 2005; Evans and Lyons, 2005a). Specifically, this finding does not necessarily imply that order flow is the underlying driver of exchange rates. Indeed, it may well be that macroeconomic fundamentals are an important underlying driving force, but that conventional measures of the macroeconomic fundamentals are so imprecise that an order-flow "proxy" performs better in estimation. This interpretation as a proxy is particularly plausible with respect to expectations–that is, even if macro variables fully describe the true model, when implemented empirically these variables may provide a poor measure of *expected*

[1] As noted by Lyons (2001), it is a variant of, rather than a synonym for, 'net demand' because in equilibrium order flow does not necessarily equal zero.

[2] Essentially, the R^2 increases from 1-5 percent for a regression of the exchange rate change on interest rate differentials to 40-60 percent in a regression which also uses order flow to explain the daily variation in exchange rates.

future fundamentals. Thus, it may be that order flow provides a more precise proxy for variation in these expectations. In this sense, unlike expectations measured from survey data, order flow represents a willingness to back one's beliefs with real money, and the Evans-Lyons results may be seen as suggesting that both public and private information matter for exchange rate determination and that information impacts on prices not only directly but also via order flow (see Evans and Lyons, 2006b). In this sense, the Evans-Lyons story is one where traditional macro analysis is augmented with simple price determination microeconomics. Their results are found to be fairly robust by the subsequent literature (e.g. Payne, 2003; Killeen, Lyons and Moore, 2006; Dominguez and Panthaki, 2006).

Building on the recent success of the microstructure approach to foreign exchange markets, a number of important hurdles remain on the route towards understanding exchange rate behavior. First, while the emphasis of this literature has primarily been on explaining exchange rate movements with order flow, the Meese-Rogoff robust findings that no available information is useful in forecasting exchange rates out of sample better than a naive random walk model remain the conventional wisdom. This stylized fact of lack implies that knowledge of the state of economy at a point in time is largely useless information to predict currency fluctuations. Second, if one were willing to accept fully the existence of the linkage between order flow and exchange rate movements and were also willing–with wishful thinking–to believe that this relationship also allows to forecast currency fluctuations, economists are still awaiting for hard empirical evidence that proves where the information in order flow stems from. In particular, while microstructure theories suggest that public, macroeconomic information will impact on exchange rates via a transmission mechanism where order flow is the key vehicle of the transmission, little is known about what information drives order flow. This second issue is important in an attempt to bridge the divide between micro and macroeconomics approaches to exchange rate economics.

In this paper, we make progress on both these issues. First, we investigate empirically the ability of simple microstructure models based on order flow to overturn the stylized fact that empirical exchange rate models cannot outperform a naive random walk benchmark. Using one year of data for three major exchange rates obtained from Reuters on special order, we find evidence that order flow is a powerful predictor of future movements in daily exchange rates in an out-of-sample exercise where an investor carries out allocation decisions based on order flow information. The economic value of order flow, measured in terms of Sharpe ratios, is generally above unity and substantially higher than the ones delivered by alternative models, including the random walk benchmark. We then document that the information in order flow is intimately related to a broad set of economic fundamentals of the kind suggested by exchange rate theories, as well as to expectational errors about these fundamentals. In turn, our interpretation is that order flow is the vehicle via which fundamentals information impacts on current and future prices, consistent with leading microstructure theories.

An important related paper is Evans and Lyons (2005a). This study documents that there is indeed forecasting power in order flow such that it is possible to outperform a random walk benchmark. However, our study is different in at least two important respects. First, while Evans and Lyons (2005a) study one exchange rate and use proprietary customer data from a particular bank which are not available publicly, we employ data for three major exchange rates from the Reuters electronic interdealer trading platform. Second, we switch the emphasis of the forecasting evaluation from *statistical* measures of forecast accuracy (like root mean squared errors) to measures of the *economic* value of the information in order flow. Specifically, we ask whether there is any additional economic value to a mean-variance investor who uses exchange rate forecasts from an order flow model relative to an investor who uses forecasts from alternative specifications, including a naive random walk model. We quantify the economic value in terms of Sharpe ratios, the most common measure of performance evaluation employed in financial markets to measure the success of asset managers and traders.[3]

We also build on recent work on understanding order flow determinants by Evans and Lyons (2005b) and Dominguez and Panthaki (2006). These studies provide evidence that several macroeconomic indicators have significant contemporaneous impact on order flow. The present study is different from this strand of the literature in that we examine the broadest set of economic indicators and market expectation about the state of the economy to date, and that we focus specifically on the role of order flow in aggregating disperse expectations about fundamentals and, hence, as the key vehicle in the transmission mechanism from real-time macroeconomic information to movements in exchange rates.

The rest of the paper is organized as follows. In the next section, we provide a short literature review and the motivation for the paper. Section 3 describes the data set used and presents some preliminary findings on the linkage between order flow and exchange rates. The forecasting setup and the investor's asset allocation problem are discussed in Section 4, where we also report the results relating to exchange rate forecasting and measure the economic value of conditioning on order flow in exchange rate models. The relationship between order flow and macroeconomic fundamentals is examined in Section 5. Section 6 concludes the paper.

[3] We wish to note that, although we focus on the most common measure of economic value, when one decides to move away from statistical criteria of forecast accuracy evaluation, there are many different ways to characterize or define economic value, and the Sharpe ratio is just one of them (e.g. see Leitch and Tanner, 1991). In this respect, we do not claim to provide a full answer to the crucial economic question of whether exchange rates can be forecast using order flow. We do claim, however, that the use of different metrics of evaluation based on economic value, such as the one presented in this paper, provides an alternative way to analyze the relationship between exchange rates and order flow that may shed light on aspects of such relationship (or lack of it) which cannot be captured by standard statistical criteria. See Elliott and Ito (1999), and Abhyankar, Sarno and Valente (2005).

2 Literature Review and Motivation

2.1 Exchange Rates, Fundamentals and Order Flow

The feeble link between exchange rates and fundamentals, in the short, medium, and to a certain extent the long run, has given rise to 'the exchange rate disconnect' puzzle (Obstfeld and Rogoff, 2000). The Meese and Rogoff (1983) results on exchange rate forecasting using macroeconomic models, that first identified the rift between the two, have become the benchmark against which failure in exchange rate literature is measured. Their results have not been convincingly overturned, despite the variety of models and econometric techniques employed (Neely and Sarno, 2002; Kilian and Taylor, 2003; Cheung, Chinn and Garcia-Pascual, 2005). Furthermore, there is ample research on the relationship between fundamental based models and exchange rates, most of which has encountered dim success in explaining exchange rate fluctuations.[4] These findings have been interpreted as reflecting the lack of a relationship between macroeconomic fundamentals and exchange rates and have given rise to two different strands of research that attempt to provide an explanation for the puzzle: one based on the stochastic properties of the macroeconomic variables used and the other on the microstructure of the exchange rate market.

Engel and West (2005) demonstrate that the lack of forecastability of exchange rates using fundamentals can be reconciled with exchange rate theories using a rational expectations model, where the exchange rate equals the discounted present value of expected economic fundamentals. Their result hinges upon two assumptions: (i) fundamentals are nonstationary (or near-random walk) processes; and (ii) the factor for discounting expected fundamentals in the exchange rate equation is relatively high, greater than 0.9 or near unity. Under these conditions, the empirical exchange rate models cannot forecast exchange rate changes, even if the fundamental's model is correct.

Concurrently, the microstructure literature has taken significant steps towards the resolution of the disconnect puzzle, especially with regards to the short run fluctuations of exchange rates. Evans and Lyons (2002a) propose a model that integrates public macroeconomic information and private heterogeneous agents' information in a microstructure trading setup, where, in equilibrium, order flow aggregates private information. In their setup, order flow serves as a mapping device from dispersed information in the market to prices.[5] The price change at the end of each period can be expressed as:

$$\Delta s_t = \beta_1 \Delta r_t + \beta_2 \Delta x_t + v_t, \tag{1}$$

[4] Frankel and Rose (1995) conclude that: "The dispiriting conclusion is that little explanatory power is found (in macroeconomic fundamentals). We ... are doubtful of the value of further time-series modelling of exchange rates at high or medium frequencies using macroeconomic models." For an overview of the literature on exchange rate determination, see e.g. Sarno and Taylor (2003, Chapter 4).

[5] Carlson and Lo (2004) present a thorough examination of the Deutsche mark/dollar exchange rate during a trading day and how order flow is mapped into the exchange rate.

where Δs_t is the daily change in the log exchange rate (domestic price of the foreign currency), Δr_t is public macroeconomic information (e.g. changes in interest rates, interest rate differentials, etc.), Δx_t is daily order flow, and v_t is the residual.

Evans and Lyons (2002a) use four months of direct interdealer daily data for Deutsche mark/dollar and Japanese yen/dollar, to test the predictions of model (1), and find that daily order flow can explain 63 and 40 percent of these currencies fluctuations, respectively. The results have been confirmed by subsequent studies for different currencies and sample periods (Payne, 2003; Berger, Chaboud, Chernenko, Howorka, Iyer, Liu, and Wright, 2005; Bjønnes, Rime and Solheim, 2005; Dominguez and Panthaki, 2006; Killeen, Lyons and Moore, 2006, etc.). In a subsequent paper, Evans and Lyons (2002b) extend the aforementioned model to include portfolio balance effects and find that the addition of other currencies order flow to own order flow can help explain between 45 and 78 percent of the fluctuations of the nine exchange rates examined. These results are impressive, if we take into account the stylized fact that fundamental-based macroeconomic models can explain less than 5 percent of the fluctuations in the exchange rate at these frequencies.

On the forecasting front, Evans and Lyons (2005a, 2006a) extend the Engel and West (2005) model to include microstructure features. They start from conventional exchange rate theories, whereby the exchange rate can be written as the discounted present value of expected fundamentals:

$$s_t = (1-b)\sum_{j=0}^{\infty} b^j E_t^m f_{t+j}, \tag{2}$$

where s_t is the log exchange rate, b is the discount factor, f_{t+j} are fundamentals at time $t+j$, and $E_t^m f_{t+j}$ is the market-maker's expectation of future fundamentals conditional on information up to time t.[6] Iterating equation (2) forward and rearranging terms one obtains:

$$\Delta s_{t+1} = \frac{(1-b)}{b}(s_t - E_t^m f_t) + \varepsilon_{t+1}^m, \tag{3}$$

where $\varepsilon_{t+1}^m \equiv (1-b)\sum_{j=0}^{\infty} b^j \left(E_{t+1}^m - E_t^m\right) f_{t+j+1}$. This implies that the future exchange rate is a function of the gap between the current exchange rate and the expected current fundamentals and an error term that comprises the change in expectations. The changes in exchange rates result from market-makers' updates in expectations, which may be based on order flow. If the changes in order flow are observed immediately (i.e. the market knows aggregate order flow all the time) then there will be only a contemporaneous relationship between exchange rates and order flow (Evans and Lyons, 2006b). Thus, in order to obtain forecastability, one needs the slow discovery of order flow as well. It is argued that due to the decentralized nature of the foreign exchange market, the currency

[6] The original Engle and West (2005) model uses the expectations of the market on the macroeconomic fundamentals not those of the market makers.

markets discover order flow through a gradual learning process, which allows for lagged effects of order flow to determine exchange rate fluctuations.

Evans and Lyons (2005a, 2006a) use six years (1993-1999) of proprietary disaggregate customer data on euro/dollar from Citigroup and find that the microstructure-model based forecasts outperform the random walk at various forecast horizons (1 to 20 trading days). On the other hand, Sager and Taylor (2005) find no evidence of better forecasting ability for the order flow model relative to the random walk model, for several major exchange rates and almost all forecasting horizons (ranging from 1 to 10 trading days). Hence, the forecasting results obtained by Evans and Lyons (2005a, 2006a) are awaiting to be confirmed from other studies, especially because their data is not available either *ex-ante* or *ex-post* to the public.

Even if we might have found in order flow the elixir to explaining exchange rate fluctuations, we have merely shifted paradigm from what explains exchange rates to what explains order flow? Hence, in order to better understand exchange rate fluctuations, it is important to understand the determinants of order flow. Order flow may be seen as a vehicle for macroeconomic information to flow from the market to the exchange rate. As such, order flow plays two important roles: it aggregates differences in interpretation of news in real time and heterogeneous expectations about the future state of economy in the market.

In previous studies, Evans and Lyons (2005b) investigate the determinants of order flow by examining the explanatory power of unexpected changes in fundamentals for Citigroup customer order flow, at the daily level. They find that several macroeconomic indicators have significant contemporaneous impact on different segments of customer euro order flow, and the impact remains significant up to four trading days. Dominguez and Panthaki (2006) conduct a similar study at the intraday level in the interdealer market for the period 10/1999-7/2000 and find that unexpected changes in fundamentals have significant impact on euro and pound order flow, but the explanatory power is very low, 2 and 1 percent respectively. Nonetheless, the role of order flow in aggregating expectations has not been addressed by the literature and its role as a vehicle of mapping macro news to exchange rates in real time has yet to be tested in all the main exchange rate markets and for longer and more recent periods of time.[7]

2.2 Questions Addressed

Building on the evidence provided by the microstructure literature, our empirical analysis is devoted to shed light on two key issues: forecasting exchange rates using order flow and the relationship between macroeconomic fundamentals and order flow. Detecting evidence of exchange rate forecasting

[7] Other studies (Love and Payne, 2003; Berger *et al.*, 2005, Evans and Lyons, 2006b) focus on the effect of macro news on exchange rates via order flow.

ability using order flow information naturally implies that nominal exchange rates are not random walks. Identifying in fundamentals the root cause of changes in order flow, implies that exchange rate fluctuations are linked to fundamentals, but not directly as classical exchange rate theory posits but via order flow. In this way, we can provide a bridge between exchange rates, macroeconomic fundamentals, and forecasting power, as well as a definitive solution to the disconnect puzzle.

We address the forecasting issue using a unique dataset for interdealer data for several currencies. This is the longest and most recent dataset in the literature comprising the three largest currencies in the market. The long dataset is necessary to built a trade-based strategy and obtain robust forecasting results, due to the large number of trading days available. On the methodological side an important contribution of this paper to the microstructure literature is the use of economic criteria to evaluate the forecasting performance of the model. Previous literature has shown that even though statistically it might be difficult to beat the random walk, exchange rate prediction for allocative purposes can yield economic value (Elliott and Ito, 1999; Abhyankar, Sarno and Valente, 2005). Lack of statistical success does not imply the impossibility for tangible economic gains and vice-versa, therefore we evaluate forecasting ability by the extent to which forecast based allocation strategies can provide earning profits. We use the trade-off between risk and returns, Sharpe ratio, to evaluate the model to be used for forecasting and the extent to which out-of-sample forecasts based on this model generate profits.

The link between order flow and macroeconomic information is tackled in two directions, using a very broad set of macroeconomic fundamentals. We examine the role of order flow as a vehicle of macro information flow from the market by measuring the impact of unexpected news on order flow. Order flow's role in aggregating expectations is addressed by using order flow between the day of the formation of expectations till the announcement date to explain the gap between actual and expected values of fundamentals.

3 Data and Preliminaries

The foreign exchange (FX) market is by far the largest financial asset market, with a daily turnover of USD 1,880 billion (BIS, 2004). It is highly decentralized and trades can be either direct or settled through brokers. In the interdealer segment, the dealer can trade directly with other dealers (D2000-1 or phone) or through brokers (voice or electronic). Electronic brokers have become the preferred means of settling trades, 50-70 percent of turnover in the major currency pairs is settled through electronic brokers (Galati, 2001; Galati and Melvin, 2004), and there are two main platforms that users can choose from: Reuters and EBS. Most of the previous studies in exchange rate microstructure have used interdealer data from the early phase of electronic brokers in FX markets (before 2000), with the exception of Berger *et al.* (2005). Since then, there have been several developments in the FX market, including the increase in financial institutions and algorithmic trading and large volumes of proprietary trading (Farooqi, 2006). We have tick-by-tick data for three major exchange rates: USD/EUR, USD/GBP, and JPY/USD - hereafter EUR, GBP, and JPY respectively, for the sample period from February 13, 2004 to February 14, 2005. The data set includes all best ask and best bid quotes as well as all trades in spot exchange rates.[8] Order flow can be inferred from trades. The data have been obtained from Reuters trading system (D2000-2) on special order and collected via a continuous feed. The Bank for International Settlement (BIS, 2004) estimates that trades in these currencies constitute up to 60 percent of the FX spot transactions, 53 percent of which are interdealer trades;[9] hence, our data comprises a substantial part of the FX market.

We aggregate the data at the daily level, between 7:00 and 17:00 (GMT).[10] Figure 1 shows that these are the times when most of the trading occurs in the EUR and GBP market.[11] In this way, we ignore periods when there is little trading, low liquidity, and order flow is not informative. In addition, weekends, holidays, and days with unusually low or no trading activity (due to feed failures) are excluded. The daily exchange rate is expressed as the domestic value of one unit of foreign currency (the US dollar is the domestic currency), and the daily change, Δs_t, is calculated as the difference between the log midpoint exchange rate at 7:00 and 17:00 (GMT).[12] Order flow, Δx_t, is measured as the difference between buyer-initiated and seller-initiated transactions for the foreign (base) currency (a positive sign implies net foreign currency purchases). The interest rates used are the overnight LIBOR fixing for the EUR, GBP, and USD and the spot/next LIBOR fixing for the JPY, obtained from EcoWin.

Market news data are provided by the Money Market Survey carried out by InformaGM. This database is a series of weekly surveys of market participants' expectations with regards to macroeconomic fundamentals to be released in the coming the week. The database includes values of the expected, announced, and revised indicators. The expectations are collected and aggregated the Thursday of the week prior to the announcement week. Note that because information on macroeconomic fundamentals is published with delay both the announcement and expected values of the

[8] We do not have data on the volume of trades, but this should not inhibit the empirical analysis and results. In the asset market, Jones, Kaul and Lipson (1994), and in the exchange rate market, Bjønnes and Rime (2005) and Killeen, Lyons and Moore (2006) show that analysis based on trade size and number of trades is not quantitatively different.

[9] According to the BIS (2004), counterparts in the interdealer market are often those institutions that actively or regularly deal through electronic platforms, such as EBS or Reuters dealing facilities.

[10] We construct daily data from the tick data to filter out liquidity effects, which are mainly transitory effects, and match our empirical framework with the theoretical setup of Evans and Lyons (2002a,b). Furthermore, analysis at the daily frequency is more relevant for macroeconomic analysis and policy makers.

[11] Several other papers (Evans, 2002; Danielsson and Payne, 2002; Payne, 2003) show that overnight trading in FX is very thin.

[12] The midpoint is half the sum of bid and ask price at a point in time.

variables do not pertain to the current period (month or quarter), but to the one before that. We use announcement information for the period 13 February, 2004 - 14 February, 2005 for the United States (US), European Monetary Union (EMU), and United Kingdom (UK).

The summary statistics for the daily exchange rate changes and order flows are reported in Panel A of Table 1. The characteristics of the exchange rate changes are very similar across currencies. The mean returns are slightly negative, but very close to zero, the standard deviations are of similar magnitude, and there is excess skewness and kurtosis. The mean daily order flows are positive, implying average positive demand for foreign currencies in the period under investigation. This does not come as a surprise given the high US budget deficit, the Iraq war, and increasing oil prices that have characterized the period under investigation. Standard deviations are fairly large, allowing for negative order flow and USD appreciation at certain periods in time. The GBP order flow exhibits the highest volatility and highest mean, while the JPY the lowest. This result might be due to the choice of aggregation for order flow, which excludes several trading hours where JPY trading is high.[13]

From Panel B of Table 1, there appears to be a high correlation between the exchange rates, not least due to the common denomination against the USD. The highest correlation is observed between EUR and GBP. Correlations between exchange rates and own order flow are very high, above 40 percent, and those with other currencies' order flows are considerable as well.

As a preliminary assessment, we estimate the contemporaneous relationship between order flow and exchange rates. We investigate the explanatory power of order flow alone, as well as the added value of order flow on the Uncovered Interest Parity (UIP) relationship. The results are presented in Table 2. The order flow coefficients are always positive and highly significant. The positive sign implies that an increase in order flow for the foreign currency will lead to an increase in the exchange rate (i.e. depreciation of the domestic currency).[14] JPY order flow impact on exchange rate changes is the highest, while GBP order flow is the lowest.[15] In the UIP regression, the interest rate differential coefficient is always statistically insignificant at the 10 percent level and has the wrong sign in the JPY equation. The Wald test statistic in this regression rejects the hypothesis that the interest rate differential coefficient is not different from zero. Hence, the power in the estimated equations comes from order flow, whose explanatory power varies between 18 percentage points for GBP and 42 percentage points for EUR.

In order to take advantage of the high correlation between exchange rate changes and order flows,

[13] In our sample 37% of the average daily trading in JPY occurs outside the chosen aggregation hours.

[14] The magnitude of the order flow coefficients is comparable to those obtained by Evans and Lyons (2002a). 1000 net purchase transactions for the EUR will cause a 2.75% increase in the exchange rate.

[15] This is consistent with the Kyle (1985) model, which predicts that order flow has more impact in the less liquid markets. In our sampling procedure, JPY is the least traded exchange rate, hence the less liquid, while the GBP is the most traded currency.

we allow for cross-currency effects for order flow (portfolio balance effects) and use Zellner's (1962) 'seemingly unrelated' (SUR) estimator to estimate:

$$S_t = A + BX_t + V_t, \tag{4}$$

where S_t is a $n \times 1$ vector of daily log exchange rate changes, $S_t = \left[\Delta s_t^1, \Delta s_t^2, ..., \Delta s_t^n\right]'$; X_t is a $n \times 1$ vector of order flows (own and other currencies), $X_t = \left[\Delta x_t^1, \Delta x_t^2, ..., \Delta x_t^n\right]'$; B is an $n \times n$ matrix of order flow (own and other currencies) coefficients; A is a vector of constant terms; and V_t is the residuals vector that incorporates public information. Our dataset comprises three currencies, hence $n = 3$. The results, presented in Table 3, show that using the portfolio balance approach yields an increase in explanatory power for all the currencies from 2 percentage points for EUR to 20 percentage points for GBP. Own order flow impact continues to be positive, albeit lower than in the single equation, and highly significant for all the exchange rate movements. The array of other exchange rates' order flow has a significant and positive effect on exchange rate changes (apart from JPY on EUR) even after accounting for own order flow impact. The Wald test statistic massively rejects the hypothesis that all the order flow coefficients in each regression are equal to zero.

4 Empirical Analysis I: The Predictive Power and Economic Value of Order Flow

We investigate the forecasting power of order flow, following the Evans and Lyons (2005a, 2006a) setup. In model (3), the individual is endowed with a larger set of information than the one available in reality, since macroeconomic information is published with delay. Defining the information set available in real time, equation (3) may be written:

$$\Delta s_{t+1} = \frac{(1-b)}{b}(s_t - E_t^m f_t | \Omega_t) + \varepsilon_{t+1}^m. \tag{5}$$

where $\varepsilon_{t+1}^m \equiv (1-b)\sum_{j=0}^{\infty} b^j \left(E_{t+1}^m - E_t^m\right) f_{t+j+1}$, and Ω_t is the information set available to economic agents at time t, which includes, *inter alia*, $E_t^m f_{t-1}$, current and lagged values of Δx_t and Δs_t. In this setup, there is scope for order flow to play a role in capturing fundamental information (the first term in equation 5) and changes in expectations (the second term in equation 5). If the market aggregates the order flow information only at the end of the day and order flow cumulates expectations, then it can provide the market with forecasting information.

We investigate the existence of forecastability using order flow information in the context of a simple portfolio balance model. The market needs one day to fully uncover aggregate order flow and daily order flow follows an AR(1) process. The exchange rate is modelled as a function of order flow and exchange rate lags, own and other currencies, as summarized by equation (6):

$$S_{t+1} = A + BX_t + \Gamma S_t + U_{t+1}, \tag{6}$$

where S_{t+1} is a 3×1 vector of exchange rate changes, X_t is a 3×1 vector of order flows, B is a 3×3 matrix of order flow (own and other currencies) coefficients, S_t is a 3×1 vector of lagged exchange rate changes, Γ is a 3×3 matrix of exchange rate change (own and other currencies) coefficients, A is a vector of constants, and U_t is the vector of residuals that incorporates public information.[16]

In this section, we discuss the set up employed to evaluate the forecasting ability of order flow for exchange rates. We use a Sharpe ratio maximizing framework to assess the portfolio performance attained by investing in a currency strategy, based on exchange rate forecasts. Subsequently, the results obtained are presented and discussed and finally, we provide evidence for the robustness of the results.

4.1 Model Selection and Portfolio Weights

In order to select the forecasting model and to evaluate the forecasts, we take the perspective of a trader who uses the general exchange rate model (6) or a restricted form of it for daily prediction of the exchange rate to allocate resources/capital and make profits. We do not assume a utility function for the investor, but instead the investor maximizes the trade off between mean and variance using the Sharpe ratio (SR). The Sharpe ratio or the return-to-variability ratio (Sharpe, 1966) measures the risk adjusted returns from a portfolio or investment strategy and is widely used by investment banks and traders to evaluate investment strategies and trading performance. The Sharpe ratio is defined as:

$$SR = \frac{R_p - R_f}{\sigma_p}, \tag{7}$$

where R_p is the annualized return from the investment, R_f is the annualized return from the risk free asset, and σ_p is the annualized standard deviation of the investment returns (assuming that the standard deviation of the risk free asset is zero).

The investor is assumed to have an initial wealth of \$1000 that he invests everyday in three risky assets (currencies) and one riskless asset (overnight deposit). He has a daily horizon and constructs a dynamically rebalanced portfolio that maximizes the Sharpe ratio. In order to choose a forecasting model, he starts from the prior that it is order flow that incorporates the relevant forecasting information, therefore he sets $\Gamma = 0$ in model (6) and follows a general-to-specific procedure starting from a portfolio balance model of order flows $S_{t+1} = A + BX_t + U_{t+1}$ to a model where the exchange rate

[16] The expanded form of equation (6) is the following:

$$\begin{pmatrix} \Delta s_{t+1}^{EUR} \\ \Delta s_{t+1}^{GBP} \\ \Delta s_{t+1}^{JPY} \end{pmatrix} = \begin{pmatrix} \alpha_{11,t} \\ \alpha_{21,t} \\ \alpha_{31,t} \end{pmatrix} + \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{pmatrix} \begin{pmatrix} \Delta x_t^{EUR} \\ \Delta x_t^{GBP} \\ \Delta x_t^{JPY} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{pmatrix} \begin{pmatrix} \Delta s_t^{EUR} \\ \Delta s_t^{GBP} \\ \Delta s_t^{JPY} \end{pmatrix} + \begin{pmatrix} \upsilon_{11,t} \\ \upsilon_{21,t} \\ \upsilon_{31,t} \end{pmatrix},$$

where Δs_t^j are exchange rate changes, Δx_t^j represent daily order flow, β_{ij} are coefficients of own and other currencies order flow, γ_{ij} are coeffiecient of own and other currencies changes in the exchange rate, α_t are constants, and υ_t are residuals.

is determined only by own order flow. After obtaining the forecast for each exchange rate ($\Delta\widetilde{s}^{j}_{t+1|t}$), he invests only in those currencies for which the expected excess return is positive:

$$\widetilde{s}^{j}_{t+1|t} - s^{j}_{t} \times (1 + i_t) > 0, \qquad j = EUR, GBP, JPY \tag{8}$$

where $\widetilde{s}^{j}_{t+1|t}$ is the forecast exchange rate at 17 (GMT) in day $t+1$, s^{j}_{t} is the exchange rate for day t at 17 (GMT).[17] The investor chooses the weights to allocate to each instrument proportionally to the expected return from each of them based on day t information $\widetilde{R}_{p,t+1|t}$, where $\widetilde{R}_{p,t+1|t} = \sum_{j=1}^{3} \Delta\widetilde{s}^{j}_{t+1|t} + i_t$, $j = EUR, GBP, JPY$, and i_t is the overnight LIBOR USD interest rate:

$$w^{j}_{t} = \frac{\Delta\widetilde{s}^{j}_{t+1|t}}{\widetilde{R}_{p,t+1|t}}, \text{ and } w^{i}_{t} = \frac{i_t}{\widetilde{R}_{p,t+1|t}} \quad j = EUR, GBP, JPY, \tag{9}$$

where w^{j}_{t} are the time-dependent weights attached to each risky asset and w^{i}_{t} is the weight on the riskless asset.[18] We do not explicitly model volatility, and the standard deviation is assumed to be constant and works purely as a scaling factor. On day $t+1$, the investor closes his position and calculates the return from the investment. At the end of the period he calculates the annualized return and standard deviation and computes the annualized Sharpe ratio. This setup implies that the investor does not do any short selling.

The forecasting model is chosen by evaluating the in-sample Sharpe ratio yielded by the strategy described above for the period 13/2/2004-14/6/2005. The investor examines the profitability of exchange rate forecasts generated by several models starting from the more general specification in (6) to a narrow specification with only lagged own order flow. The in-sample "forecasts" are the explained part of the exchange rates for day $t+1$, i.e. the difference between the exchange rate and the residual from the system estimation in day $t+1$. He forecasts the exchange rate changes between 7-17 for day $t+1$ matching the portfolio balance model setup and closes the position at 17 PM of day $t+1$. In order to allow for enough observations for the estimation, we calculate the in-sample Sharpe ratios for all the possible models (and present some of them) after the first 30 observations and allow for an increasing number of observations in-sample for the estimation of the model (thus, leave fewer observations to calculate the Sharpe ratio).

In Panel A of Table 4, we present the Sharpe ratios for four models. $M1$ is the best forecasting

[17] This decision rule ensures that observations that are not usable by the investor, but statistical criteria like RMSE, MAE, etc. take into account, are ignored.

[18] The way w^{j}_{t} is calculated is equivalent to a strategy that invests equally in all assets: $\sum_{j=1}^{3} w^{j}_{t} + w^{i}_{t} = \frac{\sum_{j=1}^{3} (\Delta\widetilde{s}^{j}_{t+1|t}/N) + (i_t)/N}{(\widetilde{R}_{p,t+1|t})/N} = \frac{\sum_{j=1}^{3} \Delta\widetilde{s}^{j}_{t+1|t} + i_t}{\widetilde{R}_{p,t+1|t}} = 1$, because $(\widetilde{R}_{p,t+1|t})/N = \sum_{j=1}^{3} (\Delta\widetilde{s}^{j}_{t+1|t}/N) + (i_t)/N$.

model selected after implementing a general-to-specific procedure and may be written as follows:

$$S_{t+1} = A + \begin{pmatrix} \beta_{11} & 0 & \beta_{13} \\ \beta_{21} & 0 & \beta_{23} \\ \beta_{31} & 0 & 0 \end{pmatrix} X_t + U_{t+1}, \tag{10}$$

where S_{t+1} is a 3×1 vector of exchange rate changes, X_t is a 3×1 vector of order flows, A is a vector of constants, and U_t is a 3×1 vector of residuals. In this model, exchange rate lags are set to zero and the forecasting power derives only from order flow. $M2$ is a more general version of $M1$ that includes lags of the exchange rate S_t to account for the possibility of feedback trading (Danielsson and Love, 2006):

$$S_{t+1} = A + \begin{pmatrix} \beta_{11} & 0 & \beta_{13} \\ \beta_{21} & 0 & \beta_{23} \\ \beta_{31} & 0 & 0 \end{pmatrix} X_t + \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{pmatrix} S_{t+1} + U_{t+1}. \tag{11}$$

$M3$ is a general model that includes lags of own and other currencies order flow as presented in equation (6), and $M4$ is classical benchmark, the random walk with a drift. The best model, $M1$ always yields Sharpe ratios around 4, while the other models exhibit either negative or lower Sharpe ratios than model $M1$.[19]

These Sharpe ratios are very high, but one must keep in mind that these are in-sample calculations, deriving from the goodness of fit of the model. The results demonstrate the superiority of lagged order flow information as compared to other variables in explaining exchange rates. In Panel B, we show a representative form of model $M1$, where the exchange rates are a function of own lagged order flow and JPY order flow is a determinant of both the EUR and GBP exchange rate. All own lagged order flow coefficients are positive and highly significant. The equality of the own lagged order flow coefficients is not rejected by the Wald test. Panel C of Table 4 shows that there is very high cross-correlation in the residual covariance matrix that drives the high explanatory power of the system of equations for the exchange rate.

An important caveat in this analysis is the assumption of constant volatility and the choice of weights that maximize only expected returns. We address this issue in the robustness section, by choosing weights that maximize the return to volatility ratio (Sharpe ratio). In this case, the investor invests in a particular currency, if the volatility adjusted excess return is greater than 0:

$$\frac{\widetilde{s}_{t+1}^{j} - s_t^j \times (1 + i_t)}{\sigma_t^j} > 0, \qquad j = EUR, GBP, JPY, \tag{12}$$

where σ_t^j is the unconditional standard deviation of the exchange rate up to time t, assuming that

[19] The superiority of model $M1$ is observed against other models, which are not presented and discussed to conserve space.

$E_t\sigma^j_{t+1} = \sigma^j_t$. The weights allocated to each currency are determined as:

$$w^j_t = \frac{\widetilde{SR}^j}{\sum\limits_{j=1}^{3}\widetilde{SR}^j} = \frac{\frac{\Delta\widetilde{s}^j_{t+1|t}}{\sigma^j_t}}{\sum\limits_{j=1}^{3}\frac{\Delta\widetilde{s}^j_{t+1|t}}{\sigma^j_t}}, \quad j = EUR, GBP, JPY, \tag{13}$$

where $\widetilde{SR}^j$ is the expected Sharpe ratio from the investment in each asset j.[20] In this case, the interest rate is not included in the investment choice, because theoretically the interest rate is a riskless asset, thus its standard deviation is equal to zero, and its Sharpe ratio is not tractable. As a result, we allow for an investment in the overnight deposit only when all the forecasts do not pass the benchmark, or when the forecasts are missing due to missing data. In this setup, the investor continues not to undertake any short-selling activity.

4.2 The Performance of the Forecasting Model Out of Sample

The remaining two-thirds of the sample, 15/6/2004-14/2/2005 are used, to evaluate the model out-of-sample. The models, strategy formation, and investment setup are the same as described in the previous section. The forecast is done differently from the in-sample estimation, because, in a realistic out-of-sample setup, the exchange rate at 7 AM in day $t+1$ is not part of the investor's information set on day t. Hence, at 17 PM of day t, the investor forecasts the exchange rate for each hour (between 7 and 17) of day $t+1$, and in day $t+1$ he closes the position at the hour for which he has made the forecast.[21] In this setup, the investor estimates the available model using as a dependent variable the change in the exchange rate between each hour (between 7 and 17) of day $t+1$, and 17 PM in day t, while the explanatory variable remains order flow aggregated between 7-17 in day t. The model parameters are re-estimated for all the forecasting times. Allowing for the parameters to change across the different times of the day, enables us to capture the different impact that each order flow variable has during the day, depending on liquidity. Forecasts are calculated recursively; thus, the estimating sample increases daily and the model parameters are re-estimated every day. Daily re-estimation of the parameters is in fact a slightly unrealistic and restrictive assumption, since a real trader would actually not only update the parameters daily, but he would update the model (i.e. explanatory variables) every week to choose the best model.

The forecasting results are presented in Table 5. The best in-sample model, $M1$, yields Sharpe ratios ranging from 0.48 to 2.74 depending on which hour of the day the investor closes his position. The average Sharpe ratio for $M1$ is 1.52 and has a standard deviation of 0.56, which implies that

[20] The calculation w^j_t is equivalent to that of a strategy where the investor equally invests in each asset. Refer to footnote 19 for a derivation of the condition.

[21] For example, he forecasts the change in the exchange rate between 17 PM of day t and 7 AM of day $t+1$, and closes the position at 7 AM on day $t+1$, realizing a return $\frac{s^{7AM}_{t+1} - s^{17PM}_t}{s^{17PM}_t}$.

the model used can yield consistently high Sharpe ratios throughout the day. These Sharpe ratios are very high, compared to others found in the literature. The typical Sharpe ratio from a buy-and-hold strategy in the S&P 500 is between 0.4 (Sharpe, 1994; Lyons, 2001a) and 0.5 (Cochrane, 1999), depending on the sample period used.[22] Research on fund performance shows that at best hedge funds reach a mean Sharpe ratio of 0.36 for the period 1988-1995 (Ackermann, McEnally and Ravenscraft, 1999), while the mean Sharpe ratios for off-shore hedge funds range between 0.94 - 1.19 (depending on how cross sectional returns are aggregated) (Brown, Goetzmann and Ibbotson, 1999). The lowest Sharpe ratio is attained at 13 PM, which is the period with the lowest liquidity in the market (Figure 1), but it is still higher than the S&P 500 and hedge funds Sharpe ratios. The addition of other explanatory variables most of the time leads to very poor out-of-sample performance of the model. Models $M2, M3$, and $M4$ can beat the best order flow model in 4 out of 11 cases, but the average Sharpe ratio from $M1$ is at least four times higher than that of the other models, and its standard deviation is the lowest. This implies that the forecasting power derives from order flow (own and other currencies) and not from other variables.

The evolution of wealth for each of the trading hours examined is presented in Figure 2. From this graph, we understand that the high Sharpe ratios are due to relatively high returns and low variance of the investment. The evolution of investment for the forecast for 16 PM is the best example of an active trading strategy with a good Sharpe ratio. We notice that most of the return in this case is generated from active trading and in the worst case scenario the investor loses 2 percent of his wealth but ultimately increases his wealth by as much as 6.5 percent in an 8 months period (3 and 9.75 percent in terms of annualized returns, respectively). The low Sharpe ratio at 13 PM appears to be due to losses in active management over a prolonged period of time at the beginning of the sample and not very high returns in the profit making period. The highest Sharpe ratio obtained by closing the position at 10 AM is due to positive returns every time there is an investment in the exchange rate and the low variance of the returns. There are two cases, 15 and 17 PM, in which the investor never incurs any losses from trading.

We consider these results to be conservative for several reasons. Firstly, in this setup the investor does not undertake short selling, hence the maximum he can lose is all his wealth. This assumption implies that the investor does not take high risks to create higher profits. Secondly, the investor is forced to close his position at a certain point (hour) in time, when realistically, he could place a limit order that allows him to make higher profits in the day. If tomorrow's exchange rate is forecast to be $\widetilde{s}^{j}_{t+1|t}$, he can place a limit order higher than $\widetilde{s}^{j}_{t+1|t}$, and if the order is hit he makes

[22] Sharpe ratio values for exchange rate investments and trading strategies are scarce. Sarno, Valente and Leon (2006) calculate Sharpe ratios from forward bias trading that vary between 0.16 and 0.88, while Lyons (2001a) reports a Sharpe ratio of 0.48 for an equally weighted investment on six exchange rates.

even higher profits. Furthermore, a trader can place limit orders that expire at every hour of the day and accumulate more profits during the day. Thirdly, in reality the investor would update the model periodically, searching for the best fitting and forecasting model every week. Our investor does not do this, but he uses the same model all the time.

4.3 Robustness Checks and Transaction Costs

4.3.1 In-Sample Robustness

In our in-sample analysis, the investment weights were chosen by assuming that volatility is constant, hence ignored in the investment choice. In this section, we relax this assumption and use the Sharpe ratio to decide on whether to invest in a currency and the weight allocated to each currency as described in equations (12) and (13). The results presented in Panel A of Table 6, show that the in-sample Sharpe ratios obtained under the Sharpe ratio rule are similar to those obtained under return maximization, albeit slightly higher. Model $M1$ continues to be the one that yields the highest in sample Sharpe ratios, and our results are not hindered by the use of expected returns only as the determinant for asset allocation.

4.3.2 Out-of-Sample Robustness and Transaction Costs

The robustness of the out-of-sample results is tested by: examining the extent to which returns come from active currency management and assessing the impact of transaction costs.

In order to determine whether the high Sharpe ratios are a function of active currency trading, we amend the trading rule and the investment opportunities, by removing the interest rate investment possibility. As a result, the investor invests in currency j only if $\widetilde{s}^j_{t+1|t} - s^j_t > 0$, and when all forecast are missing (due to missing data) or negative, he does not invest at all. In this way, we reduce the hurdle the forecast has to pass to be eligible for investment, implying an increase in active portfolio management and increased weights in not so profitable assets. The results for this strategy are presented in Panel B of Table 6. On average, all the Sharpe ratios decrease and the average Sharpe ratio for $M1$ decreases to 1.13 (still well above 0.5), but it remains much higher than the models $M2, M3$, and $M4$. This does not mean that the high Sharpe ratios reported in the previous section are due to investment in the overnight deposit rate, but that they are dependent on the hurdle rate established. There is only one instance in which the Sharpe ratio increases, for 16 PM which is the hour with the highest active trading.

To check for the profitability of the trading strategy we introduce transaction costs (TC) both in the decision rule of the investor and the return from investment. Now the investor invests only if $\widetilde{s}^j_{t+1|t} - s^j_t \times (1 + i_t) - TC > 0$ and pays a transaction cost for each unit of foreign currency bought and sold. Transactions costs are assumed to be 0.0001 cent (1 pip), 0.0002, and 0.0004 per unit of currency traded, to represent low, medium, and high costs, which ought to cover for the bid-ask spread and other institutional costs. The introduction of transaction costs implies a higher hurdle rate for investment; hence, will induce less trading and higher profits from the periods for which there is trading. Transaction costs reduce the mean Sharpe ratios for all the models estimated, as presented in Panel C of Table 6. The higher the transaction costs the lower the average Sharpe ratio and the higher the standard deviation. Nonetheless, the average Sharpe ratio for $M1$ in the worst case scenario is 0.82 (still higher than 0.5), and there are still Sharpe ratios for certain hours of the day that are higher than the baseline results and higher than 2, while for the other models the average Sharpe ratios are at best lower than 0.5 or less than 0.[23]

4.3.3 Alternative Portfolio Weights Choice

The portfolio selection procedure employed in this paper is intuitive and resembles the decision making process generally used by investment banks in this context. However, it has the shortcoming that we cannot guarantee that the resulting portfolio choice is efficient, either conditionally or unconditionally. Therefore, we test the robustness of our Sharpe ratio results to using an alternative optimization problem of the mean-variance investor. Specifically, we employ a dynamic mean-variance framework that maximizes the expected return subject to achieving a target level of volatility, to choose investment weights. In each period t, the investor maximizes expected returns as follows:

$$\max_{w_t} \left\{ \sum w_t^{j\prime} \Delta \widetilde{s}^{j}_{t+1|t} + (1 - (\sum_{j=1}^{3} w_t^j)'1) i_t \right\}, \tag{14}$$

and chooses the weights to be allocated in each asset:

$$w_t^j = \frac{\sigma_P^*}{\sqrt{C_t}} \Sigma_t^{-1} (\Delta \widetilde{s}^{j}_{t+1|t} - 1 i_t), \text{ and } w_t^i = 1 - w_t^j \quad j = EUR, GBP, JPY, \tag{15}$$

where σ_P^* is the the target conditional volatility of the portfolio returns, $C_t = (\Delta \widetilde{s}^{j}_{t+1|t} - 1 i_t)' \Sigma_t^{-1} (\Delta \widetilde{s}^{j}_{t+1|t} - 1 i_t)$, and Σ_t^{-1} is the variance-covariance matrix of Δs_t, assuming that $E_t \Sigma_{t+1}^{-1} = \Sigma_t^{-1}$.[24] As in the core results, we assume that short selling is not allowed, i.e. the investment weights are constrained to be greater than zero, $w_t^j > 0$ and $w_t^i > 0$. The target volatility is assumed to take four values (5, 10, 20, and 30 percent), encompassing a wide range of variance preferences. The average Sharpe ratios for each strategy under the different target volatilities are presented in Panel D of Table 6.[25]

[23] The same discussion follows when the interest investment and the transactions costs are applied simultaneously. The results are not reported to conserve space but are available from the authors upon request.

[24] All models considered in this paper assume constant volatility (variance-covariance matrix). Hence the only source of time variation in Σ is due to the fact that the empirical exchange rate models are re-estimated recursively over the forecast sample, so that the volatility forecast for time $t+1$ conditioned on information t is equal to the covariance estimated using data up to time t.

[25] The results according to each trading hour are not presented to conserve space, but are available from the authors upon demand.

The average Sharpe ratio for $M1$ continues to be higher than the others in the literature and the other models considered, albeit it reaches 0.65 for a target volatility of 30 percent. The average Sharpe ratios decreases with the increase in volatility, given that it increases the denominator of the Sharpe ratio.

5 Empirical Analysis II: Order Flow and Macroeconomic Fundamentals

Equation (5) implies that fluctuations in exchange rates are induced from changes in the gap between exchange rates and expected fundamentals (the first term in equation 5) and revisions in expectations (the second term in equation 5). In this section, we analyze the relationship between order flow and news on fundamentals (the change in the gap), and the role of order flow in aggregating expectations on macroeconomic fundamentals (the change in expectations). If the market aggregates the order flow information only at the end of the day and order flow is cumulates expectations, then it can provide the market with forecasting information.

5.1 The Link Between Order Flow and News

First, we investigate whether contemporaneous unexpected changes in the macroeconomic indicators (i.e. departures from expected values) can explain order flow. Unexpected changes in fundamentals are calculated as: $U_{i,t} = \frac{A_{i,t-k} - E_{i,t-n}A_{i,t-k}}{\sigma_i}$, where $A_{i,t-k}$ is the actual value of indicator i at time t pertaining to the fundamental at time $t-k$, where k is a month or a quarter, $E_{i,t-n}A_{i,t-k}$ is the expected value of the indicator formed at time $t-n$,[26] where n ranges between 1 and 5 trading days, and σ_i is the sample standard deviation for indicator i (Andersen *et al.*, 2003):

$$\Delta x_t^j = c + \sum \beta_i U_{i,t} + \eta_t. \tag{16}$$

We estimate equation (16) using ordinary least squares, where standard errors are corrected for autocorrelation and heteroskedasticity using a consistent matrix of residuals (Newey and West, 1987), and present the results in Table 8 (only coefficients significant up to the 10 percent level are shown).[27] News appear to be important determinants of order flow and have the expected signs.[28] Better than expected news on the US cause a decrease in order flow, while better than expected news in the foreign economies cause an increase in order flow. The news that have high explanatory power for

[26] Ideally, we would like to have the expectations on fundamentals just before the announcement time, since expectations can change in a week. This constraint can bias the results towards zero.

[27] Estimates for the contemporaneous effect of individual macro news $\Delta x_t^j = Constant + \beta_i U_{i,t} + u_t$ and their explanatory power for order flow are presented in Table A1 in the Appendix. It has to be noticed that the explanatory power of some of these indicators is very high and the average R^2 is around 20%. Most of the individual announcement R^2 are as high as those reported in Andersen *et al.* (2003) for exchange rate fluctuations at the intraday level.

[28] A list of all the available macroeconomic news and their expected impact sign on order flow is provided in Table A4 in the Appendix.

order flow are the ones that Andersen *et al.* (2003) find to explain exchange rate fluctuations at the intraday level around macroeconomic announcements. Macroeconomic news can explain up to 18 percent of the fluctuations in order flow.

Previous work has failed to show the effect of fundamentals on exchange rates at the daily level, with the exception of Evans and Lyons (2006b). We re-estimate equation (16) with the exchange rate as the dependent variable and use the same macroeconomic news that explain order flow changes as explanatory variables. The results in Table A2, show that these same macroeconomic news can significantly explain fluctuations in the exchange rate at the same scale as they can explain order flow. Microstructure theory predicts that not all information is impound in exchange rates via order flow, but the prevailing model in the exchange market is a hybrid one where some news impacts exchange rates directly and some indirectly, via order flow (Lyons, 2001a,b, 2002). We test this hypothesis by regressing the exchange rate changes on the macroeconomic news and order flow, and the results are presented in Table A2. It can be noticed that the addition of order flow significantly increases the explanatory power on exchange rates, as compared to news impact only. In this case we are allowing for both a price and quantity effect of news on the exchange rate. News directly affect the exchange rate by shifting the equilibrium price and transactions gather the heterogenous votes on the new equilibrium price.

These results can be compared to those obtained in the contemporaneous regressions in Table 2, to evaluate the added value of macroeconomic news information on the exchange rate fluctuations. There appears to be an incremental value attached to public information and the hybrid model has the highest explanatory power. Furthermore, in the previous section, we showed that there is substantial integration in the FX market and that portfolio balance effects contribute to higher explanatory power for the exchange rate. We test the hybrid model in this context, by adding the macro news as explanatory variables in equation (5). The results in Table A3 show that this is the setup in which the highest explanatory power is achieved for all the currencies and that the exchange rate is concurrently determined by order flow, own and others currencies, and macroeconomic news.

5.2 The Link Between Order Flow and Expectations

In a market, where agents have heterogenous beliefs and expectations on the value of fundamentals, and trade based on those expectations, microstructure theory predicts that order flow aggregates expectations about the state of the economy. Given that expectations about the fundamentals are collected and published on the Thursday before the announcement week, we can examine the hypothesis that order flow aggregates changes in expectations. We try to explain the difference between the actual and expected value of the fundamental on the sum of order flow between Thursday and the announcement date, as in equation (17):

$$(A_{i,t-k} - E_{t-n}A_{i,t-k}) = c + \sum_{m=0}^{n} \Delta x_{t-m}^{j} + \varkappa_t, \tag{17}$$

where c is a constant, $\sum\limits_{m=0}^{n} \Delta x_{t-m}^{j}$ is the sum of order flow from the day of the formation of the expectation (Thursday) to the day of the publication of the indicator n, n varies between 1 and 5, and $\varkappa_t$ is the residual. Since order flow should proxy for the change in expectations between the publication and announcement date, an increase in order flow will bring the expectation nearer to the actual value, therefore an increase in own order flow will have a negative impact on the gap between actual and expected fundamentals. The opposite will hold when we are dealing with variables whose impact on the economy is considered negative, i.e. unemployment, inflation, etc. The results presented in Table 8 imply that order flow can significantly explain the difference between actual and expected fundamentals, which we take as evidence that supports the conjecture that order flow aggregates the expectations of the market with regards to these fundamentals.

However, between a given expectation formation date and announcement date, there may be other news releases. We take this possibility into account and clean order flow from the effect of the previous news, and estimate the relationship between residual order flow, after the contemporaneous effect has been taken into account, and the difference between the actual and expected indicator value:

$$(A_{i,t-k} - E_{t-n}A_{i,t-k}) = c + \sum_{m=0}^{n} \Delta xres_{t-m}^{j} + \xi_t, \tag{18}$$

where c is a constant, $\sum\limits_{m=0}^{n} \Delta xres_{t-m}^{j}$ is the sum of the residual order flow from equation (16), from the day of the formation of the expectation to the day of the publication of the indicator n, n varies between 1 and 5, and ξ_t is the residual. Table 9 shows that residual order flow, after the contemporaneous effects have been accounted for, can explain the difference between actual and expected changes in those fundamentals where accumulated order flow did not have explanatory power previously. These results confirm order flow's role as the best means for aggregating market expectations.

6 Conclusions

This paper makes two related contributions to exchange rate economics. First, it provides empirical evidence that overturns the stylized fact that empirical exchange rate models are unable to outperform a naive random walk model in out-of-sample exchange rate forecasting. We find that order flow provides powerful information that allows to forecast daily exchange rate movements using 8 months of data for three major exchange rates. This result is obtained by measuring forecasting power in the context of a simple metric of economic value, the Sharpe ratio. We compare the Sharpe ratios to a mean-variance investor of out-of-sample exchange rate forecasts using a model that conditions on order flow information with the Sharpe ratios under alternative models, including naive random walk model. The average Sharpe ratio from using order flow models is well above unity and substantially higher than a random walk benchmark. These results are robust to high transactions costs and to various other changes in the problem setup.

Second, this paper provides evidence that a significant amount of order flow variation can be explained using macroeconomic news suitably constructed from survey data. Unexpected changes in fundamentals explain a large proportion of order flow fluctuations. In addition, order flow appears to be a predictor of future fundamentals and to aggregate expectations on fundamentals. Given that the exchange rate represents the discounted value of future fundamentals, it is understandable that order flow can successfully forecast exchange rate movements. The relation between order flow with a broad set of economic and financial fundamentals is highly comforting in that it is supportive of the importance of macroeconomic information in driving trading and asset allocation decisions of foreign exchange market participants and, as a consequence, in moving exchange rates.

Table 1. Preliminary data analysis

	Δs_t^{EUR}	Δs_t^{GBP}	Δs_t^{JPY}	Δx_t^{EUR}	Δx_t^{GBP}	Δx_t^{JPY}
	Panel A - Descriptive Statistics					
Mean	-0.03$\times 10^{-3}$	-0.03$\times 10^{-2}$	-0.02$\times 10^{-2}$	23.18	83.00	2.21
Std. Dev.	0.53$\times 10^{-2}$	0.49$\times 10^{-2}$	0.51$\times 10^{-2}$	124.90	149.20	19.50
Skewness	0.29	0.02$\times 10^{-1}$	-0.03	0.26	0.45	-0.31
Kurtosis	4.35	3.11	4.59	3.64	3.41	4.46
	Panel B - Cross Correlations					
Δs_t^{EUR}	1.00	0.70	0.46	0.65	0.35	0.20
Δs_t^{GBP}	0.70	1.00	0.46	0.53	0.42	0.28
Δs_t^{JPY}	0.46	0.46	1.00	0.43	0.30	0.49
Δx_t^{EUR}	0.65	0.53	0.43	1.00	0.38	0.23
Δx_t^{GBP}	0.35	0.42	0.30	0.38	1.00	0.15
Δx_t^{JPY}	0.20	0.28	0.49	0.23	0.15	1.00

Notes: The table reports descriptive statistics and common sample correlations for the period 13/2/2004-14/2/2005. Δs_t^j is the daily change in the log spot exchange rate (dollar/euro, dollar/pound, and dollar/yen) and Δx_t^j is the daily order flow (positive for net foreign currency purchases) cumulated between 7:00 - 17:00 (GMT).

Table 2. Contemporaneous exchange rate - order flow model

			Diagnostics			
	$(i-i^*)_{t-1}$	Δx_t	R^2	Serial	Heter	Wald
Specification	(1)	(2)	(3)	(4)	(5)	(6)
			Dollar/Euro			
I		**2.75**	0.42	[0.00]	[0.88]	
		(11.39)				
II	-0.0008	**2.78**	0.42	[0.00]	[0.25]	[0.15]
	(-1.45)	**(11.47)**				
			Dollar/Pound			
I		**1.42**	0.18	[0.98]	[0.07]	
		(4.93)				
II	-0.0002	**1.36**	0.18	[0.82]	[0.21]	[0.85]
	(-0.19)	**(4.78)**				
			Dollar/Yen			
I		**12.8**	0.24	[0.53]	[0.80]	
		(5.47)				
II	0.0002	**12.4**	0.28	[0.06]	[0.16]	[0.82]
	(0.23)	**(5.48)**				

Notes: The table reports ordinary least square estimates for the regressions: (I) $\Delta s_t = c + \beta\Delta x_t + \eta_t$ and (II) $\Delta s_t = c + \beta_1\Delta x_t + \beta_2(i-i^*)_{t-1} + \eta_t$, for the period 13/2/2004-14/2/2005. The dependent variable Δs_t^j is the daily exchange rate change (dollar/euro, dollar/pound, and dollar/yen). The regressor $(i-i^*)_{t-1}$ is the interest rate differential (overnight LIBOR) in day $t-1$ (where the asterisk denotes the foreign country interest rate). The regressor Δx_t^j is the daily interdealer order flow (number of transactions, positive for net foreign currency purchases, in thousands), cumulated between 7:00 - 17:00 (GMT). The minimum transaction size for the Reuters D2000-2 dealers is 1 million US dollars. t-statistics are shown in parenthesis and are estimated using a autocorrelation and heteroskedasticity consistent matrix of residuals (Newey and West, 1987). Coefficients in bold are significant at the 10% level of significance. Column 3 present the adjusted R^2. Column 4 presents the p-values for the Breusch-Godfrey Lagrange multiplier tests for first-order residual serial correlation. Column 5 presents the p-values for the White (1980) first-order conditional heteroskedasticity test with cross terms in the residuals. Column 6 presents the p-values for the Wald test for the null hypothesis that interest rate differential coefficients are not different from zero. All equations are estimated with a constant, which is not reported to conserve space.

Table 3. Order flow portfolio balance model

	Δs_t^{EUR}		Δs_t^{GBP}		Δs_t^{JPY}	
Δx_t^{EUR}	**2.52**	**(8.91)**	**1.59**	**(5.68)**	**1.18**	**(4.12)**
Δx_t^{GBP}	**0.41**	**(1.78)**	**0.85**	**(3.74)**	**0.45**	**(1.93)**
Δx_t^{JPY}	1.22	(0.72)	**4.18**	**(2.47)**	**10.10**	**(5.83)**
Wald Test	[0.00]		[0.00]		[0.00]	
R^2	0.44		0.38		0.36	

Notes: The table reports seemingly unrelated regression estimates for equation (2) for the period 13/2/2004-14/2/2005. Δs_t^j is the daily exchange rate change (dollar/euro, dollar/pound, and dollar/yen) and Δx_t^j is the daily order flow (positive for net foreign currency purchases, in thousands), cumulated between 7:00 - 17:00 (GMT). t-statistics are shown in parenthesis. Coefficients in bold are significant at the 10% level of significance. The Wald test presents the probability (in square brackets) for the joint null hypothesis that all order flow coefficients are equal to 0. All equations are estimated with a constant, which is not reported to conserve space.

Table 4. Model selection

Panel A: In-sample Sharpe ratios

	$M1$	$M2$	$M3$	$M4$
		7-17		
30	4.44	0.84	2.08	-3.52
40	3.82	0.93	2.11	-4.10
50	4.19	-0.65	3.23	-3.79
60	4.98	-0.31	2.81	-4.59

Panel B: Selected forecasting model

	Δs_{t+1}^{EUR}		Δs_{t+1}^{GBP}		Δs_{t+1}^{JPY}	
$Constant$	-0.0007	(-0.85)	-0.0011	(-1.42)	-0.0006	(-0.61)
Δx_t^{EUR}	0.012	(4.87)	-		-	
Δx_t^{GBP}	-		0.012	(4.87)	-	
Δx_t^{JPY}	4.42	(1.25)	4.74	(1.39)	0.012	(4.87)
$Wald\ Test$ = [0.11]						

Panel C: Covariance matrix

	Δs_{t+1}^{EUR}	Δs_{t+1}^{GBP}	Δs_{t+1}^{JPY}
Δs_t^{EUR}	2.6×10^{-5}	0.56	0.25
Δs_t^{GBP}	1.4×10^{-5}	2.5×10^{-5}	0.38
Δs_t^{JPY}	0.8×10^{-5}	1.2×10^{-5}	4.0×10^{-5}

Notes: The table presents the results on the model selection criteria and the selected model. In Panel A, we present the in-sample Sharpe ratios for four models. $M1$ is the forecasting model that maximizes the in-sample Sharpe ratio, presented in Panel B. $M2$ is the same as $M1$ plus lags of own and other exchange rate changes. $M3$ is a general model specified in equation (6), and $M4$ is the random walk. Panel B presents the in-sample estimated model in equation (10) for the period 13/2/2004-14/6/2004. Δs_{t+1}^{j} is the daily exchange rate change (dollar/euro, dollar/pound, and dollar/yen) and Δx_t^{j} is the daily order flow (positive for net foreign currency purchases, in thousands) cumulated between 7:00 - 17:00 (GMT). t-statistics are shown in parenthesis. Panel C shows the covariance/correlation matrix of residuals for the model in panel B.

Table 5. Realized Sharpe ratios out of sample

	$M1$	$M2$	$M3$	$M4$
17-7	1.23	1.34	-0.81	0.77
17-8	1.65	-0.85	-0.62	-0.34
17-9	1.94	-0.68	-1.10	-2.31
17-10	2.74	-0.34	-1.58	-1.52
17-11	0.96	-0.20	-1.77	-0.59
17-12	1.64	0.16	-0.70	0.92
17-13	0.62	-0.59	0.28	1.14
17-14	1.18	-0.45	-0.39	0.31
17-15	1.87	1.36	0.48	1.68
17-16	1.58	1.73	2.09	1.26
17-17	1.31	2.36	1.73	0.33
Average	1.52	0.35	-0.22	0.15
S.D.	0.56	1.13	1.25	1.23

Notes: The table presents realized out-of-sample Sharpe ratios for the period 15/6/2004-14/2/2005, obtained by investing based on the one period ahead forecasts from the different models and calculated from the investment strategy detailed in section 4.1. $M1$ is the forecasting model that maximizes the in-sample Sharpe ratio, presented in Panel B. $M2$ is the same as $M1$ plus lags of own and other exchange rate changes. $M3$ is the general model in equation (6), and $M4$ is the random walk.

Table 6. Robustness checks

Panel A: In-sample Sharpe ratios

	$M1$	$M2$	$M3$	$M4$
	7-17			
30	4.58	0.50	1.80	-4.12
40	4.01	0.55	1.79	-4.75
50	4.27	-1.64	2.34	-4.65
60	5.04	-1.49	2.96	-5.59

Panel B: $r_f = 0$

	$M1$	$M2$	$M3$	$M4$
17-7	0.96	0.78	-1.51	0.69
17-8	0.44	-0.62	-0.59	-0.42
17-9	1.42	-0.94	-1.47	-0.17
17-10	1.56	-1.05	-2.28	-0.23
17-11	0.93	-1.31	-2.41	-0.24
17-12	1.43	-0.60	-1.14	0.88
17-13	0.61	-1.12	0.15	1.06
17-14	0.83	-0.51	-0.50	0.34
17-15	1.74	1.06	0.50	1.59
17-16	1.68	1.51	1.82	1.20
17-17	0.88	2.21	1.46	0.31
Average	1.13	-0.05	-0.54	0.46
S.D.	0.45	1.22	1.41	0.68

Panel C: Transaction Costs

	Case 1) TC = 0.0001				*Case 2) TC = 0.0002*				*Case 3) TC = 0.0004*			
	$M1$	$M2$	$M3$	$M4$	$M1$	$M2$	$M3$	$M4$	$M1$	$M2$	$M3$	$M4$
17-7	0.75	0.99	0.27	0.57	0.95	0.81	0.57	0.33	0.76	1.27	-0.07	-1.62
17-8	1.10	0.01	-0.67	-0.77	0.94	-0.06	-1.11	-1.84	0.10	-0.16	-1.77	-1.24
17-9	1.61	-0.94	-1.18	-2.71	1.58	-0.72	-1.41	-2.24	1.09	-0.79	-1.69	-1.73
17-10	2.82	0.09	-1.28	-1.15	2.72	-0.22	-0.86	-1.07	2.18	0.76	-1.24	0.04
17-11	1.20	0.08	-0.75	-0.74	1.09	-0.41	-0.55	1.92	2.20	-0.18	-0.87	1.69
17-12	2.88	0.56	0.20	0.79	2.31	0.07	-0.05	0.13	1.29	0.20	0.20	0.75
17-13	0.16	0.06	0.39	1.38	0.44	-0.02	0.01	1.08	-0.14	-0.39	-0.30	0.14
17-14	0.28	-1.08	-0.63	0.40	1.18	-1.52	-0.83	-0.74	1.00	-1.72	-0.67	-1.42
17-15	0.93	1.80	0.47	1.31	1.00	1.58	0.14	0.88	-0.03	0.94	0.31	0.07
17-16	0.57	0.31	1.59	1.23	0.21	0.17	1.42	0.84	-0.45	0.01	1.17	0.03
17-17	1.68	2.51	2.04	-0.29	0.97	2.42	1.90	0.07	1.05	1.53	1.22	0.71
Average	1.27	0.40	0.04	0.00	1.22	0.19	-0.07	-0.06	0.82	0.13	-0.34	-0.23
S.D.	0.92	1.06	1.08	1.27	0.74	1.08	1.04	1.29	0.89	0.95	1.03	1.12

Panel D: Mean-variance determination of weights

σ_P^*	$M1$	$M2$	$M3$	$M4$
5%	1.01	0.68	-0.03	0.47
10%	0.79	0.52	-0.19	0.51
20%	0.68	0.43	-0.27	0.39
30%	0.65	0.41	-0.29	0.30

Notes: The table presents realized out-of-sample Sharpe ratios for the period 15/6/2004-14/2/2005, obtained by investing based on the one period ahead forecasts from the different models and calculated from the investment strategy detailed in section 4.1. The results in Panel A show the in-sample Sharpe ratios attained when the weights are based on a Sharpe ratio maximizing strategy defined in equation (13). The results in Panel B are based on a strategy where the interest rate is set to 0.0 both in the decision rule and the return on investment. The results in the Panel C show the Sharpe ratios when transaction costs are included in the trading strategy and applied to every trade. We apply three transaction costs of 0.0001, 0.0002 and 0.0004 cents per unit of currency traded. Panel D shows the average out-of-sample Sharpe ratios obtained under mean-variance variance framework for target volatilities σ_P^* equal to 5%, 10%, 20%, 30%.

Table 7. Contemporaneous effect of aggregated news on order flow

	Euro	Pound	Yen
Announcement	β_i	β_i	β_i
US Announcements			
GDP advance	-114.40		
GDP preliminary	-69.59		
Chicago PMI	-115.40		
Consumer confidence index			-15.30
Consumer price index		-171.41	
Construction spending			-4.02
Durable goods orders		-134.95	
Initial unemployment claims			4.21
Houseing starts		-5.05	
Michigan sentiment - final	-98.90		-5.36
Nonfarm payroll employment	-90.42	-88.23	
Trade balance	-59.74	181.22	-6.51
Unemployment rate	90.69		
EMU Announcements			
Consumer confidence balance	149.03		
Consumer price index - month	160.52		
Consumer price index - year	-148.40		
Industrial production - year	62.78		
Labor costs	101.08		
Retail sales - month	82.30		
Sentiment index	179.60		
UK Announcements			
GDP provisional - quarter		267.86	
Trade balance		93.42	
R^2	0.15	0.18	0.03

Notes: The table presents the announcement surprises that have a contemporaneous effect on the order flow (net purchases) for Euro, British Pound, and Japanese Yen. The surprise element is calculated as the difference between the actual value ($A_{i,t-k}$) of the indicator minus its expected value ($E_{t-n}A_{i,t-k}$), standardized by the standard deviation (σ_i) for the sample size, $\frac{A_{i,t-k}-E_{i,t-n}A_{t-k}}{\sigma_i}$. The regression is estimated on the total number of indicators available, for the period 13/2/2004-14/2/2005. We report only variables significant at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors, in order to conserve space. All equations are estimated with a constant, which is not reported to conserve space.

Table 8. News response to aggregate order flow

Announcement	Euro β_i	Euro R^2	Pound β_i	Pound R^2	Yen β_i	Yen R^2
US Announcements						
GDP advance					3.30	0.53
Chicago PMI			1.70	0.12	39.00	0.13
Initial unemployment claims					-55.00	0.03
ISM index			0.50	0.17		
Personal income	0.70	0.63				
Philadelphia Fed index	12.30	0.22				
Producer price index					-3.9	0.23
Retail sales					3.40	0.16
Trade balance	-9.30	0.34				
Unemployment rate			-0.03	0.65		
EMU Announcements						
GDP	-0.20	0.56				
PMI Manufacturing	-1.50	0.38				
Labor costs - preliminary	-0.70	0.55				
Labor costs - revised	2.80	0.86				
Producer price index-year	-0.20	0.24				
Trade balance	-7.30	0.30				
UK Announcements						
Average earnings			-0.30	0.41		
Manufacturing output - month			-0.20	0.12		
Producer input price index - year			0.80	0.13		
Retail price index			-0.30	0.34		

Notes: The table presents the explanatory power of cumulated order flow (1000 net purchases) for Euro, British Pound, and Japanese Yen for the difference between actual and expected fundamental value: $(A_{i,t-k} - E_{t-n}A_{i,t-k}) = c + \sum_{m=0}^{n} \Delta x_{t-m}^{j}$. $A_{i,t-k}$ is the actual value of the fundamental, $E_{t-n}A_{i,t-k}$ is the expected value for the fundamental formed the Thursday prior to the announcement date, $\sum_{m=0}^{n} \Delta x_{t-m}^{j}$ is cumulated order flow between the expectation formation day (Thursday) and the announcement day, and n varies from 1 to 5 depending on the publication date. The total number of observations for each currency is 263, for monthly announcements there are 12 observations available, while for quarterly announcements there are 4 observations available, for the period 13/2/2004-14/2/2005. We report only variables significant at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors, in order to conserve space. All equations are estimated with a constant, which is not reported to conserve space.

Table 9. News response to aggregate residual order flow

Announcement	Euro		Pound		Yen	
	β_i	R^2	β_i	R^2	β_i	R^2
US Announcements						
Construction spending	1.60	0.12			14.00	0.26
Consumer confidence index					210.00	0.43
Current account	51.40	0.94	41.30	0.32		
Initial unemployment claims	-8.90	0.05				
ISM index			1.90	0.42		
Michigan sentiment - preliminary			32.90	0.60		
Nonfarm payroll employment			6.20	0.89		
Personal income					2.00	0.30
Philadelphia Fed index	9.20	0.25	0.01	0.31	98.00	0.23
Retail sales					2.00	0.18
EMU Announcements						
GDP	-0.20	0.33				
GDP revised	-0.20	0.89				
Trade balance	-4.80	0.27				
UK Announcements						
Consumer credit			-0.50	0.18		
Manufacturing wages			2.30	0.24		
Manufacturing output - month			-0.70	0.10		
Producer input price index - month			3.10	0.61		

Notes: The table presents the explanatory power of cumulated residual order flow (net purchases) for Euro, British Pound, and Japanese Yen for the difference between expected and actual indicator value $(A_{i,t-k} - E_{t-n}A_{i,t-k}) = c + \sum_{m=0}^{n} \Delta xres^j_{t-m}$. $A_{i,t-k}$ is the actual value of the fundamental, $E_{t-n}A_{i,t-k}$ is the expected value for the fundamental formed the Thursday prior to the announcement date, $\sum_{m=0}^{n} \Delta xres^j_{t-m}$ is the cumulated residual order flow from the contemporaneous regression estimation between the expectation formation day (Thursday) and the announcement day, and n varies from 1 to 5 depending on the publication date. The total number of observations for each currency is 263, for monthly announcements there are 12 observations available, while for quarterly announcements there are 4 observations available, for the period 13/2/2004-14/2/2005. We report only variables significant at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors, in order to conserve space. All equations were estimated with a constant, which is not reported to conserve space.

A Appendix

Table A1. U.S., E.M.U,. and U.K. News Contemporaneous Impact on Order Flow

Announcement	Euro β_i	Euro R^2	Pound β_i	Pound R^2	Yen β_i	Yen R^2
US Announcements						
GDP preliminary	-113.29	0.32				
GDP preliminary	-30.17	0.04			-8.48	0.89
Chicago PMI	-10.08	0.01				
Construction spending					-3.59	0.13
Consumer credit	142.80	0.42				
Consumer confidence index			-415.43	0.56	-15.25	0.41
Consumer price index			-149.92	0.62		
Durable orders			-40.27	0.06		
Housing starts			3.36	0.02		
Initial unemployment claims					4.30	0.04
Michigan sentiment final	-11.43	0.01			-5.45	0.11
Nonfarm payroll employment	-29.93	0.03	-66.01	0.30		
Trade balance	-55.19	0.15	106.90	0.14	-6.18	0.13
Unemployment rate	78.58	0.19				
Average R^2		0.15		0.28		0.29
EMU Announcements						
Consumer confidence	46.08	0.12				
Consumer price index-month	29.77	0.05				
Consumer price index-year	-7.39	0.00				
Industrial production - year	62.60	0.33				
Labor costs	110.80	0.80				
Retail sales - month	74.77	0.14				
Sentiment index	21.73	0.03				
Average R^2		0.21				
UK Announcements						
Budget deficit			-76.44	0.59		
Manufacturing wages			-93.32	0.71		
Retail sales - year			40.57	0.16		
Trade balance			92.26	0.31		
Average R^2				0.44		

Notes: The table presents the news that have a contemporaneous effect on the order flow (net purchases) for Euro, British Pound, and Japanese Yen: $\Delta x_t^j = Constant + \beta_i U_{i,t} + u_t$. The news element is calculated as the difference between the actual value ($A_{i,t-k}$) of the indicator minus its expected value ($E_{t-n}A_{i,t-k}$), standardized by the standard deviation (σ_i) for the sample size, $U_{i,t} = \frac{A_{i,t-k} - E_{t-n}A_{i,t-k}}{\sigma_i}$. The total number of observations for each currency is 263, for monthly announcements there are 12 observations available, while for quarterly announcements there are 4 observations available, for the period 13/2/2004-14/2/2005. We report the impact of the news that were significant in the regression $\Delta x_t^j = Constant + \sum \beta_i U_{i,t} + u_t$ (from Table 7) and other news whose impact is significant at the 10% level.

Table A2. Contemporaneous effect of aggregated news on exchange rates - single equation

	Euro	Pound	Yen
Announcement	β_i	β_i	β_i
US Announcements			
GDP advance	-0.004*		
GDP preliminary	-0.001		
Chicago PMI	-0.007*		
Consumer confidence index			-0.004*
Consumer price index		-0.001	
Construction spending			-0.002**
Durable goods orders		-0.003***	
Initial unemployment claims			-0.0001
Housing starts		-0.0002***	
Michigan sentiment - final	-0.004*		-0.002*
Nonfarm payroll employment	-0.010*	-0.005**	
Trade balance	-0.002	0.003	-0.002*
Unemployment rate	0.005**		
EMU Announcements			
Consumer confidence balance	0.004*		
Consumer price index - month	0.003*		
Consumer price index - year	-0.003*		
Industrial production - year	0.002*		
Labor costs	0.005**		
Retail sales - month	0.003*		
Sentiment index	0.006*		
UK Announcements			
GDP provisional - quarter		0.007**	
Trade balance		0.004**	
R^2	0.22	0.12	0.04
R^2 with own order flow	0.58	0.24	0.31

Notes: The table presents the explanatory power of the contemporaneous macroeconomic news on the exchange rate changes: $\Delta s_t^j = Constant + \sum \beta_i U_{i,t} + u_t$ and the additional explanatory power for the order flow: $\Delta s_t^j = Constant + \sum \beta_i U_{i,t} + \gamma \Delta x_t^j + u_t$, for the period 13/2/2004-14/2/2005. Δs_t^j is the daily exchange rate change (dollar/euro, dollar/pound, and dollar/yen) and Δx_t^j is the daily order flow (positive for net foreign currency purchases, in thousands), cumulated between 7:00 - 17:00 (GMT), $U_{i,t} = \frac{A_{i,t-k} - E_{t-n} A_{i,t-k}}{\sigma_i}$ is the news variable. The explanatory variables used are the same that significantly explain Δx_t^j (from Table 7). *, **, *** imply significance at the 1, 5 and 10% level respectively.

Table A3. Order flow portfolio balance model and macro news

	Δs_t^{EUR}		Δs_t^{GBP}		Δs_t^{JPY}	
Δx_t^{EUR}	**2.23**	**(8.28)**	**1.52**	**(5.40)**	**1.22**	**(4.25)**
Δx_t^{GBP}	**0.38**	**(1.83)**	**0.74**	**(3.10)**	**0.48**	**(2.05)**
Δx_t^{JPY}	1.73	(1.09)	**4.50**	**(2.67)**	**9.07**	**(5.12)**
R^2	0.56		0.40		0.38	

Notes: The table presents the explanatory power of the contemporaneous macroeconomic news and order flow on the exchange rate changes,estimated in a panel regression: $S_t = c+\beta X_t+\sum \beta_i U_{i,t}+u_t$, for the period 13/2/2004-14/2/2005. S_t is a $n \times 1$ vector of daily exchange rate changes Δs_t, X_t is a $n \times n$ vector of order flows (own and other currencies) Δx_t, $U_{i,t} = \frac{A_{i,t-k}-E_{t-n}A_{i,t-k}}{\sigma_i}$ is the news variable, where the news included are the ones that significantly explain Δx_t^j (from Table 7).

Table A4. Announcement Variables

Panel A: U.S. announcements

	Euro	Pound	Yen
	β_i	β_i	β_i
Quarterly Announcements			
GDP advance	-	-	-
GDP preliminary	-	-	-
GDP final	-	-	-
Monthly Announcements			
Real Activity			
Capacity utilization	-	-	-
Consumer credit	-	-	-
Industrial production	-	-	-
Nonfarm payroll employment	-	-	-
Personal income	-	-	-
Retail sales	-	-	-
Unemployment rate	+	+	+
Consumption			
New home sales	-	-	-
Personal consumption expenditure	-	-	-
Investment			
Business inventories	-	-	-
Construction spending	-	-	-
Durable goods orders	-	-	-
Factory orders	-	-	-
Government purchases			
Budget deficit	-	-	-
Net exports			
Current account	-	-	-
Trade balance	-	-	-
Prices			
Consumer price index	+/-	+/-	+/-
Producer price index	+/-	+/-	+/-
Forward looking			
Consumer confidence index	-	-	-
Chicago PMI	-	-	-
Housing starts	-	-	-
Index of leading indicators	-	-	-
ISM index	-	-	-
Michigan sentiment - preliminary	-	-	-
Michigan sentiment - final	-	-	-
Philadelphia Fed index	-	-	-
Weekly Announcements			
Initial unemployment claims	+	+	+

Panel B: E.M.U. announcements

	Euro	Pound	Yen
	β_i	β_i	β_i
Quarterly Announcements			
GDP Flash	+		
GDP Revised - month	+		
GDP Revised - year	+		
Labor costs - preliminary	+/-		
Labor costs - revised	+/-		
Monthly Announcements			
Real activity			
Industrial production - month	+		
Industrial production - year	+		
Labor costs	+/-		
Retail sales - month	+		
Retail sales - year	+		
Unemployment rate	-		
Net exports			
Current account	+		
Trade balance	+		
Prices			
Consumer price index - month	+/-		
Consumer price index - year	+/-		
Money supply M3	+/-		
Producer price index-month	+/-		
Producer price index-year	+/-		
Forward looking			
Business climate index	+		
Consumer confidence balance	+		
Industrial confidence balance	+		
PMI manufacturing	+		
Sentiment index	+		
Services index	+		

Panel C: U.K. announcements

	Euro	Pound	Yen
	β_i	β_i	β_i
Quarterly Announcements			
GDP provisional - quarter		+	
GDP provisional - year		+	
GDP final - quarter		+	
GDP final - year		+	
Current Account		+	
Monthly Announcements			
Real Activity			
Average earnings		+/-	
Consumer credit		+	
Industrial production - month		+	
Industrial production - year		+	
Manufacturing wages		*/-	
Manufacturing output - month		+	
Manufacturing output - year		+	
Retail sales - month		+	
Retail sales - year		+	
Net exports			
Trade balance		+	
Prices			
Consumer price index		+/-	
Producer price index-input		+/-	
Producer price index-output		+/-	
Retail price index-month		+/-	
Retail price index-year		+/-	
Government purchases			
Budget deficit - PSNCR		-	

Notes: The table presents all the available announcement data, and the expected sign of the effect on the order flow (net purchases) of Euro, British Pound, and Japanese Yen.

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Figure 1. Share of Average Number of Trades per Hour

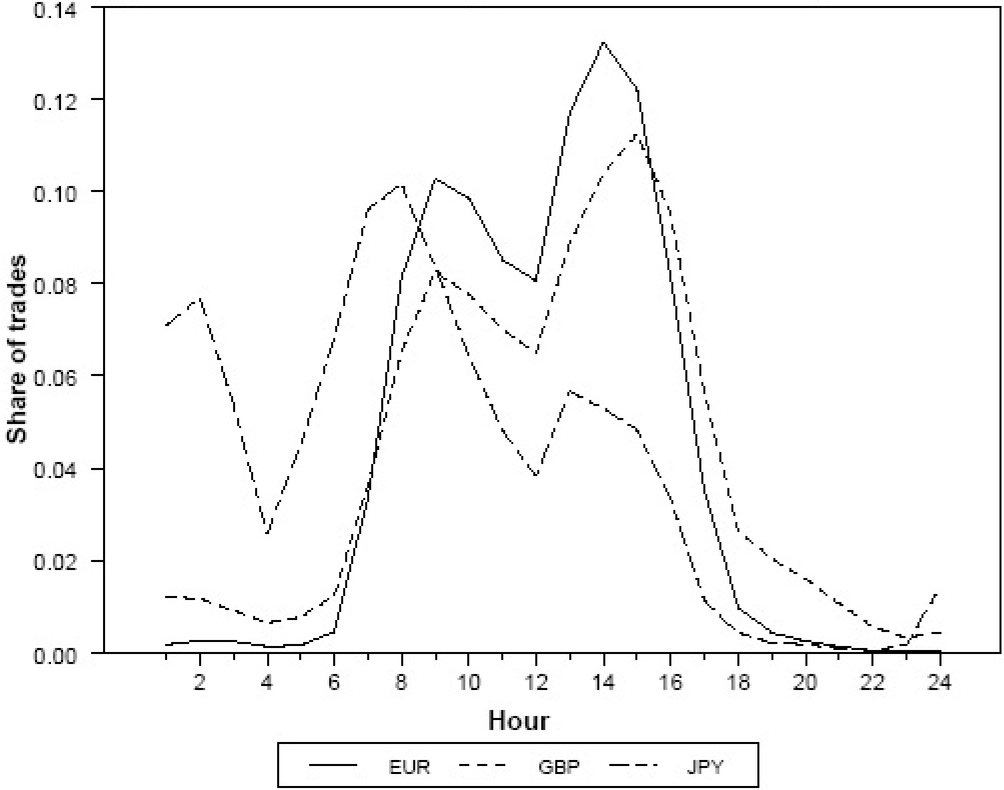

Figure 2. Wealth evolution out of sample