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by

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Exchange Rate Forecasting, Order Flow and Macroeconomic Information*

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Abstract

This paper investigates the empirical relation between order flow and macroeconomic information in the foreign exchange market, and the ability of microstructure models based on order flow to outperform a naïve random walk benchmark. If order flow reflects heterogeneous beliefs about macroeconomic fundamentals, and currency markets learn about the state of the economy gradually, then order flow can have both explanatory and forecasting power for exchange rates. Using one year of high frequency data for three major exchange rates, we demonstrate that order flow is intimately related to a broad set of current and expected macroeconomic fundamentals. More importantly, we find that order flow is a powerful predictor of daily movements in exchange rates in an out-of-sample exercise. The Sharpe ratio obtained from allocating funds using forecasts generated by an order flow model is generally above unity and substantially higher than the Sharpe ratios obtained from alternative models, including the random walk model.

Keywords: Exchange Rate; Microstructure; Order Flow; Forecasting; Macroeconomic News.
JEL Classification: F31; F41; G10.

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1 Introduction

Following decades of failure to empirically explain and forecast fluctuations in exchange rates using traditional exchange rate determination models (e.g. Meese and Rogoff, 1983; Cheung, Chinn, and Garcia-Pascual, 2005), the recent microstructure literature has provided promising evidence, pioneered by a series of papers by Evans and Lyons (e.g. 2002b; 2005b). These papers have theoretically motivated and empirically demonstrated the existence of a close contemporaneous link between daily exchange rate movements and order flow. Order flow is a measure of net buying pressure defined as the net of buyer- and seller-initiated currency transactions (Lyons, 2001).

In a simplistic macro-micro dichotomy for explaining exchange rate movements, one may view the standard macro approach as based on the assumption that only common knowledge macroeconomic information matters, and the micro approach as based on the view that heterogeneous beliefs are essential to determine prices. However, given the lack of a widely accepted model for nominal exchange rates, neither of these extreme perspectives is likely to be correct. A hybrid view, as presented in the microstructure approach to exchange rates (Evans and Lyons, 2002b), seems more plausible. In this model, macroeconomic information impacts on exchange rates not only directly, as in a standard macro model, but also indirectly via order flow. Order flow becomes a transmission mechanism that facilitates aggregation of dispersed price-relevant information such as heterogeneous interpretations of news, changes in expectations, and shocks to hedging and liquidity demands.

Evans and Lyons (2002b) provide evidence that order flow is a significant determinant of two major bilateral exchange rates, obtaining coefficients of determination substantially larger than the ones usually found using standard macroeconomic models of nominal exchange rates. Their results are found to be fairly robust by subsequent literature (e.g. Payne, 2003; Killeen, Lyons, and Moore, 2006). Moreover, Evans and Lyons (2005b, 2006b) illustrate how gradual learning in the foreign exchange (FX) market can generate not only explanatory, but also forecasting power in order flow.

The finding that order flow has more explanatory power than macro variables for exchange rate behavior gives some support to the importance of heterogeneous expectations. However, it does not necessarily imply that order flow is the underlying determinant of exchange rates. Indeed, it may well be that macroeconomic fundamentals are an important driving force for exchange rates, but that conventional measures of expected future fundamentals are so imprecise that an order-flow "proxy" performs better in estimation. Unlike expectations measured by survey data, order flow represents a willingness to back one's beliefs with real money (Lyons, 2001).

Building on the recent success of the microstructure approach to exchange rates, a number of important hurdles remain on the route towards understanding exchange rate behavior. First, if one were willing to accept the existence of a link between order flow and exchange rate movements, economists are still awaiting for conclusive empirical evidence explaining where the information in order flow stems from. This issue is important in attempting to bridge the divide between micro and macroeconomic approaches to exchange rate economics.

Second, while the emphasis of the microstructure literature has primarily been on explaining exchange rate movements with order flow, there are only few empirical results on the forecasting power of order flow. The Meese-Rogoff finding that no available information is useful in forecasting exchange rates out of sample better than a naïve random walk model is robust and remains the conventional wisdom. This stylized fact implies that knowledge of the state of the economy at a point in time is largely useless information for forecasting currency fluctuations. However, if order flow does indeed reflect heterogeneous beliefs about the state of the economy, and if currency markets do not discover order flow immediately in real time but only through a gradual learning process (due to, for example, the decentralized nature of the FX market and its relatively low degree of transparency), then order flow should also provide forecasting power for exchange rate returns.

In this paper, we make progress on both these issues. Initially, we demonstrate that the information impounded 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 expectations about these fundamentals. Then, given the intermediary role of order flow for the relation between exchange rates and macroeconomic fundamentals, we investigate empirically the ability of simple microstructure models based on order flow to outperform a naïve random walk benchmark in out-of-sample forecasting.

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 movements in daily exchange rates in an out-of-sample exercise, where an investor carries out allocation decisions based on order flow information. The Sharpe ratio of the order flow model is generally above unity and substantially higher than the Sharpe ratios delivered by alternative models, including the random walk model. Consistent with leading microstructure theories, our interpretation is that order flow is the vehicle via which fundamental information impacts on current and future prices.

Theoretically, order flow can aggregate macroeconomic information for two reasons: (i) differential interpretation of news; and (ii) heterogeneous expectations about future fundamentals. How order flow can reflect differential interpretations of news is investigated by Berger et al. (2005), Dominguez and Panthaki (2006), Evans and Lyons (2005a, 2006a), and Love and Payne (2006). These studies provide evidence that several macroeconomic indicators have statistically significant contemporaneous impact on order flow, but the explanatory power found is generally low. Compared to these papers, we examine the broadest set of economic indicators and market expectations about the state of the economy in the literature to date. More importantly, the present work differs from the previous literature in that we focus specifically on the role of order flow in capturing changes in heterogeneous expectations about future fundamentals. Hence, we directly investigate the transmission mechanism from real-time changes in expectations about future macroeconomic announcements to movements in exchange rates.

An important related paper is Evans and Lyons (2005b). This study documents that there is indeed forecasting power in order flow, making it possible to outperform a random walk benchmark. However, our work is different in at least two important aspects. First, while Evans and Lyons (2005b) examine one exchange rate and use proprietary customer order flow data from one particular bank which is not available publicly, we employ data for three major exchange rates from the Reuters electronic interdealer trading platform. Second, we shift the emphasis of the forecasting evaluation from *statistical* measures of forecast accuracy (such as root mean squared errors) to measures of the *economic* value of the information in order flow. Specifically, we examine whether there are any additional economic gains for 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 naïve random walk model. We quantify economic gains by calculating the Sharpe ratio, as this is the most common measure of performance evaluation employed in financial markets to assess the success or failure of active asset managers.[1]

The remainder of the paper is organized as follows. In the next section, we provide a short literature review. Section 3 describes the data set and presents preliminary results on the link between order flow and exchange rates. The relation between order flow and macroeconomic fundamentals is examined in Section 4. The forecasting setup and the investor's asset allocation problem are described in Section 5, where we also report the results on economic gains from forecasting models that condition on order flow. Section 6 concludes.

2 A Brief Literature Review

The failure of fundamentals-based exchange rate forecasting models has recently given rise to two different strands of research: one focusing on the careful analysis of the implications of the standard macroeconomic present value approach to asset pricing and the other based on the microstructure approach to the FX market. On the one hand, Engel and West (2005) demonstrate that the lack of forecastability of exchange rates using fundamentals can be reconciled with exchange rate theories within a rational expectations model, where the exchange rate equals the discounted present value of expected economic fundamentals. Their result is based on two assumptions: (i) fundamentals are nonstationary processes; and (ii) the discount factor for expected fundamentals in the exchange

[1] In moving away from statistical criteria of forecast accuracy evaluation, there are many different ways of measuring economic gains (e.g. Leitch and Tanner, 1991), and the Sharpe ratio is just one of them. See Elliott and Ito (1999) and Abhyankar, Sarno, and Valente (2005).

rate equation is near unity. Under these conditions, empirical exchange rate models cannot forecast exchange rate returns (which will behave as near iid processes), even if the fundamentals model is correct. Nonetheless, Engel and West's theoretical result does not imply that fundamentals information cannot explain exchange rate fluctuations; it simply shows that lack of forecastability is not the same as rejection of the underlying model. Indeed, Andersen, Bollerslev, Diebold, and Vega (2003) show that shocks to fundamentals can affect exchange rate movements at intraday frequencies, but the effects dissipate in a very short period of time.

On the other hand, the microstructure literature has taken significant steps towards understanding short-run fluctuations in exchange rates. Evans and Lyons (2002b) propose a microstructure model that integrates public macroeconomic information and heterogeneous agents' private information, where order flow serves as a mapping mechanism from dispersed information to prices. Empirically, they find that the R^2 increases from 1-5 percent for regressions of exchange rate changes on interest rate differentials (a proxy for public macroeconomic information) to 40-60 percent in regressions that use order flow to explain daily changes in exchange rates.[2]

According to FX microstructure theory, order flow may be seen as a vehicle for aggregating both differences in interpretation of news in real time and changes in heterogeneous expectations about the future state of the economy. Starting from conventional exchange rate theories, the exchange rate can be written as the discounted present value of current and expected fundamentals:

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

where s_t is the log nominal exchange rate, b is the discount factor, f_t denotes the fundamentals at time t, and $E_t^m f_{t+q}$ is the market-maker's expectation about future (q-periods ahead) fundamentals conditional on information up to time t.[3] Iterating equation (1) forward and rearranging terms one obtains:

$$\Delta s_{t+1} = \frac{(1-b)}{b}(s_t - E_t^m f_t) + \varepsilon_{t+1}, \tag{2}$$

where $\varepsilon_{t+1} \equiv (1-b)\sum_{q=0}^{\infty} b^q \left(E_{t+1}^m f_{t+q+1} - E_t^m f_{t+q+1}\right)$. This implies that the future exchange rate change is a function of (i) the gap between the current exchange rate and the expected current fundamentals, and (ii) a term that captures changes in expectations. In this setup, there is scope for order flow to coordinate agents' expectations about current fundamentals (i.e. interpretations, the

[2] Related papers confirming and extending these results include Payne (2003), Berger et al. (2005), Bjønnes, Rime, and Solheim (2005), Dominguez and Panthaki (2006), Killeen, Lyons, and Moore (2006). Evans and Lyons (2002a) also find that the addition of other currencies' order flows to own order flow can help explain between 45 and 78 percent of the fluctuations of the nine exchange rates examined. Finally, see Carlson and Lo (2006) for a thorough examination of the Deutsche mark/dollar exchange rate during one trading day and how order flow is mapped into the exchange rate.

[3] The model is adapted from Engel and West (2005) who use market expectations about macroeconomic fundamentals, not the expectations of market makers.

first term in the equation) and to capture changes in expectations about future fundamentals that agents base their trades on (i.e. the second term in the equation). As such, the strong explanatory power of order flow for exchange rate returns is also consistent with a standard macroeconomic fundamentals model.[4,5]

Previous studies have found that order flow can be linked to unexpected changes in current fundamentals (Berger et al., 2005; Dominguez and Panthaki, 2006; Evans and Lyons, 2005a, 2006a; Love and Payne, 2006), even though the explanatory power is very low. The role of order flow in aggregating expectations about future fundamentals has not yet been investigated in the literature.

If order flow reflects the two terms in an exchange rate model of the form (2), and the market does not discover aggregate order flow immediately, then order flow may provide forecasting power (Evans and Lyons, 2005b). It can be argued that due to low transparency and the decentralized nature of the FX market, market participants discover aggregate daily order flow through a gradual learning process, which allows for lagged order flow to determine exchange rate fluctuations.[6]

Evidence on the forecasting power of order flow is scant and mixed. Evans and Lyons (2005b, 2006b) use six years (1993-1999) of proprietary disaggregated customer data on US dollar-euro from Citigroup and find that the forecasts based on an order-flow model outperform the random walk at various forecast horizons (1 to 20 trading days). Danielsson, Luo, and Payne (2002) and Sager and Taylor (2005) find no evidence of better forecasting ability for order flow models relative to the random walk model for several major exchange rates and different forecast horizons. Hence, the forecasting results obtained by Evans and Lyons (2005b, 2006b) are waiting to be confirmed by other studies, especially because their data is not available either ex ante or ex post, given their confidential nature.

3 Data and Preliminaries

3.1 Data Sources

The FX market is by far the largest financial market, with a daily turnover of US dollar (USD) 1,880 billion (Bank for International Settlements, BIS, 2005). Electronic brokers have become the preferred

[4]Usually present-value models of this kind assume that $E_t f_t = f_t$, i.e. that current fundamentals are observable without error in real time. However, in practice, macroeconomic data are not available in real time, since most macro data reported at time t relate to values for a previous month or quarter. At time t, in the absence of official calculations for macro data, agents effectively need to form expectations of the fundamentals for the current period as well as for future periods. A further problem is that the first release of a data point tends to contain (sometimes substantial) measurement error, and data undergo several revisions before being finalized.

[5]Order flow is also affected by the inventory positions and liquidity concerns of market players, but we refrain from considerations of these issues. The literature on dealer behavior shows that inventory effects are short-lived (Bjønnes and Rime, 2005; Lyons, 1995).

[6]Note that even custodian banks, which record order flows for a large proportion of the FX market, typically release data to clients with significant lags. For example, State Street, a major custodian bank, releases order flow data with a 4-day delay, implying that the learning process discussed above may take several days.

means of settling trades, and 50-70 percent of turnover in the major currency pairs is settled through two main electronic platforms, Reuters and Electronic Brokerage System (EBS) (Galati, 2001; Galati and Melvin, 2004).[7] Most previous studies in exchange rate microstructure have used data from the early phase of electronic brokers in the FX market (before 2000), with the exception of Berger et al. (2005). Since then, there have been several important developments in the FX market, including a sharp rise in proprietary trading volumes (Farooqi, 2006) and increased competition for trades by non-bank customers.

This paper uses interdealer data for three major exchange rates: USD *vis-à-vis* euro, the UK sterling, and the Japanese yen (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 bid quotes as well as all trades in spot exchange rates. The data is obtained from Reuters trading system (D2000-2) on special order and collected via a continuous feed.[8] The BIS (2005) estimates that trades in these currencies constitute up to 60 percent of total FX transactions; hence, our data comprises a substantial part of the FX market.

Daily data are constructed from tick data, to filter out transitory liquidity effects, and include only the most active part of the trading day between 7:00 and 17:00 GMT, as Figure 1 shows.[9] 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 USD value of one unit of foreign currency; the daily exchange rate return, Δs_t, is calculated as the difference between the log midpoint exchange rate at 7:00 and 17:00 GMT for the in-sample estimation, whereas in the forecasting exercise we experiment with the difference between a number of time intervals for robustness purposes. Order flow, Δx_t, is measured as the aggregated difference between the number of buyer-initiated and seller-initiated transactions for the foreign (base) currency from 7:00 to 17:00 GMT; positive (negative) order flow implies net foreign currency purchases (sales).[10] The interest rates used are the overnight LIBOR fixings for euro, UK sterling, and US dollar and the spot/next LIBOR fixing for Japanese yen, obtained from EcoWin.

Data on fundamentals is provided from the Money Market Survey (MMS) carried out by InformaGM. The data set includes values for expected, announced, and revised macroeconomic variables.

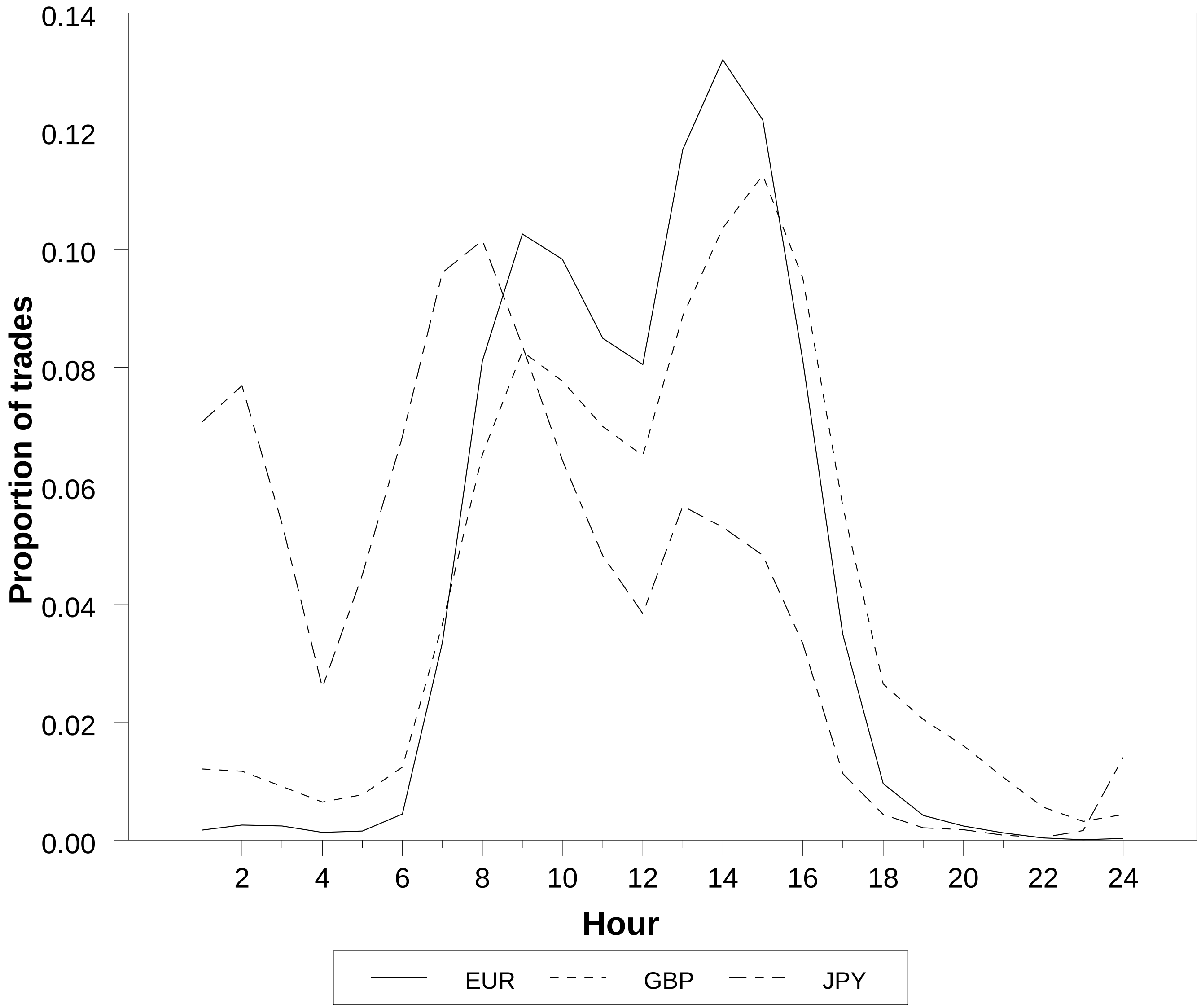
[7]For a detailed description of the structure of the FX market and electronic trading platforms, see Lyons (2001) and Rime (2003).

[8]Reuters is the platform where most of the GBP trades take place, while EBS has the highest share of trades in EUR and JPY. Reuters provides only data on the number, not the volume, of trades, but this should not influence the empirical analysis and results. Bjønnes and Rime (2005) and Killeen, Lyons, and Moore (2006) show that analysis based on trade size and number of trades is not qualitatively different.

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

[10]In a limit order book like Reuters, the initiator is the one that consumes liquidity services and pays half of the spread in order to make a transaction. Liquidity providers use limit orders; liquidity consumers use market orders.

Figure 1
Proportion of average number of trades per hour



Market participants' expectations on macroeconomic fundamentals are collected weekly and aggregated on Thursday the week prior to the announcement week. Note that because information on macroeconomic fundamentals is published with a lag, their values pertain to the month or quarter prior to the current one. We use announcements for the period from February 13, 2004 to February 14, 2005 for EMU, the UK, and the US.[11]

3.2 Preliminary Analysis

Summary statistics for daily exchange rate returns and order flows are reported in Panel A of Table 1. The properties of exchange rate returns are similar across currencies: mean returns are slightly negative and very close to zero and standard deviations are large and of similar magnitude. The mean of daily order flows is positive, implying positive demand for foreign currencies in the sample period under investigation. Standard deviations are fairly large, allowing for negative order flows and positive demand for the USD in certain periods of time during the sample.

Table 1
Preliminary data analysis

Preliminary data analysis for the period 2/13/2004 - 2/14/2005. Δs_t^j is the daily change in the log spot exchange rate from 7:00 to 17:00 GMT, and Δx_t^j is the daily order flow (positive for net foreign currency purchases) accumulated between 7:00 and 17:00 GMT, for each exchange rate j (US dollar/euro (EUR), US dollar/UK sterling (GBP), and US dollar/Japanese yen (JPY)). Panel A presents descriptive statistics for exchange rate returns and order flows. The means and standard deviations for exchange rate returns are expressed in percentage terms. Panel B exhibits common sample correlations among exchange rate returns and order flows.

	Δs_t^{EUR}	Δs_t^{GBP}	Δs_t^{JPY}	Δx_t^{EUR}	Δx_t^{GBP}	Δx_t^{JPY}
Panel A. Descriptive statistics						
Mean	-0.003	-0.03	-0.02	23.18	83.00	2.21
Std. Dev.	0.53	0.49	0.51	124.90	149.20	19.50
Skewness	0.29	0.002	-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					
Δs_t^{GBP}	0.70	1.00				
Δs_t^{JPY}	0.46	0.46	1.00			
Δx_t^{EUR}	0.65	0.53	0.43	1.00		
Δx_t^{GBP}	0.35	0.42	0.30	0.38	1.00	
Δx_t^{JPY}	0.20	0.28	0.49	0.23	0.15	1.00

[11] These data are not available for Japan over the sample period.

Panel B of Table 1 shows that there is high positive correlation among exchange rate returns, partly due to the common denomination against the USD. The highest correlation is observed between EUR and GBP. Correlations between exchange rates and own order flows are high, above 0.4, and those with other currencies' order flows are also sizable.

Table 2
Contemporaneous exchange rate-order flow model

OLS estimates for the regressions: (I) $\Delta s_t^j = c + \beta \Delta x_t^j + \varsigma_t$ and (II) $\Delta s_t^j = c + \beta_1 \Delta x_t^j + \beta_2 (i - i^*)_{t-1} + \varrho_t$, for the period 2/13/2004 - 2/14/2005. The dependent variable Δs_t^j is the daily exchange rate change for each exchange rate j (US dollar/euro (EUR), US dollar/UK sterling (GBP), and US dollar/Japanese yen (JPY)) from 7:00 to 17:00 GMT. The regressor $(i - i^*)_{t-1}$ is the interest rate differential (overnight LIBOR) on day $t-1$ (where the asterisk denotes the foreign country interest rate). The regressor Δx_t is the daily interdealer order flow (number of transactions, positive for net foreign currency purchases, in thousands), accumulated between 7:00 and 17:00 GMT. The coefficients of the explanatory variables are expressed in percentage terms. The minimum transaction size for the Reuters D2000-2 dealers is USD 1 million. 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 presents the 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 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.

			Diagnostics			
	Δx_t	$(i - i^*)_{t-1}$	R^2	Serial	Heter	Wald
Specification	(1)	(2)	(3)	(4)	(5)	(6)
			EUR			
I	**2.75**		0.42	[0.00]	[0.88]	
	(11.39)					
II	**2.78**	-0.08	0.42	[0.00]	[0.25]	[0.15]
	(11.47)	(-1.45)				
			GBP			
I	**1.42**		0.18	[0.98]	[0.07]	
	(4.93)					
II	**1.36**	-0.02	0.18	[0.82]	[0.21]	[0.85]
	(4.78)	(-0.19)				
			JPY			
I	**12.8**		0.24	[0.53]	[0.80]	
	(5.47)					
II	**12.4**	0.02	0.28	[0.06]	[0.16]	[0.82]
	(5.48)	(0.23)				

As a preliminary assessment, we estimate the contemporaneous relation between order flow and exchange rate returns using ordinary least squares (OLS). Following Evans and Lyons (2002b), we regress the daily exchange rate returns on order flow alone, to investigate its explanatory power, and on order flow and the lagged interest rate differential, to assess the added value of order flow on the Uncovered Interest Rate Parity (UIP) condition.[12] The results are presented in Table 2.

[12]UIP states that the expected exchange rate change should equal the current interest rate differential–or, in the absence of arbitrage, the forward premium (the difference between the forward and spot rates). Under UIP and in the

The estimated order flow coefficients are always positive and highly significant. The positive sign implies that net buying pressure for the foreign currency will lead to an increase in the exchange rate (i.e. depreciation of the USD). The impact of JPY order flow on exchange rate returns is the highest, while GBP order flow is the lowest. In the UIP regressions, the interest rate coefficients are statistically insignificant at the 10 percent level.[13] Hence, the explanatory power in the estimated equations comes exclusively from order flow, which yields an R^2 in the range from 0.18 for GBP to 0.42 for EUR.

Table 3
Cross-currency order flow effects

SUR estimates for equation (3) for the period 2/13/2004 - 2/14/2005. Δs_t^j is the daily exchange rate change from 7:00 to 17:00 GMT, and Δx_t^j is the daily order flow (positive for net foreign currency purchases, in thousands), accumulated between 7:00 and 17:00 GMT, for each exchange rate j (US dollar/euro (EUR), US dollar/UK sterling (GBP), and US dollar/Japanese yen (JPY)). The coefficients of the explanatory variables are expressed in percentage terms. 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.

	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	

In order to take advantage of the high correlation between exchange rate changes and order flows, we allow for cross-currency effects of order flow and use the seemingly unrelated regressions (SUR) method (Zellner, 1962) to estimate the following regression:

$$Z_t = C + BX_t + V_t, \tag{3}$$

where Z_t is the 3×1 vector of exchange rate changes, $Z_t = \left[\Delta s_t^{EUR}, \Delta s_t^{GBP}, \Delta s_t^{JPY}\right]'$; X_t is the 3×1 vector of order flows, $X_t = \left[\Delta x_t^{EUR}, \Delta x_t^{GBP}, \Delta x_t^{JPY}\right]'$; B is the 3×3 matrix of order flow coefficients; C is the vector of constant terms; and V_t is the vector of error terms. The results in Table 3 show that estimation of model (3) yields an increase in explanatory power (R^2) for all currencies from 2 percentage points for EUR to 20 percentage points for GBP. 'Own' order flow (that is the order flow of the currency pair on the left-hand side of the equation) continues to have a significant positive coefficient, albeit smaller in size than in the single equation setting, for all the

absence of arbitrage (i.e. assuming that covered interest parity holds), the forward exchange rate provides an unbiased forecast of the future spot exchange rate, or, equivalently, the forward premium provides an unbiased forecast of the future change in the spot exchange rate.

[13]The results are qualitatively similar when contemporaneous interest rate differentials or changes in interest rate differentials are used.

exchange rate movements. The other currencies' order flows have significant effects on exchange rate returns even after accounting for own order flow impact. The Wald test statistic strongly rejects the hypothesis that the order flow coefficients in each regression are jointly equal to zero. These preliminary results are generally consistent with those in Evans and Lyons (2002a,b).

4 Empirical Analysis I: Order Flow and Macroeconomic Fundamentals

In this section, we examine the link between macroeconomic information and order flow, in order to understand why order flow should have forecasting power for exchange rates using the standard present-value exchange rate model:

$$\Delta s_{t+1} = \frac{(1-b)}{b}(s_t - E_t^m f_t) + \varepsilon_{t+1}, \tag{4}$$

where $\varepsilon_{t+1} \equiv (1-b)\sum_{q=0}^{\infty} b^q \left(E_{t+1}^m f_{t+q+1} - E_t^m f_{t+q+1}\right)$. As discussed previously, in this model order flow may capture current fundamentals information (the first term in equation (4)) and changes in expectations about future fundamentals (the second term in equation (4)). Announcements on fundamentals naturally have a direct effect on $E_t^m f_t$. However, when there are different interpretations for the impact of these announcements for the exchange rate, market makers can make inference about the equilibrium exchange rate from aggregate order flow. The extent to which order flow aggregates information on heterogenous interpretations is analyzed via the contemporaneous relation between order flow and fundamentals news. Moreover, the role of order flow in aggregating changes in expectations about macroeconomic fundamentals is investigated analyzing the impact of order flow on the difference between actual and expected fundamentals (macroeconomic surprises).

4.1 The Link Between Order Flow and News

First, we investigate whether unexpected changes in macroeconomic indicators (i.e. departures from expected values) can explain order flow. Unexpected changes in fundamental values may trigger different interpretations on the implications of the news for the equilibrium exchange rate. If agents trade on the basis of these different interpretations, then news can explain order flow fluctuations. Unexpected changes in fundamentals (news) are calculated as $d_{i,t} = \frac{a_{i,t-k} - E_{t-l}a_{i,t-k}}{\sigma_i}$, where $a_{i,t-k}$ is the actual value of indicator i at time t pertaining to the fundamental at time $t-k$; k is a week, month, or quarter; $E_{t-l}a_{i,t-k}$ is the expected value of indicator i formed at time $t-l$ (the survey expectation); l ranges between 2 and 6 trading days; and σ_i is the sample standard deviation for indicator i (Andersen et al., 2003).[14] For each order flow series j, we estimate the regression

$$\Delta x_t^j = c + \sum \lambda_i d_{i,t} + \eta_t \qquad j = EUR, GBP, JPY, \tag{5}$$

using OLS, where standard errors are corrected for autocorrelation and heteroskedasticity (Newey and West, 1987). The results are presented in Table 4, which only exhibits coefficients significant up to the 10 percent level.[15] News appear to be an important determinant of order flow and have the expected sign in each case. Positive news on the US economy are associated with a decrease in order flow (higher demand for USD), whereas positive news on foreign economies are associated with an increase in order flow (higher demand for the base currency). The news variables that have high explanatory power for order flow are similar to those that Andersen et al. (2003) find significant in explaining exchange rate fluctuations at the intraday frequency around macroeconomic announcements. Macroeconomic news can explain up to 18 percent of the daily fluctuations in order flow. A list of all available macroeconomic news and their expected impact sign on order flow is provided in Table A2 in the Appendix.

The microstructure approach to FX predicts that information impacts on exchange rates both directly and indirectly via order flow (Lyons, 2001; Evans and Lyons, 2006a). The common knowledge part of news directly affects the exchange rate by shifting the equilibrium price, while order flow reflects heterogenous interpretations of this news for the new equilibrium price. We first assess the impact of news on the exchange rate, given that much previous research has not been able to document a large effect of fundamentals on exchange rates at the daily level. We re-estimate equation (5) above with the exchange rate returns as the dependent variable and use the same macroeconomic news that explains order flow changes as explanatory variables: $\Delta s_t^j = c + \sum \lambda_i d_{i,t} + \zeta_t$. The results in the lower panel of Table A3 in the Appendix show that macroeconomic news can explain fluctuations in the daily exchange rate to the same extent that they can explain order flow.

It is important to note that finding significant explanatory power for macroeconomic news on the exchange rate does not imply that order flow information is redundant. Controlling for the direct news effect, order flow could still transmit the heterogeneous interpretations of this news to the exchange rate. The added value of order flow above the direct channel is tested by regressing exchange rate changes on macroeconomic news and order flow: $\Delta s_t^j = c + \sum \lambda_i d_{i,t} + \pi \Delta x_t^j + \zeta_t'$. The results in Table A3 in the Appendix show that the addition of order flow significantly increases the

[14] Ideally, we would like to have expectations on fundamentals just before the announcement time, since expectations can change in a week (Fleming and Remolona, 1997). These data, however, are not available.

[15] The contemporaneous effect of each individual macro news on order flow is estimated using the regression $\Delta x_t^j = c + \lambda_i d_{i,t} + \nu_t$ and presented in Table A1 in the Appendix. It must be noted that the explanatory power of some of these indicators is very high and the average R^2 is around 20%. The R^2 is often as high as reported in Andersen et al. (2003). Nonetheless, our results may be less reliable due to the low number of observations available for each regression and, therefore, we rely primarily on the results from regression (5) in this section.

Table 4
Contemporaneous effect of news on order flow

OLS regression of order flow (1000 net purchases) for EUR, GBP, and JPY on contemporaneous unexpected changes in fundamentals $\Delta x_t^j = c + \lambda_i d_{i,t} + \eta_t$. Unexpected changes in fundamentals are the difference between the actual value ($a_{i,t-k}$) of the macroeconomic indicator minus its expected value ($E_{t-l}a_{i,t-k}$), standardized by the standard deviation (σ_i) of the sample, $d_{i,t} = \frac{a_{i,t-k} - E_{t-l}a_{i,t-k}}{\sigma_i}$. The regression is estimated on all the indicators available, for the period 2/13/2004 - 2/14/2005. Serial correlation presents the p-values for the Breusch-Godfrey Lagrange multiplier tests for first-order residual serial correlation. Heteroskedasticity presents the p-values for the White first-order conditional heteroskedasticity test with cross terms in the residuals. All equations are estimated with a constant, and only variables significant at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors are reported in order to conserve space.

		EUR	GBP	JPY
	Announcement	λ	λ	λ
	US Announcements			
Quarterly	GDP advance	-114.40		
	GDP preliminary	-69.59		
Monthly	Consumer credit	136.95		
	Nonfarm payroll employment	-90.42	-88.23	
	Unemployment rate	90.69		
	Construction spending			-4.02
	Durable goods orders		-134.95	
	Trade balance	-59.74	181.22	-6.51
	Consumer price index		-171.41	
	Consumer confidence index			-15.30
	Chicago PMI	-115.40		
	Housing starts		-5.05	
	Michigan sentiment - final	-98.90		-5.36
Weekly	Initial unemployment claims			4.21
	EMU Announcements			
Quarterly	Labor costs	101.08		
Monthly	Industrial production - year	62.78		
	Retail sales - month	82.30		
	Consumer price index - month	160.52		
	Consumer price index - year	-148.40		
	Consumer confidence balance	149.03		
	Sentiment index	179.60		
	UK Announcements			
Quaterly	GDP provisional - quarter		267.86	
Monthly	Trade balance		93.42	
	R^2	0.15	0.18	0.03
	Serial correlation	[0.01]	[0.76]	[0.07]
	Heteroskedasticity	[0.99]	[0.99]	[0.99]

explanatory power for exchange rate fluctuations, as compared to news alone. Furthermore, the combined explanatory power of order flow and news appears to be higher than that of order flow alone (see Table 2). There seems to be a dual impact of macroeconomic news on exchange rates, direct and via order flow.[16]

4.2 The Link Between Order Flow and Expectations

In a market where agents have heterogenous expectations about fundamentals and trade based on those expectations, microstructure theory predicts that order flow enables market makers to aggregate changes in expectations about the state of the economy. Given that the survey expectations about fundamentals are collected and published on Thursday before the announcement week, we can examine the hypothesis that order flow aggregates changes in expectations. Starting from the survey expectation day, Thursday, agents still have some time to revise their expectations from $E_{t-l}a_{i,t-k}$ to $E_t a_{i,t-k}$ and trade on these expectation changes. This implies that, in principle, revisions in expectations between the day of collecting survey expectations until the day of the announcement of the fundamentals may be reflected in order flow.

To test this hypothesis, we use the sum of order flows between Thursday and the announcement day to explain the difference between actual and expected fundamentals, as in equation (6):

$$a_{i,t-k} - E_{t-l}a_{i,t-k} = \theta \sum_{h=0}^{l-1} \Delta x_{t-h}^{j} + \varkappa_t \qquad j = EUR, GBP, JPY, \tag{6}$$

where $\sum_{h=0}^{l-1} \Delta x_{t-h}^{j}$ is the sum of order flow for currency j from the day of forming the survey expectation (Thursday) to the announcement day for indicator i; l varies between 2 and 6, and $\varkappa_t$ is the error term. The model is estimated using SUR to account for potential cross-correlation among the indicators.

The results presented in Table 5 show that order flow can explain the difference between actual and expected fundamentals for the most important indicators in all the countries investigated. If order flow is taken to be a proxy for the change in expectations between the survey and announcement day, a positive gap between the actual value and the survey expectation about the fundamental will imply an increase in order flow to bring expectations closer to the actual value. For example, if the actual industrial production figure for the US is higher than the survey expected value, then expectation revisions will lead agents to demand more USD (negative order flow). In turn, the order flow coefficient for EUR, GBP, and JPY is expected to be negative. The opposite will occur for

[16] We carry out the same exercise in the context of the model in equation (3) that allows for cross-currency order flow effects. Specifically, we augment model (3) with the macro news as explanatory variables: $Z_t = C + BX_t + \sum \lambda_i d_{i,t} + \zeta_t''$. The results in Table A4 in the Appendix show that this setup attains the highest explanatory power for all currencies (R^2 between 38 and 56 percent) and that the exchange rate is simultaneously determined by order flow (own and of other currency pairs) and macroeconomic news.

Table 5
News response to aggregate order flow

SUR regression of the expectational gap on aggregated order flow (1000 net purchases) for EUR, GBP, and JPY: $a_{i,t-k} - E_{t-l}a_{i,t-k} = \theta \sum_{h=0}^{l} \Delta x^j_{t-h} + \varkappa_t$, where $a_{i,t-k}$ is the actual value of the fundamental, $E_{t-l}a_{i,t-k}$ is the expected value for the fundamental formed the Thursday prior to the announcement date, $\sum_{h=0}^{l-1} \Delta x^j_{t-h}$ is cumulated order flow between the expectation formation day (Thursday) and the announcement day, and l varies from 2 to 6 depending on the announcement day. 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 2/13/2004 - 2/14/2005. Only variables significant at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors are reported in order to conserve space.

		EUR		GBP		JPY	
	Announcement	θ	R^2	θ	R^2	θ	R^2
	US Announcements						
Quarterly	GDP advance	-2.83	0.43				
	GDP final	-0.47	0.54				
Monthly	Capacity utilization	-0.66	0.34	-0.09	0.42	-0.38	0.43
	Consumer credit	-0.55	0.42			-21.00	0.51
	Industrial production	-1.18	0.02	-0.16	0.51	-1.39	0.51
	Nonfarm payroll employment	-3.47	0.44				
	Retail sales			-0.11	0.53		
	New home sales			-31.6	0.52		
	Business inventories	-0.17	0.45			-0.73	0.49
	Durable goods orders	-0.87	0.31	-0.21	0.48	-0.27	0.38
	Consumer price index	-0.15	0.44	-0.03	0.55	0.33	0.52
	Producer price index			0.24	0.60		
	Consumer confidence index			-2.32	0.61	-19.8	0.52
	Index of leading indicators	-0.20	0.37	-0.83	0.63	-0.11	0.30
	ISM index					-1.62	0.48
	EMU Announcements						
Quarterly	Labor costs - preliminary	-0.56	0.69				
	Labor costs - revised	3.15	0.91				
Monthly	Industrial production - year	1.98	0.25				
	Consumer price index - month	-0.12	0.45				
	Consumer price index - year	-0.14	0.48				
	Money supply M3	0.44	0.26				
	UK Announcements						
Monthly	Consumer credit			0.04	0.42		
	Manufacturing wages			-0.27	0.28		
	Consumer price index - year			-0.06	0.40		
	Producer input price index - month			0.41	0.45		
	Producer input price index - year			0.91	0.55		
	Producer output price index - month			0.12	0.51		
	Producer output price index - year			0.24	0.31		
	Retail price index - month			0.17	0.38		
	Budget deficit - PSNCR			-0.34	0.44		

variables whose impact on the economy is considered bad news, e.g. unemployment, inflation, etc. In general, the following relations between US and foreign (F) news and order flow are expected:

	"Good" News		"Bad" News	
$a^{US}_{i,t-k} > E_{t-l}a^{US}_{i,t-k}$	$\Delta x^F < 0$	$\theta < 0$	$\Delta x^F > 0$	$\theta > 0$
$a^{US}_{i,t-k} < E_{t-l}a^{US}_{i,t-k}$	$\Delta x^F > 0$	$\theta < 0$	$\Delta x^F < 0$	$\theta > 0$
$a^{F}_{i,t-k} > E_{t-l}a^{F}_{i,t-k}$	$\Delta x^F > 0$	$\theta > 0$	$\Delta x^F < 0$	$\theta < 0$
$a^{F}_{i,t-k} < E_{t-l}a^{F}_{i,t-k}$	$\Delta x^F < 0$	$\theta > 0$	$\Delta x^F > 0$	$\theta < 0$

We take these results as evidence that supports the conjecture that order flow aggregates the expectations of the market with regards to these fundamentals.[17] However, between a given expectation formation day and announcement day, there may be other news releases. We take this possibility into account and "clean" order flow from the effect of previous news. The relation between (i) "residual order flow", that is order flow after the contemporaneous effect has been taken into account, and (ii) the difference between the actual and expected indicator value is investigated by estimating the following regression:

$$a_{i,t-k} - E_{t-l}a_{i,t-k} = \phi \sum_{h=0}^{l-1} \Delta \hat{\eta}^j_{t-h} + \xi_t \qquad j = EUR, GBP, JPY, \tag{7}$$

where $\sum_{h=0}^{l-1} \Delta \hat{\eta}^j_{t-h}$ is the sum of the residual order flow $\hat{\eta}_t$ as estimated from regression (5), from the expectation formation date to the publication date for indicator i; l varies between 2 and 6, and ξ_t is the error term.

Table 6 shows that residual order flow can explain the difference between actual and expected changes in almost all the fundamentals where cumulated order flow had explanatory power previously (e.g. Table 5). These results confirm order flow's role in aggregating changes in market expectations (the second term in equation (4)).

4.3 Summary

To sum up, we find that there is a strong relation between order flow and fundamentals information. Order flow is intimately linked to both news on fundamentals (unexpected changes) and to changes in expectations about these fundamentals. Macroeconomic information is identified to be a determinant of changes in order flow, which implies that exchange rate fluctuations are linked to macroeconomic fundamentals both via a direct link, as in classical exchange rate theory, and via order flow, as in the microstructure approach to FX. These results imply that order flow's explanatory power stems (at least partly) from macroeconomic information, suggesting a potential explanation for the well documented disappointing results on the direct link between macroeconomic fundamentals and exchange rates in the literature.

[17] The results do not change if the order flow that occurs on the announcement day is not included in the sum of order flow $\sum_{h=1}^{l-1} \Delta x^j_{t-h}$.

Table 6
News response to aggregate residual order flow

SUR regression of the expectational gap on aggregated residual order flow (1000 net purchases) for EUR, GBP, and JPY: $a_{i,t-k} - E_{t-l}a_{i,t-k} = \phi \sum_{h=0}^{l} \Delta\hat{\eta}^{j}_{t-h} + \xi_t$. $a_{i,t-k}$ is the actual value of the fundamental, $E_{t-l}a_{i,t-k}$ is the expected value for the fundamental formed the Thursday prior to the announcement date, $\sum_{h=0}^{l-1} \Delta\hat{\eta}^{j}_{t-h}$ is the cumulated residual order flow from the expectation formation day (Thursday) and the announcement day, and l varies from 2 to 6 depending on the announcement day. The estimation the period is 2/13/2004-2/14/2005. Only variables significant at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors are reported in order to conserve space.

		EUR		GBP		JPY	
	Announcement	ϕ	R^2	ϕ	R^2	ϕ	R^2
	US Announcements						
Quarterly	Current account			-3.95	0.07		
	GDP advance			-0.51	0.29		
	GDP final			-0.19	0.25		
Monthly	Capacity utilization	-0.40	0.33				
	Consumer credit	-7.59	0.44				
	Industrial production			-0.46	0.23	-5.59	0.39
	Nonfarm payroll employment					-718.64	0.45
	Personal consumption expenditure			-0.29	0.25		
	Business inventories	-0.61	0.48	-0.77	0.23	-0.92	0.46
	Durable goods orders	-0.65	0.33			-18.00	0.40
	Factory orders	-0.85	0.48				
	Consumer price index	0.02	0.50	-0.34	0.42	2.81	0.38
	Producer price index			-0.46	0.41	-8.04	0.39
	Consumer confidence index	-1.20	0.50				
	ISM index					-172.3	0.56
	Index of leading indicators	-0.31	0.14	-0.78	0.07		
Weekly	Initial unemployment claims					119.83	0.34
	EMU Announcements						
Quarterly	Labor costs - preliminary	-0.69	0.67				
	Labor costs - revised	-2.05	0.47				
Monthly	Trade balance	-12.88	0.38				
	Consumer price index - month	-0.06	0.48				
	Consumer price index - year	-0.08	0.48				
	Money supply M3	0.10	0.32				
	Industrial confidence balance	3.85	0.33				
	PMI Manufacturing	1.93	0.12				
	UK Announcements						
Monthly	Manufacturing wages			0.94	0.33		
	Manufacturing output - month			1.67	0.27		
	Manufacturing output - year			2.33	0.54		
	Trade balance			-0.36	0.33		
	Consumer price index - year			-0.30	0.18		
	Producer input price index - month			1.51	0.52		
	Producer input price index - year			-1.69	0.14		

5 Empirical Analysis II: The Economic Value and Forecasting Power of Order Flow

In this section, we examine the forecasting power of order flow in a Sharpe ratio (Sharpe, 1966) maximizing framework. The Sharpe ratio, or return-to-variability ratio, measures the risk-adjusted returns from a portfolio or investment strategy and is widely used by investment banks and asset management companies to evaluate investment and trading performance. Recently, several banks have invested in technology that captures order flow information for forecasting purposes (e.g. CitiFlow system by Citibank). Daily order flow is assumed to follow an AR(1) process, because the market needs at least one day to fully uncover aggregate order flow. In the most general order-flow model considered, the exchange rate return is modelled as a function of lagged order flow and exchange rate changes of the currencies examined,

$$Z_{t+1} = C + BX_t + \Gamma Z_t + U_{t+1}, \tag{8}$$

where Z_{t+1} is the 3×1 vector of exchange rate changes, X_t is the 3×1 vector of order flows, Z_t is the 3×1 vector of lagged exchange rate changes, B and Γ are 3×3 matrices of coefficients, C is the vector of constants, and U_{t+1} is the vector of error terms.

We choose to perform one-day ahead forecasts for the following reasons: (i) one-day ahead forecasts based on order flow are implementable, (ii) it is a relevant horizon for practitioners (e.g. most currency hedge funds), (iii) unlike intraday forecasts it involves interest rate considerations, and (iv) it is unlikely that gradual learning based on this data will allow forecasting at much longer horizons.

5.1 Model Selection and Portfolio Weights

We take the perspective of an investor who uses order flow models of exchange rates of the form presented in (8) to forecast daily exchange rates and allocate capital. The investor maximizes the trade-off between mean and variance using the ex-post Sharpe ratio (SR) when choosing the model to use for forecasting. The ex-post Sharpe ratio is defined as:

$$SR = \frac{r_p - r_f}{\sigma_p}, \tag{9}$$

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.

The investor is assumed to have an initial wealth of \$1000 that he invests every day in three risky assets (currencies) and one riskless asset (overnight deposit). He has a daily horizon and constructs a dynamic portfolio that maximizes the Sharpe ratio. For the purposes of this paper, we assume that the investor believes that it is order flow that incorporates the relevant forecasting information and sets $\Gamma = 0$ in model (8), $Z_{t+1} = C + BX_t + U_{t+1}$. He follows a general-to-specific procedure to identify the best order flow model.

For each model assessed, after obtaining the forecasts for the exchange rate returns, he invests only in those currencies for which the expected excess return is positive:

$$\Delta\widetilde{r}^j_{t+1|t} - i_t > 0, \qquad j = EUR, GBP, JPY \tag{10}$$

where $\Delta\widetilde{r}^j_{t+1|t} \equiv \Delta\widetilde{s}^j_{t+1|t} + i^j_t$, i.e. is the forecast exchange rate return for day $t+1$ conditional on the information set at time t, $\Delta\widetilde{s}_{t+1|t}$, plus the overnight LIBOR foreign interest rate; and i_t is the overnight LIBOR USD interest rate, approximately equal to the logarithm of $(1 + i_t)$. The interest rate i_t represents the return attainable if the investor decides not to invest in any foreign currency. The investor chooses the weights to allocate in each instrument proportionally to the expected excess return from each asset based on day t information. Specifically, the weights invested in each asset are calculated as:

$$w^j_t = \frac{\Delta\widetilde{r}^j_{t+1|t}}{\sum_{j=1}^{3}\Delta\widetilde{r}^j_{t+1|t} + i_t}, \text{ and } w^i_t = 1 - \sum_{j=1}^{3} w^j_t, \qquad j = EUR, GBP, JPY, \tag{11}$$

where $\Delta\widetilde{r}^j_{t+1|t}$ is set to zero in the expression for w^j_t when $\Delta\widetilde{r}^j_{t+1|t} - i_t \leq 0$, as an implication of the rule in equation (10).

The weights w^j_t for each risky asset and w^i_t for the riskless asset are time-varying. There is no short-selling in this setup and, hence, the weights are bounded between zero and unity, implying that the investor's trading strategy is a long-only strategy. In essence, the amount invested in each asset (the three currencies and the USD interest rate) is proportional to the size of the expected excess return from each asset relative to each of the other assets.

On day $t+1$, the investor closes his position and calculates the return from the investment. At the end of the forecast period, he computes the annualized ex-post SR, using the realized annualized portfolio return $r_p = \sum_{t=1}^{T}\left[\sum_{j=1}^{3} w^j_t r^j_{t+1} + w^i_t i_{t+1}\right] T^{-1} \times 252$, where T denotes the number of forecasts; the annualized LIBOR USD interest rate return $r_f = \left(\sum_{t=1}^{T} i_t\right) T^{-1} \times 252$, and the realized annualized standard deviation of the portfolio returns, σ_p.

Initially, the investor evaluates the in-sample Sharpe ratio generated by the strategy described above, for the period from February 13, 2004 to June 14, 2004. In the in-sample estimations, the investor obtains the forecast value of the exchange rate for 17:00 on day $t+1$, conditioning on order flow information aggregated from 7:00 to 17:00 on day t, invests in the different currencies using equations (10)-(11), and closes the position at 17:00 on day $t+1$. The in-sample prediction is the fitted value of the exchange rate returns for day $t+1$, from 7:00 to 17:00. In order to allow a training period, we estimate the models using the first 30 data points (which is equivalent to one and a half trading months) and leave the rest of the observations to calculate the SR. We then increase the number of in-sample observations for the estimation of the model as we move forward through the in-sample period, allowing for more observations to be used in the estimation and fewer to calculate the SR.

For the purpose of our analysis, we present the Sharpe ratios for five models, the best order flow model and four alternative ones. After implementing a general-to-specific procedure for $Z_{t+1} = C + BX_t + U_{t+1}$, the best in-sample forecasting model based purely on order flow information is M^{OF}:

$$Z_{t+1} = C + \begin{pmatrix} \beta_{11} & 0 & \beta_{13} \\ \beta_{21} & 0 & \beta_{23} \\ \beta_{31} & 0 & 0 \end{pmatrix} X_t + U_{t+1}, \tag{12}$$

using the same notation as in model (8). In this model, coefficients for exchange rate lags are set to zero and the forecasting power derives only from order flow.

Model M^{POF} is a more general version of M^{OF} in that it includes lags of Δr_t^j to account for the possibility of feedback trading (Danielsson and Love, 2006):

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

Model M^{GEN} further generalizes M^{POF} in that it includes lags of own and other currencies' order flow and is identical to model (8):

$$Z_{t+1} = C + \begin{pmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \\ \beta_{31} & \beta_{32} & \beta_{33} \end{pmatrix} X_t + \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{pmatrix} Z_t + U_{t+1}. \tag{14}$$

Model M^{FB} is the well-known 'forward bias' trading strategy based on the Fama regression (Fama, 1984):

$$Z_{t+1} = C + \Lambda I_t + \Xi_{t+1}, \tag{15}$$

where Z_{t+1} is the 3×1 vector of exchange rate changes, I_t is the 3×1 vector of interest rate differentials (domestic minus foreign), Λ is the 3×3 diagonal matrix of coefficients, C is the 3×1 vector of constants, and Ξ_{t+1} is the 3×1 vector of error terms.[18] Finally, M^{RW} is the random walk with a drift.

The in-sample Sharpe ratios, calculated using equations (9)-(11), are presented in Panel A of Table 7. These Sharpe ratios are very high, but one must keep in mind that these are in-sample calculations. The best model appears to be M^{OF}, which yields Sharpe ratios larger than 4. The

[18] The Fama regression commonly estimated in the literature is: $\Delta s_{t+1} = c + \delta(fwd_t - s_t) + \mu_{t+1}$ (Fama, 1984), where the exchange rate Δs_{t+1} is regressed on the lagged difference between the forward (fwd_t) and current value of the exchange rate (s_t), i.e. the forward premium. Given the use of a daily strategy and the fact that forward contracts for daily maturity do not exist, we use the overnight interest rate differential as the predictive variable, given that $fwd_t - s_t = i_t - i_t^F$ via covered interest parity.

other models exhibit either negative or lower Sharpe ratios than M^{OF}. The results demonstrate the superiority of lagged order flow information as compared to other variables in explaining exchange rates in sample.

Table 7
Model selection

Results for the model selection criteria and the selected model. In Panel A, we present the in-sample Sharpe ratios for five models estimated over different numbers of in-sample observations. M^{OF} is the order-flow forecasting model that maximizes the in-sample Sharpe ratio, presented in Panel B. M^{POF} is the same as M^{OF} plus lags of own and other exchange rate changes. M^{GEN} is the general model specified in equation (8), M^{FB} is the forward bias model, and M^{RW} is the random walk with drift. Sharpe ratios have been rounded to the second decimal point. Panel B presents the in-sample estimated model in equation (12) for the period 2/13/2004 - 6/14/2004. Δs^j_{t+1} is the daily exchange rate change from 7:00 to 17:00 GMT, and Δx^j_t is the daily order flow (positive for net foreign currency purchases, in thousands) cumulated between 7:00 - 17:00 GMT, for each exchange rate j (US dollar/euro (EUR), US dollar/UK sterling (GBP), and US dollar/Japanese yen (JPY)). t-statistics are shown in parenthesis. Coefficients are expressed in percentages. Panel C shows the covariance/correlation matrix of residuals for the model in panel B.

Panel A: In-sample Sharpe ratios

	M^{OF}	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
			7-17		
30	5.23	0.92	2.19	4.20	-3.52
40	4.18	1.00	2.22	2.30	-4.10
50	4.53	-0.45	3.41	2.62	-3.79
60	5.38	-0.07	2.94	3.08	-4.59

Panel B: Selected forecasting model

	Δs^{EUR}_{t+1}		Δs^{GBP}_{t+1}		Δs^{JPY}_{t+1}	
$Constant$	-0.07	(-0.85)	-0.11	(-1.42)	-0.06	(-0.61)
Δx^{EUR}_t	0.01	(4.87)	-		-	
Δx^{GBP}_t	-		0.01	(4.87)	-	
Δx^{JPY}_t	0.44	(1.25)	0.47	(1.39)	0.01	(4.87)
$Wald\ Test$ = [0.11]						

Panel C: Covariance matrix

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

In Panel B of Table 7, we show representative results for model M^{OF}, where the exchange rate returns are modeled using own lagged order flow and JPY order flow is a determinant of both EUR and GBP returns. All own lagged order flow coefficients are positive and highly significant. We test for the equality of the own lagged order flow coefficients using the Wald test, and the null hypothesis of $\beta_{11} = \beta_{21} = \beta_{31}$ is not rejected. Panel C of Table 7 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 rates.

5.2 Out-of-Sample Performance

The remaining two thirds of the sample, from June 15, 2004 to February 14, 2005, are used to evaluate the model out-of-sample. The only change in our out-of-sample analysis is in the way returns are calculated in order to make the out-of-sample forecasts as realistic as possible. We start by noting that in a pure out-of-sample setup, the exchange rate at 7:00 on day $t+1$ is not part of the investor's information set on day t, hence we cannot use the exchange rate return between 7:00 and 17:00 as in the in-sample estimations. Furthermore, liquidity in the exchange rate market can be time-varying (Figure 1) and the impact order flow has on exchange rate fluctuations depends on the level of the liquidity in the market (Evans, 2002; Danielsson and Payne, 2002). Therefore, we do not want to choose a priori a time in which the position is closed, but we provide results across the day to check the robustness of the out-of-sample Sharpe ratios during various trading hours. Hence, at 17:00 of day t, the investor forecasts the exchange rate for each hour (between 7:00 and 17:00) of day $t+1$, and on day $t+1$ he closes the position at the hour for which he has made the forecast.[19]

The investor estimates each model using the change in the exchange rate between each hour (from 7:00 to 17:00) of day $t+1$ and 17:00 on day t as the dependent variable, while the explanatory variable remains order flow aggregated between 7:00 and 17:00 on day t. The model parameters are re-estimated for each of the 11 different forecast hours. Allowing the parameters to change across the different times of the day enables us to capture the impact of lagged order flow during the day depending on liquidity. Forecasts are calculated recursively: the sample available for estimation increases daily, and hence the model parameters are re-estimated every day.

The forecasting results are presented in Table 8. The best in-sample model, M^{OF}, yields Sharpe ratios ranging from 0.44 to 2.24 depending on which hour of the day the investor closes his position. The average Sharpe ratio for M^{OF} is 1.59 and has a standard deviation of 0.49, which implies that this model will yield high Sharpe ratios throughout the day with a high level of confidence. 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, 2001) and 0.5 (Cochrane, 1999), depending on the sample period.[20] Research on fund performance shows

[19] For example, he forecasts the change in the exchange rate between 17:00 of day t and 7:00 of day $t+1$, and closes the position at 7:00 on day $t+1$, realizing a return $\frac{s_{t+1}^{7:00} - s_t^{17:00}}{s_t^{17:00}}$.

[20] There are very few studies that report Sharpe ratios for exchange rate investments and trading strategies. Sarno, Valente, and Leon (2006) calculate that Sharpe ratios from forward bias trading range between 0.16 and 0.88, while Lyons (2001) reports a Sharpe ratio of 0.48 for an equally weighted investment in six currencies.

Table 8
Realized Sharpe ratios out of sample

Realized out-of-sample Sharpe ratios for the period 6/15/2004 - 2/14/2005, obtained by investing based on the one period ahead forecasts from the different models and calculated from the investment strategy detailed in section 5.1, at different times of the day. M^{OF} is the forecasting model that maximizes the in-sample Sharpe ratio, presented in Table 7 Panel B. M^{POF} is the same as M^{OF} plus lags of own and other exchange rate changes. M^{GEN} is the general model in equation (8), M^{FB} is the forward bias model, and M^{RW} is the random walk with drift. Average and S.D. are the average and standard deviation of the Sharpe ratio during the day, respectively. Sharpe ratios have been rounded to the second decimal point.

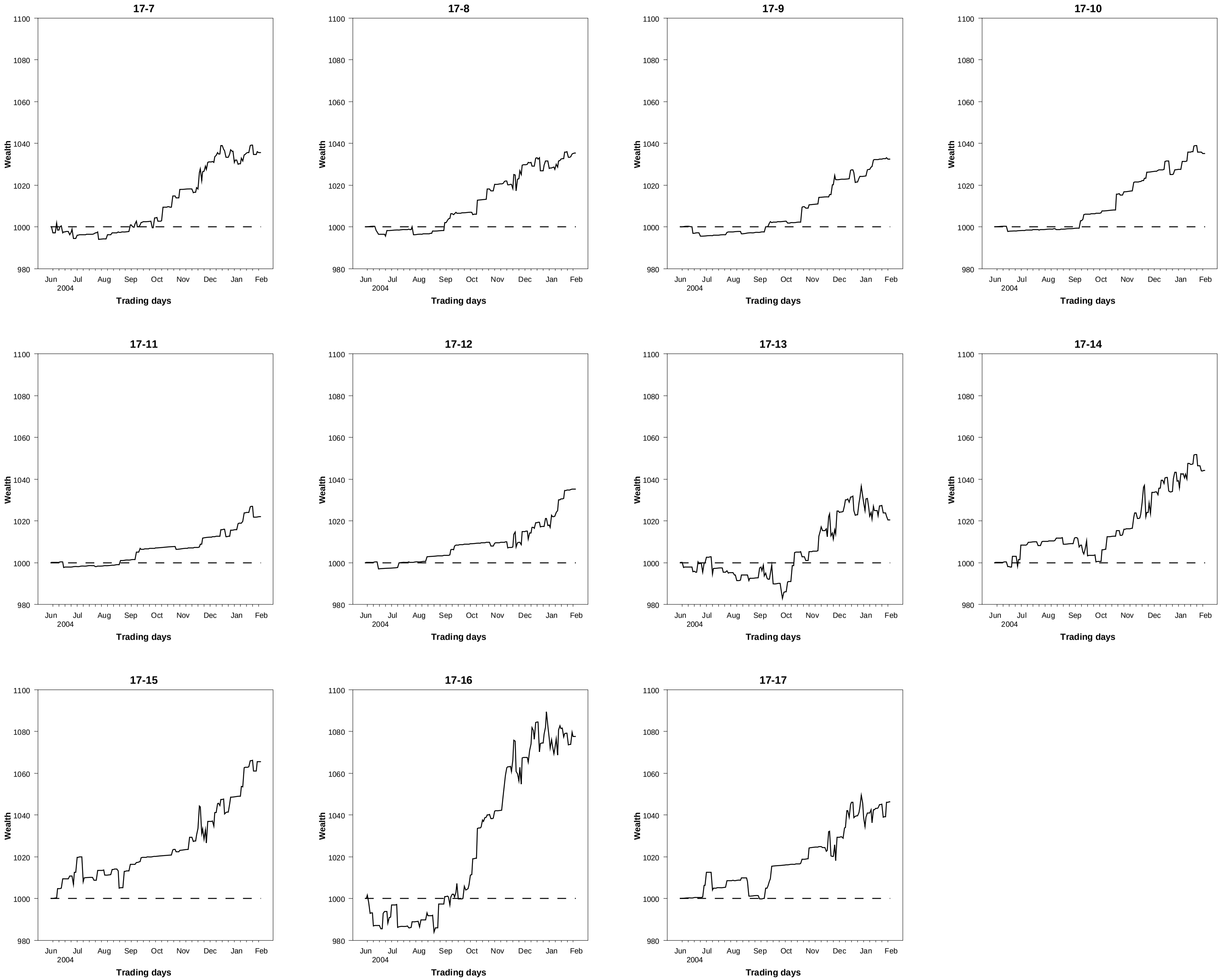
	M^{OF}	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
17-7	1.48	1.68	-0.44	0.32	1.21
17-8	1.61	-0.59	-0.27	-0.18	0.42
17-9	2.12	-0.52	-1.00	-0.50	0.06
17-10	2.24	-0.21	-1.45	0.25	-0.17
17-11	1.53	-0.24	-1.84	-0.17	-0.08
17-12	1.85	0.23	-0.53	-0.18	1.15
17-13	0.44	-0.58	0.43	0.95	1.39
17-14	1.31	-0.26	-0.24	0.18	0.73
17-15	1.95	1.43	0.64	0.71	1.87
17-16	1.64	1.86	2.21	0.97	1.65
17-17	1.34	2.43	1.78	0.96	0.48
Average	1.59	0.48	-0.06	0.30	0.79
S.D.	0.49	1.14	1.25	0.53	0.71

that hedge funds achieve average SRs of 0.36 for the period 1988-1995 (Ackermann, McEnally, and Ravenscraft, 1999), while the average SRs for off-shore hedge funds range from 0.94 to 1.19 (Brown, Goetzmann, and Ibbotson, 1999). The lowest SR for M^{OF}, 0.44, is obtained at 13:00, when there is the lowest liquidity in the market (Figure 1).

Interestingly, the addition of other explanatory variables generally leads to poorer out-of-sample performance of the model. Models M^{POF}, M^{GEN}, M^{FB}, and M^{RW} outperform the best order flow model in 4 out of 11 cases, but the average SR from M^{OF} 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 conditioning variables.

The evolution of wealth when using M^{OF} for each of the trading hours is presented in Figure 2. From this graph, we notice that the high Sharpe ratios are due to relatively high returns and low investment variance. There does not seem to be a general pattern in the evolution of wealth, and the profitability of order flow forecasting seems to evolve in different ways across the different trading hours. Some models appear to do well in parts of the sample where others do not, and vice versa. This is consistent with the stochastic nature of liquidity, which affects the model parameters at different hours of the day. A good example of an active trading strategy with a high SR is

Figure 2
Wealth evolution out of sample



the evolution of investment for the forecast for 16:00. Note 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 7.7 percent in an eight month period (3 and 11.55 percent in terms of annualized returns, respectively). The low SR at 13:00 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 10:00 is due to positive returns every time there is an investment in currencies and the low variance of the returns. It is worth noting that there are two cases, 15:00 and 17:00, in which the investor's wealth never falls below its initial value.

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 invest is his wealth. This assumption implies that the investor does not take high risks to generate higher profits. Secondly, the investor is forced to close his position at a certain point (hour) of the day when, realistically, he could place a limit order that allows him to make higher profits in the day.[21] Thirdly, in reality the investor would update the model periodically, searching for the best fitting model every week or at least every month. Our investor does not do this, but he uses the same model throughout the forecast period.

5.3 Robustness Checks

5.3.1 Model Selection

An important caveat in the in-sample analysis is the assumption of constant volatility. The weights are chosen on the basis of expected excess returns, not accounting for volatility that may be time-varying. We address this issue by choosing weights that maximize the return to volatility ratio (SR). In this case, the investor invests in a particular currency if the expected volatility-adjusted excess return is greater than 0:

$$\widetilde{SR}^{j}_{t+1|t} = \frac{\Delta\widetilde{r}^{j}_{t+1|t}}{\sigma^{j}_{|t}} - i_t > 0, \qquad j = EUR, GBP, JPY, \tag{16}$$

where $\sigma^{j}_{|t}$ is the unconditional standard deviation of the exchange rate return j up to time t, and $\widetilde{SR}^{j}$ is the expected Sharpe ratio from the investment in each asset j. The weights allocated to each currency are now determined as:

$$w^{j}_{t} = \frac{\widetilde{SR}^{j}_{t+1|t}}{\sum_{j=1}^{3}\widetilde{SR}^{j}_{t+1|t} + i_t}, \quad j = EUR, GBP, JPY, \tag{17}$$

[21] The investor can place a limit order to sell at an exchange rate level higher than the forecast exchange rate, and if the order is filled he makes even higher profits. Furthermore, a trader can place limit orders that expire at every hour of the day, or a combination of stop-loss and take-profit orders, thus accumulating more profits during the day.

and the weight on the riskless asset is $w^i = 1 - \sum_{j=1}^{3} w^j$; as for the case of rule (10), if $\widetilde{SR}^j_{t+1|t} \leq 0$ we set $\widetilde{SR}^j_{t+1|t} = 0$ in equation (17). In this setup, the investor continues to refrain from undertaking any short-selling activity.

Table 9
Robustness checks

Realized out-of-sample Sharpe ratios for the period 6/15/2004 - 2/14/2005, obtained by investing based on the one period ahead forecasts from the different models and calculated from the investment strategy detailed in section 5.1. 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 equations (16)-(17). The results in the Panel B 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 (in round brackets) and 0.0004 (in square brackets) dollars per unit of currency traded. Panel C shows the Sharpe ratios obtained using the 1/N investment rule. Average and S.D. are the average and standard deviation of the Sharpe ratio during the day, respectively. All Sharpe ratios have been rounded to the second decimal point.

Panel A: In-sample Sharpe ratios

Obs	M^{OF}	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
			7-17		
30	5.41	-1.12	0.42	4.20	-3.48
40	4.40	-1.24	-0.06	2.28	-4.05
50	4.71	1.17	3.82	2.58	-3.74
60	5.58	2.02	4.85	3.02	-4.50

Continued...

The results, presented in Panel A of Table 9, show that the in-sample Sharpe ratios obtained under the Sharpe ratio rule are similar to those obtained under return maximization, albeit slightly higher for some of the models. Model M^{OF} continues to be the model that yields the highest in-sample Sharpe ratios, and our results do not appear to have been hindered by the use of expected returns as the sole determinant for asset allocation. In other words, the investor would have chosen M^{OF} as the best model under either selection rule (10) or (17).

5.3.2 Transaction Costs

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 $\Delta\widetilde{r}^j_{t+1|t} - i_t - TC > 0$ and pays a transaction cost for each unit of foreign currency bought and sold. Transactions costs are assumed to be 0.0001 dollars (1 pip), 0.0002, and 0.0004 per unit of currency traded. These 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, this will induce less trading and higher profits (or losses) whenever trading occurs.

Table 9
Robustness checks (cont.)

Panel B: Transactions costs

Time	M^{OF}	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
17-7	0.44	1.29	0.35	-0.01	1.07
	(0.64)	(0.97)	(-0.05)	(-0.27)	(0.72)
	[0.56]	[0.62]	[0.01]	[-1.00]	[-0.50]
17-8	0.74	-0.45	-0.06	-0.20	0.53
	(1.84)	(-0.39)	(-0.30)	(-0.11)	(-0.69)
	[0.66]	[-0.52]	[-1.70]	[0.53]	[-1.41]
17-9	1.44	-0.74	-1.75	0.21	-1.06
	(1.22)	(-0.93)	(-1.57)	(-0.10)	(1.99)
	[1.17]	[-1.11]	[-1.95]	[0.09]	[-2.24]
17-10	2.06	0.36	-1.30	0.99	-2.14
	(1.77)	(-0.14)	(-1.50)	(0.65)	(-2.18)
	[2.06]	[-0.18]	[-1.05]	[0.28]	[-1.52]
17-11	1.59	0.09	-0.52	0.98	-0.65
	(1.14)	(0.20)	(-0.80)	(0.85)	(-0.28)
	[2.10]	[0.29]	[-0.70]	[0.32]	[1.23]
17-12	1.35	0.43	0.01	0.91	0.29
	(2.50)	(0.31)	(-0.13)	(0.71)	(-0.79)
	[1.06]	[0.40]	[0.08]	[0.26]	[0.48]
17-13	0.65	0.17	0.67	0.80	1.68
	(0.19)	(0.07)	(0.41)	(0.42)	(1.36)
	[-0.10]	[-0.20]	[-0.13]	[0.11]	[0.25]
17-14	-0.24	-0.64	-0.51	0.79	0.98
	(0.35)	(-0.80)	(-0.64)	(0.28)	(0.46)
	[0.67]	[1.63]	[-0.75]	[-0.25]	[-1.84]
17-15	1.28	1.00	0.84	1.07	1.60
	(1.06)	(0.59)	(0.26)	(1.23)	(1.34)
	[0.31]	[1.07]	[0.10]	[1.06]	[0.23]
17-16	0.89	0.46	1.74	1.35	1.67
	(0.65)	(0.24)	(1.63)	(1.12)	(1.31)
	[-0.15]	[0.10]	[1.36]	[0.92]	[0.48]
17-17	1.50	2.76	2.06	0.96	0.09
	(1.02)	(2.47)	(1.93)	(0.45)	(-0.57)
	[0.70]	[1.87]	[1.79]	[0.08]	[-0.07]
	1.06	0.43	0.14	0.71	0.37
Average	(1.13)	(0.24)	(-0.07)	(0.48)	(0.24)
	[0.82]	[0.36]	[-0..27]	[0.22]	[-0.45]
	0.64	1.00	1.17	0.49	1.24
S.D.	(0.69)	(0.93)	(1.12)	(0.50)	(1.25)
	[0.74]	[0.90]	[1.15]	[0.55]	[1.13]

Continued . . .

As expected, Panel B of Table 9 shows that transaction costs reduce the average Sharpe ratios for all the models estimated. The higher the transaction costs the lower the average Sharpe ratio and the higher its standard deviation. Nonetheless, the average Sharpe ratio for M^{OF} for the highest transaction costs is 0.82, and there are still Sharpe ratios for certain hours of the day that are higher than 2 and than the baseline results, while for the other models the average Sharpe ratios are at best just above 0.5.

5.3.3 Alternative Portfolio Weights Choice: 1/N Strategy

The portfolio selection procedure employed in this paper is intuitive and resembles the decision-making process generally used by investment banks. We test for the robustness of our Sharpe ratio results by implementing the simple 1/N allocation rule.

Table 9
Robustness checks (cont.)

Panel C: 1/N investment rule

Time	M^{OF}	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
17-7	1.74	1.60	0.09	1.11	1.03
17-8	2.00	0.01	-0.42	0.89	0.68
17-9	2.41	-0.86	-1.05	0.37	-0.20
17-10	1.73	0.19	0.20	1.06	0.13
17-11	2.00	-0.01	-1.16	-0.43	-0.06
17-12	1.97	0.33	0.47	0.46	1.34
17-13	0.86	0.24	0.86	1.09	1.42
17-14	1.14	-0.08	-0.54	0.36	0.47
17-15	2.31	0.91	1.18	1.17	2.01
17-16	1.48	1.79	2.32	1.37	1.43
17-17	1.47	2.29	2.17	1.29	0.58
Average	1.74	0.58	0.37	0.79	0.80
S.D.	0.47	0.95	1.18	0.54	0.70

Under the 1/N allocation rule, the investor simply puts an equal weight in all N assets. In particular, after the investor has identified all the forecasts for which $\Delta\widetilde{r}^{j}_{t+1|t} - i_t > 0$, he invests equal and fixed weights in the three currencies and the USD interest rate; in our setting, $N = 4$. The results in Panel C of Table 9 show that the out-of-sample average Sharpe ratio of all models increases using the 1/N rule and the standard deviations decrease. The use of the 1/N rule has the highest impact on the results for the forward bias model (M^{FB}). This improvement is consistent with the results obtained by De Miguel, Garlappi, and Uppal (2005), who find that the 1/N rule outperforms several more sophisticated optimal asset allocation rules out of sample.[22]

[22] As a further robustness check, we have allowed for short-selling in the trading strategy. The results remain

6 Conclusions

This paper makes two related contributions to exchange rate economics. We show that order flow (i) is related to current and expected future macroeconomic fundamentals, and (ii) can profitably forecast currency returns.

Previous research has found strong explanatory power of order flow for exchange rate movements, but weak explanatory power of macroeconomic fundamentals. We provide evidence that a significant amount of order flow variation can be explained using macroeconomic news, suitably constructed from survey data. In addition, order flow appears to aggregate changes in expectations about fundamentals and to be a predictor of future fundamentals. This finding may provide a rationale for the high explanatory power of order flow found in the literature. Furthermore, it suggests that macroeconomic fundamentals are indeed relevant for exchange rate determination, but that heterogeneous beliefs about fundamentals are also important.

The well-documented inability of standard exchange rate models to forecast better out of sample than a naïve random walk remains the conventional wisdom in the international finance profession. However, if exchange rates are determined by macroeconomic fundamentals, but order flow gradually conveys information on heterogeneous beliefs about these fundamentals as suggested above, order flow may also provide forecasting power for exchange rates. The key finding of this paper is that order flow provides powerful information that allows us to forecast daily exchange rate movements using eight months of data for three major exchange rates. This result is obtained by measuring forecasting power in the context of a simple, intuitive metric of economic gains, the Sharpe ratio. We compare the Sharpe ratios for a mean-variance investor that uses out-of-sample exchange rate forecasts obtained from a model that conditions on order flow information with the Sharpe ratios under alternative models, including a naïve random walk and a forward bias strategy. The average Sharpe ratio from using order flow models is well above unity before transactions costs (0.82 when accounting for costs) and substantially higher than any alternative model considered. These results are robust to various changes in the problem setup.

In summary, taking together the results provided in this paper, we add further evidence that order flow is key to understanding exchange rate fluctuations. We show that order flow is strongly related to fundamentals and, in turn, can profitably forecast exchange rate movements. We take this to be robust evidence that can bridge the micro-macro divide, in the sense that current and future exchange rates are not random walks but are indirectly determined by economic fundamentals.

qualitatively similar and are not presented due to space constraints, but are available from the authors upon request. We also calculated the Sharpe ratios allowing for serial correlation in returns, and again found no qualitative differences in our results.

References

Abhyankar, A., Sarno, L., and Valente, G., 2005. Exchange Rates and Fundamentals: Evidence on the Economic Value of Predictability. *Journal of International Economics* 66, 325—348.

Ackermann, C., McEnally, R., and Ravenscraft, D., 1999. The Performance of Hedge Funds: Risk, Return, and Incentives. *Journal of Finance* 54, 833–874.

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Vega, C., 2003. Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange. *American Economic Review* 93, 38–62.

Berger, D.W., Chaboud, A.P., Chernenko, S.V., Howorka, E., Iyer, R.S.K., Liu, D., and Wright, J.H., 2005. Order Flow and Exchange Rate Dynamics in Electronic Brokerage System Data. IFDP 830, Board of Governors of the Federal Reserve System.

BIS, 2005. *Central Bank Survey of Foreign Exchange and Derivative Market Activity. 2004*. Bank for International Settlements, Basel.

Bjønnes, G.H. and Rime, D., 2005. Dealer Behavior and Trading Systems in Foreign Exchange Markets. *Journal of Financial Economics* 75, 571–605.

Bjønnes, G.H., Rime, D., and Solheim, H.O.A., 2005. Liquidity Provision in the Overnight Foreign Exchange Market. *Journal of International Money and Finance* 24, 177–198.

Brown, S.J., Goetzmann, W.N., and Ibbotson, R.G., 1999. Offshore Hedge Funds: Survival and Performance, 1989–95. *Journal of Business* 72, 91–117.

Carlson, J.A. and Lo, M., 2006. One Minute in the Life of the DM/US$: Public News in an Electronic Market. *Journal of International Money and Finance* 25, 1090–1102.

Cheung, Y.W., Chinn, M.D., and Garcia-Pascual, A., 2005. Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive? *Journal of International Money and Finance* 24, 1150—1175.

Cochrane, J.H., 1999. Portfolio Advice for a Multi-Factor World. *Federal Reserve Bank of Chicago Economic Perspectives* 23, 59–77.

Daníelsson, J. and Love, R., 2006. Feedback Trading. *International Journal of Finance and Economics* 11, 35–53.

Daníelsson, J., Luo, J., and Payne, R., 2002. Exchange Rate Determination and Inter-Market Order Flow Effects. mimeo, London School of Economics.

Daníelsson, J. and Payne, R., 2002. Real Trading Patterns and Prices in Spot Foreign Exchange Markets. *Journal of International Money and Finance* 21, 203–222.

Dominguez, K.M. and Panthaki, F., 2006. What Defines News in Foreign Exchange Markets? *Journal of International Money and Finance* 25, 168–198.

Elliott, G. and Ito, T., 1999. Heterogeneous Expectations and Tests of Efficiency in the Yen/Dollar Forward Exchange Rate Market. *Journal of Monetary Economics* 43, 435–456.

Engel, C. and West, K.D., 2005. Exchange Rates and Fundamentals. *Journal of Political Economy* 113, 485–517.

Evans, M.D.D., 2002. FX Trading and Exchange Rate Dynamics. *Journal of Finance* 57, 2405–2447.

Evans, M.D.D. and Lyons, R.K., 2002a. Informational Integration and FX Trading. *Journal of International Money and Finance* 21, 807–831.

———, 2002b. Order Flow and Exchange Rate Dynamics. *Journal of Political Economy* 110, 170–180.

———, 2005a. Do Currency Markets Absorb News Quickly? *Journal of International Money and Finance* 24, 197–217.

———, 2005b. Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting. *American Economic Review Papers and Proceedings* 95, 405–414.

———, 2006a. How is Macro News Transmitted to Exchange Rates? Working paper, UC Berkeley.

———, 2006b. Understanding Order Flow. *International Journal of Finance and Economics* 11, 3–23.

Fama, E.F., 1984. Forward and Spot Exchange Rates. *Journal of Monetary Economics* 14, 319–338.

Farooqi, S., 2006. Reuters and CME to Set Up FX Markets Space. *FX Week* 17.

Fleming, M. and Remolona, E., 1997. What Moves the Bond Market? *FRBNY Economic Policy Review* 31–50.

Galati, G., 2001. Why Has Global FX Turnover Declined? Explaining the 2001 Triennial Survey. *BIS Quarterly Review* 39–47.

Galati, G. and Melvin, M., 2004. Why Has FX Trading Surged? Explaining the 2004 Triennial Survey. *BIS Quarterly Review* 67–74.

Killeen, W.P., Lyons, R.K., and Moore, M.J., 2006. Fixed versus Flexible: Lessons from EMS Order Flow. *Journal of International Money and Finance* 25, 551–579.

Leitch, G. and Tanner, J., 1991. Economic Forecast Evaluation: Profits versus the Conventional Measures. *American Economic Review* 81, 580–590.

Love, R. and Payne, R., 2006. Macroeconomic News, Order Flows and Exchange Rates. *Journal of Financial and Quantitative Analysis* Forthcoming.

Lyons, R.K., 1995. Tests of Microstructural Hypothesis in the Foreign Exchange Market. *Journal of Financial Economics* 39, 321–351.

———, 2001. *The Microstructure Approach to Exchange Rates.* MIT Press, Cambridge, MA.

Meese, R.A. and Rogoff, K., 1983. Empirical Exchange Rate Models of the Seventies. *Journal of International Economics* 14, 3–24.

Miguel, V.D., Garlappi, L., and Uppal, R., 2005. How Inefficient is the 1/N Asset-Allocation Strategy? Tech. rep., London Business School.

Newey, W.K. and West, K.D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica* 55, 703–8.

Payne, R., 2003. Informed Trade in Spot Foreign Exchange Markets: An Empirical Investigation. *Journal of International Economics* 61, 307–309.

Rime, D., 2003. New Electronic Trading Systems in the Foreign Exchange Markets. In *New Economy Handbook*, D.C. Jones, ed., chap. 21, 471–504. Academic Press, San Diego.

Sager, M.J. and Taylor, M.P., 2005. Order Flow and Exchange Rate Movements. mimeo, University of Warwick.

Sarno, L., Valente, G., and Leon, H., 2006. Nonlinearity in Deviations from Uncovered Interest Parity: An Explanation of the Forward Bias Puzzle. *Review of Finance* 10, 443–482.

Sharpe, W.F., 1966. Mutual Fund Performance. *Journal of Business* 39, 119–138.

———, 1994. The Sharpe Ratio. *Journal of Portfolio Management* 21, 49–58.

Zellner, A., 1962. An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association* 57, 348–368.

A Appendix: Tables

Table A1
US, EMU, and UK news contemporaneous impact on order flow

OLS regression of order flow (net 1,000 purchases) for EUR, GBP, and JPY on individual contemporaneous news $\Delta x_t^j = c + \lambda_i d_{i,t} + \nu_t$. Unexpected changes in fundamentals are the difference between the actual $(a_{i,t-k})$ and expected $(E_{t-l} a_{i,t-k})$ value of the indicator, standardized by the standard deviation (σ_i) for the sample, $d_{i,t} = \frac{a_{i,t-k} - E_{t-l} a_{i,t-k}}{\sigma_i}$. The total number of observations for each currency is 263, 12 and 4 observations are available for monthly and quarterly announcements respectively, for the period 2/13/2004 - 2/14/2005. We report the impact of the significant news in the regression $\Delta x_t^j = c + \sum \lambda_i d_{i,t} + \eta_t$ (Table 4) and other news whose impact is significant at the 10% level.

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

Table A2
Announcement variables and the expected sign of the news impact on order flow

Announcement	EUR λ	GBP λ	JPY λ
Panel A: US Announcements			
Quarterly Announcements			
Current account	-	-	-
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			
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	+	+	+

Continued...

Table A2
Announcement variables and the expected sign of the news impact on order flow (cont.)

Announcement	EUR λ	GBP λ	JPY λ
Panel B: EMU Announcements			
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	+		
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	+		

Continued...

Table A2
Announcement variables and the expected sign of the news impact on order flow (cont.)

Announcement	EUR	GBP	JPY
	λ	λ	λ
Panel C: UK Announcements			
Quarterly Announcements			
Current account		+	
GDP provisional - quarter		+	
GDP provisional - year		+	
GDP final - quarter		+	
GDP final - year		+	
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 - year		+/-	
Producer input price index - month		+/-	
Producer input price index - year			
Producer output price index - month		+/-	
Producer output price index - year			
Retail price index - month		+/-	
Retail price index - year		+/-	
Government purchases			
Budget deficit - PSNCR		-	

Table A3
Contemporaneous effect of news on exchange rates — single equation

OLS regression of the exchange rate on contemporaneous news: $\Delta s_t^j = c + \sum \lambda_i d_{i,t} + \zeta_t$ and the additional explanatory power of order flow: $\Delta s_t^j = c + \sum \lambda_i d_{i,t} + \pi \Delta x_t^j + \zeta_t^{'}$, for the period 2/13/2004-2/14/2005. Δs_t^j is the daily exchange rate change from 7:00 to 17:00 GMT, and Δx_t^j is the daily order flow (positive for net foreign currency purchases, in thousands), cumulated between 7:00 - 17:00 GMT, for each exchange rate j (US dollar/euro (EUR), US dollar/UK sterling (GBP), and US dollar/Japanese yen (JPY)). $d_{i,t} = \frac{a_{i,t-k} - E_{t-l} a_{i,t-k}}{\sigma_i}$ is the news variable. The explanatory variables used are the same that significantly explain Δx_t^j (from Table 4). *, **, *** imply significance at the 10, 5 and 1% level respectively.

		EUR	GBP	JPY
	Announcement	λ	λ	λ
	US Announcements			
Quarterly	GDP advance	-4.30***		
	GDP preliminary	-0.76		
Monthly	Nonfarm payroll employment	-9.74***	-4.83**	
	Unemployment rate	4.86**		
	Construction spending			-1.71**
	Durable goods orders		-3.41*	
	Trade balance	-2.45	2.78	-3.02***
	Consumer price index		-0.72	
	Chicago PMI	-7.52***		
	Consumer confidence index			-4.52***
	Housing starts		-0.18*	
	Michigan sentiment - final	-3.91***		-1.76***
Weekly	Initial unemployment claims			0.25
	EMU Announcements			
Quarterly	Labor costs	4.58**		
Monthly	Industrial production - year	1.98***		
	Retail sales - month	3.44***		
	Consumer price index - month	3.09***		
	Consumer price index - year	-2.91***		
	Consumer confidence balance	3.79***		
	Sentiment index	6.26***		
	UK Announcements			
Quarterly	GDP provisional - quarter		6.66**	
Monthly	Trade balance		3.67**	
	R^2	0.22	0.12	0.04
	Order flow	0.03***	0.01***	0.12***
	R^2 with own order flow	0.58	0.24	0.31

Table A4
Order flow portfolio balance model and macro news

SUR regression of exchange rate changes on contemporaneous news and order flow: $Z_t = c + BX_t + \sum \lambda_i d_{i,t} + \zeta_t^{''}$, for the period 2/13/2004-2/14/2005. Z_t is the 3×1 vector of daily exchange rate changes Δs_t, X_t is the 3×3 vector of order flows (own and other currencies) Δx_t, and $d_{i,t} = \frac{a_{i,t-k} - E_{t-n} a_{i,t-k}}{\sigma_i}$ is the news variable, where the news included are those that significantly explain Δx_t^j (from Table 4). Coefficients in bold are significant at the 10% level.

	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	

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