

Exchange Rate Forecasting, Order Flow and Macroeconomic Information^{*†}

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Abstract

This paper adds to the research efforts that aim to bridge the divide between macro and micro approaches to exchange rate economics by examining the linkages between foreign exchange order flow, expectations of macroeconomic variables, and exchange rate movements. The basic hypothesis tested is that 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 collected via a live feed from Reuters for three major exchange rates, we find that: i) order flow is intimately related to a broad set of current and expected macroeconomic fundamentals; ii) more importantly, order flow is a powerful predictor of daily movements in exchange rates in an out-of-sample exercise, on the basis of economic value criteria such as Sharpe ratios and performance fees implied by utility calculations.

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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 (Meese and Rogoff, 1983; Cheung, Chinn, and Garcia-Pascual, 2005; Engel, Mark and West, 2007), the recent microstructure literature has provided promising evidence, pioneered by a series of papers by Evans and Lyons (2002a; 2005a). 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 defined as the net of buyer- and seller-initiated currency transactions, and may be thought of as a measure of net buying pressure (Lyons, 2001).

In a macro-micro dichotomy of exchange rate determination, 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 (e.g. Evans and Lyons, 2002a; Bacchetta and van Wincoop, 2006), seems more plausible. In this framework, 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 (2002a) 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; Froot and Ramadorai, 2005; Marsh and O'Rourke, 2005; Killeen, Lyons and Moore, 2006). Moreover, Evans and Lyons (2005a, 2006) 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 (Bacchetta and van Wincoop, 2006). However, it does not necessarily imply that order flow is the underlying determinant of exchange rates. 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 macro 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 its forecasting power. 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 available at a point in time is largely useless information for predicting currency fluctuations. However, if order flow does indeed reflect heterogeneous beliefs about the current and future 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. We start from noting that theoretically order flow can aggregate macroeconomic information through two channels: (i) differential interpretation of news (currently available information); and (ii) heterogeneous expectations about future fundamentals. We provide evidence 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 and changes in expectations about these fundamentals, implying that both channels suggested by theory are at work. 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.

The forecasting analysis relies on the use of economic criteria. Statistical evidence of exchange rate predictability in itself does not guarantee that an investor can earn profits from an asset allocation strategy that exploits this predictability. In practice, ranking models is useful to an investor only if it leads to tangible economic gains. Therefore, in this paper the economic value of exchange rate predictability is assessed by evaluating the impact of predictable changes in the conditional FX returns on the performance of dynamic allocation strategies. Building on previous research by West, Edison and Cho (1993), Fleming, Kirby and Ostdiek (2001) and Della Corte, Sarno and Tsiakas (2008), we employ mean-variance analysis as a standard measure of portfolio performance

and apply quadratic utility to examine whether there are any 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. Economic gains are evaluated mainly using two measures: the Sharpe ratio and the performance fee. The Sharpe ratio is the most common measure of performance evaluation employed in financial markets to assess the success or failure of active asset managers; it is calculated as the ratio of the realized portfolio excess return to their variability. The performance fee measures how much a risk averse investor is willing to pay for switching from a dynamic portfolio strategy based on the random walk model to one which conditions on order flow. In addition, we calculate the break-even transaction cost, that is the transaction cost that would remove any economic gain from a dynamic asset allocation strategy relative to a simple random walk strategy.¹

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 around unity and substantially higher than the Sharpe ratios delivered by alternative models, including the random walk. Furthermore, we find that a risk averse investor would be prepared to pay high performance fees to switch from the random walk model to a model based on order flow. Consistent with leading microstructure theories, our interpretation is that order flow is a key vehicle via which fundamental information impacts on current and future prices.

This paper is also related to research investigating how order flow can reflect differential interpretations of news, including Dominguez and Panthaki (2006), Evans and Lyons (2005b, 2008), Love and Payne (2008) and Berger *et al.* (2008). 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 its specific focus is 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 forthcoming macroeconomic announcements to movements in exchange rates.

Another important related paper is Evans and Lyons (2005a). This study documents that there is indeed forecasting power in order flow, making it possible to outperform a random walk

¹In 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 metrics used here are just two of them. See also Elliott and Ito (1999) and Abhyankar, Sarno and Valente (2005).

benchmark. However, our work is different in at least two important aspects. First, while Evans and Lyons (2005a) 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. This is important since our order flow data are likely to capture a larger fraction of the market for the currencies concerned. Second, and more importantly, 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. Thus, our calculations allow a direct assessment of the economic significance of order flow in exchange rate determination.

The remainder of the paper is organized as follows. In the next section, we provide a brief 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, and the results on the economic value of forecasting models that condition on order flow are reported in Section 6. Section 7 concludes.

2 A Brief Literature Review

The failure of conventional structural models to explain and forecast exchange rates has recently given rise to two different strands of research: one focusing on the implications of the standard 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 determination 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: fundamentals are nonstationary processes; and the discount factor for expected fundamentals in the exchange rate equation is near unity. Under these conditions, empirical exchange rate models based on current and past macroeconomic information cannot forecast exchange rate returns, even if the fundamentals model is correct, because FX returns will behave as near white noise processes. 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, and Engel, Mark and West (2007) and Molodtsova and Papell (2008) find evidence that fundamentals can outperform a random walk.

On the other hand, the microstructure literature has also taken significant steps towards understanding short-run fluctuations in exchange rates. Evans and Lyons (2002a) 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 Evans and Lyons (2002b) also find that the exchange rate between two currencies is explained not only by the relevant order flow for that currency pair, but also by other currencies' order flows, consistent with an order-flow portfolio rebalancing approach.

At a theoretical level, Evans and Lyons (2007) formalize the notion that order flow conveys fundamental information about exchange rates in a dynamic general equilibrium model where information is first manifested at the micro (agent) level and is not symmetrically observed among agents. The model essentially combines a number of classical ingredients of the new open-economy macroeconomics literature with the insights of the FX microstructure literature, predicting an exchange rate behavior that matches several empirical facts. In a related theoretical paper, Bacchetta and van Wincoop (2006) show the existence of a close relation between order flow and exchange rates in a stylized dynamic rational-expectations model without information asymmetries about the state of the economy. The information about macroeconomic fundamentals is assumed to be dispersed across agents, and this heterogeneity generates a larger impact of non-fundamental (e.g. hedging) trades on the exchange rate; thus a disconnect between exchange rates and fundamentals arises in the short run. However, the relation between order flow and exchange rates is strong at both short and longer horizons. In essence, Evans and Lyons (2007) and Bacchetta and van Wincoop (2006) provide significant steps forward towards understanding the theoretical linkages between macroeconomic fundamentals, order flow and exchange rate fluctuations in a general equilibrium setting.

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 (see Evans and Lyons, 2005a). Starting from conventional exchange rate theories, the exchange rate can be written as the discounted present value of current and expected fundamentals:

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

where s_t is the log nominal exchange rate (defined as the domestic price of the foreign currency), 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

²Related papers confirming and extending these results include Payne (2003), Bjørnnes, Rime and Solheim (2005), Carlson and Lo (2006), Dominguez and Panthaki (2006), Killeen, Lyons and Moore (2006), and Berger *et al.* (2008).

expectation about future (q -periods ahead) fundamentals conditional on information available at time t .³ Iterating equation (1) forward and rearranging terms one obtains:

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

where $\varepsilon_{t+1} \equiv (1-b) \sum_{q=0}^{\infty} b^q (E_{t+1}^m f_{t+q+1} - E_t^m f_{t+q+1})$.⁴ 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 about fundamentals. In this setup, there is scope for order flow to reflect agents' expectations about current fundamentals (i.e. interpretations, the first term in the equation) and changes in expectations about future fundamentals that agents base their trades on (the second term in the equation). As such, the strong explanatory power of order flow for exchange rate returns can be related to a standard macroeconomic fundamentals model.⁵

Previous studies have found that order flow is linked to news (Dominguez and Panthaki, 2006; Evans and Lyons, 2005b, 2008; Love and Payne, 2008; Berger *et al.*, 2008), even though the explanatory power is either not reported or documented to be very low. The role of order flow in aggregating expectations about future fundamentals has not yet been investigated in the literature. Moreover, if order flow is a proxy for the two terms in an exchange rate model of the form in equation (2), and the market does not discover aggregate order flow immediately, then order flow may provide forecasting power.

Evidence on the forecasting power of order flow is scant and mixed. Studies that argue in favor of the forecasting power of order flow suggest that daily order flow follows an AR(1) process, because the market needs at least one day to fully uncover aggregate order flow. Given the strong contemporaneous link between exchange rates and order flow, serial correlation in order flow time series would of course generate predictive power. Evans and Lyons (2005a, 2006) argue that end-user order flow is discovered slowly by the market, but the same argument can be applied for several other banks that have an informative clientele. Thus, it can be argued that the whole market will take at least one day to uncover the heterogeneous information embedded in order flow.⁶

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

⁴Usually 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 errors, and data undergo several revisions before being finalized (see Faust, Rogers and Wright, 2003; Sarno and Valente, 2008; Molodtsova and Papell, 2008).

⁵Order flow is also affected by the inventory positions and the liquidity concerns of market players, but we refrain from considerations of these issues (Lyons, 1995; Bjørnnes and Rime, 2005).

⁶Note that even custodian banks, which record order flows for a large proportion of the FX market, typically release

Evans and Lyons (2005a, 2006) use six years 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 ranging from 1 to 20 trading days. Froot and Ramadorai (2005) also report that flows contain some information about future excess returns, although this information is not found to be strongly linked to future fundamentals and the exercise is designed to investigate low frequency predictability. However, Danielsson, Luo and Payne (2002) and Sager and Taylor (2008) find no evidence of better forecasting ability in order flow models relative to a random walk benchmark for several major exchange rates and different forecast horizons. Hence, the forecasting results obtained by Evans and Lyons (2005a, 2006) are waiting to be tested by other studies and with alternative data sources, especially because their data is not available either *ex ante* or *ex post*, given their confidential nature. It is, however, important to note that all these studies carry out forecast accuracy tests using conventional statistical methods. As mentioned earlier, in this paper we move away from standard statistical metrics of forecast evaluation and rely on measures of the economic value of order flow in an asset allocation setting.

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) 3,210 billion (Bank for International Settlements, BIS, 2007), a third of which is in spot transactions. Electronic brokers have become the preferred means of settling trades, and 50-70 percent of turnover in the major currency pairs is settled through the 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 this market (before 2000), with the exception of Berger *et al.* (2008). 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 (financial and non-financial) customers.

This paper uses interdealer data for three major exchange rates: USD *vis-à-vis* the 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

data with significant lags in order to protect clients' confidentiality and meet compliance requirements. For example, State Street, a major custodian bank, releases FX order flow data with a 4-day delay, implying that the learning process discussed above may take several days. Evidence of serial correlation is also found in our order flow data, as described below in Section 3.2.

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

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 live feed.⁸ The BIS (2005) estimates that trades in these currencies constituted up to 60 percent of total FX transactions in 2004, the period we are investigating; hence, our data comprises a substantial part of the FX market.

Daily data are constructed from tick data and include 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. Using daily data allows to filter out transitory liquidity effects and to focus on a horizon that is relevant to market participants. 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, whereas in the forecasting exercise it is defined as the difference between the midpoint rate at 17:00 of day t and 17:00 of day $t - 1$. The former definition matches exactly the definition of order flow and is useful for contemporaneous regressions, whereas the latter is more appropriate for the forecasting exercise where the investor is assumed to forecast exchange rates one-day-ahead on the basis of information that is available at 17:00 GMT on day t to forecast exchange rates at 17:00 on day $t + 1$. 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

It is important to note that the data used here are different from the end-user order flow data employed in some of the papers cited earlier (e.g. Evans and Lyons, 2005a). While the end-user order flow data are proprietary (hence not publicly available), the Reuters data can be observed directly on a Reuters screen. However, it is hardly possible to define this data as public since Reuters does not provide historical data on order flow. In essence, utilization of this data first requires a special order and authorization to download via a live feed, then careful analysis is necessary to aggregate the data from tick frequency to generate signed daily order flow data. This cumbersome process demands both special authorizations and IT resources that constitute a serious barrier to data gathering for the uninitiated in this area of research. In this sense, we would argue that Reuters order flow data do not constitute public information in the sense that they are not simply available by any data provider in real time.

The interest rates used are the overnight LIBOR fixings for euro, UK sterling, US dollar and the

⁸Reuters is the platform where most of the GBP trades take place, while EBS has the highest share of trades in EUR and JPY. Reuters generally 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.

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

¹⁰In 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.

spot/next LIBOR fixing for Japanese yen, obtained from *EcoWin*. Data on economic 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. 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 have data for announcements over 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 very close to zero and standard deviations are large and of similar magnitude across currencies. 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.

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 currency pairs and the relevant order flows are high, above 0.4, and those with other currency pairs' order flows are also sizable.

Panel C of Table 1 exhibits the first-order serial correlation of the order flow time series (ranging from 8% to 12%). Also there is some evidence of sizable correlations from order flow in one currency and the next-day order flow in another currency. This is the case for the order flow of JPY, which appears to be correlated with next-day order flow in both EUR and GBP. In turn, the strong correlations reported in Panels B-C suggest that system estimation of regressions involving exchange rates and order flow may be superior to single-equation models (see Evans and Lyons, 2002b).

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 (2002a), 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 over and above the interest rate differential. The interest rate differential is the predictor of exchange rate returns predicated by the Uncovered Interest Rate Parity (UIP) condition.¹² The results are presented in Table A1 in the Appendix. The estimated order flow coefficients are always positive and

¹¹This data is not available for Japan over the sample period.

¹²UIP 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).

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 interest rate coefficients are not statistically significant at conventional significance levels.¹³ Hence, the explanatory power in the estimated equations comes exclusively from order flow, which yields an R^2 that ranges from 0.18 for GBP to 0.42 for EUR. These results merely replicate the seminal results of Evans and Lyons (2002a).

In order to allow for cross-currency effects of order flow, as in Evans and Lyons (2002b) and Marsh and O'Rourke (2005), we use the seemingly unrelated regressions (SUR) method to estimate the following regression:

$$P_t = C + BX_t + V_t, \quad (3)$$

where P_t is the 3×1 vector of exchange rate changes, $P_t = [\Delta s_t^{EUR}, \Delta s_t^{GBP}, \Delta s_t^{JPY}]'$; X_t is the 3×1 vector of order flows, $X_t = [\Delta x_t^{EUR}, \Delta x_t^{GBP}, \Delta x_t^{JPY}]'$; 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 2 show that estimation of model (3) yields very strong explanatory power (R^2) for all currencies. 'Own' order flow (that is the order flow of the currency pair on the left-hand side of the equation) has a significant positive coefficient for all the exchange rate movements, but the cross-currency order flows also have significant effects on exchange rate returns, consistent with the above cited studies. The Wald test statistic strongly rejects the null hypothesis that the order flow coefficients in each regression are jointly equal to zero.

4 Order Flow and Macroeconomic Fundamentals

In this section, we examine the link between macroeconomic information and order flow using the standard present-value exchange rate model:

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

where $\varepsilon_{t+1} \equiv (1-b) \sum_{q=0}^{\infty} b^q (E_{t+1}^m f_{t+q+1} - E_t^m f_{t+q+1})$. 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)). We investigate empirically both links between order flow, expectations and news implied by equation (4).

4.1 The Link Between Order Flow and News

First, we investigate whether news explain order flow. News about fundamentals, defined as the difference between actual and expected fundamentals, naturally have a direct effect on $E_t^m f_t$. News

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

may trigger different interpretations for the equilibrium exchange rate (e.g. Bacchetta and van Wincoop, 2006) and induce agents to trade, so that news could explain order flow fluctuations. Put another way, heterogenous interpretations of the impact of news on the exchange rate leads market makers to make inferences about the equilibrium exchange rate from aggregate order flow.

News are calculated as $d_{n,t} = \frac{a_{n,t-k} - E_{t-l}a_{n,t-k}}{\sigma_n}$, where $a_{n,t-k}$ is the actual value of indicator n (say GDP, inflation, etc.) at time t pertaining to the indicator at time $t - k$; k is a week, month or quarter; $E_{t-l}a_{n,t-k}$ is the expected value of indicator n formed at time $t - l$ (the survey expectation), where l ranges between 2 and 6 trading days; and σ_n is the sample standard deviation for indicator n .¹⁴ For each order flow series, we estimate the regression

$$\Delta x_t = \phi_0 + \sum_{n=1}^N \phi_n d_{n,t} + u_t \quad (5)$$

using OLS.¹⁵ In theory, positive news about a country ought to lead to an appreciation of its currency, but it is important to note that this does not necessarily mean that order flow has to be positively related to good news. In a hybrid model with rational expectations and order flow, it is possible that the initial reaction of exchange rates to news fully captures the news or even over-reacts to it; in this case subsequent trading (order flow) may even be negatively related to positive news. In other words, the sign of the relation between news and order flow is ambiguous since it will depend on the extent to which the exchange rate adjusts directly in response to the news (see Evans and Lyons, 2007 for a discussion of this issue).

The results from estimating equation (5) are presented in Table 3. The estimated coefficients are statistically significant at least at the 10 percent level, suggesting that news are an important determinant of order flow.¹⁶ Moreover, our results suggest that demand for a currency is stronger in response to good news, i.e. positive news on the US economy are associated with a decrease in order flow (stronger demand for USD), whereas positive news on foreign economies are associated with an increase in order flow (stronger demand for the base currency), consistent with related evidence in Love and Payne (2008). Such a response may be explained by an initial under-reaction of the exchange rate to news.¹⁷

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

¹⁵A list of all available macroeconomic news in our data set is provided in Table A2 in the Appendix.

¹⁶Standard errors are corrected for autocorrelation and heteroskedasticity (Newey and West, 1987). We also examine the contemporaneous effect of each individual macro news on order flow; these results are presented in Table A3 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 are based on a much lower number of observations than Andersen *et al.* (2003), and hence we rely primarily on the results from regression (5) in this section.

¹⁷A microstructural interpretation of this under-reaction is that, when the positive news comes in, this is an uncertain signal to each market maker that the exchange rate should appreciate. So market makers increase their rates simultaneously, but less than their private beliefs because they are uncertain about the reaction of others. They then see

The news that have the highest 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. These include, for example, news related to economic activity, inflation, non-farm payroll and confidence indicators. Macroeconomic news can explain up to 18 percent of the daily fluctuations in order flow.¹⁸

The microstructure approach predicts that information impacts on exchange rates both directly and indirectly via order flow (Lyons, 2001; Evans and Lyons, 2008). The common knowledge part of news directly affects the exchange rate by shifting the equilibrium price, while order flow reflects heterogeneous interpretations of this news for the new equilibrium price. First, we 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) with exchange rate returns as the dependent variable and use the same macroeconomic news that explain order flow changes as explanatory variables: $\Delta s_t = \psi_0 + \sum_{n=1}^N \psi_n d_{n,t} + u_t$. The results (reported in Table A4 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: $\Delta s_t = \psi_0 + \sum_{n=1}^N \psi_n d_{n,t} + \psi_{N+1} \Delta x_t + u_t$. The results in the lower panel of Table A4 in the Appendix show that the addition of order flow significantly increases the 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 A1). Thus, there is evidence of a dual impact of macroeconomic news on exchange rates, both direct and indirect via order flow.¹⁹

that others increase their rates, confirming that the rate actually will appreciate, as predicted by their private belief. Market makers then start trading on their own information. There is under-reaction due to higher-order beliefs leading to less weight being initially put on private beliefs.

¹⁸Note that inflation can be, in theory, associated with both an appreciation and a depreciation of the domestic currency. It is often found that the US dollar appreciates when higher-than-expected inflation is announced (e.g. Engel, Mark and West, 2007), although a standard monetary model would imply a depreciation.

¹⁹We also 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. The results in Table A5 in the Appendix show that this setup attains the highest explanatory power for all currencies (R^2 between 38 and 56 percent), confirming that the exchange rate is determined both by order flow (own and cross-currency) and macroeconomic news.

4.2 The Link Between Order Flow and Expectations

In this sub-section, we examine the hypothesis that order flow aggregates changes in expectations. Given that the survey expectations about fundamentals are collected and published each Thursday before the announcement week, starting from the survey expectation day (i.e. Thursday), agents can revise their expectations from $E_{t-l}a_{n,t-k}$ to $E_t a_{n,t-k}$ 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 macroeconomic announcement 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 news, $d_{n,t}$ using equation (6):

$$d_{n,t} = \theta_0 + \theta_1 \text{sum}x_t + \epsilon_t \quad (6)$$

where $\text{sum}x_t = \sum_{h=0}^{l-1} \Delta x_{t-h}$ is the sum of order flow for each currency from the day of forming the survey expectation (Thursday) to the announcement day for indicator n ; l varies between 2 and 6; and ϵ_t is the error term. For example, if the actual industrial production figure for EMU (US) is higher than the survey expected value, then rational expectation revisions prior to the news release will lead to more demand for EUR (USD). In turn, the order flow coefficient for EUR is expected to be positive (negative). The opposite will occur for variables whose impact on the economy is considered bad news, e.g. unemployment, inflation, etc. The table below indicates how order flow and the coefficients of equation (6) are expected to behave if order flow is taken to be a proxy for the change in expectations between the survey and the announcement days, for US and foreign (F) news:

	“Good” News	“Bad” News
$a_{n,t-k}^{US} > E_{t-l}a_{n,t-k}^{US}$	$\Delta x^F < 0$ $\theta_1 < 0$	$\Delta x^F > 0$ $\theta_1 > 0$
$a_{n,t-k}^{US} < E_{t-l}a_{n,t-k}^{US}$	$\Delta x^F > 0$ $\theta_1 < 0$	$\Delta x^F < 0$ $\theta_1 > 0$
$a_{n,t-k}^F > E_{t-l}a_{n,t-k}^F$	$\Delta x^F > 0$ $\theta_1 > 0$	$\Delta x^F < 0$ $\theta_1 < 0$
$a_{n,t-k}^F < E_{t-l}a_{n,t-k}^F$	$\Delta x^F < 0$ $\theta_1 > 0$	$\Delta x^F > 0$ $\theta_1 < 0$

Estimation of equation (6) is, unfortunately, based on a small number of observations, and regression estimates are likely to suffer from small sample size bias. Since we are primarily interested in the sign of the relation between order flow and news, Figures 2-6 show the scatter plots of news against aggregated order flow to gauge whether the relation is positive or negative. The scatter plots suggest that order flow and news exhibit the expected relation for most indicators in all the countries investigated. We take these results as illustrative evidence that supports the conjecture that order flow aggregates changes in market expectations with regard to these fundamentals.²⁰

²⁰The results do not change if the order flow that occurs on the announcement day is not included in the sum of order flow, $\text{sum}x_t = \sum_{h=1}^{l-1} \Delta x_{t-h}$.

4.3 Summing Up

To sum up, the evidence in this section suggests that there is a strong relation between order flow and macroeconomic information. Order flow is intimately linked to both news on fundamentals and to changes in expectations about these fundamentals. Macroeconomic information is identified to be a determinant of order flow, which implies that exchange rate fluctuations may be 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, lending support to the explanations for the well-documented disappointing results on the direct link between macroeconomic fundamentals and exchange rates in the literature proposed by Evans and Lyons (2002a, 2008) and Bacchetta and van Wincoop (2006).

5 Empirical Models and Asset Allocation: The Framework

Recently, several banks have invested in technology that captures order flow information for forecasting purposes (e.g. the CitiFlow system by Citigroup and similar systems built at UBS, Royal Bank of Scotland and HSBC). The microstructure literature has used some of these data (e.g. Evans and Lyons, 2005a; Marsh and O'Rourke, 2005; Sager and Taylor, 2008) as well as data constructed from electronic platforms, Reuters and EBS (e.g. Evans and Lyons, 2002a,b; Payne, 2003; Berger *et al.*, 2008). In this section, we examine the forecasting power of order flow in a stylized asset allocation framework, where a mean-variance investor maximizes expected returns subject to a chosen target volatility of portfolio returns.

We rank the performance of the competing models using two main criteria: the Sharpe ratio, arguably the most common measure of performance evaluation among market practitioners; and the performance fee that a risk-averse investor would be willing to pay to switch from a random walk strategy to an active management strategy based on an alternative model that uses order flow information. In addition, we calculate the break-even transaction cost, that is the transaction cost that would remove any economic gain from a dynamic asset allocation strategy relative to a simple random walk strategy. We choose to perform one-day ahead forecasts for the following reasons: one-day ahead forecasts based on order flow are implementable; it is a relevant horizon for practitioners (e.g. most currency funds); unlike intraday forecasts, it involves interest rate considerations; and it is less likely that gradual learning based on this data will allow forecasting at much longer horizons.

5.1 Forecasting Models

Consider an investor who forecasts exchange rate returns daily and allocates capital across currencies. We investigate four models that this investor might use: two models based on order flow, a model based on the Fama (1984) regression that exploits the forward bias (carry trade strategy), and a random walk with drift, used as the benchmark against which the other models are evaluated.

A skeptical view of the ability of order flow to explain exchange rates could be that order flow simply captures serial correlations in exchange rate returns rather than genuine fundamentals information. Alternatively, order flow could reflect the impact of exchange rate movements on trading activities via mechanisms of feedback or momentum trading (e.g. Danielsson and Love, 2006). Hence, the first model we consider allows each exchange rate return to depend on lagged order flow of the relevant currency pair, lagged order flow of other currency pairs and also lagged exchange rate changes (capturing momentum) of the currencies examined:

$$P_{t+1} = C + \Lambda X_t + \Gamma P_t + U_{t+1}, \quad (7)$$

where $P_{t+1} = [\Delta s_{t+1}^{EUR}, \Delta s_{t+1}^{GBP}, \Delta s_{t+1}^{JPY}]'$ is the 3×1 vector of exchange rate returns; X_t is the 3×1 vector of order flows; Λ and Γ are 3×3 matrices of coefficients; C is the vector of constant terms; and U_{t+1} is the vector of error terms. We term the model in equation (7) M^{GEN} . It is illustrative to write M^{GEN} fully as follows:

$$P_{t+1} = C + \begin{pmatrix} \lambda_{11} & \lambda_{12} & \lambda_{13} \\ \lambda_{21} & \lambda_{22} & \lambda_{23} \\ \lambda_{31} & \lambda_{32} & \lambda_{33} \end{pmatrix} X_t + \begin{pmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{pmatrix} P_t + U_{t+1}. \quad (8)$$

The second model we consider relies only on order flow information, and we term this model ‘pure’ order-flow model, or M^{POF} . In essence, M^{POF} is obtained from imposing $\Gamma = \mathbf{0}$ in equation (7): $P_{t+1} = C + \Lambda X_t + U_{t+1}$.²¹

The third model examined, M^{FB} , is the well-known ‘forward bias’ trading strategy based on the Fama regression:

$$P_{t+1} = C + \Pi Z_t + U_{t+1}, \quad (9)$$

where $Z_t = (\mathbf{1}i_t - \Upsilon^*)$ is the 3×1 vector of interest rate differentials (domestic minus foreign); $\Upsilon_t^* = [i_t^{EUR}, i_t^{GBP}, i_t^{JPY}]'$ denotes the 3×1 vector of foreign interest rates; and $\mathbf{1}$ is a vector of ones.²²

²¹In an earlier version of the paper, we also investigated another variant, where exchange rate returns for a currency pair are related only to the lagged value of order flow for that currency pair. In this model, coefficients for other currencies’ order flows (the off-diagonal elements in Λ) and for all exchange rate lags (Γ) are set to zero, so that the forecasting power on a specific exchange rate derives only from that currency’s own order flow, exactly as in Evans and Lyons (2005a). The results are not reported to conserve space, but remain available upon request.

²²The Fama regression commonly estimated in the literature is: $\Delta s_{t+1} = \alpha_0 + \alpha_1 fp_t + v_{t+1}$ (Fama, 1984), where the exchange rate Δs_{t+1} is regressed on the lagged 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 $fp_t = i_t - i_t^*$ via covered interest parity.

Finally, the benchmark model is the random walk with drift, M^{RW} :

$$P_{t+1} = C + U_{t+1}. \quad (10)$$

5.2 Asset Allocation

This section discusses the framework we use in order to evaluate the impact of predictable changes in exchange rate returns on the performance of dynamic allocation strategies. We employ mean-variance analysis as a standard measure of portfolio performance to calculate Sharpe ratios. Assuming quadratic utility, we also measure how much a risk-averse investor is willing to pay for switching from the naïve random walk strategy that assumes no predictability in exchange rates to a dynamic strategy which conditions on order flow or on the interest rate differential.

5.2.1 Portfolio Weights

The investor is assumed to have an initial wealth of \$1 million that he invests every day in three risky assets (foreign overnight deposits) and one riskless asset (overnight deposit). He chooses the weights to invest in each risky asset by constructing a dynamically re-balanced portfolio that maximizes the conditional expected return subject to a target conditional volatility. Let $\mu_{s,t+1|t} = E_t(P_{t+1} + \mathbf{Y}_t^*)$ be the 3×1 vector of conditional expectations for the risky asset returns, then the weights invested in each asset are calculated to solve:

$$\begin{aligned} \max_{w_t} & \left\{ \mu_{p,t+1|t} = w_t' \mu_{s,t+1|t} + (1 - w_t' \mathbf{1}) i_t \right\} \\ \text{s.t.} & \quad (\sigma_p^*)^2 = w_t' \Sigma_{t+1|t} w_t, \end{aligned} \quad (11)$$

where $\mu_{p,t+1|t}$ is the conditional expected return of the portfolio that combines the risky assets and risk free rate; w_t is the 3×1 vector of portfolio weights on the risky assets; σ_p^* is the target level of risk for the portfolio; $\Sigma_{t+1|t}$ is the 3×3 variance-covariance matrix of the risky assets and is estimated recursively as the investor updates forecasts and dynamically rebalances his portfolio every day. The solution to this maximization problem yields the risky assets investment weights:

$$w_t = \frac{\sigma_p^*}{\sqrt{Q_t}} \Sigma_{t+1|t}^{-1} \left(\mu_{s,t+1|t} - \mathbf{1} i_t \right), \quad (12)$$

where $\mu_{s,t+1|t} - \mathbf{1} i_t$ is the foreign exchange excess return (the deviation from UIP); and $Q_t = \left(\mu_{s,t+1|t} - \mathbf{1} i_t \right)' \Sigma_{t+1|t}^{-1} \left(\mu_{s,t+1|t} - \mathbf{1} i_t \right)$. The weight invested in the risk free asset is $1 - w_t' \mathbf{1}$.

The models considered in this paper assume constant volatility (variance-covariance matrix). Hence the only source of time variation in Σ is due to the fact that the models are re-estimated recursively, so that the volatility forecast for time $t + 1$ conditioned on information t is equal to the covariance estimated using data up to time t . However, the literature on volatility timing suggests

that suitable models of conditional volatility add economic value in asset allocation in this context (e.g. Della Corte, Sarno and Tsiakas, 2008), so that the models in this paper could be enhanced by modeling time-varying volatility. We report evidence below that a simple multivariate GARCH model for conditional volatility does indeed provide additional economic value. However, given our focus on forecasting conditional means, we confine the bulk of the discussion to the first moment of exchange rate returns.

5.2.2 Sharpe Ratio

The first economic criterion we employ is the Sharpe ratio (SR), or return-to-variability ratio, which 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. The ex-post SR is defined as:

$$SR = \frac{\bar{r}_p - r_f}{\sigma_p}, \quad (13)$$

where $\bar{r}_p - r_f$ is the average (annualized) excess portfolio return over the risk free rate, and σ_p is the (annualized) standard deviation of the investment returns.

This measure is commonly used to evaluate performance in the context of mean-variance analysis. However, Marquering and Verbeek (2004) and Han (2006) show that the SR can underestimate the performance of dynamically managed portfolios. This is because the SR is calculated using the average standard deviation of the realized returns, which overestimates the conditional risk (standard deviation) faced by an investor at each point in time. Thus, we use the performance fee as an additional economic criterion to quantify the economic gains from using the exchange rate models considered.

5.2.3 Performance Fees Under Quadratic Utility

We calculate the maximum performance fee a risk-averse investor is willing to pay to switch from the benchmark portfolio (based on the random walk model, M^{RW}) to an alternative portfolio. The specific measure adopted is based on mean-variance analysis with quadratic utility (West, Edison and Cho, 1993; Fleming, Kirby and Ostdiek, 2001; Della Corte, Sarno and Thornton, 2008). Under quadratic utility, at the end of period $t + 1$ the investor's utility of wealth can be represented as:

$$U(W_{t+1}) = W_{t+1} - \frac{\rho}{2}W_{t+1}^2 = W_t R_{p,t+1} - \frac{\rho}{2}W_t^2 R_{p,t+1}^2 \quad (14)$$

where W_{t+1} is the investor's wealth at $t + 1$; $R_{p,t+1}$ is the gross portfolio return, equal to $1 + r_{p,t+1}$; and ρ determines his risk preference. To quantify the economic value of each model the degree of relative risk aversion (RRA) of the investor is set to $\delta = \frac{\rho W_t}{1 - \rho W_t}$, and the same amount of wealth is invested every day. Under these circumstances, West, Edison and Cho (1993) show that the average

realized utility (\bar{U}) can be used to consistently estimate the expected utility generated from a given level of initial wealth. The average utility for an investor with initial wealth $W_0 = 1$ is:

$$\bar{U} = \frac{1}{T} \sum_{t=0}^{T-1} \left(R_{p,t+1} - \frac{\delta}{2(1+\delta)} R_{p,t+1}^2 \right). \quad (15)$$

At any point in time, one set of estimates of the conditional returns is better than a second set if investment decisions based on the first set leads to higher average realized utility, \bar{U} . Alternatively, the optimal model requires less wealth to yield a given level of \bar{U} than a suboptimal model. Following Fleming, Kirby and Ostdiek (2001), we measure the economic value of our FX strategies by equating the average utilities for selected pairs of portfolios. Suppose, for example, that holding a portfolio constructed using the optimal weights based on M^{RW} yields the same average utility as holding the optimal portfolio implied by the pure order flow model, M^{POF} that is subject to daily expenses Φ , expressed as a fraction of wealth invested in the portfolio. Since the investor would be indifferent between these two strategies, we interpret Φ as the maximum performance fee he will pay to switch from the M^{RW} to the M^{POF} strategy. In other words, this utility-based criterion measures how much a mean-variance investor is willing to pay for conditioning on order flow as in the M^{POF} strategy for the purpose of forecasting exchange rate returns. The performance fee will depend on the investor's degree of risk aversion. To estimate the fee, we find the value of Φ that satisfies:

$$\sum_{t=0}^{T-1} \left\{ (R_{p,t+1}^{AM} - \Phi) - \frac{\delta}{2(1+\delta)} (R_{p,t+1}^{AM} - \Phi)^2 \right\} = \sum_{t=0}^{T-1} \left\{ R_{p,t+1}^{RW} - \frac{\delta}{2(1+\delta)} (R_{p,t+1}^{RW})^2 \right\}, \quad (16)$$

where $R_{p,t+1}^{RW}$ is the gross portfolio return obtained using forecasts from the benchmark M^{RW} model, and $R_{p,t+1}^{AM}$ is the gross portfolio return constructed using the forecasts from the alternative model (M^{GEN} , M^{POF} and M^{FB}).

5.2.4 Transaction Costs

In dynamic investment strategies, where the individual rebalances the portfolio every day, transaction costs can play a significant role in determining returns and comparative utility gains. However, traders charge transaction costs according to counter-party types and trade size. Thus, instead of assuming a certain cost, we compute the break-even transaction cost τ , which is the minimum daily proportional cost that cancels the utility advantage of a given strategy. We assume that transaction costs at time t equal a fixed proportion τ of the amount traded in currency j :²³

$$\tau \sum_{j=1}^3 \left| w_t^j - w_{t-1}^j \left(\frac{1 + \Delta s_t^j + i_{t-1}^j}{R_{p,t}^{AM}} \right) \right|. \quad (17)$$

It is assumed that these costs are the same across currencies, which is consistent with the bid-ask spreads observed in the currency market for EUR, GBP and JPY.

²³This measure of break-even transaction costs has been previously used by Marquering and Verbeek (2004), Han (2006) and Della Corte, Sarno and Tsiakas (2008).

6 The Predictive Power of Order Flow: Empirical Results

We begin our economic evaluation of one-day-ahead exchange rate predictability by performing in-sample estimations of the 4 candidate models: M^{GEN} , M^{POF} , M^{FB} and M^{RW} . The estimation is carried out over the period from February 13, 2004 to June 14, 2004, comprising about one third of the available observations. While the number of observations used in the in-sample estimation is relatively small, all models are particularly parsimonious linear models, with a small number of parameters. This allows us to make an assessment of the in-sample performance of the models, to have initial estimates of the parameters over a ‘training’ period prior to the out-of-sample analysis, and to conduct the latter analysis using two thirds of the observations in the data set.

6.1 Models Estimation and In-Sample Analysis

Initially, we evaluate the in-sample performance of the strategy described in the previous section, for the period from February 13, 2004 to June 14, 2004. In our setting, the investor obtains the predicted value of exchange rate returns for 17:00 on day $t+1$, conditioning on order flow information aggregated from 7:00 to 17:00 on day t ; he then chooses investment weights and invests in the different currencies using equations (11)-(12). He closes the position at 17:00 on day $t+1$. The in-sample prediction is the fitted value of the exchange rate return for day $t+1$, from 17:00 to 17:00, using the models described in Section 5.1.²⁴

The in-sample performance results include the Sharpe ratio, performance fees and break-even transaction costs calculated using equations (13)-(17) for an annual target volatility of $\sigma^* = 0.10$ and assuming that the coefficient of relative risk aversion $\delta = 5$.²⁵ The results are presented in Table 4. The Sharpe ratios range between 2.23 and 7.05, pertaining to M^{RW} and M^{GEN} respectively. These Sharpe ratios are very high, but one must keep in mind that these are in-sample calculations over the period from February 13 to June 14, 2004. The best models appear to be M^{POF} and M^{GEN} , which yield Sharpe ratios of 5.8 and 7.05. Also, an investor would be willing to pay large performance fees of 29.43 and 43.76 percent per annum in order to switch from a random walk strategy to a strategy based on order-flow models M^{POF} and M^{GEN} . The transaction costs that would cancel the above differences in utility between the order flow models and the random walk are above 14 basis points per day.

In short, the two order flow model (M^{POF} and M^{GEN}) deliver fairly similar results, although there is some additional power deriving from lagged exchange rate information (used in M^{GEN} but not in M^{POF}). These results provide *prima facie* evidence of the predictive power of order flow

²⁴Put another way, the investor forecasts the change in the exchange rate between 17:00 of day t and 17:00 of day $t+1$ and closes the position at 17:00 on day $t+1$, realizing a return $\Delta s_{t+1} = s_{t+1}^{17:00} - s_t^{17:00}$.

²⁵Note also that robustness checks where we experimented with other values of the risk aversion coefficient δ (e.g. $\delta = 2, 8$) do not qualitatively change any of our conclusions.

information as compared to two common benchmarks, the forward bias and the random walk models. However, the analysis until this stage is in sample, while we are ultimately interested in the economic value of order flow as a conditioning variable out of sample.

6.2 The Out-of-Sample Economic Value of Order Flow

The in-sample procedure applied so far allowed us to achieve estimation of the relation between spot exchange rates and the conditioning variables used as predictors. In order to assess the usefulness of the exchange rate models, out-of-sample forecasts of spot returns are constructed using all candidate models estimated in the previous sub-section. In particular, we perform one-day-ahead forecasting exercises on the remaining two thirds of the sample, from June 15, 2004 to February 14, 2005. The out-of-sample forecasts are constructed according to a standard recursive procedure, namely conditional only upon information up to the date of the forecast and with successive re-estimation as the date on which forecasts are conditioned moves through the data set, implying that the model parameters are re-estimated daily.

The forecasting results are presented in Panel A of Table 5. The best in-sample model, M^{GEN} , yields a modest Sharpe ratio of 0.44, whereas the best out-of-sample model is M^{POF} . M^{POF} delivers a Sharpe ratio of 1.06, which is very high compared to others found in the literature. There are a 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.²⁶ The forward bias and the random walk models exhibit negative Sharpe ratios. This may well be due to the small size of our sample period, since the literature typically records positive risk-adjusted returns from forward bias trading over longer samples (e.g. Della Corte, Sarno and Tsiakas, 2008; Burnside, Eichenbaum, Kleshchelski and Rebelo, 2008). However, the difference in performance between order flow models and the model based on the forward bias has the interesting implication that the forecasting power in order flow stems from fundamentally different information than ‘carry trades’ of the kind that would be implied by forward bias models. At the same time, the fact that M^{POF} performs better than M^{GEN} also suggests that momentum effects are not particularly important in forecasting exchange rate returns. This is further corroborating evidence that the information in order flow cannot be captured by simple momentum or forward bias strategies, and it is likely to be related to more fundamental information.

Turning to the calculation of performance fees, Panel A of Table 5 presents performance fees for

²⁶For equities, the typical Sharpe ratio from a buy-and-hold strategy in the S&P500 is between 0.4 (Sharpe, 1994; Lyons, 2001) and 0.5 (Cochrane, 1999), depending on the sample period. Research on fund performance shows 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 representative case of an annual target volatility $\sigma^* = 0.10$ and relative risk aversion coefficient $\delta = 5$. On average an investor is prepared to pay rather high performance fees to switch from the random walk strategy to the order flow based strategies. Specifically, the investor would pay just under 17 annual percentage points of the portfolio value, to switch to the M^{POF} strategy. The performance fee for M^{GEN} is lower (13 percent) but still sizable. The investor would not be willing to shift from the random walk model to the forward bias model. The results are consistent with what was previously found using the Sharpe ratio criterion and are quite high compared to those found in the literature.²⁷

Panel A of Table 5 also presents the break-even transaction costs (τ). The results show that conditioning on order flow information leads to high τ values. Specifically, the break-even transaction cost for model M^{POF} is 4.77 basis points per day. This break-even transaction cost is much higher than the transaction costs implied by the bid-ask spread observed in the market, making it highly unlikely that the transaction costs would cancel the high returns generated from M^{POF} . The corresponding τ value for M^{GEN} is 4.17, also comfortably high to conclude that the economic value of order flow allows to build strategies that dominate the random walk and forward bias benchmark, even after allowing for reasonable transactions costs.²⁸

To provide a visual illustration of the portfolio results obtained using the four candidate models, we present in Figure 7 the evolution of wealth for each of M^{POF} , M^{GEN} , M^{FB} and M^{RW} . From this graph, we notice that the high Sharpe ratios under M^{POF} and, to a lesser extent, M^{GEN} are due to relatively high returns for the desired target investment volatility. In fact, the wealth evolution under M^{POF} and M^{GEN} appears very close for a long period of time where M^{GEN} performs slightly better, and the outperformance of M^{POF} over M^{GEN} is due to sharp losses incurred under M^{GEN} towards the end of the sample.^{29 30}

Finally, Panel B of Table 5 reports out-of-sample results for the case where we depart from the assumption of a constant variance in the error term. As documented in Fleming, Kirby and Ost-diek (2001) and Della Corte, Sarno and Tsiakas (2008), adequate modelling of conditional volatility

²⁷The differences between the realized portfolio returns of M^{POF} and the corresponding realized returns of the random walk benchmark is also statistically significant at the 5 percent significance level, with a t -statistic of 1.86. This is not the case for M^{GEN} and M^{FB} , for which we find t -statistics of 1.19 and 0.48, respectively.

²⁸The bid-ask spread for the exchange rates examined here is in the range between 1 and 2 basis points.

²⁹Comparing the evolution of wealth in Figure 7 with the time series patterns of exchange rates and overnight interest rate differentials over the sample period (Figure 8), one notices that the order flow model does well regardless of whether the USD appreciates or depreciates, or whether there is high or low volatility, dispelling at least the most obvious doubts with regard to the predictive power of order flow.

³⁰These results may be considered conservative because in our setting the investor is forced to close his position at a certain point (hour) of the day (namely 17:00); realistically, he could place limit orders that allow him to make higher profits in the day. 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.

provides economic value in an asset allocation context. For illustrative and robustness purposes, we carry out the out-of-sample asset allocation problem with the errors assumed to follow a multivariate GARCH(1,1) process (Engle and Kroner, 1995)—the estimation results from the multivariate GARCH(1,1) are not reported to conserve space. The outcome from this exercise confirms that the performance fees, Sharpe ratios and the break-even transaction costs increase when modelling conditional volatility.

7 Conclusions

This paper makes two related contributions to empirical exchange rate economics. We show that order flow is related to current and expected future macroeconomic fundamentals, and can profitably forecast risk-adjusted currency returns.

Previous research has found that order flow has strong explanatory power for exchange rate movements, whereas macroeconomic fundamentals have weak explanatory power. 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. 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 the order flow channel is key to link exchange rates to fundamentals, as argued by Evans and Lyons (2002b, 2007) and Bacchetta and van Wincoop (2006).

The well-documented inability of standard exchange rate models to forecast out of sample better 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, then order flow should provide forecasting power for exchange rates. The key finding of this paper is that order flow provides powerful information that allows us to forecast the daily exchange rate movements of three major exchange rates. This result is obtained by measuring forecasting power in the context of simple, intuitive metrics of economic gains. We show the Sharpe ratios and the performance fees against the random walk strategy for a mean-variance investor that uses out-of-sample exchange rate forecasts obtained from different models that condition on order flow or forward bias. The Sharpe ratio from using the proposed order flow model is well above unity and substantially higher than any alternative model considered, while the performance fees are just under 17 percent per annum.

In summary, taking together the results provided in this paper, we add further evidence that order flow is key to understanding exchange rate fluctuations. Order flow is strongly related to

fundamentals and, in turn, can provide useful guidance to forecast exchange rate movements. We also take this as evidence that can bridge the micro-macro divide, in the sense that current and future exchange rates are not random walks but are, at least indirectly, determined by economic fundamentals.

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Table 1
Preliminary data analysis

Preliminary analysis for the period 2/13/2004 - 2/14/2005. Δs_t^j is the daily exchange rate return 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 points. Panel B exhibits sample contemporaneous correlations among exchange rate returns and order flows. Panel C shows the autocorrelations in order flow time series and the lagged cross-correlations of order flows. The diagonal elements show the autocorrelations, i.e. $corr(\Delta x_t^j, \Delta x_{t-1}^j)$. The off-diagonal elements are the lagged cross-correlations, i.e. $corr(\Delta x_t^j, \Delta x_{t-1}^i)$, where $i \neq j$.

	Δs_t^{EUR}	Δs_t^{GBP}	Δs_t^{JPY}	Δx_t^{EUR}	Δx_t^{GBP}	Δx_t^{JPY}
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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. Contemporaneous 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

Panel C. Order flows correlations

Δx_{t-1}^{EUR}			0.12	0.12	0.00
Δx_{t-1}^{GBP}			-0.01	0.08	-0.01
Δx_{t-1}^{JPY}			0.06	0.22	0.12

Table 2
Order flow model

SUR estimates of equation (3) for the period 2/13/2004 - 2/14/2005. Δs_t^j is the daily exchange rate return 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 least at the 10% level of significance. The Wald test presents the p -value (in square brackets) for the joint null hypothesis that all order flow coefficients are equal to zero. 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)
<i>Wald Test</i>	[0.00]	[0.00]	[0.00]
R^2	0.44	0.38	0.36

Table 3
Contemporaneous effect of news on order flow

OLS regression of order flow (1,000 net purchases) for EUR, GBP and JPY on contemporaneous news: $\Delta x_t = \phi_0 + \sum_{n=1}^N \phi_n d_{n,t} + u_t$. News are the difference between the actual value ($a_{n,t-k}$) of the macroeconomic indicator minus its expected value ($E_{t-l} a_{n,t-k}$), standardized by the sample standard deviation (σ_n), $d_{n,t} = \frac{a_{n,t-k} - E_{t-l} a_{n,t-k}}{\sigma_n}$. 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 shows the p -values for the White first-order conditional heteroskedasticity test with cross terms in the residuals. Only variables significant at least at the 10% level using heteroskedasticity- and autocorrelation-consistent standard errors are reported. All equations are estimated with a constant, which is not reported in order to conserve space. The total number of observations for each of the three equations is 263, for the period 2/13/2004 - 2/14/2005.

Announcement		EUR	GBP	JPY
		Estimated parameters		
US				
<i>Quarterly</i>	GDP advance	-114.40		
	GDP preliminary	-69.59		
<i>Monthly</i>	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
<i>Weekly</i>	Initial unemployment claims			4.21
EMU				
<i>Quarterly</i>	Labor costs	101.08		
<i>Monthly</i>	Industrial production (yoy)	62.78		
	Retail sales (mom)	82.30		
	Consumer price index	160.52		
	Consumer confidence balance	149.03		
	Sentiment index	179.60		
UK				
<i>Quarterly</i>	GDP provisional - quarter		267.86	
<i>Monthly</i>	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]

Table 4
In-sample performance

In-sample performance over the period 2/13/2004 - 6/14/2004. The dependent variable is Δs_{t+1} , the daily exchange rate return from 17:00 GMT on day t to 17:00 GMT on day $t + 1$; daily order flow (positive for net foreign currency purchases) is cumulated between 7:00 - 17:00 GMT, for each exchange rate: EUR, GBP and JPY. Note that only lagged (not contemporaneous) order flow is used in the information set, and the exercise is considered in-sample only because the model parameters are estimated during the period 2/13/2004 - 6/14/2004 rather than recursively. We present the following in-sample performance criteria: Sharpe ratio (SR), performance fee (Φ , annual percentage points), and break-even transaction cost (τ , daily basis points) for four models: M^{POF} , M^{GEN} , M^{FB} and M^{RW} as described in Section 5.1, for target volatility $\sigma^* = 10\%$. The fees denote the amount an investor with quadratic utility and a degree of relative risk aversion $\delta = 5$ is willing to pay for switching from the random walk benchmark to an alternative model based on other information (order flow and interest rate differential). τ is defined as the minimum daily proportional cost which cancels out the utility advantage (and hence positive performance fee) of a given strategy over the random walk benchmark. "-" indicates that the random walk model is superior to the alternative model. All the evaluation criteria are rounded to the second decimal point.

<i>Criteria</i>	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
<i>SR</i>	5.79	7.05	2.37	2.23
Φ	29.43	43.76	0.89	-
τ	15.21	14.19	-	-

Table 5
Out-of-sample performance

The table presents out-of-sample performance measures for the four models investigated: M^{POF} , M^{GEN} , M^{FB} and M^{RW} as described in Section 5.1. The out-of-sample period is 6/15/2004 - 2/14/2005. The investment is based on the one-period-ahead forecasts generated by the models and calculated from the investment strategy detailed in Section 5.2, for an annual target volatility $\sigma^* = 10\%$. We present: the Sharpe ratio (SR), performance fee (Φ , annual percentage points), and the break-even transaction cost (τ , daily basis points). The fees denote the amount an investor with quadratic utility and a degree of relative risk aversion $\delta = 5$ is willing to pay for switching from the random walk benchmark to an alternative model based on other information (order flow and interest rate differential). τ is defined as the minimum daily proportional cost which cancels out the utility advantage (and hence positive performance fee) of a given strategy over the random walk benchmark. "-" indicates that the random walk model is superior to the alternative model. All the evaluation criteria are rounded to the second decimal point. In Panel A we report results from models where the error term is assumed to have a constant variance. In Panel B we report the results for the case where the error terms are modelled as a multivariate GARCH process (Engle and Kroner, 1995).

Models with constant variance

	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
<i>SR</i>	1.06	0.44	-1.08	-1.27
Φ	16.75	12.54	1.38	-
τ	4.77	4.17	-	-

Models with multivariate GARCH errors

	M^{POF}	M^{GEN}	M^{FB}	M^{RW}
<i>SR</i>	1.45	0.50	-1.06	-1.35
Φ	24.83	16.28	0.75	-
τ	5.96	4.91	-	-

A Appendix: Further Results

Table A1
Contemporaneous exchange rate-order flow model

OLS estimates of the regressions: (I) $\Delta s_t = \zeta_0^{(1)} + \zeta_1^{(1)} \Delta x_t + \zeta_t^{(1)}$ and (II) $\Delta s_t = \zeta_0^{(2)} + \zeta_1^{(2)} \Delta x_t + \zeta_2^{(2)} (i - i^*)_{t-1} + \zeta_t^{(2)}$, for the period 2/13/2004 - 2/14/2005. The dependent variable Δs_t is the daily exchange rate return for each exchange rate 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 an autocorrelation and heteroskedasticity consistent matrix of residuals (Newey and West, 1987). Coefficients in bold are significant at the 1% level of significance. Column 3 presents the R^2 . Column 4 exhibits the p -values for the Breusch-Godfrey Lagrange multiplier tests for first-order residual serial correlation. Column 5 shows the p -values for the White first-order conditional heteroskedasticity test with cross terms in the residuals. All equations are estimated with a constant, which is not reported to conserve space.

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

Table A2
Announcement variables

<i>US</i>	<i>EMU</i>	<i>UK</i>
Quarterly		
Current account	GDP flash	Current account
GDP advance	GDP revised (mom)	GDP provisional - quarter
GDP preliminary	GDP revised (yoy)	GDP provisional - year
GDP final	Labor costs (preliminary)	GDP final - quarter
	Labor costs (revised)	GDP final - year
Monthly		
Budget deficit	Business climate index	Average earnings
Business inventories	Consumer confidence balance	Budget deficit - PSNCR
Capacity utilization	Consumer price index (mom)	Consumer credit
Chicago PMI	Consumer price index (yoy)	Consumer price index - year
Construction spending	Current account	Industrial production - month
Consumer confidence index	Industrial confidence balance	Industrial production - year
Consumer credit	Industrial production (mom)	Manufacturing output - month
Consumer price index	Industrial production (yoy)	Manufacturing output - year
Durable goods orders	Money supply M3	Manufacturing wages
Factory orders	PMI manufacturing	Producer input price index - month
Housing starts	Producer price index (mom)	Producer input price index - year
Index of leading indicators	Producer price index (yoy)	Producer output price index - month
Industrial production	Retail sales (mom)	Producer output price index - year
ISM index	Retail sales (yoy)	Retail price index - month
Michigan sentiment - preliminary	Sentiment index	Retail price index - year
Michigan sentiment - final	Services index	Retail sales - month
New home sales	Trade balance	Retail sales - year
Nonfarm payroll employment	Unemployment rate	Trade balance
Personal consumption expenditure		
Personal income		
Philadelphia Fed index		
Producer price index		
Retail sales		
Trade balance		
Unemployment rate		
Weekly		
Initial unemployment claims		

Table A3
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 $\Delta x_t = \phi_0 + \phi_n d_{n,t} + u_t$. News are the difference between the actual ($a_{n,t-k}$) and expected ($E_{t-l} a_{n,t-k}$) value of the indicator, standardized by the sample standard deviation (σ_n), $d_{n,t} = \frac{a_{n,t-k} - E_{t-l} a_{n,t-k}}{\sigma_n}$. We report the impact of the significant news in the regression $\Delta x_t = \phi_0 + \sum_{n=1}^N \phi_n d_{n,t} + u_t$ (Table 4) and other news whose impact is significant at least at the 10% level.

		EUR		GBP		JPY	
Announcement		$\hat{\phi}_n$	R^2	$\hat{\phi}_n$	R^2	$\hat{\phi}_n$	R^2
US							
<i>Quarterly</i>	GDP advance	-113.29	0.32				
	GDP preliminary	-30.17	0.04			-8.48	0.89
<i>Monthly</i>	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
<i>Weekly</i>	Initial unemployment claims					4.30	0.04
Average R^2			0.15		0.28		0.29
EMU							
<i>Quarterly</i>	Labor costs	110.80	0.80				
<i>Monthly</i>	Industrial production (yoy)	62.60	0.33				
	Retail sales (mom)	74.77	0.14				
	Consumer price index (mom)	29.77	0.05				
	Consumer price index (yoy)	-7.39	0.00				
	Consumer confidence balance	46.08	0.12				
	Sentiment index	21.73	0.03				
Average R^2			0.21				
UK							
<i>Monthly</i>	Manufacturing wages			-93.32	0.71		
	Retail sales (yoy)			40.57	0.16		
	Trade balance			92.26	0.31		
	Budget deficit			-76.44	0.59		
Average R^2					0.44		

Table A4
Contemporaneous effect of news on exchange rates - single equation

OLS regression of exchange rate returns on contemporaneous news, $\Delta s_t = \psi_0 + \sum_{n=1}^N \psi_n d_{n,t} + u_t$; and the additional explanatory power of order flow, $\Delta s_t = \psi_0 + \sum_{n=1}^N \psi_n d_{n,t} + \psi_{N+1} \Delta x_t + u_t$, for the period 2/13/2004-2/14/2005. Δs_t is the daily exchange rate return from 7:00 to 17:00 GMT, and Δx_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: US dollar/euro (EUR), US dollar/UK sterling (GBP) and US dollar/Japanese yen (JPY). $d_{n,t} = \frac{a_{n,t-k} - E_{t-l} a_{n,t-k}}{\sigma_n}$ is the news variable. The explanatory variables used are the same that significantly explain Δx_t (from Table 4). The coefficients of the order flow variable are expressed in percentage terms. *, **, *** imply significance at the 10, 5 and 1% level respectively.

Announcement		EUR	GBP	JPY
		Estimated Parameters		
US				
<i>Quarterly</i>	GDP advance	-4.30***		
	GDP preliminary	-0.76		
<i>Monthly</i>	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***
<i>Weekly</i>	Initial unemployment claims			0.25
EMU				
<i>Quarterly</i>	Labor costs	4.58**		
<i>Monthly</i>	Industrial production (yoy)	1.98***		
	Retail sales (mom)	3.44***		
	Consumer price index (mom)	3.09***		
	Consumer price index (yoy)	-2.91***		
	Consumer confidence balance	3.79***		
	Sentiment index	6.26***		
UK				
<i>Quarterly</i>	GDP provisional		6.66**	
<i>Monthly</i>	Trade balance		3.67**	
	R^2	0.22	0.12	0.04
	Order flow	2.48***	1.27***	12.0***
	R^2 with own order flow	0.58	0.24	0.31

Table A5
Order flow portfolio balance model and macro news

SUR regression of exchange rate returns on contemporaneous news and order flow, i.e. equation (3) augmented with news $d_{n,t}$ in each equation, for the period 2/13/2004-2/14/2005. The news included are those that significantly explain Δx_t (from Table 3). Coefficients in bold are significant at least 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	

Figure 1

Proportion of number of trades per hour (sample average)

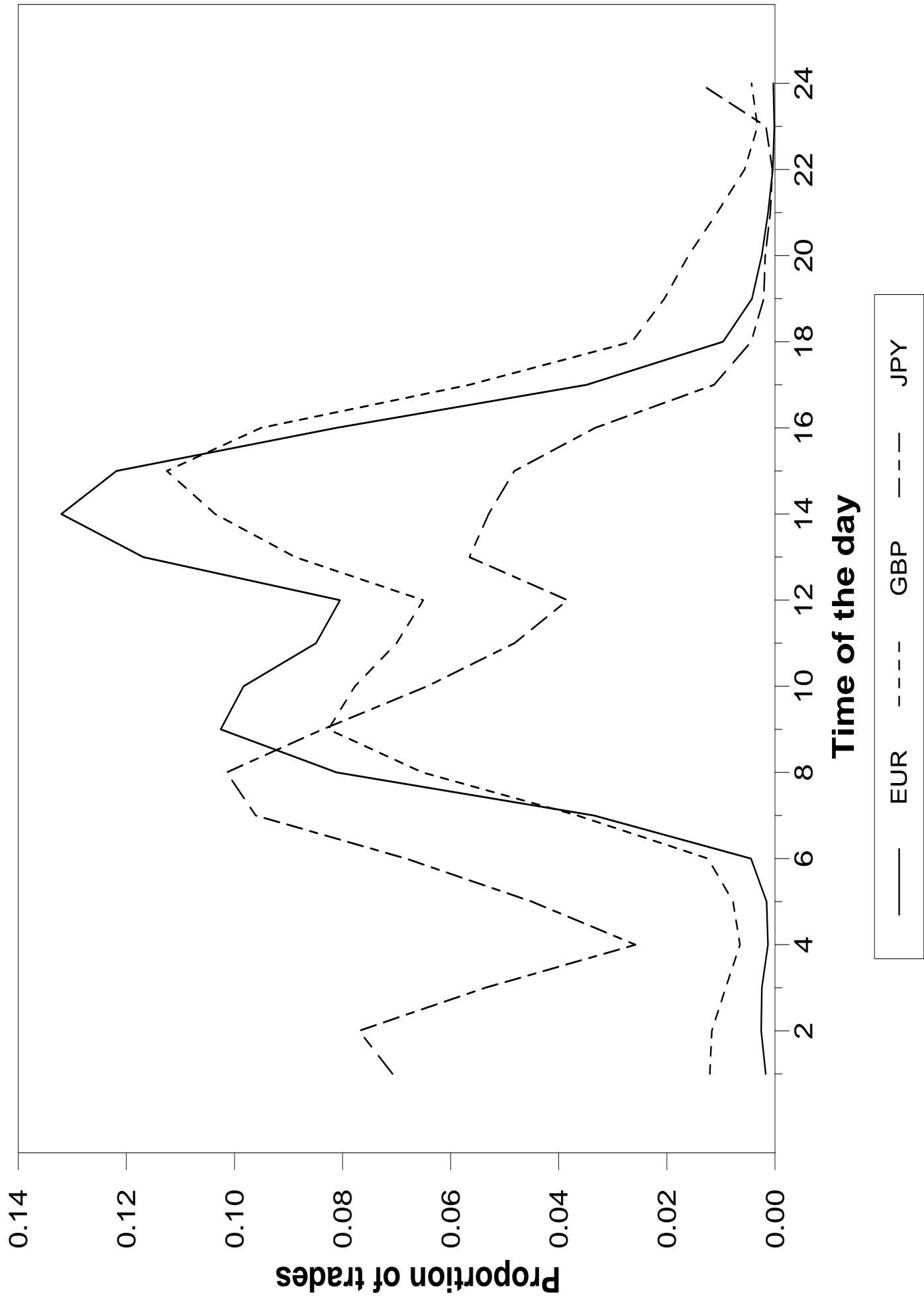


Figure 2
EMU news and order flow

The figure presents the scatter plot of cumulated EUR order flow ($sumx$, on the horizontal-axis) and the standardized expectations gap (on the vertical-axis) for EMU news. The line describes the linear relation between order flow and news. Theta is the elasticity of the standardized expectations gap to one unit of order flow.

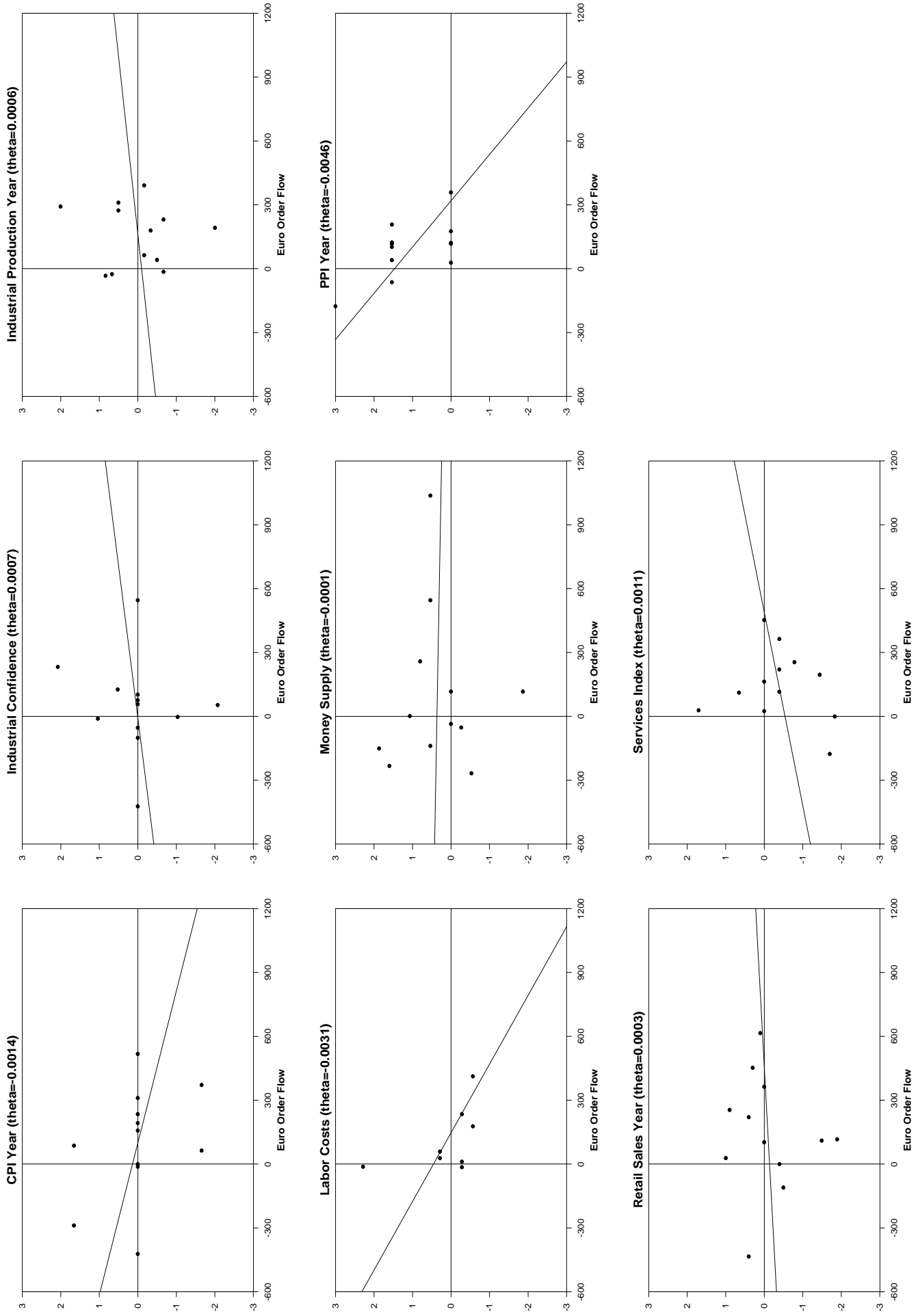


Figure 3
UK news and order flow

The figure presents the scatter plot of cumulated GBP order flow (*sumx*, on the horizontal-axis) and the standardized expectations gap (on the vertical-axis) for UK news. The line describes the linear relation between order flow and news. Theta is the elasticity of the standardized expectations gap to one unit of order flow.

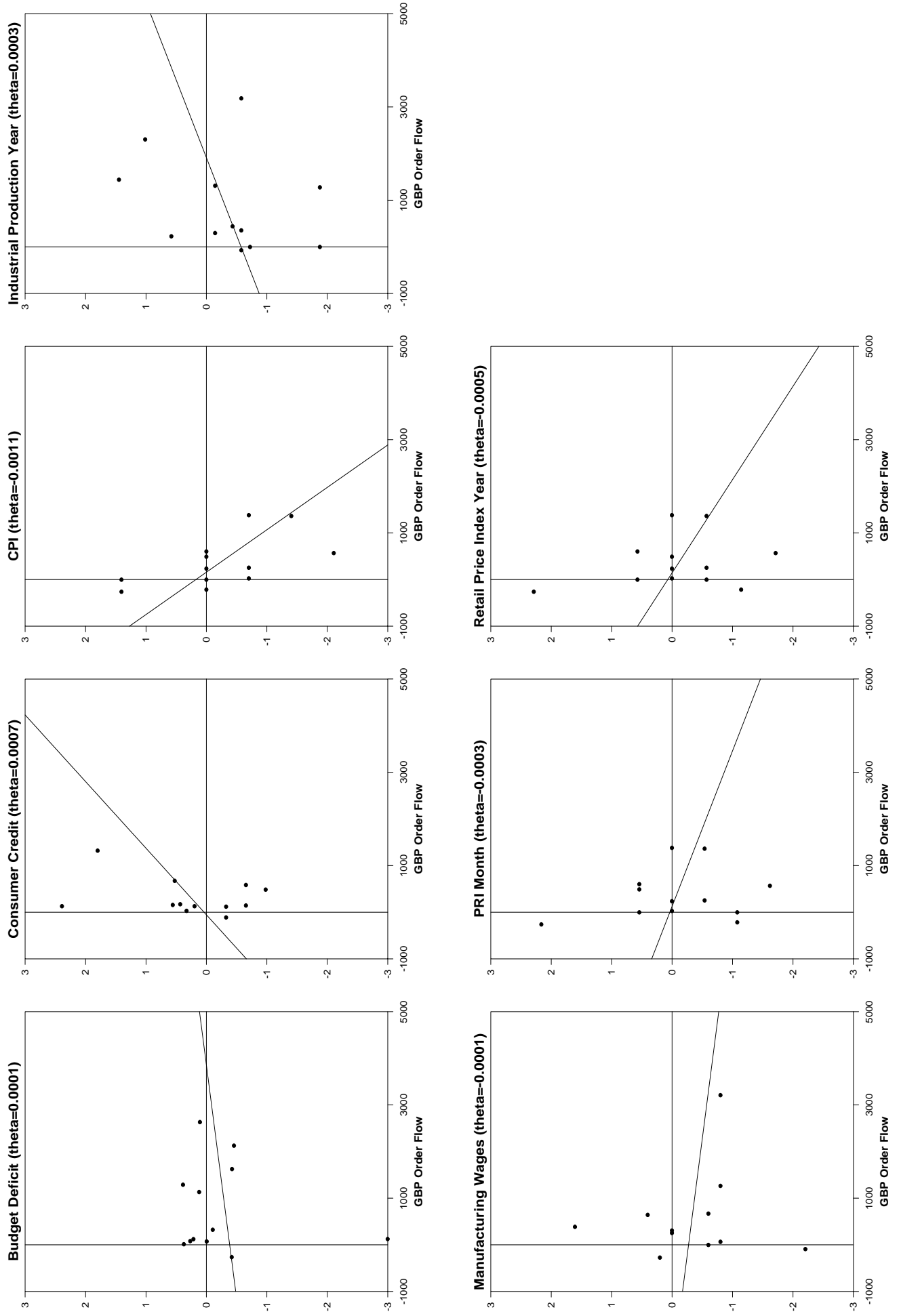


Figure 4
US news and EUR order flow

The figure presents the scatter plot cumulated EUR order flow (*sumx*, on the horizontal-axis) and standardized expectations gap (vertical-axis) for the US news. The line describes the linear relation between order flow and news. Theta is the elasticity of the standardized expectations gap to one unit of order flow.

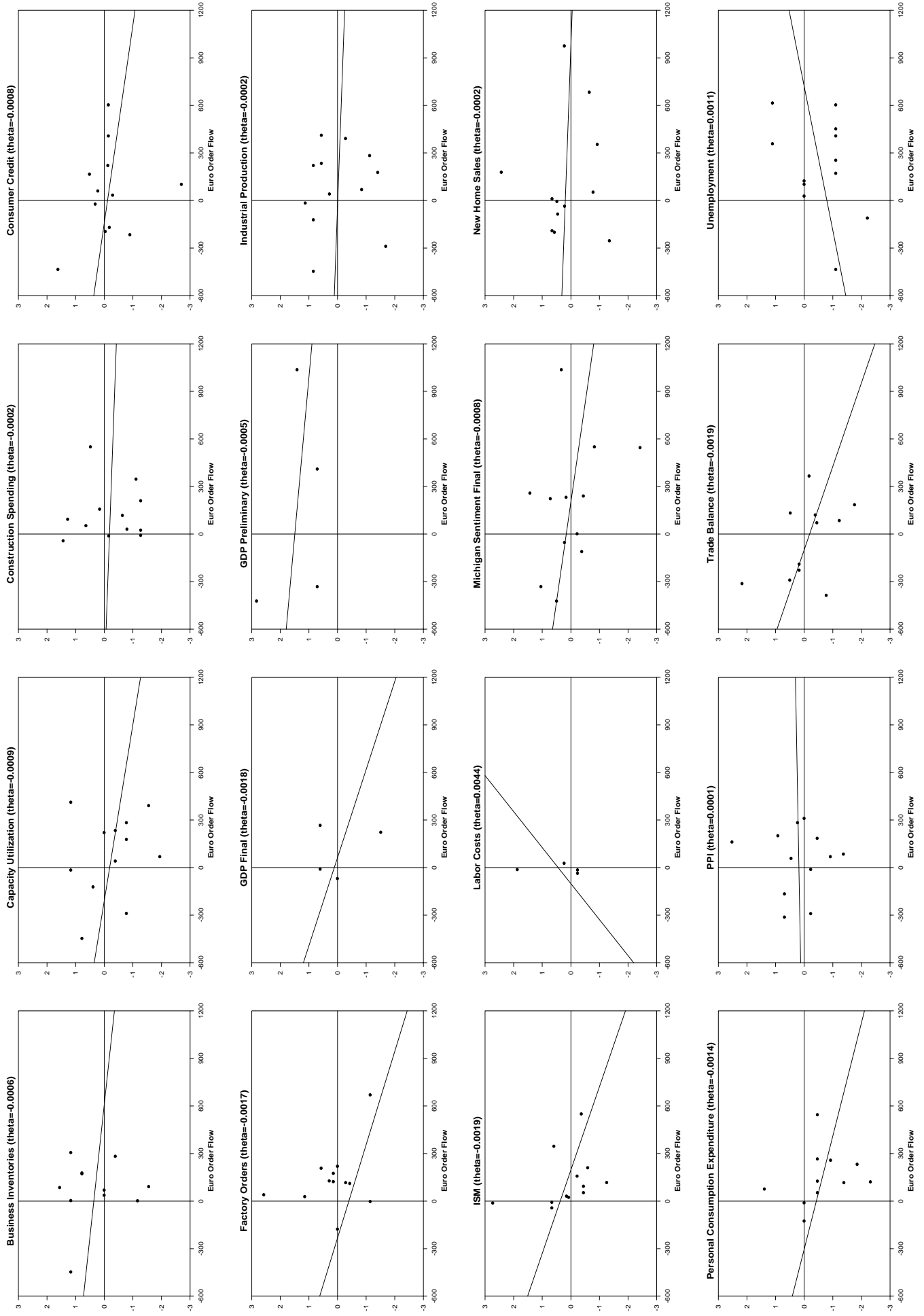


Figure 5
US news and GBP order flow

The figure presents the scatter plot cumulated GBP order flow (*sumx*, on the horizontal-axis) and standardized expectations gap (on the vertical-axis) for the US news. The line describes the linear relation between order flow and news. Theta is the elasticity of the standardized expectations gap to one unit of order flow.

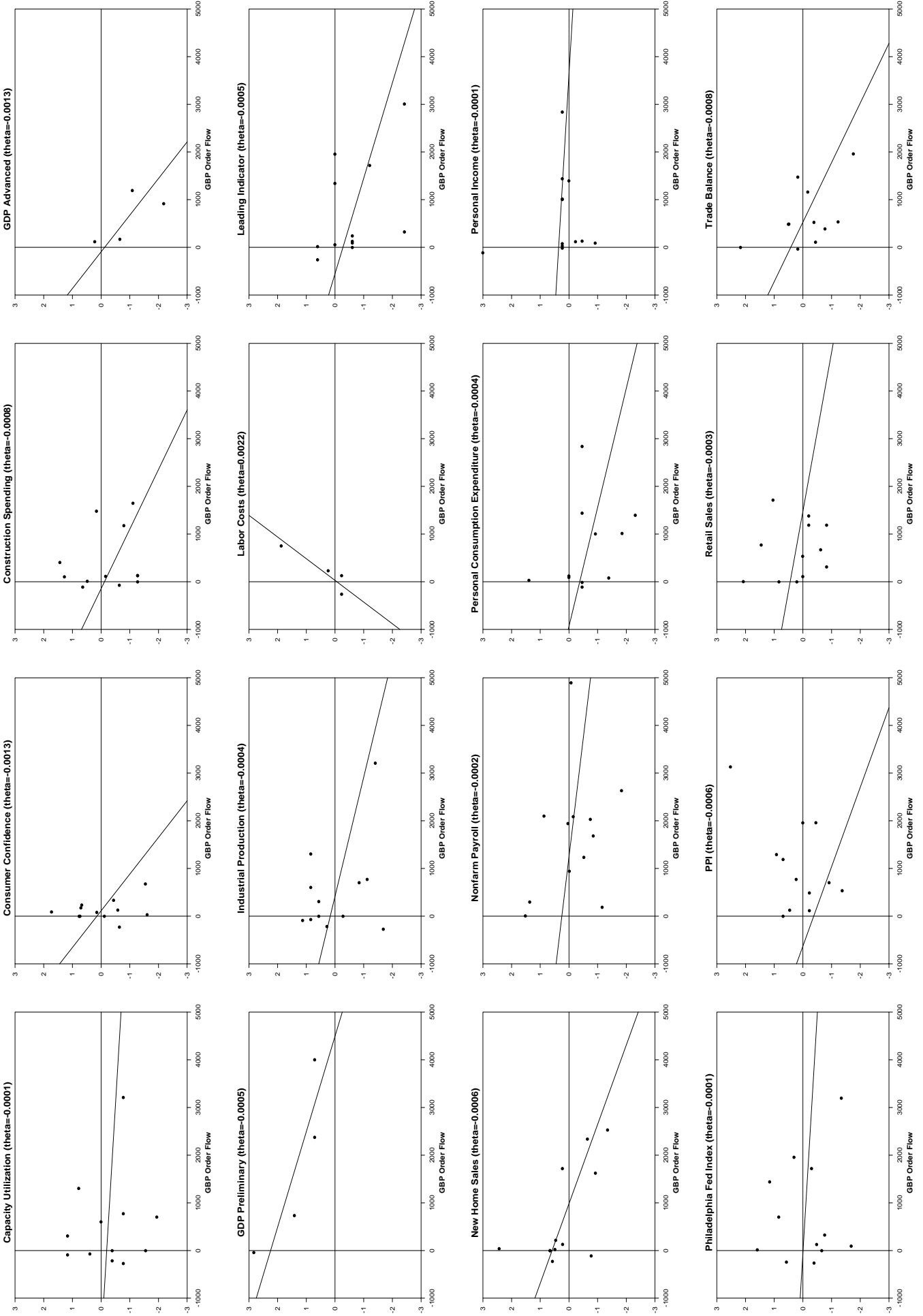


Figure 6
US news and JPY order flow

The figure presents the scatter plot cumulated JPY order flow (*sumx*, on the horizontal-axis) and standardized expectations gap (on the vertical-axis) for the US news. The line describes the linear relation between order flow and news. Theta is the elasticity of the standardized expectations gap to one unit of order flow.

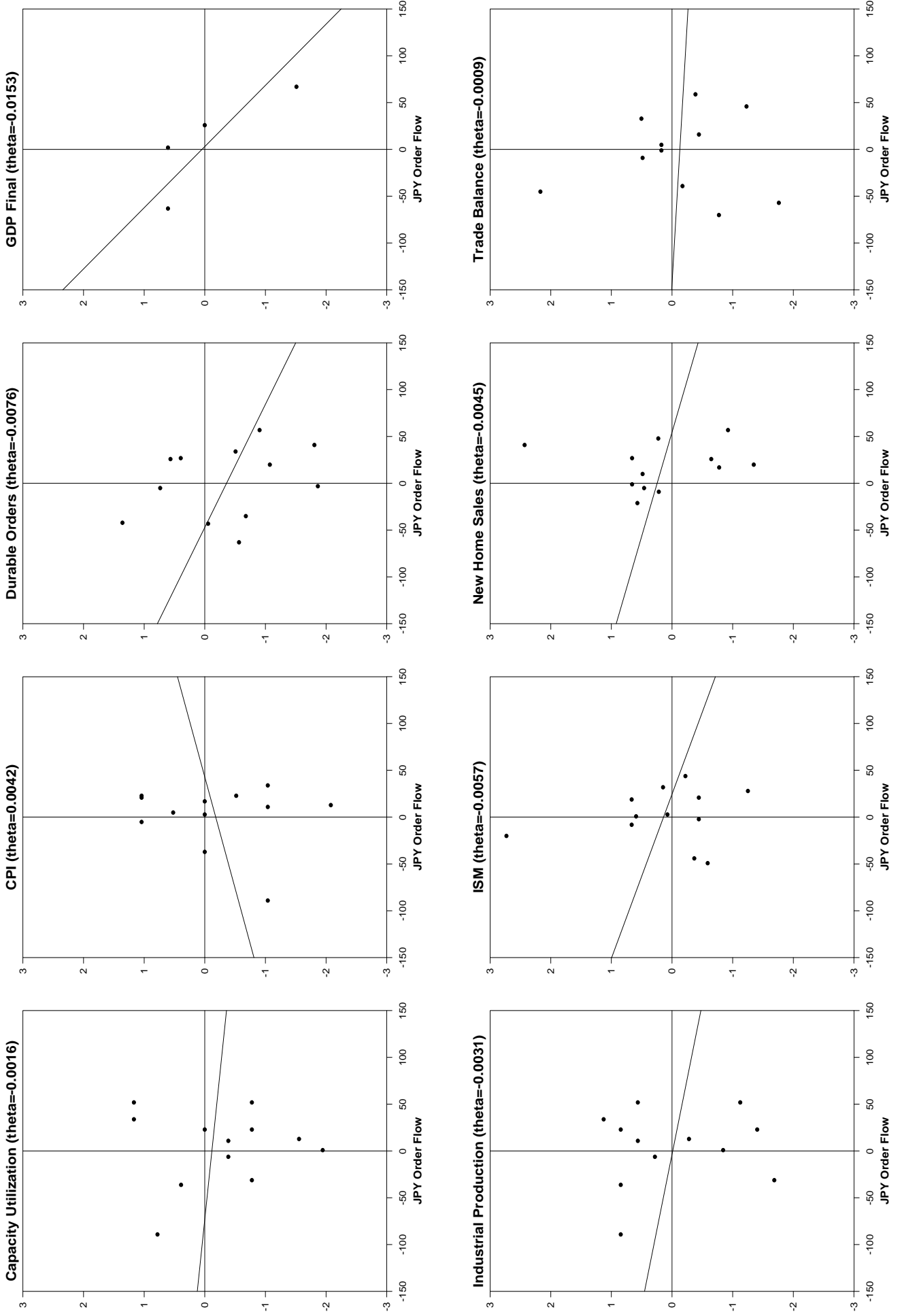


Figure 7

Wealth evolution out of sample

The out-of-sample wealth evolution for each trading hour, for the period 6/15/2004 - 2/14/2005. The black line presents the pure order flow M^{POF} wealth evolution, the blue line presents the general model M^{GEN} wealth evolution, the green line presents the forward bias M^{FB} wealth evolution and the red line presents the random walk M^{RW} wealth evolution. All investments start from an equal initial wealth of \$1 million.

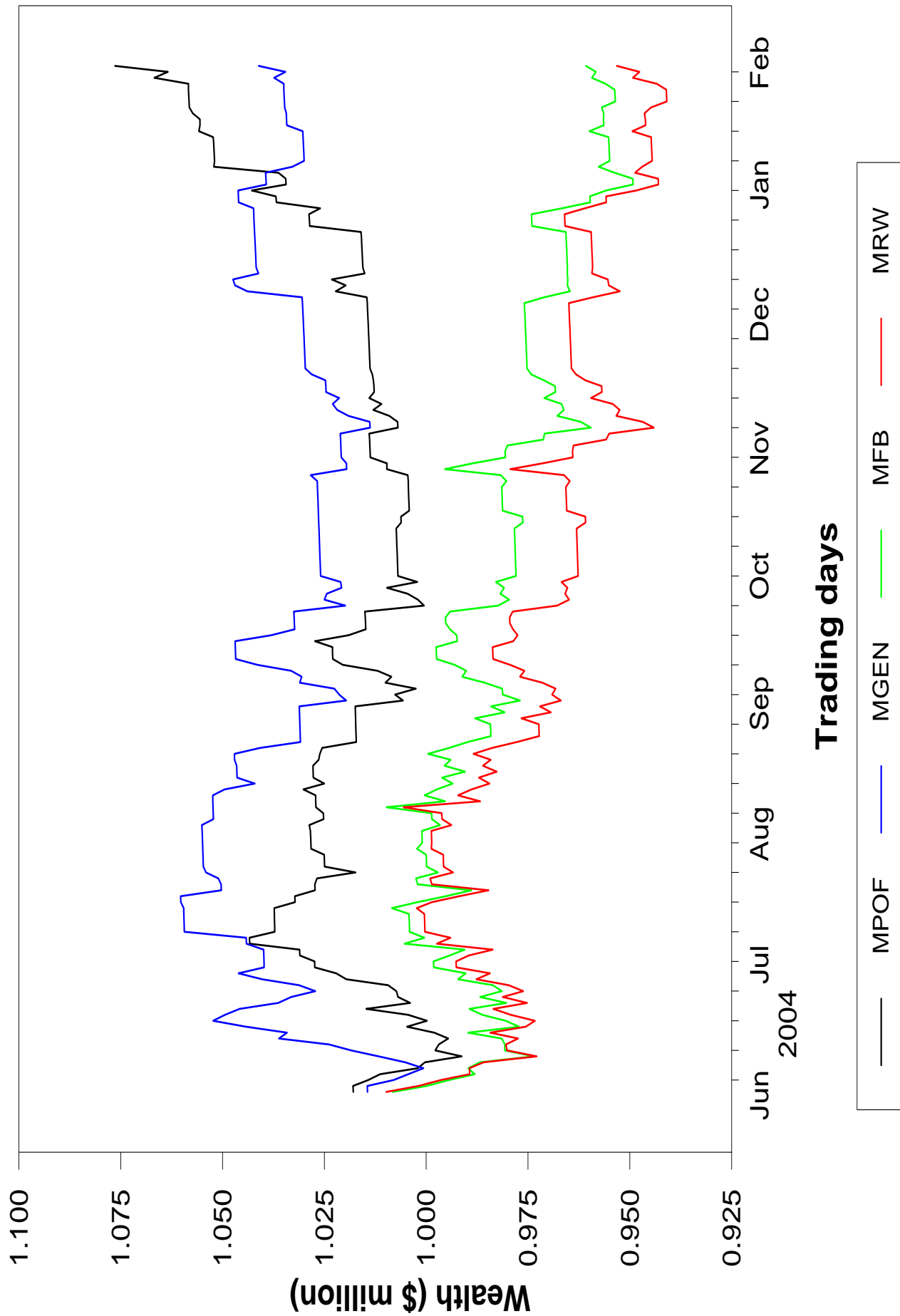
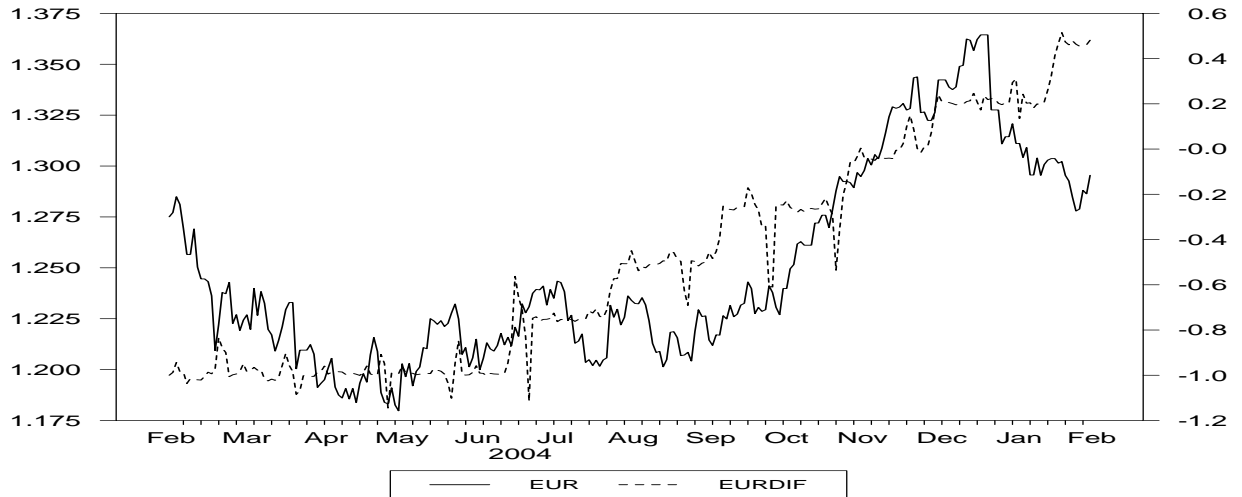


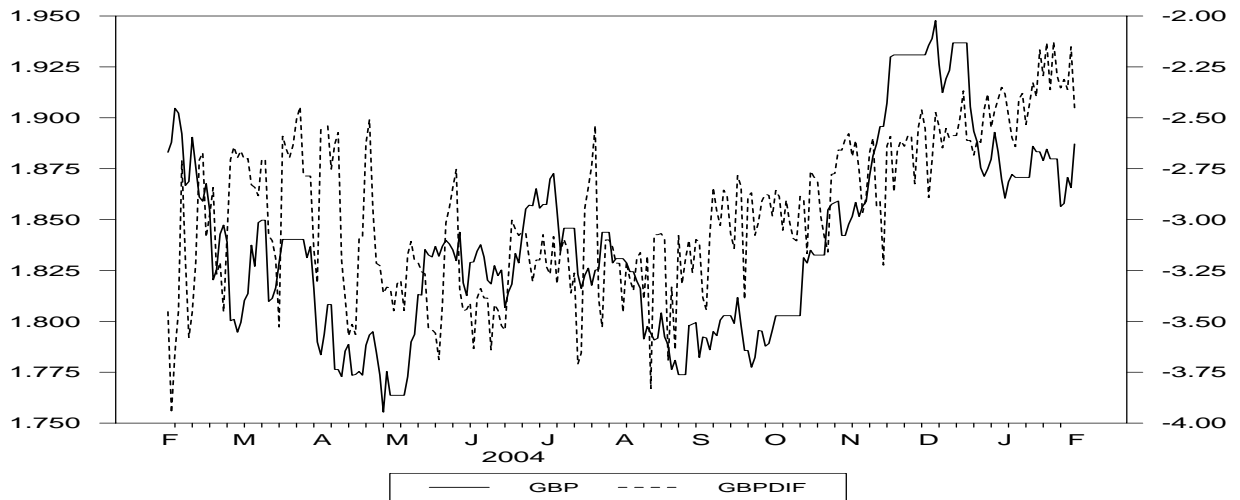
Figure 8
Exchange rates and interest rate differential

The figure presents the levels of EUR, GBP, and JPY (dotted line, on the right axis) and the interest rate differentials in annual percentage points (solid line, on the left axis) for the period 2/13/2004 - 2/14/2005.

(a) EUR/USD



(b) GBP/USD



(c) USD/JPY

