Exchange Rate Determination and Inter–Market Order Flow Effects*

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Abstract

The dependence of foreign exchange rates on order flow is investigated for four major exchange rate pairs, EUR/USD, EUR/GBP, GBP/USD and USD/JPY, across sampling frequencies ranging from 5 minutes to 1 week. Strong dependence and explanatory power is discovered across sampling frequencies. In a new result, inter–market effect of order flows is discovered, where the GBP exchange rate is dominated by EUR/USD order flow. The Meese and Rogoff (1983a,b) framework is used to investigate the forecasting power of order flow and it is shown that the order flow specifications reduce RMSEs, relative to a random walk, for virtually all exchange rates and sampling frequencies.

JEL: F0, F3, G1. Keywords: exchange rate determination, order flow

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Empirical models of exchange rate determination, especially at intermediate estimation horizons, have frustrated economists at least since the Meese and Rogoff (1983a,b) result that macro–based exchange rate models under–perform a random walk in forecasting ability. In the empirical finance literature, there is, however, a long tradition of studying the higher frequency relationship between the price of financial assets and total volume of trade.[1] Such analysis can not help resolve the Meese–Rogoff conclusion, not least because volume is directionless, i.e., a change in volume cannot predict the direction of FX changes. Recently, researchers have investigated the impact of *signed volume*, i.e., the decomposition of volume into transactions initiated by sellers and buyers, separately. The difference between seller and buyer initiated volume is termed *order flow*.[2] Order flow has been shown in empirical market microstructure research to be a key determinant in high frequency asset price changes.[3] Several authors, e.g. Lyons (1995), Payne (2002), and Evans (2002) study the relationship between order flow and foreign exchange rates. Evans and Lyons (2002a) consider cross exchange rate order flows in their study of information integration. The objective of this paper is to investigate the relationship between order flow and FX rates, extending extant research in two areas: The simultaneous use of multiple exchange rates to investigate cross exchange rate relationships and a Meese–Rogoff test of the order flow model.

From the perspective of benchmark rational expectations models of exchange rate determination, the importance of order flow is puzzling. Such models predict that prices should respond to new information without any consistent effect on order flow. Intuitively, when new information arrives each agent immediately revises his/her estimate of value and thus there are no reasons/opportunities for one–sided trading. Thus one must look beyond these models to find a rationale for order flow's effects on prices.

In this context, order flow conveys information about both micro information

[1] See e.g. Clark (1973); Epps and Epps (1976); Tauchen and Pitts (1983); Karpoff (1987).

[2] Note that in defining order flow one must distinguish between buyer and seller initiated transactions. Of course every trade consummated in a market has both a buyer and a seller, but from the current perspective the important member of this pair is the aggressive trader, the individual actively wishing to transact at another agents prices.

[3] e.g. by Hasbrouck (1991) and Madhavan and Smidt (1991) who study equity markets, and Cohen and Shin (2002) and Daníelsson and Saltoğlu (2002) who study fixed income markets.

(e.g. shifts in hedging demands) as well as macro information (e.g. public announcements). While the micro information is specific to individual agents, macro information can also be interpreted differently across agents. Consider an economy where agents have asymmetric information and/or disagree about the asset pricing model. In that case, the agents trading strategies, in particular aggressiveness, might reveal underlying information, e.g. regarding future payoffs or future risk premia, and hence affect asset price changes. In such an environment, a relationship between order flow and asset prices persists across sampling frequencies because information has permanent effects on asset prices. Recent empirical work supports this intuition, e.g. Evans and Lyons (2002b) who find strong dependence of daily exchange rate changes on daily order flows, even after accounting for macroeconomic fundamentals.[4]

These results provide an intriguing contrast to results from traditional international macroeconomic modelling of exchange rates which only have provided weak evidence of the explanatory and forecasting power of fundamentals, such as money supply, inflation and interest rates.[5] In particular, Meese and Rogoff (1983a,b) demonstrate that macro–based exchange rate models under–perform random walk in forecasting ability. In contrast, we provide new evidence that the order flow model passes the Meese–Rogoff tests, suggesting that order flow should be one of the right side variables in foreign exchange models.

Our objective is to investigate the importance of order flow for exchange rate determination. In this we extend the earlier results of Evans and Lyons (2002b) who only consider the daily sampling frequency and one currency pair at a time. We investigate the relationship between order flow and exchange rates across frequencies, ranging from five minutes to one week. Furthermore, we study four currency pairs (EUR/USD, EUR/GBP, GBP/USD, USD/JPY) and explicitly model the the impact of order flow across currencies, e.g., investigating the impact of EUR/USD order flow on EUR/GBP. Finally, we apply the Meese–Rogoff methodology to test whether the order

[4]Similarly, Chordia et al. (2001) show that daily changes in US equity market levels are strongly related to market wide order flow measures.

[5]Frankel (1993), for example, provides evidence that flexible price monetary models fit recent exchange rate data badly, Backus (1984) shows that sticky-price monetary models are also poor in terms of fit and portfolio balance models are rejected by a number of authors including Branson et al. (1977).

models beat a random walk in forecasting.

Our data derives from transaction–level information obtained from the Reuters D2000–2 electronic brokers, where we have approximately 10 months of data for EUR/USD, EUR/GBP and eight months of data for GBP/USD, USD/JPY. The sample starts in 1999 and ends in 2000. Our analysis consists of three sets of empirical exercises.

First, we evaluate how order flow is contemporaneously related to changes in exchange rates across sampling frequencies. Taking advantage of the relatively long time-series dimension of our data and the fact that we have four exchange rates to consider, we can examine how the explanatory power of order flow changes with sampling frequency and whether the effects of flows are consistent across currency pairs.

Second, we look at the dependence of exchange rate changes on order flows from other markets by investigating whether order flows in one currency pair have explanatory power for another currency pair.

Finally, in order to investigate order flow from a macroeconomic perspective, we evaluate the forecasting power of order flows for exchange rates. Here we seek to understand whether, using order flows and perhaps past returns, we can generate forecasts that improve upon naïve statistical alternatives. Thus we test whether the order flow model passes the Meese–Rogoff test.

The results from these three research questions provide new insights both into the market microstructure analysis of high frequency exchange rates as well as the macroeconomic analysis of medium term exchange rate determination.

First, we demonstrate that contemporaneous order flow significantly explains exchange rates, across the sampling frequencies. We however observe considerable differences in the explanatory power of the various regressions. For the EUR/USD rate, R^2 hovers around 40% across frequencies, while for USD/JPY the R^2 increases with aggregation, from 6% at five minutes to 67% at one week. In contrast, the R^2 for both GBP rates decreases with aggregation from 26% at five minutes to 1% at one week. Taken in isolation, the results from the GBP regressions are somewhat puzzling.

We subsequently extend the model by including order flow from the other currency pairs. For the EUR/USD and USD/JPY this makes little difference. However, for the GBP rates, especially at lower frequencies, order flow from other currencies has strong and significant impact, especially for the

EUR/GBP rate where the EUR/USD order flow is found to be the primary exchange rate determinant. There are several possible explanations for this. For example, suppose a currency trader has private information about the future value of the USD , perhaps in expectations that it will appreciate. He can exploit this information by trading in e.g. GBP/USD or EUR/USD. Since the EUR is more liquid, the price impact is expected to be lower in that market, implying that more profits can be gained by trading in the EUR than in GBP. In that case, EUR/USD order flow would help to explain the EUR/USD rate. Since traders in both EUR/GBP and GBP/USD observe the change in EUR/USD order flow, and the appreciation of the USD , this implies a change in the value of the GBP, without the accompanying order flow change.

These results suggest that the while the basic own order flow model may be appropriate for the largest currencies, it is less so for smaller currencies with many traded exchange rates such as GBP.[6] While Rime (2000) finds that order flows are significant in explaining SEK/EUR, the EUR contract is the only traded currency for the SEK. In contrast, there are multiple traded currency pairs for the GBP. As a result information regarding either EUR or SEK comes though the EUR/SEK contract, while for the GBP information can flow though any of the traded currencies. Furthermore, this provides significant evidence of strong information links between currencies, with small currencies dominated by the larger. These effects persist across our frequencies, and strengthening with aggregation, suggesting that these information links may persist beyond our sampling frequency.

Out final key result is on the forecasting of exchange rates. First, we use the Meese and Rogoff (1983a,b) framework, and find that the order flow model almost always yields a better forecast (in RMSE terms) than does a random walk model. This result is consistent across sampling frequencies and currencies. Therefore, the order flow model passes the Meese–Rogoff test that macroeconomic models have failed so often. We note however that the Meese–Rogoff test is not a genuine out–of–sample forecasting test. When we run such a test, albeit with a simple specification, we find that order flow does not perform particularly well in forecasting exchange rates. We find

[6]Indeed, according to the Bank for International Settlements (2002) in April 2001 the EUR/USD represented 30% of all spot FX trading, the JPY/USD 21%, GBP/USD 7% and GBP/EUR 3%. The first three of these are the three largest currency pairs while GBP/EUR is only the eighth.

however that order flow itself can be forecasted with own lags and lagged returns. This suggests that an alternative specification for a pure forecast model for exchange rates may provide significant forecasting power.

In sum, our results suggest that order flow analysis can be very useful in understanding exchange rate determination. From a low frequency, macroeconomic perspective, order flows can contribute strongly to our ability to explain exchange rate changes while they allow one to improve exchange rate forecasts most dramatically at a microstructure level. While further work using longer data samples would be useful to verify and clarify our results, the analysis here clearly points to the information content of order flow.

The rest of the paper is structured as follows. Section 1 outlines our data sources and our processing of the data. Section 2 presents our analysis of the explanatory power of order flow for exchange rates and Section 3 presents multi-variate flow analysis. The following Section presents our forecasting results. Some discussion of our findings is given in Section 5 and Section 6 concludes.

1 Data Description and Organization

1.1 The Data

Our data sets comes from the Reuters D2000–2 system, which is a brokered inter–dealer FX market. Thus our data contains no information on customer–dealer FX trades or on direct (i.e. non–intermediated) trades between dealers. Moreover, it should be noted that the trades occurring on D2000–2 should be regarded as public in the sense that they are visible to anybody looking at a D2000–2 screen as they occur.[7]

The raw data set is composed of transaction level information, covering four major floating rates: EUR/USD, EUR/GBP, GBP/USD and USD/JPY. Each transaction record contains a time stamp for the trade, a variable indicating whether the trade was a market buy or sell and the transaction price. Thus we do not have to use potentially inaccurate, ad hoc algorithms to

[7]For a full description of the segments of the spot FX market and the data available from each see the excellent descriptions contained in Lyons (2001)

assign trade direction. The samples for EUR/USD and GBP/USD cover a period of ten months from 28 September 1999 to 24 July 2000. Samples for EUR/GBP and USD/JPY cover a period of eight months from 1 December 1999 to 24 July 2000. A limitation of the data supplied is a lack of information about the size of each trade. Therefore we cannot analyze whether the monetary value of order flow matters over and above order flow measured simply in terms of numbers of trades. Nevertheless this high frequency data set has two valuable characteristics: long sample periods and multiple exchange rates. The long sample period ensures reasonable statistical power for the various econometric tests and the broad currency scope provides a platform to check the robustness of model estimation cross-sectionally on major floating exchange rates.

1.2 Filtering and Time Aggregation

For the analysis later in the paper, we time aggregate the transaction–level data to various degrees. Prior to time aggregation, however, we remove sparse trading periods from the data. Such sparse trading periods include the overnight period, weekends, some world–wide public holidays and certain other dates where the feed from D2000–2 is very low.[8]

In our analysis we focus on 8 different time aggregation levels: 5 minutes, 15 minutes, 30 minutes, 1 hour, 4 hours, 6 hours, 1 day and 1 week.[9] Note that our definition of one day corresponds to a trading day defined as the interval between 6 and 18 DST. Thus one day covers 12 rather than 24 hours. Similarly, one week covers 5 trading days. The time aggregation is done as follows. First, we scan along the sample in calendar time minute by minute. At every observation point, the last transaction price is recorded along with the excess of the number of market buys over market sells since the last observations point. From the price data we construct logarithmic price changes.

After filtering and aggregation, we are left with 32 databases (8 sampling

[8]In this paper we define the overnight as a period from 18:00 to 6:00 DST next day. It should be noted that this definition is only proper for the traders in London and New York, but not for the traders in Asian markets. It corresponds the to the portion of the day when trade on D2000-2 is least intensive, even for USD/JPY.

[9]We have experimented with denser time aggregation levels and the results do not alter the pattern we reported in this paper.

frequencies × 4 exchange rates). We summarize their statistical properties in Table 1. At the daily level, we have 201 observations for EUR/USD and GBP/USD and 160 observations for EUR/GBP and USD/JPY. Our sample periods covers a time during which there was a depreciation of EUR against USD and GBP, a depreciation of GBP against USD and a depreciation of JPY against USD . These market trends are reflected in the columns of each panel in Table 1 that display mean returns. Comparing panel (b) with the other three panels, we see that the number of trades in USD/JPY is far less than for the other three markets. GBP/USD is the most heavily traded pair with EUR/USD and GBP/USD just behind. These numbers reflect two things. First, Reuters D2000-2 has relatively poor coverage of JPY markets and, compared to its competitor EBS, has a minority share in EUR/USD trade. In contrast, D2000–2 dominates trade in GBP rates.

2 Own Order Flow and Foreign Exchange Rate Determination

The study of the high frequency relationship between price changes and order flow has a long tradition in the microstructure literature. In contrast, it is only recently that such relationships have been studied at lower sampling frequencies, such as daily and weekly.

We first track how the explanatory power of order flow for price changes varies across sampling frequencies and across currencies by running a set of regressions of the following form;

$$\Delta P(k)_{i,t} = \alpha(k)_i + \beta(k)_i F(k)_{i,t} + \varepsilon_t \tag{1}$$

where $\Delta P(k)_{i,t}$ is the transaction price change for currency pair i at sampling frequency k and $F(k)_{i,t}$ is the order flow in the interval ending at t for currency pair i at sampling frequency k. We consider sampling frequencies of 5 minutes all the way through one week. Table 2 contains the estimation results for model (1) for our four exchange rates and over the entire spectrum of time aggregation levels.[10]

[10]Since the normality of our return data is rejected by the Jarque-Bera test (not reported), we also experimented with a LAD estimator for these regressions, but the results were not qualitatively affected.

At the highest frequencies (less than one hour) we observe significant effects from order flow for all currencies, with the strongest effects for EUR/USD where R^2 ranges from 33% to 45%. These results confirm what microstructure economists have long known — order flow carries information for high–frequency asset price determination. There's no prior reason to believe that these very high frequency results have any bearing on exchange rate determination since they might simply reflect market liquidity effects.

As a result, from the point of view of exchange rate determination, lower frequency results are more relevant. Consider first results from the daily frequency, initially for EUR/USD and USD/JPY in order to provide comparability with Evans and Lyons (2002b).[11] Their daily USD/DEM and USD/JPY regression R^2 is just over 60% and 40% respectively which is broadly consistent with our results. Our results therefore directly corroborate Evans and Lyons (2002b).

However, our results on the GBP related exchange rates are much less supportive of their results. By looking at the low frequency regressions in the final two panels of Table 2, we see that the explanatory power of order flow for GBP/EUR and GPB/USD is very poor. At sampling frequencies exceeding one hour, in no single case does the regression R^2 exceed 0.10, although in five of the eight cases the order flow variable is statistically significant. Thus, at least for GBP, the assertion that order flow matters for exchange rate determination when one moves towards sampling frequencies that matter to international macroeconomists appears less secure than our EUR/USD and USD/JPY results suggest.

A graphical representation of these results using a somewhat more larger set of sampling frequencies is given in Figure 1. The figure clearly demonstrates the importance of order flow regardless of sampling frequency for EUR/USD and USD/JPY but also points to the declining effect of order flow in the GBP markets.

[11]Note that our definition of the aggregation time interval is slightly different from that in Evans and Lyons (2002b). Whilst their 'daily' aggregation interval is defined as a period from 4:00 pm to 4:00 pm next day our definition is a period from 6:00 am to 6:00 pm excluding overnight period. We also experimented with a interval definition that includes overnight period in this comparison study and find results that do not differ qualitatively from those reported here.

3 Inter–Market Order Flow Analysis

Most existing order flow research focuses on one asset at a time. However, since exchange rates are relative prices, and three of our exchange rates form a triangular relationship, it is of interest to investigate how order flow in one currency pair might be used to explain the exchange rate of a second currency pair. We denote this as *inter–market order flow* analysis.

The reason for considering inter–market effects is the peculiar nature of currencies, in particular the fact that an informed trader can use any number of currency pairs to exploit his information. Consider, e.g., a trader who has superior information regarding the future value of the USD, perhaps that the USD can be expected to appreciate vis–à–vis other currencies. The trader can exploit this information by trading in USD/JPY, EUR/USD, GBP/USD, and so on. The question arising is which market (if not all of them) will he choose for trade? If he chooses not to trade in all markets but to focus on one, perhaps because it offers small transaction costs and low price impacts, then the possibility exists that order flow in this market might drive price changes in other markets. Liquidity suppliers in other markets observe the order flow just posted in the chosen market and therefore revise their valuations of all USD rates.

We incorporate inter–market effects by extending (1) to include order flow from all currency pairs, while still remaining within the linear specification that relates price changes in market i to contemporaneous order flows;

$$\Delta P(k)_{i,t} = \alpha(k)_i + \sum_j \beta(k)_{i,j} F(k)_{j,t} + \epsilon_{i,t} \ , \quad i,j = ED, SD, ES, YD \quad (2)$$

where, k indexes sampling frequency, i is the rate to be explained and the summation over j gives an explanatory term that is linear in all four order flow variables. Table 3 presents the main results from estimating (2), while the change in R^2 is shown in Figure 2.

Consider first the results for USD/JPY as it is the only JPY rate and because the other three rates form a triangulating relationship. We see that for USD/JPY, aside from the strong own flow effects uncovered in Section 2, there are few other significant flow variables. As one might expect, the GBP/EUR flow is not significant. A couple of the EUR/USD and GBP/USD flows are significant and, as expected given the definition of the rates, they enter with negative signs.[12] In all cases the improvement in the R^2 of the regressions as compared to the univariate specifications in Section 2 is small.

For EUR/USD, the order flow coefficients of EUR/GBP and GBP/USD are, as expected, consistently positive and significant at the 1% level at relatively high frequencies. The significance of the GBP/USD flow persists to the daily level. Also, the USD/JPY flow is significant, with the expected negative coefficient, at very high sampling frequencies. Overall, these effects lead to improvements in explanatory power (change in R^2, or ΔR^2) up to 6%, and for all specifications below the daily level this improvement is significant.

For the GBP rates, the results are very interesting. Flows in the other GBP rate (EUR/GBP flow in the GBP/USD price change regressions and vice versa) are strongly significant at higher frequencies while USD/JPY flows have virtually no effects. However, the dominant new right–hand side variable in these regressions is the EUR/USD flow. In each and every case for these two exchange rates, EUR/USD flows are strongly significant with a positive coefficient. These extended specifications show markedly improved explanatory power (ΔR^2) over the univariate models in Section 2, of between 5% and 35% with the largest improvements being at the lowest sampling frequencies. In all cases, the extra right–hand side variables can be shown to significantly improve the explanatory power of the regression. It is for the EUR/GBP that the effects of EUR/USD flow is strongest, providing virtually all explanatory power at the lower frequencies.

These results provide clear evidence of flow information being transmitted across linked exchange rate markets, especially for the less liquid markets. The EUR/USD exchange rate is the largest and most liquid the world, and its order flow is shown to dominate across all three triangular currency pairs. This is especially apparent for the least liquid of these three currency pairs, EUR/GBP.

In our view, the presence of significant inter–market spillovers reinforces the notion that order flow is a significant determinant of exchange rates. Furthermore, the fact that the order flow from the largest currencies dominates the determination of the smaller currencies, suggests that new information first flows to the most liquid markets, i.e. where the new information can be

[12] A negative flow in these rates means USD sales, thus driving the JPY price of a USD down.

best exploited.

4 Forecasting Ability Analysis

The order flow models estimated above (1) and (2) used contemporaneous order flow to forecast exchange rate changes. However, as e.g. argued by Frankel and Rose (1995, pp. 1702) "Fitting exchange rates to contemporary observable variables, in-sample, is one thing. Forecasting out of sample is quite another" The forecast ability of exchange models is examined by Meese and Rogoff (1983a,b) who study the out–of–sample forecasting ability of various structural and time series models from 1 to 12 months and conclude that none of these models performed any better than a random walk model at short horizons (one month). We provide a first investigation of the out–of–sample forecasting performance of the order flow model for exchange rates, across different sampling frequencies using a variety of forecasting specifications. We first use the methodology proposed by Meese and Rogoff (1983a,b), and then extend this to genuine out–of–sample forecasts testing.

4.1 Meese–Rogoff Out–of–Sample Forecasts

The Meese and Rogoff (1983a,b) test requires using data up until time t to estimate the parameters of the relationship between price changes and order flow, and then using the estimated relationship to forecast the price change at $t+1$ based on observed order flow at $t+1$. The root mean squared error (RMSE) from the order flow (OF) model is then compared to the RMSE from a random walk (RW) model with a drift. The Meese–Rogoff test is therefore not a genuine out–of–sample forecasting experiment since observed future order flow is used in the forecasting.

We consider sampling frequency ranging from 30 minutes to 1 day where we for each sampling frequency we look at forecasting horizons from one to 12 observations.[13] The forecasting equation that is equivalent to the regression model (1) is given by;

[13] Take a frequency of four hours and a horizon of 6 as an example. The forecast horizon, in terms of hours, is 24 hours (4×6). Since 12 hours represents one trading day (as the overnight period has been excluded) 24 hours represents a two-day forecast

$$\Delta P(k)_{i,t+h} = \alpha(k)_{i,t} + \beta(k)_{i,t} F(k)_{i,t+h} + \varepsilon_{t+h} \tag{3}$$

where $\Delta \hat{P}(k)_{i,t+h}$ is a return of a specific time interval (defined by the sampling frequency) h–step–ahead of time t and forecast at time t. $\hat{\alpha}(k)_{i,t}$ and $\hat{\beta}(k)_{i,t}$ are the estimate of the regression model based on information up to time t. $F(k)_{i,t+h}$ is the order flow of the time interval over which the return is forecasted. We have added time subscripts to the regression intercept and slope to emphasize that they are estimated using information until t only.

The benchmark forecasting model is a drifting random walk (RW) where log price follows a random walk the a drift. The h horizon price change is forecast to be the h times the average exchange rate change from the beginning of the sample till time t.

$$\Delta P(k)_{i,t+h} = \mu(k)_{i,t} + \eta_{t+h} \tag{4}$$

where μ is the estimated drift based on information up to time t only. We do this forecast recursively for both models. We initiate the forecast estimation using the first four months of data in all cases.

Our results are reported in Table 4. The columns headed 'OF' and 'RW' are the RMSEs generated by forecast models (3) and (4) respectively. The t–stats comparing forecast accuracy are those given in Diebold (2001, pp. 293). The most striking feature of Table 4 is that the RMSEs generated by the order flow model are virtually all lower than those generated by the random walk model. Furthermore, for all exchange rates, this forecast improvement is significant at higher sampling frequencies, while the low frequency order flow based forecasts are largely significant for EUR/USD and USD/JPY. Thus our order flow model outperforms the macro models considered by Meese and Rogoff (1983a,b). Here we show that even at the daily and weekly sampling frequency, very heavily traded exchange rates such as EUR/USD and USD/JPY can be forecasted using order flow. Furthermore, since these results are generated only by using own order flow, the GBP results would probably improve considerably by using the other order flows as an explanatory variable.

4.2 Genuine Forecasting

Since the Meese–Rogoff test is not a genuine forecast test, we extend the forecast results above by considering true forecasts of price changes. In this case we only use order flow information available at the forecast date. Thus, we would expect these forecasting results to be less impressive than those from the Meese–Rogoff test. We concentrate on one–step ahead forecasting for each of our sampling frequencies and exchange rates. Our order flow based forecasts are drawn from the following specification;

$$\Delta P(k)_{i,t+1} = \alpha(k)_{i,t} + \beta(k)_{i,t}F(k)_{i,t} + \varepsilon_{t+1} \tag{5}$$

We compare the ability of specification (5) to forecast price changes with the forecast produced by the random walk model (4). Results are presented in Table 5 for the entire spectrum of sampling frequencies and exchange rates.

The results indicate that if there is any statistical significance in our somewhat naïve linear specification then it is concentrated at the highest frequency, i.e. 5 minutes. For virtually all of the regressions considered here, the RMSE of the order flow forecast model is only marginally below that of the random walk forecast. Thus, the explanatory power of our genuine forecasting regressions is poor and there is little evidence that these simple linear specifications contain a true forecasting power. Only at the highest frequencies is the relationship between order flow at t and the one–period price change to $t+1$ positive and significant.

4.3 Order Flow Forecasting

We finally investigate the predictability of order flow itself, and test whether flows can be forecast with past information on flows themselves and price changes. If this was the case, then another route to forecasting exchange rate changes would possibly exist. One could combine the strong contemporaneous relationship between price changes and order flows uncovered in Section 2 and an order flow forecast to construct a price forecast. Thus we consider the following forecasting model for flows;

$$F(k)_{i,t+1} = \alpha(k)_{i,t} + \sum_{j=1}^{J} \beta(k)_{j,i,t} \Delta P(k)_{i,t-j+1} + \sum_{k=1}^{K} \gamma(k)_{j,i,t} F(k)_{t-j+1} + \epsilon_{t+1} \quad (6)$$

i.e. for a given sampling frequency (k) and exchange rate (i) we regress flow at $t+1$ on it's own first K lags and on J lags of the price change. In the estimations we set both j and k at 2 after some experimentation with alternative lag lengths. The results are presented in Table 6.

The results indicate that the majority of the statistical significance in the forecasting regressions comes at very high frequencies. Even though there is evidence of high–frequency positive dependence in order flow, in all cases the RMSE from the random walk model and (6) are virtually identical.

For the GBP exchange rates there is also evidence of negative dependence of current flow on past returns. Thus, when prices have been rising in the recent past, order flows tend to become negative — a manifestation of contrarian or negative feedback trading. This causality is reversed for USD/JPY. Thus, in this case there would seem to be evidence of aggressive momentum type trades.

While there are significant relationships between current flows and past return and flow information, our simple linear specifications cannot be used to forecast price changes. The results do suggest however that there is some potential for the creation of a sophisticated forecast model for prices (and order flow).

5 Discussion

We have presented a number of new results on the explanatory power, forecasting ability, and multi–variate implications of order flow analysis. We affirm previous results and demonstrate that order flow has strong explanatory power for exchange rate changes, furthermore, our results indicate that these patterns persist across sampling frequencies. Indeed, for the major currencies there is no indication that the explanatory power drops off with aggregation. This suggests that the explanatory power of order flow can genuinely be considered of interest to international macroeconomists. Thus we provide strong evidence that currency flows carry information, confirming the evidence contained in Payne (2002), Evans and Lyons (2002b) and Rime (2000) amongst others.

While our results on the longer–run relationships between flows and exchange rate changes are similar to those derived by Evans and Lyons (2002b), we note some interesting and important differences between both their results and data source. First, our data is drawn from the electronically brokered segment of the market while theirs derives from direct trading. In the former case this implies pre–trade anonymity where trades are published to the market at large. In the latter case, quoting and trading is clearly non–anonymous but the occurrence and details of trades are both kept private to the counterparties. Based on this, brokered trades may have different information content, and we find strong evidence of information effects in the brokered segment. Our results therefore provide strong corroborating evidence for results of Evans and Lyons (2002b), especially when considering the different data sources and sampling periods.

However, our results contain a very important difference to those in Evans and Lyons (2002b). Our univariate regressions of price changes on order flow for GBP exchange rates perform very poorly at lower sampling frequencies, with explanatory power close to zero. This appears to fly in the face of the preceding discussion — perhaps the USD/JPY and EUR/USD results are anomalous and order flow has no long run effect on exchange rates for the majority of currency pairs. While this is clearly a possibility (despite empirical evidence to the contrary from the SEK/EUR exchange rate in Rime, 2000), we feel that such a conclusion would be unwarranted. Indeed, our multi–flow regressions demonstrate that once one allows for aggressive buying and selling pressure in related markets, order flows have strong effects on all four of the exchange rates at every sampling frequency. This is a key new result. Therefore, order flow carries information that not only affects exchange rate changes in its own market but also in other markets. Empirically we see information instantly spilling over from market A to prices in market B.

It is interesting to note that the dominant flow variable in our data set is EUR/USD flow. Aggressive buying and selling pressure in this market has clear and persistent effects on both EUR/GBP and GBP/USD rates. This result is intuitive since because the EUR/USD is the most liquid and heavily traded currency pair in the world, one can expect any information to hit it first due to its low transaction costs and massive participation. Thus those quoting prices in related pairs will very likely keep an eye on EUR/USD developments, including order flow, in forming of their prices.

A final point to note regarding the inter–market flow analysis carried out in Section 3 is that in this analysis we see prices for a given exchange rate move in the absence of trade in that exchange rate, as they are affected by flows occurring in *other markets*. Thus, one cannot explain away the importance of order flow in an inter–market context by simply asserting that aggressive buying or selling pressure is just temporarily moving prices due to low market liquidity and that after such "digestion effects" have run their course prices would revert — here there is nothing to digest aside from information. This, in our view, only serves to reinforce evidence that order flows do carry information and also information that is relevant at macroeconomic sampling frequencies.

Our final area of analysis is the forecasting power of order flows for exchange rates. Here we have three sets of results. First, the order flow model beats the same random walk benchmark that macroeconomic models of the 70s and 80s lost out to. The second is a true one–step ahead out–of–sample experiment. We show that order flow forecasts can only reduce RMSEs relative to random walks in this experiment at the highest sampling frequencies (i.e. 5 minutes). Finally, order flow it can be genuinely forecasted.

6 Conclusion

We study the explanatory and forecasting power of order flow for exchange rates changes at sampling frequencies ranging from 5 minutes to one week using a 10 month span of new data for EUR/USD, EUR/GBP, GBP/USD and USD/JPY. We demonstrate that order flow analysis has strong power to both explain and forecast exchange rate changes at virtually all frequencies. Our key results are as follows;

1. The contemporaneous relationship between flows and changes in exchange rates is very strong at intra–day frequencies for all four rates.

2. At the daily and weekly level, there is still strong explanatory power of order flow for exchange rates changes for EUR/USD and USD/JPY. This is not the case for EUR/GBP and GBP/USD.

3. However, when one examines the inter–market effects of order flows, one sees that price changes for EUR/GBP and GBP/USD are strongly affected by EUR/USD order flow. Taking these effects into account, overall flows have strong explanatory power for the GBP rates. The result that EUR/USD order flow significantly explains EUR/GBP exchange rates, while the own flow does not, suggests that GBP rates are dominated by trading in EUR/USD.

4. An analysis of the forecasting power of order flows, using the technique of Meese and Rogoff (1983a,b), demonstrates that the order flow analysis outperforms a naïve benchmark across essentially all sampling frequencies for all exchange rates.

5. A true out-of-sample forecasting experiment, however, demonstrates that order flows do not provide very valuable exchange rate forecasts aside from sampling frequencies below one hour.

6. Order flow can be forecasted out of sample.

These results serve to emphasize the role played by order flow in foreign exchange, and possibly other markets. We provide clear evidence that order flows can be used to explain and forecast rates at very high frequencies as well as observations intervals relevant to international macroeconomics. The information content of order flow implies that simple symmetric information, rational expectations models of exchange rate determination are not consistent with the data. Further work on modelling exchange rates to take account of these effects as well as further empirical work to clarify the role of order flow in exchange rate determination can only help move exchange rate analysis out of the cul–de–sac in which it has resided for the last two decades or so.

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Table 1: Summary of time aggregated databases

k is sampling frequency, Obs. is the total number of (derived) observations in that database, returns are defined as $100 \times (log(P_t) - log(P_{t-1}))$ and $\bar{r}$ is the average return for that sampling frequency. Columns headed Trades, Quotes, Buys and σ give the average number of trades, average number of quotes, average number of buys and standard error of returns for that frequency.

	EUR/USD (a)						USD/JPY (b)					
k	Obs	Trades	Quotes	Buys	$\bar{r}$	σ	Obs	Trades	Quotes	Buys	$\bar{r}$	σ
5m	29107	16	51	8	-0.0006	0.06	23148	1	7	1	0.0004	0.08
15m	9701	49	153	25	-0.0017	0.10	7715	4	21	2	0.0008	0.10
30m	4850	98	306	49	-0.0038	0.13	3857	7	41	4	0.0022	0.13
1hr	2424	196	611	99	-0.0050	0.20	1928	15	83	8	0.0038	0.18
4hr	605	782	2444	395	-0.0196	0.40	481	58	330	30	-0.0052	0.37
6hr	404	1174	3669	593	-0.0313	0.47	321	88	496	45	0.0089	0.41
12hr	201	2347	7317	1185	-0.0676	0.62	160	175	988	90	0.0351	0.56
1wk	42	11305	35831	5702	-0.3373	1.53	33	1024	5961	526	0.2785	1.22

	EUR/GBP (c)						GBP/USD (d)					
k	Obs	Trades	Quotes	Buys	$\bar{r}$	σ	Obs	Trades	Quotes	Buys	$\bar{r}$	σ
5m	23148	14	34	8	-0.0002	0.05	29107	17	44	9	-0.0004	0.04
15m	7715	43	103	23	-0.0007	0.09	9701	52	131	27	-0.0012	0.07
30m	3857	87	206	45	-0.0015	0.13	4850	104	263	53	-0.0029	0.09
1hr	1928	174	411	90	-0.0025	0.18	2424	208	525	106	-0.0049	0.13
4hr	481	694	1646	362	-0.0106	0.37	605	832	2098	424	-0.0200	0.26
6hr	321	1041	2468	542	-0.0160	0.45	404	1249	3150	636	-0.0291	0.32
12hr	160	2085	4944	1086	-0.0384	0.61	201	2496	6280	1271	-0.0603	0.45
1wk	33	10383	25506	5423	-0.0482	1.36	42	13245	35328	6753	-0.2299	0.92

Table 2: Explaining Exchange Rates with Order Flow

$$\Delta P(k)_{i,t} = \alpha(k)_i + \beta(k)_i F(k)_{i,t} + \varepsilon_t \ , \quad i = ED, DY, ES, SD$$

where $\Delta(k)P_{i,t}$ is price change at sampling frequency k for exchange rate i at time t and $F(k)_{i,t}$ is order flow for the same exchange rate and sampling frequency. All t-stats are constructed using the Newey-West estimator of the coefficient variance-covariance matrix. The order flow is scaled by 10^{-2}.

	EUR/USD			USD/JPY			EUR/GBP			GBP/USD		
k	$\hat{\beta}$	t-stats	R^2	$\hat{\beta}$	t-stats	R^2	$\hat{\beta}$	t-stats	R^2	$\hat{\beta}$	t-stats	R^2
5m	0.40	72.39	0.33	1.08	24.71	0.06	0.41	60.30	0.26	0.29	65.07	0.26
15m	0.38	53.25	0.43	1.17	26.53	0.15	0.38	32.01	0.26	0.26	36.58	0.24
30m	0.36	45.30	0.45	1.19	20.96	0.25	0.33	20.51	0.21	0.23	21.30	0.21
1hr	0.36	29.91	0.38	1.25	18.98	0.30	0.30	12.85	0.16	0.21	13.95	0.16
4hr	0.34	17.63	0.38	1.14	9.70	0.30	0.16	3.00	0.05	0.13	3.95	0.05
6hr	0.34	15.35	0.38	1.21	10.59	0.42	0.10	2.00	0.02	0.11	3.66	0.05
12hr	0.30	11.04	0.35	1.17	10.70	0.50	0.02	0.36	0.00	0.14	4.12	0.08
1wk	0.31	5.51	0.45	0.91	11.43	0.67	0.06	0.59	0.01	0.05	0.70	0.01

Table 3: Inter-market Information flow

$$\Delta P(k)_{i,t} = \alpha(k)_i + \sum_j \beta(k)_{i,j} F(k)_{j,t} + \epsilon_{i,t} \ , \quad i = ED, DY, ES, SD$$

where k indexes sampling frequency, i is the rate to be explained and the summation over j gives an explanatory term that is linear in all four order flow variables. Column headed ΔR^2 gives the changes in R^2 between the model with and without the order flow from other markets. The last column in each panel is the p-value of the F-test of the null $H_0 : \beta_j = 0$ for $j \neq i$. The order flow is scaled by 10^{-2}. ^{a,b,c} indicate the 1%, 5% or 10% significance level by using the Newey-West coefficient variance-covariance estimator.

	EUR/USD (a)						USD/JPY (b)					
k	$\hat\beta_{ED}$	$\hat\beta_{DY}$	$\hat\beta_{ES}$	$\hat\beta_{SD}$	ΔR^2	p-value	$\hat\beta_{ED}$	$\hat\beta_{DY}$	$\hat\beta_{ES}$	$\hat\beta_{SD}$	ΔR^2	p-value
5m	0.32^a	-0.05^a	0.18^a	0.14^a	0.054	0.01	-0.02^b	1.07^a	-0.01	-0.01	0.001	0.01
15m	0.31^a	-0.05^b	0.16^a	0.13^a	0.056	0.01	-0.02^c	1.17^a	-0.00	-0.01	0.001	0.05
30m	0.31^a	-0.10^a	0.13^a	0.11^a	0.048	0.01	-0.01	1.19^a	0.00	-0.01	0.001	> 0.10
1hr	0.32^a	-0.01^b	0.11^a	0.12^a	0.039	0.01	-0.02	1.24^a	-0.00	-0.03^b	0.005	0.01
4hr	0.35^a	-0.05	0.03	0.10^a	0.016	0.01	-0.04^c	1.13^a	0.05	-0.03	0.010	0.10
6hr	0.34^a	-0.09	0.03	0.12^a	0.029	0.01	0.01	1.22^a	0.01	-0.03	0.002	> 0.10
12hr	0.33^a	-0.03	-0.05	0.08^c	0.015	> 0.10	0.02	1.17^a	-0.02	-0.02	0.003	> 0.10
1wk	0.39^a	-0.01	-0.00	0.15	0.044	> 0.10	0.04	0.89^a	0.06	-0.12^b	0.057	> 0.10

	EUR/GBP (c)						GBP/USD (d)					
k	$\hat\beta_{ED}$	$\hat\beta_{DY}$	$\hat\beta_{ES}$	$\hat\beta_{SD}$	ΔR^2	p-value	$\hat\beta_{ED}$	$\hat\beta_{DY}$	$\hat\beta_{ES}$	$\hat\beta_{SD}$	ΔR^2	p-value
5m	0.21^a	-0.02	0.30^a	-0.13^a	0.099	0.01	0.10^a	-0.03^b	-0.11^a	0.27^a	0.041	0.01
15m	0.23^a	-0.02	0.26^a	-0.13^a	0.130	0.01	0.09^a	-0.03	-0.10^a	0.25^a	0.045	0.01
30m	0.23^a	-0.05	0.22^a	-0.11^a	0.142	0.01	0.08^a	-0.03	-0.10^a	0.22^a	0.048	0.01
1hr	0.23^a	-0.03	0.19^a	-0.09^a	0.146	0.01	0.10^a	-0.06	-0.09^a	0.20^a	0.055	0.01
4hr	0.26^a	-0.05	0.07	-0.02	0.220	0.01	0.10^a	-0.02	-0.07^b	0.10^a	0.065	0.01
6hr	0.28^a	-0.04	0.01	0.01	0.235	0.01	0.09^a	-0.09	-0.01	0.09^b	0.053	0.01
12hr	0.28^a	-0.11	-0.03	-0.04	0.263	0.01	0.10^a	-0.00	-0.02	0.12^a	0.054	0.01
1wk	0.29^a	-0.07	0.01	0.08	0.335	0.01	0.12^b	0.05	-0.00	0.07	0.107	0.05

Table 4: Meese-Rogoff (1983) forecasting experiments: Root Mean Squared Errors (RMSE)

h is forecast horizon in observations, k is the sampling interval. Forecasting horizon in real time is defined as $h \times k$. The columns under OF and RW give the RMSEs of the *h-step-ahead* return forecast for the order flow and random walk models (3) and (4). The t-statistic for forecast improvement of the order flow model over the random walk is as given in Diebold [2001] (pp. 293).

		EUR/USD			USD/JPY			EUR/GBP			GBP/USD		
Freq	h	OF	RW	t-stats	OF	RW	t-stats	OF	RW	t-stats	OF	RW	t-stats
5m	1	0.05	0.06	-6.23	0.07	0.08	-0.52	0.05	0.05	-4.38	0.03	0.04	-4.28
	6	0.05	0.06	-6.23	0.07	0.08	-0.52	0.05	0.05	-4.38	0.03	0.04	-4.28
	12	0.05	0.06	-6.23	0.07	0.08	-0.52	0.05	0.05	-4.38	0.03	0.04	-4.28
15m	1	0.07	0.10	-7.82	0.09	0.10	-1.30	0.08	0.09	-3.44	0.06	0.07	-2.99
	6	0.07	0.10	-7.82	0.09	0.10	-1.30	0.08	0.09	-3.44	0.06	0.07	-2.98
	12	0.07	0.10	-7.82	0.09	0.10	-1.29	0.08	0.09	-3.43	0.06	0.07	-2.98
30m	1	0.10	0.13	-7.84	0.11	0.13	-1.72	0.12	0.13	-2.16	0.08	0.09	-2.32
	6	0.10	0.13	-7.84	0.11	0.13	-1.70	0.12	0.13	-2.15	0.08	0.09	-2.32
	12	0.10	0.13	-7.84	0.11	0.13	-1.70	0.12	0.13	-2.16	0.08	0.09	-2.31
1hr	1	0.16	0.20	-4.03	0.14	0.17	-2.57	0.18	0.19	-1.19	0.13	0.14	-1.29
	6	0.16	0.21	-4.03	0.14	0.17	-2.56	0.18	0.19	-1.20	0.13	0.14	-1.28
	12	0.16	0.21	-4.00	0.14	0.17	-2.55	0.18	0.19	-1.20	0.13	0.14	-1.28
4hr	1	0.33	0.42	-2.50	0.32	0.37	-0.94	0.36	0.37	-0.25	0.27	0.27	-0.04
	6	0.33	0.42	-2.46	0.33	0.38	-0.90	0.37	0.38	-0.26	0.27	0.27	-0.04
	12	0.33	0.41	-2.31	0.33	0.38	-0.89	0.37	0.38	-0.28	0.27	0.27	-0.05
6hr	1	0.39	0.50	-2.40	0.32	0.43	-2.97	0.48	0.48	-0.04	0.32	0.33	-0.08
	6	0.40	0.50	-2.38	0.32	0.43	-2.96	0.48	0.49	-0.02	0.32	0.33	-0.08
	12	0.40	0.49	-2.20	0.32	0.44	-2.97	0.48	0.48	-0.01	0.32	0.33	-0.08
12hr	1	0.54	0.66	-2.07	0.40	0.58	-2.63	0.67	0.66	0.07	0.46	0.47	-0.16
	6	0.53	0.65	-1.94	0.41	0.58	-2.47	0.69	0.68	0.12	0.47	0.47	-0.13
	12	0.54	0.66	-1.82	0.42	0.60	-2.47	0.68	0.67	0.16	0.47	0.47	-0.14
1wk	1	1.28	1.62	-1.10	0.76	1.20	-1.86	1.68	1.63	0.12	0.97	0.94	0.15
	6	1.39	1.76	-1.18	0.80	1.24	-1.51	1.85	1.84	0.04	0.97	0.94	0.12
	12	1.51	1.96	-1.16	0.62	1.18	-1.60	1.31	1.32	-0.02	0.98	1.01	-0.17

Table 5: Out-of-sample forecast experiments

$$\Delta P(k)_{i,t+1} = \alpha(k)_{i,t} + \beta(k)_{i,t} F(k)_{i,t} + \varepsilon_{t+1} \ , \quad i = ED, DY, ES, SD$$

where $\Delta(k)P_{i,t+1}$ is price change at sampling frequency k for exchange rate i at time $t+1$ and $F(k)_{i,t}$ is order flow for the same exchange rate and sampling frequency at time t. The columns under OF and RW give the forecast RMSEs of the model above and random walk models and the t-statistic for the forecast improvement over random walk is reported in the last column of each panel. The order flow is scaled up 10^{-2}. ^{a,b,c} indicate the 1%, 5% or 10% significance level by using the Newey-West coefficient variance-covariance estimator.

	EUR/USD (a)					USD/JPY (b)				
Freq	$\hat{\beta}$	R^2	OF	RW	t-stats	$\hat{\beta}$	R^2	OF	RW	t-stats
5m	0.03^a	0.002	0.06	0.06	-0.02	0.09^b	0.000	0.09	0.09	0.00
15m	-0.01^c	0.000	0.10	0.10	0.00	-0.01	0.000	0.09	0.09	0.00
30m	-0.00	0.000	0.13	0.13	0.01	-0.12^a	0.003	0.13	0.13	0.03
1hr	0.01	0.001	0.20	0.20	0.00	0.02	0.000	0.17	0.17	0.00
4hr	0.01	0.000	0.42	0.42	0.02	0.09	0.002	0.37	0.37	0.01
6hr	0.00	0.000	0.50	0.50	0.02	0.03	0.000	0.43	0.43	0.04
12hr	-0.04	0.007	0.67	0.66	0.02	0.03	0.000	0.58	0.58	0.03
1wk	-0.10^b	0.041	1.62	1.62	-0.01	0.12	0.011	1.22	1.20	0.10

	EUR/GBP (a)					GBP/USD (b)				
Freq	$\hat{\beta}$	R^2	OF	RW	t-stats	$\hat{\beta}$	R^2	OF	RW	t-stats
5m	0.05^a	0.004	0.05	0.05	-0.04	0.02^a	0.001	0.04	0.04	0.00
15m	-0.01	0.000	0.08	0.08	0.02	-0.04	0.000	0.07	0.07	0.00
30m	-0.00	0.000	0.13	0.13	0.02	0.00	0.000	0.09	0.09	0.01
1hr	-0.00	0.000	0.19	0.19	0.02	0.00	0.000	0.14	0.14	0.01
4hr	-0.07^b	0.011	0.38	0.37	0.04	0.04^c	0.005	0.27	0.28	0.00
6hr	0.01	0.000	0.48	0.48	0.03	0.01	0.001	0.33	0.33	0.02
12hr	-0.01	0.000	0.67	0.66	0.12	0.00	0.000	0.47	0.47	0.06
1wk	-0.01	0.001	1.69	1.63	0.14	0.04	0.006	1.00	0.94	0.37

Table 6: Forecasting Order Flow Out-of-Sample

$$F(k)_{i,t+1} = \alpha(k)_{i,t} + \sum_{j=1}^{J} \beta(k)_{j,i,t} \Delta P(k)_{i,t-j+1} + \sum_{k=1}^{K} \gamma(k)_{j,i,t} F(k)_{t-j+1} + \epsilon_{t+1}, \quad i = ED, DY, ES, SD$$

where $\Delta(k)P_{i,t}$ is price change at sampling frequency k for exchange rate i at time t and $F(k)_{i,t+1}$ is order flow for the same exchange rate and sampling frequency at time $t+1$. The columns under OF and RW give the forecast RMSEs of model (5) and random walk models and the t-statistic for the forecast improvement over RW is reported in the last column. ^{a,b,c} indicate 1%, 5% or 10% significance level by using the Newey-West variance-covariance estimator.

	k	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	R^2	OF	RW	t-stats
EUR/USD	5m	3.15^{a}	0.22	0.13^{a}	0.01	0.020	8.45	8.49	-0.10
	15m	2.53	-4.65^{c}	0.05^{a}	1.55	0.005	17.01	17.01	0.00
	30m	1.32	-2.77	0.04^{c}	0.72	0.002	25.97	25.95	0.01
	1hr	4.93	-3.66	0.04	5.44^{c}	0.003	31.39	31.34	0.03
	4hr	4.97	13.61	0.03	-7.44	0.007	70.46	70.23	0.04
	6hr	4.24	6.39	0.03	9.79	0.026	83.29	82.66	0.10
	12hr	37.13^{b}	14.59	0.01	-0.16	0.048	120.40	117.32	0.24
	1wk	-32.57	51.87	0.04	-27.96	0.072	331.68	278.70	1.10
USD/JPY	5m	2.44^{a}	0.79^{a}	0.19^{a}	0.04^{a}	0.064	1.72	1.79	-0.56
	15m	4.21^{a}	0.22	0.10^{a}	3.41^{c}	0.040	3.59	3.63	-0.09
	30m	5.25^{a}	1.29	0.03	9.20^{a}	0.032	5.96	6.03	-0.09
	1hr	5.86^{a}	0.99	0.09^{b}	0.88	0.039	8.35	8.55	-0.25
	4hr	-1.08	2.44	0.09^{c}	0.11	0.010	18.93	18.78	0.10
	6hr	1.82	-0.83	0.09	7.59	0.018	22.79	22.62	0.08
	12hr	9.59	14.30^{b}	-0.04	-0.11	0.050	35.25	35.39	-0.03
	1wk	-4.62	-50.06^{b}	0.34	0.42^{c}	0.161	126.06	108.08	0.71
EUR/GBP	5m	-5.70^{a}	-5.55^{a}	0.12^{a}	0.04^{a}	0.013	6.53	6.57	-0.11
	15m	-14.96^{a}	-10.00^{a}	0.10^{a}	0.04^{b}	0.016	12.25	12.37	-0.11
	30m	-19.20^{a}	-4.07	0.09^{a}	-0.00	0.017	15.43	15.45	-0.03
	1hr	-18.91^{a}	-3.56	0.05^{c}	0.04	0.018	24.62	24.95	-0.19
	4hr	-3.39	-10.91	0.09^{b}	-0.04	0.017	53.35	53.09	0.06
	6hr	-8.26	3.94	0.02	0.06	0.008	68.27	67.30	0.16
	12hr	21.92^{c}	9.53	0.09	0.01	0.036	104.24	97.68	0.65
	1wk	-26.99	82.14^{b}	0.25^{b}	-0.08	0.249	273.88	262.86	0.21
GBP/USD	5m	-8.12^{a}	-11.83^{a}	0.07^{a}	0.04^{a}	0.007	7.03	7.08	-0.18
	15m	-23.80^{a}	-10.67^{a}	0.07^{a}	0.03^{b}	0.015	12.20	12.21	0.00
	30m	-27.30^{a}	-14.76^{a}	0.08^{a}	0.04^{c}	0.021	17.77	18.07	-0.29
	1hr	-31.37^{a}	-16.52^{a}	0.06^{b}	0.09^{a}	0.034	23.59	23.82	-0.18
	4hr	-14.35^{b}	7.23	0.13^{a}	0.03	0.021	49.42	49.46	-0.01
	6hr	-10.36	24.78^{b}	0.06	0.04	0.022	67.76	67.43	0.06
	12hr	18.99	4.51	0.09	0.05	0.027	90.09	88.26	0.23
	1wk	-13.88	41.59	0.09	0.05	0.044	271.59	244.34	0.80

Figure 1: Variation in R^2 of order flow model across sampling frequencies

R^2 from regression model (1) over sampling frequencies from 5 minutes to one week for each exchange rate. Labels 'm', 'hr', 'dly', 'wkly' represent minute, hour, daily and weekly respectively.

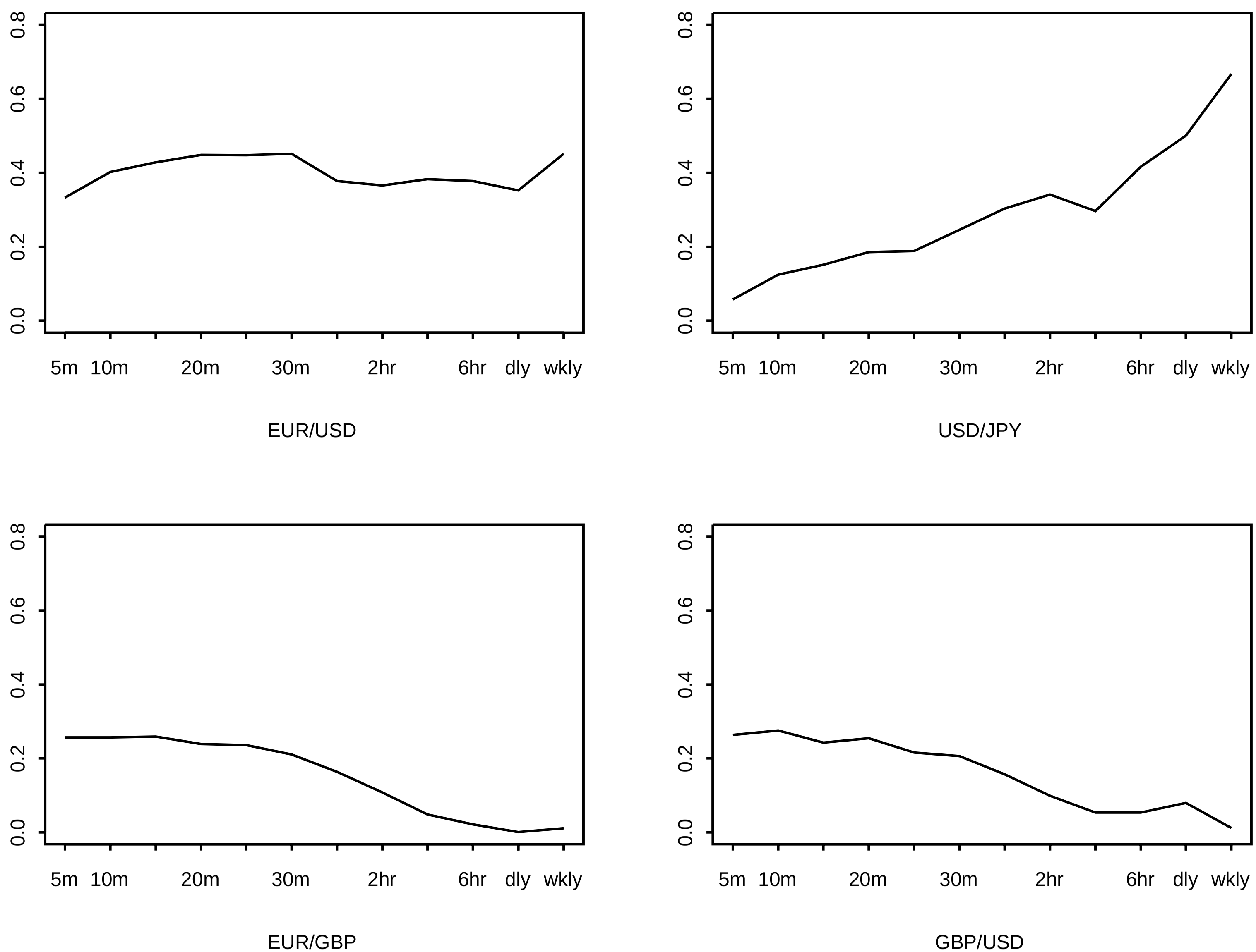

Figure 2: R^2 for univariate and multivariate order flow models

The solid and dotted lines are R^2s from model (1) and (6) respectively. Each model is estimated over sampling frequencies from 5 minutes to one week. Labels 'm', 'hr', 'dly', 'wkly' represent minute, hour, daily and weekly respectively.