Exchange Rate Determination and Inter–Market Order Flow Effects*

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April 12, 2011

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 explanatory power is discovered for all sampling frequencies. We also uncover cross-market order flow effects e.g. GBP exchange rates are very strongly influenced by EUR/USD order flow. The Meese and Rogoff (1983a,b) framework is used to investigate the predictive power of order flow for exchange rate changes and it is shown that the order flow specifications reduce RMSEs relative to a random walk for all exchange rates at high-frequencies and for EUR/USD and USD/JPY at lower sampling frequencies.

JEL: F0, F3, G1.

Keywords: exchange rate determination, order flow

*Thanks to Charles Goodhart, Richard Lyons, the editors, an anonymous referee and participants in the 2002 Venice Summer Institute for excellent comments. Thanks also to the Bank of England for providing the transactions data used in this study. All remaining errors are our own.

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1 Introduction

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 model in predictive ability. In the empirical finance literature there is, however, a long tradition of studying the higher frequency relationship between features of prices of financial assets and measures derived from trading activity.[1] Simple analysis of trading volume, however, does not help resolve the Meese–Rogoff problem, not least because volume is directionless i.e. a change in volume cannot predict the direction of FX changes.

Recently, though, 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 buyer and seller initiated volume is termed *order flow*.[2] Order flow has been shown in empirical market microstructure research to be a key determinant of high frequency asset price changes, with several authors, e.g. Lyons (1995), Evans (2002), and Payne (2003) studying the relationship between order flow and foreign exchange rates.[3]

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

[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 agent's prices.

[3] See also Hasbrouck (1991) and Madhavan and Smidt (1991) who study equity markets, and Cohen and Shin (2002) who study fixed income markets.

respond to new information without any consistent effect on order flow. Intuitively, when new information arrives each agent immediately revises his estimate of value and there is no reason for trade. Thus one must look beyond those models to find a rationale for the effects of order flow on prices.

Work which can be used to justify the explanatory power of order flow suggests that flows may convey information about asset payoffs or discount factors. Standard private information arguments (e.g. Glosten and Milgrom (1985)) imply that order flow carries information about exchange rate payoffs. Alternatively Evans and Lyons (2002b) suggest that order flow aggregates dispersed information about FX risk premia. Finally, some recent empirical work suggests that public information is partially impounded into exchange rates via order flow (Love and Payne, 2008; Rime et al., 2010). These arguments also suggest that the relationship between order flow and asset prices persists across sampling frequencies, for example because information has permanent effects on asset prices. Some 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] However, Berger et al. (2008) use 6 years of high-frequency data on EUR/USD and USD/JPY to show that order flows and exchange rate returns are strongly related for sampling frequencies from 1 minute to 2 weeks, but the relationship weakens at lower frequencies. They proceed to show that the flow-return relationship is stronger at times of low market liquidity and use this result to argue that liquidity effects are at least a

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

part of the story behind the correlations of flows and returns. Finally, Froot and Ramadorai (2005) use a decomposition for FX returns into permanent, intrinsic value shocks and deviations from intrinsic value (similar to that of Campbell and Shiller (1988)), plus a long span of flow data for many currencies (this time from a global custodian bank) to draw conclusions about the long-run effects of flows on exchange rates. They conclude that order flow is related to transitory exchange rate movements and show that positive correlations between returns and flows turn negative at very low frequencies.

The objective of this paper is to refine and deepen our understanding of the relationship between FX order flows and exchange rate changes. Our investigation extends prior work in that we have data on 4 key exchange rates (EUR/USD, EUR/GBP, GBP/USD, USD/JPY) covering between 8 and 10 months each. Using these data we focus on three empirical issues. First, we examine how the flow-return relationship varies across sampling frequencies from 5 minutes to 1 week. Second, we empirically model cross-market order flow effects e.g. the effects of EUR/USD order flow on GBP/USD. Last, we evaluate the predictive power of order flows for exchange rate changes using the Meese-Rogoff approach and genuine out-of-sample forecast analysis.

Our data derives from transaction–level information obtained from the Reuters D2000–2 electronic brokerage and we have approximately 10 months of data for EUR/USD and EUR/GBP and eight months of data for GBP/USD and USD/JPY. The sample starts in 1999 and ends in 2000.

Our first set of results shows that contemporaneous order flow significantly explains exchange rates across sampling frequencies. However, we observe considerable differences in the explanatory power of the various regressions. For the EUR/USD rate, R^2 hovers around 40% for all frequencies, while for USD/JPY the R^2 increases with aggregation, from 6% at five minutes to 67% at one week. These results are comparable to those reported by Evans and Lyons (2002b) and Berger et al. (2008) and, in the latter case, directly corroborate their findings for EUR/USD and USD/JPY using data from a different sample and trading system. In contrast, the R^2 for both GBP rates decreases with aggregation from 26% at five minutes to 1% at one week. On first inspection, the inconsistency between the GBP regression results and those for EUR/USD and USD/JPY are somewhat puzzling.

Our analysis of cross-market flow effects partially resolves the preceding puzzle, however. Including other order flows as explanatory variables in the EUR/USD and USD/JPY regressions makes little difference to their explanatory power. However, for the GBP rates, especially at lower frequencies, order flow from other currencies has a strong and significant impact, greatly increasing explanatory power. Our results are especially clear in the case of the EUR/GBP rate where EUR/USD order flow is found to be the primary exchange rate driver at low frequencies. Cross-market flow effects similar to these are also reported in Evans and Lyons (2002a) and Lyons and Moore (2009). The former paper studies pre-Euro data and shows that German mark and Swiss franc flows directly affect returns on other European currencies. The latter studies triangular arbitrage in a Yen-Dollar-Euro setting and shows cross-market effects from flow in that context. Our results support theirs in that we derive results from a different triangle i.e. Sterling-Dollar-Euro.

There are several possible explanations for the cross-market order flow effects we find. For example, suppose a currency trader has private information about the future value of the USD , perhaps he expects 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, he expects his market impact from trading to be lower in that market, implying that more profits can be gained by trading in the EUR than in GBP. In this case, EUR/USD order flow would help to explain the EUR/USD rate. However, liquidity suppliers in GBP/USD who understand the incentives of informed traders will interpret the EUR/USD flow as possibly signalling USD appreciation and will adjust their GBP/USD quotes accordingly. Thus, the EUR/USD flow has an effect on the GBP/USD rate. A similar argument can be made for other cross-market flow effects from liquid to less liquid currency pairs.

In sum, the cross-market flow effects suggest that the while the basic own order flow model may be appropriate for the largest currencies, it is less so for less liquid currencies.[5] Information revealed in more liquid pairs spills over to less liquid rates such that flows from liquid pairs significantly contribute to the ability to explain them. These effects persist across our sampling frequencies, and strengthen with aggregation.

Our final results are on the prediction of exchange rates. First, we use the Meese and Rogoff (1983a,b) framework, and find that the order flow model almost always yields a

[5]To compare the size of these markets, 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.

better prediction (in RMSE terms) than does a random walk model. This result is consistent across sampling frequencies and currencies. Therefore, albeit at a somewhat higher sampling frequency than macroeconomists would usually examine, 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 linear specification, we find that order flow does not perform particularly well in forecasting exchange rates except at the highest frequencies. Such results contrast with those from Evans and Lyons (2005) and Rime et al. (2010) who suggest that order flows have out-of-sample forecasting power for FX rates at daily and longer horizons. Our findings are supported by Sager and Taylor (2008), who use inter-dealer and customer FX flows. Last of all we find, as do Sager and Taylor (2008), that order flow itself can be forecasted with own lags and lagged returns.

In sum, our results suggest that order flow contributes strongly to exchange rate determination. Across sampling frequencies from the highest intra-day level to those relevant to macroeconomists, flows help explain exchange rate changes. On this front, our analysis corroborates the work of, inter alia, Evans and Lyons (2002a), Evans and Lyons (2002b), Payne (2003), Berger et al. (2008) and Lyons and Moore (2009). We go on to show that flow based forecasts can outperform a random walk model within a Meese-Rogoff setting, although in a genuine out-of-sample setting flow-based forecasts are only helpful at relatively high frequencies. In this area, our results are at odds with those of Evans and Lyons (2005) and Rime et al. (2010), although they support the findings of Sager and Taylor

(2008).

The rest of the paper is structured as follows. Section 2 outlines our data sources and our processing of the data. Section 3 presents our analysis of the explanatory power of order flow for exchange rates and Section 4 presents multi-variate flow analysis. The following Section presents our forecasting results. Some discussion of our findings is given in Section 6 and Section 7 concludes.

2 Data Description and Organization

2.1 The Data

Our data come from the Reuters D2000–2 system, which is a brokered inter–dealer FX trading platform. 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 published to the D2000–2 screen as they occur.[6]

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

[6]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)

algorithms to 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.

2.2 Filtering and Time Aggregation

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 failed.[7]

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.[8] Note that our definition of one day corresponds to a trading day defined as the interval between 6:00 and 18:00. Thus one

[7]In this paper we define the overnight period to be 18:00 to 6:00 the following day. It should be noted that this definition is only proper for traders in London and New York, but not for 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.

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

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 observation point. From the price data we construct logarithmic price changes.

After filtering and aggregation, we are left with 32 data sets (8 sampling frequencies $\times$ 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 period 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.

3 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 fairly 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;

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

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 order flow in the interval ending at t for currency pair i at sampling frequency k. Table 2 contains the estimation results for model (1) for our four exchange rates and over the entire spectrum of time aggregation levels.[9]

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

[9]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.

flow carries information for high–frequency asset price determination. However, there is no immediate reason to believe that these very high frequency results have any bearing on exchange rate determination at lower frequencies. They might simply reflect transitory market liquidity effects, for example.

Thus we shift focus to a lower frequency. Consider first results at the daily frequency, initially for EUR/USD and USD/JPY in order to provide comparability with Evans and Lyons (2002b).[10] Their daily USD/DEM and USD/JPY regression R^2 are just over 60% and 40% respectively and these numbers are broadly consistent with our results. Berger et al. (2008) study EUR/USD and USD/JPY and find that daily R^2 from the basic order flow specification are at similar levels to those in Evans and Lyons (2002b), although these authors suggest that the R^2 drops significantly as one moves to a monthly sampling frequency.

However, our results on the GBP exchange rates are much less supportive of the findings of Evans and Lyons (2002b) and Berger et al. (2008). 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 the GBP, the assertion that order flow matters for exchange rate determination when one moves towards

[10]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.

sampling frequencies relevant to international macroeconomics appears less secure than our previous EUR/USD and USD/JPY results suggest.

A graphical representation of these results using a 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 shows the declining explanatory power of order flow with sampling frequency in the GBP markets.

That the low frequency GBP results are poor relative to EUR/USD and USD/JPY is puzzling given Reuters dominance in inter-dealer trade in GBP markets. Ex ante, one might have thought that Reuters' GBP flows would thus carry more power than their EUR/USD and USD/JPY counterparts.

4 Inter–Market Order Flow Analysis

Most existing FX 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. This issue has been addressed in other papers. Evans and Lyons (2002a) show, using data from before the introduction of the Euro, that order flows in the German mark and Swiss franc spill over to various other European exchange rates. More recently, Lyons and Moore (2009) study information spillovers between currencies that are linked via triangular arbitrage relationships and empirically identify cross-market order flow effects in the EUR-JPY-USD triangle.

The reason for considering inter–market effects is the peculiar nature of exchange rates, 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 will 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 in which market (if not all of them) will he choose to 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. Rational liquidity suppliers in other markets observe the order flow just traded in the chosen market and 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;

$$\Delta P(k)_{i,t} = \alpha(k)_i + \sum_j \beta(k)_{i,j} F(k)_{j,t} + \varepsilon_{i,t} \tag{2}$$

where both i and j index currency pairs such that i is the rate to be explained and the summation over j gives an explanatory term that is linear in order flow variables from all four markets. The parameter k indexes sampling frequency. Table 3 presents the main results from estimating (2), while the R^2 from the multiple-flow regressions are shown in Figure 2 alongside those from the own-market flow models.

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 3, there are few other significant flow variables. 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. In all cases the improvement in the R^2 of the regressions as compared to the univariate specifications in Section 3 is small.

For EUR/USD, the order flow coefficients of EUR/GBP and GBP/USD are, as a triangular arbitrage argument would predict, 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 over the single flow specification (labelled ΔR^2 in the table) of up to 6%, and for all specifications below the daily level this improvement is significant.

For the GBP rates, the results are 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. The extended specifications show markedly improved explanatory power (ΔR^2) over the univariate models in Section 3, 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. The effect of EUR/USD flow is strongest for the EUR/GBP, providing virtually all explanatory power at the lower frequencies.

Thus, our results provide clear evidence of flow information being transmitted across linked exchange rate markets, from more to less liquid markets. Moreover, our results on the GBP-EUR-USD triangle support those of Lyons and Moore (2009) on the JPY-EUR-USD triangle. The EUR/USD exchange rate is the largest and most liquid in the world, and its order flow is shown to contribute strongly to all three currency pairs involved in the GBP triangle at all sampling frequencies. This is especially apparent for the least liquid of these three currency pairs, EUR/GBP. The fact that the order flow from the largest currencies dominates the determination of the smaller currencies, suggests that new information flows first to the most liquid markets, i.e. where the new information can be best exploited.

Note that, while EUR/USD is clearly the most liquid of spot exchange rate pairs, only a fraction of its volume is traded on Reuters' D2000-2. Conversely, while the GBP markets are much smaller than EUR/USD, D2000-2 is the venue for the bulk of the electronically brokered trade. If then, Reuters' market in EUR/USD is relatively poor, why do its

EUR/USD flows exert such influence on other exchange rates? Our view is that D2000-2 and its competitor market, EBS, move very tightly together due to the effects of cross market arbitrage. As such, EBS and D2000-2 bid/offer quotes are essentially identical, although EBS is somewhat deeper. Due to this, and to the fact that trades on D2000-2 and EBS tend to be very small on average, an informed (or indeed an uninformed) trader will rationally split his flow across venues. This likely leads to strongly correlated flows on D2000-2 and EBS and thus allows D2000-2 flows to share the information content of those on EBS. While this has not been tested, to our knowledge, given our understanding of how these markets work, it is a plausible argument.

5 Forecasting Analysis

The order flow models (1) and (2) estimated above used contemporaneous order flow to explain exchange rate changes. However, as 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 predictive 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 investigation of the forecasting performance of the order flow model for exchange rates, across different sampling frequencies using a variety of specifications. We first use the methodology proposed by Meese and Rogoff (1983a,b), and then extend this to genuine out–of–sample forecast testing.

5.1 Meese–Rogoff Forecast Analysis

The Meese and Rogoff (1983a,b) test is based on 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 drift. The Meese–Rogoff test is therefore not a genuine out–of–sample forecasting experiment since observed future order flow is used in the forecast construction.

We consider sampling frequency ranging from 5 minutes to 1 week and for each sampling frequency we evaluate one-step ahead forecasts.[11] The forecasting equation that is equivalent to the regression model (1) is given by;

$$\Delta P(k)_{i,t+1} = \alpha(k)_{i,t} + \beta(k)_{i,t} F(k)_{i,t+1} + \varepsilon_{i,t+1} \tag{3}$$

where $\Delta P(k)_{i,t+1}$ is a one-step ahead return (based on sampling frequency k) . $\alpha(k)_{i,t}$ and $\beta(k)_{i,t}$ are the estimates of the regression model based on information up to time t.

[11] We have performed multi-step forecast analysis but it added little new information to the results we present here. Results are available on request.

$F(k)_{i,t+1}$ is the order flow of the one-step ahead interval.

The benchmark forecasting model is a random walk with drift (RW) for the log price. Under this specification, the one-step ahead forecast for the price change is nothing more than the average exchange rate change from the beginning of the sample until time t.

$$\Delta P(k)_{i,t+1} = \mu(k)_{i,t} + \eta_{i,t+1} \tag{4}$$

where $\mu(k)_{i,t}$ is the estimated drift based on sampling frequency k using information up to time t only and $\eta_{i,t+1}$ is a noise term. For both models and all rates we initiate the estimation using the first four months of data.

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) and, even at the daily and weekly sampling frequency, very heavily traded exchange rates such as EUR/USD and USD/JPY can be predicted 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.

5.2 Genuine Forecasting

Since the Meese–Rogoff test is not based on an out-of-sample forecast, we extend the results above by moving to a true out-of-sample setting. In this case we only use order flow information available at the forecast date. Thus, we would expect these results to be less strong 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 derived from the following specification;

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

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 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.

5.3 Order Flow Forecasting

Finally, as in Sager and Taylor (2008), we investigate the predictability of order flow itself, and test whether flows can be forecasted with past information on flows themselves and price changes. If this was the case, then another route to forecasting exchange rate changes might exist. One could combine the strong contemporaneous relationship between price changes and order flows uncovered in Section 3 and an order flow forecast to construct a price forecast.

We consider the following forecasting model for flows;

$$F(k)_{i,t+1} = \alpha(k)_{i,t} + \sum_{j=1}^{J} \beta(k)_{j,i,t} \Delta P(k)_{i,t-j+1} + \sum_{m=1}^{M} \gamma(k)_{m,i,t} F(k)_{i,t-m+1} + \varepsilon_{i,t+1} \qquad (6)$$

i.e. for a given sampling frequency (k) and exchange rate (i) we regress flow at $t+1$ on its own first M lags and on J lags of the price change. In the estimations we set both M and J 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. In this case there would seem to be evidence of aggressive momentum type trades.

6 Discussion

We have presented a number of results on the explanatory power, forecasting ability, and multi–variate implications of order flow for FX rates. 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 those working in international macroeconomics. We thus confirm the evidence contained in Evans and Lyons (2002b), Payne (2003), and Berger et al. (2008) amongst others.

However, our results contain a very important difference to those in Evans and Lyons (2002b) and Berger et al. (2008). Our univariate regressions of price changes on order flow for GBP exchange rates perform very poorly at lower sampling frequencies (e.g. 1 day), 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, 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 all sampling frequencies. This is a key result. Order flow may carry 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* via order flow. This analysis corroborates the findings of Evans and Lyons (2002a) and Lyons and Moore (2009).

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 as EUR/USD is the most liquid and heavily traded currency pair in the world and, as such, one would expect any relevant information to hit it first due to its low transaction costs and massive participation. Thus those quoting in related pairs will very likely keep an eye on EUR/USD developments, including order flow, when setting their prices.

A final point to note regarding the inter–market flow analysis carried out in Section 4 is that 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*. One cannot explain away the importance of order flow in an inter–market context by simply asserting that aggressive buying or selling pressure is 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 conveyed by flows in other markets. 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 failed to dominate. This would seem to provide a strong argument in favour of a focus on the order flow approach to exchange rates. Indeed, in a recent paper, Chinn and Moore (2009) embed order flow in a monetary exchange rate model and use this hybrid to forecast monthly exchange rates. Their results indicate that the hybrid model outperforms the random walk and a simple macro model out-of-sample. 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). It should be noted that this result is weaker than that of Evans and Lyons (2005), who find consistent out-of-sample forecasting power from flows over horizons from 1 to 20 trading days, and also that of Rime et al. (2010) who show that order flow can forecast exchange rate returns one day ahead based on economic value criteria. Our return forecasting results do support the findings of Sager and Taylor (2008), however. Last of all, as also reported in Sager and Taylor (2008), order flow itself can be forecasted out-of-sample at high-frequencies using information on its own past and on lagged returns.

7 Conclusion

We study the explanatory and forecasting power of FX order flow for exchange rate changes at sampling frequencies ranging from 5 minutes to one week using a 10 month span of data for EUR/USD, EUR/GBP, GBP/USD and USD/JPY. We demonstrate that order flow analysis has power both to explain and predict 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 rate changes for EUR/USD and USD/JPY. This is not the case for EUR/GBP and GBP/USD.

3. 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 at all sampling frequencies.

4. An analysis of the forecasting power of order flows, using the technique of Meese and Rogoff (1983a,b), demonstrates that exchange rate regressions based on order flows outperform a naïve random walk benchmark across the majority of 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 at sampling frequencies below one hour.

6. Order flow can be forecasted out-of-sample at high frequencies.

These results serve to emphasize the role played by order flow in foreign exchange, and possibly other markets. Order flows can be used to explain and forecast rates at very high frequencies as well as observation 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 forward in the coming decades.

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Table 1: Summary statistics for time aggregated data sets

	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

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

Table 2: Explaining Exchange Rates with Order Flow

	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

Notes; the table presents parameter estimates and inference from the following model;

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

where $\Delta P(k)_{i,t}$ 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}.

Table 3: Inter-market Information flow

	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

Notes; the table presents parameter estimates and inference from the following model;

$$\Delta P(k)_{i,t} = \alpha(k)_i + \sum_j \beta(k)_{i,j} F(k)_{j,t} + \varepsilon_{i,t}$$

where k indexes sampling frequency, i denotes the rate to be explained and the summation over j gives an explanatory structure that is linear in all four order flow variables. The column headed ΔR^2 gives the change 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 a factor of 10^{-2}. ^{a,b,c} indicate significance at the 1%, 5% and 10% levels respectively (based on the Newey-West coefficient variance-covariance estimator). In the column headers, 'ED' is shorthand for EUR/USD, 'SD' is shorthand for GBP/USD, 'ES' is shorthand for EUR/GBP and 'DY' is shorthand for USD/JPY.

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

	EUR/USD			USD/JPY			EUR/GBP			GBP/USD		
Freq	OF	RW	*t*-stats	OF	RW	*t*-stats	OF	RW	*t*-stats	OF	RW	*t*-stats
5m	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	0.07	0.10	-7.82	0.09	0.10	-1.30	0.08	0.09	-3.44	0.06	0.07	-2.99
30m	0.10	0.13	-7.84	0.11	0.13	-1.72	0.12	0.13	-2.16	0.08	0.09	-2.32
1hr	0.16	0.20	-4.03	0.14	0.17	-2.57	0.18	0.19	-1.19	0.13	0.14	-1.29
4hr	0.33	0.42	-2.50	0.32	0.37	-0.94	0.36	0.37	-0.25	0.27	0.27	-0.04
6hr	0.39	0.50	-2.40	0.32	0.43	-2.97	0.48	0.48	-0.04	0.32	0.33	-0.08
12hr	0.54	0.66	-2.07	0.40	0.58	-2.63	0.67	0.66	0.07	0.46	0.47	-0.16
1wk	1.28	1.62	-1.10	0.76	1.20	-1.86	1.68	1.63	0.12	0.97	0.94	0.15

Notes; the first column gives the the sampling interval. The columns under OF and RW give the RMSEs of the *1-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.

Table 5: Out-of-sample forecast experiments

	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

Notes; the table presents parameter estimates and inference from the following model;

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

where $\Delta P(k)_{i,t+1}$ 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 a random walk model, respectively, and the t-statistic for the forecast improvement of the model above over the random walk is reported in the last column of each panel. The order flow is scaled up by a factor of 10^{-2}. ^{a,b,c} indicate significance at the 1%, 5% or 10% levels respectively, based on the Newey-West coefficient variance-covariance estimator.

Table 6: Forecasting Order Flow Out-of-Sample

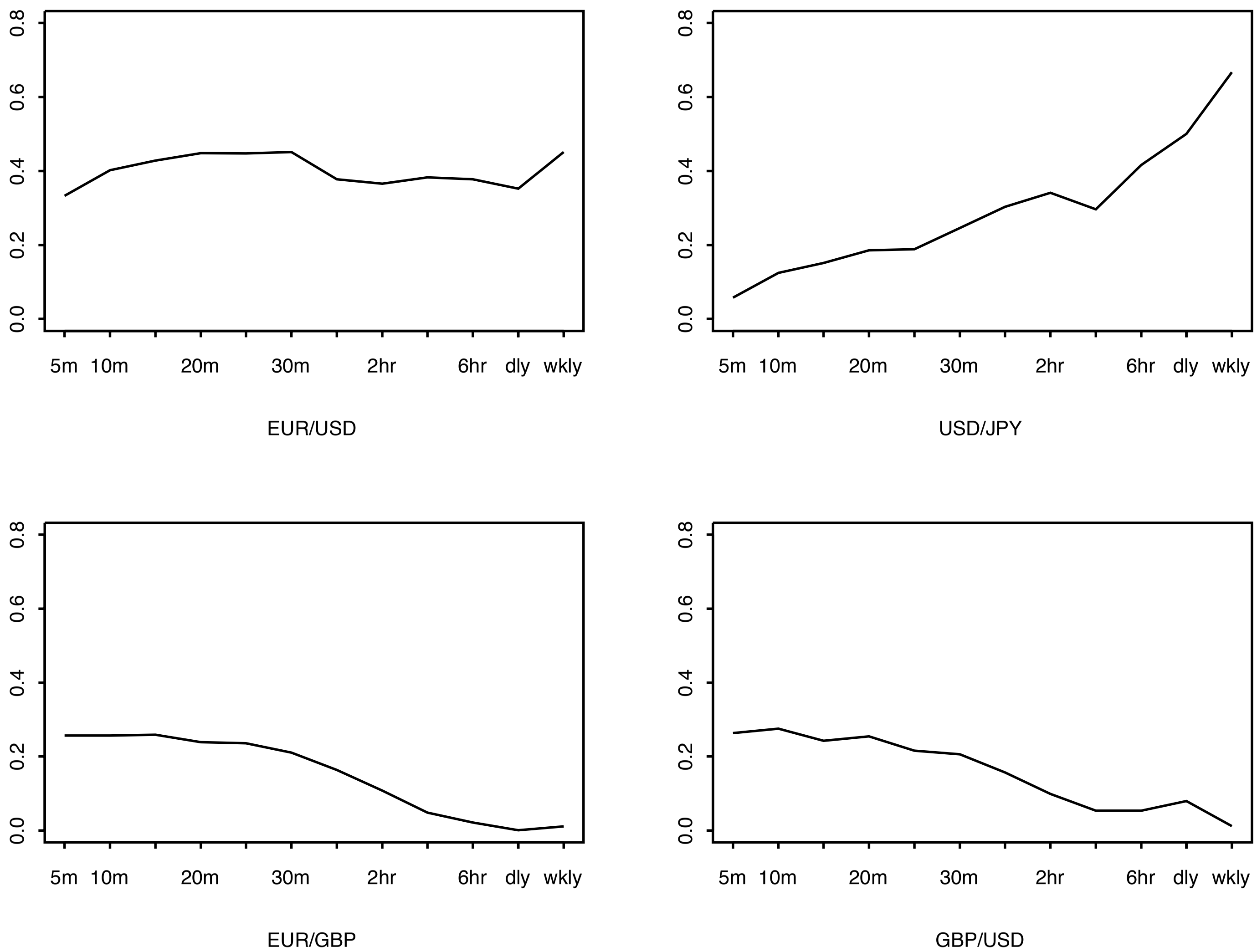
	k	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	R^2	OF	RW	t-stats
EUR/USD	5m	3.15^a	0.22	0.13^a	0.01	0.020	8.45	8.49	-0.10
	15m	2.53	-4.65^c	0.05^a	1.55	0.005	17.01	17.01	0.00
	30m	1.32	-2.77	0.04^c	0.72	0.002	25.97	25.95	0.01
	1hr	4.93	-3.66	0.04	5.44^c	0.003	31.39	31.34	0.03
	4hr	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

Notes; the table presents parameter estimates and inference from the following model;

$$F(k)_{i,t+1} = \alpha(k)_{i,t} + \sum_{j=1}^{J} \beta(k)_{j,i,t} \Delta P(k)_{i,t-j+1} + \sum_{m=1}^{M} \gamma(k)_{m,i,t} F(k)_{i,t-m+1} + \varepsilon_{i,t+1}$$

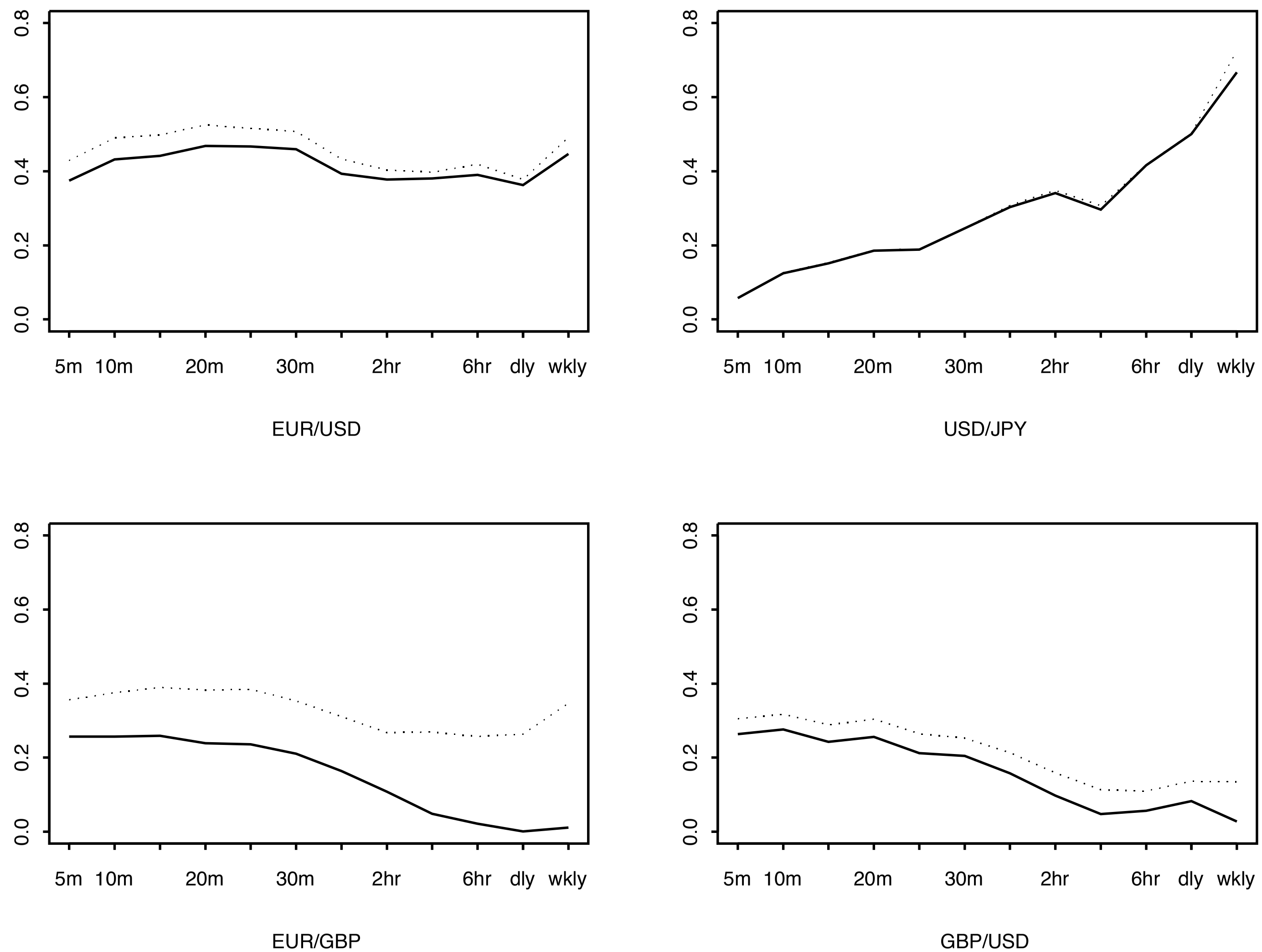
where $\Delta P(k)_{i,t}$ is price change at sampling frequency k for exchange rate i at time t and $F(k)_{i,t+1}$ is order flow for the same exchange rate and sampling frequency at time $t+1$. The columns under OF and RW give the forecast RMSEs of model (5) and a random walk model respectively and the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

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 models (1) and (2) 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.