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AN INVESTIGATION OF CUSTOMER ORDER FLOW IN THE FOREIGN EXCHANGE MARKET

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Abstract

This paper examines the effect that heterogeneous customer orders flows have on exchange rates by using a new propreitary dataset of weekly net order flow segmented by customer type across nine of the most liquid currency pairs. We make three contributions. First, we investigate the extent to which order flow can help to explain exchange rate movements over and above the influence of macroeconomic variables. Second, we look at the usefulness of order flow in forecasting exchange rate movements at longer horizons than those generally considered in the microstructure literature. Finally we address the question of whether the out-of-sample exchange rate forecasts generated by order flows can be employed profitably in the foreign exchange markets.

Keywords: Customer order flow; exchange rates; microstructure; forecasting

JEL Classification: F31; F41; G10

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1. Introduction

Currency markets are among the most liquid and economically important in the world but also, in terms of transaction information, among the most opaque. Over $1.9tn is traded on the foreign exchange (FX) market everyday according to the BIS[3], FX transactions facilitate international trade which, through the principle of comparative advantage, should be economically beneficial to all parties. The exchange-rate is therefore very important for an international economy. It impacts on international competitiveness, growth and inflation through its effect on both import and export prices.

Given their importance, currency markets have received a lot of interest in the academic literature. However, exchange rate determination and forecasting has remained something of an enigma ever since Meese and Rogoff's seminal 1983 paper. In fact the so called "macro approach" (see Lyons, 2002) based on traditional exchange rate determination models has failed empirically.

The failure of traditional empirical models has generated a body of research, led by Martin Evans and Richard Lyons, to identify micro-determinants of the exchange rates (i.e. order flows). This work aims to examine the micro-structure of the FX market to see if it has a better record in explaining and forecasting exchange rate movements. Evans and Lyons (2002) assert that order flow, that is, the detail on the size, direction and initiator of transactions, does have significant explanatory power on exchange rates, at least at a high-frequency, intraday or daily level. The main conclusion of this research is that the FX market may act as an aggregator of information regarding the expectations and circumstances of the participants, and order flow is the signal (i.e. can be viewed as a random variable acting as a mapping of disperse information in the economy into price discovery). Moreover, due to the nature of how this private signal is revealed, inferred from trades in the inter-dealer market, the effect on the spot price should not be transient and should improve the forecastability of exchange rates. Of course one would expect a lag[4] between

[3] Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in April 2004 Bank of International Settlements – March 2005

[4] Sometimes it may take few days until when the order flow information are revealed to the markets. See discussion in Rime *et al* (2009).

the time when the information contained in the order flow is formed and when it is fully revealed to the market[5].

The objective of this paper is to explore and test some of these micro-structural relationships and examine their significance using weekly exchange rates and order flows. Specifically, it looks at customer order flow (a great majority of the present micro-structure literature has focused on inter-dealer or brokered markets). The reason for this focus is that customer order flow is the active side of the trade; the FX market is decentralized with market-makers who quote prices to a wide variety of customers. They then use the brokered market to adjust their inventory to the required level[6] amongst themselves (thus adding "hot-potato effects" which greatly increase the total volume traded). Customer order flow can therefore be viewed as the 'source' of a lot of the transactions conducted in the inter-broker market. By definition all order flow must sum to zero, if we accept that dealers do not carry large inventory positions (see Bjønnes and Rime (2005) for evidence supporting this), therefore if there is a long term impact on FX rates, this must be due to a differential information content of individual orders, dependent on the (perceived) information of the person trading, the reason and size of the trade.

The paper therefore examines the effect that heterogeneous customer orders (and the information contained in them) may have on exchange rates by using a unique proprietary dataset of weekly net order flow segmented by customer type across nine of the most liquid currency pairs over a six-year period. This is the larget order flow dataset ever used in the literarure.

If order flow does indeed assist in the information transmission of heterogeneous agents' expectations, there should be differential information signals from each customer segment. Presumably the motivation for trading of a large corporation will be very different from that of a leveraged hedge fund and therefore the information transmitted by the order should have a different impact on spot rates. Therefore we are interested in three separate issues. The first major issue follows from the previous literature and try to address the usefulness of order flow as a conduit through which private information becomes embedded within market prices. This involves an investigation of the extent to which order flow can help to explain exchange rate movements over and above the influence of macroeconomic variables. The second issue

[5] This may also be a reason why some studies using daily order flows find little evidence of (days) out of sample forecasts for exchange rates returns. In fact it is not a coincidence that, for example, studies like Evans and Lyons (2007) report strong out-of sample forecastability power at one to three weeks horizons.

addresses the usefulness of order flow in forecasting exchange rates. Given our span of data we are able to shed some light on whether order flows are useful in forecasting exchange rate movements at longer horizons (one and two weeks ahead) than those generally considered in the microstructure literature[7]. Finally we address the question of whether order flow could be used to generate forecasts that can be employed profitably in the FX market (this approach is similar to that taken recently by Rime *et al* (2009)).

The paper is organised as follows. Section 2 provides a review of the main literature on the microstructure approach to exchange rates. Section 3 describes our dataset of customer order flows and of the other macro variables. Sections 4, 5 and 6 present the empirical results on the estimates and forecasting performance of the model with aggregate and disaggregate order flows. Section 7 examines the profitability of exchange rate forecasts from the order flow model via a simulating trading astrategy. The final section summarises the main empirical findings.

2. Microstructure Models

Given the failure of traditional economic fundamentals-based models in explaining and forecasting exchange rate movements, it is unsurprising that researchers began to look in other directions. One direction was to look at the underlying microstructure of the FX market in search of answers – the FX market is structured differently from the centralised exchanges of, for example, stock and financial derivative markets. This may have important effects for price discovery and movement. Part of the literature, following Scheifer (2000), has focused on the presence of noise and chartist traders as the principal agents causing distortions in the Forex market. Menkhoff and Taylor (2007) being the most recent example. However, the most fruitful avenue of investigation in this area has probably came from the work of Lyons (1997) and (2001) on order-flow.

The underlying model postulates that what is important to market-makers and FX brokers who, after all, set the price at which we all transact is the order-flows that they receive. By examining price-by-price movements Lyons (1997) and (2001) found some support for the explanatory

[6] All the evidence suggests that the typical dealer holds positions for a very short half-life (10 minutes) and does not carry significant overnight inventory (see Lyons, 1998).

[7] Obviously hedge funds may not be interested in forecasting exchange rates at one or two week horizons as we do in this study. However pension funds and asset management companies in general are interested at these horizons. Central banks may be interested even in longer horizons than one or two weeks.

power and persistence of these order-flows. For example in a regression of changes in the spot exchange rate against interest-rate differentials, used as a proxy for all macro information, and order-flow he finds highly significant parameters for order-flow and a high explanatory R^2 (t-statistics of 10.5 and 6.3 and R^2 0.64 and 0.45 for both DM/$ and Yen/$) compared with insignificant coefficients for interest rate differentials. The rationale for focusing on order flows being that by using the order flow, market participants are actually getting an accurate distillation of market expectations in aggregated form. This is actual, instant, money-backed expectations not those gained from collecting survey evidence.

To better understand this premise we need to understand more about institutional setting of the FX market. Therefore in what follows we briefly describe the way transactions in the FX market occur.

2.1. The Forex Market

There is no centralised exchange or regulatory authority for trading foreign exchange, trading is conducted via different channels depending on the participant. This gives rise to some unique features and makes it difficult to classify the market into a strict auction or quote based model.

There are multiple dealers for each currency pair, indicative quotes are posted on various platforms (most notably Reuters FXFX and EBS) but for a firm price the customer must contact the dealer directly. Once orders are executed there is no regulatory obligation to publish that a trade has been agreed or its respective price. This makes the FOREX market less transparent than, for example, the equity markets, where dealers are obligated to publish the details of trades almost as soon as they occur (although large trades can be delayed). In addition order books are held by individual brokers so there is little transparency regarding the depth of a particular market or currency pair.

In the FX market there is considerable trading between the dealers themselves[8], this is generally for inventory control of positions and risk after an imbalance is created by a customer trade. This can be done directly by calling another broker in the same way a customer would or indirectly via an electronic broker. These electronic brokers serve only to post anonymous quotes from other dealers, once a deal is agreed both counterparties are released the details so they can effect the

[8] The BIS tri-ennial survey estimates 53% of trades are between reporting dealers down from 64% in 1998. The explanation for the decline being a consolidation of FX traders and growth of electronic brokers.

trade. All dealers can see limited details on these trades, the rate and if the trade was a buy (paid) or a sell (given) but no amounts.

This channel, which has seen significant growth (spot trading using EBS is up 45% from their 2003 number according to a Financial Times (2007) article), works to provide some centralisation in the FX markets with more of a limit-order auction setting rather than the multiple dealer model that clients trade with. Any model would need to attempt to capture both aspects of the foreign exchange market.

Given these preliminaries on the institutional aspects of the FX market we shall present below some of the models that attempt to capture the microstructure of the market.

2.2 Microstructure Models: a Selective Literature Review

Microstructure models can be split into 2 broad categories – those focusing on order-driven auction type markets and the ones focusing on quote-driven dealer markets. The model developed in Kyle (1985) belongs to the former class of models. This model involves one risky asset traded over a single period. The participants are one market-maker or auctioneer, who acts as the price setter, an informed trader with knowledge of future prices (v with mean p and variance σ_v^2) and many uniformed traders who trade randomly with no directional bias (variable u with mean 0 variance σ_u^2). All traders give their orders to the market-maker simultaneously, precluding strategic conditioning on the "noise" trades by the informed trader, who sets the execution prices based on the aggregate trades (he is unable to discern informed from noise trades).

In equilibrium traders will maximise their expected return (they are risk-neutral) and the market is efficient (in the sense that the market-maker must not earn excess return or others will be attracted to compete). The informed trader` order flow (X) function and price (P) can be written as

$$X = \hat{a}(v - p) \qquad (1)$$

$$P = p + e(X + u) \qquad (2)$$

where $a = (\sigma_u^2 / \sigma_v^2)^{\frac{1}{2}}$, and $e = (\sigma_u^2 / \sigma_v^2)^{-\frac{1}{2}}$

Equilibrium is determined by the ratio of the variance of the noisy traders and the informed trader's information. If σ_v^2 is high the auctioneer must protect himself against the possibility that the informed trader has substantial information (although the informed trader is less sure of the value). On the other hand if σ_u^2 is high then the trader can put his positions on without moving the market price rapidly against him. In this sense $1/e$ measures the "depth" of the market defined by Kyle as the size of a trade that is required to change prices by a given amount.

Kyle then extends the model firstly to multiple periods and then to discuss the general results in continuous time. The general result is that an informed trader will gradually trade based on his information over several periods to maximise profits. Information is therefore gradually incorporated into price. This is a different result than standard economics or rational expectations equilibrium models would suggest: where market prices will jump to the new fair value and does not even require trading for this move to be effected.

Whilst the model captures some of the insights related to order-flow, particularly its gradual incorporation into pricing and the strategic nature of client-dealer interactions, a number of assumptions are too simple for the FX market. Market-maker risk neutrality and the simultaneity of the trading process in particular are too stylistic. Empirical evidence (see Bjønnes and Rime (2005)) on market-makers suggest that inventories are kept low and managed closely and the level of inter-dealer trading (although declining in recent years – see BIS (2007) survey) adds support that these assumptions are probably violated..

Lyons (1997) presents a more detailed model specific to current FX markets with the aim of capturing some of the specific institutional features of the market. Strategic behaviour and risk aversion in market-makers play important interacting roles with private customer flow. The model assumes constant risk aversion using a negative utility function for dealers and asset returns that are distributed normally. This leads to preferences that can be defined by just mean and variance of wealth, and asset demand that is a linear function of its return and variance (in the one risky asset case).

In this model dealers initially receive a public signal, S (macro announcement), a private signal, S_i (customer trading motives for example). They then provide a quote to the market P_{1i}

on which customers trade C_i, dealers then trade amongst themselves to hedge positions to desired target T_{i1}, this net orderflow is revealed to the market as a whole, X. In the 2nd period dealers again provide a quote P_{i2} receive trades from each other T_{i2} before the payoff V is realised. The dealer's task is then to maximise their utility:

$$\max E(-\exp(-eW_{i2} \mid U_i)) \tag{3}$$

$$\begin{aligned} s.t W_{i2} &= W_{i0} + C_i(P_{i1} - P_{i1}^{'}) + (D_{i1} + E(T_{i1}^{'} \mid U_{i1})(P_{i2}^{'} - P_{i1}^{'}) + \\ &+ (D_{i2} + E(T_{i2}^{'} \mid U_{i2})(V - P_{i2}^{'}) - T_i^{'} E(P_{i2}^{'} - P_{i1}) - T_{i2}^{'}(V - P_{i2}) \end{aligned} \tag{4}$$

where W_{i2} is the end of period wealth of the dealer i and U the information set.

Under the assumptions of this model all dealers quotes must be the same in each period (otherwise there would be irrational arbitrage opportunities), the consequence of this is that quotes will be linear functions of the common information (S and X for period 2). The optimal trading strategy is therefore also a linear function:

$$T_{i2} = a_1 C_i + a_2 S_i + a_3 S + a_4 T_{i1}^{'} + a_5 X + a_6 P_2 \tag{5}$$

Period 1 equation has the same 1st three terms (albeit with different a coefficients) and a final term reflecting P_1.

One of the assumptions of this model is that, as there is no bid-ask spreads and quotes are the same for any size, all dealers prices, to avoid arbitrage, must be identical. This leads to a quoting strategy that is based only on the public information (S in the 1st period and S and X in the 2nd). In addition dealers extract and take speculative positions based on their private customer order information (knowing that executing them will produce some positive impact) this actually distorts and reduces the information transmission to the market as a whole as dealers behave strategically. Unanticipated inventory imbalances also lead to inter-dealing activity that is a stylised fact of the FX market today. Risk averse traders move these imbalances between themselves until they find the dealer who neutralises (or wishes to have) the position.

A number of these assumptions may be too strong, not least there is no modelling of the broker market (where traders deal between themselves but through a 3rd party to preserve confidentially) which is not captured and may have significant implications. However, the Lyons model does seem to capture effects seen in some of the empirical studies:

Sapp (2002) shows that certain banks are price leaders in the sense that their quotes incorporate information before others (Deutsche Bank and Chemical) and so act in effect as price leaders. This result also receives support from other empirical works such as Peiers (1997) who, when examining causality around Bundesbank interventions, finds that Deutsche Bank is a price leader. Therefore private information seems to be very relevant in these models. However if private information exists in the FOREX market, how is it revealed and incorporated into market prices?

Several studies seem to indicate that there are information asymmetries in the FX market and therefore order flow can potentially be informative. Probably one of the most important contributions in this context comes from Lyons (1995). Lyons (1995) using a dataset of market-maker and broker quotes and positions found a significant and correctly signed information role in incoming customer order flow even allowing for inventory effects. This was largely confirmed by Bjønnes and Rime (2005) who also find that inventory control is typically tight. Anderson and Bollerslev's (1998) study in DM-$ volatility finds evidence of consistent daily activity patterns and elevated trading and volatility for several hours after macroeconomic announcements which at least implies that there is clustered informed trading and learning.

Ito *et al* (1998) find that volatility doubles after trading is introduced in the lunch hour. In the absence of any public information (and the announcement of public information remained unchanged) it is likely that this increase in volatility was due to customer order flow and therefore at least to some extent it must have some informative content. Boehmer and Wu (2007) using propriety data on NYSE find institutional order imbalances to have a greater effect on stocks where information is likely to be more important (for example those with high R&D expenditure) and have explanatory power to predict next day returns.

It seems that the information from orders is gradually impounded into the price and not the instantaneous price adjustment process that would be the case under the efficient market hypothesis. Copeland and Friedman (1991) also confirm this phenomenon with some interesting investigations. They create computerised experimental markets where subjects trade and are given varying levels of both public and private information. The evolution of prices was consistent with a partially revealing equilibrium.

More recent work has focused on order flow as containing information on "fundamentals" that is more timely than the data releases – this would at least partially explain the Meese-Rogoff anomaly – once the official data is released it has mostly been impounded into prices by previous indicators (for example a corporate client might convert their export sales into their home currency well before any current account data is collated and released officially). Evans and Lyons (2007) develop a general equilibrium model based on the assumption that dealers will adjust their view of fundamentals and therefore their quotes, on the basis of the signals received from customer order flow. As it takes time for the customer order flow to be fully revealed to the market there should then be some forecasting power not just for the exchange rate but also for the macro fundamentals. Evans and Lyons (2007) find using proprietary Citibank customer flow that it does help to forecast both the spot rates and fundamentals (price level, growth and money supply), moreover, as the forecast horizon increases to 4 weeks the improvements are more significant. This result suggests customer order flow may be informative on two levels. Not just, as perhaps implicitly assumed in earlier studies, as a guide to evolving investor preferences and changes in their discount rates, but also as a real-time aggregator of expectations of and changes in macroeconomic fundamentals.

Evans and Lyons (2005) look at disaggregated data over an extended period but only for one currency pair EUR/USD. The results reported show the disaggregated model (by user type and also location (non-US or US)) improves forecastability but they do not mention anything about the characteristics of each end user segment.

Given the body of work above it appears that order flow does have some role to play as an aggregator of heterogeneous expectations or transactors and potentially there is a delay in this being impounded into price.

3. The Dataset

The dataset used in this study consists of a unique propreitary order flow from UBS[9], weekly nominal exchange rates and a set of macro economic and financial variables spanning the period 02.11.01 to 23.11.07. To the best of our knowledge it is the largest dataset ever used in the literature. The data is unique in that it is a proprietary dataset from one of the largest market makers in the FX markets (>10% daily FX volume). The data is aggregated across currency pairs

[9] Currencies (order flows) considered are Canadian Dollar (CAD), Swiss Frank (CHF), Euro (EUR), Australian Dollar (AUD), New Zealand Dollar (NZD), UK Pound (GBP), Japanese Yen (JPY), Norwegian Krone (NOK) and Swedish Krone (SEK).

at a weekly frequency, going back to 2001 and with customers split into 4 classifications: "real" money (asset managers), leveraged (hedge funds), corporate and private clients.

The aggregation proceeds as follows. Each traded booked in the bank's execution system is tagged with a client type. The sum of all such trades between Singapore Monday and New York Friday close are aggregated and extracted from the database. The data is in billions of US dollars of order flow and is windsorised to 3 standard deviations so large M&A transactions (which are pre-announced months or weeks in advance) do not skew the data. Cross-border merger and acquisition deals involve large purchases of foreign currency by the acquiring company to pay any cash portion of the deal. Although they involve large amounts they are usually well-published so market participants are already aware of and have adjusted to the flow. The dataset is therefore constrained so net flow is a maximum of 3 standard deviations from the average.

This dataset is unique from the current literature for several reasons. Firstly most empirical studies have focused on the inter-dealer market where, it is hypothesised, that dealers trading with each other gradually reveal their customer orders to the market (inducing much increased volume by hot potato trading). This inter-dealer data is signed order flow (i.e. the direction of the initiator is known). However in the majority of studies it is just the direction and not the Dollar $ amount of the trade (see for example Rime *et al* (2009) or Evans and Lyons (2002)). On the other hand our data set is not partially revealed to the market (as happens with commercially available ones such as EBS) but proprietary. Secondly our data set consists of raw data with little (albeit still some) filtering , in contrast to Sager and Taylor (2008) , and many others who use filtered indices. Thirdly we use disaggregate data divided according to respective clients (asset managers, corporate clients, hedge funds, private clients). Finally, it covers 6 years from November 2001 to November 2007 and nine currency pairs, while most customer data sets have been either for a relatively short period of time (Carpenter and Wang 2003) or for only one currency pair (Fan and Lyons (2000), Evans and Lyons (2005).

All rates are foreign currency per US dollar (from Bloomberg 16:00GMT mid prices)) and order flow is also transformed to reflect this – i.e. a positive coefficient indicates dollar buying (foreign currency selling) and therefore the rate will increase as the foreign currency weakens. All FX rates are transformed for comparability purposes into foreign currency per US$ so a decline in this rate represents a strengthening of the foreign currency relative to the US dollar. Macro fundamentals are obtained from the OECD database. When estimating the regressions we transform the data into logarithms. For consistency purposes the term “foreign currency” will be used for anything that is not the US dollar for the remainder of this paper.

Table 1 below shows descriptive statistics for order flow (aggregated by all customer segments to conserve space).

Table 1. Summary statistics for order flow

	CAD	CHF	EUR	AUD	NZD	GBP	NOK	SEK	JPY
Mean	-0.0690	-0.5761	1.0746	-0.0288	0.0654	0.0927	0.0325	-0.0515	-1.0059
Median	-0.1257	-0.2468	0.8798	0.0440	0.0426	0.0601	0.0073	-0.0769	-0.8296
Maximum	1.5565	2.9885	10.0474	1.6584	0.9571	2.9609	1.0420	1.4908	3.1537
Minimum	-1.3557	-8.7598	-7.4539	-2.0469	-0.5143	-10.7172	-0.6151	-0.7927	-7.0637
Std. Dev.	0.5105	1.8724	3.1312	0.6865	0.2250	1.7935	0.2268	0.3272	1.7608
Skewness	0.4718	-1.4832	0.1069	-0.4735	1.0910	-3.0112	1.0044	1.8302	-0.6881
Kurtosis	3.6189	7.2033	3.6874	4.1095	7.2928	19.7537	9.1330	9.9338	4.7383
Jarque-Bera	3.7672	78.2976	1.5330	6.2947	68.6032	937.6594	123.2119	181.8651	14.5422
Probability	0.1520	0.0000	0.4646	0.0430	0.0000	0.0000	0.0000	0.0000	0.0007
Sum	-4.8962	-40.9015	76.2946	-2.0474	4.6459	6.5814	2.3049	-3.6586	-71.4179
Sum Sq. Dev.	18.2428	245.4000	686.2961	32.9867	3.5425	225.1667	3.5996	7.4943	217.0321
Observations	71	71	71	71	71	71	71	71	71

We can see that the EUR and the JPY have the biggest net order flow imbalances, and by far the biggest overall volume. SEK, NOK and NZD have appreciably smaller volumes. The EUR is the only order flow that could be characterised as normal. The ADF stationarity tests, not reported to save space, confirm that orderflow is I(0) stationary.

Correlations for order flow are shown in Table 2. Although CHF and EUR and GBP and SEK show negative correlation and AUD and SEK show a positive correlation, there are no distinct patterns except perhaps that GBP and JPY order flow seems to move inversely with most other currencies.

Table 2. Correlation coefficients for order flow

	CAD	CHF	EUR	AUD	NZD	GBP	NOK	SEK	JPY
CAD	1	0.13	0	0.09	0.02	0.07	0.19	0.05	0.03
CHF		1	0.54	0.09	0.03	0.2	0.13	0.31	0.3
EUR			1	0.05	0.1	0.24	0.03	0.02	0.24
AUD				1	0.09	0.18	0.08	0.41	0
NZD					1	0.15	0.12	0.14	0.28
GBP						1	0.14	0.46	0.31
NOK							1	0.11	0.24
SEK								1	0.2
JPY									1

We now consider the exchange rates. Stationarity tests, not reported to save space, confirm the empirical result that has been accepted since Meese and Singleton (1982) that exchange rates are I(1) non-stationary processes. Non-stationarity is dealt with by log differencing of rates. We next look at the statistics of the log differenced exchange rates in Table 3.

Table 3. Summary statistics for exchange rate changes

	ΔCAD	ΔCHF	ΔEUR	ΔAUD	ΔNZD	ΔGBP	ΔNOK	ΔSEK	ΔJPY
Mean	-0.0065	-0.0049	-0.0066	-0.0076	-0.0085	-0.0051	-0.0071	-0.0072	-0.0010
Median	-0.0081	-0.0011	-0.0047	-0.0096	-0.0110	-0.0039	-0.0094	-0.0094	-0.0009
Maximum	0.0460	0.0437	0.0449	0.0559	0.0972	0.0471	0.0770	0.0514	0.0655
Minimum	-0.0575	-0.0716	-0.0618	-0.0820	-0.0785	-0.0534	-0.0736	-0.0763	-0.0472
Std. Dev.	0.0218	0.0259	0.0238	0.0269	0.0313	0.0216	0.0305	0.0297	0.0231
Skewness	0.2848	-0.4032	-0.2890	-0.0071	0.7743	0.1117	-0.0475	-0.1559	0.2664
Kurtosis	2.8941	2.7186	2.7402	2.8803	4.3131	2.6364	2.8946	2.3973	3.0188
Jarque-Bera	0.9789	2.1274	1.1714	0.0424	12.0229	0.5312	0.0588	1.3429	0.8292
Probability	0.6130	0.3452	0.5567	0.9790	0.0025	0.7667	0.9710	0.5110	0.6606
Sum	-0.4567	-0.3409	-0.4628	-0.5305	-0.5959	-0.359	-0.5	-0.501	-0.0706
Sum Sq. Dev.	0.03273	0.04616	0.03921	0.04997	0.06752	0.03214	0.06418	0.06087	0.03692
Observations	70	70	70	70	70	70	70	70	70

We notice that the average monthly return for the sample period shows an appreciation in the foreign currency with similar orders of standard deviation and in most cases we cannot reject the hypothesis that the returns are normally distributed (NZD being the notable exception).

Correlations between exchange rate changes are reported in Table 4 below.

Table 4. Correlation between exchange rate changes

	ΔCAD	ΔCHF	ΔEUR	ΔAUD	ΔNZD	ΔGBP	ΔNOK	ΔSEK	ΔJPY
ΔCAD	1	0.3	0.38	0.57	0.42	0.19	0.28	0.38	0.28
ΔCHF		1	0.95	0.45	0.47	0.74	0.83	0.85	0.6
ΔEUR			1	0.56	0.51	0.76	0.83	0.91	0.53
ΔAUD				1	0.78	0.48	0.41	0.58	0.37
ΔNZD					1	0.49	0.35	0.53	0.23
ΔGBP						1	0.57	0.66	0.39
ΔNOK							1	0.81	0.46
ΔSEK								1	0.41
ΔJPY									1

4. Aggregate Order Flow Model and Macroeconomic Variables

As discussed in Lyons (2002), if on the one hand foreign exchange models using the so called public information (i.e. money demand, interest rates changes, etc…) approach have failed empirically (see for example Meese and Rogoff, 1983 amongst the others), on the other hand micro-models have enjoyed some success. A variable that plays an important role in the micro-model approach is order flow. One can therefore view the order flow as a transmission mechanism that links heterogeneous beliefs in the market with price discovery. Therefore Lyons suggests using what he defines as a "hybrid model", namely a model which establishes a link between macro and micro models. In this section we follow this approach. We use the traditional sticky-price monetary model, estimated in first differences to avoid stationarity issues and spurious regressions, in a similar specification as in Lyons (2002) and Evans and Lyons (2002):

$$\Delta s_t = \beta_0 + \beta_1 \Delta(m_t - m_t^*) + \beta_2 \Delta(y_t - y_t^*) + \beta_3 \Delta(i_t - i_t^*) + \beta_4 \Delta(\pi_t - \pi_t^*) + \beta_5 X_{tot} + u_t \quad (6)$$

where X is the total period order flow across customer segments, s_t is the logarithm of the exchange rate, $m_t - m_t^*$ is the logarithm of relative money supply, $y_t - y_t^*$ is the logarithm of relative output, $i_t - i_t^*$ is the short term interest rate differential, $\pi_t - \pi_t^*$ is the long term interest rate differential (measured by the CPI inflation rate), and Δ is the first difference operator.

Equation (6) was estimated using the OLS method and monthly data (since data on macroeconomic variables are not available on higher frequency). Other currency pair order flows were also included to understand possible interrelationships between currencies, for example if Euro (EUR) demand leads to Swiss Frank (CHF) appreciation. This is achieved by amending the last term of the equation by $\sum_{i=1}^{n} \beta_{5i} X_{tot(i)}$ for each currency pair. Where currencies are strongly correlated with one another (e.g. NOK, SEK and CHF) they were only included in regressions with EUR currency pair due to the high degree of correlation[10].

It should be noted that the model assumes that order flow and macro variables are determined exogenously from the exchange rate and causality runs strictly to price. See Killeen *et al* (2006) for empirical studies showing that order flow Granger causes returns but not the other way. This approach also follows Chinn and Meese (1995) and Cheung *et al* (2002).

All rates are foreign currency per US dollar and order flow is also transformed to reflect this[11] – i.e. a positive coefficient indicates dollar buying (foreign currency selling) and therefore the rate will increase as the foreign currency weakens – it takes more of the currency to buy 1 US$. In terms of parameter signs therefore ex ante we would expect positive coefficients on own order flow. This applies to all the estimates reported in the next sections. The macroeconomic variables also go into the model on a relative basis i.e. as differences versus its US counterpart as showed in the equation above.

In the above hybrid model, an increase in money supply relative to the US would lead to a depreciation (i.e. positive change in rate and coefficient), and an increase in income a negative change (appreciation). Since the price level and money supply move exactly together in the monetary model, increases in relative CPI inflation would lead to a weakening of the currency (i.e. depreciation, therefore positive coefficient) whereas interest rate increases are postulated to lead to strengthening the relative attractiveness of a currency and therefore a negative coefficient. Table 5 shows the estimates of model (6).

[10] This is done for reasons of parsimony.

[11] In FX markets convention varies for currency pair e.g. Euro's are quoted EURUSD as dollars per EUR whereas C$ is number of CAD per US$. The order flow data also follows this convention so is transformed to enable comparability.

Table 5. OLS Estimates of model (6)

	CAD	CHF	EUR	AUD	NZD	GBP	NOK	SEK	JPY
C	-0.0087	-0.0054	-0.0064	-0.0083	-0.0087	-0.0094	-0.0093	-0.0110	0.0014
	-2.64*	-1.43	-1.63	**-2.19***	**-1.99***	**-2.42***	-1.61	**-2.48***	0.36
OWN FLOW	-0.0002	0.0019	0.0029	0.0077	0.0449	0.0029	-0.0071	-0.0052	0.0034
	-0.04	0.91	**2.65***	**1.71***	**2.63***	**1.82***	-0.40	-0.41	**1.84***
CAD FLOW			0.0117	0.0000	0.0001	0.0034	0.0106	0.0106	1.3961
			2.14*	-0.01	0.01	0.62	1.41	1.55	1.84
AUD FLOW	-0.0003	-0.0039	-0.0022		0.0026	0.0005	-0.0026	-0.0023	0.0000
	-0.08	-0.85	-0.51		0.49	0.13	-0.47	-0.41	-0.01
EUR FLOW	0.0001	0.0030		0.0014	0.0005	0.0017	0.0013	0.0024	0.0012
	0.11	**2.53***		1.35	0.45	**1.87***	1.01	**2.13***	1.31
GBP FLOW	-0.0004	0.0006	-0.0003	0.0014	0.0040		0.0012	0.0004	0.0005
	-0.27	0.30	-0.17	0.76	1.37		0.52	0.18	0.27
JPY FLOW	0.0021	0.0025	0.0018	0.0045	0.0055	0.0004		0.0018	
	1.38	1.21	1.00	**2.33***	**2.54***	0.26		0.80	
NZD FLOW	0.0157	-0.0073	-0.0026	0.0300		0.0051	-0.0017	0.0133	-0.0122
	1.38	-0.51	-0.19	**1.94***		0.41	-0.10	0.83	-0.90
CHF FLOW			0.0033						
			1.75*						
CPI	0.5421	-1.6828	-1.8518	0.7533	-0.0678	-0.3336	-1.4432	-1.8465	-0.7731
	0.62	**-2.36***	**-2.1***	0.85	-0.08	-0.50	-1.52	**-2.38***	-0.85
LIBOR	-0.0739	0.0421	0.0431	-0.1523	-0.1587	-0.0982	-0.0479	-0.0570	0.0044
	-1.68*	1.46	0.75	**-2.62***	**-2.28***	**-2.08***	-0.77	-1.08	0.24
M1	0.8422	0.1382	0.2503	-0.1076	-0.0177	0.3062	0.0897	0.1561	-0.2214
	2.57*	0.76	0.71	-0.53	-0.07	0.60	0.22	0.77	-1.04
GDP	1.1579	0.0166	0.1096	0.8544	-0.3030	-0.4325	0.7142	0.1727	-0.1517
	1.91*	0.05	0.41	1.61	-0.90	-1.17	1.63	0.82	-0.62
Adj R2	0.16	0.12	0.13	0.15	0.18	0.03	0.04	0.15	0.00

Note: CAD is the Canadian dollar, CHF the Swiss Frank, EUR the Euro, AUD the Australian dollar, GBP the British pound, JPY the Japanese Yen, NZD the New Zealand Dollar, NOK the Norwegian Krone and SEK the Swedish Krona. CPI (consumer price) is the inflation rate differential, LIBOR is the London interbank rate (used for the short term interests rate) differential, M1 is relative money supply and GDP is relative real gross domestic product.
R-squared is the adjusted R-square and values below the coefficients are t-statistics based on Newey-West standard errors. *,**,*** indicate significance levels at 1%, 5%, 10% respectively.

The results in Table 5 show that trends are important in currency markets with all currencies except the Yen strengthening against the US$ over the period. Five out of the nine coefficients are significant at the 10% level (four at 5%). Own order flow is also significant with five currencies being correctly signed and holding significant coefficients. As expected CHF and SEK exchange rates, which are highly correlated with the euro, show to be significantly affected by the EUR order flow. The Yen order flow is also significant in explaining AUD and NZD currencies move and NZD flow significant to explain AUD exchange rate changes. These empirical results may provide evidence that regions may matter in FX markets. All significant coefficients are correctly signed; foreign currency buying leads to appreciation. In order to understand how to interpret some of these results, note, for example, that buying $1bn of a currency leads, in general, to a 30 – 70 basis point move in exchange rates with the exception of the New Zealand dollar where the impact is much greater. This may be due to the fact the NZD is a lot less liquid than other currencies. These results are in line with those reported by Lyons (2002) and Bjønnes and Rime (2005) (although for the interdealer market and using daily data).

Let us now look at the macro factors. As we can see the picture now is much less clear with CPI inflation differential being significant for the Euro region and incorrectly signed in nearly all other cases. LIBOR rate differentials are significant and correctly signed for four of the nine equations. M1 and GDP growth do not seem to have much explanatory value with only the Canadian dollar showing significance even at the 10% level and inconsistently signed. Therefore macro variables do not seem to play a predominate role in explaining exchange rates changes. In the next section we follow the prevalent literature and use interest rates differential as a proxy for macro economic variables.

5. Aggregate Order Flow Model with Interest Rate Differential

In this section, we follow Sager and Taylor (2008) and Evans and Lyons (2002) to investigate the relationship between order flows and changes in the exchange rate by proxying the macro-variables with the interest rate differentials which are available on a weekly frequency. We start considering aggregate order flows. The main objective is to see if (aggregate) order flow can explain the behaviour of weekly exchange rates. We start with a standard regression (with no publication lag-contemporaneous variables) as in Evans and Lyons (2002):

$$\Delta s = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \varepsilon_t \tag{7}$$

where Δs_t is the weekly change of the log of the exchange rate from 4pm GMT on day $t-1$, on the exchange rate at the same time next day (i.e. day t). We use the interest rate (i.e. LIBOR rate) differerntial for the same period as a proxy for economic fundamentals[12]. Results using OLS (Newey-West) are reported in Table 6.

Table 6. Estimates of model (7): Contemporaneous order flows-aggregate data

	β_0	Flow	LIBOR	R-squared
EUR	-0.02	0.001	-0.031	0.04
	3.11*	**2.11****	**-2.66***	
JPN	-0.001	0.004	-0.020	0.07
	0.68	**4.48***	-1.11	
GBP	-0.001	0.002	-0.034	0.05
	-1.92***	**2.5****	**-1.74*****	
CHF	-0.001	0.0005	-0.009	0.004
	-1.71***	0.65	-0.61	
AUD	-0.002	0.012	-0.035	0.09
	-2.31**	**3.57***	-1.52	
CAD	-0.002	0.005	-0.054	0.07
	-2.74*	**2.10****	**-4.61***	
NOK	-0.002	0.016	-0.036	0.06
	-2.76*	**2.75***	**-3.00***	
SEK	-0.002	-0.001	-0.042	0.03
	-2.60*	**-0.24**	**-3.25***	
NZD	-0.002	0.041	-0.026	0.10
	-3.17	**3.40***	-1.05	

Note: Flow is the order flow, R-squared is the adjusted R-square and values below coefficients are t-statistics based on Newey-West standard errors.. *,**,*** indicate significance levels at 1%, 5%, 10% respectively.

Order flow appears to be significant in seven currencies out of the nine considered, and correctly signed in eight cases. The interest rate differential is significant only in five cases. The adjusted R-squared are much smaller than the ones reported in Evans and Lyons (2002) but in line with

[12] Note that we have inserted an intercept in the model. The reason for that is threefold. Firstly the intercept may capture the trend in the currency in relation to the numeraire US Dollar. Secondly, one may reasonably impose an intercept equal to zero if one imposes that all dealers in the market have zero inventories. This would imply that all customers flow would sum up to zero. Finally the intercept in the model may reasonably set equal to zero if one assumes that the order flow data we have characterizes the market as a whole. Although UBS is the largest primary broker such assumption seems to be a bit restrictive.

other studies such as Evans and Lyons (2005), Marsh and Rourke (2004) and Sager and Taylor (2008).

As discussed in Sager and Taylor (2008), regression in (7) may be spurious in the sense that it implies perfect predictability of order flow and interest rates differential. Therefore we also present our empirical results by replacing it with an alternative regression which considers publication lag (i.e. lags of variables)

$$\Delta s = \beta_0 + \beta_1 \Delta(i_{t-1} - i^*_{t-1}) + \beta_2 X_{t-1} + \varepsilon_t \tag{8}$$

The empirical results are reported in Table 7 below.

Table 7. Estimates of model (8): Lagged order flows-aggregate data

	β_0	Flow	LIBOR	R-squared
EUR	-0.001	-0.001	0.013	0.014
	-1.77* **	**-3.34***	0.66	
JPN	-0.0003	0.001	0.006	-0.005
	-0.34	0.13	0.50	
GBP	-0.001	0.0002	-0.017	0.003
	-1.90* **	0.29	-1.81	
CHF	-0.001	0.001	-0.01	-0.002
	-1.68* **	0.83	-0.03	
AUD	-0.002	-0.264	-0.931	-0.005
	-2.18**	-0.93	-0.14	
CAD	-0.002	-0.264	-0.931	-0.005
	-2.58*	-0.93	-0.14	
NOK	-0.002	-0.002	-0.023	0.012
	-2.34**	-0.68	**-2.15****	
SEK	-0.002	-0.002	-0.014	-0.0002
	-2.31**	0.30	-1.02	
NZD	-0.002	0.005	-0.045	0.03
	-2.09**	0.40	**-2.78****	

Note: Flow is the order flow, R-squared is the adjusted R-square and values below coefficients are t-statistics based on Newey-West standard errors.. *,**,*** indicate significance levels at 1%, 5%, 10% respectively.

As noted in Sager and Taylor (2008), the estimated coefficients and R-squared now change drastically. The coefficient on lagged order flow is statistically insignificant in all cases but the Euro. This result may provide an answer to the question raised in Sager and Taylor (2008) on whether the main empirical evidence supporting the micro-model approach as in Lyons (2002), Evans and Lyons (2005) and Marsh and Rourke (2004) comes from using proprietary order flows data. The empirical results presented in this section seem to suggest instead that it is the modelling approach used in the literature that might be questionable.

5.1 Forecasting

Next we consider the forecasting power of the order flow with respect to the exchange rate changes[13]. We follow Sager and Taylor (2008) and employ the following limited information model to generate out-of-sample forecasts

$$\begin{aligned} \bar{s}_{t+k} - s_t &= \sum_{j=1}^{k} \bar{\Delta} s_{t+j} = \bar{\beta}_t \sum_{j=1}^{k} \Delta(i_t - i_t^*) + \bar{\beta}_2 \sum_{j=1}^{k} X_t \\ &= \bar{\beta}_1 k\Delta(i_t - i_t^*) + \bar{\beta}_2 kX_t \end{aligned} \tag{9}$$

We use this approach to overcome the assumption of perfect foresight implicitly with the recursive approach used in many studies (see for example Evans and Lyons (2002). This approach involves using current values of the explanatory variables to produce forecasts at the horizon $t + j$. We use the first 117 observations to estimate the parameters of the model, with the remaining periods retained for evaluating the out-of-sample forecasting performance. As a benchmark we use a simple drift less random walk.

We report one week and two weeks-ahead forecasts in Table 8. The results show that the order flow model produces lower forecast errors than the random walk for all the currencies. However

[13] Note in all our forecasts we do not conside system based estimations which have been found to carry superior forecast performance (see MacDonald and Marsh, 1997). We leave this issue, as well as, non-linearity and structural breaks on the agenda for future research.

the Diebold-Mariano statistics suggest that the differences between the forecast errors from the two competing models are not statistically significant[14].

Table 8: Out-of-sample forecasting performance using aggregate order flows

	k	(a) Random Walk	(b) Order flow model	(b)/(a)	Diebold-Mariano
EUR	1	1.1339	1.1218	0.9893	-0.8771
	2	1.6034	1.5934	0.9938	
JPN	1	1.3233	1.3233	1.0000	-0.00058
	2	1.8098	1.8068	0.9983	
GBP	1	1.1647	1.1589	0.9950	-0.2894
	2	1.6519	1.6515	0.9997	
CHF	1	1.2603	1.2520	0.9935	-0.4234
	2	1.7958	1.7887	0.9960	
AUD	1	1.4846	1.4702	0.9903	-0.4999
	2	2.1709	2.1577	0.9939	
CAD	1	1.0378	1.0273	0.9899	-0.7196
	2	1.5350	1.4796	0.9639	
NOK	1	1.4871	1.4786	0.9943	-0.9724
	2	2.0852	2.0826	0.9987	
SEK	1	1.3536	1.3398	0.9898	-0.7611
	2	1.9890	1.9837	0.9974	
NZD	1	1.7756	1.7459	0.9833	-1.0752
	2	2.4862	2.4846	0.9994	

Note: Columns (a) and (b) report the RMSFEs (root mean square forecast error) are multiplied by 100. The Diebold-Mariano (1995) statistic tests the null hypothesis of equal forecast accuracy between the two models (its 5% critical value is -1.96). k is the forecast horizon.

6. Disaggregate Order Flows

We now turn to disaggregate order flows and therefore break down the order flow into its constituent segments: Short-term (hedge funds), Long-term (Asset Managers), Corporate Clients and Private Clients. Therefore the following regression is now used

[14] We have also considered an AR(1) process. However results were identical and therefore not reported to save space.

$$\Delta s_t = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + u_t \qquad (10)$$

where the effect of the macroeconomic variables is embedded into the interest rate differential.

The aim now is to see how different client segments impacts on exchange rate changes and test how and if this information can improve on a random walk model. The results are reported in Table 9.

Table 9. Estimates of model (10): Contemporaneous order flows-disaggregate data

	C	CO	HF	PC	AM	LIBOR	R-squared
EUR	-0.0283 **-4.23***	0.0002 0.116	0.0032 **5.68***	-0.001 **-9.67***	0.0025 **4.99***	-0.019 -1.87	0.34
JPN	-0.001 -1.01	-0.013 **-3.20****	0.005 **3.49****	-0.023 **-7.99***	0.0034 **3.15****	-0.0027 -0.21	0.35
GBP	-0.0011 **2.12*****	0.0031 1.12	0.0045 **2.86****	-0.019 **-3.94***	0.0014 1.35	-0.020 -1.38	0.26
CHF	-0.0003 -0.45	-0.0043 -1.91	0.0050 **4.47***	-0.025 **-7.19***	0.0023 1.90	-0.012 -0.87	0.33
AUD	-0.0018 **-2.68****	-0.0050 -1.17	0.010 **2.00*****	-0.021 **-2.21*****	0.0201 **4.91***	-0.032 -1.56	0.17
CAD	-0.0011 **-2.18*****	0.0121 1.09	0.0034 1.37	0.0056 **-5.41***	0.0049 1.26	-0.048 **-4.44***	0.22
NOK	-0.0025 **-3.09****	-0.026 -0.89	0.023 **2.08*****	0.063 1.91	0.011 1.33	-0.039 **-2.98****	0.06
SEK	-0.0028 **-3.72****	-0.0453 **-2.27*****	0.0218 **2.50****	0.0290 0.82	-0.0045 -0.76	-0.044 **-3.68****	0.08
NZD	-0.0027 **-3.30****	0.0762 1.47	0.084 **5.97***	-0.077 **-3.32****	0.047 **6.15***	-0.0211 -1.06	0.20

Note: C is the intercept, CO denotes corporate clients, HF hedge funds, PC private client and AM asset managers. R-squared is the adjusted R-square and and values below coefficients are t-statistics based on Newey-West standard errors.. *,**,*** indicate significance levels at 1%, 5%, 10% respectively.

Once again order flows are significant in most cases, while the interest rate differential is significant only for three currencies (none of which is highly liquid). These results show that order flows are an important determinant of exchange rates and, moreover, different customer types do have different effects. The most important segment appears to be the hedge funds which are significant for eight out of nine currencies and display the correct sign. The private client sector is highly significant in seven of the nine currencies. However, net $ buying in this sector leads to a rate decline (a strengthening of the foreign currency vis a vis the US$), this is contrary to expectations as one would expect demand to exert upward pressure on a currency. These results are in line with Evans and Lyons (2007) who find differently signed coefficients for the corporate sector as opposed to traders (analogous to leveraged or hedge fund segment here) and asset managers (real money). Our result may reflect the nature of private investors who could have a tendency to be technical traders attempting to buy or sell at price inflection points[15] or the private client sector may be passive liquidity providers in a similar way to corporates. Bjønnes *et al* (2005a) discuss this aspect of FX markets in more detail particularly in reference to the corporate segment. The asset manager sector comes third in significance, with the corporate client sector the least significant.

Asset managers and leveraged investors seem to be the more informative of traders, in the sense that buying always causes prices to rise. The asset management sector also has the biggest dollar value of flows in absolute terms, generally between 2-3 times larger than private clients. The leveraged segment is more comparable to private client although larger in a number of cases. These are important results and confirm results such as Evans and Lyons (2002), Carpenter and Wang (2003) and Bjønnes *et al* (2005b) and offer primae facie evidence that order flow may act as a mechanism for transmission of market participant expectations.

We also consider the inclusion of lags of the order flow variables and of the interest rate differential in model (10), for reasons explained in Section 5 . Results are reported in Table 10. The empirical findings appear to be rather different now than the ones reported above. In fact, there seem to be a significant drop in the significance of the order flows with incorrectly signed coefficients in most cases and R-squared in many cases very close to zero.

[15] See Allen and Taylor (1990) and Menkhoff and Taylor (2007)) for accounts of a significant minority of technical traders in FX markets.

Table10. Estimates of model (10): Lagged order flows-disaggregate data

	C	CO	HF	PC	AM	LIBOR	R-squared
EUR	-0.0013 -1.53	-0.001 -1.22	-0.0014 **-1.96*** **	-0.002 -1.59	-0.001 -1.22	0.008 0.71	0.010
JPN	-0.0001 -0.24	0.001 0.15	0.001 0.82	0.0034 1.38	-0.001 -0.45	0.004 0.26	-0.01
GBP	-0.001 -1.83	0.0035 1.12	-0.0015 -0.90	0.0013 0.49	0.001 0.88	-0.020 **-2.14*** **	0.002
CHF	-0.0012 -1.66	0.003 1.75	0.0002 0.18	0.0012 0.38	0.0005 0.38	-0.012 -0.92	-0.007
AUD	-0.002 -1.92	0.0050 0.84	-0.0032 -0.67	-0.0043 -0.45	-0.0003 -0.10	-0.028 **-2.23*** **	0.001
CAD	-0.002 **-3.023** **	-0.009 -1.47	-0.0015 -0.45	-0.016 -1.58	0.0020 0.69	-0.005 -0.34	0.003
NOK	-0.0018 **-2.11*** **	0.0013 0.05	-0.0062 -0.44	-0.007 -0.24	0.001 0.16	-0.022 **-2.00*** **	0.001
SEK	-0.0022 **-2.91** **	-0.029 -153	0.013 1.72	0.006 0.24	-0.002 0.26	-0.016 -1.25	0.007
NZD	-0.002 **-2.10*** **	0.028 0.56	0.005 0.41	-0.009 -0.23	0.007 0.69	-0.043 **-2.62*** **	0.024

Note: C is the intercept, CO denotes corporate clients, HF hedge funds, PC private client and AM asset managers. R-squared is the adjusted R-square and and values below coefficients are t-statistics based on Newey-West standard errors.. *,**,*** indicate significance levels at 1%, 5%, 10% respectively.

6.1. Forecasting

In this section we investigate the forecasting power of disaggregate order flows using model (10). Once again we employ the limited information model (9) and the methodology described in Section 5.1 to generate out-of-sample forecasts. The forecasting results are reported in Table 11.

The RMSFEs statistics show that the order flow model has smaller forecast errors than the random walk[16]. This seems to imply that disaggregate order flows may be useful in predicting changes in nominal exchange rates at one and two weeks horizons. These results support recent

[16] Again we have also considered an AR(1) model but results were substantially unchanged. We do not report these results to save space.

studies such are Evans and Lyons (2007). However, the Diebold-Mariano statistics indicate that the forecasting improvement over the random walk is not statistically significant.

Table 11: Out-of-sample forecasting performance using disaggregate order flows

	k	(a) Random Walk	(b) Order flow model	(b)/(a)	Diebold-Mariano
EUR	1	1.1339	1.1203	0.9880	-0.5943
	2	1.6034	1.5844	0.9882	
JPN	1	1.3233	1.3143	0.9931	-0.2182
	2	1.8098	1.7972	0.9931	
GBP	1	1.1647	1.1452	0.9832	-0.6503
	2	1.6519	1.6495	0.9985	
CHF	1	1.2603	1.2548	0.9956	-0.3642
	2	1.7958	1.7871	0.9952	
AUD	1	1.4846	1.4662	0.9877	-0.5586
	2	2.1709	2.1416	0.9865	
CAD	1	1.0378	1.0045	0.9679	-1.2741
	2	1.5350	1.3993	0.9116	
NOK	1	1.4871	1.4767	0.9930	-0.5045
	2	2.0852	2.0569	0.9864	
SEK	1	1.3536	1.3159	0.9721	-1.3842
	2	1.9890	1.9221	0.9664	
NZD	1	1.7756	1.7462	0.9834	-0.6879
	2	2.4862	2.4863	1.0000	

Note: Columns (a) and (b) report the RMSFEs (root mean square forecast error) are multiplied by 100. The Diebold-Mariano (1995) statistic tests the null hypothesis of equal forecast accuracy between the two models (its 5% critical value is -1.96). k is the forecast horizon.

7. Profitability of Using Order Flow Models

The previous analysis focused on assessing the statistical value of forecasting. We now turn to assessing the economic value of forecasting for two of the most highly liquid currencies (i.e. the Euro and the British pound) by employing the Sharpe ratio (Sharpe 1966). This is the ratio of the return of a strategy to its risk; its use is prevalent in investment companies as a means of evaluating trading strategies. We use observations between 2nd November 2001 to the 6th February 2004 to estimate the parameters and the remaining period for forecasting and trading.

Using the forecasts we generate weights based on the expected appreciation or depreciation of the currency. For example, if a currency is forecast to depreciate by 1% it is given a -1% weight in a portfolio. We then simulate the (carry-adjusted) returns from holding such a portfolio. The portfolio is updated at the end of each week as the new forecasts become available using the close FX rates. Here holdings refer to the actual positions taken, while performance refers to how well the strategy has worked out. Therefore, if for example the forecast is 1% appreciation in the GBP, we take +1% position in that currency for that week. The outcome is showed in the holding graph. The performance shows the return implied by our strategy.

Both the aggregate flow (7) and disaggregate flow (10) models, converted to the forecasting specification (9), were used to generate out-of-sample forecasts and trading signals. The trading results are shown in Figures 1 and 2 for the aggregate and disaggregate order flows respectively.

Figure 1: Trading performance: Aggregate order flows

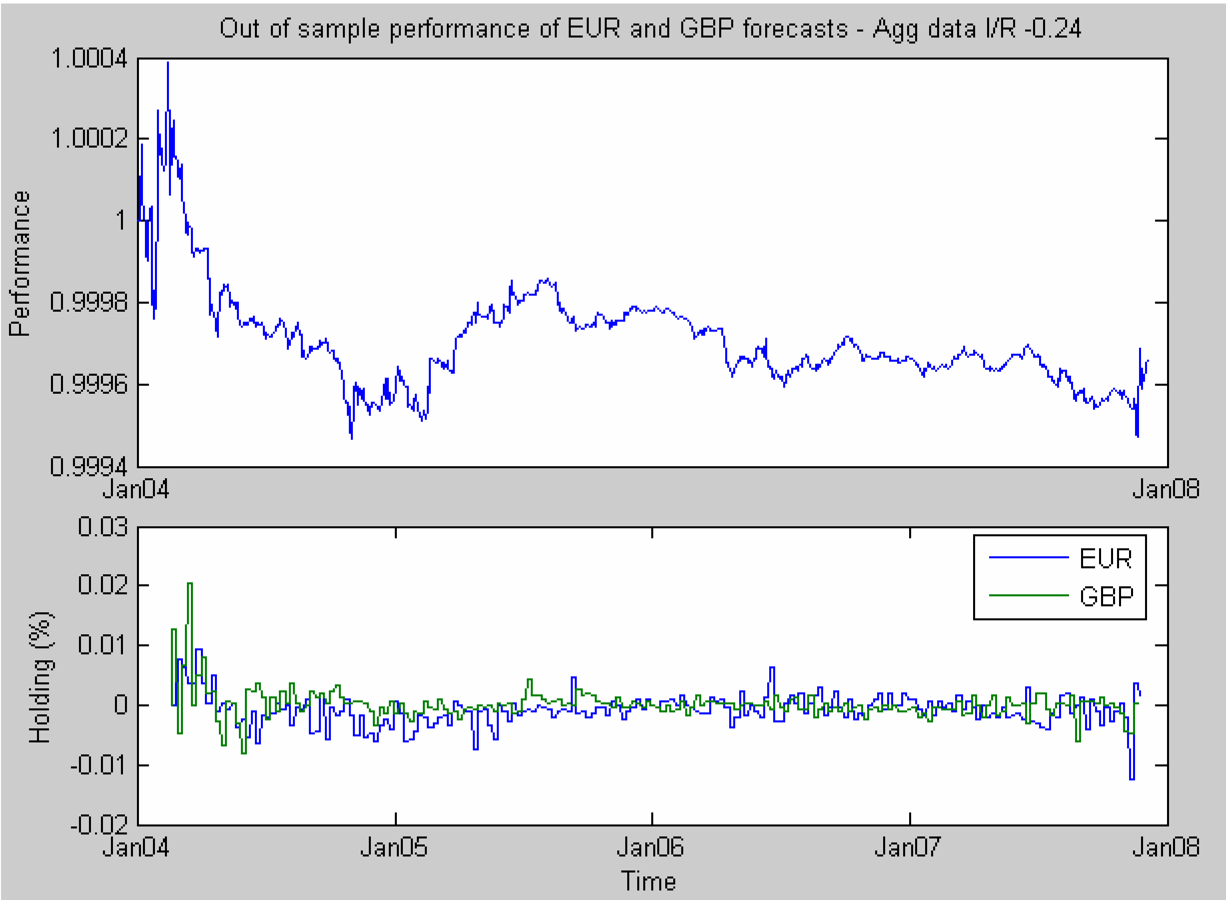
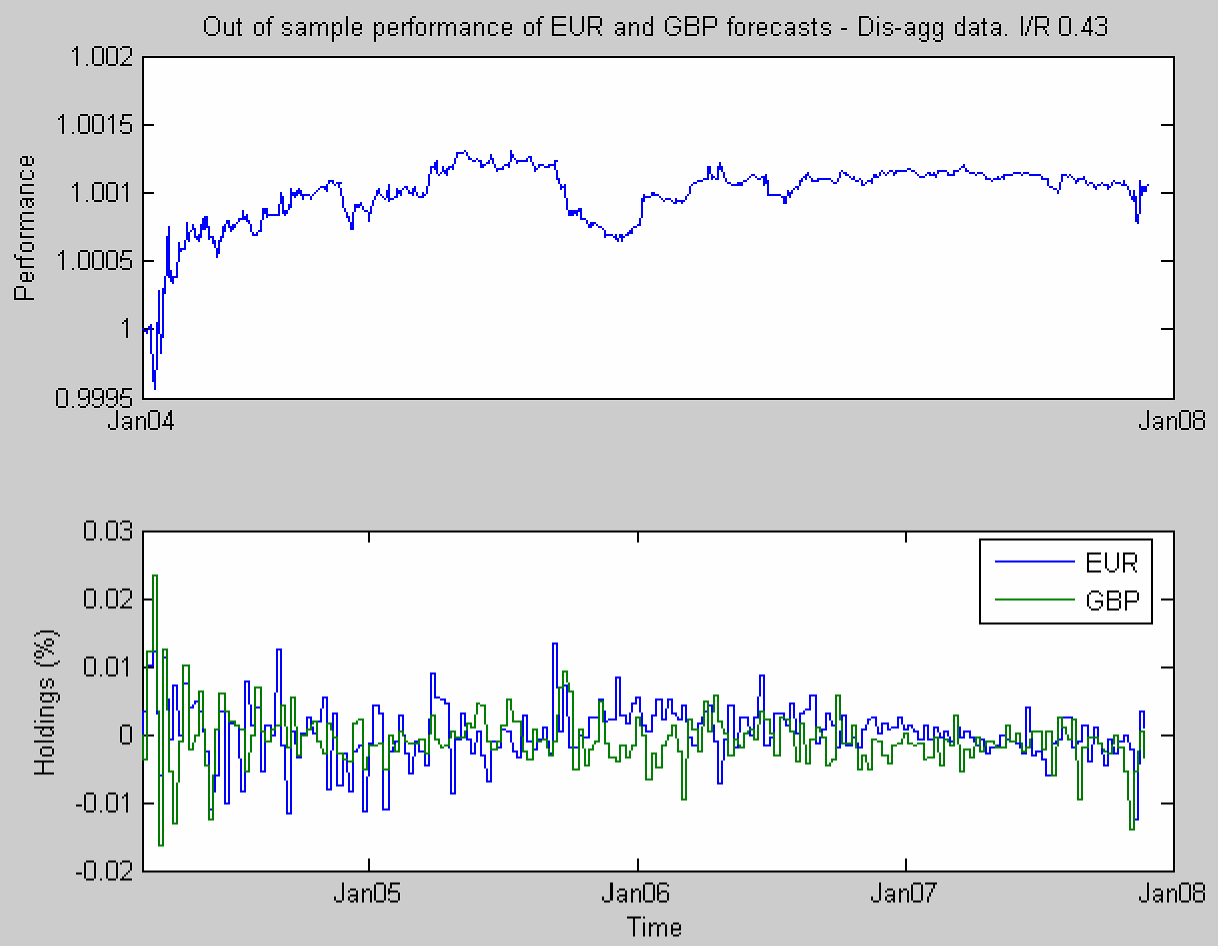


Figure 2: Trading performance: Disaggregate order flows



We find little profitability in using the aggregate order flows, with a negative Sharpe ratio indicating that following such a strategy would lose money over the period. The disaggregate order flows do improve things somewhat yielding a Sharpe ratio of 0.4, thus showing the importance of knowing who is transacting. However this would not be an attractive strategy to follow given that the majority of gains come in the first year of using the forecasts, although an improvement on random walk they cannot be profitably exploited using this simple strategy.

These results are again in line with Sager and Taylor (2008) who find little forecasting power in commercially available order flow but contrast with Rime *et al* (2009) who find Sharp ratios greater than 1 even out of sample. However note that they use AR(1) processes across the border. Also their result may depend on their use of an inter-dealer data-set that is available at the tick level and aggregated to daily rather than weekly frequency (as in this study) in testing profitability.

8. Conclusions

This paper shows that order flow is a significant determinant of exchange rate movements, in contrast to macroeconomic variables which do not appear to play a predominate role, thus confirming the benefits of the microstructure approach posited by Lyons some 10 years ago. Using a new proprietary dataset for nine of the most liquid currency pairs, the largest dataset ever used in the literature, we are able to focus directly on the initiating customer trades, rather than inferring them from inventory-balancing trades undertaken in the inter-dealer markets.

It appears that it is not just that flow is informative but the reason for the flow is also critical. Our data is also disaggregated by customer type, which gives us the opportunity to examine the differential impact of different customer types. We find evidence that profit-motivated traders (leveraged or hedge fund investors and asset managers) have a greater impact on exchange rates and are more informed, and that corporate and private clients act more as liquidity providers, 'leaning against the wind' in response to price moves[17] (confirming the results of Bjønnes *et al*, 2003 & 2004). This is an important result, it suggests that order flow is a determinant of exchange rates but it is the motive for the trade that is key. This supports the view that order flow is useful as a 'backed-by-money" gauge of changes in investors' expectations of macro-economic fundamentals put forward by Evans and Lyons (2007).

In contrasts to their strong explanatory power, order flows appear to have limited power in forecasting exchange rate movements. This result is obtained both from statistical tests and from a trading strategy based on out-of-sample forecasts of exchange rate movements. One explanation for this finding might be the medium term forecast horizon (one and two weeks-ahead) considered in this paper; it may well be that order flows have more predictive power over shorter forecast horizons (i.e. daily or intra-daily) as considered by some previous studies. Another potential explanation is the specification of the order flow model. As Sarantis (2006) shows, if we allow for time-varying papameters and non-linearities, exchange rate models can strongly outperform the randon walk and produce forecasts that can be used to generate significant excess returns in foreign exchange markets. We leave these issues for future research.

[17] Intuitively, one could think of the behaviour of a corporate treasurer, with profitability of foreign operations budgeted around current prevailing exchange rates. As the currency rises he would want to take the profits and reduce hedges whereas if the rate goes against him he would want to mitigate the exchange rate risk and increase his hedges.

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