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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, and the largest, proprietary dataset of weekly net order flow segmented by customer type across nine of the most liquid currency pairs. We make several contributions. Firstly, we investigate the extent to which customer order flow can help to explain exchange rate movements over and above the influence of macroeconomic variables. Secondly, we address the issue of whether order flows contain (private) information which explain exchange rates changes. Thirdly, 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 $3.2tn is traded on the foreign exchange (FX) market everyday according to the BIS[1], 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 attention 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 can act as an aggregator of information regarding the expectations and circumstances of participants, and order flow is the signal (i.e. it can be viewed as a variable mapping disperse information in the economy towards FX 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[2] between the

[1] Triennial Central Bank Survey of Foreign Exchange and Derivatives Market Activity in April 2007 Bank of International Settlements – December 2007

[2] Sometimes it may take few days until the order flow information are revealed to the markets. See discussion in Rime *et al* (2010).

time when the information contained in the order flow is formed and when it is fully revealed to the market[3].

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[4] 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 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 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 largest order flow dataset ever used in the literature.

It is important to make the distinction between 'customer order flow' and 'interdealer order flow'. As described above, a large proportion of the empirical literature on microstructure has focused on interdealer order flow (see Lyons (2001) and extensive references therein for examples). This data has been made available to researchers by some of the platforms used by market-makers to conduct their business. More recently (see Bjønnes *et al* (2005b), Evans and Lyons (2007) and Sager and Tayler (2008) for examples), data on customer order flow, that is the initiated underlying trade that is given to one or several market-makers, has become available in various forms from some of the top FX trading investment banks in the world. As we shall discuss later in the paper, given market-makers' risk-aversion to holding large inventory

[3] 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.
[4] 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, 2001).

positions over-night (Bjønnes and Rime (2005)), customer order flow can be assumed to be the underlying information revealed through inter-dealer activity. For the rest of the paper the use of the term order flow is associated to this "source," customer order flow unless we explicitly reference inter-dealer market.

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 attempts 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 is to assess 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[5]. 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* (2010)).

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 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 strategy. The final section summarises the main empirical findings.

[5] Obviously this may be too long a horizon for some hedge funds. However, asset management companies will be interested in the one to two week forecasts used here. Pension funds and central banks generally have even longer investment horizons.

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 are the order-flows that they receive. By examining price-by-price movements Lyons (1997) and (2001) found some support for the explanatory 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 inter-dealer order-flow[6] 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 have some knowledge of the institutional setting of the FX market. This is described in the following section.

[6] Again, we stress that, in the present study, we are focusing on customer rather than interdealer order flow. On a theoretical ground causality should be in one direction. Since customer order flows come from underlying customers, they are linked directly to the underlying sources of demand in the economy and represent the external 'shocks' to the inderdealer market that trigger trading. As Lyons (2001) p.244 puts it, "the ultimate driver of interdealer flow is customer flow". For future research it might be useful to test this causality direction by looking at the relationship between customer flow and interdealer flow. Our dataset is not of a sufficiently high enough frequency to conduct this investigation however. We have tried to address this issue in this paper using data from Tresury Bulletin. We recognize that this data-set is rather limitated. However, an important result we obtain is that

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 D2 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 FX 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[7], 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 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. EBS also shows some limited information on the orderbook for a currency pair (3 levels in most cases). It is therefore possible for dealers to infear about the size of the most recent trades from the side of the trade and consequent changes in the orderbook.

This decentralised multi-dealer structure leads to a majority of FX trades being market orders rather than limit orders (80% according to the authors' anecdotal discussions with traders). This applies for both customer orders and those in the interdealer market. The Reuters platform operates in a similar way and the choice of venue is largely driven by the currency pair with one

when we observe higher than average activity in the customer market, we observe higher than average activity in the dealer market (given the limitation of our data-set, we cannot say anything on the direction).

[7] The BIS tri-ennial survey estimates 43% of trades are between reporting dealers down from 53% in 2004 and 64% in 1998. The explanation for the decline being a consolidation of FX traders and growth of electronic brokers and ECNs.

platform typically dominating liquidity in each.[8] 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.

We should also note that the growth in ECNs (electronic communications networks) offers market participants an alternative way to access liquidity in the FX market, since firm prices are now available on a number of streaming ECNs.[9] EBS has also loosened its access restrictions in recent years, granting non-dealer firms access to its platform.

2.2 Microstructure Models: a Selective Empirical Literature Review

Lyons (1997) presents a 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. One of the implications of this model is that, as there are 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. In addition dealers extract information 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 via a 3rd party to preserve confidentially) or ECNs. Neither of these aspects are fully captured and may have significant implications. However, the Lyons model does seem to capture effects seen in some of the empirical studies:

[8] We consider G10 currencies here and don't differentiate by venue (the frequency of our data would make it difficult to discern institutional platform differences, if any, at that level).

[9] An interesting corrollory to this is that currency prices have become much more transparent and available to the general public, one example is the OANDA platform. This increased transparency has probably diminished (but not eliminated) the capability for brokers to quote much wider spreads depending the client and there access to market prices. There has also been a growth in margin trading platforms used by small investors for FX speculation

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 they 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. Thus, 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[10], 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 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.

[10] 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).

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* (2010) or Evans and Lyons (2002)). On the other hand our data set is not partially revealed to the market (as it 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)[11].

Table 1. Summary statistics for order flow

	EUR	JPY	CHF	GBP	AUD	NZD	CAD	SEK	NOK
Mean	0.277	-0.239	-0.129	-0.005	-0.0007	0.014	-0.016	-0.007	0.0097
Median	0.195	-0.212	-0.062	0.028	-0.011	0.004	-0.013	-0.0156	0.0018
Std.Dev.	1.466	0.826	0.752	0.808	0.303	0.115	0.252	0.146	0.1104
Skewness	0.946	0.801	-0.357	-3.974	0.877	1.319	0.918	1.5908	0.891
Kurtosis	11.14	10.83	2.833	34.51	6.053	13.304	9.407	8.429	7.226
Jarque-Bera	4.52	11.12	2.41	5.34	22.31	59.21	78.2	101.1	30.23
Probability	0.16	0	0.17	0.051	0	0	0	0	0
Observations	317	317	317	317	317	317	317	317	317

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 having a normal distribution. Order flows are rather volatile in almost all cases, with the EUR, JPY and GBP (which are the most traded currencies) displaying the highest volatility. 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. We notice some interesting patterns. The EUR order flow moves inversely with most other currency order flows (except the CAD, SEK and NOK). Generally, a EUR/JPY trade would be broken down into a EUR/USD and USD/JPY trade. Thus, this correlation may reflect these positions. The JPY, GBP and CHF order flows are positively correlated among themselves but show negative correlation with most other currencies. We note a small but generally positive correlation amongst those characterised as “commodity” currencies (AUD, CAD, NOK, NZD) and a positive correlation between JPY and CHF which have usually had lower interest-rates and are, generally, the funding side of “carry” trades. These correlations may represent broad investment themes in currency markets over the long time period considered.

[11] Note that order flows are expressed in $ billions, thus, for example, in the case of the JPY mean, -0.239 means a net average sale of $239m worth of Yen per week..

Table 2. Correlation coefficients for order flow

	EUR	JPY	CHF	GBP	AUD	NZD	CAD	SEK	NOK
EUR	1								
JPY	-0.22	1							
CHF	-0.31	0.135	1						
GBP	-0.31	0.23	0.073	1					
AUD	-0.04	0.01	-0.018	-0.171	1				
NZD	-0.07	-0.013	-0.013	0.060	0.020	1			
CAD	0.103	-0.101	-0.059	-0.013	0.046	-0.036	1		
SEK	0.084	-0.079	-0.168	-0.337	0.166	0.035	0.049	1	
NOK	0.069	-0.135	-0.144	0.034	0.121	-0.046	0.119	0.059	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

	EUR	JPY	CHF	GBP	AUD	NZD	CAD	SEK	NOK
Mean	-0.001	-0.047	-5E-04	-0.0017	-0.0026	-0.0018	-0.01	-0.0129	-0.004
Median	-0.002	-0.01	-9E-04	-0.002	-0.0045	-0.0028	-0.018	-0.021	-0.007
Std.Dev	0.011	1.518	0.0065	0.0176	0.0197	0.0131	0.1023	0.10823	0.0264
Skew	-0.39	0.248	0.1608	0.5822	0.3058	0.4319	0.2056	0.64412	0.633
Kurtosis	-0.02	0.419	-0.052	-0.2702	0.4518	0.0509	0.2919	-0.0383	-0.036
Jarque-Bera	0.892	1.832	1.201	0.0671	18.45	1.331	1.451	20.11	1.233
Probability	0.551	0.455	0.551	0.962	0.0011	0.541	0.481	0.0002	0.541
Observations	316	316	316	316	316	316	316	316	316

We notice that the average weekly 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. The most noticeable feature is the the strong correlation of the EUR with all currencies.

Table 4. Correlation between exchange rate changes

	EUR	JPY	CHF	GBP	AUD	NZ	CAD	SEK	NOK
EUR	1								
JPY	0.511	1							
CHF	0.723	0.405	1						
GBP	0.942	0.566	0.683	1					
AUD	0.569	0.303	0.479	0.474	1				
NZD	0.477	0.223	0.348	0.393	0.574	1			
CAD	0.817	0.437	0.593	0.796	0.488	0.415	1		
SEK	0.857	0.439	0.650	0.805	0.538	0.458	0.766	1	
NOK	0.502	0.218	0.446	0.412	0.795	0.432	0.441	0.468	1

3.1. Customer Order Flow Statistics: Disaggregated Data

We also report some statistics for the average size and volatility of the order flow broken down by each client segment. As can be seen from Table 5, asset manager and hedge fund order flows have typically the largest size and are much more volatile (typically double) than those from private or corporate clients. In addition to their large size, asset managers and hedge funds are also using the market explicitly for profit-making purposes and can change investment decisions quickly, which may explain the high volatility of their order flows. It is also worth noticing that order flows are most volatile for the EUR, JPY and GBP (the most highly traded currencies) for all types of customers.

Table 5. Disaggregate order flows: average size and volatility

	Asset Manager	Corporate	Hedge Fund	Private Client
EUR	-0.0454	0.1917	0.1987	-0.0673
Std.	0.949106758	0.460564	0.91558664	0.585329213
NZD	-0.0007	0.0052	0.0078	0.0015
Std.	0.073354803	0.020233	0.07063741	0.039235628
JPY	-0.0985	-0.0485	-0.0783	-0.0145
Std.	0.635931223	0.145959	0.58367869	0.237842817
CAD	0.0080	-0.0258	-0.0006	0.0026
Std.	0.18513117	0.076119	0.18728353	0.066000856
CHF	-0.0608	0.0001	-0.0867	0.0184
Std.	0.501723576	0.421986	0.55483996	0.237301251
SEK	-0.0038	-0.0131	0.0082	0.0015
Std.	0.114209293	0.046982	0.08054128	0.024223223
GBP	-0.0446	0.0105	0.0247	0.0044
Std.	0.669147343	0.190762	0.39839843	0.240048407
NOK	0.0036	-0.0043	0.0078	0.0026
Std.	0.081556323	0.024278	0.06336461	0.029680525
AUD	-0.0048	-0.0151	0.0161	0.0031
Std.	0.200896586	0.101324	0.2020239	0.103661395

Note: the first row in the table shows the average size of the order flow.
Std are standard deviations as measure of volatility.

We have also considered correlations among the order flows from the different types of customers, but the data is too large to usefully reproduce here (but is available on request). To summarise the results, we typically see a positive correlation between asset manager and hedge fund flows (which probably reflects their large size and strong profit-making motivation) and both of these are negatively correlated with the corporate and private client segments. This affect seems to dimish as we go down the liquidity spectrum i.e. it is relatively strong for EUR, JPY, CHF,GBP and AUD but less so for NZD, NOK and SEK.

Finally, to see if different types of customer order flows granger cause each other, we report below granger causality tests for different customer groups and for each currency.

Table 6. Granger causality tests

	EUR	JPY	CHF	GBP	AUD	NZD	CAD	SEK	NOK
CO/AM	0.4485	0.5116	0.0226	0.1323	0.1381	0.0801	0.0818	0.0211	0.003
AM/CO	0.9235	0.308	0.029	0.0196	0.0387	0.0668	0.3569	0.7014	0.5623
HF/CO	0.8692	0.0582	0.7957	0.0145	0.003	0.2501	0.0031	0.1139	0.0001
CO/HF	0.8393	0.0841	0.4833	0.103	0.0058	0.087	0.9385	0.169	0.0453
HF/AM	0.4045	0.4574	0.0012	0.0241	0.563	0.0344	0.0216	0.0124	0.2751
AM/HF	0.7764	0.3256	0.5497	0.2776	0.5717	0.9667	0.0398	0.8368	0.1422
PC/HF	0.6289	0.6115	0.9574	0.0607	0.0239	5.00E-06	0.2934	0.003	0.2533
HF/PC	0.6938	0.048	0.1977	0.0019	0.2679	3.00E-05	0.3265	0.5623	0.3145

Note: the table reports probability values for Granger causality tests between different customer groups for each currency.

It is difficult to draw any clear cut conclusion about causality from these results. Although there is a very slight tendency for asset management and hedge fund flows to Granger cause corporates, it is not significant in a statistical sense. It is interesting to note that there is no causality among any of the different types of customers for the most highly traded EUR and JPY currencies.

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)[12]:

[12] Note that model (6), and its variants (7) and (10), is a 'hybrid' model that incorporates microstructure components and macroeconomic components, and has been used extensively in the empirical literature as indicated above. Customer order flow plays a central role in microstructure theory. As explained in Sections 1 and 2,

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

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 Franc (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[13].

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* (2005).

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customer order flow is the 'source' of information, and ultimate driver of interdealer activity, that generates the trading signals and leads to price changes. Unfortunately it has been impossible to obtain data on customer order flows until recently because the leading FX trading banks regard these data as being highly proprietary. This explains why Evans and Lyons (2002) and most other studies in this area have been using inderdealer order flow data, which are made available by various platforms (i.e. Reuters, EBS, etc.), to reveal the underlying customer order flow. Furthermore, in our study we do not have interdealer data. However, to try to address this issue, we have used the weekly data available in the Treasury Bulletin. For two random currencies (Canadian Dollar and UK Pound), we have calculated the correlation coefficient between the monthly (gross) buys + sells flow available in the Tresury Bulletin and the respective (absolute) monthly customer order flow. By taking the absolute values of the order flow we can see if there is more or less customer flow during that period (regardless buys or sell). By measuring the gross (buys+sells) we can see if there is more or less trading during that period than on average. The estimated correlations are 0.04 for CAD and 0.19 for GBP. Given our data limitation, we believe that these results are strong enough to say that there is a correlation between the two markets and more customer sell orders lead to more inter-dealer sell orders.

[13] This is done for reasons of parsimony.

All rates are foreign currency per US dollar and order flow is also transformed to reflect this[14] – 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 7 shows the estimates of model (6).

[14] 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 7. 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 Franc, 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 7 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 effected by the EUR order flow[15]. 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 Customer 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 customer 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):

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

[15] One potential explanation for the significant impact of the EUR flow on CHF and SEK is that one could trade into these currencies by using the EUR as a vehicle currency. For example, instead of going from JPY into SEK, you trade JPY fro EUR and then EUR for SEK.

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) differential for the same period as a proxy for economic fundamentals[16]. Results using OLS (Newey-West) are reported in Table 8.

Table 8. 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 other studies such as Evans and Lyons (2005), Marsh and Rourke (2004) and Sager and Taylor (2008)[17]. As discussed in Sager and Taylor (2008), regression in (7) may be spurious in the sense

[16] Note that we have inserted an intercept in the model. The reason for this 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 one of the largest primary brokers such an assumption seems to be a bit restrictive.

[17] We have also considered augmenting the regression in (7) using all the (aggregate) order flow data. The (adjusted) coefficients of determination, in this case, were in general higher than the ones reported in Table 6. The

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)

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

The empirical results are reported in Table 9.

Table 9. 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),

Euro, the UK Pound and the NZ Dollar had the highest coefficients of 7%, 13% and 14% respectively. In general the order flows coefficients were significant and with the expected sign. For example, when either the EURO, JPY or GBP regressions were considered, both the EUR, the JPY and the GBP order flows were found statistically

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 that might be questionable. This is an important first result.

5.1 Forecasting

We are now interested to see if end users (i.e. customer) order flows have forecasting power for futures changes in the exchange rate. This is an important issue at least for two reasons. Firstly, if customer order flows can be used to forecast exchange rates, then dealers can exploit this information for trading. Secondly, although the majority of studies in this area have focused on finding evidence that order flows can explain changes in the exchange rate, relatively little work has been done on the forecasting power of order flows, particularly using customer order flows for a large number of currencies. Since our dataset is the largest and most recent customer order flow dataset available, we believe there is scope for addressing these issues.

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

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

We use this approach to overcome the assumption of perfect foresight implicit within 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 do undertake a forecasting exercise using contemporaneous values of order flow to estimate the move in the current exchange rate (see Table 1A of the Appendix for the details). The results show significant improvements over a random walk process for disaggregated flows. These results are important for two reasons: Firstly, this goes some way towards resolving the conundrum posed by Meese and Rogoff (1983) that it was difficult to find

significant –generally at 5%-and with the correct sign. In the case of NZD or AUD regressions, the NZD and AUD variables that improved forecast performance, even if these were assumed to be known prior to the period on which they were released. Order flow is clearly an important determinant of the exchange rate and, in that sense, may be acting as an aggregator of the unseen changing expectations market participants have of the macroeconomic variables. However, simultaneity and causality issues make it difficult to conclusively test this assertion. Secondly, there is a significant improvement in forecasting performance from using the disaggregated flow. It is important to know not just the amount traded but who is doing the trading (as Bjønnes *et al* (2005b) also found).

However, although this framework might be useful from a theoretical perspective, as the order flow variable in question is not observed until after the period is over (and is determined simultaneously), it is necessary to examine forecasting power in the more realistic setting using lagged (one week) information in equation 9. The main body of this work focuses on the assessing the usefulness of order flow data using methodology that can actually be implemented.

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. The parameters of the model are updated as each successive observation is added during the forecasting period. As a benchmark we use a simple drift-less random walk.

We report one and two-week ahead forecasts in Table 10. The results show that the order flow model produces lower forecast errors than the random walk for almost all the currencies. However the Diebold-Mariano test suggests that the differences between the forecast errors from the two competing models are, in general, not statistically significant[18].

order flows were always found significant and with the correct sign. Detailed results are available upon request.

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

Table 10: Out-of-sample forecasting performance: Lagged model using aggregate order flows

	k	(a) RW	(b) Evans and Lyons	(b)/(a)	DM
EUR	1	1.1368	1.1258	0.9904	0.1558
	2	1.6074	1.6132	1.0036	
JPN	1	1.3267	1.3091	0.9868	0.1916
	2	1.8144	1.7999	0.9920	
GBP	1	1.1677	1.1755	1.0067	-0.0633
	2	1.6561	1.6735	1.0105	
CHF	1	1.2635	1.2643	1.0006	0.0253
	2	1.8004	1.8134	1.0072	
AUD	1	1.4883	1.4777	0.9929	0.1284
	2	2.1764	2.1619	0.9933	
CAD	1	1.0404	1.0181	0.9786	0.3363
	2	1.5389	1.4409	0.9363	
NOK	1	1.4909	1.4902	0.9995	0.0398
	2	2.0905	2.0642	0.9874	
SEK	1	1.3570	1.3569	0.9999	0.0356
	2	1.9940	1.9856	0.9958	
NZD	1	1.7801	1.7800	0.9999	0.0320
	2	2.4925	2.5154	1.0092	

Note: Columns (a) and (b) reported 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). The asterisk means 5% statistically significant. k is the forecast horizon.

6. Disaggregate Customer Order Flows

It is interesting at this point to break down the order flow into its constituent segments: Short-term (hedge funds), Long-term (Asset Managers), Corporate Clients and Private Clients. Thus, the following regression is now used

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

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

The aim is twofold. Firstly we want to confirm the previous empirical results. Secondly, we want 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 11.

Table 11. Estimates of model (10): Contemporaneous order flows-disaggregate data

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

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 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 casees, while the interest rate differential is significant only for three currencies (none of which is highly liquid). R-squared terms are much higher that those obtained with aggregate data, reaching a maximum of 35% (34%) for the Japanese Yen and the Euro respectively. These values are comparable in size to the ones reported in the literature.

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 (CAD is the only exception) 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[19] 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.

In terms of individual currencies, most types of customer order flows are significant in the cases of the JPY, EUR, AUD and NZD currencies. At the other end, NOK has only one significant customer (hedge funds).

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[20].

We now consider the inclusion of lags of the order flow variables and of the interest rate differential in model (10), for the same reasons as in Section 5. Results are reported in Table 12. The empirical findings appear to be rather different 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.

Thus, the empirical results in this section are in line with those in Section 5 and may indicate that the empirical findings in the literature may be driven, amongst other things, by model misspecification.

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

[20] It would be useful to know whether there are differences in the time it takes for the information contained in the order flow from different customers to filter through to the exchange rates. If different types of customer order flows have different time lags on exchange rates, one would expect the information to filter through within the same trading day and any difference to be measured in minutes. Thus, to properly test this hypothesis one would need intra-day data. Weekly data may not detect any difference in time lag (as Table 12 illustrates).

Table12. Estimates of model (10): Lagged order flows-disaggregate data

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

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 values below coefficients are t-statistics based on Newey-West standard errors. *,**,*** indicate significance levels at 1%, 5%, 10% respectively.

6.1. Forecasting

For the same reasons as already explained in section 5.1, we now 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 13. For comparison, Tables 1A and 2A in Appendix show the out-of-sample forecasts using a contemporaneous model.

The RMSFEs statistics show that the order flow model has smaller forecast errors than the random walk for all currencies[21]. It is interesting to note that the RMSFEs for the order flow model are smaller than those obtained from aggregate order flows. This seems to imply that disaggregate order flows may be useful in predicting changes in nominal exchange rates at one and two week horizons. These results support recent studies such are Evans and Lyons (2007).

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

However, the Diebold-Mariano statistics indicate that the forecasting improvement over the random walk, in general, is not statistically significant[22].

In order to see which customer order flow is better at predicting at certain horizons, we have repeated the forecasting exercise using one of the four customer groups each time. Overall the results were very similar to those reported in Table 13, with hedge funds and private clients producing the smallest RMSFEs that reflects their highest significant impact on the exchange rates. However, potentially significant differences in the predictive information of different customer order flows are more likely to be apparent in intra-day trading.

Table 13: Out-of-sample forecasting performance: Lagged model using disaggregate order flows

	k	(a) RW	(b) Evans and Lyons	(b)/(a)	DM
EUR	1	1.1368	1.1325	0.9962	0.2151
	2	1.6074	1.6126	1.0032	
JPN	1	1.3267	1.2995	0.9795	0.4098
	2	1.8144	1.7873	0.9851	
GBP	1	1.1677	1.1644	0.9972	0.2382
	2	1.6561	1.6764	1.0123	
CHF	1	1.2635	1.2600	0.9972	0.2076
	2	1.8004	1.7991	0.9993	
AUD	1	1.4883	1.4705	0.9880	0.3282
	2	2.1764	2.1258	0.9767	
CAD	1	1.0404	1.0105	0.9713	0.5879
	2	1.5389	1.4074	0.9145	
NOK	1	1.4909	1.4637	0.9818	0.4173
	2	2.0905	2.0274	0.9698	
SEK	1	1.3570	1.3418	0.9887	0.3270
	2	1.9940	1.9444	0.9751	
NZD	1	1.7801	1.7585	0.9879	0.3097
	2	2.4925	2.4745	0.9928	

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). The asterisk means 5% statistically significant. k is the forecast horizon.

7. Does Customer Order Flow Explain Exchange Rate Changes?

[22] However, it should be noticed that when disaggregated data is used there is, overall, a better evidence of forecasting ability of the (customer) order flow model.

The empirical results reported above seem to suggest few important points. Firstly, customer order flows are an important determinant of the exchange rate when disaggregate order flows are considered and a contemporaneous order flow model is used. However, the result is weaker when a lagged order flow model is used. Secondly, there is no clear cut evidence that order flow models of the exchange rate perform better than a simple random walk model in out-of-sample forecasting. In this section, we shall focus more on the former issue. We shall look at the latter issue in the next section.

If order flow contains relevant information about expected values of future exchange rates fundamentals, and if this information becomes embedded in the exchange rate gradually, one would expect to observe cointegration between cumulative order flows and exchange rates. We report the cointegration results using the Engle and Granger and Johansen cointegration[23] methods in the table below.

Table 14: Engle and Granger and Johansen Cointegration

	EUR	JPN	GBP	CHF	AUD	CAD	NOK	SEK	NZD
AGGREGATE	0.26	0.33	0.67	0.18	0.52	0.29	0.07***	0.61	0.21
TRACE	0.26	0.02**	0.33	0.17	0.76	0.87	0.36	0.67	0.73
PRIVATE	0.28	0.23	0.25	0.83	0.55	0.42	0.002*	0.16	0.08***
TRACE	0.61	0.03**	0.32	0.34	0.42	0.72	0.19	0.51	0.45
HEDGE FUNDS	0.17	0.35	0.45	0.22	0.54	0.99	0.06***	0.16	0.41
TRACE	0.49	0.61	0.44	0.41	0.55	0.81	0.06***	0.71	0.65
ASSET MANAG.	0.36	0.34	0.68	0.10***	0.41	0.26	0.02**	0.33	0.17
TRACE	0.9	0.76	0.56	0.35	0.9	0.4	0.24	0.76	0.001*
CORPORATE	0.33	0.33	0.03**	0.37	0.2	0.3	0.4	0.37	0.25
TRACE	0.002*	0.09*	0.59	0.27	0.48	0.10***	0.13	0.12	0.52

Note: The statistics reported in Table 14 are probability values. *,**,*** indicate significance levels at 1%, 5%, 10% respectively. The first row for each group refers to the Engle and Granger cointegration method. The second to the Johansen method (Trace statistic).

The empirical results in Table 14 show some evidence of cointegration between cumulative order flows and exchange rates when disaggregate data is used. The cointegration tests seem to suggest that investors with longer horizons (i.e. corporates and asset managers)) attach more attention to exchange rate fundamentals than those with short term horizons (i.e. hedge funds).

[23] We include one lag in the VAR and consider a model with intercept. Thus, practically we are considering demeaned cumulative order flows. Cumulative order flows were found to be non-stationary in all the cases.

8. Profitability of Forecasts from Order Flow Models

While the previous analysis focused on assessing the statistical value of forecasts, we now focus on assessing the economic value of forecasts. What matters to investors and traders is not so much the size of forecast errors but whether the forecasts generate profitable signals. We investigate the profitability of both individual currencies and of a portfolio of currencies and use a simple Sharpe ratio (Sharpe 1966) to assess our results. The Sharpe ratio 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.

We create a hypothetical trading strategy via a simple mean-variance optimisation – we use the forecasts as our expected returns for each asset and construct a covariance matrix using the previous 52 week historical returns. We arbitrarily specify a required expected weekly return of 0.18% (representing an approximate target volatility for hedge funds operating in this investment space and allow ourselves to go long or short each asset up to 100% of the portfolio value) and generate optimised portfolio holdings targeting this return.

We then simulate the (carry-adjusted) returns[24] 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. The outcome is shown at the portfolio level and each individual asset level in the graph below. The performance shows the return implied by investing $1 in our strategy.

Both the aggregate flow (7) and disaggregate flow (10) models, converted to the forecasting specification (9), and lagged information 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[25].

[24] We also looked at the results without carry adjustment, just looking at the spot returns, this has similar results to those reported.

Figure 1: Trading performance of individual currencies Aggregate order flows

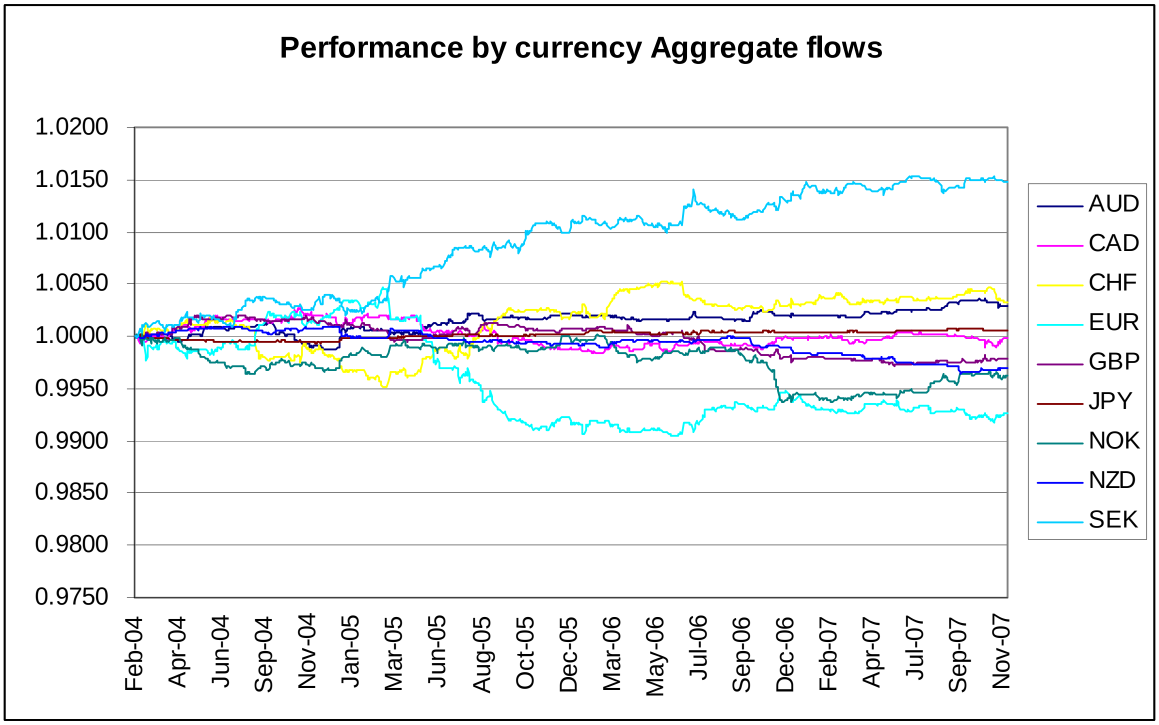


Figure 2: Trading performance of individual currency: Disaggregate order flows

[25] This result is consistent with Berger *et al* (2008).

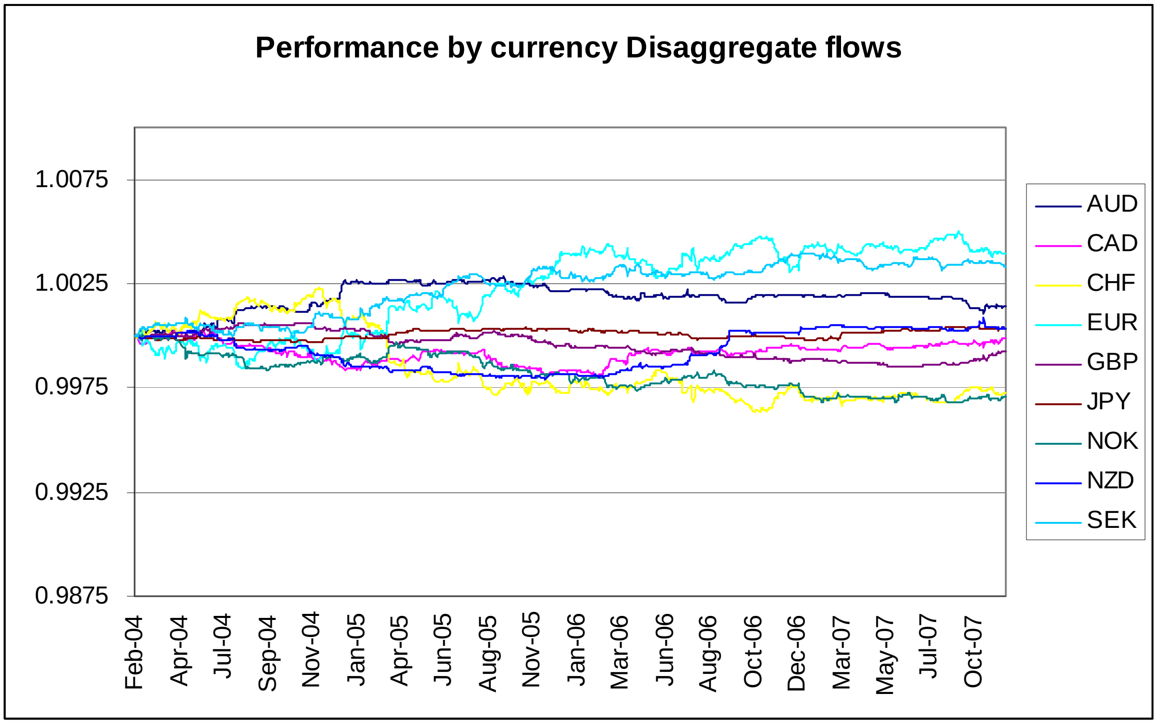
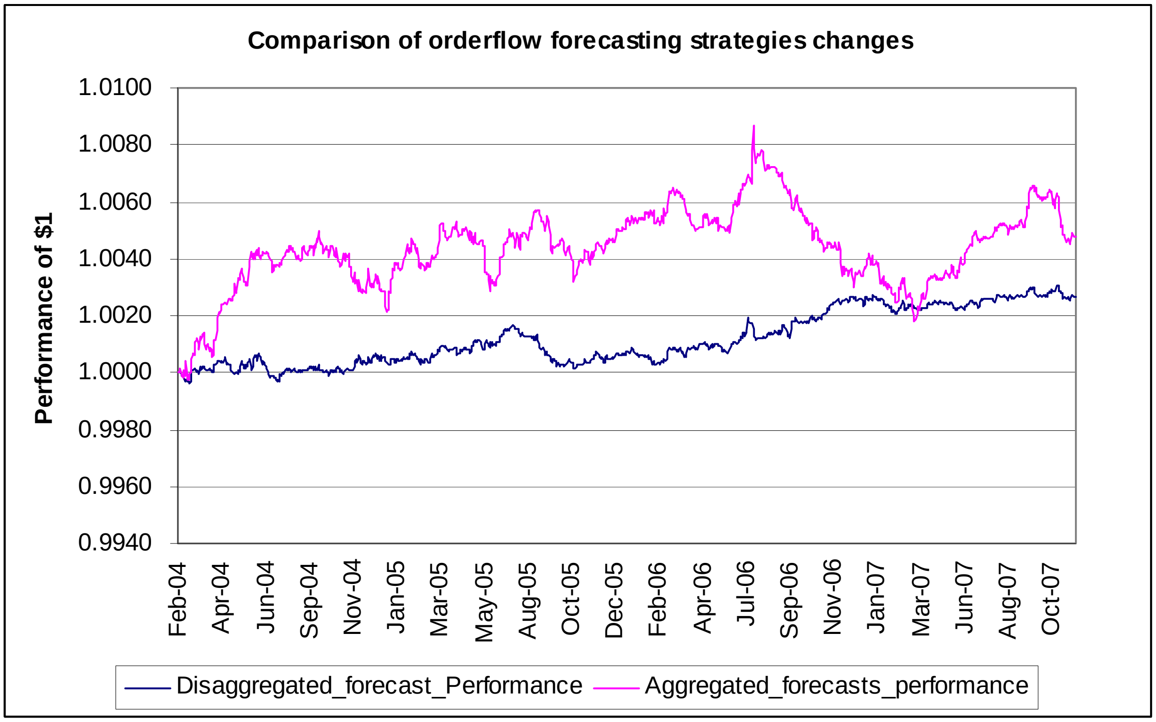


Figure 1 and Figure 2 show the trading performance of individual currencies (in the portfolio) using aggregate and disaggregate order flows data, while Figure 3 shows the performance of an optimal portfolio. The exchange rate performance in the two figures are, at least in a statistical sense, equivalent. Disaggregate flows produce much less volatile forecasts (the scale on the figure is halved). SEK is profitable for both so is AUD, but EUR is not in the aggregate forecasts. This suggests that it is important to know who is trading in this market (being a highly liquid currency pair one would expect to see money managers, corporates and private clients to all be active trading through EUR). Interestingly CHF is profitable on an aggregate basis but not when these flows are broken into their constituent traders. The contemporaneous regression results show little statistical significance (hedge funds and private clients have large (but only significant at the 10% level) and differently signed coefficients, suggesting there is a lot of volatility around flows through the Swiss Franc.

Figure 3: Trading performance of an Optimal Portfolio



The portfolio as a whole achieves, given our target, Sharpe ratios of 0.42 and 0.54 for aggregate and disaggregate order flows respectively. Thus, there is same profitability from trading these portfolios. The disaggregate model, whilst achieving a much lower overall return outperforms on a risk adjusted basis with much more consistent forecasts. However, both strategies are likely to be an unattractive strategy given anecdotal evidence (see Sager and Taylor (2008)) that proprietary traders are looking for strategies with Sharpe ratios in advance of 1. Finally, we also report the individual t-statistics for aggregate and disaggregate order flows data.

Table 15: Metrics on average returns of the strategy

	Average Return (%p.a.)		t-statistics		Sharpe Ratio	
	Agg	Dis_Agg	Agg	Dis_Agg	Agg	Dis_Agg
AUD	0.07%	0.04%	0.91	1.03	0.52	0.46
CAD	0.00%	0.00%	-0.09	-0.04	-0.02	-0.05
CHF	0.09%	-0.07%	-0.83	0.60	0.31	-0.42
EUR	-0.19%	0.10%	1.02	-1.14	-0.58	0.52
GBP	-0.05%	-0.02%	-0.76	-0.71	-0.36	-0.38
JPY	0.01%	0.01%	0.53	0.56	0.28	0.27
NOK	-0.10%	-0.08%	-1.68	-0.87	-0.44	-0.85
NZD	-0.08%	0.01%	0.30	-1.64	-0.83	0.15
SEK	0.37%	0.09%	1.62	2.49	1.26	0.82

Portfolio	0.12%	0.07%	0.83	1.08	0.42	0.54

Table 15 shows the annualised returns, t-statistics and Sharpe ratios for the individual currencies held in the portfolio. The annualised returns are low given our optimised target of 3%, as show in the lagged regressions the effect of one week's orderflow is greatly dimished when we look at the following week's return; the lower than expected returns are generated by taking a lower than expected risk, so we focus on the Sharp ratios and t-statistics for the remainder of this discussion . The disaggregate data performs slightly better than aggregate flow as one would expect from the information ratios (although this is a marginal improvement) and only the SEK position has any statistical significance. Most of the t-statistics are consistent between the two models although the EUR and CHF are performance is reversed (this could be a consequence of the optimisation as both assets are highly correlated) and the NZD position performs poorly in the disaggregate model.

Overall, the results presented in this section and the out-of-sample forecasting results in the previous sections are in line with Sager and Taylor (2008) who find little forecasting power in commercially available order flow but contrast with Rime *et al* (2010) who find Sharpe ratios greater than 1 even out of sample. However note that they use AR(1) processes across the border. Other studies (see Evans and Lyons, 2007 amongst the others) have been able to produce more convincing results, than the present one, on the forecasting power of order flow. But, these studies are either more limited than the present one in terms of currencies investigated, or they use much shorter forecast horizons, generally daily data.

9. Conclusions

This study uses a new proprietary dataset for nine of the most liquid currency pairs, the largest dataset ever used in the literature. Thus, this allows us to focus directly on the initiating customer trades, rather than inferring them from inventory-balancing trades undertaken in the inter-dealer markets.

It addresses two important issues which have been investigated in the literature with contrasting empirical results. Firstly, it investigates whether (customer) order flows contain private information which helps to explain exchange rates returns. The in-sample analysis reported shows that this is the case. This result is in line with most of the previous empirical evidence. Additionally, the present study shows that the content of the private information is even more important if one has knowledge of the provenience of the transaction (i.e. with disaggregate data).[26]

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[27] (confirming the results of Bjønnes *et al*, 2003 & 2004). This is an important result, it suggests that while the order flow is a determinant of exchange rates, 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).

The second issue the paper focuses on is using these (customer) order flows to forecast exchange rates. The paper addresses this issue by using both statistical and economic measures of forecasting power and the results are not encouraging, once publication and implementation lags are properly accounted for. This contrasts with the supportive evidence for order flows obtained from the econometric estimates. It may be that weekly data is not timely enough and the information contained within the order flow is already impounded into the exchange rate. How quickly the market discovers and absorbs this information remains an open question that requires a much richer dataset then those currently available. Other fruitful areas for further research include looking at non-linear models[28], the time-structure of order flows, causality between flow and price and the behaviour of flows in reaction to macroeconomic variables and surprises.

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[26] At least when considering a contemporaneous order flow model, as the one generally used in the literature, and particularly with disaggregate order flow data..

[27] 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.

[28] For example, Sarantis (2006) shows that exchange rate models that allow for time-varying parameters and non-linearities strongly outperform the random walk and produce forecasts that can be used to generate significant excess returns in foreign exchange markets.

References

Allen, H. and Taylor, M., 1990, Charts, Noise and Fundamentals in the London Foreign Exchange Market, *Economic Journal*, 100, 49-59.

Anderson, T. and Bollerslev, T. 1998, Deutsche Mark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies, *Journal of Finance*, 53, 219-265.

Berger, W., David, Alain, P., Chabout, Sergey, V., Chernenko, Edword, Howorka, and Jonathan, H., Writh, 2008, Order Flow and Exchange Rate Dynamics in Electronic Brokerage System Data, *Journal of International Economics*, 75, 93-109.

Boehmer, E. and Wu, J., 2007, Order Flow and Prices, American Finance Association, Chicago Meetings Paper.

Bjønnes, G. and Rime, D., 2005, Dealer Behaviour and Trading Systems in the Foreign Exchange Markets, *Journal of Financial Economics*, 75, 571-605.

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

Bjønnes, G, Rime. D. and Solheim, H., 2005b, Volume and Volatility in the FX Market: Does it Matter who you are? In: P. De Grauwe (ed.), *Exchange Rate Economics: Where do we Stand?*, MIT Press.

Carpenter, A. and Wang, J., 2003, Sources of Private Information in FX Trading, University of New South Wales, typescript.

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

Chinn, M. and Meese, R., 1995, Banking on Currency Forecasts: How Predictable is Change in Money, *Journal of International Economics*, 38, 161-178.

Copeland, T. and Friedman, D., 1991, Partial Revelation of Information in Experimental Asset Markets, *Journal of Finance*, 42, 265-295.

Diebold, F. X. and Mariano, R. S., 1995, Comparing Predictive Accuracy, *Journal of Business and Economic Statistics*, 13, 253-263.

Evans, M, and Lyons, R., 2002, Order Flow and Exchange Rate Dynamics, *Journal of Political Economy*, 110, 170-180.

Evans, M. and Lyons, R., 2005, Meese-Rogoff Redux: Micro-Based Exchange Rate Forecasting, *American Economic Review*, 95, 405-414.

Evans, M. and Lyons, R., 2007, Exchange Rate Fundamentals and Order Flow, NBER Working Paper W13151.

Fan, M. and Lyons, R., 2000, Customer-Dealer Trading in the Foreign Exchange Market, UC Berkeley, Typescript.

Financial Times (2007) *Fragmentation or a plethora of choice* – February FT mandate section

Harvey, David I., Stephen J. Leybourne, and Paul Newbold, 1998, Tests for Forecast Encompassing, *Journal of Business and Economic Statistics*, 16, 254-59.

Ito, T., Lyons, R. and Melvin, M., 1998, Is there Private Information in the FX Market? The Tokyo Experiment, *Journal of Finance*, 53, 1111-1130.

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

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

Lyons, R., 1997, A Simultaneous Trade Model of the Foreign Exchange Hot Potato, *Journal of International Economics*, 42, 275-298.

Lyons, R., 1998, Profits and Position Control: A Week in FX Dealing, *Journal of International Money and Finance*, 17, 97-115.

Lyons, R., 2001, *The Microstructure Approach to Exchange Rates.* MIT Press

Lyons, R., 2002, Foreign Exchange: Macro Puzzles, Micro Tools, Federal Reserve Bank of San Francisco, *Economic Review, 51-69.*

Marsh, I. and O' Rourke, C., 2004, Customer Order Flows and Exchange Rates Movements: Is There Really Information Content?, Cass Business School, Working Papers.

Meese, R. and Rogoff, K., 1983, Empirical Exchange Rate Models of the Seventies: Do they Fit out of Sample? *Journal of International Economics*, 14, 3-24.

Meese, R. and Singleton, K., 1982, On Unit Roots and the Empirical Modeling of Exchange Rates, *Journal of Finance*, 37, 1029-1035.

Menkhoff, L. and Taylor, M., 2007, The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis, *Journal of Economic Literature*, 45, 936-972.

Peiers, B., 1997, Informed Traders, Intervention, and Price Leadership: A Deeper View of the Microstructure of the Foreign Exchange Market, *Journal of Finance*, 52, 1589-1614.

Rime, D., Sarno, L. and Sojli, E., 2010, Exchange Rate Forecasting, Order Flow and Macroeconomic Information, *Journal of International Economics*, 80, pp. 72-88.

Sager, M. and Taylor, M., 2008, Commercially Available Order Flow Data and Exchange Rate Movements: Caveat Emptor, *Journal of Money, Credit and Banking*, 40, 583-625.

Sapp, S., 2002, Price Leadership in the Spot Foreign Exchange Market, *Journal of Financial and Quantitative Analysis*, 37, 425-448.

Sarantis, N., 2006, On the Short-Term Predictability of Exchange Rates: A BVAR Time-Varying Parameters Approach, *Journal of Banking and Finance*, 30, 2257-2279.

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

Shleifer, A., 2000, *Inefficient Markets: An Introduction to Behavioural Finance.* Oxford University Press.

Appendix

In this appendix we report the contemporaneous forecasting results using the following model:

$$\Delta s_{t+1} = \hat{\beta}_1 \Delta(i_{t+1} - i^*_{t+1}) + \hat{\beta}_2 X_{t+1}$$

where all variables are defined in the same way as in the text. X_{t+1} is the aggregated or disaggregated order flow variable.

Table 1A. Out-of-sample forecasts: Contemporaneous model using aggregate order flows

	k	(a) RW	(b) Meese and Rogoff	(b)/(a)	DM
EUR	1	1.1368	1.1348	0.9982	0.0542
	2	1.6074	1.5902	0.9893	
JPN	1	1.3267	1.2536	0.9449	0.7168
	2	1.8144	1.7602	0.9701	
GBP	1	1.1677	1.1350	0.9720	0.4806
	2	1.6561	1.6416	0.9913	
CHF	1	1.2635	1.2531	0.9918	0.1439
	2	1.8004	1.7732	0.9849	
AUD	1	1.4883	1.4116	0.9485	0.7498
	2	2.1764	2.1094	0.9692	
CAD	1	1.0404	1.0281	0.9882	0.1870
	2	1.5389	1.4861	0.9657	
NOK	1	1.4909	1.4796	0.9924	0.1354
	2	2.0905	2.0503	0.9808	
SEK	1	1.3570	1.3625	1.0040	-0.0204
	2	1.9940	1.9757	0.9908	
NZD	1	1.7801	1.6716	0.9391	0.8024
	2	2.4925	2.3822	0.9557	

RMSFE multiplied by 100

Table 2A. Out-of-sample forecasts: Contemporaneous model using disaggregate order flows

	k	(a) RW	(b) Meese and Rogoff	(b)/(a)	DM
EUR	1	1.1368	0.8334	0.7331	3.9360
	2	1.6074	1.4511	0.9027	
JPN	1	1.3267	1.0230	0.7711	2.9948
	2	1.8144	1.5376	0.8475	
GBP	1	1.1677	0.9400	0.8050	3.0878
	2	1.6561	1.5162	0.9155	
CHF	1	1.2635	1.0268	0.8127	2.8977
	2	1.8004	1.5650	0.8693	
AUD	1	1.4883	1.3082	0.8789	1.9072
	2	2.1764	1.8609	0.8550	
CAD	1	1.0404	0.8916	0.8570	1.9287
	2	1.5389	1.3069	0.8492	
NOK	1	1.4909	1.4488	0.9717	0.5344
	2	2.0905	2.0191	0.9658	
SEK	1	1.3570	1.3188	0.9718	0.5667
	2	1.9940	1.9227	0.9642	
NZD	1	1.7801	1.5368	0.8633	1.9412
	2	2.4925	2.1936	0.8801	