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Foreign Exchange Market Microstructure and Forecasting

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Declaration

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Abstract

Using two unique datasets, one at a daily frequency including six currency pairs, and another tick-by-tick dataset in €/US$, we investigate some of the unanswered questions in the field of foreign exchange market microstructure.

We confirm the contemporaneous relationship between flows and exchange rates found in the literature in the daily data, but in the forecasting experiments we find no forecasting power, regardless of model, history used forecast horizon or currency pair. The forecasting performance is not improved by considering a system of exchange rates, or by evaluating based on directional ability instead of the more usual RMSE ratio.

Subsequently we estimate two standard market microstructure models - Madhavan-Smidt and Huang-Stoll – using the high-frequency dataset in order to gain an insight into the information content of customer order flow. While we are unable to find any evidence of information content from financial customer trades, we find strong evidence that large corporate customer trades are perceived to have statistically and economically significant information content.

Lastly we turn our attention to the issue of causality. Using a distributed lag model to investigate the impact of flows on exchange rates and vice versa, corporate orders are found to have a small long-term impact, but more significantly we find evidence of positive feedback trading in both corporate and financial customers.

We explore the long-run dynamics of the system using a VECM, and find that all counterparty types have a positive equilibrium relationship with the exchange rate. Crucially, the adjustment dynamics show that all of the weight of adjustment to restore equilibrium after a shock falls to flows. Lastly, we conduct a high frequency forecasting experiment, but again find no evidence of forecasting power.

Two important themes emerge from the high-frequency investigation. The first is the apparent importance of corporate customers, and the second is that the direction of causality runs not from flows to exchange rates, but from exchange rates to flows.

We conclude that the weight of the evidence suggests that feedback rather than information content is what drives the strong contemporaneous relationship between exchange rates and flows.

1 Introduction

Running 24 hours a day, with a daily turnover in excess of US$3trn, the foreign exchange (FX) market is by far the largest financial market in the world. It is also arguably the most important of the financial markets, since FX rates affect prices and competitiveness for all other assets and commodities around the world. The BIS Triennial Central Bank Survey 2007 estimated daily turnover of $3.2 trillion includes spot, forward and swaps volumes, although for the purpose of our study, the spot market, with an estimated daily trading volume of $1 trillion, is the most important segment that we plan to look at.

In the post-Bretton-Woods era, FX rates have been very volatile and have proven notoriously hard to forecast. A series of macroeconomic models were developed in the seventies that were both elegant and theoretically appealing. They represented a shift in thinking, from the "elasticities" approach to the "asset" approach, and are based on solid theoretical foundations. An influential series of papers by Meese and Rogoff in the early eighties however, demonstrated that these models are an empirical failure particularly in the short term. For decades since, the inability of researchers to come up with models to explain or forecast exchange rate changes using macroeconomic variables except over the very long-run has been a source of embarrassment to the profession (Meese and Rogoff, 1983; Cheung and Chinn, 2004).

The FX market has undergone some major changes in recent years with the advent of electronic trading, and this change in market structure has had important implications when considering how to explain and forecast FX rates. From an academic perspective, this switch to electronic trading has provided transactions level data that can be studied, adding another layer to the analysis of FX movements and their determinants. The analysis of foreign exchange order flows—either those of customers themselves or as they are reflected in the inter-bank market—has consistently revealed a positive contemporaneous correlation between order flows of financial customers and exchange rate movements (Evans and Lyons, 2002; Marsh and O'Rourke, 2005). This new approach to FX – the micro approach – was pioneered by Lyons (1995).

The microstructure approach to FX moves the thinking about how FX rates are set from a rather abstract theoretical approach to a more realistic information-theoretic approach, recognizing that it is important to understand what information the dealers have available to them, and what forces influence their decisions. "Whether we like it or not, it is a stubborn fact that in the major currency markets, there is no exchange rate other than the price these people [FX dealers] set." (Lyons, 2001) Micro based models focus on the mechanism through which market makers get information. There is no assumption that all information is symmetrically disseminated and immediately impounded in price, and it is a central premise of the micro approach to FX that market makers learn about the macro economy by observing order flow, which is defined as the net of buyer-initiated and seller-initiated currency orders submitted to a particular FX dealer. It may be interpreted as 'buying pressure' originating in shocks to customers' hedging or liquidity demands, differential interpretation of public news, etc. The results point to the presence of dispersed, fundamental-related information in order flow. The basic premise is that the FX market, like any other securities market, acts to aggregate dispersed information.

The main participants in the FX market are central banks, commercial banks, institutional investors, traders, hedge funds, commercial companies and retail investors. Currencies are traded in an interbank exchange system by market making currency dealers. The high liquidity in the interbank market has driven spreads to very low levels, making even large volume transactions very cost effective for the investor. In contrast to the equity markets however, the FX market is relatively opaque. Only FX dealers have access to the interbank market, and although dealers can extract a noisy signal of other bank's customer order flow by observing interbank trading, the order flow seen by each individual dealing bank is essentially private information.

The very heterogeneous nature of the market participants and their objectives when entering into currency transactions is the major reason for the hypothesis that order flow from different customer types will have different price impact. While some actors like hedge funds and financial institutions trade currencies mostly for speculative reasons, others buy and sell currencies without the *primary* objective of achieving speculative gains. Central banks for example intervene in the foreign exchange market to reach their macroeconomic and monetary policy objectives. Corporate hedgers trade currencies to diminish the impact of currency fluctuations on their firm's core business activities. Traditional asset managers' currency transactions also tend not to be driven by currency forecasts. A switch from holding Japanese equity to holding European equity is not usually motivated by expectations that the Euro is going to outperform the Yen, but a currency transaction will still be necessary to buy the Euro and sell the Yen. Observing the trades from this varied group of investors each trading for different reasons, can give dealers a view – albeit a partial one – of the market's interpretation of the macro economy.

In contrast to the macro approach, micro FX has enjoyed considerably more empirical success in explaining exchange rates (Evans and Lyons, 2002a,b). Furthermore, Evans and Lyons (2005,b) presents a micro model of forecasting using customer order flow that achieves extraordinary results compared to any other short term forecasting model in the literature. The contemporaneous relationship between order flows and exchange rates is by now undisputed and has been verified in a number of different datasets. (see inter alia Menkhoff et al 2006, Bjonnes and Rime 2006) The reasons for this relationship, the direction of causality, and whether there is information in order flow that has stable implications that can be used for prediction and trading are all questions that remain without clear answers however.

Based on this relative empirical success of FX microstructure, and using two new customer order flow datasets, one from the Royal Bank of Scotland (RBS), spanning three and a half years at a daily frequency, and another a high-frequency order flow dataset from a major European bank we attempt to address some of the questions that remain unanswered in the micro FX literature. First we replicate and extend the Evans and Lyons (2005b) forecasting experiment. Since the RBS data covers six bilateral exchange rates, it will allow us to test whether the E&L results are generaliseable to other exchange rates beyond euro-dollar, as well as to order flow data from a different bank and in a more recent time period. The high frequency dataset will enable us to investigate the impact of customer trades on a dealer's own quotes, as well as the lead

– lag relationship between order flows and market clearing prices, answering the question whether the exchange rate adjusts to flows or whether flows react to changes in exchange rates.

The rest of this document will be structured as follows: first a very brief description of some of the key literature in macro FX is necessary to help situate micro FX in the broader FX literature. An overview of the structure of the FX market follows, and then a more detailed coverage of the micro FX literature. The first empirical chapter (chapter 4) describes a number of forecasting experiments motivated by E&L (2005, b) at a daily frequency and lower. We then study the pricing of customer transactions at a tick-by-tick frequency in chapter 5. Chapter 6 examines the price impact of order flow on market prices, looks for forecasting power in high-frequency order flow, and looks at the long-run relationship between exchange rates and order flow in an error correction framework, attempting to determine the direction of causality. Chapter 7 concludes.

2 From Macro to Micro – A Brief Look at the FX Literature and the FX Market

2.1 Macro Models

The seventies were an interesting time for foreign exchange. The new floating exchange rate system had just replaced a long-standing fixed exchange rate regime, and it was a period of adjustment when the implications of the new FX system were not fully understood. At the time, there was a great deal of excitement in academia, over a new approach to FX forecasting that had thus far been shown to have very promising results. The "asset approach to exchange rates" pioneered by Dornbusch, Frenkel, Mussa and others, seemed to provide a new and very plausible explanation for the high volatility observed in the new flexible exchange rates. The thinking up to that time had been that the FX rate depended on supply and demand for imports and exports – the elasticities approach. The new theory postulated that FX rates depended not only on this, but also on expectations of future developments in variables such as outputs, money supplies, interest rates, trade balance and other macroeconomic variables. This theory explained the volatility in the exchange rates, since the monetary policies themselves were very volatile. The literature on macro models of FX is vast, and beyond the scope of this document. Here we will focus only on the very specific stream of literature that motivates the focus on the microstructure of the foreign exchange market, stemming from the seminal Meese and Rogoff papers.

2.2 Meese and Rogoff – A Benchmark for FX Forecasting

The main focus of the Meese-Rogoff study was to examine how well existing empirical exchange rate models fit out-of-sample compared to a naïve forecast of no change. As a first step in evaluating the models, they constructed forecasts based on actual realized values of the fundamentals, although this would obviously not have any real value as a forecasting tool, since it would be impossible to replicate this method in real time. The benchmark they used for comparison was the random walk, and they used both Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) as comparison criteria. Including MAE is important if the FX rate distribution has fat tails or if exchange rates are governed by a stable Paretian process (infinite variance) (Clements and Hendry, 1993). Surprisingly, the random walk forecast beat all the models at forecast horizons below 2 years, and this result was robust to data set, model specification, error term specification, estimation technique, choice of theoretical model etc.

The forecasting interpretation of the results of this study is counterintuitive. What they had shown was that even if you were given the actual, realized values of the future fundamentals, the structural models could not predict the future FX rate any better than the random walk model could. In fact, the models performed worse than the random walk. In a follow up paper, the constraints on the models were relaxed even further, testing simply whether the structural models could predict the direction if not the magnitude of change in FX rates given the realized values of the fundamentals (Rogoff, 2001). Once again they were surprised to find that the random walk performed consistently better than any of the structural models they tested at horizons less than two years.

More than two decades of research have failed to overturn the Meese-Rogoff result - empirical exchange rate models perform poorly at predicting exchange rates over shorter horizons. Meese himself says “empirical researchers have shown considerable imagination in their specification searches, so it is not easy to think of variables that have escaped consideration in an exchange rate equation” (Meese 1990, 130). The weight of evidence seems overwhelming, but at the same time it is important to examine some of the reasons why these models fail before dismissing them.

Exchange rates are determined by a large number of variables in the short, medium and long term, and it is the precise nature of all these interactions that eventually determine the level of the spot exchange rate that proves so evasive. In the short run, exchange rates can vary far more than the macroeconomic fundamentals that influence them in the longer term. This rather chaotic behaviour of exchange rates over shorter time horizons can create “noise” that makes it hard to discern a definite relationship between the level of FX rates and the underlying fundamentals.

Short term technical, or bandwagon effects, can also cause FX rates to move away from their equilibrium values. Market participants tend to have extrapolative expectations over the short term, and mean-reverting expectations over the longer term. “Extrapolative expectations can tend to accentuate and perpetuate FX rate movements in the short term far beyond the path justified by fundamentals” (Rosenberg, 2003). In addition to these effects, there is also the question of “peso problems” and “finance minister problems”. Peso problems arise when an event, such as a change in monetary policy, is expected to occur in the future, and the path of the exchange rate changes in anticipation of this event. This can pose a problem for a model that cannot take anticipations into account. The finance minister problem arises when an event is expected to occur, anticipations change the path of the exchange rate, and then the event does not transpire. In this case, expectations will appear unrelated to the past. (Saidi, p.109, 1983)

One of the reasons that the Meese-Rogoff study had such a great impact was the fact that when testing their empirical exchange rate models, they used future, realized values for the underlying fundamentals, seemingly giving the models an artificial advantage. This was seen as giving the results added credibility, since it suggests that even knowing the future values of fundamentals does not help the models to perform better than the random walk. Faust et al (2003) challenge this notion. Work on evaluating FX rate forecasting models generally uses the most recent data available. The problem with this however, is that macroeconomic data used is often subject to revisions that can be both large and unpredictable. Using the most recent data assumes that agents can anticipate data revisions perfectly. In their paper, Faust et al examine the real time forecasting power of standard exchange rate models, using an international real time dataset that they constructed. They used real time data on lagged economic fundamentals instead of ex post realized values, and also used forecasts of future values of fundamentals instead of actual future values in a real time forecasting exercise.

The conclusions reached by Faust et al are that measured forecasting ability is quite sensitive to data revisions and to sample period. They found that the predictive power of the exchange rate models they tested is almost uniformly better using original release data than using revised data. This conclusion suggests that giving the models the supposed advantage of using final revised data is actually more of a hindrance than a help. The problem with this method is that the availability of a time series database of original release data is very limited.

The bottom line however is that macro models are an empirical failure in the short term – at the very least at horizons less than 3 months, and Meese-Rogoff have provided the benchmark against which any forecasting model must be measured – can you beat the random walk? There is reason for optimism however, as all these sources of 'error' can be at least partially addressed, not by changing the theory per se, but by shifting its focus. This is where the microstructure approach can add some value, and is the topic of the following section.

2.3 Shifting the Focus to Microstructure Models

If macro models can't be used to forecast exchange rates in the short term, we are still left with the problem of how to forecast or even explain FX at shorter horizons. Empirical analysis has been based on the following specification:

$$
\begin{aligned}
s &= \left(1-\delta\right)\sum_{j=0}^{\infty}\delta^{j}\hat{E}_{t}\left(f_{t+j}^{m}\right)+\xi_{t} \\
\xi_{t} &= \underbrace{\left(1-\delta\right)\sum_{j=0}^{\infty}\delta^{j}E_{t}\left(f_{t+j}^{u}\right)}_{\text{unmeasured fundamentals}}+\underbrace{\left(1-\delta\right)\sum_{j=0}^{\infty}\delta^{j}\left(E_{t}-\hat{E}_{t}\right)\left(f_{t+j}^{m}\right)}_{\text{expectational errors}}
\end{aligned}
\tag{2.1}
$$

All the "action" so to speak is in the error term, and over twenty years of research has failed to uncover any fundamentals that have not been included in the specification that would rescue the model. To elaborate on this point, empirical analysis has approached the problem of exchange rate determination by considering that the exchange rate represents the present value of future macroeconomic fundamentals. Since no set of fundamentals has been found – despite extensive research – that adequately describes the movement of exchange rates, this implies that almost all explanatory power remains in the error term. Decomposing the error term into a part corresponding to unmeasured fundamentals and a part corresponding to expectational errors can maybe help us to extract what information contained in the error term is helping to determine the path of the exchange rate.

Specifically, the microstructure approach looks at the second part of the error term – expectational errors, and argues that changes to expectations about measured fundamentals are important. More specifically, it studies how dispersed information about fundamentals gets impounded into exchange rates via trading decisions. Here we return to the valid criticism of Faust et al (2003) who argue that using ex post measured fundamentals should not in fact be helpful in explaining exchange rates. What matters is not what the fundamentals turned out to be exactly, but what the *expectations* of future fundamentals were. Using ex-post measured fundamentals implies perfect foresight in the market and realistically this cannot be true. The micro approach then in effect shifts the focus, not away from fundamentals per se, but to the mechanism through which fundamentals affect prices. The argument is not that fundamentals are not important, but that they are not necessarily observable, so we need a proxy for them. In FX microstructure, this proxy is order flow. FX microstructure argues that the market's expectations about future fundamentals are mirrored in their *aggregated* trading decisions, and it is in this sense that order flow is said to contain information.

More formally, under the microstructure approach, like the asset market approach, the demand for currencies comes from purchases and sales of assets. The micro approach however relaxes three of the asset approach's most uncomfortable assumptions:

(1) **Information:** micro models recognize that some information relevant to exchange rates is not publicly available.
(2) **Players:** microstructure models recognize that market participants differ in ways that affect prices.
(3) **Institutions:** microstructure models recognize that trading mechanisms differ in ways that affect prices.

Of the three, information is the main focus of the FX micro approach, and one of the hallmarks of microstructure is order flow. Order flow is transaction volume signed according to the aggressor or initiator of trade. It is the channel through which dispersed information gets aggregated and incorporated into prices. Order flow has no role in the macro approach because macroeconomists believe that all information that is relevant to exchange rates is publicly known and is instantaneously included in prices. The microstructure approach therefore allows the FX market itself – its structure, participants and trading mechanisms - to affect exchange rates, replacing the abstract "Walrasian auctioneer" with the reality of multiple FX dealers, and allowing for a heterogeneous pool of market participants who are not all equally well informed and who all have distinct motivations for trading. It recognizes that the FX market acts to aggregate information just like any other financial market. We need to understand the structure of the FX market then before examining micro FX in more detail. To this end, the following section gives a very brief overview of the FX market and its participants. Additional information including some summary statistics and recent trends from the latest BIS survey (2007) can be found in Appendix A.

2.4 The Foreign Exchange (FX) Market

2.4.1 The Main Characteristics of the FX Market in Summary

The main characteristics of the FX market can be summarized as follows:

i. Huge size – trading volume in FX dwarfs that of other markets.
ii. Interdealer risk sharing (hot potato trading) – 43% of the volume in FX is due to FX dealers trading amongst themselves to share risk.
iii. Trade transparency is low – there is physical separation of trading and customers do not have access to the interdealer market. This distinction is becoming less clear as trading in FX evolves however.
iv. Credit risk management is very important in FX.
v. "Private" information in the form of dispersed information is present in the FX market. This information is "contained" in customer order flow.

These characteristics will be examined in more detail in the following sections.

2.4.2 The Market

The FX market is unique in its structure and operations. Daily trading volume is huge compared to other markets - $3.2 trillion according to the 2007 BIS survey – and trading is continuous around the clock and around the globe, with the exception of weekends. It is thus a decentralized market with multiple dealers in many locations quoting and trading simultaneously. "The introduction of telecommunications allowed decentralized trade of FX as is most natural. Banks want to be present where the customers are, and because an exchange rate is the relative price of two assets from two different countries, it is natural to have a decentralized market. Given that customers are in different time zones and may have an interest in the same asset, say \$, trading must also be continuous around the clock. Finally, given the geographical pattern of customers and the fact that several banks serve them, it is natural to have a number of dealers acting as liquidity providers in each currency pair." (Rime, 2003) The fact that the FX market is not centralized means that it is also mostly unregulated. The structure of this market has evolved endogenously, largely without regulation, in response to the demands and peculiarities of the asset being traded – foreign exchange. The resulting structure and the lack of disclosure requirements in FX make this market far more opaque than other markets such as the equity market.

2.4.3 FX Market Participants

Trading in FX can be divided into customer trading and interbank trading. Interbank trading can be either direct or brokered, and in recent years broking has moved onto electronic platforms such as EBS and Reuters dealing. As such, the main participants in FX can be divided into customers and dealers. Customers are the end-users of foreign exchange, and in essence are the aggressors in FX deals. Dealers stand ready to provide liquidity and trade with each other on the interbank market to manage their positions. Customers are active in FX for disparate reasons, with different needs and ways to conduct transactions. They can be large multinational corporations, central banks, governments or financial institutions, and they generally do not have direct access to the interbank market, hence the aforementioned lack of transparency. Customers trade FX for a variety of reasons. For example, a hedge fund may trade FX in order to speculate, while a corporation may trade FX in order to repatriate profits from an overseas operation. The order flows from customers are only seen by the individual dealer handling the transaction, and as such it is private information for banks. In the microstructure approach to FX, order flow is the mechanism through which dispersed information gets impounded into price, and thus provides a tool for dealers to learn about the expectations and interpretation of the state of the economy of their customers.

2.4.4 Electronic Brokers

Electronic brokers were first introduced in 1992 with Reuters Dealing 2000-2. There are two electronic brokers in the FX interdealer market today, Reuters Dealing 3000 and EBS, and electronic broking now represents the main trading channel in this market. Electronic brokers are well suited to a market such as FX due to its huge volume, decentralized structure and need of fast, efficient matching of orders. The two systems have each carved out a niche for themselves, with EBS being dominant in EUR/USD, USD/JPY, EUR/JPY, USD/CHF and EUR/CHF, and Reuters being used for all other currency pairs. In terms of volume EBS is larger since it dominates in the larger USD, EUR and JPY markets. These systems, which can also be described as electronic matching systems, do just that – they collect orders from screens in dealing rooms around the world connected in a network and match them automatically, using strict time priority according to time of entry for market orders. Order entry is anonymous, but once a transaction has taken place both parties see the counterparty's identity.

In short, electronic brokers bring some degree of centralization to a decentralized market. They offer more transparency in the interbank market, are cheaper, and for liquid, standardized instruments are more efficient at matching orders. This is not to say that the market has gone, or even should go, completely electronic. Many smaller currencies without much liquidity are not traded electronically, and voice brokers can still fulfil a useful function in less liquid currencies by using their knowledge of the market and the players in the market to find suitable counterparties for trades. The optimal level of transparency in FX is not an issue with a clear answer. Complete transparency will discourage participation by informed dealers resulting in less information being aggregated by the market. It would also become more risky for dealers to take on large trades because managing inventory before the entire market is aware of the deal will become very difficult. As will be discussed in a subsequent section, inventory management is very important for FX dealers. This could have the effect of increasing spreads to customers to compensate dealers for the additional risk they would have to take on. However, the current increase in transparency offered by electronic broking seems to have been beneficial to the FX market as the level of transparency before was so low. This can be deduced by the fact that trading has not decreased due to the increased transparency. (Rime 2003)

2.4.5 Competing FX Platforms

The FX market is a dynamic environment that is constantly innovating and evolving. In recent years, technology has enabled an ongoing revolution in how we trade in FX. In the mid 1990s non-bank internet trading sites for FX, such as OANDA and ChoiceFX appeared. Most of these sites operate as crossing networks, depending on prices obtained from another venue. This implies that there is no price discovery in these networks. Others, such as ChoiceFX depend on limit orders from customers. These sites all act as a counterparty to all trades (customers must all place a margin account before trading). Since they depend on the interbank market for their existence, crossing networks can never replace the interbank network, but they could influence it if they were to draw enough customers away from banks. Banks response to the emergence of these non-bank trading sites was to create their own, multi bank state-of-the-art dealer-to-client electronic communication networks, including California-based Currenex (launched in 1999), New York-based and dealer-owned FXall (launched in 2000) and Hotspot (launched in 2001), all of which gained market share. These allow customers to get quotes from multiple banks quickly and easily therefore increasing the efficiency of the market from the customer perspective, and increasing competition between banks. (Jung 2007)

The success of electronic platforms has had a significant impact on the FX market. Besides simplifying transactions, technology has enabled greater price transparency and a wider range of agents to participate in the marketplace. Newer players include smaller fund managers, individuals and algorithmic traders—all of whom participate mostly or exclusively through e-trading systems, particularly in the spot market.

2.4.6 Prime Brokerage

Yet another innovation is the prime brokerage service offered to small banks without direct access to the interbank market and to hedge funds by EBS and Reuters. Large hedge funds, quantitative trading firms and active currency managers have investment strategies that require them to trade FX high frequency and to seek deep liquidity. On the spot interdealer platforms - EBS and Reuters Dealing - hedge funds cannot trade directly, and instead must have their trades executed through their prime brokers. Both EBS and Reuters now provide prime brokerage services to large buy-side institutions through EBS Prime and Reuters Prime Brokerage respectively, through which a designated prime broker can extend credit to small banks or hedge funds and execute trades on their behalf. Customers pay a fee to the partner bank for its services and also pay a brokerage fee. Services such as these, address the issue of credit risk, but leave dealers at a disadvantage, as they would not know who is on the other side of the trade. EBS does not require full-name give-up for hedge funds trading on EBS Prime, meaning banks would not know who the end counterparty is.

2.4.7 Settlement Risk

Credit risk management is an important structural aspect of FX. Counterparty credit risk is currently managed by the banks, and is one issue that complicates the movement of the FX market onto an exchange. Counterparty trading limits – credit lines - are extremely important in FX, and at times even the major banks in FX are unable to transact with each other if they have exhausted their bilateral credit lines. Dealer screens will in fact show both the best bid and ask prices in the market and the best bid and ask prices available to the particular dealer taking into account bilateral credit lines. Continuous Linked Settlement (CLS) is a major development in FX that was started in 2002 by a number of the world's largest banks in response to the need for an efficient method of dealing with "temporal" settlement risk.

In 1996 the G10 central banks endorsed a strategy to reduce the systemic risk arising from the settlement of foreign exchange trades. The strategy was motivated by the finding that banks' foreign exchange settlement exposures to their counterparties were in many cases extremely large relative to their capital, lasted overnight or longer and were poorly understood and controlled. Foreign exchange settlement risk is the risk that one party to an FX trade pays out the currency it sold but does not receive the currency it bought. It consists of both liquidity risk (the risk that the purchased currency is not received when due) and credit risk (the risk that the purchased currency is not received when due or at any time thereafter). In this situation, a party's foreign exchange settlement exposure equals the full amount of the purchased currency. (BIS,1996) Settlement risk numbers dwarf any other risk category in many institutions. In some cases, large banks have almost three times more exposure to settlement risk than to credit risk. In FX, the largest market by value, transactions can involve settlement exposures amounting to tens of billions of dollars each day to individual counterparties and in some cases, exposure to a single counterparty exceeds that institution's capital. (BIS – CPSS 2008) CLS is at least a partial solution to this issue. "CLS is a real-time system that enables simultaneous settlement globally, irrespective of time zones. Settlement is final and irrevocable or funds are returned same day. Participating banks get real-time settlement information that helps them to manage liquidity more efficiently, reduce credit risks and introduce operational efficiencies". (CLS website) Since it began operations, CLS has rapidly gained significant market share, becoming the market-standard for foreign exchange settlement between major banks. It currently settles on average more than $3 trillion each day in FX-related payment obligations. (Progress in reducing foreign exchange settlement risk, CPSS Publications No 83, May 2008)

2.4.8 Separation of Trading

Lyons (2001) describes the physical separation of trading in the FX market as "rings of trading" as can be seen in the diagram below. It is important to recognize however, that as the market changes the lines are becoming increasingly blurred. The introduction of electronic brokers and their rapid gain of market power has increased price transparency, and customers now have a more precise view of spreads in the interbank market, leading to tighter spreads for customers themselves. All the new developments in FX outlined above have resulted in a more fragmented market, and changes in market structure may eventually change the mechanisms of price discovery. We therefore propose possible simplified models of price discovery, but with the understanding that this may change as the market itself changes.

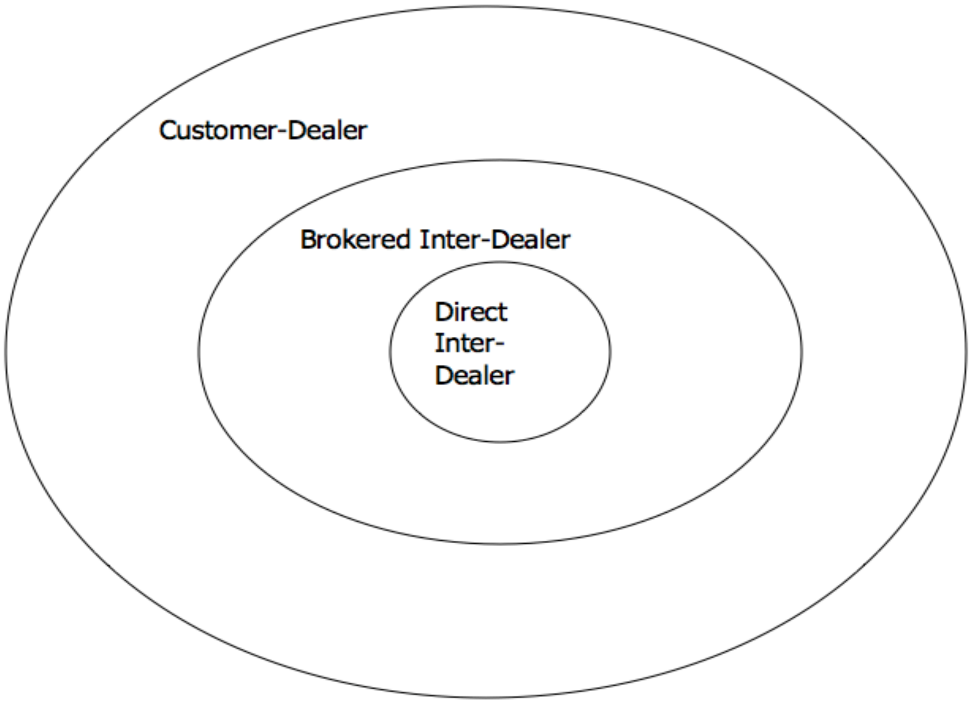


Figure 2-1 - Rings of Trading Lyons (2001)

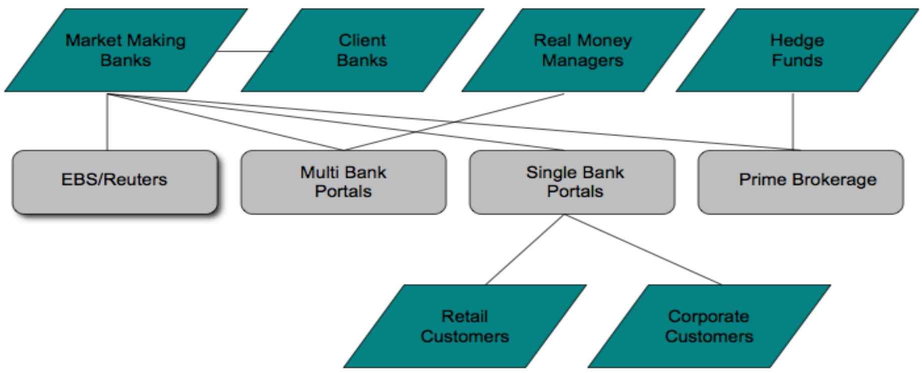


Figure 2-2 – A Changing Relationship between the players in FX

2.4.9 FX dealers

Just as the FX market itself differs from other financial markets, so do FX dealers differ from market makers in the other markets. In a groundbreaking paper for international finance, Richard Lyons followed an FX dealer for a week, observing how he conducted his business. This paper was groundbreaking not only for the fact that it effectively spawned the field of micro FX (along with Charles Goodhart), but for actually bothering to go to the horse's mouth so to speak and observe and interact with the people who actually deal with FX every day and set prices without econometric models to guide them in their second by second decisions. The Lyons dealer can teach us something about how some dealers in FX operate. Microstructure theory, which is based mainly on studies of the equity market, tells us that the spreads quoted by dealers are functions of four components: (i) adverse selection, i.e. protection against potentially informed customers, (ii) inventory costs, (iii) fixed costs or order processing costs and (iv) monopoly power. Fixed costs are generally modelled as a constant and the monopoly power component is not relevant in a competitive market such as the FX market. (Osler, 2006) Asymmetric information and inventory costs are the components of spread that we are most interested in. A dealer should widen spreads to protect himself against trades from informed customers – spreads increase with trade size. Larger trades also mean that the dealer takes on more risk by holding onto large positions that will need to be managed. This again implies that spreads should increase with trade size. The Lyons (1995) dealer can give us some insight into whether the equity microstructure theory holds in an FX setting, as well as giving a picture of the behaviour of a "typical" FX dealer. A plot of his net position is shown below.

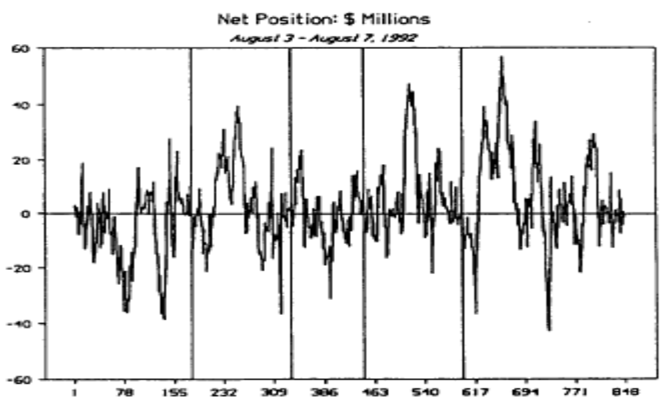


Figure 2-3 – Net Position of an FX dealer (Lyons, 1997)

The Lyons dealer does in fact increase spreads with increasing trade size. He also learned from the order flow he observed and adjusted his mid-point to take this information into account, i.e. he engaged in bid shading to control his inventory. Some other interesting facts that emerge from observing this particular dealer are that he always closed flat at the end of each day thus avoiding the need to manage positions overnight. This is clearly shown on the graph above, and also points to the fact that a dealer's comparative advantage comes from monitoring the market and his order flows at his desk so it would be very risky to maintain overnight positions. This is in contrast to the behaviour of dealers in other markets who regularly maintain large positions over long periods of time. The average half-life of his positions was 10 minutes, again in sharp contrast to a half-life of 7 days in the equity markets. This dealer had an average of 340 transactions per day, an average volume of $1.4 billion, and he made $500,000 profit in the one week Rich Lyons was observing him. This contrasts again to the average equity dealer who makes $10,000 per day on volume of $10 million. (Lyons 1997)

Of course it is hard to suggest that all dealers in FX operate in the same way, and in fact not all FX dealers do. This particular dealer observed no customer order flow, so he was effectively uninformed about things like sentiment shifts or portfolio shifts. Lyons finds that he speculated very little and made his profits simply by market making. In this sense, for a dealer in an investment bank with no customer order flow to glean information from, the Lyons dealer is a typical *type* of FX dealer. Lyons argues that he is representative because he was experienced in this market and had traded for a number of years, he was well-known and maintained $10 million quote relationships with other dealers and he traded very large volumes in excess of $1 billion per day. (Lyons 1997)

A final point to make about FX dealers is that they do not use currency options, futures or forward markets to hedge risk, finding it cheaper to use the interdealer spot market. (Fan and Lyons, 2002)

2.4.10 *Hot Potato Trading*

Hot potato trading refers to the "repeated passing of inventory imbalances between dealers" (Lyons 1997). The trading volume in FX is enormous and is far larger than the volume in other financial markets. Interdealer trading accounts for an estimated 43% of total trading volume. (BIS 2007) FX dealers are risk-averse, and as we have seen in a previous section manage their inventory aggressively, not holding on to positions for long, and actively driving their inventory to zero at close of business each day. Incidentally, this is not inconsistent with the 24 hour nature of the FX market as dealers do not pass along positions to their counterparties e.g. from Tokyo to London or from London to New York. What does get passed around the globe is the order book, not the positions themselves. A direct consequence then of the risk-averse nature of FX dealers is that as soon as they are hit with a customer order they will seek to restore their inventory equilibrium by trading in the interbank market.

"When hit with an incoming order, a currency dealer seeks to restore his own equilibrium by going to another marketmaker or the broker market for a two-way price. A game of 'hot potato' has begun… It is this search process for a counterparty who is willing to accept a new currency position that accounts for a good deal of the volume in the foreign exchange market" (James Burnham, 1991)

Understanding the source of the huge volume in FX is very important from a policy perspective. Some who attribute this large volume to excessive and "destabilizing" speculation support the imposition of a tax on FX trades to provide disincentives to speculation. Considering the fact that as Flood (1994) says, "the large volume of interbank trading is not primarily speculative in nature, but rather represents the rather tedious task of passing undesired positions along until they happen upon a marketmaker whose inventory discrepancy they neutralize", imposing such a tax would only impede the process of risk sharing. When marketmakers can share risks more easily, for example through a large and liquid interdealer market, they are willing to quote narrower spreads. Lyons (1997) however disagrees with the hypothesis that hot potato trading is innocuous. He formulates a simultaneous trade model of the FX hot potato showing that it produces an informational asymmetry, the intuition being that the interdealer market is where the private information coming from customer trades gets aggregated and revealed. Lyons argues that the precision of this information is lowered as a result of hot potato trading.

2.4.11 A Rapidly Changing Landscape

The huge growth in daily turnover in the global foreign exchange market, revealed in the BIS 2007 survey, continues to solidify FX as an asset class, and the changing demands of market participants is naturally gradually changing the structure of the FX market itself.

Unlike the equity or bond markets, the foreign exchange market is highly fragmented, with more than 20 dealer-to-client spot platforms, two interdealer spot platforms and three interdealer options platforms - and with the spot currency dealer-to-client platforms also trying to expand into options. EBS allowed hedge funds to trade on its platform in 2004 and Reuters followed suit in July 2005. (Jung 2007) In 1995, 64% of the foreign exchange trades were executed on interdealer platforms; by 2007, that figure had dropped to 43% despite an increase in the overall market. (BIS 2007) Reuters and EBS continue to be at the centre of FX trading, but their share has reduced as alternative liquidity providers have emerged. Multi bank platforms allow customers to access prices and to trade with any of the participating dealers with whom they have an established credit relationship, thus facilitating investors' access to market-makers, and also providing tools for algorithmic trading.

The distinction between banks that are market makers in the interbank market and other financial institutions continues to become less apparent as these other financial institutions increasingly provide market liquidity. The Federal Reserve Bank of New York pointed to the greater role of hedge funds "behaving more like dealers with regard to pricing and the liquidity they are willing to provide to the market". This trend is underpinned by the consolidation in the banking industry, the growth of banking organizations that play a number of different roles in foreign exchange markets, the strong growth in prime brokerage and the granting of access to electronic brokers in the interbank market to hedge funds (Jung (2007)). While the impact of these changes is difficult to assess, it does suggest that the ability to characterize the behaviour of different counterparty types may be more difficult.

These features of the FX market are likely to complicate attempts at modelling and forecasting exchange rates, and although this is at best a superficial description of the market it gives us the requisite knowledge of its most important aspects that allows us to move on to the micro FX literature, and examine some of its organizing ideas in more detail.

3 Micro FX

Having briefly covered the different focus of the micro approach as compared to the macro approach, and discussed some of the main features of the FX market itself, in this chapter we will analyze in more detail what micro FX can offer to the FX literature, firstly in terms of explaining FX movements and then in terms of forecasting, which is the main focus of this document. We start with the seminal Evans and Lyons (2002) paper demonstrating the striking contemporaneous relationship between order flow and changes in the exchange rate. Backing up these results is a simplified model of trading, providing a very plausible theoretical basis for the empirical results. We then proceed to the literature dealing with some of the main issues facing micro FX, mainly the question of private information and direction of causality. Subsequently we discuss the micro literature on macro news announcements and some puzzles of international finance.

Much of the empirical work in micro FX uses interdealer data, largely because of issues of availability. However the most important section of the micro literature in terms of relevance to our empirical focus which is forecasting and price impact, is the work done using customer order flow data. The last part of this chapter describes some of the literature using customer order flow data, which in turn leads us to the rather limited literature on forecasting FX using order flow which is the topic of the first empirical chapter.

3.1 Order Flow – Could it be the Omitted Variable in Macro Specifications?

Evans and Lyons (2002a) use interdealer data from Reuters D2000-1, a direct dealing platform, on DEM/USD and JPY/USD. The data is sampled at a daily frequency and spans four months from May 1 to August 31, 1996. The equation estimated is:

$$\Delta p_t = \beta_0 + \beta_1 \Delta(i_t - i_t^*) + \beta_2 X_t + \varepsilon_t \qquad (3.1)$$

Δp_t is the change in log spot FX rate

$\Delta(i_t - i_t^*)$ is the change in nominal interest rate differential

X_t is interdealer order flow from the end of day t-1 to the end of day t

The coefficient on order flow is correctly signed (positive) and significant in both the DEM and JPY equations, suggesting that excess demand for currency is positively correlated with the return of the currency. The coefficient on the interest differential is correctly signed (positive according to theoretical models) but is only significant in the JPY equation. Most importantly, the fit of the model is unheard of in the FX literature, with an R^2 of 64% for the DEM equation and 45% for the JPY equation. Furthermore, removing order flow from the model reduces the R^2 to less than 1% in both cases and results in coefficients on the interest differential that are statistically insignificant, implying that almost all the explanatory power in the regression is due to order flow. In the JPY equation therefore, adding order flow makes the coefficient on the macro variable – interest differential – significant. This result suggests that order flow is the omitted variable that could "rescue" macro specifications, albeit by adding a micro component.

3.2 Micro FX and the Evans and Lyons Model of Trading

The microstructure approach to FX moves the thinking about how FX rates are set from a rather abstract theoretical approach to a more realistic information-theoretic approach. It introduces friction to the system if you will, recognizing that it is important to understand what information the dealers have available to them, and what forces influence their decisions. "Whether we like it or not, it is a stubborn fact that in the major currency markets, there is no exchange rate other than the price these people [FX dealers] set." (Lyons, 2001)

Evans and Lyons (2002a) propose a simplified model of quoting and trading that incorporates the idea of the informational content of order flow, as well as the stylized facts on FX dealers concerning their risk aversion and aggressive inventory management. In this model there are three rounds of trading. In the first round, dealers quote prices to customers. Each dealer then observes some customer order flow based on these quotes. Then each dealer quotes prices in the interdealer market, and dealers trade amongst themselves to manage their inventory. Interdealer trading is simultaneous and it is possible to trade with multiple partners. In the third round of trading dealers trade with customers again to share overnight risk with the market, as we have seen that dealers do not provide overnight liquidity. All prices are publicly observed and are assumed to be good for any quantity. This condition implies that all dealers will choose to quote the same price within a given round, otherwise they would be vulnerable to arbitrage. The no-arbitrage condition ensures this aspect of dealer behaviour, since dealers are setting prices based on *common knowledge* information. In this model dealers will trade on private information gained from their customer order flow, but will not find it optimal to change their quotes based on this information and thus reveal their private signal. They will instead wait for a more precise signal that they get by observing order flow in the interdealer market, the intuition being that interdealer flows, which are caused by customer order flows, can give a better – though noisy – indication of the "true" value of *aggregate* order flow.

The timeline of trading in this model can be represented graphically as follows (Evans & Lyons, 2002):

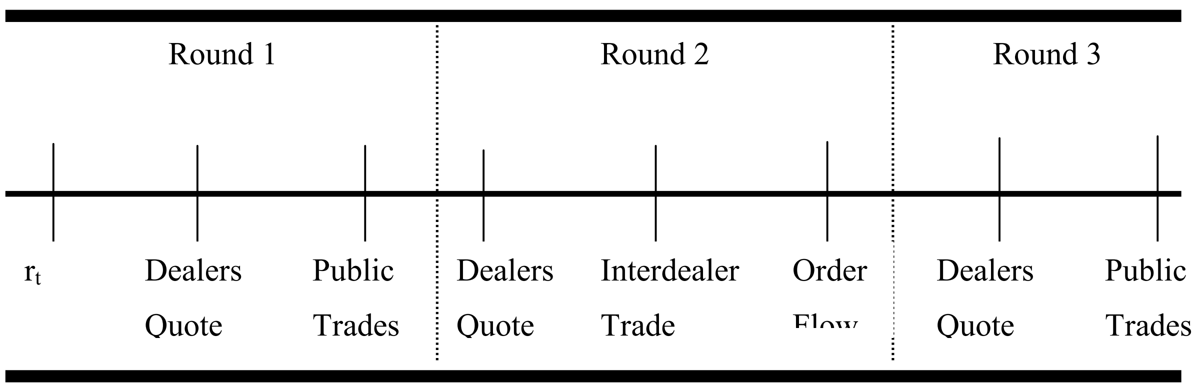


Figure 3-1 – Daily Timing – Evans and Lyons Model of Trading

Mathematically, the period-t quote can be represented as:

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i E[f_{t+i} | \Omega_t^D]$$
$$0 < b < 1$$
$$s_t := \text{log price of foreign currency quoted by all dealers} \tag{3.2}$$
$$f_t := \text{FX rate fundamentals}$$
$$\Omega_t^D := \text{information common to all dealers at start of period t}$$

Of course, saying that the quote must be a function of the information known to all dealers does not imply that all dealers have the same information set. In fact, since each dealer observes his own distinct customer order flow, each dealer has a different information set. Due to fear of arbitrage however, as we have seen, individual dealers will not use their private information to set quotes, but will use it to trade with other dealers, and in this way will contribute to the process by which all dealers get information.

If we re-write the period t quote as:

$$\Delta s_{t+1} = \frac{1-b}{b}\left(s_t - E\left[f_t \middle| \Omega_t^D\right]\right) + \varepsilon_{t+1} \tag{3.3}$$

where

$$\Delta s_{t+1} = s_{t+1} - s_t, \tag{3.4}$$

and

$$\varepsilon_{t+1} = \frac{1-b}{b}\sum_{i=1}^{\infty} b^i \left(E\left[f_{t+1} \middle| \Omega_{t+1}^D\right] - E\left[f_{t+i} \middle| \Omega_t^D\right]\right) \tag{3.5}$$

we can see that changes in the log spot rate can be decomposed into an expected part, the first term, and an unexpected part expressed in the ε_{t+1} term. New information affects the price quoted in period t+1 because it revises the forecasts of the present value of fundamentals based on the dealer's common information set Ω_t^D. This last point points to a great advantage that micro models have over macro models, in that they attempt to quantify exactly how new information about the macro economy gets to dealers and how it induces them to change their quotes. In macro models this process is assumed to be somehow instantaneous.

Based on the mechanism of trading described above, although dispersed information reaches the market in the form of customer orders seen by individual dealers, this information can have no impact on quotes until it becomes known to all dealers. This information aggregation will take place in the interdealer market when the individual dealers use the private information they gleaned from their customer order flow to inform their trading decisions.

Importantly, in this simplified model of trading, prices are set in round 3, conditioned on round 2 interdealer order flows. In contrast to round 1 trading, customer's motives for trading are non-stochastic and purely speculative, and dealers must set prices at a level at which the public will willingly absorb dealer inventory imbalances. This implies that dealers not only need to know the size of the total inventory that the public needs to absorb, but also the risk bearing capacity of the public which is less than infinite. "Specifically, given negative exponential utility, the public's total demand for the risky asset in round 3, denoted C3, is a linear function of the expected return conditional on public information:"

$$C3 = \gamma\left(\mathrm{E}\left[P_{3,t+1} \middle| \Omega_3\right] - P_{3,t}\right) \tag{3.6}$$

The positive coefficient γ captures the aggregate risk-sharing capacity of the public, and Ω_3 is the public information available at the time of trading in round 3 (Evans and Lyons, 2002a).

It is important to note at this point that round 3 is a simplifying assumption. It is necessary to complete the model and may not be entirely realistic. Particularly for FX dealers outside the US, even if we accept that all dealers close out their day flat, as one financial centre closes, another opens so interdealer trade is still possible. Customers do not necessarily need to be induced to take on overnight risk.

Alternative models suggest that information is priced at different times. Osler et al (2006a) make a very convincing argument that price discovery in the FX market does not operate in the way predicted by the standard adverse selection theory of spreads, and in fact a dealer who does observe large volumes of customer order flow would not find it advantageous to behave in the same manner as the "Lyons dealer" discussed in a previous section. The stylized facts that FX dealers do not hold on to positions for long, actively and aggressively manage their inventory and close flat each day still hold, but a dealer who observes customer order flow covets the information in large trades so would be willing to pay for this information by quoting narrower spreads for large trades. Adverse selection theory posits that the exact opposite should happen, however Osler et al claim that conversations with dealers suggest that this mechanism more closely reflects the realities of spreads in FX trading.

Using a dataset comprised of the entire USD/EUR transaction record of a bank in Germany from 11 July 2001 to 9 November 2001 (87 trading days), they find that customer spreads are inversely related to deal size. This means that spreads are narrower for customers the bank considers to be informed, and in fact they find variation in spreads between different customer types. Commercial customers who are generally considered to be less informed pay substantially wider spreads than financial customers. The traditional components of spreads mentioned above cannot explain these observations. Osler et al (2006a) suggest that asymmetric information may affect spreads through two channels that are distinct from adverse selection.

The first is market power. In a quote-driven market, market-power comes from knowledge of the market, and commercial customers typically know much less about the conditions prevailing in the market than their financial counterparts. It has been suggested by Greene et al. (2004) that dealer quotes are directly proportional to their market power. This would explain why commercial clients pay wider spreads.

The second channel is strategic dealing, which refers to the argument that FX dealers strategically vary spreads in order to gain from the information in customer order flow. Effectively this suggests that FX dealers are willing to "pay" through tighter spreads in order to attract order flow from better-informed customers that they can then use to speculate. A dealer who observes customer order flow in FX would have incentives to speculate and his profits would not come mainly from market making. The strategic dealing argument successfully explains why spreads were narrowest for large trades from financial customers as these would be the trades expected to be the most informative.

Based on their observations, Osler et al proceed to suggest how information may get embedded in prices without involving the key mechanism considered by adverse selection theory which considers spreads in the customer market. They suggest that the process by which information gets into price involves the behaviour of dealers managing their inventory in the interbank market. The intuition is that trading with informed customers generates strong incentives for dealers to place a market order in the interdealer market both for inventory control and speculative reasons. This will trigger changes in interdealer prices. In contrast, trading with a customer who is not perceived to be informed is more likely to trigger a limit order thus generating liquidity in the interdealer market rather than driving exchange rates. In this scenario therefore, prices begin to reflect information during interbank trading – round two in the Evans and Lyons (2002) model.

3.3 Order Flow and the FX Rate, Private Information and Causality

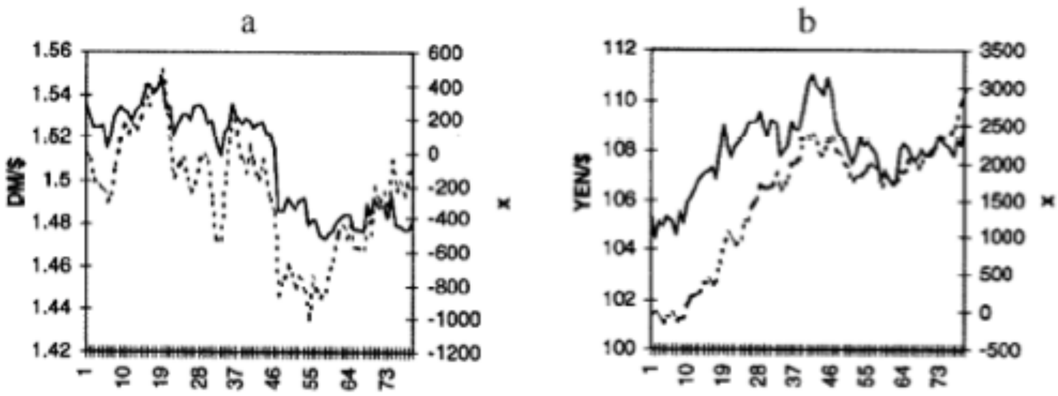


Figure 3-2 – Contemporaneous Relationship (E&L 2002)

Four months of exchange rates (solid) and cumulative order flow (dashed) May 1 – August 31, 1996: a, deutsche mark/dollar; b, yen/dollar. Evans and Lyons (2002)

The contemporaneous correlation between order flow and the FX rate is obvious even if we just rely on the two graphs above from Evans and Lyons (2002). The cause of this correlation is not undisputed however, and certain points need to be dealt with at this stage. It should be pointed out that if a positive correlation between order flow and FX rates seems like nothing more than simple demand, we should recall that in text book models actual trades are not necessary for price movements.

One of the main hurdles to accepting the microstructure way of thinking is the idea that there could be any private information in the FX market. In one sense, this is a perfectly reasonable objection – there is no private information in FX in the sense of insider information in equities. What the FX microstructure approach does suggest however is that there is a great deal of *dispersed* information in FX. What we mean by that is that market participants in the form of end-users of FX – the customers – observe the market, news, fundamentals etc. and based on their own interpretation of this information, which is conditioned on their needs and reasons for trading, they place orders. This is the idea that order flow measures individuals' changing expectations and reflects a "willingness to back one's beliefs with money" (Lyons, 2001). The change in price can be represented by the following:

$$\Delta P_t = f(z_t, z^e_{t+1}) + \varepsilon_t \tag{3.7}$$

Where:

z_t = current macro fundamentals

z^e_{t+1} = expected future fundamentals

Expected future fundamentals are not well captured by macro-econometric techniques, and estimates are slow-moving and imprecise. Order flow can serve as an expectation proxy, and in this sense it is very much a means of transmitting information to price. Allowing for an information role for order flow simply entails relaxing two assumptions in macro-asset models: that all information relevant to exchange rates is publicly known, and that the mapping from information to price is also known. This second assumption is especially stringent, especially in FX where most, if not all, news can have very ambiguous effects on any particular exchange rate. In a realistic micro framework, FX dealers learn about the macro economy directly from news, but crucially also from the order flow they observe.

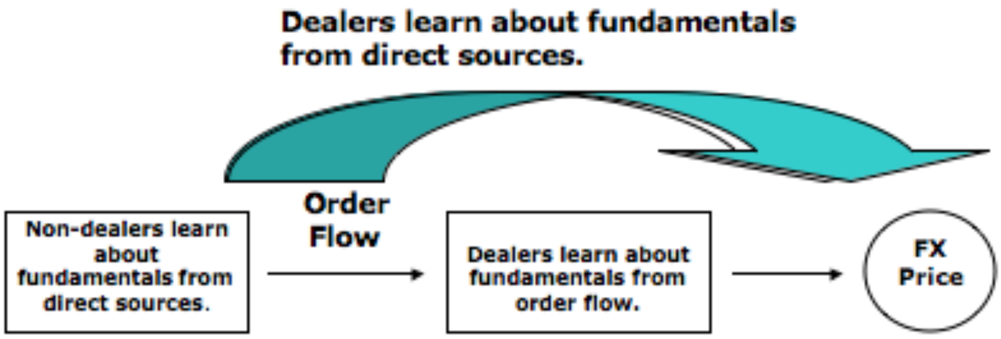


Figure 3-3 – How Dealers Learn about Macro Economy

An interesting property of order flow is that it can be disaggregated according to customer type. For example you can separate order flow into order flow from financial customers (hedge funds, mutual funds, pension funds etc.) and order flow from commercial customers (large multinationals, shipping companies etc.). The financials category can even be subdivided into leveraged and unleveraged financials. Disaggregating order flow in this way is very useful since these separate groups of end-users of FX all trade for very different reasons, and the information contained in their order flow could therefore be very different. Financial customers, particularly hedge funds, might be assumed to be more knowledgeable about the state of the markets, since that is essentially what they are paid to do. As such, their order flow should be very informative. Corporate client trades are mostly need-based – they will trade FX to repatriate profits for example, or because they are planning a project. Corporate order flow might be considered to be the least informative for short term FX movements, but possibly should be the most informative were we to use order flow to forecast future fundamentals since it will be reflecting the needs of companies on whose performance figures such as industrial production or GDP are ultimately based, albeit in an aggregate form, not on the basis of individual companies. Perhaps most importantly though, disaggregating order flow allows us to answer the question of whether order flow is simply undifferentiated demand.

Microstructure sceptics can legitimately argue that FX dealers simply demand a risk premium for holding unwanted inventory and any correlation between order flow and price is simply the effect of a liquidity premium and not due to any information content of order flow. Evans and Lyons (2003b), among others, show that the price impact of orders from financial customers is, dollar for dollar, significantly higher than the price impact from non-financial customers. This definitively tells us that order flow cannot *just* be undifferentiated demand and cannot account for a liquidity premium explanation since a \$10M buy from a corporate and a \$10M buy from a hedge fund should have the exact same impact in such a scenario. Of course this result alone cannot make the case for information content.

Using a dataset of over 6 million FX transactions from State Street Corporation, Froot and Ramadorai (2002) examine the relationship between order flow, exchange rate returns and fundamentals. Their dataset includes FX transactions for 111 currencies by 13,230 funds. All fixed and pegged currencies are removed from the data, as are currencies with few transactions, leaving 19 currency areas. The sample runs from January 1, 1994 to February 9, 2001, a period of 1,855 trading days. Using this novel dataset, Froot and Ramadorai attempt to differentiate between the three scenarios that they consider as possible explanations for the strong contemporaneous correlation between flows and returns. Evans and Lyons argue that this correlation exists because flows contain information about future fundamentals, which would therefore have permanent effects on exchange rates. They call this the ‘strong flow-centric view’. In a weaker version of this theory they consider the possibility that institutional flows contain information about deviations from fundamentals, which would have only transitory price effects. Lastly they submit the possibility that a contemporaneous relationship may simply reflect flows passively responding to fundamentals rather than revealing them.

As a first step Froot and Ramadorai essentially replicate Evans and Lyons (2002), considering the following regression:

$$r_{t+1,j}(P) = \alpha + \beta_{z,j} z_{t,j}(P) + \varepsilon_{t,j} \tag{3.8}$$

$r_{t+1,j}(P)$ = P-period cumulative excess return on currency j (against basket of major currencies),

$$r_{t+1,j}(P) = \sum_{i=1}^{P} r_{t+1-i,j} \tag{3.9}$$

$z_{t,j}(P)$ = corresponding cumulate for signed trade size (value in US$ of all currency j inflow in the interval (t, t+1])

They find a strong contemporaneous relationship of about 30%, also finding that the flow/return correlation rises with the horizon over which they are calculated, peaking at around 45% for major currencies at the one month horizon and then declining sharply as horizon continues to increase, actually falling below zero at long horizons. This interesting result suggests that there are significant non-contemporaneous correlations between returns and flows, although it can give no indication of the direction of the causality, and in addition to this it appears that the impact of flows on returns is transitory.

Expanding on this line of research, Froot and Ramadorai then used a VAR and the Cambell-Shiller return decomposition to separate excess currency surprises into a permanent and a transitory component. This approach allows us to examine the dynamic interactions of flows, returns and measures of fundamentals. They consider the following VAR for $x_t = (r_t, z_t, i_t - i_t^*, \pi_t - \pi_t^*)'$ (excess return, flow, interest rate differential, inflation differential respectively):

$$x_t = \Gamma x_{t-1} + \varepsilon_t \tag{3.10}$$

Since they are interested in the short and long-run interaction between order flow, fundamentals and returns, they are particularly interested in the impulse response functions associated with the VAR. Their results indicate that order flow positively anticipates 1-month ahead movements in FX rates, but at longer horizons the co-movement between order flow and expected long-term future returns is negative. They also show that there is positive covariance between current excess returns and expected short-term cumulative innovations in order flow. Over longer horizons this relationship changes sign becoming strongly negative. This could indicate that some traders follow positive feedback trading rules over short horizons but then unwind their positions in the longer term.

In short, Froot and Ramadorai conclude that there is no clear link between order flow and permanent components of exchange rates, and any positive impact of order flow on the FX rate is transitory and unrelated to fundamental information. They do also examine short and long run covariance between order flow and interest rate differentials and excess returns and interest rate differentials. They find a positive correlation between returns and expected short-term future changes in interest rates, and a positive correlation between order flow and expected short-term future changes in interest rates. In view of this result, Vitale (2004) suggests that order flow is at least related to some short-term fundamental information.

Breedon and Vitale (2004) use six months of interdealer flows from EBS and Reuters and propose a simple structural model of exchange rate determination to disentangle the liquidity and information effects of order flow on FX rates. They present evidence that most of the correlation between FX rates and order flow is due to liquidity effects. This result is hard to reconcile with results from disaggregated customer order flow that, as mentioned above seem to discount a pure liquidity effect. One explanation offered by Marsh and O'Rourke (2005) is that a dealer with private information may prefer to transact in the less transparent direct interdealer market to protect his informational advantage, and only trade in the brokered interdealer market to manage inventory positions caused by uninformed trades.

A difficult issue that remains unresolved when considering the correlation between order flow and exchange rates is that of direction of causality. Is order flow causing changes in spot rates or are changes in spot rates causing changes in desired positions and therefore causing order flow? This is not as simple a question to answer, but disaggregating order flow can help us to take a position. Corporate order flows have a negative correlation with spot changes, and financials have a positive correlation. (Lyons, 1995, Marsh and O'Rourke 2005) If we consider the possibility of feedback trading, these opposite correlations would imply that corporates follow negative feedback trading – buy a currency that has just fallen, and financials follow positive feedback trading – buy a currency that has just risen. Both these possibilities are plausible, but are hard to test without high frequency, intraday, order flow.

If FX movements cause order flow, a problem of simultaneity bias emerges, and this would in turn imply that OLS estimates of beta coefficients would be biased. To take into account possible feedback effects of the FX rate on order flow, Payne (2003) uses an alternative methodology based on the study of a simple linear VAR model for trades and quote revisions, originally used by Hasbrouck (1991) in his study of the NYSE. Payne (2003) applies the VAR methodology to a transaction dataset on the brokered section of the FX spot market. His data gave information on the size of transactions, so he was able to investigate the theoretical assumption from rational expectations models that in the presence of asymmetric information there is a clear relationship between trade size and information content, i.e. the larger the trade, the more information it can be expected to contain. In fact, neither trade size, nor squared trade size were found to be significant, although this could be due to the small variability in trade size observed in the data sample. From the VMA representation, it is found that a market buy[1] causes an approximately 1 basis point increase in the value of the US$. From the variance decomposition Payne finds that over 40% of FX rate variability can be attributed to unpredictable trading activity. In addition, he finds that the asymmetric information coefficients are not stable, changing according to the level of market liquidity and across different time intervals. This implies that time of day and liquidity effects complicate the relationship between order flow and excess returns. The Payne (2003) results suggest that even when possible feedback from the FX rate to order flow is accounted for order flow imbalance remains a determinant of FX rate movements, although the relationship is not as clear-cut as we might have hoped.

Killeen, Lyons and Moore (2002), henceforth KLM, also address the question of causality. They estimate a VAR consisting of the FX rate, cumulative order flow and the interest differential, as well as a constant and a trend, and find one cointegrating vector in the system. We know that a system of variables that is cointegrated must have an error correction representation, which can then provide clues about direction of causality by allowing us to estimate whether adjustment to long run equilibrium occurs via the exchange rate or via order flow. The KLM results indicate that the

[1] The transaction indicator in the VAR was constructed to take a value of unity for a market buy, zero for no trade and minus one for market sell. Payne (2003)

burden of adjustment falls to the exchange rate, suggesting that causality does indeed run from order flow to price. They also find no evidence of Granger causality from the FX rate to order flow, and taken together with the conclusions from the ECM this implies that cumulative order flow is strongly exogenous. This conclusion can seem somewhat counterintuitive, as order flow might be considered to be almost by definition endogenous.

This small sampling of papers should give a good indication that although order flow has been shown empirically to have a definite role to play in FX rate determination, there are as yet no clear cut answers as to what that role is.

3.4 Macro Announcements, Surprises and FX Rate Movements

Understanding how, if at all, order flow affects how macro news announcements are interpreted and incorporated in prices is extremely important, perhaps particularly in terms of forecasting. If order flow loses its importance as an information transmission mechanism, or conversely if this importance is enhanced around periods of news announcements, this will have consequences as we try to model and predict exchange rates. As such, another focus of the research on order flow and FX rates is the effect of macro news on both FX rate movements and order flow itself. Naturally researchers are interested in how macro news gets into prices – is information incorporated in prices immediately as efficient markets theory suggests, or is there room for order flow to play a role? If we accept that order flow does convey information, there are two types of information that it can convey: (i) information about the stream of future cash flows, which in FX also includes future interest differentials and (ii) information about market-clearing risk premia. Similarly, macro announcements can be understood to contain two kinds of information: (i) common knowledge (CK) information and (ii) dispersed incremental information that can be inferred from order flow. Announcements relative to FX rarely have unambiguous interpretations however. To use an example from Andersen et al (2003), a positive US inflation surprise could produce US$ depreciation in an environment in which the Fed places little weight on the level of inflation, or conversely could produce US$

appreciation when the Fed shows a strong preference for low inflation. Andersen et al (2003) examine whether high frequency FX rate movements are linked to fundamentals. Using six years of Reuters high frequency returns data on 6 major currencies observed at 5 minute intervals, and International Money Market Services (MMS) data on money managers' expectations on 41 macro variables for the US and Germany as well as the realized (announced) values, they attempt to measure the effects of the expected and unexpected components of macro announcements. News is defined as the difference between expectations and realized values. Modelling the 5-minute spot exchange rate R_t as a linear function of I lagged values of itself (I=5), and J lags (J=2) of news on each of K fundamentals (K=41):

$$\begin{aligned} &R_t = \beta_0 + \sum_{i=1}^{I} \beta_i R_{t-i} + \sum_{k=1}^{K} \sum_{j=0}^{J} \beta_{kj} S_{k,t-j} + \varepsilon_t \\ &t = 1,....T \\ &T = 496{,}512 \end{aligned} \tag{3.11}$$

They find that unexpected fundamental shocks affect FX rates significantly and immediately – most of the effect felt within a 5 minute interval, whereas adding a variable for the expected component of news had no effect on the FX rate. They also find an asymmetry in the way in which the market reacts to news with bad news having greater impact. They link this last finding with the model in Veronesi (1999) where the effect of bad news in good times is amplified due to increased state uncertainty. Lastly they find that many US indicators have statistically significant news effects across all the currencies they studied.

It would be wrong to conclude from the results of Andersen et al. (2003) among others that public news is the major determinant of exchange rate variation. As Evans and Lyons (2006b) points out, less than 5% of total exchange rate variation is accounted for by public news arrivals. To reconcile this fact with results such as those in Andersen et al (2003), it is important to realize that the papers linking exchange rates and news are event studies, and therefore focus on explanatory power within event windows, not across full samples.

Love & Payne (2003) use 10 months of transaction level data from Reuters D2000-2 in 1999-2000 on USD/GBP, USD/EUR, and GBP/EUR coupled with Euro-area, UK and US macro announcement and expectations data to study the relationships between order flow, spot rates and macro news, both simultaneously and separately, at a 1 minute sampling frequency. Like Andersen et al, they also find an immediate reaction to macro news by FX rates, but interestingly also find that news also affects order flow with both immediate and delayed effects. Following on from this result, they test whether order flow has a greater or smaller role in FX rate determination around the time of macro news announcements, by estimating a non-linear regression. They find that FX rates are more sensitive to order flow around times of macro announcements. Lastly, Love and Payne estimate a multivariate VAR for rates and flows to measure the contribution of order flow to the overall FX rate response to news.

$$\begin{bmatrix} \Delta P_t \\ F_t \end{bmatrix} = \alpha + \delta(z_{t-1}) + \begin{bmatrix} \beta \\ 0 \end{bmatrix} F_t + \sum_{i=1}^{m} \Gamma_{(i)} \begin{bmatrix} \Delta P_{t-i} \\ F_{t-i} \end{bmatrix} + \sum_{j=0}^{n} \Theta_j N_{t-j} + \varepsilon_t \qquad (3.12)$$

ΔP_t = 3 by 1 vector of FX rate returns

F_t = corresponding 3 by 1 vector of order flows

N_t = 3 by 1 vector of standardized euro-area, UK and US news

Studying the impulse response function of the VAR following news releases, Love and Payne are able to separate the direct (no role for trading) and indirect (through order flow) channels through which news gets impounded in price. They do this by estimating the IRF, imposing the restriction that order flow is not affected by news, and again without this restriction and calculating the difference. The hypothesis that all news is immediately impounded in price with no role for trading is rejected, and the results suggest that 50%-66% of the reaction of FX rates to public news announcements that are simultaneously available to all market participants is mediated by order flow. Regardless of the mechanism, all price changes occur within 2 minutes of announcement so there is no question of inefficiency in the FX market. As to providing a reason for why order flow is so important, the authors find the argument that the mapping from news about fundamentals to price varies among market participants, and these differing beliefs induce order flow that moves price to a new equilibrium level to be the most plausible explanation.

A problem with all empirical work on the effect of news is one that has already been mentioned – the "sign" that should be given to any particular news announcement is not necessarily obvious as the same announcement can have opposite effects on a currency depending on other factors in the macro economy. To avoid this problem, Evans and Lyons (2006) focus on the effect of announcements on the second moment of exchange rates and order flow, i.e. on the effects of news on the volatility of FX rates and order flow. Their data covers 4 months (May – August 1996) on Reuters D2000-1 in DEM/USD. This is a bilateral direct trading system where quotes are very short lived, thus avoiding any stale quotes problem that could cloud inferences. The Love and Payne data described above is exposed to such a problem since it is derived from limit order trading. Evans and Lyons also do not limit their announcement data to scheduled announcements (only 10% of all announcements on trading desk screens), thus getting a more complete picture of the dynamics of order flow and FX rates. In their intraday analysis, they estimate a model for the joint dynamics of FX prices and order flow at a 5 minute frequency. The focus is on the relative importance of the direct and indirect information channels operating immediately after an announcement. This relative importance is quantified using a variance decomposition of FX price changes. Unlike Love and Payne, Evans & Lyons suggest that only the private component of information has an effect on FX rates through order flow, and that the public component is immediately reflected by a change in FX rates. The following 2 equations are at the heart of their model (an extension of Evans (2002)):

$$\Delta p_i = B(L)\xi_i + \varepsilon_i \tag{3.13}$$

$$y_i = C_y(L)\xi_i \tag{3.14}$$

Δp_i = change in spot rate
y_i = order flow initiated by customers in period i
ε_{i} = common knowledge news
ξ_{i} = dispersed information shocks

Common knowledge news is immediately impounded into price, whereas dispersed information shocks will first affect order flow and only subsequently will be impounded into price. B(L) and $C_y(L)$ are the lag polynomials that determine the dynamic response of prices and order flow to dispersed information shocks.

Using GMM to estimate the model, the intraday analysis concludes that order flow contributes more to changing FX prices in the period immediately following the arrival of news than at other times. Evans and Lyons also conduct a daily analysis, which finds that about two-thirds of the effect of macro news on FX prices is transmitted via order flow, the remainder being the direct effect of news. In total, they estimate that macro news accounts for 36% of total FX price variance in daily data, a much higher figure than the 5% found in previous studies.

3.5 Puzzles of International Economics: Macro Questions, Micro Answers?

The field of international macroeconomics is replete with a number of obstinate puzzles, and an entire literature review could be devoted to the research dedicated to trying to solve these puzzles. This is obviously beyond the scope of this document but the interested reader can look to Obstfeld and Rogoff (2000) and Sarno (2005) for an excellent treatment of the topic. Here we will limit ourselves to the contributions that the micro literature has made towards resolving some of these puzzles. Lyons (2001) reviews the progress made in resolving two major FX puzzles – the determination or exchange rate disconnect puzzle and the excess volatility puzzle – by applying a dispersed information approach.

The exchange rate disconnect or determination puzzle refers to the fact that empirical evidence shows that fundamentals have little explanatory power for exchange rates – the by now famous, or infamous, Meese-Rogoff result. In a sense, the entire field of FX microstructure is an attempt to resolve this puzzle in that it has provided a well specified – if not a macro – model that can account for exchange rates empirically. Evans and Lyons (2002), using 4 months of interdealer data, find that the flow of buy and sell transactions explains up to 2/3 of the daily variance in the USD/DEM rate and about ½ of the daily variance in the USD/YEN rate. Others such as Payne (2000), Rime (2000) and Marsh and O'Rourke (2005) find similar results. In this sense therefore the micro approach, i.e. an information theoretic modelling approach has provided some insight into the Meese-Rogoff puzzle. It is important to note however that since order flow is not an underlying cause of FX movements but is only a proximate cause, until we understand what is driving order flow this puzzle cannot be satisfactorily resolved, but a growing micro FX literature is tackling precisely this issue.

Bacchetta and Van Wincoop (2003) seek to tackle the exchange rate determination puzzle by introducing investor heterogeneity into an otherwise standard monetary model of exchange rate determination. They introduce two types of heterogeneity to their model: heterogeneous information of market participants about future macroeconomic fundamentals, since surveys show that investors have different views about the macroeconomic outlook, and non-fundamentals based heterogeneity. This second type of heterogeneity includes noise traders, but more generally involves rational investors who trade for non-speculative reasons. The study reaches a number of conclusions. First, under heterogeneous information, the FX rate becomes a source of information about future fundamentals, so whereas under homogeneous information non-fundamentals based trade has little or no effect, when information is no longer common to all investors a small amount of non-fundamentals based trade can become the dominant source of exchange rate volatility. The impact of non-fundamentals trade on the exchange rate can then be significantly amplified as agents rationally misinterpret the resulting exchange rate movements as information about future fundamentals. Second, this confusion can be persistent, and therefore an endogenous persistence of the impact of non-fundamentals based trade on the exchange rate is created. In other words, in this framework, order flow variability accounts for much of the volatility in FX over the short term. Finally, they conclude that the amount of FX rate volatility explained by fundamentals increases as the time horizon increases as investors learn about or observe fundamentals. This result is consistent with other empirical evidence such as Mark (1995).

Killeen, Lyons and Moore (2002) - henceforth KLM - address the excess volatility puzzle, which refers to the fact that exchange rates are excessively volatile relative to our best measures of fundamentals. Exchange rates are generally less volatile when they are managed rather than allowed to float freely. KLM use the switch from the European Monetary System (EMS) to the European Monetary Union (EMU) which was a switch from a target zone to a fixed rate regime, and focus their analysis on the role of order flow to address this puzzle. Using one year of daily EBS data on the DEM/FRF, their analysis concludes that FX rates are more volatile under floating rate regimes because of order flow. This is because under floating regimes order flow conveys more information and in turn increases volatility. Under fixed regimes there is no role for order flow as a determinant of FX rates. The intuition for this is tied to demand elasticity, which is low under floating regimes due to higher volatility and therefore more risk aversion, but infinite under fixed regimes as return volatility shrinks to zero and holding FX becomes effectively riskless. As such, under floating there is room for portfolio-balance effects and this allows a role for order flow to convey information about these effects as in the Evans-Lyons model. Under fixed any portfolio balance effects are eliminated and consequently so is any information role for order flow. (Lyons, 2001)

The puzzles of international macroeconomics are far from solved, but we can see that the micro approach to FX has some definite insights to offer even in this decidedly macro area of international finance.

3.6 Customer Order Flow

Much of the FX microstructure literature focuses on the interdealer market. This is in large part because of data availability issues since interdealer data is more readily available than customer order flow data, but it is not without theoretical merit also. As has been discussed previously, the interdealer market is the only part of the FX market that is at least somewhat transparent, at least to FX dealers. As such it can be argued that the interdealer market is more immediately relevant to FX price determination than customer-dealer order flow (Lyons, 2001a), and many of the papers discussed in other sections deal with interdealer flows. It is indisputable however, that although interdealer trading accounts for much of the volume in FX (43% according to the latest BIS survey), this is in a sense derivative, and it is the demands of the end-users of currency – the customers – that represent underlying demand for FX in the real economy (Fan and Lyons, 2002). Why are customer orders the "crack cocaine" of the FX market as one trader put it? Because customer orders are the catalyst that causes FX movements, and as such customer order flow is much coveted by banks and is jealously guarded. Fan and Lyons (2002) use over 5 years of daily customer order flow data from Citibank – one of the top three FX trading banks with a 10-15% market share in the major-currency customer business (at the time of the study). The data covers the USD/EUR and USD/JPY markets and includes both spot and forward transactions. FX swaps are not included since they do not have any net order flow implications. Lastly, the data is divided into the trades of three customer types: corporates, unleveraged financials and leveraged financials. The mainly graphical analysis in this paper broadly yields the following results: (i) Citibank customer order flow shows little evidence of mean reversion, and cumulated over time is approximately a random walk. (ii) Customer order flow and FX rate movements are closely correlated at lower frequencies (e.g. annual). (iii) The different components of disaggregated order flow behave quite differently. (iv) Extreme exchange-rate movements at high-frequency are generally associated with large net flows from financial institutions, while low frequency trends are associated with flows from corporates.

Marsh and O'Rourke (2005) also use customer order flow, this time from RBS, a leading European bank. They confirm the findings of strong contemporaneous correlation between order flow and FX rates, and discount the possibility that this correlation is simply due to a liquidity effect as they find that order flow from different customer types has different correlations with FX rate changes. Since the RBS dataset covers six bilateral FX rates between four currencies (euro, dollar, yen and pound), they are able to show that information relevant to one exchange rate is contained in customer order flows observed for other exchange rates. Finally, they apply a tool from equity microstructure, namely Easely, Keifer and O'Hara's probability of information based trading measure, and show that the correlation between FX rate changes and customer order flow is positively correlated to P.I.N., a result that they interpret as an additional indication that customer order flows contain information.

A more recent paper is Evans and Lyons (2006b), that develops a model for understanding customer order flow in the FX market. They present both simulation results that address the relationship between FX rates and customer order flow in the model, and empirical estimates based on the Citibank customer flow data.

The simulations show that: Customer flows provide more accurate information about fundamentals when there are more longer-horizon customers; flows from customer segments can produce negative coefficients in contemporaneous return regressions, even when they are positively correlated with fundamentals, and customer flows forecast returns because they are correlated with the future market-wide information flow that dealers use to revise their FX prices. The empirical analysis shows that: both the aggregated and disaggregated customer flows are positively auto-correlated; contemporaneous correlations across flow segments are high at the monthly frequency but decrease as frequency increases to daily; the coefficients on some customer groups can be negative in contemporaneous regressions; the explanatory power of flows increases with horizon; and about one-third of order flows power to forecast exchange rates one month ahead comes from flows ability to forecast future flow, with the remaining two-thirds applying to price components unrelated to future flow.

3.7 Forecasting Using Order Flow

A large body of literature exists describing the inability of fundamentals based models to even explain FX rate movements (e.g. Meese and Rogoff, 1983a, b, Mark, 1995). The microstructure approach has had considerably more success, with strong empirical evidence to support a significant contemporaneous relationship between order flow and exchange rates (see inter alia Evans and Lyons 2002a, b, Marsh and O'Rourke 2005, Fan and Lyons 2000). An important question however is whether this contemporaneous relationship can be extended to a forecasting one. It is a stubborn fact that FX rates cannot be successfully forecast using traditional macro models, but this has become the yardstick by which models are judged. The motivation for this study is Evans and Lyons (2005b), which presents a microstructure model of forecasting that achieves unprecedented success. Evans and Lyons (2005b) conduct a true ex-ante forecasting experiment, using a 3 year forecasting sample and over horizons ranging from 1 day to 1 month. They compare the results of their forecasts to a naïve random walk as well as to a standard macro model, and find that the micro model consistently outperforms both, with micro-based forecasts accounting for almost 16% of the sample variance in monthly spot rate changes.

3.7.1 Theoretical Foundations

The theoretical basis for the Evans and Lyons (2005b) model stems from a new perspective on the forecastability of FX rates, first described by Engel and West (2004a,b). The fundamentals in most macro models do not follow random walks, so if there is some *unobserved* fundamental that does follow a random walk, this could offer an explanation for the random walk nature of exchange rates. Engel and West (2004a,b) show that “if fundamentals are I(1), but not necessarily random walks, then as the discount factor in the present value relation approaches one, the exchange rate will follow a process arbitrarily close to a random walk.” (Evans and Lyons, 2005b) If we consider that an I(1) process can be split into a stationary and a non-stationary component, we can see that a discount factor close to one implies that most of the weight is placed on future fundamentals, whose expectations will be dominated by the random walk component. It is reasonable to conclude therefore that stationary components of fundamentals provide little promise for forecasting. Therefore, “one needs to focus on where all the action is, namely, exchange rate dynamics that come from expectational surprises.” (E&L 2005b)

We can illustrate this issue more formally, starting with the present value expression for the spot rate (equation (1) in E&L 2005b):

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i E_t f_{t+i} \tag{3.15}$$

s_t = log nominal FX rate

f_t = current macro fundamentals

b = discount rate

E denotes expectation

Iterating forward and rearranging, gives us (equations (2) and (3) in E&L 2005b):

$$\Delta s_{t+1} = \frac{1-b}{b}\left(s_t - E_t f_t\right) + \varepsilon_{t+1} \tag{3.16}$$

where :

$$\varepsilon_{t+1} \equiv (1-b)\sum_{i=0}^{\infty} b^i \left(E_{t+1} - E_t\right) f_{t+i+1} \qquad (3.17)$$

Engel and West's analysis tells us that forecasting based on $\left(s_t - f_t\right)$ is difficult as b is close to unity and changes in fundamentals are not very predictable. A logical next step therefore is to focus on the error term ε_{t+1} and examine the FX rate dynamics that come from expectational surprises, $\left(E_{t+1} - E_t\right) f_{t+i+1}$ in the equation above.

3.7.2 A Micro Model

The micro based model in E&L (2005b) is based on the present value relation discussed in the previous section, with one main difference. Micro based models focus on the mechanism through which marketmakers get information. There is no assumption that all information is symmetrically disseminated and immediately impounded in price, and in fact this is the major difference between macro and micro models. As such, the difference in the present value relation is one of expectations, namely that expectations now refer to the marketmakers expectations conditioned on information at the start of period t, making the present value relation:

$$s_t = (1-b)\sum_{i=0}^{\infty} b^i E_t^m f_{t+i} \qquad (3.18)$$

$E_t^m f_{t+i}$ = marketmaker expectations of future fundamentals

Therefore, iterating forward and rewriting gives us:

$$\Delta s_{t+1} = \left(\frac{1-b}{b}\right)\left(s_t - E_t^m f_t\right) + \varepsilon_{t+1}^m \qquad (3.19)$$

$$\varepsilon_{t+1}^m \equiv (1-b)\sum_{i=0}^{\infty} b^i \left(E_{t+1}^m - E_t^m\right) f_{t+i+1} \qquad (3.20)$$

The above specification implies that innovations in spot rates are driven by the present value of revisions in marketmaker forecasts of future fundamentals. It is a central premise of the micro approach to FX that marketmakers learn about the macro economy by observing order flow. This need not imply that customers have private information per se. Customers trading for allocative reasons can still, in aggregate, convey information, although on a customer-by-customer basis there would not be significant information in the trades. "When a large number of agents are trading for correlated reasons, the resulting transaction flow during period t (after s_t is set) will convey information to marketmakers that causes them to revise their fundamentals forecasts" (E&L, 2005b).

The contemporaneous relationship between order flow and exchange rate innovation has been demonstrated empirically in a number of papers as discussed in a previous section, (e.g. E&L 2002a,b) but from a forecasting standpoint this is not helpful. What does interest us is whether order flow observed before the start of period t is correlated with exchange rate innovation between t and t+1. Consequently, two conditions need to be satisfied in order for micro-based models to be useful for forecasting:

(i) Orders must contain information either due to customers trading because they feel they have superior information that they can take advantage of, or due to the aggregate flow of allocative trades signalling information about the macro-economy that is not yet publicly known; and

(ii) There must be a lag between the time information triggers order flow and the time it is seen by all marketmakers and therefore impounded into price.

The second condition is not an unreasonable one in a market as opaque as the FX market. Each dealer will only observe part of the order flow in any period, and will only learn of the aggregate order flow with a lag, and even then this knowledge will be received indirectly by observing trading on the interbank market. "The forecasting power of order flow arises precisely because it takes time for the implications of aggregate order flow to be recognized across all market makers and hence reflected in spot prices" (E&L, 2005b).

Before extending this theoretical construct to create a model that can then be tested empirically, we must first consider a model of marketmaker behaviour, i.e. we must answer the question whether dealers will revise their quotes based on any information they gain from observing their own customer order flow. The models of marketmaker behaviour in Lyons (1997) and Evans and Lyons (2002a) suggest that this does not happen. The dealers in the FX market are involved in a repeating game of incomplete information. Each dealer's information set consists only of information about prior aggregate order flow, his own private order flow signal, and the fact that other dealers cannot know what order flow he has observed in each period. It would not be optimal therefore to reveal his private signal (i.e. any information gained from his individual order flow) through a price quote. Rather, he will prefer to trade on any information at the prices quoted by other dealers. The Bayes-Nash equilibrium of this model dictates that dealers will wait until they have a precise signal before updating their quotes, and this happens after they observe trading in the interdealer market, when they can infer the "true" value of aggregate order flow during the period t to t+1. At the start of period t+1, aggregate order flow during the previous period has become common knowledge to all dealers.

Combining all these ideas allows us to formulate a model of fundamentals and order flow, which can then be rewritten to give a forecasting equation. Assuming fundamentals follow an autoregressive process, but splitting the innovations into a common-knowledge component and a part correlated with the innovation in aggregate order flow, we get the following specification:

$$\Delta f_t = \phi \Delta f_{t-1} + u_t + v_t \tag{3.21}$$

Δf_t = changes in fundamentals

u_t = common knowledge component observed contemporaneously

v_t = component correlated with innovation in aggregate order flow, becomes known to all dealers with a 1 period lag

$$x_t = \lambda x_{t-1} + v_t \tag{3.22}$$

x_t = aggregate order flow

Under these assumptions, dealers learn about the state of the macro economy with a lag, i.e.

$$E_t^m f_{t-1} = f_{t-1} \tag{3.23}$$

$$E_t^m f_t = (\phi + 1) f_{t-1} - \phi f_{t-2} + u_t \tag{3.24}$$

therefore

$$f_t - E_t^m f_t = \delta v_t \tag{3.25}$$

Using these assumptions with the present value relation for the spot rate, and substituting for v_t gives the following forecasting equation (equation 11 in E&L, 2005b):

$$\Delta s_{t+1} = \frac{1-b}{b}\left(s_t - E_t^m f_t\right) + \frac{1}{1-b\phi} u_{t+1} + \frac{\left[1+\phi(1-b)\right]\delta}{1-b\phi}\left(x_t - \lambda x_{t-1}\right) \tag{3.26}$$

"This equation shows that lagged order flows can have forecasting power for spot rates even when the discount factor is very close to unity: the coefficient on the last term has a limiting value of $\delta/(1-\phi)$ as $b \to 1$." (E&L 2005b)

Regression Specification in Evans and Lyons (2005b)

Based on the above forecasting equation, E&L (2005b) consider the two following regressions in their empirical analysis:

Micro 1:

$$\Delta s_{t+1} = a_0 + a x_t^{agg} + e_{t+1} \tag{3.27}$$

x_t^{agg} = aggregate order flow

Micro 2:

$$\Delta s_{t+1} = a_0 + \sum_{j=1}^{6} a_j x_{j,t}^{dis} + e_{t+1} \tag{3.28}$$

$x_{j,t}^{dis}$ = order flow from segment j (1 of 6 separate customer segments)

3.7.3 Empirical Analysis in Evans and Lyons (2005b)

The Micro 1 and Micro 2 models are run on a dataset comprised of customer order flows and spot rates over six and a half years, from January 1993 to June 1999, in the USD/EUR market. The data is provided by Citibank, and is disaggregated into six different customer types: (i) corporations, (ii) investors such as mutual and pension funds and (iii) leveraged traders such as hedge funds. These three categories are further divided into US and non-US customers to make up the six customer categories. The forecast sample starts at 6/3/1996, and 5 different forecast horizons, h, are examined: 1, 5, 10, 15 and 20 trading days, with 20 trading days corresponding to one calendar month. The order flows used for each model are taken from transaction that occur over the h trading days starting at day t-h, i.e. for the 5 day forecast horizon, 5 days of history are used. The forecast performance of each model is compared to a random walk by means of a MSE ratio in the spirit of Meese and Rogoff (1983). Two macro models are also examined, although no details are given here since the results simply reiterate the findings of Meese and Rogoff (1983) and those of the voluminous literature that followed them, in stating that macro models are of little use as a forecasting tool for FX rates. The results of this forecasting experiment, summarized in the table below are unheard of in the FX literature. The Micro 1 model performs better than the RW at horizons longer than 10 days, and the Micro 2 model outperforms the RW model at all forecast horizons. They also report values for β which estimates the contribution of the model forecasts to the variance of the spot changes over the forecast period, and although at the daily frequency the micro 2 model only accounts for 2% of the sample variance, this proportion increases with the forecast horizon, reaching a value of almost 16%, i.e. the micro 2 model accounts for almost 16% of the sample variance in monthly spot rate changes.

Table 1: Forecast Comparisons

	Horizon h (trading days)				
	1	5	10	15	20
UIP					
MSE	1.001	1.006	1.012	1.016	1.021
p-value	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
β	0.000	0.000	0.000	0.000	0.000
p-value	(0.058)	(0.597)	(0.542)	(0.488)	(0.414)
Fama					
MSE Ratio	1.005	1.011	1.022	1.035	1.054
p-value	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
β	0.000	0.003	0.002	0.003	0.010
p-value	(0.533)	(0.332)	(0.457)	(0.452)	(0.359)
Micro I					
MSE Ratio	1.026	1.015	1.001	0.946	0.896
p-value	(1.000)	(1.000)	(1.000)	(0.357)	(0.106)
β	0.002	0.024	0.092	0.133	0.129
p-value	(0.398)	(0.118)	(0.000)	(0.000)	(0.000)
Micro II					
MSE Ratio	0.961	0.876	0.848	0.810	0.806
p-value	(0.124)	(0.024)	(0.091)	(0.045)	(0.055)
β	0.027	0.057	0.102	0.122	0.157
p-value	(0.005)	(0.018)	(0.005)	(0.007)	(0.002)

Notes: MSE ratio is the ratio of mean squared forecast errors for the non-RW model to the RW model. The p-value from a one-sided test for the RW null is reported in parenthesis under the MSE ratios. These p-values are computed as in Mark (1995) with the Andrews AR(1) rule for the truncation lag The p-values below the estimates of β are for the null $\beta = 0$ and are computed from the asymptotic distribution of the OLS estimates using Newey-West estimator with $h - 1$ lags.

Table 3-1 - Forecast Comparisons, Evans and Lyons (2005b)

4 Forecasting with RBS Order Flow

4.1 Meese-Rogoff Redux…Redux

Based on the mostly positive results of the small but growing microstructure literature inspired by Lyons (1995), as well as the results of E&L (2006a) described in the previous section – thus far the only published paper demonstrating forecasting power using customer order flows – we were motivated to conduct a forecasting experiment of our own. We attempt to replicate the Evans and Lyons results using a new dataset from RBS, a leading European bank. Replication of published results is an essential part of the scientific method, but unfortunately economic research faces problems with "replicability". This stems from the fact that in order to replicate a study a researcher needs not only the same data, but the same software and code the original authors used. "Few journals would even attempt to publish a description of all an article's data sources and every programming step, but without knowledge of these details, results frequently cannot be replicated or, at times, even fully understood" (Anderson et al, 2005). Compounding this problem in our case is the fact that the data used in the Evans and Lyons studies is proprietary, so naturally we do not have access to it. Nevertheless, we establish that the RBS data is the same *type* of data, and is directly comparable to the Citibank data. Using this equivalent dataset, we seek to demonstrate whether the Evans and Lyons results can be generalized to the customer flows of other banks. In addition, since our data contains information on multiple currencies we examine whether the relationship extends to currencies other than the Euro-Dollar.

Our data spans three and a half years, starting 01/08/2002 to 02/03/2006, and is comprised of spot rates and customer order flows in six major currency pairs: EURO_GBP, EURO_JPY, EURO_USD, GBP_USD, USD_JPY and GBP_JPY. RBS maintains a 24-hour foreign exchange trading service for its customers, and the order flows are aggregated across a 24-hour window from Sydney open to US close. All spot transactions are included in the data, but no forward deals or deals in the interbank market are included. Once currency specific holidays are excluded, we are left with 878 trading days of order flow data.

Similarly to the Evans and Lyons dataset, order flows are disaggregated into four categories of customer: non-financial corporates (Corp), unleveraged financials such as mutual funds and pension funds (Unlev), leveraged financials such as hedge funds (Lev), and other financials (Other). The last group contains trades of smaller banks that do not have access to the interbank market, as well as trades of central banks.

Contemporaneous spot FX rate data was provided by RBS and is from Reuters. We used the daily rate at NY 4pm to calculate log changes in exchange rates. Earlier limited experimentation using Sydney open and New York close did not affect our results.

Section B in the appendix contains descriptive statistics of both the actual and absolute values of net order flows in all currency pairs and for all customer categories. Net order flows are very volatile, and in many cases the standard deviation is larger than the mean absolute net flow. In this sample period the EUR_USD market had the largest average absolute net order flow, followed by USD_JPY. EUR_GBP and GBP_USD follow with similar average absolute net flows. The GBP_JPY market trails the other five markets with significantly smaller average absolute net flows.

4.2 Contemporaneous OLS – Total Order Flow

Before even considering whether the RBS order flow data can be used to forecast exchange rates, it is important to establish if the contemporaneous correlation found by Evans and Lyons in the Citibank data exists in our data. To this end, we ran a series of contemporaneous OLS regressions on both total order flow and disaggregated order flow for each of our six exchange rates. The regressions were estimated at the daily, 5 day, 10 day and 15 day horizons. The 20-day horizon was omitted since our dataset is slightly shorter than the Evans and Lyons dataset. Non-overlapping windows were used thus avoiding any problems of induced serial correlation in the residual, and Newey-West (HAC) standard errors were used throughout. The specification for the first set of regressions using total order flow is shown below:

$$\Delta S_t = \beta_0 + \beta_1 x_t + \varepsilon_t \tag{4.1}$$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

The results from these regressions are summarised in table 4-1 at all time horizons examined.

Contemporaneous OLS with Aggregated Flows			
	Coefficient	**p-value**	**R-Squared**
DAILY:			
Euro_USD	0.1100	0.2010	0.0020
Euro_JPY	**1.4280**	0.0000	0.0710
Euro_GBP	**0.2180**	0.0470	0.0050
GBP_USD	**0.4210**	0.0080	0.0110
USD_JPY	**0.5050**	0.0000	0.0350
GBP_JPY	**1.6620**	0.0360	0.0100
5 DAY			
Euro_USD	0.2500	0.1110	0.0130
Euro_JPY	**1.9630**	0.0000	0.1760
Euro_GBP	0.1630	0.4050	0.0040
GBP_USD	-0.0560	0.8670	0.0000
USD_JPY	**0.7070**	0.0000	0.0740
GBP_JPY	0.7780	0.4680	0.0020
10 DAY			
Euro_USD	0.2330	0.3020	0.0140
Euro_JPY	**1.9760**	0.0000	0.1350
Euro_GBP	-0.0410	0.8550	0.0000
GBP_USD	0.4240	0.3190	0.0090
USD_JPY	**1.1440**	0.0000	0.2080
GBP_JPY	2.1750	0.2390	0.0140
15 DAY			
Euro_USD	-0.0500	0.8450	0.0010
Euro_JPY	**1.7360**	0.0000	0.1640
Euro_GBP	-0.1110	0.6670	0.0030
GBP_USD	0.6850	0.2900	0.0240
USD_JPY	**1.0240**	0.0000	0.2060
GBP_JPY	-1.8200	0.4390	0.0160
Regression specification:	$\Delta S_t = \beta_0 + \beta_1 x_t + \varepsilon_t$		
where:	ΔS_t : *change* in log spot FX rate		
	x_t : total net customer order flow		

Table 4-1 - Contemporaneous OLS – Total Order Flow

The results of the aggregated order flow regressions are not particularly encouraging, with only the coefficients on Euro_JPY and USD_JPY significant at all time horizons. A positive coefficient in this regression implies that net buying pressure results in currency appreciation, so it is encouraging that most coefficients are positive, although many are not significant.

4.3 Contemporaneous OLS – Disaggregated Order Flow

A significant drawback of the regression equation using total order flows is that it assumes that the impact of order flow from each customer type is the same. If order flow does in fact serve as a source of private information this is not a reasonable assumption to make. Relaxing this constraint involves regressing FX rate changes on disaggregated net order flows. The regression specification now becomes:

$$\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t \tag{4.2}$$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Sample results for the EUR_USD are shown in Table 4-2. Results for the remaining currency pairs can be found in the appendix.

It is important to note that "in this setting, estimated coefficients are not unbiased reflections of the total price-impact of order flow from a given segment and … specifications that include contemporaneous flows only are reduced-forms for complex microeconomic dynamics, and cannot produce structural estimates of the price-impact of incremental trades" (E&L 2005c). This introduces a certain amount of difficulty interpreting price-impact from these regressions. Even a bank as large as Citibank only sees a fraction of total order flow, and as such, customer flows may be representative of the flows seen by other large dealers, but they do not represent the means through which information gets impounded in prices. Customer order flows are one factor driving interdealer flows, which in turn are also a source of information to dealers if we recall the model of trading introduced in a previous section.

"Individual coefficients simply map variations in customer flows into an estimate of the information flow being used by dealers across the market" (E&L, 2005c).

Contemporaneous OLS - Disaggregated Order Flow €/$					
	Corporate	**Unlevered**	**Levered**	**Other**	**R-Squared**
Daily:					
Coefficient	***-0.3680***	**0.9860**	**1.1200**	-0.0580	0.0520
p-value	0.0630	0.0050	0.0000	0.5540	
5 DAY:					
Coefficient	**-1.5770**	**1.1350**	0.6940	-0.0320	0.1280
p-value	0.0360	0.0440	0.1320	0.9480	
10 DAY:					
Coefficient	0.0990	**1.5640**	**2.0270**	-0.0580	0.1200
p-value	0.8060	0.0170	0.0060	0.8110	
15 DAY:					
Coefficient	0.4030	1.3440	1.1410	-0.3890	0.1030
p-value	0.4560	0.1930	0.2210	0.1220	
Regression	$\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$ ΔS_t : *change* in log spot FX rate x_t : total net customer order flow				

Table 4-2 – Contemporaneous OLS – Disaggregated Order Flow €/$

The results of the disaggregated regressions are clearly indicative of heterogeneity among customer types. Corporate customer flows have negative coefficients when significant, and profit-maximizing financials (both levered and unlevered) have positive coefficients. Comparing these results to those of Evans and Lyons summarized in table 4-3 below from E&L (2006a) we see that the patterns are broadly comparable. In other words, the RBS data share the contemporaneous properties of the Citibank data. There is a contemporaneous relationship between order flow and changes in spot rates, and just as in the Citibank data this relationship is sharpened by disaggregating order flows into distinct customer types. R squared values are similar, and although the size of coefficients are not the same, their signs are.

Table 2: Contemporaneous Return Regressions

	Corporate		Hedge		Investors			
Horizon	US	Non US	US	Non US	US	Non US	R^2	χ^2
1 day	-0.155	-0.240					0.015	15.133
	(0.113)	(0.067)						(0.001)
			0.174	0.204			0.024	21.791
			(0.055)	(0.060)				(<0.001)
					-0.047	0.369	0.044	38.261
					(0.120)	(0.060)		(<0.001)
	-0.147	-0.214	0.153	0.194	-0.029	0.353	0.078	75.465
	(0.107)	(0.064)	(0.054)	(0.056)	(0.121)	(0.059)		(<0.001)
1 week	-0.118	-0.469					0.061	32.07
	(0.138)	(0.083)						(<0.001)
			0.349	0.114			0.077	27.965
			(0.069)	(0.096)				(<0.001)
					-0.005	0.523	0.105	37.728
					(0.154)	(0.086)		(<0.001)
	-0.167	-0.358	0.275	0.069	-0.051	0.447	0.195	111.527
	(0.133)	(0.077)	(0.064)	(0.090)	(0.143)	(0.080)		(<0.001)
1 month	0.065	-0.594					0.129	22.434
	(0.266)	(0.126)						(<0.001)
			0.389	0.166			0.103	8.75
			(0.135)	(0.225)				(0.013)
					-0.091	0.719	0.205	34.636
					(0.215)	(0.119)		(<0.001)
	0.120	-0.376	0.214	-0.074	0.000	0.583	0.299	58.424
	(0.185)	(0.102)	(0.137)	(0.196)	(0.208)	(0.130)		(<0.001)

Notes: The table reports OLS estimates of the coefficients in the regression of excess returns, er_{d+h}, on the customer order flow segments that aggregate net orders for the euro in \$m on days d to $d+h-1$. Estimates are computed at the daily frequency, with $h = 5$ and 20 for the 1-week and 1-month horizon regressions. The table reports asymptotic standard errors corrected for heteroskedasticity in parentheses. For the 1-week and 1-month results, standard errors are also corrected for the induced MA(h-1) process in from overlapping observations. The right hand column reports Wald tests and p-values for the null that all the coefficients on the order flows are zero.

Table 4-3 – Contemporaneous return regressions (E&L, 2005c)

4.4 A Forecasting Experiment

Having established that the RBS dataset is closely equivalent to the Citibank dataset in many ways – both are comprised of customer order flows, disaggregated into broadly similar categories and share the same contemporaneous correlation with spot FX rates – the next logical step would be to replicate the E&L (2005b) forecasting experiment described in chapter 3. Both the Micro 1 and Micro 2 models are tested on our data, using daily, 5 day, 10 day and 15 day historical order flow to forecast forward over a large number of forecast horizons. At the daily frequency, order flow observed in period t is used to forecast change in spot FX in period t+1, t+2, t+3, t+4, and t+5 respectively. This is a departure from the E&L (2005b) methodology in that they use symmetric history and forecast horizons - i.e. one day history to forecast one day ahead, 5 day history to forecast 5 days ahead etc. We felt that it was important to include the intermediate forecast horizons as we do not know how quickly order flow information gets reflected in price. To go back to the theoretical model discussed in section (ii), we don't know how long it takes for the "true" aggregate order flow to become common knowledge to all dealers, and in our model of dealer behaviour quotes will not change until this happens. When using 5 days of order flow history, forecast horizons are extended from t+1 to t+10, 10 days order flow history extend the forecast horizon in daily increments to t+15, and 15 days order flow history are used to forecast out to t+20. In general if h is the history used (h=1, 5, 10, 15) each model uses order flow in t-h to forecast t+1, t+2…[t+(h+5)].

As in the contemporaneous regressions, non-overlapping windows were used to avoid the problem of induced serial correlation in the error term, and HAC standard errors were used throughout. The 20 day horizon estimated in the E&L(2005b) paper could not be estimated in our dataset since it is shorter and we would run the risk of our results suffering from small-sample bias. An advantage of the RBS dataset is that it is comprised of 6 major exchange rates as opposed to just 1, so we can extend the E&L(2005b) forecasting experiment to include more than just the EUR_USD market. This allows us to test whether these forecasting models are generaliseable beyond the EUR_USD market, at least to the major, liquid FX markets.

In all cases, a true out of sample forecasting exercise is performed. We retain 2/3 of our data sample to estimate the model and use the remaining 1/3 to perform the out of sample forecasts. Forecasting model performance was evaluated on the basis of RMSE ratio of each model to that of a simple random walk, making our results comparable to most other FX forecasting studies post Meese-Rogoff.

Micro 1 Model

$$\Delta s_{t+f} = a_0 + a x_t^{agg} + e_{t+f} \tag{4.3}$$

x_t^{agg} = aggregate order flow, f = forecast horizon

This model tests the forecasting power of total (aggregated) net order flow, i.e. we want to test whether observing net buying or selling pressure, regardless of customer type, gives us information that will allow us to forecast the exchange rate. Regression output for each model is summarized in table 4-4 below for the EUR_USD.

It is immediately obvious that the contemporaneous correlation we found earlier has disappeared in the forecasting regressions. No coefficients are significant and R-squared values are all essentially zero. Nevertheless we compare the performance of each forecasting model in terms of RMSE ratio to the random walk model for the sake of completeness, and so that our results can be directly comparable to the E&L(2005b) results. RMSE ratio results are summarized in Table 6-5. Forecast evaluations for the remaining currency pairs can be found in Appendix D.

A RMSE ratio below 1 would signify that the model performs better than a naïve random walk model. As we can see however, although the RMSE ratio does dip below 1 in a few cases (shown in bold in the table), it is only marginally below one and appears to be random. We would expect to have some RMSE ratios below 1 simply by chance, and in view of the results of the forecasting regressions themselves, we consider the above results to be indicative of a complete failure of the Micro 1 model as a forecasting tool, at least using RMSE as a measure of performance.

Micro 2 Model

$$\Delta s_{t+f} = a_0 + \sum_{j=1}^{4} a_j x_{j,t}^{dis} + e_{t+f} \tag{4.4}$$

$x_{j,t}^{dis}$ = order flow from segment j (1 of 4 separate customer segments)
f = forecast horizon

Using the same reasoning as in the contemporaneous regressions, we extend our forecasting model by disaggregating our net daily order flows according to customer type. To reiterate, the intuition behind using disaggregated net order flows stems from the informational properties of order flow. If we assume that order flow contains information, distinguishing between the types of customers placing orders should serve to sharpen the precision of the information content. This hypothesis is supported by the results of the contemporaneous regressions, as we saw that corporate net order flow is negatively correlated with spot FX changes, while financial customer net order flow is positively correlated. This difference may be due to the fact that different customer types have distinct motives for trading and by extension their order flow would have different information content.

Regression output and RMSE ratio to the random walk model are summarized in Tables 4-6 to 4-9 for the EUR_USD models. Once again, we find that in the forecasting regressions our coefficients have lost all significance and R-squared values are essentially zero. RMSE ratio results confirm the poor forecasting performance of the model regardless of history used and at all forecast horizons.

We do not report the results of the forecasting regressions for the other currency pairs here for the sake of brevity, since they reach the same conclusions, i.e. lack of significance for most coefficients and poor forecasting performance. RMSE ratio tables for all currency pairs and for both models (Micro 1 and Micro 2) can be found in Appendix D.

Micro 1 forecasting Model - Aggregated Order Flow *(Currency pair : €/$)*				
	Coefficient	**p-value**	**R-Squared**	**RMSE**
1 day history:				
Horizon 1	-0.0460	0.7340	0.0000	0.5570
Horizon 2	0.0300	0.8680	0.0000	0.7880
Horizon 3	0.0730	0.7400	0.0000	0.9650
Horizon 4	0.0260	0.9200	0.0000	1.1080
Horizon 5	-0.0930	0.7400	0.0000	1.2350
5 day history:				
Horizon 1	0.1320	0.3540	0.0090	0.5510
Horizon 2	0.0490	0.7940	0.0010	0.8080
Horizon 3	0.0350	0.8730	0.0000	0.9950
Horizon 4	0.0630	0.8200	0.0010	1.1900
Horizon 5	0.0630	0.8320	0.0000	1.3250
Horizon 10	0.2170	0.6000	0.0030	1.8910
10 day history:				
Horizon 1	0.0820	0.5230	0.0080	0.5890
Horizon 2	-0.1480	0.3390	0.0170	0.9250
Horizon 3	0.1050	0.5730	0.0060	1.2380
Horizon 4	0.0660	0.7590	0.0020	1.3570
Horizon 5	0.0830	0.7040	0.0030	1.5420
Horizon 10	-0.0500	0.8870	0.0000	1.9270
Horizon 15	-0.1310	0.7580	0.0020	2.3870
15 day history:				
Horizon 1	0.0660	0.5320	0.0100	0.7400
Horizon 2	0.0680	0.6070	0.0070	1.0930
Horizon 3	0.1920	0.2230	0.0390	1.3690
Horizon 4	0.2170	0.2790	0.0310	1.5110
Horizon 5	0.0730	0.7710	0.0020	1.4680
Horizon 10	-0.3510	0.3280	0.0250	2.1560
Horizon 15	-0.2370	0.5640	0.0090	1.9670
Horizon 20	-0.2720	0.5580	0.0090	2.7310

Micro 1 model: $\Delta s_{t+f} = a_0 + a x_t^{agg} + e_{t+f}$

x_t^{agg} = aggregate order flow, f = forecast horizon

Table 4-4 – Micro 1 Forecasting Regressions: Aggregated Order Flow €/$

Micro 1 Model Forecast Evaluation

Currency: €/$

History Used:	1	5	10	15
Forecast Horizon:				
1	1.004	1.048	1.037	1.092
2	1.007	1.042	1.042	1.032
3	1.010	1.008	1.047	1.090
4	1.014	1.014	1.053	**0.998**
5	1.017	1.016	1.052	**0.983**
6	-	1.027	1.095	**0.997**
7	-	1.047	1.121	**0.989**
8	-	1.030	1.067	**0.999**
9	-	1.033	1.059	**0.991**
10	-	1.043	1.083	1.020
11	-	-	1.082	**0.998**
12	-	-	1.137	1.024
13	-	-	1.149	1.020
14	-	-	1.196	1.063
15	-	-	1.189	1.127
16	-	-	-	1.121
17	-	-	-	1.145
18	-	-	-	1.122
19	-	-	-	1.085
20	-	-	-	1.074

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Table 4-5 – Micro 1 Forecast Evaluation – RMSE ratio to RW

Micro 2 Forecasting Regression Estimation (A)

(Currency forecast: €/$)

	Corporate	(p-value)	Unlevered	(p-value)	Levered	(p-value)	Other	(p-value)	R-Squared	RMSE
Daily										
Horizon:										
1	-0.235	0.323	0.376	0.261	0.209	0.590	-0.127	0.475	0.006	0.559
2	-0.051	0.874	0.405	0.369	0.436	0.406	-0.126	0.599	0.004	0.787
3	0.269	0.492	-0.094	0.864	0.446	0.485	-0.053	0.857	0.002	0.959
4	-0.021	0.964	-0.334	0.598	0.562	0.445	0.075	0.825	0.002	1.111
5	0.015	0.975	-0.645	0.356	0.853	0.294	-0.144	0.698	0.004	1.233
5 Day										
Horizon:										
1	0.100	0.661	-0.416	0.194	0.529	0.190	0.291	0.116	0.058	0.633
2	0.179	0.566	-0.224	0.606	-0.185	0.735	0.139	0.579	0.010	0.813
3	0.223	0.532	-0.215	0.665	-0.605	0.335	0.179	0.533	0.020	0.995
4	-0.068	0.881	-0.076	0.904	0.168	0.833	0.188	0.608	0.004	1.213
5	-0.017	0.972	-0.808	0.235	0.768	0.370	0.319	0.416	0.030	1.407
6	0.097	0.858	-0.862	0.255	1.600	0.095	0.273	0.532	0.044	1.564
7	-0.361	0.544	-1.142	0.170	1.389	0.185	0.279	0.560	0.046	1.736
8	-0.175	0.771	-0.578	0.491	1.487	0.161	0.284	0.558	0.029	1.809
9	-0.546	0.405	-0.742	0.416	1.184	0.303	0.599	0.256	0.044	2.047
10	0.062	0.926	-1.166	0.214	1.175	0.319	0.684	0.207	0.043	2.085

Micro 2 Model: $$\Delta s_{t+f} = a_0 + \sum_{j=1}^{4} a_j x_{j,t}^{dis} + e_{t+f}$$

$x_{j,t}^{dis}$ = order flow from segment j (1 of 4 separate customer segments)

f = forecast horizon

Table 4-6 – Micro 2 Forecasting Regression Estimation (A)

Micro 2 Forecasting Regression Estimation (B)

(Currency forecast: €/$)

	Corporate	(p-value)	Unlevered	(p-value)	Levered	(p-value)	Other	(p-value)	R-Squared	RMSE
10 Day										
Horizon:										
1	0.088	0.670	-0.053	0.875	0.589	0.130	-0.125	0.574	0.061	0.591
2	-0.041	0.872	-0.262	0.529	0.104	0.825	-0.384	0.160	0.045	0.928
3	0.366	0.230	0.104	0.835	-0.226	0.689	-0.117	0.719	0.036	1.169
4	0.243	0.494	0.201	0.729	-0.327	0.620	-0.073	0.847	0.017	1.306
5	0.503	0.161	-0.257	0.659	-0.119	0.857	-0.247	0.517	0.052	1.464
6	0.607	0.111	-0.476	0.442	0.506	0.471	-0.208	0.605	0.080	1.518
7	0.463	0.288	-0.978	0.172	0.862	0.287	-0.164	0.724	0.079	1.605
8	0.393	0.409	-0.344	0.659	0.630	0.477	-0.253	0.618	0.036	1.631
9	0.234	0.671	-1.208	0.184	0.568	0.580	0.230	0.697	0.045	1.972
10	0.058	0.920	-0.914	0.334	0.011	0.992	0.275	0.655	0.024	2.026
11	0.220	0.724	-0.846	0.409	-0.601	0.605	0.522	0.435	0.035	2.210
12	0.371	0.581	-0.937	0.396	-0.506	0.686	0.397	0.581	0.029	2.259
13	0.187	0.774	-1.081	0.314	-0.592	0.626	0.409	0.559	0.035	2.411
14	0.462	0.485	-0.699	0.519	-1.095	0.374	0.831	0.242	0.057	2.635
15	0.194	0.779	-0.854	0.452	-1.455	0.260	0.534	0.471	0.051	2.591

See footnote for Micro 2 Panel (A)

Table 4-7 – Micro 2 Forecasting Regression Estimation (B)

Micro 2 Forecasting Regression Estimation (C)

(Currency forecast: €/$)

	Corporate	(p-value)	Unlevered	(p-value)	Levered	(p-value)	Other	(p-value)	R-Squared	RMSE
15 Day										
Horizon:										
1	0.097	0.561	-0.232	0.417	0.188	0.603	0.114	0.505	0.050	0.815
2	0.179	0.202	-0.323	0.355	0.224	0.612	0.284	0.181	0.090	1.347
3	0.098	0.693	0.158	0.709	0.077	0.886	0.387	0.134	0.066	1.577
4	-0.016	0.957	-0.299	0.545	0.156	0.804	0.809	**0.010**	0.201	2.042
5	-0.053	0.885	-0.988	0.116	-0.095	0.903	0.815	**0.034**	0.200	2.103
6	0.038	0.930	-1.090	0.147	-0.205	0.828	0.521	0.247	0.102	1.900
7	0.164	0.736	-1.450	0.087	0.264	0.802	0.192	0.701	0.093	1.729
8	0.091	0.858	-1.160	0.185	0.018	0.987	0.092	0.860	0.052	1.810
9	0.037	0.949	-1.809	**0.069**	0.041	0.973	0.124	0.832	0.096	1.907
10	-0.323	0.561	-1.506	0.116	-0.184	0.878	0.087	0.879	0.088	2.193
11	-0.243	0.680	-1.560	0.126	0.568	0.656	0.212	0.726	0.089	2.352
12	-0.017	0.978	-2.069	**0.050**	-0.095	0.942	0.138	0.824	0.111	2.274
13	-0.121	0.846	-1.830	**0.090**	-0.137	0.919	0.518	0.419	0.109	2.547
14	0.323	0.608	-1.535	0.157	-0.808	0.553	0.483	0.455	0.080	2.521
15	0.034	0.958	-1.465	0.182	-1.039	0.453	0.282	0.667	0.070	2.395
16	0.208	0.754	-1.700	0.137	-0.933	0.516	0.131	0.847	0.071	2.474
17	0.223	0.742	-1.564	0.181	-0.643	0.662	-0.044	0.950	0.054	2.349
18	0.102	0.878	-1.848	0.108	-0.487	0.735	0.032	0.962	0.074	2.859
19	0.326	0.639	-1.789	0.137	-0.971	0.520	0.111	0.876	0.071	2.834
20	0.605	0.393	-2.221	**0.071**	-1.554	0.312	-0.074	0.919	0.115	2.899

See footnote for Micro 2 Panel (A)

Table 4-8 – Micro 2 Forecasting Regression Estimation (C)

Micro 2 Model Forecast Evaluation

Currency: €/$

History Used:	1	5	10	15
Forecast Horizon:				
1	1.008	1.205	1.041	1.202
2	1.005	1.048	1.045	1.272
3	1.004	1.007	**0.989**	1.255
4	1.016	1.033	1.013	1.349
5	1.015	1.079	**0.999**	1.408
6	-	1.137	1.03	1.199
7	-	1.19	1.104	1.115
8	-	1.134	1.048	1.028
9	-	1.177	1.128	1.019
10	-	1.15	1.139	1.037
11	-	-	1.167	1.113
12	-	-	1.167	1.113
13	-	-	1.216	1.354
14	-	-	1.331	1.287
15	-	-	1.29	1.373
16	-	-	-	1.224
17	-	-	-	1.141
18	-	-	-	1.174
19	-	-	-	1.15
20	-	-	-	1.14

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Table 4-9 – Micro 2 Forecast Evaluation – RMSE ratio to RW

4.5 Cross-Sectional Advantages of the RBS Data

Since the RBS data gives information on six bilateral exchange rates between four currencies (euro, dollar, yen, pound), this allows for a more comprehensive analysis of inter-currency information content than is possible in the E&L (2005b) data that is limited to just the EUR_USD rate. It is a natural extension of the dispersed information model to relax the restriction that customer trades in one exchange rate should only contain information relevant to that exchange rate. A customer with information on the Yen who trades USD_JPY reveals information to that market directly, but could also be revealing information to the "related" EUR_JPY and GBP_JPY markets through the Yen side of the deal, and the EUR_USD and USD_GBP markets through the USD side of the deal, and through these possibly even to seemingly unrelated markets like EUR_GBP. Evans and Lyons (2002b) use direct inter-dealer flows in a system of nine bilateral FX rates against the US dollar, and find that information relevant to one exchange rate is contained in order flows observed in other exchange rates. In addition, Marsh and MacDonald (2004) suggest that currencies can be forecast if a system of exchange rates are estimated together, rather than modelling them one by one.

This leads to regressions of "related" exchange rates on Euro flows, Yen flows, Dollar flows and Pound flows. For example, the EUR_USD rate is regressed against Euro flows as well as against Dollar flows, first in contemporaneous form and then as forecasting regressions at various horizons. The contemporaneous regression specification is shown below:

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t \qquad (4.5)$$

Euro Flows Equation R= {€/$, €/¥, €/£}

GBP Flows Equation R= {€/£, £/$, £/¥}

USD Flows Equation R= {€/$, £/$, $/¥}

JPY Flows Equation R= {€/¥, $/¥, £/¥}

This less restrictive model allows changes in the euro-dollar rate for example to be affected not only by the flows observed in the euro-dollar market, but also by flows observed in the euro-yen and euro-pound market in the euro flows equation, and in the pound-dollar and dollar-yen markets in the dollar flows equation. Sample output from the euro-dollar regressions are presented in table 4-10. All remaining output can be found in Appendix F.

As we can see adding related flows improves the fit of the regression. Coefficients retain their significance and in most cases keep the same sign as in the bilateral regressions, i.e. coefficients on corporate flows are negative and coefficients on financial flows are positive. Exchange rates react to both 'own' and 'related' order flows as expected.

Cross-Currency Regression

Dependent Variable: €/$
(EURO FLOWS)

DAILY				**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	***-0.316***	***0.093***	0.089	-0.243	0.456	0.184
€/$ Leveraged	**1.081**	**0.000**		**1.886**	**0.000**	
€/$ Unleveraged	**0.947**	**0.007**		**1.332**	**0.017**	
€/$ Other	-0.073	0.446		-0.140	0.395	
€/£ Corporate	**-0.946**	**0.004**		-0.779	0.211	
€/£ Leveraged	***0.672***	***0.063***		0.151	0.890	
€/£ Unleveraged	-0.089	0.849		-0.621	0.558	
€/£ Other	0.247	0.137		0.033	0.926	
€/¥ Corporate	-0.320	0.596		-0.978	0.523	
€/¥ Leveraged	-0.412	0.608		-1.210	0.436	
€/¥ Unleveraged	**2.069**	**0.049**		1.535	0.371	
€/¥ Other	**0.756**	**0.000**		**0.993**	**0.012**	

Cross-Currency Regression

Dependent Variable: €/$
(DOLLAR FLOWS)

DAILY				**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	***-0.355***	***0.070***	0.083	-0.232	0.530	0.174
€/$ Leveraged	**1.067**	**0.000**		**1.725**	**0.000**	
€/$ Unleveraged	**0.947**	**0.005**		**1.315**	**0.024**	
€/$ Other	-0.063	0.515		-0.054	0.776	
£/$ Corporate	-0.544	**0.030**		-0.894	0.133	
£/$ Leveraged	1.185	**0.003**		0.208	0.828	
£/$ Unleveraged	0.990	0.141		***2.454***	***0.096***	
£/$ Other	-0.182	0.368		-0.625	0.172	
$/¥ Corporate	0.188	0.563		0.277	0.713	
$/¥ Leveraged	-0.424	0.238		-0.015	0.986	
$/¥ Unleveraged	**-0.671**	**0.034**		-0.171	0.839	
$/¥ Other	**-0.291**	**0.006**		-0.303	0.247	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}
GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Table 4-10 – Cross-Currency OLS: Using ‘own’ and ‘related’ flows to model FX

Since the contemporaneous relationship is confirmed, the forecasting version of these regressions is then tested to see if forecasting performance improves by adding lagged order flows in related markets. Forecasting performance is evaluated using history h=1, 5, 10, 15 and forecast horizons for h=1 at 1 and 5 days ahead, for h=5 at 1, 5 and 10 days ahead, for h=10 at 1, 5, 10 and 15 days ahead and for h=15 at 1, 5, 10, 15 and 20 days ahead. The regression specification is shown below:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f} \tag{4.6}$$

Euro Flows Equation R= {€/\$, €/¥, €/£}

GBP Flows Equation R= {€/£, £/\$, £/¥}

USD Flows Equation R= {€/\$, £/\$, \$/¥}

JPY Flows Equation R= {€/¥, \$/¥, £/¥}

Regression output is omitted for brevity but RMSE ratios are reported in Table 4-11 and in Appendix G for all forecasting regressions. As in the bilateral forecasting exercise, coefficients lost all significance and there was no improvement in forecasting performance. RMSE ratios to the random walk model fall below one in a limited number of cases and in a random fashion, and as in the bilateral models we judge that even these results are no more than would arise simply by chance.

4.6 Problems with RMSE?

In the real world, forecasts are made for specific purposes, and as such conventional statistical measures of forecast accuracy may not be the most appropriate. A forecast is a tool that enables a decision maker to make better decisions. In the case of FX forecasts for example, it should enable traders to make better trading decisions. Since we know the purpose the forecast is to be used for, a method of forecast evaluation that takes this into account may be more relevant than statistical measures of accuracy of point forecasts. Leitch and Tanner (1991) make just such an argument. Using interest rate forecasts, which allowed them to easily calculate a profit measure, they argue that profitability and not the size of the forecast error or its squared value is a more appropriate test of forecast accuracy. They calculate the correlation between various forecast evaluation criteria – Root Mean Squared Error (RMSE), Average Absolute Error (AAE), Theil U Coefficient and Directional Ability (DA) – and profits generated by using the forecasts, and find no relationship. “Regardless of the profit rule followed, there is little systematic relationship between profits and the conventional measures of forecast quality. The only conventional measure of forecast quality that is related to profits is directional accuracy, and it is infrequently used” Leitch and Tanner (1991). This result suggests that, in the event that profits are not directly observable, directional ability may serve as the best proxy, giving a more realistic evaluation of the usefulness of a forecasting model.

4.6.1 Testing for Directional Ability

Bearing this result in mind, we tested the forecasting ability of both the Micro 1 and Micro 2 models on the basis of directional ability. This was done very simply by taking the point forecasts from our models and comparing them to the actual realized changes in FX rates, but evaluating them only on the basis of direction, not magnitude. This allowed us to calculate a directional percent correct value for each model. Sample results for the euro-dollar Micro 2 model are shown in Table 4-12 below, while all remaining directional ability tables can be found in Appendix D.

Our results show us that even when we relax the requirement of the forecasting model to simply indicate the direction of the move if not the size, performance is still uniformly poor among all models for all currency pairs.

4.7 Conditional Models – Order Flow as a Trading Signal

Unwilling to give up on finding some forecasting power in the RBS order flows, we hypothesized that perhaps there was only forecasting power some of the time. To test this hypothesis we ran a number of conditional models, ranging from very simple to quite restrictive. While in the regression-based models we are assuming trading based on the forecasts generated every period, in this case trades are only triggered when a certain set of conditions is satisfied. We restricted ourselves to daily and 5 day frequencies as we continue to use non-overlapping windows to retain comparability with our previous results, and at longer histories we had very little trading triggered. We assume that a trader’s investment horizon is one day, so he will close out any positions triggered by the model at close of business without waiting for the model itself to give a sell signal for example. This is consistent with the model of trader behaviour in Lyons (1998) where FX traders manage their positions to close flat each day. This also implies that in the conditional models we are focusing only on one day ahead forecasts. Also, we are again only trying to forecast direction, so each model is evaluated on the basis of simple percent correct values.

Obviously the conditions we tested are only a small sample of the possible permutations we could use. Theoretically we could have run an algorithm on our estimation sample to pick out the best combination of conditions to forecast, variably weighting the importance of each customer groups' order flow to create a set of conditions that produce optimal forecasts. This methodology, while it may have been successful, runs the risk of over-fitting the data, as well as raising issues of possible data mining. As such we chose to focus on a small set of conditions that follow on from the theory of order flow as a means of information aggregation, while allowing for heterogeneity in our customer base. The set of conditions chosen are summarized in Tables 4-13 and 4-14.

Sample results for the Euro_USD models are shown in Tables 4-15 and 4-16, while summary results from all conditional models for all currency pairs are included in Appendix H. Unfortunately we find that in the vast majority of cases the percent correct value is around 50%, and in the more restrictive models where a number of conditions must be satisfied there is almost no trading. We are forced to conclude that there is little value added by using these conditional models to inform trading decisions.

4.7.1 Testing for Profitability

Lastly, we must of course acknowledge that, despite directional ability being the only *statistical* measure of forecast accuracy that has been found to be related to profitability, directional ability and profitability are not the same thing. It is possible that even if the model has only a 50% directional accuracy, if it is accurately predicting large moves, or 'tail' events, the model could still be profitable. We test for profitability of the order flow forecasts from the disaggregated forecasting model using three very simple trading rules. The first model triggers a buy order if the model forecasts a positive change and a sell order otherwise. Positions are assumed to be closed at the end of the day. In the second model, buys and sells are triggered in the same way, but positions are accumulated until an opposite signal is given by the model. The third model is similar to the second, but in this case positions are not accumulated but held until an opposite signal is given. All three models are tested on the out-of-sample data, and are also run based on signals given only by movements in the exchange rate itself rather than on flows. The results are summarised in table 4-17 below. The results are mixed, both across currency pairs and across trading rules. For EUR_USD the results are dismal, with huge trading losses seen, particularly for model B. We note however that there is very infrequent trading in models B and C. This appears to be a peculiarity of the flows in this particular sample. Performance is also bad for USD_JPY with the exception of model B, but for the remaining currencies the strategies are profitable over our sample period. At the same time however we note that the mean profit hovers around zero in the majority of cases, and the volatility is huge.

Ultimately, the profitability measure of forecasting ability is far more promising than any of our other measures. The trading rules chosen are unrealistically simple, but we chose these rules for transparency rather than applicability. We wanted a measure of profitability that was determined solely on the ability of the flows models to generate trading signals, and so purposely did not implement models that include stop-loss or take-profit rules based on volatility or on the level of profits or losses for example. We also intentionally omit other inputs to our trading models that are unrelated to flows, as we are seeking as pure a measure of profitability based on flows alone as possible. More sophisticated models could therefore conceivably be more successful, and intelligent stop-loss and take-profit levels should decrease the volatility, although they could also increase trading and thus transactions costs.

The development of trading strategies based around order flows seems at least initially to be a promising avenue for further research and deserves more attention. We leave this for a subsequent paper however, as we are currently left with the huge disparity in statistical results between our results and the existing literature that is yet to be explained, and which will be the subject of the rest of this document.

Cross-Currency Forecast Evaluation
(1 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
Euro Flows			
	EUR_GBP	1	1.0930
	EUR_JPY	1	1.0270
	EUR_USD	1	1.0370
	EUR_GBP	5	1.0670
	EUR_JPY	5	1.0360
	EUR_USD	5	1.0320
GBP Flows			
	EUR_GBP	1	1.0400
	GBP_JPY	1	1.0210
	GBP_USD	1	1.0150
	EUR_GBP	5	1.0430
	GBP_JPY	5	1.0250
	GBP_USD	5	1.0320
USD Flows			
	EUR_USD	1	1.0130
	GBP_USD	1	1.0210
	USD_JPY	1	1.0100
	EUR_USD	5	1.0440
	GBP_USD	5	1.0290
	USD_JPY	5	1.0590
JPY Flows			
	EUR_JPY	1	1.0290
	GBP_JPY	1	1.0360
	USD_JPY	1	1.0300
	EUR_JPY	5	1.0480
	GBP_JPY	5	1.0430
	USD_JPY	5	1.0340

This table evaluates the forecasting performanse of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}
GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}

The ratio of RMSE of each model to that of the RW is used.
A ratio smaller than 1 would indicate outperformance of the model.

Table 4-11 – Cross-Currency Forecast Evaluation (daily freq.)

Directional Ability (% correct) of Micro 2 Forecasting Model *(Currency Pair Forecast: €/$)*				
History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	49.87 (1.008)	44.59 (1.205)	**56.25** (1.041)	43.75 (1.202)
2	**51.31** (1.005)	40.54 (1.048)	**62.50** (1.045)	50.00 (1.272)
3	50.00 (1.004)	**55.41** (1.007)	40.63 **(0.989)**	37.50 (1.255)
4	44.59 (1.016)	48.65 (1.033)	50.00 (1.013)	50.00 (1.349)
5	50.00 (1.015)	47.30 (1.079)	46.88 **(0.999)**	**56.25** (1.408)
6	-	45.95 (1.137)	43.75 (1.030)	50.00 (1.199)
7	-	**52.70** (1.190)	43.75 (1.104)	50.00 (1.115)
8	-	43.24 (1.134)	34.38 (1.048)	**56.25** (1.028)
9	-	50.00 (1.177)	46.88 (1.128)	**56.25** (1.019)
10	-	**51.35** (1.150)	40.63 (1.139)	50.00 (1.037)
11	-	-	**53.13** (1.167)	**62.50** (1.113)
12	-	-	46.88 (1.167)	**56.25** (1.113)
13	-	-	37.50 (1.216)	50.00 (1.354)
14	-	-	37.50 (1.331)	50.00 (1.287)
15	-	-	37.50 (1.290)	43.75 (1.373)
16	-	-	-	50.00 (1.224)
17	-	-	-	**56.25** (1.141)
18	-	-	-	43.75 (1.174)
19	-	-	-	43.75 (1.150)
20	-	-	-	**62.50** (1.140)

This table evaluates the Micro 2 Model (using disaggregated customer flows) on the basis of directional ability. I.e. Can the model predict direction if not magnitude.

Note: Number in brackets is RMSE ratio of the Micro 2 model to the random walk model.

Table 4-12 – Directional Ability of Micro 2 Model

Rules for Conditional Models

Simple Conditional	Simple Conditional Rules
1 Follow leveraged customers	If leveraged clients buy then buy if leveraged clients sell then sell
2 Contrary to corporate customers	If corporate clients buy then sell If corporate clients sell then buy
3 Follow unleveraged customers	If unleveraged clients buy then buy If unleveraged clients sell then sell
4 Follow financial customers (levered and unlevered)	If leveraged clients AND unleveraged clients buy then buy If leveraged clients AND unleveraged clients sell then sell
5 Follow corporates	If corporate clients buy then buy If corporate clients sell then sell
6 Contrary to financials	If leveraged clients buy AND unleveraged clients buy then sell If leveraged clients sell and unleveraged clients sell then buy
7 Contrary to corporates AND Follow leveraged Order Flow	If corporate clients sell AND leveraged clients buy then buy If corporate clients buy AND leveraged clients sell then sell
8 Contrary to corporates AND Follow Financial (levereged and unleveraged) Order Flow	If corporate clients sell AND leveraged clients buy AND unleveraged clients buy then buy If corporate clients buy AND leveraged clients sell AND unleveraged clients sell then sell
9 Contrary to corporates AND follow leveraged, unleveraged and other Order Flow	If corporate clients buy AND leveraged clients sell AND unleveraged clients sell AND others sell then sell If corporate clients sell AND leveraged clients buy AND unleveraged clients buy AND others buy then buy
10 Contrary to corporates and others, follow financials	If corporate clients sell and others sell AND leveraged clients buy and unleveraged clients buy then buy If corporate clients buy and others buy AND leveraged clients sell and unleveraged clients sell then sell

Table 4-13 – Rules for Simple Conditional Trading Models

Rules for Conditional Models with Added Threshold

Threshold conditional

2 Rules same as simple conditional but trade only triggered if absolute size of net OF is larger than absolute mean of estimation sample (e.g. first 500 days in daily).
i.e. artificial band created : orders larger than negative absolute mean and smaller than absolute mean do not trigger a trade.

3 Rules same as simple conditional but trade only triggered if absolute size of net OF is larger than mean of estimation sample (e.g. first 500 days in daily).
i.e. artificial band created : orders larger than negative absolute value of mean and smaller than absolute value of mean do not trigger a trade.

4 Rules same as simple conditional but trade only triggered if size of order flow is larger than mean (buy) or smaller than mean (sell)
Mean calculated over estimation sample (e.g. first 500 days in daily)

5 Rules same as simple conditional but trade only triggered if size of order flow is larger than mean plus 1 st. dev. (buy) or
smaller than mean minus 1 st. dev. (sell). Mean and standard deviation calculated over estimation sample (e.g. first 500 days in daily)

INVESTMENT HORIZON IS ONE DAY
FREQUENCY REFERS TO HOW MANY DAYS OF ORDER FLOW ARE USED TO DECIDE ON A TRADE:
Daily freq. - observe one day O.F. and forecast 1 day ahead
5 day freq. - observe 5 days O.F. and forecast 1 day ahead.

Table 4-14 – Rules for Conditional Models with added Threshold

Conditional Models - Summary Results (A)

(Currency : €/$, Frequency : Daily)

	1	2	3	4	5	6	7	8	9	10
	Follow leveraged O.F.	Contrary to corporates	Follow unleveraged O.F.	Follow financials	Follow corporates	Contrary to financials	Contrary to corporates + Follow leveraged O.F.	Contrary to corporates + Follow financials	Contrary to corporates + Follow financials & others	Contrary to corporates & others + Follow financials
Simple Conditional Model - No threshold										
Trading days	387	387	387	387	387	387	387	387	387	387
Trades Triggered	386	386	384	190	386	190	208	97	51	46
% correct	**49.48**	**44.3**	**51.3**	**51.05**	**54.92**	**47.89**	**44.71**	**51.55**	**58.82**	**43.48**
Conditional 2 with absolute mean over first 500 days of data as threshold value creating artificial band at + and - value of absolute mean.										
#BUYS:	112	156	44	18	23	18	48	6	4	0
#SELLS	103	23	59	18	156	18	9	1	1	0
TOTAL TRADES:	215	179	103	36	179	36	57	7	5	0
%correct:	**51.63**	**45.81**	**47.57**	**41.67**	**53.63**	**55.56**	**47.37**	**28.57**	**40**	**NA**
Conditional 3 with mean over first 500 days of data as threshold value creating artificial band at + and - absolute value of mean.										
#BUYS:	194	273	138	69	87	93	144	53	31	22
#SELLS	177	87	183	93	273	69	46	20	9	11
TOTAL TRADES:	371	360	321	162	360	162	190	73	40	33
%correct:	**49.87**	**45.56**	**49.84**	**51.85**	**53.89**	**46.91**	**46.32**	**52.05**	**57.5**	**45.45**

Table 4-15 – Conditional Models – Summary Results (A)

Conditional Models - Summary Results (B)

(Currency : €/$, Frequency : Daily)

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Follow leveraged O.F.	Contrary to corporates	Follow unleveraged O.F.	Follow financials	Follow corporates	Contrary to financials	Contrary to corporates + Follow leveraged O.F.	Contrary to corporates + Follow financials	Contrary to corporates + Follow financials & others	Contrary to corporates & others + Follow financials
Conditional 4 with mean over first 500 days of data as threshold value.										
#BUYS:	194	273	204	110	114	99	144	86	48	38
#SELLS	193	114	183	99	273	110	64	27	13	14
TOTAL TRADES:	387	387	387	209	387	209	208	113	61	52
%correct:	**49.87**	**45.48**	**50.65**	**50.72**	**53.75**	**48.33**	**46.15**	**49.56**	**54.1**	**44.23**
Conditional 5 with mean +/- 1st. dev. over first 500 days of data as threshold values.										
#BUYS:	77	87	16	8	15	3	13	0	0	0
#SELLS	81	15	16	3	87	8	6	0	0	0
TOTAL TRADES:	158	102	32	11	102	11	19	0	0	0
%correct:	**53.8**	**47.06**	**28.13**	**18.18**	**51.96**	**72.73**	**57.89**	**NA**	**NA**	**NA**

Table 4-16 – Conditional Models – Summary Results (B)

Evaluation of Forecasts Using a Profit Measure

	[A] 1 day trading horizon	[B] accumulate position and wait for opposite signal	[C] BUY(SELL) on signal and HOLD until opposite signal is given	[A] 1 day trading horizon	[B] accumulate position and wait for opposite signal	[C] BUY(SELL) on signal and HOLD until opposite signal is given
EURUSD						
Profit/Loss	-1.37	-1085.22	-0.96	-4.75	9.16	-0.67
# take profits / losses	381	4	4	381	133	132
Mean	0.00	-2.85	0.00	-0.01	0.02	0.00
SD	0.56	52.75	0.22	0.56	1.12	0.47
EURGBP						
Profit/Loss	5.27	2.88	2.71	8.15	1.96	1.99
# take profits / losses	384	23	23	383	125	123
Mean	0.01	0.01	0.01	0.02	0.01	0.01
SD	0.35	2.69	0.24	0.35	0.71	0.30
EURJPY						
Profit/Loss	8.86	18.24	5.49	-2.14	-11.30	-0.79
# take profits / losses	378	75	75	378	123	123
Mean	0.02	0.05	0.01	-0.01	-0.03	0.00
SD	0.49	2.37	0.43	0.49	0.66	0.36
GBPUSD						
Profit/Loss	4.69	69.27	5.01	-9.43	-4.12	-4.35
# take profits / losses	378	39	39	381	129	128
Mean	0.01	0.20	0.02	-0.02	-0.01	-0.01
SD	0.52	6.56	0.50	0.52	0.90	0.43
USDJPY						
Profit/Loss	-5.23	33.78	-9.03	0.78	0.43	-5.91
# take profits / losses	381	88	87	381	132	132
Mean	-0.01	0.09	-0.02	0.00	0.00	-0.02
SD	0.55	2.38	0.41	0.55	0.94	0.44

This table shows the profit or loss realized when following each of 3 simple trading strategies. The left hand panel trading signals are based on order flows, while the right hand panel signals are based only on the movement of the exchange rate.

Table 4-17 - Forecasting Ability based on Profitability

4.8 Conclusion

To briefly recap, in this study we have replicated and extended the Evans and Lyons (2005b) forecasting experiment using a new three and a half year customer order flow dataset from the RBS. We first confirmed that our data shared the same contemporaneous properties as the Citibank dataset by running a series of contemporaneous OLS regressions. Having shown that these results were broadly comparable to those obtained by Evans and Lyons, we proceeded to replicate the E&L (2005b) paper, running both their Micro 1 and Micro 2 models on our own data, using the same history and forecast horizons, but also including both intermediate and longer forecast horizons. We could not replicate their 20-day forecasting window since we have a slightly shorter dataset, but in all other respects we followed their methodology exactly.

Our results however were not the same. Where E&L (2005b) found significant forecasting power at longer horizons using the Micro 1 model and at all horizons using the Micro 2 model, we found no forecasting power whatsoever in our data, regardless of model, history used or forecast horizon. This lack of forecasting power was the same across all six currency pairs we tested the models on.

Building on MacDonald and Marsh (2004) who suggest that exchange rates can be forecast if they are modelled together as a system, and wanting to fully exploit the cross-sectional advantages of the RBS dataset, we attempt to forecast exchange rates using both 'own' and 'related' flows, after first confirming that a contemporaneous relationship exists. Although the contemporaneous relationship is strengthened by the addition of 'related' flows, forecasting performance is not improved.

Wanting to give the models the benefit of the doubt, and drawing on a growing body of literature pointing out the limitations of RMSE as a means of forecast evaluation (Leitch and Tanner, 1991, Granger and Pesaran 2000) we proceeded to evaluate all models on the basis of their ability to predict direction. Again we found lack of forecasting power across the board.

Lastly, we hypothesize that a forecasting relationship may not always be present, i.e. order flows may not convey information all the time as is implicitly assumed in the regression based forecasts. Instead, we test a series of conditional models in which trades are only triggered if certain conditions are satisfied. Once again we find no evidence of forecasting power in the RBS flows.

In the FX literature, a result showing that FX rates cannot be forecast is, in and of itself, uninteresting. Considering the Evans and Lyons (2005b) result however, this complete lack of forecasting power in the RBS data which is, for all intents and purposes, the equivalent data to that of Citibank, and moreover as we have shown shares the same contemporaneous properties, is curious, and we are left to speculate on the reasons for this discrepancy.

E&L (2006a) states that 1/3 of order flow's power to forecast FX comes from flow's ability to forecast future flow, with the remaining 2/3 coming from flow's ability to act as a conduit for information aggregation, letting dealers know about customer expectations of future fundamentals. This is done by regressing returns on concurrent flows and using the fitted values from the regression to separate the return series into a flow explained part (the fitted values) and the flow-unrelated part (the regression residual). This allows us to determine whether flow tends to forecast the flow-explained part of the return or the flow-unrelated part (Lyons, 2003). The E&L empirical analysis shows that both aggregated and disaggregated Citibank customer flows are significantly positively auto-correlated, as well as cross-correlated across customer types. These correlations increase with time horizon. "Estimated autocorrelation coefficients are small but many are positive and highly statistically significant. These statistical patterns are repeated at the weekly and monthly frequency… At the daily frequency correlations between flow segments are small, but at the monthly frequency they range from approximately -0.95 to 0.95" (E&L 2005c). This is a statistical property of the Citibank data that RBS flows do not share, despite being the same type of data.

Appendices B9-B12 show autocorrelation and partial autocorrelation coefficients for net order flows in all currency pairs and for all customer types. The results for RBS autocorrelation are mixed. Although most series show no evidence of autocorrelation, some are autocorrelated to a limited extent. Namely EUR_JPY corporate, other financial and total order flow, EUR_GBP other financial and total order flow, EUR_USD corporate and other financial, and USD_JPY unleveraged financials and total order flow. Even in the cases where there is autocorrelation however, coefficients are small and there does not seem to be any discernible pattern in positive and negative coefficients. As flows are aggregated over longer time horizons, the number of order flow series that are autocorrelated decreases, with the notable exception of the EUR_USD order flows. Once again coefficients are small and alternate between positive and negative.

Sections B13-B16 in the Appendix shows the cross-correlations between the RBS order flows of the four customer types in each currency pair. Order flows from different customer types are not typically highly correlated. The exception is flows from other financials, which in some cases are significantly negatively correlated with flows from other customer types. Note particularly the cross-correlation between other financials and unleveraged financials in the GBP_JPY market. Aggregating order flows over time does not seem to consistently affect the properties of the data and correlations remain low apart from the other financials category.

As the RBS data does not exhibit the significant positive autocorrelation of the Citibank data, we are obviously missing the 1/3 of forecasting power that comes from flows forecasting future flows. This takes us part of the way towards answering the question of why we find absolutely no forecasting power in RBS flows, but a significant 2/3 forecasting power still remains unaccounted for. Our results indicate that RBS flows do not forecast news, or put differently do not convey information about customers' expectations of future fundamentals. We suggest two explanations for this. First we must at least consider the possibility that RBS flows simply do not have any information content. This seems unlikely, especially considering the results of the contemporaneous regressions, and it would also be hard to explain such a fundamental difference in the customer base of two otherwise relatively comparable banks. Alternatively, particularly considering that the Evans and Lyons data runs only up to 1999 and our RBS data spans the more recent 2002 – 2006 time period, a very plausible explanation is that information from order flows is being priced into the market too quickly, so we are not able to capture any forecasting power at the daily frequency and beyond. The high-frequency properties of customer order flow will be the topic of the next chapters.

In conclusion, the results of our study seem to indicate that, though striking, the Evans and Lyons results deserve a second look. The complete lack of forecasting power of the RBS flows brings into question not necessarily the validity of the E&L (2005b) findings, but how generaliseable they are. Irrespective of the reasons for the failure of the RBS flows to forecast exchange rates, the fact remains that an inability to replicate the Evans and Lyons result with an equivalent dataset, points to the possibility that their findings may be specific to the Citibank data.

5 The Pricing of Customer Transactions in the FX Market

5.1 Introduction

The complete lack of forecasting power in our daily order flow data described in the previous section indicates a number of possibilities for future research. One possible explanation for the inability of flows to forecast spot FX is that the information in the order flows is being priced in too quickly, so at daily and lower frequencies we are seeing no power to forecast. We propose to investigate this possibility by increasing the focus to intraday FX movements.

Although trading in the euro-dollar pair alone averages over $840 billion per day (BIS 2007) – over 10 times daily trading on all NYSE stocks – the details of the overall price discovery process remain largely unspecified. This chapter investigates the price discovery process in the foreign exchange market using a unique tick-by-tick dataset from a leading European Bank.

The very heterogeneous nature of the market participants and their objectives when entering into currency transactions is the major reason for the hypothesis that order flow from different customer types will have different price impact. The fact that not all participants in the FX market base their trading decisions on the objective of profit maximization may make it possible for specialized portfolio managers to generate positive returns from managing currencies actively. It also implies that order flow from precisely this type of customer may have more value due to its information content. Previous literature such as Osler et al (2006a) suggests that dealers are willing to "pay" for informed order flow by quoting narrower bid-ask spreads.

Microstructure theory, which is based mainly on studies of the equity market, tells us that the spreads quoted by dealers are functions of four components: (i) adverse selection, i.e. protection against potentially informed customers, (ii) inventory costs, (iii) fixed costs or order processing costs and (iv) monopoly power. Fixed costs are generally modelled as a constant and the monopoly power component is not relevant in a competitive market such as the FX market. (Osler et al, 2006) Asymmetric information and inventory costs are the components of spread that we are most interested in. A dealer should widen spreads to protect himself against trades from informed customers – spreads increase with trade size. Larger trades also mean that the dealer takes on more risk by holding onto large positions that will need to be managed. This again implies that spreads should increase with trade size.

However, price discovery in the FX market does not operate in the way predicted by the standard adverse selection theory of spreads. In fact, empirical evidence suggests that a dealer who does observe large volumes of customer order flow covets the information in large trades so would be willing to pay for this information by quoting narrower spreads for large trades. Adverse selection theory posits that the exact opposite should happen, however conversations with dealers suggest that this mechanism more closely reflects the realities of spreads in FX trading.

Due to the opaque nature of decentralized foreign exchange markets, a dealer's order flow clearly represents private information. Thus, FX dealers are not uninformed market makers as in Kyle (1985), and may exploit this private information for future trades in the interdealer market. Alternatively, the trader may consider order flow information when quoting future spreads in the customer market, which is intensively investigated in the microstructure literature (eg. Huang and Stoll, 1997; Madhavan and Smidt, 1991). Independently of the dealer's decision on which market segment to choose in order to benefit from his private information, the logic of information aggregation in FX implies that customer order flow will consistently be more important in the determination of exchange rates than interdealer flow (Sager and Taylor, 2005). Indeed, Lyons (1995), Ito et al. (1998), and Bjønnes and Rime (2001) find that customer order flow is the primary source of private information in the FX market. Given that dealers maintain relationships with a broad range of different customers such as corporations, asset management firms, hedge funds, central banks, etc, it is natural to ask which group of customers provides the order flow that contains significant information (Evans and Lyons, 2005a).

5.2 *Description of the Data*

We have access to data from a major European commercial bank that wishes to remain anonymous, describing every trade that took place through the banks' own electronic trading platforms in Euro-Dollar over 25 trading days from October 10th to November 11th 2005. This data include both customer orders and interdealer orders initiated by the counterparty. That is, the data excludes all deals initiated by the bank supplying the data, and all customer orders that were not routed through the bank's electronic platform. Conversations with dealers suggest that non-electronic orders are only a small proportion of the total customer orders, so their exclusion should not have much impact. Counterparties are identified by a code, and we have the size of each trade, as well as the price and exact time at which it was executed. Although we cannot see the identity of individual counterparties, the codes allow us to differentiate between types of counterparty, which we break down into the following categories: corporate customers, financial customers, i.e. asset managers, interbank counterparties, and internal.

Each trade record contains the following information: (1) currency pair, (2) date and time stamp of the trade, (3) direction, (4) transaction price, (5) market clearing price from EBS, (6) deal size, and (7) counterparty. Incoming trades are generally initiated by customers for whom the dealer will always be the supplier of liquidity, however, in interbank trades the dealer may also provide liquidity to other dealers. Consistent with existing literature, order flow variables are calculated from the perspective of the deal initiator, implying that customers' buy orders have a positive sign, and sell orders have a negative sign. All overnight changes are removed from the sample, so that any price effects are related only to intraday order flow. In addition, any 'suspicious' entries, such as trades with a dealt price entirely inconsistent with the market price which would indicate data entry error were deleted, as were trades with a settlement date shorter than two days as these orders are priced differently.

This dataset is similar to other proprietary datasets used in Lyons (1995) and Bjonnes and Rime (2005), however it is unique in that it gives us the opportunity to examine pricing behaviour at a major FX dealing bank that sees a great deal of customer order flow. This contrasts sharply with the Lyons (1995) dealer who sees no customer order flow and must continually shade his prices to induce interbank trades. In addition to this difference, our data sample is significantly longer than both Lyons (1995) and Bjonnes and Rime (2005) who analyze only 5 days of data. Although our sample is shorter than that of Osler et al (2006a) who analyze 87 days of trading of one dealer in euro-dollar, and Reitz et al (2007) who analyze 251 days of trading, our bank sees considerably higher transaction volume - 27,830 transactions (€100.1 billion) in 25 days compared to 3,600 transactions (€4.3 billion) in 87 days and 11,830 transactions (€12.1) billion in 254 days for Osler et al and Reitz et al respectively. Perhaps the most significant advantage of our dataset however stems from the composition of our bank's customer base, with 32% of transactions coming from financial customers, compared to only 5% of financial customer flow for Osler et al and 1.6% for Reitz et al. Bjonnes and Rime (2005) only differentiate between customer trades and interbank trades. The differences between our dataset and those of the two most comparable datasets from Osler et al and Reitz et al are summarized in Table 5-1 below.

Data Comparison with Similar Studies

Study	Days	Year	Transactions	Volume (billions)	Financial	Corporate	Interbank
Own data	25	2005	27,830	€ 100.10	32.00%	9.30%	51.90%
Osler et al (2006)	87	2001	3,600	€ 4.30	5.00%	42.00%	44.00%
Reitz et all (2007)	251	2002 / 03	11,830	€ 12.10	1.60%	44.00%	49.00%

This table summarizes some of the main characteristics of our high-frequency dataset, particularly how it compares to the two most similar datasets that have been studied in the literature.

Table 5-1 – Comparison of data features

One drawback of our dataset is that it does not contain outgoing deals, i.e. deals initiated by the bank itself, so we cannot calculate the bank's inventory position. However, Bjonnes and Rime (2005), Osler et al (2006a) and Reitz et al (2007) find no evidence of inventory control through dealers' own prices. To understand the lack of any price effect from inventory, it is important to remember the multiple dealer structure of the market. In a single dealer structure, such as the one in the Madhavan and Smidt (1991) model, which is described in detail in section 5.3.1, the dealer must wait for the next order to arrive. His only possibility for inventory adjustment is to shade his quotes to attract orders. On the other hand, in the hybrid structure of the FX market, inventory-based price shading has declined in importance since the introduction of electronic brokers. Using the interbank market to unload/manage inventory is both cheaper and faster than price shading. FX dealers also do not use currency options, futures or forward markets to hedge risk, finding it cheaper to use the interdealer spot market. (Fan and Lyons, 2002) In light of this therefore, we do not consider the lack of inventory data to be a major problem.

Figure 5-1 below shows the tick-by-tick dealt €/$ rate for all the transactions that took place in this currency pair over the 25 trading days between 10/10/2005 and 11/11/2005. For much of the sample no particular trend seems apparent, although in the last one-third there is a definite downward trend in the exchange rate.

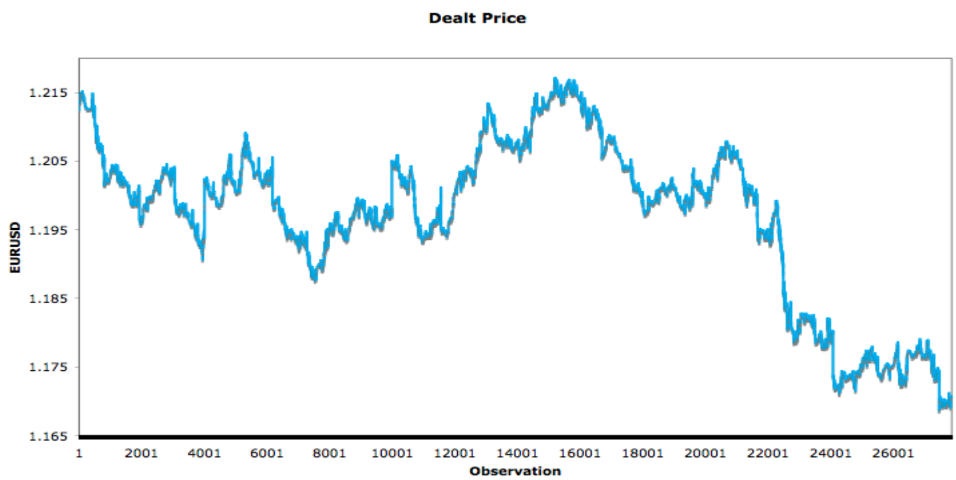


Figure 5-1 – Dealt price (€/$) 10/10/2005 – 11/11/2005

The following section examines some of the characteristics of the data in more detail, breaking down the trading activity seen both in terms of transactions and by volume. Figures 5-2 and 5-3 show the bank's cumulative Euro position over the sample period in aggregate and broken down into individual counterparties respectively, in keeping with the hypothesis of heterogeneity among customer groups.

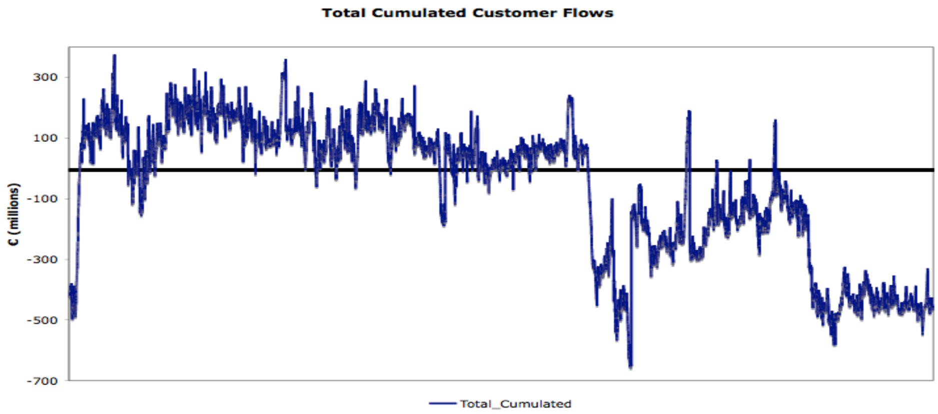


Figure 5-2 - Bank's Cumulative € position 10/10/2005 – 11/11/2005

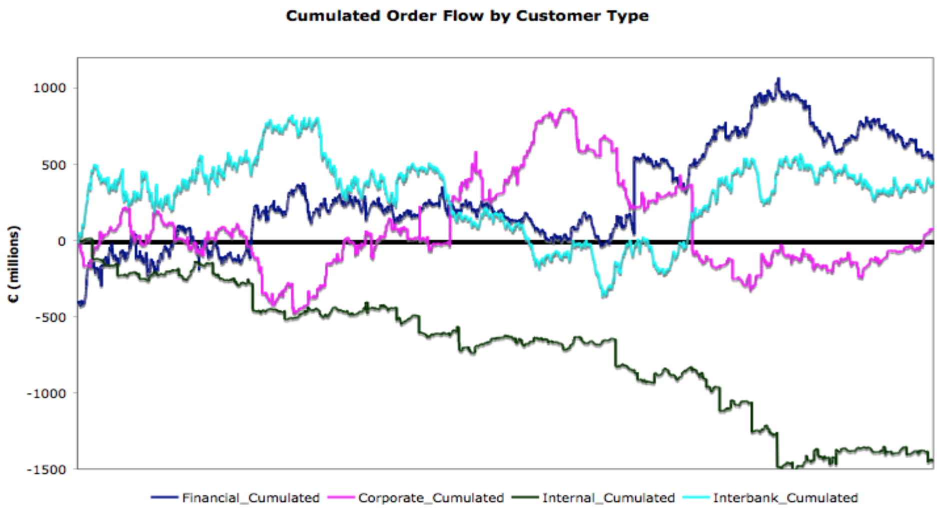


Figure 5-3 - Bank's Cumulative € position by Counterparty Type

Table 5-2 summarises the trading activity of our bank by number of transactions as well as by volume. The bank clearly sees a great deal of order flow from all counterparty types, with a large percentage as expected coming from interbank trades.

Order volume is very volatile, with large standard deviations seen. Interbank orders have a far smaller standard deviation, again as would be expected with a higher degree of standardization of order size for interbank trades. Interestingly, corporate flows are significantly larger on average than the trades of all other counterparties. Although the largest individual orders seen are from financial customers, the average corporate order is almost twice as large as the average financial order. It is also indicative that corporate orders make up only 9.28% of total flow in terms of number of transactions, but make up 19.50% of total volume seen, a difference that is also illustrated in Figures 5-4 and 5-5. This is in sharp contrast to the Reitz et al bank that sees a large number of corporate orders, but whose mean trade size is only approximately 20% of the mean trade size across all counterparties.

Trading Activity of a Large European Bank
25 trading days - 10/10/2005 - 11/11/2005

	Financials	Corporates	Internal	Interbank	Total
Transactions	8,898	2,584	1,905	14,443	27,830
Per Trading Day	355.92	103.36	76.20	577.72	1,113.20
Percent	31.97%	9.28%	6.85%	51.90%	100.00%
Net Flow (€ million)	534.84	88.00	-1445.38	384.02	-438.52
Volume (€ million)	34,555.07	18,479.44	8,927.60	37,123.33	100,085.44
Average (€ million)	3.88	7.54	4.69	2.57	3.60
St. Deviation	9.48	14.97	12.63	4.00	8.42
Mode (€ million)	1.00	1.00	1.00	1.00	1.00
Median (€ million)	2.00	2.52	2.00	1.00	2.00
Minimum (€ million)	0.50	0.50	0.50	0.50	0.50
Maximum (€ million)	500.00	228.64	220.00	137.28	500.00
Percent by Volume	34.50%	19.50%	8.90%	37.10%	100.00%

This table summarises the trading activity of a major European Bank by transactions as well as by volume. Descriptive statistics of volume of trading seen are given both in aggregate and broken down by counterparty.

Table 5-2 – Summary of trading activity of a large European Bank

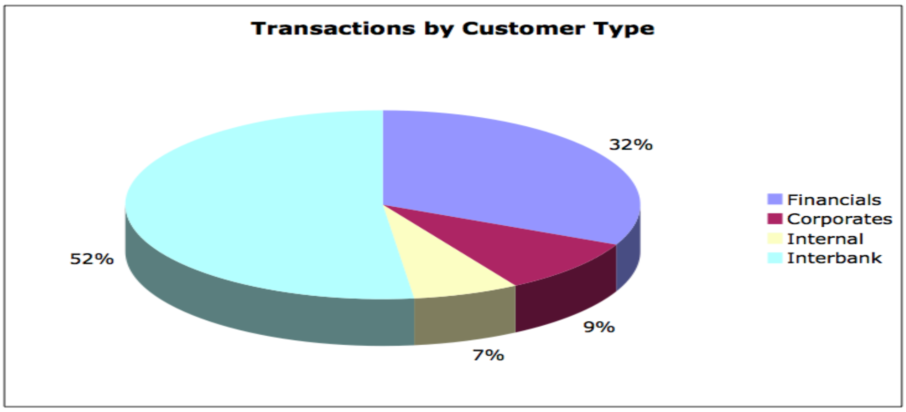


Figure 5-4 Transactions by Counterparty Type

Pie-chart showing number of transactions by counterparty type seen over the 25 trading days between 10/10/2005 and 11/11/2005

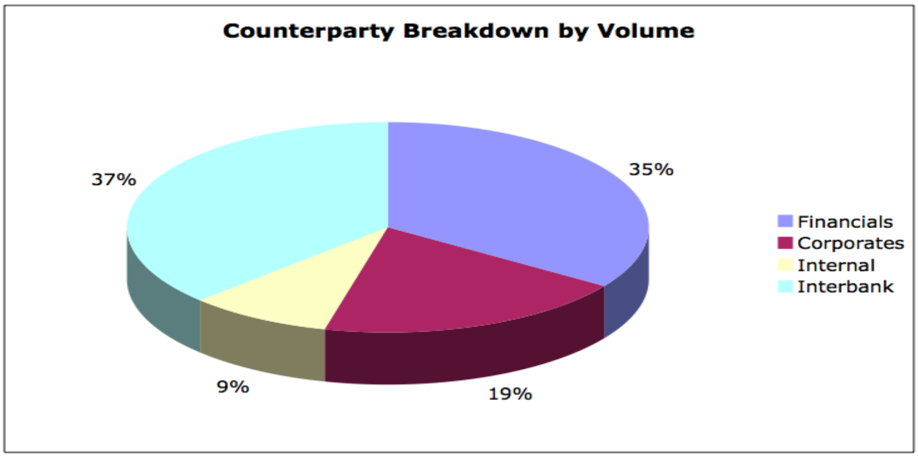


Figure 5-5 – Counterparty Breakdown by Volume

Pie-chart showing the volume of transactions attributable to each counterparty type over the 25 trading days between 10/10/2005 and 11/11/2005

5.3 Price Impact of Order Flow – Theoretical Models

Having examined the properties of our data, we proceed to describe the two theoretical models of price formation we will be using – the Madhavan-Smidt model, and the Huang-Stoll model.

5.3.1 The Madhavan and Smidt (1991) Model

A Bayesian model of intraday price formation

The Madhavan-Smidt (MS) model is standard in transactions-based studies in FX (Lyons 1995; Bjonnes and Rime 2005; Osler et al 2006). The model assumes a representative dealer in a competitive market whose counterparty has private information about the asset's fundamental value. Agents are fully rational, and there is a detailed information setting. In this section we will examine the derivation of the MS model.

The market microstructure literature has identified three mechanisms through which order flow can generate price movements. (i) Transaction costs produce 'bid-ask bounce' as buy and sell orders arrive randomly. (ii) Inventory carrying costs create incentives for market makers to shade their prices in order to manage their inventories. (iii) The existence of traders with private information implies that rational market makers adjust their beliefs, and hence prices, in response to order flow. Both the inventory effect and the information asymmetry effect predict that prices will move in the direction of order flow, although for different reasons.

In the MS model, prices change when new public information reaches the market, as well as in response to trading. In the case of a public news announcement, prices can change without any trades occurring. Alternatively, the process of trading itself can cause price movement. The idea underlying the measure of information asymmetry in the MS model is simple. If a representative market maker uses Bayesian rules to update his beliefs, then the expected value of the stock can be represented as a combination of the prior mean – representing public information – and the noisy signal regarding private information contained in order flow.

Order flow conveys a noisy signal to market makers because of the heterogeneous nature of market participants. Some traders have private information about the asset value, while other traders deal for liquidity purposes. The weight placed on prior beliefs provides a natural measure of the degree of information asymmetry in the market. If order flow is uninformative, because the ratio of public to private information is small, the weight will be close to unity. Conversely, with severe information asymmetries, the market makers beliefs are very sensitive to order flow, therefore the weight placed on prior beliefs will be negligible. Madhavan and Smidt derive an estimating equation from which the weight the dealer places on the information content of order flow can be estimated, therefore enabling us to directly measure information asymmetry. The model also allows us to evaluate the relative importance of information asymmetry and inventory control in the price formation process, and provides a method of assessing the implicit costs of trading.

5.3.2 The model framework:

Madhavan and Smidt assume a multi-period model with two assets: a riskless bond and a stock which is traded at times t=1,2,…,T. In each period, given the quoted bid and ask prices of the market maker, the trader decides whether and how much to trade. Following the trade the market maker can revise his quotes based on new information.

The time T price of the risky asset, $\tilde{v}$, is composed of a series of zero mean iid increments or innovations, so that

$$\tilde{v} = \sum_{i=0}^{T} d_i \tag{5.1}$$

The increment d_t is realized immediately after trading in period t, and the announcements of the increments represent the flow of information signals over time. Given a sequence of increments $d_0,....,d_t$, the value of the risky asset is $v_t = \sum_{i=0}^{t} d_t$.

However at time t just before $\tilde{d}_t$ is realized, v_t is a random variable, $\tilde{v}_t$. In the absence of transaction costs or private information, the price would be modeled as a martingale, i.e. using p_t to denote the price at time t, $E\left[p_{t+1}|p_t\right]=p_t$.

In reality, microstructure effects will cause prices to deviate from expected values. Inventory effects for example cause the market maker to adjust his pricing policy depending on the current level of his inventory. Intuitively, the market maker will raise or lower his prices to attract trades that will return his inventory position to a desired level. In inventory control models, the price set by Dealer i (P_{it}), is linearly related to the dealer's conditional expectation about the true value μ_{it}, and current inventory measured at the beginning of the period, I_{it}

$$P_{it}=\mu_{it}-\gamma(I_{it}-I_{it}^{*})+\psi D_t \tag{5.2}$$

I_{it}^{*} is Dealer i's desired inventory level, which is assumed to be constant, and the inventory response effect, γ is negative to capture ''quote shading''. A non-zero coefficient γ suggests price shading, which would mean that the dealer changes prices in response to undesired inventory. The term D_t is a direction dummy that takes the value +1 if Dealer i sells (trades at the ask) and -1 if Dealer i buys (trades at the bid). The constant ψ can be interpreted as compensation for per share execution costs, although it may also reflect price discreteness.

5.3.3 The evolution of market maker beliefs

Equation 5.2 cannot be estimated as we cannot observe μ_{it} - the market maker's beliefs. Therefore in order to obtain a testable model, it is necessary to first describe the evolution of the market maker's beliefs. We assume that just before time t, all agents observe a noisy public information signal $\tilde{y}_t$ concerning the value of the increment d_t at time t. The asset's value at time t-1 is public information at time t, and $\tilde{y}_t$ can be expressed as:

$$\begin{aligned}\tilde{y}_t &= v_t+\tilde{\varepsilon}_t\\ \tilde{\varepsilon}_t &\sim N(0,\sigma_{\varepsilon}^2)\end{aligned} \tag{5.3}$$

The dealer's distribution over the asset's value v_t is therefore Normal with mean y_t and variance σ_ε^2.

The trader also receives a private signal, $\tilde{w}_t$ about the value of the asset, which takes the form:

$$\begin{aligned}\tilde{w}_t &= v_t + \tilde{\omega}_t \\ \tilde{\omega}_t &\sim N(0,\sigma_\omega^2)\end{aligned} \tag{5.4}$$

Since the trader's prior distribution of $\tilde{v}_t$, and the private signal is also drawn from a normal distribution, the posterior mean is given by:

$$\begin{aligned}m_t &= \theta w_t + (1-\theta) y_t \\ \theta &= \sigma_\varepsilon^2 \big/ (\sigma_\varepsilon^2 + \sigma_\omega^2)\end{aligned} \tag{5.5}$$

The trader's order quantity Q_{jt} is a linear function of the perceived mispricing ($m_{jt} - P_{it}$) and x_{jt} which is an idiosyncratic shock that represents liquidity trading:

$$Q_{jt} = \alpha(m_{jt} - P_{it}) - x_{jt} \tag{5.6}$$

Here m_{jt} is agent j 's expectation of the true currency value conditional on the public signal as well as his private signal. If traders have mean-variance utility functions, then equation 5.6 represents the optimal demand of the trader given the price-setting behavior of the market maker.

The demand equation enables the market maker to extract information from Dealer j's trade using Bayes' rule, hence private information effects enter the pricing equation through the conditional expectation term μ_{it}. The price set by the dealer is regret-free in the sense that it reflects the dealer's expectations conditional on the information as to whether the calling agent is buying or selling foreign currency. The trader's liquidity shock is private information, so x_t is regarded as the realization of the iid $N(0,\sigma_x^2)$ random variable $\tilde{x}_t$. Since the liquidity component of trade x_t is not known to the dealer, order flow conveys a noisy signal about the asset's fundamental value, with the statistic

$$\tilde{v}(Q_t) \equiv \frac{\alpha p_t + Q_t - \alpha(1-\theta)y_t}{\alpha\theta} \tag{5.7}$$

Substituting (5.5) and (5.6) and rearranging gives us:

$$\begin{aligned} &\hat{v}(Q_t) = v_t + \omega_t - (\alpha\theta)^{-1} x_t \\ &\hat{v}(Q_t) \sim N(v_t, \sigma_s^2) \\ &\text{where } \sigma_s^2 = \sigma_\omega^2 + (\sigma_x^2 / \theta\alpha)^2 \end{aligned} \tag{5.8}$$

The Bayesian updating rule yields the dealer's posterior mean,

$$\begin{aligned} &\mu_t = \zeta y_t + (1-\zeta)\hat{v}(Q_t) \\ &\text{where } \zeta \equiv \sigma_s^2 / (\sigma_\varepsilon^2 + \sigma_s^2) \text{ is a constant} \end{aligned} \tag{5.9}$$

The posterior mean can be re-written using equation (5.7) as:

$$\begin{aligned} &\mu_t = \pi y_t + (1-\pi)(p_t + \alpha^{-1} Q_t) \\ &\text{where } \pi \equiv (\zeta + \theta - 1)/\theta \\ &\pi \in (0,1) \end{aligned} \tag{5.10}$$

Equation (5.10) shows that the posterior mean can be represented as a weighted average of prior information and the signal conveyed by order flow. The parameter π is the weight placed on prior beliefs.

5.3.4 Information asymmetry and the parameter π

Expressing π using the definitions of ζ and θ shows us that the weight π is inversely related to the degree of information asymmetry in the market:

$$\pi = 1 - \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + (\sigma_x^2 / \alpha)^2 (1 + \sigma_\omega^2 / \sigma_\varepsilon^2)} \qquad (5.11)$$

Expressing π in this form clearly shows that π is an increasing function of 3 variables:

The volume of liquidity trading (σ_x^2)

The imprecision of private information (σ_ω^2)

The accuracy of public information (σ_ε^{-2})

As such we need an econometric model whose parameter estimates can be used to infer the weight π.

Substituting the equation for the posterior mean (5.9) into the standard inventory control model (5.2), yields an equation that explicitly incorporates the effect of order flow Q on market maker beliefs μ_t through Bayes' rule:

$$p_t = \pi y_t + (1-\pi)\left[p_t + \alpha^{-1} Q_t \right] - \gamma (I_t - I_d) + \psi D_t \qquad (5.12)$$

Since the variable y_t representing dealer's prior mean at time t is unobservable, it is necessary to find a proxy for the unobservable prior beliefs based on the previous price after adjusting for transaction costs and inventory effects. Using the inventory control model we write the prior mean as:

$$\begin{aligned} & y_t = p_{t-1} + \gamma (I_{t-1} - I_d) - \psi D_{t-1} + \eta_t \\ & \text{where } \eta_t \equiv y_t - \mu_{t-1} \end{aligned} \qquad (5.13)$$

The prior and posterior means differ because of public information signals, therefore η_t represents the innovation in the dealer's conditional expectations of the security's value. *This innovation cannot be predicted ex ante and is the source of the error term in the model.*

5.3.5 The Econometric Model

Substituting the proxy for prior beliefs into equation (5.12) yields the econometric model relating the change in price from trade to trade to current and lagged variables related to order flow.

$$\begin{aligned} &\Delta p_t = \kappa + \lambda Q_t - \left(\frac{\gamma}{\pi}\right) I_t + \gamma I_{t-1} + \left(\frac{\psi}{\pi}\right) D_t - \psi D_{t-1} + \eta_t \\ &\text{where } \Delta p_t \equiv p_t - p_{t-1} \\ &\kappa \equiv -\gamma(1 - 1/\pi) I_d \\ &\lambda \equiv (1-\pi)/(\alpha\pi) \end{aligned} \tag{5.14}$$

Lambda captures the responsiveness of price to order flow, i.e the information effect, but the estimate of the weight π also gives a measure of the significance of asymmetric information in price formation. Although (5.14) is a linear function of the independent variables, it must be noted that the econometric model is a nonlinear function of the parameters $\pi, \psi, \gamma, \lambda, I_d$. Furthermore, the term η_t cannot be observed and is interpreted as the error term in the regression equation.

5.3.6 Error Structure

We can explicitly derive the properties of the error structure in the model. If the model is perfectly specified then errors represent unanticipated news events, so the R-squared measures the percentage contribution of public information shocks to price variance, while 1-R^2 measures the percentage of price volatility generated by trading. Using the definitions of the prior and posterior means and equation (5.8) for $\hat{v}(Q_{t-1})$ we see that

$$\begin{aligned} &\eta_t = \varepsilon_t - \zeta\varepsilon_{t-1} + u_t \\ &\text{where } \mathrm{u_t} \text{ is defined as:} \\ &\mathrm{u_t} = (v_t - v_{t-1}) - (1-\zeta)\left[\omega_{t-1} - (\alpha\theta)^{-1} x_{t-1}\right] \end{aligned} \tag{5.15}$$

Under the assumptions about the stochastic process followed by innovations, $E\left[\tilde{v}_t \middle| v_{t-1}\right] = v_{t-1}$. By assumption, $E\left[\tilde{x}_t, \tilde{x}_{t'}\right] = E\left[\tilde{\omega}_t, \tilde{\omega}_{t'}\right] = 0 \forall t \neq t'$,which coupled with the martingale property of $\hat{v}_t$ implies that $E\left[\tilde{u}_t\right]=0, E\left[\tilde{u}_t\tilde{u}_{t-1}\right]=0$. Taking expectations in (5.15) and using the martingale property yields:

$$\begin{aligned} &E\left[\tilde{\eta}_t\right]=0 \\ &E\left[\tilde{\eta}_t\tilde{\eta}_{t-1}\right]=-\zeta\sigma_\varepsilon^2 \end{aligned} \tag{5.16}$$

Therefore the error structure can be explicitly shown to follow an MA(1) process. Actually, η_t is composed of two moving average processes: the first MA process given by $\varepsilon_t-\zeta\varepsilon_{t-1}$ has parameter ζ, and the second MA process is the one associated with u_t, which (trivially) has a zero MA parameter.

5.3.7 The Huang and Stoll (1997) Model

A Generalized Trade Indicator Model

In the MS model, information costs increase with trade size. Although not obvious, this can be a natural assumption in a typical dealer market with bilateral trades. In a limit order-based market, however, it is less clear that trade size will affect information costs. For instance, in these systems it is Dealer i (submitter of the limit order) that determines trade size. A large market order may thus be executed against several limit orders. However, the dealer submitting a limit order must still consider the possibility that another dealer (or other dealers) trade at his quotes for informational reasons. Furthermore, on the electronic brokers, which represent the most transparent trading channel, only the direction of trade is observed at the market-wide level. In the baseline Huang-Stoll (HS) model, by assumption, it is the direction and not the size of the trade that is important. Hence, here Q equals Dt. As informed traders' profits would surely decrease in the presence of learning dealers, there is a strong incentive to camouflage private information by splitting up orders into a number of (smaller) standardized transactions. Thus, dealers have lost a source of information and the trade direction is the remaining variable to capture the price impact of asymmetric information. In this section we will examine the derivation of the HS model.

The objective of the baseline HS model is to construct a basic trade indicator model of spread components. A distinguishing characteristic of trade indicator models is that they are driven solely by direction of trade, a characteristic that may make them ideally suited to studies of the FX market as noted above.

5.3.8 The Basic Model

In the basic HS framework, the unobservable fundamental value of the asset in the absence of transaction costs, V_t, is determined just prior to posting bid and ask quotes at time t. The quote midpoint, M_t, is calculated form the bid and ask quotes that prevail just before a transaction. The price of the transaction at time t is denoted P_t, and the trade indicator variable D_t is defined as before according to the initiator of the trade. The unobservable V_t is modelled as:

$$V_t = V_{t-1} + \alpha \frac{S}{2} D_{t-1} + \varepsilon_t \tag{5.17}$$

where S is the constant spread, α is the percentage of the half-spread due to adverse selection, and ε_t is the serially uncorrelated public information shock. Equation (5.17) is of course a hypothetical construct, however we do observe the midpoint of the bid-ask spread. Inventory theories postulate that liquidity suppliers adjust the quote midpoint relative to fundamental value on the basis of accumulated inventory, in other words they shade their quotes to manage inventory. Under these models, the midpoint is related to fundamental value according to:

$$M_t = V_t + \beta \frac{S}{2} \sum_{i=1}^{t-1} I_i \tag{5.18}$$

where β is the proportion of the half-spread due to inventory holding costs, and $\sum_{i=1}^{t-1} \mathrm{I}_i$ is the cumulated inventory until time t-1. In the absence of inventory holding costs, there would be a one-to-one mapping between the midpoint and the fundamental value.

The first difference of equation (5.18) combined with equation (5.17) implies that quotes adjust to reflect information revealed by the last trade as well as inventory cost of the last trade as follows:

$$\Delta M_t = (\alpha + \beta)\frac{S}{2}D_{t-1} + \varepsilon_t \tag{5.19}$$

There is also a constant spread assumption, which is specified as:

$$P_t = M_t + \frac{S}{2}D_t + \eta_t \tag{5.20}$$

where the error term captures the difference between the observed half-spread $P_t - M_t$ and the constant half-spread, and includes rounding errors due to price discreteness.

5.3.9 The Econometric Model

Combining equations (5.19) and (5.20) yields the basic regression model:

$$\begin{aligned} &\Delta P_t = \frac{S}{2}(D_t - D_{t-1}) + \lambda\frac{S}{2}D_{t-1} + e_t \\ &\text{where } \lambda = \alpha + \beta \\ &\text{and } e_t = \varepsilon_t + \Delta\eta_t \end{aligned} \tag{5.21}$$

This indicator variable model is a nonlinear equation with within-equation constraints, whose only determinant is the indicator variable D. The model provides estimates of the traded spread, S, and the total adjustment of quotes to trades, $\lambda(S/2)$. We can estimate the portion of the half-spread not due to adverse information or inventory as $1-\lambda$, which can be considered as an estimate of order processing costs. It is impossible to separate the adjustment due to adverse selection (α) and that due to inventory (β) based on (5.21) alone. Given the multiple dealer structure of the FX market which makes it easy for dealers to manage inventory using the interbank market, coupled with the findings in the literature by Bjonnes and Rime

(2005), Osler et al (2006a) and Reitz et al (2007) who find no evidence of inventory control through price shading as discussed in a previous section, we can assume that λ is a reasonable estimate of adjustment due to information.

5.4 Empirical Results

5.4.1 Estimating the Madhavan and Smidt Model

As a starting point, we estimate the Madhavan and Smidt (1991) (MS) model, because, as described in sections 5.3.1 – 5.3.7, its structural equations are consistent with agents' optimizing behavior and an informational setup is explicitly provided applying Bayesian expectations. The MS model is structural in the sense that the equations are consistent with those of optimizing models, they have an explicit informational setting, and agents' expectations are formed by Bayes' rule.

To recap, in the Madhavan-Smidt framework, the econometric model relating the change in price from trade to trade to current and lagged variables related to order flow is as follows:

$$\begin{aligned}
&\Delta p_t = \kappa + \lambda Q_t - \left(\frac{\gamma}{\pi}\right) I_t + \gamma I_{t-1} + \left(\frac{\psi}{\pi}\right) D_t - \psi D_{t-1} + \eta_t \\
&\text{where } \Delta p_t \equiv p_t - p_{t-1} \\
&\kappa \equiv -\gamma(1 - 1/\pi) I_d \\
&\lambda \equiv (1-\pi)/(\alpha\pi)
\end{aligned} \tag{5.22}$$

Lambda captures the responsiveness of price to order flow, i.e the information effect, but the estimate of the weight π also gives a measure of the significance of asymmetric information in price formation. Although (5.22) is a linear function of the independent variables, the econometric model is a nonlinear function of the parameters $\pi, \psi, \gamma, \lambda, I_d$. Furthermore, the term η_t cannot be observed and is interpreted as the error term in the regression equation, explicitly modelled as an MA(1) process.

The empirical exchange rate equation that results from the MS model is as follows:

$$\begin{aligned} \Delta P_t &= \beta_0 + \beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1} + \beta_4 I_t + \beta_5 I_{t-1} + \eta_t \\ \eta_t &= \tilde{\varepsilon}_t - \zeta \tilde{\varepsilon}_{t-1} \end{aligned} \tag{5.23}$$

where ΔP_t is the change in the exchange rate between two incoming trades. The dealer is assumed to manage existing inventories by shading prices so that :

$$\beta_4 < 0 < \beta_5 \tag{5.24}$$

Moreover, the model of anonymous currency trading predicts an asymmetric information effect on prices ($\beta_1 > 0$), because the dealer rationally infers the agent's private signal about the true asset value from deal size. Lastly, the structure of the model expects the dummy coefficients to satisfy:

$$\begin{gathered} \beta_3 < 0 < \beta_2 \\ \text{and} \\ \beta_2 > |\beta_3| \end{gathered} \tag{5.25}$$

the difference between the absolute values of the coefficients increasing in line with the information content of the deal flow. Thus, calculating the ratio $|\beta_3|/\beta_2$ gives us an estimate of the average weight put on prior information. The absolute value of the estimated coefficient of the lagged direction dummy ($|\beta_3|$) gives us the average half spread.

5.4.2 The Baseline Madhavan-Smidt Model

We estimate the MS model with the inventory terms omitted, as we do not have inventory information in our dataset, making our regression specification:

$$\begin{aligned} \Delta P_t &= \beta_0 + \beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1} + \eta_t \\ \eta_t &= \tilde{\varepsilon}_t - \zeta \tilde{\varepsilon}_{t-1} \end{aligned} \tag{5.26}$$

Essentially we are estimating the model with the assumption that $\beta_4 = \beta_5 = 0$, an assumption that is borne out by previous studies as previously mentioned. All models are estimated using non-linear least squares, explicitly modelling an MA(1) error structure, and correcting for autocorrelation and heteroskedasticity of unknown form using the Newey-West correction.

The results of the baseline Madhavan-Smidt model are presented in Table 5-3 below. Total order flow consists of the order flow from financial, corporate and internal customers. Interbank deals are estimated separately as counterparties with access to the interbank market would not be considered as customers, and would likely have a different price function. The coefficient on order flow is positive as expected, but not statistically significant. From equation (5.22) the coefficient on order flow corresponds to lambda ($\lambda \equiv (1-\pi)/\alpha\pi$). Lambda captures the information effect, i.e. the responsiveness of price to order quantity, although estimates of lambda capture the effects of costs that vary with order size. If lambda is statistically zero, this implies either that alpha (i.e. cost) is very large, and/or that $\pi \approx 1$. In the FX market very high costs are unrealistic, leading us to conclude that $\pi \approx 1$, i.e. there is no information content in order flow. Coefficients on the directional and lagged directional variables are of the expected sign and are statistically significant. However, we would expect that $\beta_2 > |\beta_3| \equiv \dfrac{\psi}{\pi} \geq \psi$. This is a necessary condition in order for $\pi \in (0,1)$ which is not the case here, a result that is confirmed by a Wald test with a p-value of 0.0001. The baseline model is clearly misspecified, but insofar as any conclusions can be reached, it suggests that there is no price impact and therefore no perceived information in total customer order flow. There is strong evidence that the error structure does indeed follow an MA(1) process, as the moving average parameter is of the correct sign and highly significant. Estimating the model without explicitly modelling the error structure results in a significant loss of explanatory power.

Baseline Madhavan-Smidt Model

Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
Q_t	0.0024	0.6787	0.1218
D_t	*0.1031*	0.0710	
D_{t-1}	**-0.2070**	0.0000	
η_t	**-0.3809**	0.0000	

Model estimated is: $\Delta P_t = \beta_0 + \beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1} + \eta_t$

$$\eta_t = \tilde{\varepsilon}_t - \zeta \tilde{\varepsilon}_{t-1}$$

D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

Table 5-3 – Baseline Madhavan-Smidt Model

This result is not entirely unexpected. We know that different participants in the FX market trade for distinct reasons, and as such, aggregating the order flow from heterogeneous groups of customers is likely to blur any possible information content. Dealers may also react differently to different sized trades, and the perceived information content of trades at different times during the trading day may vary. To investigate variations in dealer behavior, we estimate the MS model including dummies for deal size, counterparty type, deal size and counterparty type, as well as a model incorporating counterparty type, time of day and a dummy variable to capture any effects due to FX relevant news announcements. The table of size cutoffs and news announcements is included in the appendix. As in the baseline case, all models are estimated using Newey-West correction for heteroskedasticity and autocorrelation.

5.4.3 Its not the size that counts…

To investigate the possibility that dealers react differently to different sized orders, we interact the variables in equation (5.26) with size dummies.

$$
\begin{aligned}
&\Delta P_t = \beta_0 + \sum_{i=1}^{4} q_i \ \left[\beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1}\right] + \eta_t \\
&\eta_t = \tilde{\varepsilon}_t - \zeta \tilde{\varepsilon}_{t-1} \\
&q1 \in (0,1] \quad q3 \in (4,10) \\
&q2 \in (1,4] \quad q4 \in [10,\infty)
\end{aligned}
\tag{5.27}
$$

The results of this model, summarized in Table 5-4, are largely insignificant. Where coefficients are significant, their interpretation is counterintuitive. For example in the case of the modal size group (q1), the coefficient on order flow is negative and significant. Recall that this is the estimate of lambda, which from equation (5.14) is $\lambda \equiv (1-\pi)/\alpha\pi$. A negative lambda implies negative costs and/or $\pi > 1$, both of which are impossible. Coefficients on the directional and lagged directional variables are of the expected sign and are statistically significant for this size category, and $\beta_2 > |\beta_3|$, which would suggest information content, but we cannot reconcile this result with the negative coefficient on order flow. Results are similarly mixed for the remaining size categories, and we conclude that the model is again misspecified.

Madhavan-Smidt Model With Size Dummies			
Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
q_1Q_t	**-3.0958**	0.0001	0.1251
q_1D_t	**2.9561**	0.0001	
q_1D_{t-1}	*-0.1148*	0.1291	
q_2Q_t	0.0219	0.7955	
q_2D_t	0.1920	0.4213	
q_2D_{t-1}	**-0.2991**	0.0003	
q_3Q_t	0.0747	0.3664	
q_3D_t	-0.2202	0.6404	
q_3D_{t-1}	*-0.1712*	0.1022	
q_4Q_t	-0.0026	0.7589	
q_4D_t	*0.3156*	0.1060	
q_4D_{t-1}	-0.0719	0.5200	
η_t	**-0.3821**	0.0000	

Model estimated is: $$\Delta P_t = \beta_0 + \sum_{i=1}^{4} q_i \; [\beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1}] + \eta_t$$

$$q1 \in (0,1] \quad q3 \in (4,10)$$
$$q2 \in (1,4] \quad q4 \in [10,\infty)$$

D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

Table 5-4 – Madhavan-Smidt Model with Size Dummies

5.4.4 …its who you're trading with

Once again, the results of the size specific model are not surprising, considering the fact that in FX, players with any informational advantage are likely to break up their orders to avoid the possibility of revealing any information. Counterparty type on the other hand is a distinction that should make a difference. As previously noted, different players trade FX for distinct reasons, so their trades could be expected to have different price impacts. Previous FX microstructure literature also supports this differentiation on the basis of customer type (Lyons 2001, Marsh and O'Rourke 2005).

To investigate this hypothesis at the transaction level, we estimate equation (5.26) again, this time interacting the variables of the MS model with dummies for the three counterparty categories – financial, corporate and internal customers. The results are shown in Table 5-5 below. The model specification is as follows:

$$\Delta P_t = \beta_0 + \sum_{i=1}^{3} CP_i \left[\beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1}\right] + \eta_t$$
$$\eta_t = \tilde{\varepsilon}_t - \zeta\tilde{\varepsilon}_{t-1} \tag{5.28}$$
$$CP1 \text{ - Financial; CP2 - Corporate; CP3 - Internal}$$

The results of this model are interesting if initially unexpected. Traditionally in the FX microstructure literature it is the financial customers who are considered to have superior information. This hypothesis is intuitively appealing since hedge funds and financial institutions trade currencies with the primary objective of achieving speculative gains, so the trades of these customers should contain information. The results of the counterparty specific MS model do not support this idea however. The coefficient on order flow is positive but insignificant, and the coefficients on the directional and lagged directional variable are of the correct sign, but $\beta_2 < |\beta_3|$ which would suggest $\pi > 1$ which is impossible.

Looking at the results for corporate customers however, although the coefficient on order flow is not statistically different from zero, the coefficients on D_t and D_{t-1} are of the correct sign and magnitude. Since the MS model is based on a rational market-maker who sets regret-free prices, so that all adjustments are made in anticipation of a trade, if there is lagged price adjustment the estimates of the information effect λ may be understated. The estimate of π from the directional variables is a 'cleaner' estimate. We can conclude therefore that there is information content in corporate customer order flow.

Madhavan-Smidt Model With Counterparty Dummies			
Variable	**Coefficient**	**P-Value (HAC)**	**Adj. R-Squared**
CP_1Q_t	0.0036	0.7385	0.1241
CP_1D_t	0.0203	0.7787	
CP_1D_{t-1}	**-0.1762**	0.0024	
CP_2Q_t	-0.0066	0.3491	
CP_2D_t	**0.5626**	0.0000	
CP_2D_{t-1}	**-0.2841**	0.0128	
CP_3Q_t	0.0036	0.6865	
CP_3D_t	-0.0832	0.4432	
CP_3D_{t-1}	**-0.1916**	0.0642	
η_t	**-0.3812**	0.0000	

Model estimated is: $$\Delta P_t = \beta_0 + \sum_{i=1}^{3} CP_i \left[\beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1}\right] + \eta_t$$

$CP1$ - Financial CP2 - Corporate

CP3 - Internal

D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

Table 5-5 – Madhavan-Smidt Model with Counterparty Dummies.

This is not as counterintuitive as one might at first believe. Corporate clients trade currencies for reasons directly related to the firm's core business activities. If order flow is the medium through which information about the macro economy makes its way into FX prices, then it is precisely the trades of corporate clients that in aggregate contain this information. Furthermore, even within the class of financial customers, traditional asset managers' currency transactions also tend not to be driven by currency forecasts. Since we cannot further differentiate within the class of financial customers, it is harder to pick out whose trades could possibly contain information. Within the class of corporate customers we do not have this problem, and in fact aggregating corporate orders may enhance rather than degrade the picture we can get from order flow, since macro numbers such as GDP are essentially made up of all the aggregate actions of corporations. As a final consideration, even if we accept that hedge fund managers are the smartest guys in town, and that their trades should contain information, they are more likely than corporate clients to split their trades among multiple dealers so as not to reveal their strategies, and are also likely to have access to services such as EBS Prime, which allow them greater anonymity. It will not generally be possible for a dealer, who can only see his own order flow, to differentiate between a hedge fund purchasing currency to initiate, or to close out a position – two scenarios with different implications for currency movements. Corporate clients on the other hand tend to maintain relationships with banks for all their business activities, and since they are not primarily at least trading for speculative gain, they have far less reason to try to hide their trades.

5.4.5 Disaggregating further

Given the results for the counterparty-specific regression we then disaggregate the data further hoping to determine whether order flow from certain counterparties is perceived to be more or less informative depending on the size of the trade or depending on the time at which the trade is placed. One model is run interacting the MS variables with counterparty and size dummies, and another interacting the MS variables with time-of-day and counterparty dummies, as well as a dummy for FX-related news announcements. The results of these two models are included in appendix K. Further disaggregation did not uncover any information content in the trades of financial or internal customers. For corporate trades however, the models show that very large trades of over €10M are perceived to be informative, as well as trades taking place between 14:00 and 16:00 and around news announcements.

5.4.6 Robustness Checks

All models were run including interbank orders in the initial database, as well as dropping internal customers from the initial database. This involves actually removing internal orders and recalculating price changes from trade to trade and setting the directional and lagged directional dummies, not simply dropping the variables from the regression. Neither change affects the results significantly. The time of day regression was also run without disaggregating by customer type to investigate the possibility that aggregate order flow is perceived to be informative depending on the time the trade is placed. The model was found to be misspecified, so results are omitted for brevity. In addition, given the sensitivity of OLS estimation to outliers, all models were re-estimated with observations with large changes in price (50 pips, 20 pips, 10 pips) both dropped and Winsorized. There was no change in inference so the output of these estimations is not reported.

5.4.7 Estimating the Huang and Stoll Model

The results concerning the importance of deal size from the Madhavan-Smidt regressions, consistent with the results reported in Osler et al. (2006a) and Bjønnes and Rime (2005), suggest that deal size is relatively unimportant for pricing in foreign exchange markets. As discussed in section 5.3.7, this may be due to traders' response to the strategy of dealers inferring information from order flow (Huang and Stoll, 1997). Having verified this in our data, we proceed to estimate the Huang-Stoll (HS) model. As before HAC standard errors are used to correct for heteroscedasticity and autocorrelation. The econometric model in the Huang-Stoll framework is:

$$\Delta P_t = \frac{S}{2}(D_t - D_{t-1}) + \lambda \frac{S}{2} D_{t-1} + e_t \tag{5.29}$$

The model provides estimates of the traded spread, S, and the total adjustment of quotes to trades, $\lambda(S/2)$. We recall that λ represents the adjustment due to adverse selection (α) as well as any adjustment due to inventory (β). Although we cannot separate λ into its components, given the multiple dealer structure of the FX market which makes it easy for dealers to manage inventory using the interbank market, coupled with the findings in the literature that inventory control through price shading is not a feature of FX dealers, we can assume that λ is a reasonable estimate of adjustment due to information.

5.4.8 *The Baseline Huang-Stoll Model*

As with the Madhavan-Smidt model we initially estimate the baseline case with total aggregated order flow. The regression specification is as follows:

$$\Delta P_t = \beta_1(D_t - D_{t-1}) + \beta_2 D_{t-1} + e_t$$
$$\text{where } \beta_1 := \frac{S}{2} \tag{5.30}$$
$$\text{and } \beta_2 := \lambda\frac{S}{2}$$

Results are presented in Table 5-6 below. Both coefficients are significant, and the model suggests a negative adjustment of quotes to trades. This would indicate that our dealer, faced with a buy order for example, would adjust his quotes downward. The simple model is not likely to be correctly specified given that we have already established a difference in the impact of different customer categories. We therefore interact the variables in equation (5.29) with counterparty dummies for financial and corporate customers, as well as dummies for time of day and news announcements. These results are examined in the following two sections.

Baseline Huang-Stoll Model

Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
$(D_t - D_{t-1})$	**0.1675**	0.0034	0.0028
D_{t-1}	**-0.0763**	0.0124	

Model estimated is: $\Delta P_t = \beta_1(D_t - D_{t-1}) + \beta_2 D_{t-1} + e_t$

where $\beta_1 := \frac{S}{2}$ and $\beta_2 := \lambda\frac{S}{2}$

D is a directional variable indicating whether the trade was a buy or a sell.
S is an estimate of the quoted spread, and lamda approximates the informativeness of a trade.
The change in price (from trade to trade) is calculated in pips.

Table 5-6 – Baseline Huang-Stoll Model

5.4.9 Huang-Stoll Model with Counterparty Dummies

In this variation of the baseline HS model we interact the variables with counterparty dummies for financial and corporate customers, which based on the results of the MS models are the two categories we are most interested in. The model is run including all four counterparty categories with no statistically significant difference in the result. The model to be estimated is as follows:

$$\Delta P_t = \sum_{i=1}^{2} CP_i \left[\beta_1 (D_t - D_{t-1}) + \beta_2 D_{t-1} \right] + e_t$$
$$CP1 \text{ - Financial} \qquad (5.31)$$
$$\text{CP2 - Corporate}$$

We note that by specifying the model in this way we are allowing the spread to vary among customer categories as well as the adjustment of the quote due to information (i.e. λ). This less restrictive version of the model seems to fit better with the hypothesis that spreads do vary in reality among customer types. Results of the counterparty specific model are summarised in Table 5-7.

The results are very interesting for the corporate customer category, but the model seems to be badly specified for financial customers. The estimate of the half-spread for financials is statistically zero, though even if we were to take the coefficient of 0.0749 as the estimate, this would imply that the half-spread for corporate customers, at 0.6755, is an order of magnitude larger, a conclusion that does not seem reasonable. Given these results we can make no inference about the information content of financial orders. In the case of corporate order flow on the other hand, the results are very encouraging, almost exactly matching the Madhavan-Smidt outcome. The estimate of λ - i.e. the adjustment of the quote due to information, for corporate customers is 47%. In the equivalent Madhavan-Smidt model the average weight put on order flow information from corporates is estimated at 50% (with the other 50% being the weight put on prior information). We note however that the two models are not entirely consistent, as the estimated half-spread is quite different – HS estimating it at 0.6755 pips for corporates, while the equivalent MS estimate is 0.2841 pips. This is not an insignificant difference, but we recognize that the two models are sufficiently different – chiefly in the complete absence of a size effect in the HS model – to make this less of a concern. We now proceed to disaggregate further to look at differences within the trading day.

Huang-Stoll Model with Counterparty Dummies

	Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
CP1 (Financial):				
	$(D_t - D_{t-1})$	0.0749	0.2281	0.0059
	D_{t-1}	**-0.1417**	0.0000	
CP2 (Corporate):				
	$(D_t - D_{t-1})$	**0.6755**	0.0000	
	D_{t-1}	**0.3190**	0.0024	

Model estimated is: $$\Delta P_t = \sum_{i=1}^{2} CP_i \left[\beta_1 (D_t - D_{t-1}) + \beta_2 D_{t-1} \right] + e_t$$

$CP1$ - Financial

CP2 - Corporate

See footnote for Baseline Huang-Stoll Model for more details.

Table 5-7 – Huang-Stoll Model with Counterparty Dummies

5.4.10 Huang-Stoll Model with Counterparty, Time of Day and News Dummies

In this second variation of the baseline HS model we interact the variables with counterparty dummies for financial and corporate customers, but also with dummies for six 2-hour periods during the day, to account for any differences in the perceived information content of trades at different times. In addition we include a dummy for FX specific news announcements, to test whether trades are considered to be more or less informative around news releases.

The model estimated is as follows:

$$\Delta P_t = \sum_{j=1}^{7}\sum_{i=1}^{2} TD_j CP_i \left[\beta_1 (D_t - D_{t-1}) + \beta_2 D_{t-1}\right] + e_t$$

$$\begin{array}{cc} CP1 \text{ - Financial;} & \text{CP2 - Corporate} \\ TD1 \text{ - 06:00 - 08:00;} & \text{TD2 - 08:00 - 10:00} \\ TD3 \text{ - 10:00 - 12:00;} & \text{TD4 - 12:00 - 14:00} \\ TD5 \text{ - 14:00 - 16:00;} & \text{TD6 - 16:00 - 18:00} \\ \multicolumn{2}{c}{\text{TD7 - News}} \end{array} \tag{5.32}$$

Results are summarized in Table 5-8. Disaggregating further does not 'rescue' the specification for financial customers. The adjustment coefficients on financial trades are negative where they are significant, although most results are statistically zero. We are forced to conclude again that the model is not well specified for financial customers.

The results for corporate trades are once more very encouraging. They have positive and significant adjustment coefficients, with one exception very early in the morning. We address this discrepancy first, by looking at the breakdown of trading activity by each customer type during each 2-hour window within the trading day. A summary can be found in Tables 5-10 and 5-11. We see that in the case of corporate orders, the time period from 06:00 – 08:00 is not an active one, with only 102 trades occurring over the 25 days. This would correspond to only about 4 trades per day in this time period, and may account for the wrongly signed coefficients in the Huang-Stoll model. In the remaining intervals, the biggest discrepancy with the Madhavan-Smidt results is for the interval 08:00 – 10:00. In the MS model, although the coefficients were of the correct sign, only the coefficient on the directional variable was significant. Calculating the weight placed on order flow information regardless would give us an estimate of 72%, compared to the HS λ of 82%. In the 14:00 – 16:00 interval, which is significant in the MS model, giving an estimated weight put on information of 25%, the corresponding HS estimate is 30%. In this case it is the HS β_2 that has the expected sign but is not statistically significant.

Both models find corporate flow to be informative around news announcements, with 47% and 35% adjustment due to information assigned by MS and HS respectively, again with the caveat that the HS β_2 has the expected sign but is not statistically significant. The section of the MS model with counterparty, time and news dummies corresponding to corporate customers only is reproduced in Table 5-9 below for comparison.

The Huang-Stoll models therefore broadly support the conclusions reached using the Madhavan-Smidt models. We cannot confirm the MS result that assigns 41% weight to information in very large corporate trades using the HS model, as it disregards size by construction. In all other cases however, there are strong indications from both models that there is information in corporate trades. The results for financial trades on the other hand are, at best, inconclusive.

Huang-Stoll Model with Counterparty, Time and News Dummies				
	Variable	**Coefficient**	**P-Value (HAC)**	**Adj. R-Squared**
CP1 (Financial) :				
	$TD_1(D_t - D_{t-1})$	-0.2025	0.5314	0.0068
	TD_1D_{t-1}	-0.2576	0.1296	
	$TD_2(D_t - D_{t-1})$	0.1016	0.2825	
	TD_2D_{t-1}	**-0.1301**	0.0508	
	$TD_3(D_t - D_{t-1})$	0.0334	0.8104	
	TD_3D_{t-1}	**-0.1405**	0.0508	
	$TD_4(D_t - D_{t-1})$	0.1604	0.2060	
	TD_4D_{t-1}	-0.0423	0.5670	
	$TD_5(D_t - D_{t-1})$	0.1205	0.3191	
	TD_5D_{t-1}	-0.0964	0.2324	
	$TD_6(D_t - D_{t-1})$	0.1242	0.7320	
	TD_6D_{t-1}	-0.3504	0.2168	
	News $(D_t - D_{t-1})$	-0.2814	0.3285	
	News D_{t-1}	**-0.2872**	0.0492	
CP2 (Corporate) :				
	$TD_1(D_t - D_{t-1})$	-0.0161	0.9676	
	TD_1D_{t-1}	***-0.5323***	0.0739	
	$TD_2(D_t - D_{t-1})$	**0.5190**	0.0358	
	TD_2D_{t-1}	**0.4273**	0.0165	
	$TD_3(D_t - D_{t-1})$	***0.6822***	0.0532	
	TD_3D_{t-1}	0.1404	0.6200	
	$TD_4(D_t - D_{t-1})$	0.3174	0.2357	
	TD_4D_{t-1}	**0.3736**	0.0479	
	$TD_5(D_t - D_{t-1})$	**0.6782**	0.0115	
	TD_5D_{t-1}	0.2039	0.2676	
	$TD_6(D_t - D_{t-1})$	1.0944	0.1258	
	TD_6D_{t-1}	0.5697	0.3313	
	News $(D_t - D_{t-1})$	**1.7541**	0.0022	
	News D_{t-1}	0.6117	0.1234	

$$\Delta P_t = \sum_{j=1}^{6}\sum_{i=1}^{2} TD_j CP_i \left[\beta_1 (D_t - D_{t-1}) + \beta_2 D_{t-1}\right] + e_t$$

*CP*1 - Financial. CP2 - Corporate
*TD*1 - 06:00 - 08:00.TD2 - 08:00 - 10:00
*TD*3 - 10:00 - 12:00. TD4 - 12:00 - 14:00
*TD*5 - 14:00 - 16:00. TD6 - 16:00 - 18:00

See footnote for Baseline Huang-Stoll Model for more details.

Table 5-8 – HS model with Counterparty, Time and News Dummies

Madhavan-Smidt Model with Counterparty, Time and News Dummies

(results for Corporate Customers only)

	Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
CP2 (Corporate) :				
	TD_1Q_t	**-0.0321**	**0.0119**	
	TD_1D_t	0.3370	0.3843	
	TD_1D_{t-1}	-0.5572	0.1216	
	TD_1Q_t	-0.0132	0.3641	
	TD_2D_t	**0.5420**	**0.0357**	
	TD_2D_{t-1}	-0.1525	0.5099	
	TD_3Q_t	-0.0053	0.6756	
	TD_3D_t	0.3771	0.2249	
	TD_3D_{t-1}	-0.2899	0.2870	
	TD_4Q_t	0.0003	0.9830	
	TD_4D_t	0.1663	0.4802	
	TD_4D_{t-1}	0.1288	0.5615	
	TD_5Q_t	-0.0097	0.5729	
	TD_5D_t	**0.6044**	**0.0189**	
	TD_5D_{t-1}	**-0.4532**	**0.0329**	
	TD_6Q_t	-0.0063	0.8238	
	TD_6D_t	0.9887	0.1106	
	TD_6D_{t-1}	-0.4584	0.4099	
	News $(D_t - D_{t-1})$	**1.5943**	**0.0003**	
	News D_{t-1}	**-0.8396**	0.0542	
	MA(1)	**-0.3825**	**0.0000**	

$$\Delta P_t = \sum_{j=1}^{6}\sum_{i=1}^{3} TD_j CP_i\left[\beta_1 Q_t + \beta_2 D_t + \beta_2 D_{t-1}\right] + \eta_t$$

*CP*1 - Financial; CP2 - Corporate; CP3 - Internal

*TD*1 - 06:00 - 08:00.TD2 - 08:00 - 10:00

*TD*3 - 10:00 - 12:00. TD4 - 12:00 - 14:00

*TD*5 - 14:00 - 16:00. TD6 - 16:00 - 18:00

D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

Table 5-9 – MS Model with Counterparty, Time and News Dummies

Number of transactions per 2-hour window within the trading day *(over the 25 day data sample)*					
	Corporate	**Financial**	**Internal**	**Interbank**	**All**
06:00 - 07:59	102	494	96	797	1489
*	*3.95%*	*5.55%*	*5.04%*	*5.52%*	*5.35%*
**	*6.85%*	*33.18%*	*6.45%*	*53.53%*	*100.00%*
08:00 - 09:59	493	1928	390	3199	6010
	19.08%	*21.67%*	*20.47%*	*22.15%*	*21.60%*
	8.20%	*32.08%*	*6.49%*	*53.23%*	*100.00%*
10:00 - 11:59	410	1844	350	2876	5480
	15.87%	*20.72%*	*18.37%*	*19.91%*	*19.69%*
	7.48%	*33.65%*	*6.39%*	*52.48%*	*100.00%*
12:00 - 13:59	602	2008	443	3341	6394
	23.30%	*22.57%*	*23.25%*	*23.13%*	*22.98%*
	9.42%	*31.40%*	*6.93%*	*52.25%*	*100.00%*
14:00 - 15:59	728	2178	505	3473	6884
	28.17%	*24.48%*	*26.51%*	*24.05%*	*24.74%*
	10.58%	*31.64%*	*7.34%*	*50.45%*	*100.00%*
16:00 - 17:59	249	446	121	757	1573
	9.64%	*5.01%*	*6.35%*	*5.24%*	*5.65%*
	15.83%	*28.35%*	*7.69%*	*48.12%*	*100.00%*
Total (06:00 - 18:00):	2584	8898	1905	14443	27830

* percentage of total flow from customer category

** percentage of total flow from all customers in the 2-hour window

Table 5-10 – Number of transactions per 2-hour window

	Corporate	Financial	Internal	Interbank	All
06:00 - 07:59					
*	5.9443	4.6818	5.7089	2.3962	3.6111
**	*(15.31)*	*(19.49)*	(22.33)	*(3.72)*	*(13.55)*
***	0.85 - 140.00	0.5 - 400.00	0.5 - 220.00	0.5 - 54.00	0.5 - 400.00
08:00 - 09:59					
	7.7642	3.5525	3.3952	2.4584	3.3054
	(14.36)	*(5.69)*	(5.05)	*(3.74)*	*(6.20)*
	0.5 - 115.85	0.5 - 75.00	0.5 - 50.00	0.5 - 100.00	0.5 - 115.85
10:00 - 11:59					
	7.3958	3.8236	3.3301	2.5859	3.4098
	(12.00)	*(6.44)*	(5.11)	*(3.61)*	*(5.90)*
	0.5 - 67.00	0.5 - 100.00	0.5 - 50.00	0.5 - 50.00	0.5 - 100.00
12:00 - 13:59					
	8.1759	3.7459	7.4691	2.6594	3.8532
	(19.20)	*(6.17)*	(21.86)	*(4.59)*	*(9.71)*
	0.5 - 228.64	0.5 - 100.00	0.6 - 197.99	0.5 - 137.28	0.5 - 228.64
14:00 - 15:59					
	7.3156	3.6107	3.645	2.6158	3.5031
	(12.75)	*(5.46)*	(3.99)	*(4.14)*	*(6.20)*
	0.5 - 128.20	0.5 - 96.00	0.5 - 50.00	0.5 - 101.78	0.5 - 128.20
16:00 - 17:59					
	7.0903	6.6286	6.1183	2.5657	4.7072
	(14.58)	*(27.11*	(9.70)	*(3.30)*	*(16.09)*
	0.5 - 105.97	0.5 - 500.00	0.5 - 68.00	0.65 - 35.00	0.5 - 500.00
Total:	7.5385	3.8834	4.6864	2.5703	3.5963
(06:00 - 18:00)	*(14.97)*	*(9.48)*	*(12.63)*	*(4.00)*	*(8.42)*
	0.5 - 228.64	0.5 - 500.00	0.5 - 220.00	0.5 - 137.28	0.5 - 500.00

Descriptive Statistics (volume) per 2-hour window within the trading day
(over the 25 day data sample, in € million)

* Average
** Standard Deviation
*** Range

Table 5-11 – Descriptive statistics (volume) per 2-hour window

5.5 Conclusion

In this chapter we have looked at a unique, ultra-high-frequency, large volume customer order flow database from a leading commercial bank. The dataset, while relatively short in time span, is significantly rich in volume, number and counterparty balance. We use this database in conjunction with two standard market microstructure models in order to gain an insight into the information content of customer order flow.

The first model is the one by Madhavan and Smidt (1991). In its basic form, the model does not differentiate between trades in any way. All trades are considered to be the same, irrespective of the size of the trade, or what type of counterparty initiated it. The model can easily be extended however to allow for customer heterogeneity in these dimensions. Our results suggest that these extensions are important. In particular, while we are unable to find any evidence of information content from financial customer order flow, however partitioned, we find strong evidence that large corporate customer order flows are perceived to have statistically and economically significant information content.

The second model, by Huang and Stoll, does not admit differences in size by construction. It is a less structural model, with fewer assumptions made about the particular trading mechanism, possibly making it more suitable for the FX market. Nevertheless, it too indicates that corporate order flow can contain meaningful information content.

These results are in fairly stark contrast to the literature, where it is usually found that the information content in flows comes from financial customers. We have several explanations for this. Firstly, we find that the information content in our data is concentrated in large corporate customer orders, i.e. orders greater than €10 million. Previous work has relied on transactions seen by much smaller banks than ours, where such deals are few and far between at best. For example, in the Reitz et al data, although approximately 44% of transactions seen are from corporate customers, the mean corporate order size is only €0.2 million. In fact, in their dataset, large orders are defined as orders larger than €0.5 million.

The informativeness of corporate flow therefore could have been missed in the existing literature simply because of a lack of data. This does not explain the lack of information in financial flows in our data however.

One reason for the lack of any clear result from the financial customer trades may well be related to the time period from which our data comes. The original Evans and Lyons Citibank data is from the late 90's, and the Osler et al data and Reitz et al data are from 2001 and 2002/03 respectively. Our data sample - in late 2005 – may not seem to be that far removed, but in the FX market the last decade has been a time of tremendous change. In fact, the very change that spawned the field by making transactions data available – electronic trading – has caused an ongoing revolution of sorts in how FX is traded. FX has also established itself quite firmly as an asset class in its own right, a change that is likely to have further increased investor heterogeneity, and blurred the distinctions between different investor categories. As an example, global corporates with enough resources in their financial department to be directly trading in FX could be considered to have more in common with financial customers than corporates simply executing international trades. Heterogeneity is a major concept in the microstructure literature – market participants are active in FX for disparate reasons with different needs and ways to conduct transactions. Advances in technology and investor demand have meant that platforms are developing functionalities that meet their customer segment requirements. In the financials category there is a large degree of heterogeneity *within* the group itself, and the type of financial customer whose trades were assumed to carry information – large hedge funds, quantitative trading firms and active currency managers – increasingly have access to the interbank market directly as both EBS and Reuters provide prime brokerage services to large buy-side institutions. These changes mean that it is much more difficult to extract clear signals from financial trades.

Furthermore, even though we do see substantial order flow, it is reasonable for financial customers with any informational advantage to try to hide this from the relatively sophisticated dealers at our bank. One indication of this is the apparent order splitting in the financials group. Very few orders are greater than €10 million –

less than 10% in fact, and about 40% of financial orders are for €1 million. Appendix I gives a breakdown of orders falling into various size groups by customer type.

Nevertheless, we recognize the limitations of our analysis in this chapter, perhaps most importantly our lack of dealer's inventory. The existing literature suggests that this is not a major issue because inventory effects are negligible. However, as argued above, much of the existing literature is based on data from small/medium-sized banks. It is conceivable that large corporate orders, which are driving our results, have an inventory effect that we are wrongly ascribing to information content. Still, we take heart from the Lyons results, which also reveal no inventory effect from a large bank.

6 Information Content vs. Feedback Trading

6.1 *Introduction*

The results of the previous chapter show that there is no evidence of impact of customer trades on dealer quotes, and what little impact there is comes from corporate customers. In this chapter, we turn our attention to the relationship between customer flows seen by one bank, and *market clearing* prices. We aim to use the high-frequency dataset to determine the causality in this relationship, i.e. is there meaningful information in the trades of customers that can forecast subsequent price moves, or is it that price moves themselves are providing the incentive to trade that results in order flow?

6.2 *Price Impact of Flows on Market Prices*

Microstructure theory suggests that trades carry information and hence have permanent effects on prices. The information content of these trades is normally quantified by examining their price impact. The greater the cumulated effect, or impulse response, the more information trades are argued to carry. To the extent that perhaps there is information content in the flows seen by our bank's dealers, but it is getting impounded in market prices via dealer trades in the interbank market rather than by quote revisions, we estimate the price impact models used by Ito and Hashimoto (2006), matching the trades to the EBS market clearing rate rather than the dealt rate.

6.2.1 Ito and Hashimoto (2006)

Ito and Hashimoto (2006) use interbank data to examine the forecasting power of order flow. The data used in their analysis is extracted from EBS, and spans the period from January 1999 to October 2003. The data includes all quotes and trades on the platform in EUR/USD and USD/JPY. Berger et al. (2005) also examine the correlations between order flows and exchange rate movement on EBS at various time aggregations: 1 minute, 5 minutes, 10 minutes, 1 hour, and 1 day, and find strong positive association of order flows and exchange rate changes, i.e. buying pressure is associated with rising prices. They find that the contemporaneous relationship weakens as the time horizon increases. Despite the positive contemporaneous price impact of order flow, Berger et al. (2005) argue that there is little evidence for predictability, namely lagged trades impacting on the price change in the next minute.

Ito and Hashimoto (2006) find that order flows resulting in buying pressure or selling pressure do move the exchange rate, and the effect is strong up to, at least, the following 5 minutes. The predictability is already very weak at 15 minutes, and predictability definitely disappears by 30 minutes. To test exactly how long the predictive power persists, the lagged effects of flows on price changes are measured cumulatively, to see how long order flow information remains valuable. To this end, the following specification is estimated at a 1-minute frequency:

$$\begin{aligned}&\Delta s_t = \alpha + \sum_{i=1}^{30} \beta_i x_{t-i} + \varepsilon_t \\ &\text{where } \Delta s_t := \text{ log return} \\ &\text{and } x_{t-i} := \text{order flow}\end{aligned} \tag{6.1}$$

This specification therefore examines the cumulative effect of order flows on exchange rate changes. Price impact is defined as $\sum_{i=0}^{p} \beta_i$, and in this case price impact is calculated up to 30 minutes. Results show that overall, the contemporaneous price impact is small but positive, the past one minute impact is the largest and then the cumulative price impact gradually decreases. Repeating the experiment for every year in the sample however they find that the duration of positively significant returns following order flows is getting shorter recently. In fact, for EURUSD, the price impact becomes significantly negative in recent years.

6.2.2 *Estimating the Price Impact Model*

Following the same methodology, we estimate the following model for each customer category in our dataset.

$$\Delta s_t = \alpha + \sum_{i=1}^{30} \beta_i x_{t-i} + \varepsilon_t \tag{6.2}$$

Including the contemporaneous effect (i.e. lag 0) implies that causality runs strictly from flows to the exchange rate. Since we cannot confirm this assumption, and to avoid endogeneity issues we omit lag 0 in our estimation. The results for corporate and financial customers are plotted in Figure 6-1 and Figure 6-2 respectively.

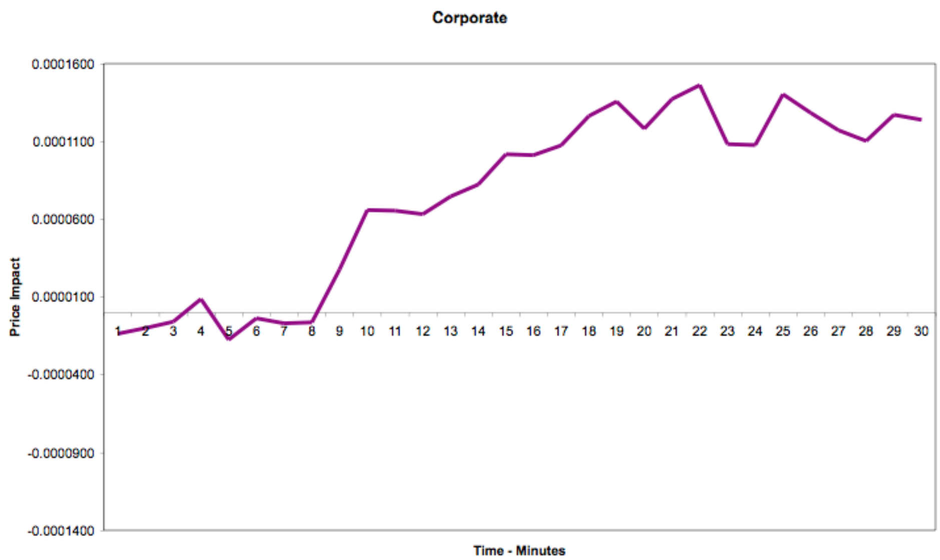


Figure 6-1 – Price Impact Plot for Corporate Trades

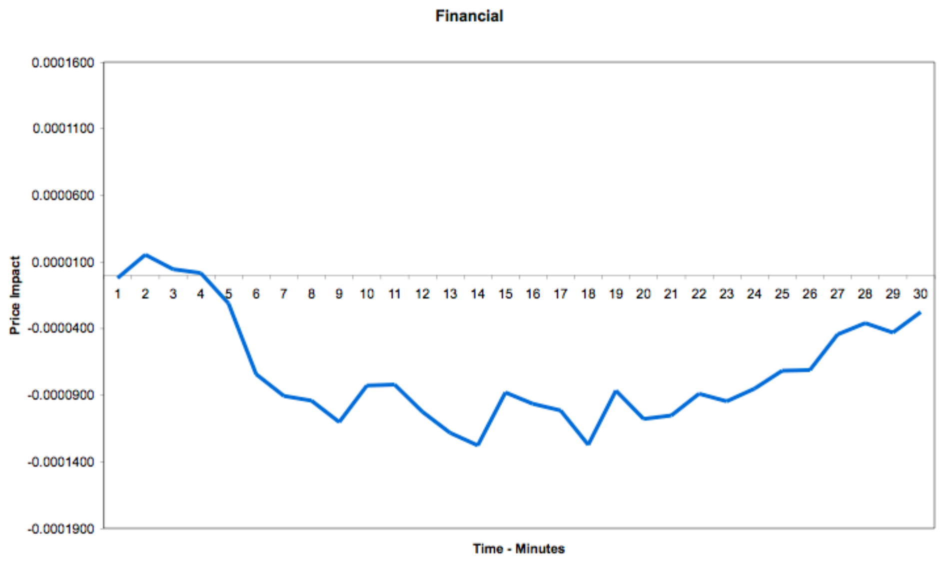


Figure 6-2 – Price Impact Plot for Financial Trades

Once again, we see a striking difference between the two customer categories. In the case of corporate trades, we see a positive price impact that stabilizes after 20-25 minutes. For financials on the other hand there is a very small initial positive impact, but then the price impact becomes negative, dying out to zero within about half an hour. A negative price impact from financial trades seems counterintuitive and is hard to explain, however the 'long-term' impact here is really zero.

These results appear consistent with the models of the previous chapter, suggesting that there is some information in corporate flows that is having a permanent impact on the market-clearing rate. We must introduce some important caveats here however. First, there is a distinction to be made between our study and the Ito and Hashimoto (2006) study; Ito and Hashimoto are looking at the whole market – albeit the interbank market. Our data represents one section of the market – the orders seen by one bank. This introduces a certain amount of difficulty interpreting price-impact from these regressions. Even Deutsche Bank – the largest FX dealing bank in the Euromoney 2009 survey - only sees a fraction of total order flow (20.96%), and as such, customer flows may be representative of the flows seen by other large dealers, but they do not represent the means through which information gets impounded in prices. Customer order flows are one factor driving interdealer flows, which in turn are also a source of information to dealers if we recall the model of trading introduced in chapter 3.

Furthermore, we don't know what the transmission mechanism is from this bank receiving a customer order and the interbank market price. We know from the literature that the bank would not alter its quotes for fear of revealing private information to the market. We also know that this bank, due to the high volume of customer orders it sees, can attempt to offset customer trades without recourse to the interbank market.

The previous chapter suggests that some orders – specifically very large orders over €10 million from corporates – have the expected positive impact on the bank's quoted price. This price however refers to the price quoted to customers, which is not necessarily the same as that quoted on the interbank market. To determine whether the price quoted to customers is significantly different to interbank prices we compare the two and find that the average absolute deviation is only 1.27 pips. A plot of the market price and the dealt price can be seen in Figure 6-3 below, and we can see that the two series track extremely closely.

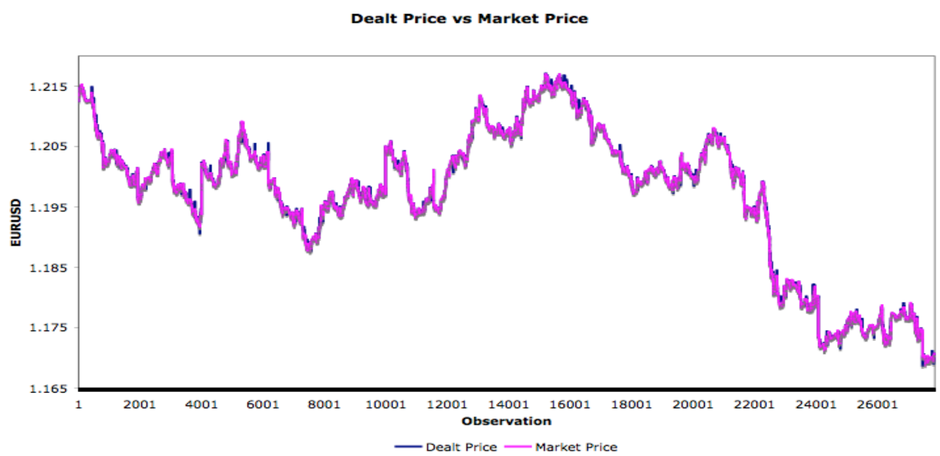


Figure 6-3 – Dealt Price vs. Market Price

There seems to be some evidence of price impact of flows on prices, but the picture is still not quite clear. In the following section, we proceed to estimate the relationship in the opposite direction, to investigate the impact of price changes on customer trades.

6.3 Feedback Trading

A significant unresolved issue in the Micro FX literature, is the relationship between flows and exchange rates is the direction of causality. It is difficult to determine with certainty whether order flow leads spot FX changes or whether it is changes in spot rates that are themselves inducing order flow. Using this high frequency flows data, we can now attempt to resolve the question of whether the contemporaneous relationship between flows and exchange rates is due to information or simply due to feedback trading.

Danielsson and Love (2006) examine the spot USD/EUR (US dollar per euro) foreign exchange market and compare the price impact/informativeness of order flow shocks with and without feedback trading. Their results suggest that positive feedback trading is present in the spot USD/EUR market and significant at high frequencies. Intra-minute feedback trading is significant but not large, possibly because of the time it takes for traders to react to the price movements.

The existence and profitability of feedback trading strategies has been considered in a number of papers. De Long, Shleifer, Summers, and Waldmann (1990) build a model of feedback trading with rational speculators who will buy (sell) when the price rises (falls). The profitability of a number of feedback trading strategies in stock markets is considered in Jegadeesh and Titman (1993) and the existence of high frequency positive feedback trading in the US treasury market is documented in Cohen and Shin (2003). Momentum trading strategies are widely used in FX, and are increasingly being used even by traditional asset managers. Significant trending in FX rates over the time period covered by our dataset is likely to have made such strategies especially popular.

6.3.1 Estimating a feedback model

To test the cumulative effects of lagged exchange rate changes on order flows, we estimate the following regression:

$$X_t = \alpha_t + \sum_{i=1}^{30} \beta_t \Delta S_{t-i} + \varepsilon_t$$
$$\text{where } X_t := \text{ order flow} \tag{6.3}$$
$$\Delta S_{t-i} := \text{lagged FX change}$$

Results for corporate and financial customers are plotted in Figures 6-4 and 6-5 below. We see a strong feedback relationship in both customer categories. In the case of corporates there is clear indication of widespread trend following. In the financials category we again see a positive feedback relationship, although it is not as clear-cut as in the corporates case. This is quite natural as financials probably follow a variety of trading strategies in addition to trend following, and the resulting overall pattern would not be likely to follow any one specific trend.

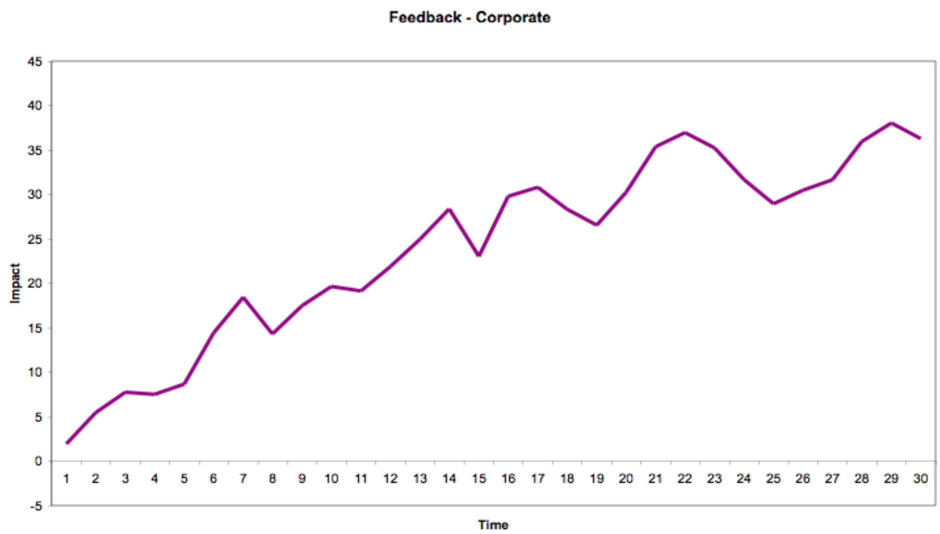


Figure 6-4 – Feedback Trading – Corporate Customers

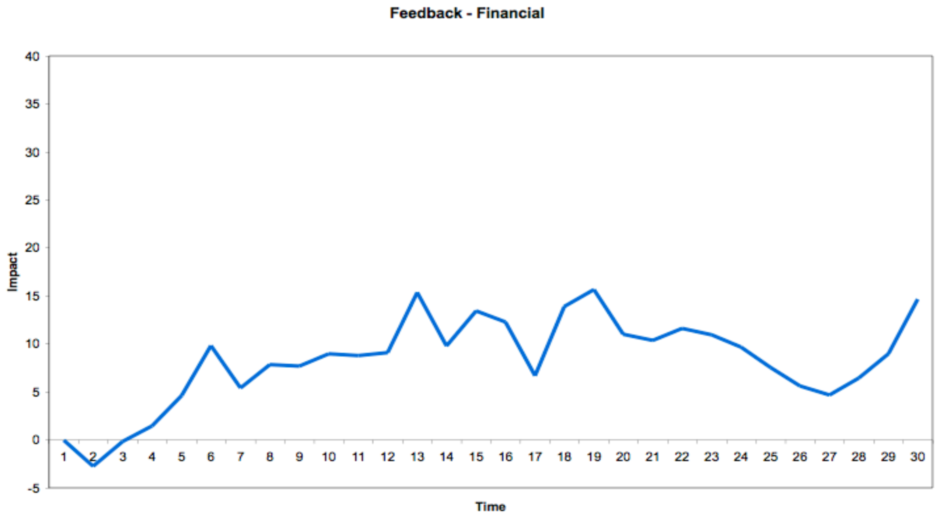


Figure 6-5 – Feedback Trading – Financial Customers

The indication from both customer categories is that there is significant positive feedback occurring. This cannot account for the negative coefficient on corporate order flow found in the contemporaneous daily regressions (Table 4-2), and also commonly found in the literature. Aggregating the high frequency data to lower frequencies to re-estimate the contemporaneous regression does result in a positive coefficient on corporate order flow, but we are wary of drawing conclusions based on such a short sample – only 25 observations at a daily frequency.

Our results so far are inconclusive. There is evidence of feedback trading, but also some indication of price impact of flows on market prices. The literature is all based on the positive contemporaneous relationship at a daily frequency between order flow and exchange rate movements. Using our high frequency database, we now use the cointegration and error correction approach to illuminate causation, which is difficult to infer from low frequency data.

6.4 Cointegration and a Vector Error Correction Model

The order flow data of a single dealer is unlikely to significantly predict next period's order flow in the interdealer market, where exchange rates are actually set. However, dispersed information about unobservable fundamentals is slowly compounded in every dealer's customer order flow. Thus, a single dealer's customer order flow has long-run forecasting power, because it is correlated with future market-wide order flow that dealers use to set prices. To provide evidence for this complex mechanism we first test for the equilibrium relationship by means of cointegration analysis. Second, the adjustment process of deviations from equilibrium is investigated by estimating the related vector error correction model.

Before estimating the model, we must first account for the fact that because our dataset covers only London trading hours, there will be a jump in the exchange rate series corresponding to overnight price changes that would affect our model. One way of accounting for the jumps would be to use dummy variables corresponding to the overnight changes, effectively removing the effect of the jumps from the sample without deleting the observations. Given that the Johansen cointegration test does not take into account exogenous variables in testing for the number of cointegrating relationships, making the test statistics invalid unless bootstrapped, we account for the jumps by indexing the exchange rate. Figure 6-7 below shows the adjustment for the 1-minute aggregation at the first overnight change.

As a robustness check we estimate all models using the unadjusted exchange rate, as well as using dummy variables to account for jumps in the series, and find no change in inference. Output for these models is not reported for brevity.

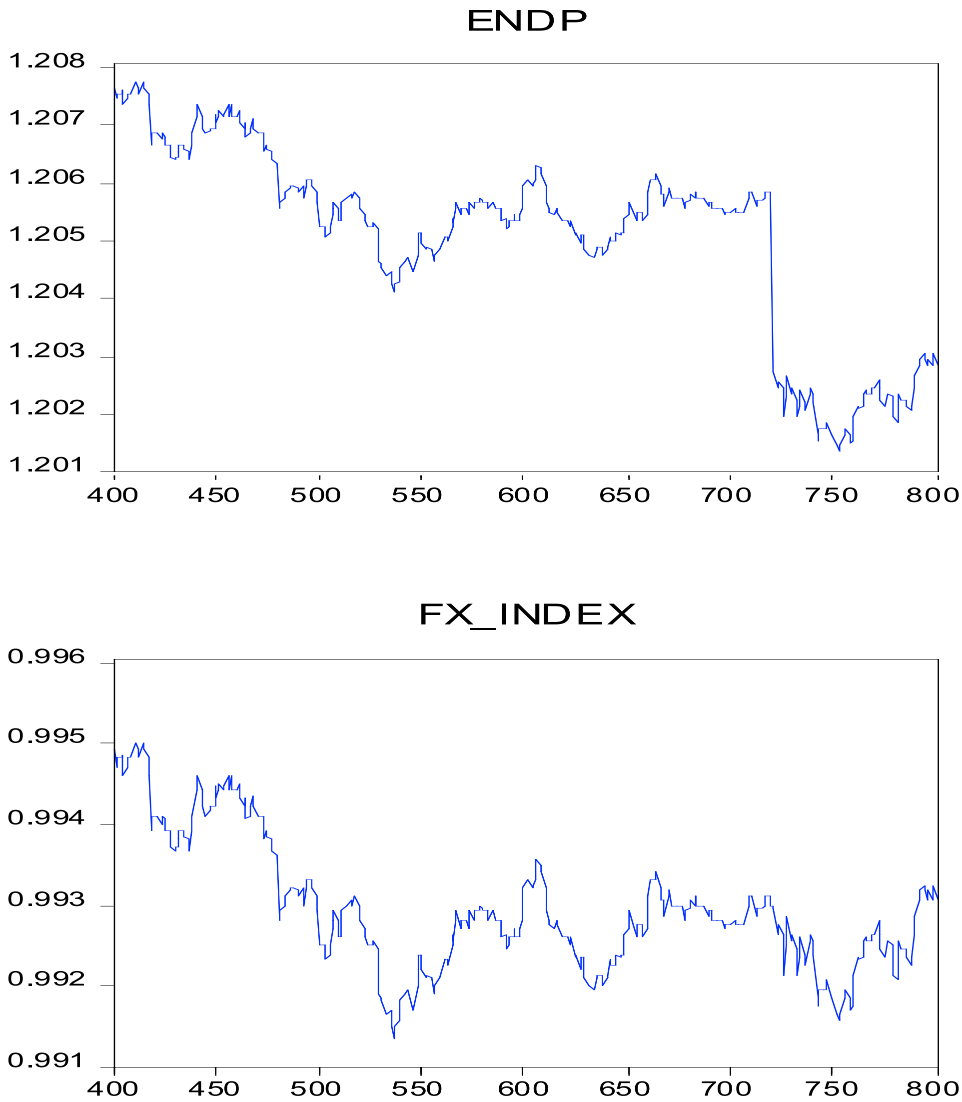


Figure 6-6 – Adjusting the FX rate for overnight jumps by indexing

Before analyzing cointegration relationships we test for stationarity of the individual cumulated order flow series and the exchange rate. The results of unit root tests suggest non-stationarity of cumulative incoming order flow of the different counterparty types, as well as the level of the exchange rate as expected. Results of unit-root tests are summarized in Table 6-1 below.

Unit-Root Tests

Series	**ADF test statistic**	**p-value***
€/$ index	-0.9159	0.7838
Cumulated (Financials)	-1.5717	0.4970
Cumulated (Corporates)	-1.5793	0.4931
Cumulated (Internal)	-0.6865	0.8482
Cumulated (Interbank)	-2.1322	0.2321

Null Hypothesis: series has a unit root
*MacKinnon (1996) one-sided p-values.

Table 6-1 – Unit-Root Tests

We follow the Johansen procedure in order to test for cointegration of the exchange rate and the different types of order flow. First, the unrestricted VAR model is estimated.

$$\begin{pmatrix} P_t \\ X_{i,t} \end{pmatrix} = \begin{pmatrix} \beta_0^P \\ \beta_0^{X_i} \end{pmatrix} + \sum_{j=1}^{2} \Gamma_j \begin{pmatrix} P_{t-j} \\ X_{i,t-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_t^P \\ \varepsilon_t^{X_i} \end{pmatrix}$$
$$\text{where } \mathrm{X} := \text{cumulated order flow} \qquad (6.4)$$
$$\mathrm{P} := \text{ FX rate}$$

The lag order of the system is set to two according to the recommendation of the information criteria. Table 6-2 summarizes the various criteria examined. We select a lag order of two – selected by the Hainan-Quinn, Akaike and Final Prediction Error criteria. Log-Likelihood selects a longer lag length of four, but we prefer the more parsimonious two lags.

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-82418.540	NA	5.870E+13	45.893	45.901	45.896
1	-35054.160	94570.520	209.606	19.535	19.59*	19.553
2	-34981.800	144.288	204.15*	19.51*	19.603	19.54*
3	-34961.020	41.376	204.630	19.511	19.648	19.560
4	-34941.580	38.64*	205.266	19.514	19.695	19.578
5	-34927.780	27.400	206.550	19.520	19.744	19.600
6	-34913.240	28.837	207.756	19.526	19.793	19.621
7	-34899.570	27.067	209.071	19.532	19.842	19.643
8	-34887.930	23.022	210.632	19.539	19.893	19.665

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 6-2 – VAR Lag-length Criteria

Subsequently, Maximum Eigenvalue statistics and trace statistics are calculated to test the null hypothesis of no cointegration. Results are presented in Table 6-3. Both statistics indicate one cointegrating relationship at the 5% level, suggesting a relationship between end-user order flow and market prices.

Unrestricted Cointegration Rank Tests

Trace Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Prob.**
None *	0.012272	83.63065	0.0027
At most 1	0.007267	39.21675	0.2517
At most 2	0.002893	12.98188	0.8924
At most 3	0.000624	2.558985	0.9833
At most 4	8.72E-05	0.313745	0.5754

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level

Maximum Eigenvalue Test

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Prob.**
None *	0.012272	44.4139	0.002
At most 1	0.007267	26.23488	0.0736
At most 2	0.002893	10.42289	0.7043
At most 3	0.000624	2.24524	0.984
At most 4	8.72E-05	0.313745	0.5754

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 6-3 – Cointegration Rank Tests

Given this result, we then proceed to estimate a Vector Error Correction model, now setting the lag length at one. The model is estimated at the 1, 2 and 5-minute aggregation levels, and results are shown in Table 6-4.

Vector Error Correction Estimates

Cointegrating Equation:					
	FX	**FINANCIAL**	**CORPORATE**	**INTERNAL**	**INTERBANK**
1 minute	-1	0.000102	0.000088	0.000075	0.000055
		[7.17429]	[7.33421]	[7.69634]	[4.31175]
2 minute	-1	0.000100	0.000089	0.000074	0.000056
		[6.57827]	[6.89157]	[7.09695]	[4.11630]
5 minute	-1	0.000104	0.000082	0.000072	0.000050
		[6.74728]	[6.92592]	[7.50519]	[4.00043]

Error Correction:					
	FX	**FINANCIAL**	**CORPORATE**	**INTERNAL**	**INTERBANK**
1 minute	0.000127	25.88434	15.04383	11.22708	12.67451
	[0.84375]	[5.02333]	[3.23040]	[3.63993]	[2.99285]
2 minute	0.000331	50.65535	26.62391	17.03988	26.53992
	[1.09341]	[4.84148]	[2.83453]	[2.76734]	[3.04835]
5 minute	0.000930	134.3445	69.26282	45.0416	71.61118
	[1.14360]	[4.81401]	[2.71393]	[2.72140]	[2.94013]

Table 6-4 – Vector Error Correction Estimates

The coefficients of the cointegrating vector, which represent the equilibrium relationship between the variables, are all positive and statistically significant. In the case of financial customers, this confirms the standard result in market microstructure that cumulative order flow is positively correlated with the exchange rate. Interestingly, this is also true for order flow from corporate customers. This result is consistent with our previous results, but contradicts results in the literature that find that buying pressure from corporate customers increases when the spot rate decreases and vice versa. (Evans and Lyons (2005b), Bjønnes et al. (2005), Osler et al. (2006a))

We are particularly interested in which variables adjust to restore equilibrium, thus the most important part of Table 6-4 is the second panel, which shows the adjustment dynamics of the cointegrated system. These numbers show the reaction of the denoted variable to a disequilibrium between price and order flow. In each case, we see that the exchange rate does not significantly adjust to restore equilibrium. Conversely, in every case, order flows do adjust in the expected direction. The ECM coefficients suggest that the adjustment is driven by the order flow, with the coefficient on financial order flow being significantly larger than the other categories.

The results of the error correction model are supportive of the picture that has emerged from the results of previous sections, namely little evidence of information in flows, and evidence of feedback trading, however they strongly contradict the Killeen, Lyons and Moore (2002), henceforth KLM, results. KLM estimate a VAR consisting of the FX rate, cumulative order flow and the interest differential, as well as a constant and a trend, and find one cointegrating vector in the system. The KLM results indicate that the burden of adjustment falls to the exchange rate. They also find no evidence of Granger causality from the FX rate to order flow, and taken together with the conclusions from the ECM they conclude that cumulative order flow is strongly exogenous. This conclusion can seem somewhat counterintuitive, as order flow might be considered to be almost by definition endogenous. Most importantly however, the study is done using daily data, which is unlikely to be a high enough frequency to determine causality. Froot and Ramadorai (2001) use a VAR and the Cambell-Shiller return decomposition to examine the dynamic interactions of flows, returns and measures of fundamentals. They conclude that there is no clear link between order flow and permanent components of exchange rates, and any positive impact of order flow on the FX rate is transitory and unrelated to fundamental information.

Clearly we are far from any consensus on this issue, so we proceed to test for cointegration using our daily dataset in the hope of enriching the current picture.

6.5 Cointegration and Error Correction at Low Frequency

We follow the same procedure as in the previous section to test for cointegration and subsequently estimate the VECM. Of course there are some differences in the counterparty categories for the daily data; we have no interbank category, the financials are separated into levered (e.g. mutual funds) and unlevered (e.g. hedge funds), and we also have an ‘others’ category, which we omit in this estimation for maximum comparability. There is no need to adjust the exchange rate for overnight jumps as the daily data runs 24-hours. We create a financials category by adding together the flows for levered and unlevered customers, and estimate the model in both ways. We begin by estimating the unrestricted VAR – equation 6.5. The lag-length is chosen, as before, using selection criteria, and is set to 1. The lag-length selection criteria are summarized in Table 6-7.

$$\begin{pmatrix} P_t \\ X_{i,t} \end{pmatrix} = \begin{pmatrix} \beta_0^P \\ \beta_0^{X_i} \end{pmatrix} + \sum_{j=1}^{2} \Gamma_j \begin{pmatrix} P_{t-j} \\ X_{i,t-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_t^P \\ \varepsilon_t^{X_i} \end{pmatrix}$$
$$\text{where } \mathrm{X} := \text{cumulated order flow} \qquad (6.5)$$
$$\mathrm{P} := \text{ FX rate}$$

We test for a unit root by looking at the inverted AR roots and find that at least one root lies outside the unit circle. As expected therefore the VAR is non-stationary, and we can test for cointegration. Maximum eigenvalue and trace tests indicate one cointegrating relationship. Figure 6-8 shows the results of the cointegration test for the VAR with financial flows separated into levered and unlevered client trades. Output for the remaining VAR models estimated is omitted for brevity, but reaches the same conclusions.

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-31694.08	NA	3.22E+23	68.31698	68.3430	68.3269
1	-19569.19	24093.0*	1.52e+12*	42.239*	42.397*	42.299*
2	-19552.57	32.8364	1.55E+12	42.2577	42.5441	42.3670
3	-19540.74	23.2590	1.59E+12	42.2861	42.7027	42.4450
4	-19532.45	16.2013	1.65E+12	42.3221	42.8689	42.5307
5	-19523.7	17.0071	1.71E+12	42.3571	43.0342	42.6154
6	-19511.53	23.5219	1.76E+12	42.3848	43.1920	42.6927
7	-19504.89	12.7649	1.83E+12	42.4243	43.3618	42.7819
8	-19493.31	22.1420	1.88E+12	42.4533	43.5209	42.8605

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 6-5 – VAR Lag Length Criteria – Daily Frequency

Unrestricted Cointegration Rank Tests

Trace Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Prob.**
None *	0.1276	161.3724	0.0000
At most 1	0.0188	33.8461	0.0694
At most 2	0.0105	16.1217	0.1688
At most 3	0.0066	6.2230	0.1742

Trace test indicates 1 cointegrating equation at the 0.05 level

Maximum Eigenvalue Test

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Prob.**
None *	0.1276	127.5263	0.0000
At most 1	0.0188	17.7245	0.1929
At most 2	0.0105	9.8986	0.3437
At most 3	0.0066	6.2230	0.1742

Max-eigenvalue test indicates 1 cointegrating equation at the 0.05 level

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 6-6 – Cointegration Rank Tests – Daily Frequency

Table 6-7 below summarises the main results of the VECM model, specified with zero lags. We estimate the error correction model with financial trades aggregated (model A in Table 6-7) as well as disaggregated into levered and unlevered (model B). In both cases we see that only corporate flow retains a long-run relationship with the exchange rate. We therefore estimate the error correction model with corporate flow only (model C).

Vector Error Correction Estimates - Daily Frequency

Cointegrating Equation:

	FX	CORPORATE	FINANCIAL*	LEVERED	UNLEVERED
A	-1	0.000014	-0.000003	-	-
		[4.07024]	[0.05264]		
B	-1	0.000020	-	0.000086	-0.000038
		[4.41561]		[1.56351]	[- 0.90555]
C	-1	0.000014	-	-	-
		[5.24553]			

Error Correction:

	FX	CORPORATE	FINANCIAL*	LEVERED	UNLEVERED
A	0.000407	147.453	4.723	-	-
	[0.52527]	[11.374]	[0.357]		
B	0.000595	179.972	-	-16.298	17.715
	[0.63414]	[11.489]		[-1.351]	[1.788]
C	0.000402	147.055	-	-	-
	[0.51973]	[11.374]			

** FINANCIAL category is made up of LEVERED + UNLEVERED customers*

Table 6-7 - Vector Error Correction Estimates – Daily Frequency

Again, we are particularly interested in which variables adjust to restore equilibrium, and looking at the second panel of Table 6-7 we see that the exchange rate does not significantly adjust to restore equilibrium, with the adjustment is driven by the corporate order flow.

The VECM results at a daily frequency are different than those in the high frequency data. There are a few reasons this could be the case, chief among which is the fact that we are unable to include exactly equivalent counterparty categories. Every customer category is found to be important in the high frequency VECM, so the omission of the interbank group could skew the results. Capturing a long-run relationship is no easy task, but despite the other differences in inference between high and low frequency, one key finding does remain, namely that the exchange rate does not react to restore equilibrium.

Given the results of this chapter so far, the case for information content in order flow seems weak. If flows do contain information, we should be able to use flow to forecast exchange rate movements, so to this end we conduct a high-frequency forecasting experiment in the following section.

6.6 High Frequency Forecasting

The objective of this section is to analyze the forecasting power of order flows on future exchange rate movements at various horizons. The analysis can be conducted in transaction time also, but for forecasting we feel it more useful to aggregate trades over certain time periods, e.g. 1 second, 5 seconds, 30 seconds, 1 minute… 1 hour. Similarly to our previous forecasting exercise in chapter 6, for each period of order flow history used a number of forecasting horizons are examined since we don't know how fast information is impounded in prices. The following model is estimated:

The Forecasting Model

$$\Delta s_{t,t+j} = \alpha_0 + \sum_{i=1}^{4} \beta_i x_{i,t-k,t}^{Dis} + \varepsilon_{t+j} \tag{6.6}$$

$x_{t-k,t}^{Dis}$ = *Disaggregated* order flow (1 of 4 separate customer segments)

{j = 1 sec, 5 sec,15sec, 30sec, 1min, 5 min, 10min, 30min}

{k = 1 sec, 5 sec,15sec, 30sec, 1min, 5 min, 10min, 30min, 1 hour}

Figure 6-7 shows a graphical representation of the forecasting experiment.

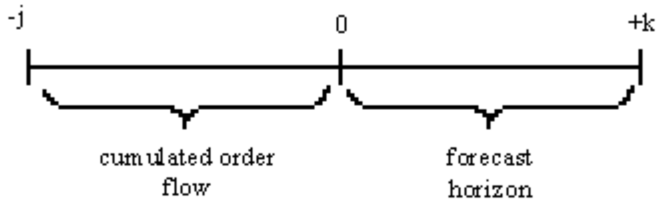


Figure 6-7 – A Forecasting Experiment

In all cases, a true out of sample forecasting exercise is performed. We retain 2/3 of our data sample to estimate the model and use the remaining 1/3 to perform the out of sample forecasts. In the high frequency dataset this translates to estimating the model using the data from 10/10/2005 – 31/10/2005, and retaining the sample from 01/11/2005 – 11/11/2005 for out-of-sample forecasts.

Forecasting model performance was evaluated on the basis of the Root Mean Squared Error (RMSE) ratio of each model to that of a simple random walk, i.e. a naïve forecast of no change. This is the standard benchmark in FX forecasting. We also report the Theil Inequality coefficient – a scaled measure of forecast accuracy ranging from 0 to 1, with 0 implying perfect forecasts. Lastly, in keeping with the methodology of chapter 4, we also use directional accuracy to evaluate the forecasts.

The ability of a forecasting model to forecast direction if not magnitude is certainly a less stringent requirement, but it is also not lacking in theoretical merit. Leitch and Tanner (1991) find that statistical measures of forecast accuracy have little correlation to profit. “The only conventional measure of forecast quality that is related to profits is directional accuracy, and it is infrequently used” Leitch and Tanner (1991). Realistically, a trader cares far less whether a forecasting model can give exact point forecasts, as long as the model is providing accurate directional forecasts. This suggests that directional ability may serve as a more realistic evaluation of the usefulness of a forecasting model. Figures 6-8, 6-9 and 6-10 summarize the various measures of forecast accuracy for each model.

Forecast Evaluation - High Frequency (A)

Forecast horizon:		*1 sec.*	*5 sec.*	*15 sec.*	*30 sec.*	*1min.*	*5min.*
History used:							
1 second	RMSE ratio*	0.99998	0.99992	1.00006	0.99998	0.99996	0.99989
	Theil inequality coef.	0.99764	0.99690	0.99697	0.99745	0.99749	0.99480
	Direction % correct	8.15%	20.38%	28.64%	33.88%	38.71%	45.97%
	Direction % wrong	7.63%	20.80%	30.22%	35.31%	39.21%	44.62%
	% no move**	84.22%	58.82%	41.14%	30.81%	22.08%	9.41%
5 seconds	RMSE ratio*	1.00003	1.00001	1.00002	0.99998	0.99999	0.99992
	Theil inequality coef.	0.99493	0.99407	0.99551	0.99531	0.99593	0.99181
	Direction % correct	8.18%	20.59%	29.78%	34.01%	39.20%	46.02%
	Direction % wrong	8.36%	20.64%	29.07%	35.32%	38.82%	44.52%
	% no move**	83.46%	58.78%	41.15%	30.67%	21.98%	9.46%
15 seconds	RMSE ratio*	0.9999	1.0001	1.0001	1.0000	1.0000	0.9999
	Theil inequality coef.	0.9899	0.9902	0.9954	0.9945	0.9947	0.9885
	Direction % correct	8.22%	20.63%	29.89%	35.03%	39.37%	46.13%
	Direction % wrong	8.13%	20.63%	29.14%	34.43%	38.72%	44.41%
	% no move**	83.65%	58.74%	40.97%	30.55%	21.91%	9.46%
30 seconds							
	RMSE ratio*	1.0001	1.0003	1.0000	1.0000	1.0000	0.9999
	Theil inequality coef.	0.9906	0.9809	0.9906	0.9915	0.9963	0.9845
	Direction % correct	8.24%	20.68%	30.20%	35.33%	39.46%	46.17%
	Direction % wrong	8.39%	20.36%	28.68%	34.44%	38.58%	44.32%
	% no move**	83.37%	58.97%	41.12%	30.23%	21.96%	9.52%

* Ratio of RMSE of model to RMSE of naïve Random Walk
** % observations when FX rate did not change

Table 6-8 – Forecast Evaluation: RMSE Ratio and Directional Accuracy (A)

Forecast Evaluation - High Frequency (B)

Forecast horizon:		***1 sec.***	***5 sec.***	***15 sec.***	***30 sec.***	***1 min.***	***5 min.***	***10 min.***	***30 min.***	***1 hour***
History used:										
1 minute	RMSE ratio*	1.0001	1.0003	1.0003	1.0004	1.0000	1.0001	0.9999	0.9993	0.9994
	Theil inequality coef.	0.9809	0.9810	0.9863	0.9893	0.9912	0.9803	0.9818	0.9764	0.9679
	Direction % correct	8.17%	20.80%	28.33%	34.30%	39.55%	45.88%	47.68%	49.07%	49.45%
	Direction % wrong	8.42%	19.77%	30.35%	35.40%	38.32%	44.47%	46.30%	47.37%	47.27%
	% no move**	83.42%	59.43%	41.32%	30.30%	22.13%	9.65%	6.02%	3.57%	3.28%
5 minutes	RMSE ratio*	1.0012	1.0006	0.9999	1.0002	1.0022	1.0008	0.9994	1.0000	1.0024
	Theil inequality coef.	0.9575	0.9868	0.9677	0.9839	0.9747	0.9670	0.9543	0.9506	0.9317
	Direction % correct	8.33%	23.17%	28.75%	36.33%	36.25%	44.83%	47.00%	49.17%	49.92%
	Direction % wrong	8.50%	18.92%	29.58%	34.33%	42.33%	46.17%	46.83%	47.50%	46.75%
	% no move**	83.17%	57.92%	41.67%	29.33%	21.42%	9.00%	6.17%	3.33%	3.33%

* Ratio of RMSE of model to RMSE of naïve Random Walk
** % observations when FX rate did not change

Table 6-9 - Forecast Evaluation: RMSE Ratio and Directional Accuracy (B)

Forecast Evaluation - High Frequency (C)

Forecast horizon:		***1 sec.***	***5 sec.***	***15 sec.***	***30 sec.***	***1 min.***	***5 min.***	***10 min.***	***30 min.***	***1 hour***
History used:										
10 minutes	RMSE ratio*	1.0006	1.0021	1.0025	1.0025	1.0040	1.0012	1.0012	1.0013	1.0069
	Theil inequality coef.	0.9644	0.9644	0.9715	0.9664	0.9652	0.9557	0.9595	0.9553	0.9158
	Direction % correct	7.33%	19.83%	29.83%	34.33%	36.50%	47.83%	47.50%	48.50%	50.00%
	Direction % wrong	6.50%	19.83%	31.50%	38.17%	42.00%	44.33%	46.33%	48.83%	46.00%
	% no move**	86.17%	60.33%	38.67%	27.50%	21.50%	7.83%	6.17%	2.67%	4.00%
30 minutes										
	RMSE ratio*	1.0000	1.0010	1.0009	1.0014	1.0024	1.0267	1.0216	1.0274	1.0222
	Theil inequality coef.	0.9620	0.9751	0.9389	0.9286	0.9481	0.9077	0.9148	0.8989	0.8942
	Direction % correct	10.00%	29.00%	34.00%	34.50%	42.50%	43.00%	46.50%	45.00%	52.00%
	Direction % wrong	10.00%	18.00%	30.50%	37.50%	38.00%	48.00%	48.00%	51.50%	44.00%
	% no move**	80.00%	53.00%	35.50%	28.00%	19.50%	9.00%	5.50%	3.50%	4.00%

* Ratio of RMSE of model to RMSE of naïve Random Walk
** % observations when FX rate did not change

Table 6-10 - Forecast Evaluation: RMSE Ratio and Directional Accuracy (C)

Clearly there is little evidence of forecasting power here, even intra-day. In our first forecasting experiment using daily customer order flow data, despite confirming the contemporaneous relationship between flow and exchange rates – for six different exchange rates no less – we found a complete lack of forecasting power. At the time, one explanation offered was that flows *do* contain information, but the information is getting priced in too quickly within the day, so we were finding no forecasting power at the daily frequency and lower. A glance at the numbers in the 3 tables above quickly shows that this is not the case. A RMSE ratio below 1 would indicate that the model is outperforming the random walk. We see that in every case, the RMSE ratio is essentially 1 – the model is performing as well – or as badly if you prefer – as the random walk. Theil inequality coefficients stay resolutely in the high nineties. There is no statistical evidence of forecasting power.

Mindful of the criticism of statistical measures of forecast accuracy, discussed briefly above and in more detail in chapter 4, we could choose to focus on the directional accuracy of the model, i.e. does order flow contain information that can predict the subsequent *direction* of change in the FX rate? Taking the symmetric 1 second of order flow forecasting 1 second ahead case in Table 8-8 above as an example, the first number to note is the last one – percent no move: 84.22%. The naïve model of no change seems to be not so naïve in this case. The model predicts the change in direction correctly only about 8% of the time, though it gets the direction completely wrong only 7.63% of the time. When there is a change therefore the model correctly predicts the direction about half the time. This pattern is identical across all histories and forecast horizons. Hardly a ringing endorsement when the model performs about as well as flipping a coin. We are forced to conclude that we find no evidence of forecasting power, regardless of the evaluation criteria we choose.

6.7 Conclusion

The entire FX microstructure literature is based on the strong, and well-documented contemporaneous correlation between exchange rate movements and order flow. There is no consensus as to what is driving this relationship however, and in this chapter we use a unique, ultra-high-frequency, large volume customer order flow database from a leading commercial bank, significantly rich in volume, number and counterparty balance to determine causality.

The two main competing theories are information and feedback. If flows contain information, they should have a permanent impact on prices, and we should be able to use flows to forecast subsequent moves in exchange rates. If on the other hand it is changes in the exchange rate itself that are creating incentives to trade at the intra-day frequency, thus generating order flow, we would see this at a daily frequency as a contemporaneous correlation, but there would be no expectation of flows forecasting FX movements.

We initially estimate a distributed lag model as in Ito and Hashimoto (2006), to determine the price impact of flows on market rates. We find some indication of corporate flows having a small positive price impact, but in the case of financial trades the impact dies out to zero within half an hour. We then reverse the causality in the model in order to test the impact of past changes in the exchange rate on subsequent customer orders. These regressions show strong evidence of positive feedback trading in both corporate and financial customer categories.

Momentum trading strategies are especially popular in FX, but the presence of positive feedback does not explain the negative coefficient on corporate order flow commonly found in the literature. We therefore proceed to test for cointegration between the exchange rate and cumulated customer flows, hoping the resulting error correction model can clarify the long-run dynamics of the system. The results of the high frequency VECM are particularly illuminating. We find that all counterparty types have a positive equilibrium relationship with the exchange rate, but most importantly, the adjustment dynamics show that all of the weight of adjustment to restore equilibrium after a shock falls to flows. We repeat the experiment at a daily frequency using the RBS dataset, and although in the low frequency VECM only corporate trades are found to be significant, once again the exchange rate bears none of the burden of adjustment to equilibrium.

Despite the evidence favouring the feedback version of causality, we also perform a series of high-frequency forecasting experiments, wanting to give the information theory the benefit of the doubt. The forecasting performance was uniformly poor, whether evaluated using the standard benchmark of RMSE ratio to the random walk model, or using directional ability as a measure. We find no forecasting power in flows, and by extension no support for the informational role of order flow.

The results of this chapter point to feedback as the driving force of the contemporaneous relationship between order flow and exchange rates. Again this result is in contrast to some of the results in the literature. Evans and Lyons (2002a) reject feedback trading at a daily frequency, as do Killeen, Lyons and Moore (2002). These results are not in fact all that troubling since the analysis was done at a daily frequency, and it is unlikely that the issue of causality in FX could be elucidated at anything other than ultra-high-frequency. What does remain to be reconciled however is the success of the Evans and Lyons Citibank data in forecasting. In this, one could certainly argue that the quality of Citibank's customers is hard to match, and that their trades do in fact contain information. Our data comes from a major player in the FX market however, so we find the argument that the FX market itself has changed significantly since the late 90s to be a more compelling reason for the different results. As discussed in chapter 5, increased competition among electronic trading platforms, access granted to large hedge funds and active currency managers to EBS and Reuters through prime brokerage services, and a rather staggering increase in participation in FX has changed the playing field. Ironically, the success of the Evans and Lyons research may also have made market participants more wary of revealing their trading strategies.

Realistically, it is the nature of this research that there will be discrepancies in results that are hard to reconcile, since the data used is not public. Each researcher can only draw conclusions from their own data, and unfortunately each dataset itself represents only a small fraction of the overall information set. We feel that our dataset is of sufficiently high quality to draw conclusions, and the results have shown internal consistency, with corporate flows emerging as important in different models. The true overall picture can only reveal itself incrementally as more datasets are analyzed, and in this we feel our results make this incremental contribution.

7 Conclusion

The foreign exchange literature is replete with research showing that exchange rates cannot be effectively explained, let alone forecast. Macroeconomic models of exchange rate determination, while elegant and intuitively appealing, have been shown repeatedly to be an empirical failure at horizons shorter than three months. A series of influential papers by Meese and Rogoff in the 1980's showed that at shorter horizons, structural models of exchange rates perform no better at out-of-sample forecasting than the naïve random walk. Decades of research have failed to overturn this result, and even now this remains in large part the accepted wisdom in international finance. In the last ten years however, exchange rate researchers were offered a much-needed glimmer of hope, in the form of the microstructure approach to exchange rate determination.

Pioneered by Richard Lyons and Charles Goodhart, the microstructure approach studies how dispersed information about fundamentals gets impounded into exchange rates via trading decisions, effectively shifting the focus, not away from fundamentals per se, but to the mechanism through which fundamentals affect prices. FX microstructure argues that the market's expectations about future fundamentals are mirrored in their *aggregated* trading decisions, and in this sense order flow is said to contain information.

The seminal paper that started the micro FX 'revolution' was Evans and Lyons (2002a) in which, using daily interdealer data from Reuters D2000-1 on DEM/USD and JPY/USD, they demonstrated a striking contemporaneous relationship between order flow and changes in the exchange rate, with R^2 values unheard of in the FX literature - 64% for the DEM equation and 45% for the JPY equation. They backed up these results with a simplified model of trading, providing a very plausible theoretical basis for the empirical results, and a new chapter in exchange rate modelling was born.

The contemporaneous relationship between exchange rates and order flow has been verified empirically in a number of papers (Payne, 2003, Marsh and O'Rourke, 2005), but micro FX remains a very new field, and many questions remain unanswered. Using two unique datasets, one at a daily frequency from the Royal Bank of Scotland spanning three and a half years (2002/06) and including six currency pairs, and another tick-by-tick dataset in €/US$ spanning 25 trading days in late 2005 from a major European bank, we attempt to add to the growing body of knowledge in this topic that has proved remarkably resistant to explanation.

To briefly recap, in our first empirical chapter, we replicate and extend the Evans and Lyons (2005b) forecasting experiment using the daily data from RBS. We confirm the contemporaneous properties once again, but in the forecasting experiments we find no forecasting power whatsoever in our data, regardless of model, history used, forecast horizon or currency pair. Building on MacDonald and Marsh (2004) who suggest that exchange rates can be forecast if they are modelled together as a system, and wanting to fully exploit the cross-sectional advantages of the RBS dataset, we attempt to forecast exchange rates using both 'own' and 'related' flows. Although we find the contemporaneous relationship is strengthened by the addition of 'related' flows, forecasting performance is not improved.

Wanting to give the models the benefit of the doubt, and drawing on a growing body of literature pointing out the limitations of RMSE as a means of forecast evaluation (Leitch and Tanner, 1991, Granger and Pesaran 2000) we proceed to evaluate all models on the basis of their ability to predict direction. Again we find lack of forecasting power across the board.

Lastly, we hypothesize that a forecasting relationship may not always be present, i.e. order flows may not convey information all the time as is implicitly assumed in the regression based forecasts. Instead, we test a series of conditional models in which trades are only triggered if certain conditions are satisfied. Once again we find no evidence of forecasting power in the RBS flows. Testing forecasting ability via profitability using simple trading rules yielded mixed but slightly more promising results, albeit with huge volatility.

In the FX literature, a result showing that FX rates cannot be forecast is, in and of itself, uninteresting. Considering the Evans and Lyons (2005b) result however, this complete lack of forecasting power in the RBS data which is, for all intents and purposes, the equivalent data to that of Citibank, and moreover shares the same contemporaneous properties, is curious, and we are left to speculate on the reasons for this discrepancy.

One of the main reasons we consider for the failure of the RBS data to forecast exchange rates is that, since the data comes from a more recent time period, the forecasting power could be concentrated intra-day. In the next two empirical chapters therefore we focus on the high frequency data. In the second empirical chapter we use the tick-by-tick data in conjunction with two standard market microstructure models - Madhavan-Smidt and Huang-Stoll - in order to gain an insight into the information content of customer order flow. In stark contrast to the literature, while we are unable to find any evidence of information content from financial customer order flow, however partitioned, we find strong evidence that large corporate customer order flows are perceived to have statistically and economically significant information content.

In the last empirical chapter we turn our attention to the issue of causality. Although the contemporaneous relationship is undisputed, the underlying reasons for this relationship remain unclear. The ultra-high-frequency data provides an excellent tool to shed some light on this matter. We approach this issue from a number of angles. If there is an informational component to flows, then flows should have a permanent impact on interbank prices. We investigate this using a distributed-lag model. Corporate orders are again found to have a small long-term impact. We then turn the model around to examine the effect of exchange rate changes on subsequent flows, and find significant evidence of positive feedback trading in both corporate and financial customers.

Most importantly, we estimate a vector error correction model to clarify the long-run dynamics of the system. We find that all counterparty types have a positive equilibrium relationship with the exchange rate, but crucially, the adjustment dynamics show that all of the weight of adjustment to restore equilibrium after a shock falls to flows. Lastly, if exchange rates are determined by macroeconomic fundamentals, but order flow gradually conveys information on heterogeneous beliefs about these fundamentals, then order flow should provide forecasting power for exchange rates. Despite the growing evidence of feedback rather than information as the driver of the contemporaneous relationship, we conduct a high frequency forecasting experiment, but as in the daily RBS data we find no evidence of forecasting power.

What overall conclusions can we draw from our results, and how do we reconcile what we have learned with the existing literature? Since this entire field is necessarily data driven, replication of results is very important, but also problematic as the required data is very difficult to get. This has resulted in a literature that is in fact dominated by *one* dataset – the Evans and Lyons Citibank data. Most other studies on customer order flow are based on data from small to medium sized banks that are at best marginal players in the enormous FX market. In this respect our research is given a great deal of credibility due to the quality of our data. RBS is currently ranked number 4 in the 2009 Euromoney FX poll, and even at the time of our data sample was one of the top FX dealing banks. The source of our high frequency data prefers to remain anonymous, but the volume and composition of the dataset speak for themselves.

Replication of results is of the utmost importance in research, and in this respect economic and financial research can be found severely lacking compared to other disciplines. In order to replicate a study on financial data, a researcher needs access to the data itself, but often also needs to know precisely what steps were taken in collecting and 'cleaning' the data. Compounding these problems, in the FX microstructure literature, order flow data is closely guarded by the banks making it very difficult to come by. Even the Evans and Lyons Citibank data has not been updated, so not only do other researchers not have access to the same data to attempt to replicate the results, the authors themselves are unable to update their study to establish whether their findings continue to be valid.

It would not be an over-statement to say that the Evans and Lyons results caused a revolution of sorts in the FX literature. However that single data set has served as the basis for the majority of the literature in FX microstructure, and while we in no way question the quality of the research, we must question the wisdom of basing universal conclusions on a single data set, from a single bank, at a single point in time.

The first conclusion we draw is one that permeates all three empirical chapters – the relationship between flows and exchange rates, while striking, is not as simple as initially believed. This is perhaps not the most encouraging of conclusions, but it is nonetheless important. The microstructure approach to FX seems inherently logical – it is extremely appealing, and in a field characterized by so many negative results it is almost seductive. This must not stop us from questioning its results however, particularly considering the current over-reliance on one dataset.

The next conclusion is very much reflected in the contrast between the results of all three chapters with the results in the literature that are based on data not as recent as ours. The original Evans and Lyons Citibank data is from the late 90's, and the Osler et al data and Reitz et al data are from 2001 and 2002/03 respectively. Our data sample - in late 2005 – may not seem to be that far removed, but in the FX market the last decade has been a time of tremendous change. In fact, the very change that spawned the field by making transactions data available – electronic trading – has caused an ongoing revolution of sorts in how FX is traded.

FX has established itself quite firmly as an asset class in its own right, a change that is reflected in the huge growth in daily turnover in the global foreign exchange market revealed in the BIS 2007 survey. This is likely to have further increased investor heterogeneity, and blurred the distinctions between different investor categories, and the changing demands of market participants is naturally gradually changing the structure of the FX market itself.

Unlike the equity or bond markets, the foreign exchange market is highly fragmented, with more than 20 dealer-to-client spot platforms, two interdealer spot platforms and three interdealer options platforms - and with the spot currency dealer-to-client platforms also trying to expand into options. EBS allowed hedge funds to trade on its platform in 2004 and Reuters followed suit in July 2005. (Jung 2007) In 1995, 64% of the foreign exchange trades were executed on interdealer platforms; by 2007, that figure had dropped to 43% despite an increase in the overall market. (BIS 2007) Reuters and EBS continue to be at the centre of FX trading, but their share has reduced as alternative liquidity providers have emerged. Multi bank platforms allow customers to access prices and to trade with any of the participating dealers with whom they have an established credit relationship, thus facilitating investors' access to market-makers, and also providing tools for algorithmic trading.

The distinction between banks that are market makers in the interbank market and other financial institutions continues to become less apparent as these other financial institutions increasingly provide market liquidity. The Federal Reserve Bank of New York pointed to the greater role of hedge funds "behaving more like dealers with regard to pricing and the liquidity they are willing to provide to the market". This trend is underpinned by the consolidation in the banking industry, the growth of banking organizations that play a number of different roles in foreign exchange markets, the strong growth in prime brokerage and the granting of access to electronic brokers in the interbank market to hedge funds (Jung (2007)).

It is difficult to assess exactly the impact of these changes, but it does suggest that the ability to characterize the behaviour of different counterparty types may be more difficult, and these features of the FX market are likely to complicate attempts at modelling and forecasting exchange rates.

Heterogeneity is a major concept in the microstructure literature – market participants are active in FX for disparate reasons with different needs and ways to conduct transactions. Advances in technology and investor demand have meant that platforms are developing functionalities that meet their customer segment requirements. In the financials category in particular, there is a large degree of heterogeneity *within* the group itself. The type of financial customer whose trades might be assumed to carry information – large hedge funds, quantitative trading firms and active currency managers – increasingly have access to the interbank market directly as both EBS and Reuters provide prime brokerage services to large buy-side institutions.

These changes in market structure mean that it is much more difficult to extract clear signals from trades. Furthermore, it is reasonable for customers with any informational advantage to try to hide this from relatively sophisticated dealers. Perhaps ironically, the success of the Evans and Lyons research may have made market participants more wary of revealing their intentions through trading, and the changing structure of the market has made it particularly easy to 'hide' trades by breaking them up among multiple banks and/or platforms. Tight spreads in FX also mean that there will be little impact due to increased transaction costs associated with such a strategy. This hiding of information simply reflects the fact that agents learn, and trading strategies evolve to maximise any advantage, and this is to be expected in a market as competitive as FX.

Clearly the playing field has changed, and we must note here that we are not alone in finding a decline in forecastability of FX based on flows. Of particular note are the Ito and Hashimoto (2006) results that show that the duration of positively significant returns following order flows is getting shorter in recent years, in fact becoming significantly negative in the case of EURUSD.

These first conclusions represent the more 'conceptual' contributions of our research. On a more specific front, two important themes emerge from the high-frequency investigation. The first is the importance of corporate customers – a category that was largely overlooked in previous studies. The picture is not entirely clear, as we do not claim our results are without limitations, but the findings of the second chapter are suggestive of an informational role for extremely large corporate order flow, as it is shown to be the only category to have an impact on dealer quotes. This outcome is not as surprising as it might first seem, as the aggregate trades of corporate customers can be thought of as indicative of future macroeconomic variables such as industrial production or GDP. Despite the fact that this is a reasonable and even intuitive explanation, we must admit that perhaps it wouldn't be expected at ultra-high-frequencies. This, coupled with the fact that the price impact is concentrated in extremely large trades, and then furthermore considered alongside the results of the third empirical study that finds no real evidence of forecasting power for market prices, could suggest an inventory effect that we cannot account for in our data.

This brings us to the last, and possibly most important contribution, which is the evidence from the error correction model of the direction of causality in the exchange rate / order flow relationship. We find no evidence of the exchange rate adjusting to restore equilibrium, with the entire burden of adjustment left to customer flows from all four counterparty types. This finding, together with the results of the distributed lag models which show significant evidence of positive feedback trading, implies that the direction of causality runs not from flows to exchange rates, but from exchange rates to flows.

Our results perhaps seem quite cautious, even negative compared to the bulk of the micro FX literature. We must acknowledge however, that in the end we are limited in our understanding of exchange rate determination by our data, as is everyone else in this field. The FX market is vast, fast moving, highly competitive and constantly evolving. As researchers, much like the blind men and the elephant, we have access to only a tiny fraction of the information set, what amounts to a snapshot in time, and from one bank's perspective only no less. Given this information we try to elucidate an entire structure, and we must be careful not to draw too far-reaching conclusions. As more datasets are analysed from the perspective of different players in the market, the picture should slowly come into clearer focus, and in this sense at least we feel that our findings have a small but definite contribution to make towards understanding

Appendix A – FX Market Statistics and Recent Trends[2]

BIS Survey 2007: Statistics on the FX Market

We summarize some of the key findings from the latest BIS Central Bank survey of foreign exchange and derivatives market activity, which took place in April 2007.

Global FX Turnover

The 2007 survey shows a substantial rise in activity in traditional foreign exchange markets compared to 2004. Average daily turnover rose to $3.2 trillion in April 2007, an increase of 69% at current exchange rates and 63% at constant exchange rates. The expansion in FX swap turnover was particularly strong and made the largest contribution to aggregate growth, in sharp contrast to the period between 2001 and 2004.

Global foreign exchange market turnover[1]

Daily averages in April, in billions of US dollars

	1992	1995	1998	2001	2004[2]	2007
Spot transactions	394	494	568	387	631	1,005
Outright forwards	58	97	128	131	209	362
Up to 7 days	...	50	65	51	92	154
Over 7 days	...	46	62	80	116	208
Foreign exchange swaps	324	546	734	656	954	1,714
Up to 7 days	...	382	528	451	700	1,329
Over 7 days	...	162	202	204	252	382
Estimated gaps in reporting	44	53	60	26	106	129
Total "traditional" turnover	820	1,190	1,490	1,200	1,900	3,210
Memo: Turnover at April 2007 exchange rates[3]	*880*	*1,150*	*1,650*	*1,420*	*1,970*	*3,210*

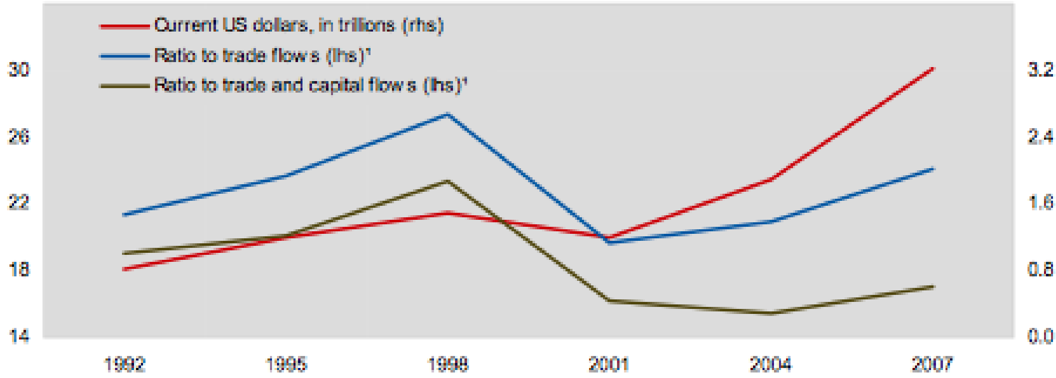
[1] Adjusted for local and cross-border double-counting. Due to incomplete maturity breakdown, components do not always sum to totals. [2] Data for 2004 have been revised. [3] Non-US dollar legs of foreign currency transactions were converted from current US dollar amounts into original currency amounts at average exchange rates for April of each survey year and then reconverted into US dollar amounts at average April 2007 exchange rates. Table B.1

The ratio of foreign exchange turnover to the value of international trade and capital flows has increased over the past three years, recovering some of the decline observed in the 2001 triennial survey. This can be seen in the graph below.

[2] Source for all statistics, tables and graphs in this appendix is the BIS 2007 Central Bank Survey on Foreign Exchange and Derivatives Market Activity.

Foreign exchange turnover

Daily averages in April



[1] 2007 trade and capital flow data are estimated by extrapolating annualised growth between 2004 and 2006.

Source: IMF. Graph B.1

Turnover by Counterparty

Reported foreign exchange market turnover by counterparty[1]

Daily averages in April, in billions of US dollars and per cent

	1998		2001		2004[2]		2007	
	Amount	% share	Amount	% share	Amount	% share	Amount	% share
Total	1,430	100	1,173	100	1,794	100	3,081	100
with reporting dealers	908	64	688	59	956	53	1,319	43
with other financial institutions	279	20	329	28	585	33	1,235	40
with non-financial customers	242	17	156	13	252	14	527	17
Local	657	46	499	43	695	39	1,185	38
Cross-border	772	54	674	57	1,099	61	1,896	62

[1] Adjusted for local and cross-border double-counting. Excludes estimated gaps in reporting. Due to incomplete counterparty breakdown, components do not always sum to totals. [2] Data for 2004 have been revised. Table B.3

Financial customers were the main drivers of the strong rise in global turnover. Growth in this segment has accounted for half of the increase in total turnover over the past three years, compared with 29% for interbank trading and 21% for the non-financial customer segment.

Turnover between reporting dealers and non-financial customers also more than doubled between the 2004 and 2007 surveys. This is likely to be related to the substantial growth in international trade in goods and services between 2004 and

2007, and possibly to an expansion in hedging activity.

Even while the interbank market contributed almost one third of the growth in aggregate turnover, the share of the interbank market in total turnover fell to 43% from 53% in 2004, largely because the growth in turnover for the other segments was so rapid. Consolidation of the banking system was one reason put forth in the past to explain a reduction in the share of the interbank market, since consolidation would result in efficiency gains as well as allowing the netting of trades within an organization. Although it appears that consolidation in the banking sector has continued, the rate at which this is occurring has slowed significantly, so it probably was not a major driver of the reduction in interbank turnover.

Concentration in the banking industry

Number of banks accounting for 75% of foreign exchange turnover

	1998	2001	2004	2007
United Kingdom	24	17	16	12
United States	20	13	11	10
Switzerland	7	6	5	3
Japan	19	17	11	9
Singapore	23	18	11	11
Hong Kong SAR	26	14	11	12
Australia	9	10	8	8
France	7	6	6	4
Germany	9	5	4	5
Canada	5–7[1]	4–6[1]	4	6

[1] Depending on the market segment.

Table B.4

The spread of electronic broking platforms is a factor that represents an important driver of efficiency gains and could be contributing to the falling share of interbank foreign exchange transactions. While it is difficult to assess the impact of changes in execution methods on trading volumes, it is clear that electronic broking systems play a very important role in some interbank markets. For example, for Germany and Switzerland 55% and 44%, respectively, of total interbank transactions are executed through electronic broking platforms. These shares rise to 67% and 58% when electronic trading systems are included in the calculation.

Most Traded Currencies

Currency	**% of all transactions**
USD	86.3%
Euro	37.0%
JPY	16.5%
GBP	15.0%
USD/Euro: most traded currency pair (27% global turnover – US$840 billion average daily volume) **USD/JPY:** 13% global turnover **USD/GBP:** 12% global turnover	

The share of turnover accounted for by currency pairs among the US dollar, euro and yen has declined by 6% since 2004. Most of this fall can be explained by the decline in the share of the US dollar/yen pair. More broadly, there appears to have been an increase in the share of emerging market currencies in total turnover: in April 2007, emerging market currencies were involved in almost 20% of all transactions.

Geographical Distribution

The geographical distribution of FX trading has remained largely unchanged, although of the major financial centers Singapore, Switzerland and the UK gained market share, while the shares of Japan and the United States dropped.

Trading Centre	% share
UK	34.1%
US	16.6%
Switzerland	6.1%
Japan	6%
Trading Centre	**% share**
Singapore	5.8%
Hong Kong SAR	4.4%
Australia	4.3%
France	3.0%
Germany	2.5%

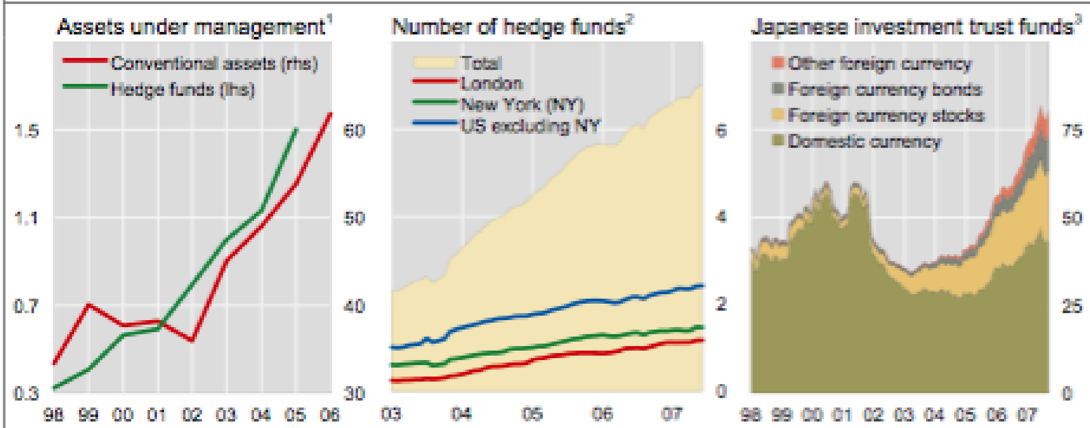
Interpreting the Statistics – Trends and Implications

The increasing recognition and acceptance of foreign exchange as an asset class in its own right has led to a surge in global FX activity as more players seek access to this highly attractive market. The significant growth in global FX trading volumes is attributed in part to increased activity from the non-interbank market, particularly hedge funds, fund managers and commodity trading advisors. The appeal of FX is that it is non-cyclical, highly liquid and shows no strict correlation to other asset classes.

Over the three years since the 2004 survey, exchange rates were broadly trending and financial market volatility was at historically low levels, therefore FX offered investors with short-term horizons relatively attractive risk-adjusted returns. Strategies such as the carry trade and momentum trading, which are attractive in a low volatility environment, have been profitable over the past three years. In addition, there is evidence that longer-term investors, such as pension funds, have contributed to the increase in turnover by systematically diversifying their portfolios internationally, but also because even 'traditional' money managers are increasingly viewing FX as a distinct asset class and are taking a more active approach to managing currency exposure. Both these avenues are creating direct and indirect demand for foreign exchange. Furthermore, the value of funds managed by these investors has grown significantly as can be seen in the graph below, which amplifies the effects of changing approaches to FX.

Market commentary suggests that leveraged investors such as hedge funds have been primary players in foreign exchange market activity in recent years. Although it is difficult to obtain precise numbers, it is clear that hedge fund activity, measured by either estimates of assets under management or the number of funds, has increased significantly over the past six years. Hedge fund growth in foreign exchange markets has benefited from the development of prime brokerage services. With prime brokerage, a customer, for example a hedge fund, can obtain liquidity from a variety of sources while at the same time maintaining a credit relationship, placing collateral and settling transactions with a single bank – the prime broker (Foreign Exchange Committee (2005)).

Managed funds



[1] In trillions of US dollars. [2] Number of funds reporting to the HFR database; in thousands. [3] In trillions of yen.

Sources: Hedge Fund Research (HFR); IFSL; Investment Trust Association Japan. Graph 3

Finally, an increase in high frequency algorithmic trading by some investors, mostly investment banks, facilitated by the spread of electronic trading platforms, has also increased turnover, particularly in the spot market. Electronic trading platforms have also provided significantly more access to retail investors. Leveraged retail investors appear to be a growing presence in FX markets, albeit still with a relatively small impact on global turnover (Galati et al (2007)).

Some of the drivers of these results seem to reflect structural changes and are therefore likely to continue affecting developments in foreign exchange turnover. For example, the increase in portfolio diversification by longer-term fund managers appears to be the result of a fundamental shift in approach. The expansion of activity by leveraged retail traders could also add momentum to this trend. In contrast, the potential role for investors with a shorter-term horizon, such as those following carry trade strategies, is more dependent on factors such as financial market volatility that affect the attractiveness of foreign exchange as an asset class.

Further above average growth in turnover in emerging market currencies is also likely going forward, although this is dependent on emerging market economies continuing to experience robust growth, as well as a further deepening and opening of their domestic financial markets.

Appendix B – Descriptive Statistics

Appendix B1
Descriptive Statistics on actual values of net (buy-sell) order flow - Daily Frequency.
(all values * 10^9)

USD_JPY

	Corporate	Levered	Unlevered	Other	Total
Mean	0.002	0.003	0.001	-0.009	-0.004
Median	0.000	0.002	-0.001	-0.004	-0.009
Maximum	0.517	0.286	0.371	0.914	0.923
Minimum	-0.694	-0.264	-0.359	-0.824	-0.936
Std. Dev.	0.072	0.061	0.053	0.180	0.210
Skewness	-0.583	-0.032	0.527	0.029	0.170
Kurtosis	17.758	6.074	11.467	6.924	5.457
Jarque-Bera	8017.514	345.740	2663.663	563.523	225.141
Probability	0.000	0.000	0.000	0.000	0.000
Sum	1.321	2.956	0.545	-8.197	-3.375
Sum Sq. Dev.	4.524	3.238	2.486	28.513	38.601
Observations	878.000	878.000	878.000	878.000	878.000

Euro_USD

	Corporate	Levered	Unlevered	Other	Total
Mean	-0.036	0.004	-0.005	0.025	-0.013
Median	-0.032	0.000	-0.003	0.017	-0.018
Maximum	0.536	0.467	0.810	1.609	1.679
Minimum	-0.629	-0.343	-0.576	-0.788	-0.919
Std. Dev.	0.128	0.096	0.079	0.217	0.269
Skewness	0.162	0.209	0.531	0.735	0.517
Kurtosis	5.727	5.496	29.147	7.955	6.028
Jarque-Bera	275.973	234.366	25052.760	977.389	374.610
Probability	0.000	0.000	0.000	0.000	0.000
Sum	-31.947	3.189	-4.493	21.737	-11.514
Sum Sq. Dev.	14.273	8.039	5.435	41.152	63.428
Observations	878.000	878.000	878.000	878.000	878.000

Euro_GBP

	Corporate	Levered	Unlevered	Other	Total
Mean	0.019	-0.001	0.000	0.016	0.034
Median	0.020	0.000	0.000	0.016	0.037
Maximum	0.498	0.323	0.287	0.568	0.717
Minimum	-0.660	-0.701	-0.474	-0.689	-0.634
Std. Dev.	0.071	0.049	0.037	0.114	0.142
Skewness	-1.648	-4.094	-2.359	-0.682	-0.465
Kurtosis	22.184	71.841	49.859	12.460	7.833
Jarque-Bera	13861.540	175822.600	81141.660	3342.157	886.253
Probability	0.000	0.000	0.000	0.000	0.000
Sum	16.558	-0.941	0.200	14.121	29.937
Sum Sq. Dev.	4.435	2.117	1.229	11.375	17.668
Observations	878.000	878.000	878.000	878.000	878.000

Appendix B1 cont/d
Descriptive Statistics on actual values of net (buy-sell) order flow - Daily Frequency.
(all values * 10^9)

Euro_JPY

	Corporate	Levered	Unlevered	Other	Total
Mean	-0.001	0.000	0.001	-0.005	-0.006
Median	0.000	0.000	0.000	-0.005	-0.006
Maximum	0.217	0.152	0.257	0.357	0.503
Minimum	-0.483	-0.115	-0.097	-0.833	-0.820
Std. Dev.	0.040	0.023	0.020	0.099	0.109
Skewness	-4.540	0.104	3.262	-1.654	-1.024
Kurtosis	56.775	12.373	39.088	15.608	12.595
Jarque-Bera	108805.000	3215.318	49201.700	6216.015	3521.288
Probability	0.000	0.000	0.000	0.000	0.000
Sum	-0.912	-0.272	0.600	-4.499	-5.084
Sum Sq. Dev.	1.415	0.476	0.363	8.670	10.358
Observations	878.000	878.000	878.000	878.000	878.000

GBP_USD

	Corporate	Levered	Unlevered	Other	Total
Mean	0.003	0.001	0.003	0.005	0.011
Median	0.000	0.000	0.000	0.000	0.005
Maximum	0.535	0.274	0.353	1.225	1.109
Minimum	-0.335	-0.407	-0.222	-0.517	-0.664
Std. Dev.	0.070	0.048	0.038	0.101	0.133
Skewness	0.734	-0.899	1.974	1.984	0.888
Kurtosis	10.437	15.068	20.984	28.681	10.564
Jarque-Bera	2102.121	5446.032	12401.420	24703.390	2208.293
Probability	0.000	0.000	0.000	0.000	0.000
Sum	2.616	0.657	2.419	4.163	9.856
Sum Sq. Dev.	4.324	1.999	1.284	8.953	15.598
Observations	878.000	878.000	878.000	878.000	878.000

GBP_JPY

	Corporate	Levered	Unlevered	Other	Total
Mean	0.001	0.000	-0.001	-0.002	-0.003
Median	0.000	0.000	0.000	-0.001	-0.002
Maximum	0.307	0.075	0.107	0.496	0.294
Minimum	-0.066	-0.200	-0.506	-0.517	-0.521
Std. Dev.	0.016	0.009	0.019	0.032	0.033
Skewness	11.312	-11.623	-19.827	-0.416	-3.132
Kurtosis	209.048	290.176	519.281	142.603	79.005
Jarque-Bera	1571896.000	3036790.000	9808672.000	713002.000	212769.400
Probability	0.000	0.000	0.000	0.000	0.000
Sum	0.638	-0.182	-1.106	-1.577	-2.227
Sum Sq. Dev.	0.211	0.071	0.332	0.914	0.982
Observations	878.000	878.000	878.000	878.000	878.000

Appendix B2
Descriptive Statistics on absolute values of net (buy-sell) order flow - Daily Frequency.
(all values * 10^9)

USD_JPY

	Corporate(A)	Levered(A)	Unlevered(A)	Other(A)	Total(A)
Mean	0.046	0.041	0.033	0.123	0.151
Median	0.030	0.026	0.020	0.083	0.111
Maximum	0.694	0.286	0.371	0.914	0.936
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.055	0.045	0.041	0.132	0.146
Skewness	4.002	1.927	3.055	2.279	1.935
Kurtosis	33.772	7.464	17.034	9.699	7.851
Jarque-Bera	36985.830	1272.454	8570.737	2401.237	1408.873
Probability	0.000	0.000	0.000	0.000	0.000
Sum	40.724	35.848	29.285	108.208	132.657
Sum Sq. Dev.	2.637	1.784	1.510	15.253	18.571
Observations	878.000	878.000	878.000	878.000	878.000

Euro_USD

	Corporate(A)	Levered(A)	Unlevered(A)	Other(A)	Total(A)
Mean	0.097	0.066	0.043	0.155	0.197
Median	0.074	0.046	0.024	0.112	0.147
Maximum	0.629	0.467	0.810	1.609	1.679
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.090	0.069	0.066	0.153	0.183
Skewness	1.858	1.822	5.154	2.568	2.060
Kurtosis	7.957	7.059	42.443	15.832	10.432
Jarque-Bera	1404.089	1088.452	60801.210	6988.231	2641.686
Probability	0.000	0.000	0.000	0.000	0.000
Sum	85.602	58.307	37.884	136.098	173.209
Sum Sq. Dev.	7.090	4.179	3.823	20.594	29.409
Observations	878.000	878.000	878.000	878.000	878.000

Euro_GBP

	Corporate(A)	Levered(A)	Unlevered(A)	Other(A)	Total(A)
Mean	0.047	0.021	0.017	0.069	0.100
Median	0.033	0.009	0.007	0.042	0.066
Maximum	0.660	0.701	0.474	0.689	0.717
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.056	0.044	0.034	0.092	0.107
Skewness	4.335	7.713	6.427	3.203	2.318
Kurtosis	33.587	92.947	62.744	15.192	9.603
Jarque-Bera	36976.030	304679.200	136623.600	6938.573	2381.455
Probability	0.000	0.000	0.000	0.000	0.000
Sum	41.492	18.659	14.522	60.345	87.480
Sum Sq. Dev.	2.786	1.722	0.989	7.455	9.972
Observations	878.000	878.000	878.000	878.000	878.000

Appendix B2 cont/d
Descriptive Statistics on absolute values of net (buy-sell) order flow - Daily Frequency.
(all values * 10^9)

Euro_JPY

	Corporate(A)	Levered(A)	Unlevered(A)	Other(A)	Total(A)
Mean	0.018	0.013	0.010	0.061	0.070
Median	0.008	0.006	0.005	0.036	0.044
Maximum	0.483	0.152	0.257	0.833	0.820
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.036	0.019	0.017	0.078	0.083
Skewness	7.271	3.065	5.548	3.761	3.419
Kurtosis	72.778	14.835	57.562	25.661	20.964
Jarque-Bera	185856.800	6498.775	113413.100	20856.320	13516.020
Probability	0.000	0.000	0.000	0.000	0.000
Sum	15.661	11.375	9.213	53.995	61.487
Sum Sq. Dev.	1.137	0.329	0.267	5.372	6.081
Observations	878.000	878.000	878.000	878.000	878.000

GBP_USD

	Corporate(A)	Levered(A)	Unlevered(A)	Other(A)	Total(A)
Mean	0.047	0.029	0.022	0.066	0.093
Median	0.032	0.016	0.013	0.045	0.064
Maximum	0.535	0.407	0.353	1.225	1.109
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.052	0.038	0.031	0.077	0.096
Skewness	3.065	3.443	4.449	5.288	3.090
Kurtosis	18.089	23.466	32.089	64.690	22.271
Jarque-Bera	9704.319	17057.090	33852.540	143314.600	14983.280
Probability	0.000	0.000	0.000	0.000	0.000
Sum	41.332	25.522	19.398	57.954	82.000
Sum Sq. Dev.	2.386	1.258	0.863	5.147	8.051
Observations	878.000	878.000	878.000	878.000	878.000

GBP_JPY

	Corporate(A)	Levered(A)	Unlevered(A)	Other(A)	Total(A)
Mean	0.006	0.002	0.004	0.013	0.017
Median	0.003	0.000	0.001	0.006	0.009
Maximum	0.307	0.200	0.506	0.517	0.521
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.014	0.009	0.019	0.030	0.029
Skewness	13.951	14.894	21.438	11.416	8.358
Kurtosis	260.751	308.411	549.081	179.066	119.311
Jarque-Bera	2458906.000	3444797.000	10976574.000	1153133.000	505134.500
Probability	0.000	0.000	0.000	0.000	0.000
Sum	5.095	1.763	3.534	11.273	14.736
Sum Sq. Dev.	0.182	0.067	0.319	0.772	0.740
Observations	878.000	878.000	878.000	878.000	878.000

Appendix B3
Descriptive Statistics on actual values of net (buy-sell) order flow - 5 Day Frequency.
(all values * 10^9)

USD_JPY

	Corporate(5)	Levered(5)	Unlevered(5)	Other(5)	Total(5)
Mean	0.007	0.017	0.003	-0.046	-0.019
Median	0.007	0.008	-0.002	-0.046	-0.057
Maximum	0.616	0.574	0.414	1.594	1.804
Minimum	-0.833	-0.295	-0.321	-1.112	-1.258
Std. Dev.	0.161	0.137	0.130	0.410	0.505
Skewness	-0.187	0.447	0.386	0.436	0.592
Kurtosis	8.442	4.461	3.840	5.195	4.446
Jarque-Bera	218.204	21.523	9.547	40.892	25.613
Probability	0.000	0.000	0.008	0.000	0.000
Sum	1.299	2.951	0.507	-8.151	-3.395
Sum Sq. Dev.	4.513	3.265	2.961	29.386	44.643
Observations	176.000	176.000	176.000	176.000	176.000

Euro_USD

	Corporate(5)	Levered(5)	Unlevered(5)	Other(5)	Total(5)
Mean	-0.182	0.018	-0.026	0.124	-0.066
Median	-0.191	0.031	-0.015	0.063	-0.095
Maximum	0.775	0.919	0.862	2.953	2.487
Minimum	-1.273	-0.734	-0.756	-1.034	-1.524
Std. Dev.	0.320	0.221	0.186	0.531	0.639
Skewness	0.159	0.328	-0.212	1.618	0.777
Kurtosis	3.663	4.597	8.614	8.669	5.165
Jarque-Bera	3.966	21.853	232.448	312.455	52.087
Probability	0.138	0.000	0.000	0.000	0.000
Sum	-32.060	3.189	-4.496	21.811	-11.557
Sum Sq. Dev.	17.889	8.556	6.041	49.256	71.422
Observations	176.000	176.000	176.000	176.000	176.000

Euro_GBP

	Corporate(5)	Levered(5)	Unlevered(5)	Other(5)	Total(5)
Mean	0.094	-0.005	0.001	0.080	0.170
Median	0.104	-0.005	0.004	0.074	0.186
Maximum	0.813	0.399	0.302	1.213	1.250
Minimum	-0.660	-0.843	-0.351	-1.433	-1.218
Std. Dev.	0.175	0.114	0.079	0.295	0.357
Skewness	-0.025	-2.455	-0.759	-0.400	-0.414
Kurtosis	5.914	21.691	8.186	8.628	4.622
Jarque-Bera	62.276	2738.721	214.146	236.949	24.318
Probability	0.000	0.000	0.000	0.000	0.000
Sum	16.523	-0.941	0.172	14.114	29.868
Sum Sq. Dev.	5.334	2.277	1.081	15.280	22.296
Observations	176.000	176.000	176.000	176.000	176.000

Appendix B3 cont/d
Descriptive Statistics on actual values of net (buy-sell) order flow - 5 Day Frequency.
(all values * 10^9)

Euro_JPY

	Corporate(5)	Levered(5)	Unlevered(5)	Other(5)	Total(5)
Mean	-0.005	-0.001	0.003	-0.026	-0.029
Median	-0.002	-0.003	-0.002	-0.019	-0.010
Maximum	0.361	0.211	0.285	0.671	0.789
Minimum	-0.473	-0.164	-0.124	-1.319	-1.320
Std. Dev.	0.087	0.050	0.049	0.278	0.289
Skewness	-1.755	0.484	2.025	-1.329	-0.866
Kurtosis	14.233	5.786	11.673	8.447	6.983
Jarque-Bera	1015.723	63.800	671.885	269.368	138.324
Probability	0.000	0.000	0.000	0.000	0.000
Sum	-0.943	-0.243	0.582	-4.511	-5.114
Sum Sq. Dev.	1.318	0.433	0.416	13.485	14.634
Observations	176.000	176.000	176.000	176.000	176.000

GBP_USD

	Corporate(5)	Levered(5)	Unlevered(5)	Other(5)	Total(5)
Mean	0.014	0.004	0.014	0.023	0.055
Median	-0.004	0.001	0.006	0.012	0.051
Maximum	0.882	0.417	0.360	1.160	0.961
Minimum	-0.496	-0.318	-0.320	-0.515	-1.044
Std. Dev.	0.162	0.101	0.090	0.219	0.269
Skewness	0.773	0.237	0.623	0.681	0.103
Kurtosis	7.540	4.850	6.298	6.489	4.725
Jarque-Bera	168.701	26.737	91.160	102.857	22.129
Probability	0.000	0.000	0.000	0.000	0.000
Sum	2.524	0.706	2.424	3.983	9.638
Sum Sq. Dev.	4.584	1.790	1.418	8.426	12.651
Observations	176.000	176.000	176.000	176.000	176.000

GBP_JPY

	Corporate(5)	Levered(5)	Unlevered(5)	Other(5)	Total(5)
Mean	0.004	-0.001	-0.006	-0.009	-0.013
Median	0.001	0.000	-0.002	-0.007	-0.009
Maximum	0.290	0.068	0.107	0.497	0.310
Minimum	-0.077	-0.224	-0.503	-0.551	-0.571
Std. Dev.	0.034	0.022	0.044	0.074	0.077
Skewness	4.646	-5.658	-8.552	-0.505	-1.870
Kurtosis	38.023	62.294	97.761	30.119	18.882
Jarque-Bera	9628.188	26721.220	67995.820	5400.687	1952.335
Probability	0.000	0.000	0.000	0.000	0.000
Sum	0.638	-0.182	-1.106	-1.577	-2.228
Sum Sq. Dev.	0.199	0.085	0.334	0.964	1.047
Observations	176.000	176.000	176.000	176.000	176.000

Appendix B4
Descriptive Statistics on absolute values of net (buy-sell) order flow - 5 Day Frequency.
(all values * 10^9)

USD_JPY

	Corporate(5A)	Levered(5A)	Unlevered(5A)	Other(5A)	Total(5A)
Mean	0.110	0.102	0.095	0.293	0.375
Median	0.076	0.080	0.063	0.210	0.285
Maximum	0.833	0.574	0.414	1.594	1.804
Minimum	0.000	0.001	0.001	0.002	0.002
Std. Dev.	0.117	0.092	0.089	0.290	0.338
Skewness	2.742	1.635	1.300	1.710	1.546
Kurtosis	13.545	7.116	4.046	6.168	5.980
Jarque-Bera	1036.122	202.653	57.569	159.324	135.257
Probability	0.000	0.000	0.000	0.000	0.000
Sum	19.384	18.019	16.663	51.504	66.017
Sum Sq. Dev.	2.388	1.470	1.385	14.691	19.946
Observations	176.000	176.000	176.000	176.000	176.000

EURO_USD

	Corporate(5A)	Levered(5A)	Unlevered(5A)	Other(5A)	Total(5A)
Mean	0.294	0.171	0.126	0.370	0.485
Median	0.257	0.142	0.094	0.280	0.377
Maximum	1.273	0.919	0.862	2.953	2.487
Minimum	0.000	0.002	0.000	0.001	0.002
Std. Dev.	0.221	0.141	0.139	0.399	0.419
Skewness	1.004	1.874	2.776	3.007	1.851
Kurtosis	4.400	8.554	12.554	15.784	8.031
Jarque-Bera	43.953	329.147	895.536	1463.755	286.120
Probability	0.000	0.000	0.000	0.000	0.000
Sum	51.753	30.059	22.088	65.159	85.447
Sum Sq. Dev.	8.511	3.480	3.384	27.836	30.697
Observations	176.000	176.000	176.000	176.000	176.000

EURO_GBP

	Corporate(5A)	Levered(5A)	Unlevered(5A)	Other(5A)	Total(5A)
Mean	0.153	0.066	0.050	0.203	0.310
Median	0.130	0.037	0.029	0.140	0.251
Maximum	0.813	0.843	0.351	1.433	1.250
Minimum	0.002	0.000	0.000	0.002	0.000
Std. Dev.	0.126	0.093	0.061	0.229	0.244
Skewness	1.850	4.590	2.491	2.394	1.299
Kurtosis	8.288	33.211	10.165	10.195	4.973
Jarque-Bera	305.482	7311.038	558.471	547.766	78.047
Probability	0.000	0.000	0.000	0.000	0.000
Sum	26.886	11.536	8.757	35.766	54.587
Sum Sq. Dev.	2.779	1.526	0.645	9.144	10.434
Observations	176.000	176.000	176.000	176.000	176.000

Appendix B4 cont/d
Descriptive Statistics on absolute values of net (buy-sell) order flow - 5 Day Frequency.
(all values * 10^9)

EURO_JPY

	Corporate(5A)	Levered(5A)	Unlevered(5A)	Other(5A)	Total(5A)
Mean	0.048	0.035	0.032	0.185	0.199
Median	0.024	0.023	0.022	0.128	0.142
Maximum	0.473	0.211	0.285	1.319	1.320
Minimum	0.000	0.000	0.000	0.000	0.004
Std. Dev.	0.072	0.035	0.037	0.208	0.211
Skewness	3.610	1.937	3.461	2.757	2.375
Kurtosis	18.096	7.946	20.574	13.141	10.822
Jarque-Bera	2053.582	289.486	2616.109	977.048	614.194
Probability	0.000	0.000	0.000	0.000	0.000
Sum	8.511	6.148	5.648	32.495	35.030
Sum Sq. Dev.	0.912	0.219	0.236	7.601	7.811
Observations	176.000	176.000	176.000	176.000	176.000

GBP_USD

	Corporate(5A)	Levered(5A)	Unlevered(5A)	Other(5A)	Total(5A)
Mean	0.116	0.075	0.063	0.161	0.210
Median	0.089	0.057	0.045	0.124	0.160
Maximum	0.882	0.417	0.360	1.160	1.044
Minimum	0.002	0.000	0.000	0.001	0.005
Std. Dev.	0.113	0.068	0.066	0.150	0.176
Skewness	2.592	1.794	2.256	2.296	1.912
Kurtosis	14.641	7.429	8.742	13.074	7.919
Jarque-Bera	1190.836	238.327	391.024	898.765	284.702
Probability	0.000	0.000	0.000	0.000	0.000
Sum	20.443	13.194	11.001	28.389	37.020
Sum Sq. Dev.	2.245	0.804	0.764	3.937	5.392
Observations	176.000	176.000	176.000	176.000	176.000

GBP_JPY

	Corporate(5A)	Levered(5A)	Unlevered(5A)	Other(5A)	Total(5A)
Mean	0.017	0.008	0.014	0.038	0.049
Median	0.010	0.003	0.006	0.018	0.034
Maximum	0.290	0.224	0.503	0.551	0.571
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.029	0.020	0.042	0.064	0.061
Skewness	6.405	7.351	9.593	5.365	4.408
Kurtosis	53.742	73.000	109.401	39.190	33.254
Jarque-Bera	20084.990	37517.990	85720.470	10449.030	7282.166
Probability	0.000	0.000	0.000	0.000	0.000
Sum	3.016	1.468	2.513	6.705	8.584
Sum Sq. Dev.	0.149	0.073	0.305	0.722	0.656
Observations	176.000	176.000	176.000	176.000	176.000

Appendix B5
Descriptive Statistics on actual values of net (buy-sell) order flow - 10 Day Frequency.
(all values * 10^9)

USD_JPY

	Corporate(10)	Levered(10)	Unlevered(10)	Other(10)	Total(10)
Mean	0.015	0.034	0.006	-0.093	-0.039
Median	0.011	0.018	-0.009	-0.112	-0.038
Maximum	0.714	0.614	0.598	1.580	1.758
Minimum	-0.746	-0.448	-0.607	-1.399	-1.428
Std. Dev.	0.236	0.185	0.200	0.598	0.736
Skewness	-0.195	0.112	0.187	0.324	0.327
Kurtosis	4.418	3.766	4.095	3.257	2.783
Jarque-Bera	7.931	2.337	4.907	1.785	1.743
Probability	0.019	0.311	0.086	0.410	0.418
Sum	1.299	2.951	0.507	-8.151	-3.395
Sum Sq. Dev.	4.854	2.969	3.465	31.101	47.123
Observations	88.000	88.000	88.000	88.000	88.000

Euro_USD

	Corporate(10)	Levered(10)	Unlevered(10)	Other(10)	Total(10)
Mean	-0.364	0.036	-0.051	0.248	-0.131
Median	-0.476	0.038	-0.059	0.072	-0.134
Maximum	0.903	0.761	0.875	3.916	2.992
Minimum	-1.675	-0.602	-1.382	-1.387	-2.399
Std. Dev.	0.527	0.251	0.276	0.870	0.973
Skewness	0.354	0.230	-0.464	1.608	0.437
Kurtosis	2.796	3.515	9.795	6.813	3.731
Jarque-Bera	1.987	1.750	172.439	91.219	4.757
Probability	0.370	0.417	0.000	0.000	0.093
Sum	-32.060	3.189	-4.496	21.811	-11.557
Sum Sq. Dev.	24.187	5.485	6.629	65.826	82.443
Observations	88.000	88.000	88.000	88.000	88.000

Euro_GBP

	Corporate(10)	Levered(10)	Unlevered(10)	Other(10)	Total(10)
Mean	0.188	-0.011	0.002	0.160	0.339
Median	0.178	-0.012	0.013	0.125	0.367
Maximum	1.214	0.397	0.322	1.372	1.779
Minimum	-0.773	-0.740	-0.377	-0.629	-0.694
Std. Dev.	0.275	0.166	0.108	0.370	0.498
Skewness	0.186	-1.146	-0.682	0.728	0.086
Kurtosis	5.475	7.918	6.173	4.183	2.922
Jarque-Bera	22.971	107.968	43.732	12.900	0.131
Probability	0.000	0.000	0.000	0.002	0.936
Sum	16.523	-0.941	0.172	14.114	29.868
Sum Sq. Dev.	6.567	2.409	1.010	11.921	21.614
Observations	88.000	88.000	88.000	88.000	88.000

Appendix B5 cont/d
Descriptive Statistics on actual values of net (buy-sell) order flow - 10 Day Frequency.
(all values * 10^9)

Euro_JPY

	Corporate(10)	Levered(10)	Unlevered(10)	Other(10)	Total(10)
Mean	-0.011	-0.003	0.007	-0.051	-0.058
Median	-0.004	-0.007	0.002	-0.041	-0.055
Maximum	0.351	0.158	0.277	1.060	0.989
Minimum	-0.510	-0.185	-0.130	-1.479	-1.402
Std. Dev.	0.126	0.063	0.066	0.363	0.383
Skewness	-1.182	0.004	1.014	-0.615	-0.259
Kurtosis	8.031	3.211	5.519	5.775	4.290
Jarque-Bera	113.312	0.164	38.341	33.785	7.079
Probability	0.000	0.921	0.000	0.000	0.029
Sum	-0.943	-0.243	0.582	-4.511	-5.114
Sum Sq. Dev.	1.376	0.345	0.384	11.450	12.758
Observations	88.000	88.000	88.000	88.000	88.000

GBP_USD

	Corporate(10)	Levered(10)	Unlevered(10)	Other(10)	Total(10)
Mean	0.029	0.008	0.028	0.045	0.110
Median	-0.002	0.010	0.014	0.023	0.086
Maximum	0.717	0.450	0.442	1.238	1.158
Minimum	-0.569	-0.330	-0.411	-0.970	-1.511
Std. Dev.	0.226	0.143	0.133	0.334	0.416
Skewness	0.152	0.543	0.243	0.327	-0.462
Kurtosis	3.457	4.110	4.440	4.589	4.772
Jarque-Bera	1.106	8.841	8.467	10.823	14.644
Probability	0.575	0.012	0.014	0.004	0.001
Sum	2.524	0.706	2.424	3.983	9.638
Sum Sq. Dev.	4.434	1.777	1.542	9.682	15.060
Observations	88.000	88.000	88.000	88.000	88.000

GBP_JPY

	Corporate(10)	Levered(10)	Unlevered(10)	Other(10)	Total(10)
Mean	0.007	-0.002	-0.013	-0.018	-0.025
Median	0.000	0.000	-0.007	-0.010	-0.019
Maximum	0.278	0.075	0.097	0.514	0.288
Minimum	-0.055	-0.220	-0.495	-0.550	-0.546
Std. Dev.	0.046	0.031	0.060	0.109	0.108
Skewness	3.366	-3.875	-6.128	-0.096	-1.269
Kurtosis	18.982	29.403	49.684	13.954	8.836
Jarque-Bera	1102.724	2776.337	8541.671	440.138	148.511
Probability	0.000	0.000	0.000	0.000	0.000
Sum	0.638	-0.182	-1.106	-1.577	-2.228
Sum Sq. Dev.	0.181	0.084	0.312	1.037	1.006
Observations	88.000	88.000	88.000	88.000	88.000

Appendix B6
Descriptive Statistics on absolute values of net (buy-sell) order flow - 10 Day Frequency.
(all values * 10^9)

USD_JPY

	Corporate(10A)	Levered(10A)	Unlevered(10A)	Other(10A)	Total(10A)
Mean	0.172	0.142	0.148	0.459	0.586
Median	0.127	0.121	0.114	0.333	0.447
Maximum	0.746	0.614	0.607	1.580	1.758
Minimum	0.001	0.001	0.007	0.002	0.012
Std. Dev.	0.162	0.122	0.133	0.391	0.443
Skewness	1.534	1.360	1.480	0.908	0.802
Kurtosis	5.324	4.954	5.279	2.909	2.814
Jarque-Bera	54.305	41.122	51.165	12.123	9.553
Probability	0.000	0.000	0.000	0.002	0.008
Sum	15.136	12.524	13.060	40.427	51.545
Sum Sq. Dev.	2.269	1.285	1.529	13.284	17.062
Observations	88.000	88.000	88.000	88.000	88.000

Euro_USD

	Corporate(10A)	Levered(10A)	Unlevered(10A)	Other(10A)	Total(10A)
Mean	0.546	0.197	0.190	0.587	0.739
Median	0.506	0.178	0.138	0.389	0.549
Maximum	1.675	0.761	1.382	3.916	2.992
Minimum	0.009	0.001	0.000	0.001	0.001
Std. Dev.	0.333	0.158	0.206	0.686	0.642
Skewness	0.605	1.348	3.122	2.459	1.131
Kurtosis	3.360	5.242	16.095	10.225	3.954
Jarque-Bera	5.849	45.071	771.649	280.080	22.088
Probability	0.054	0.000	0.000	0.000	0.000
Sum	48.020	17.340	16.735	51.635	65.032
Sum Sq. Dev.	9.664	2.183	3.676	40.934	35.903
Observations	88.000	88.000	88.000	88.000	88.000

Euro_GBP

	Corporate(10A)	Levered(10A)	Unlevered(10A)	Other(10A)	Total(10A)
Mean	0.253	0.112	0.071	0.296	0.497
Median	0.198	0.081	0.045	0.236	0.440
Maximum	1.214	0.740	0.377	1.372	1.779
Minimum	0.003	0.000	0.001	0.006	0.034
Std. Dev.	0.216	0.123	0.081	0.273	0.340
Skewness	1.531	2.678	2.031	1.731	1.093
Kurtosis	6.300	12.150	6.907	6.359	4.630
Jarque-Bera	74.305	412.159	116.469	85.295	27.275
Probability	0.000	0.000	0.000	0.000	0.000
Sum	22.230	9.867	6.236	26.053	43.719
Sum Sq. Dev.	4.053	1.313	0.568	6.471	10.031
Observations	88.000	88.000	88.000	88.000	88.000

Appendix B6 cont/d
Descriptive Statistics on absolute values of net (buy-sell) order flow - 10 Day Frequency.
(all values * 10^9)

Euro_JPY

	Corporate(10A)	Levered(10A)	Unlevered(10A)	Other(10A)	Total(10A)
Mean	0.075	0.049	0.048	0.260	0.288
Median	0.037	0.041	0.035	0.197	0.196
Maximum	0.510	0.185	0.277	1.479	1.402
Minimum	0.001	0.000	0.001	0.009	0.002
Std. Dev.	0.101	0.039	0.046	0.257	0.257
Skewness	2.510	1.054	2.098	2.117	1.579
Kurtosis	9.100	3.899	9.534	8.963	6.238
Jarque-Bera	228.821	19.273	221.100	196.155	74.988
Probability	0.000	0.000	0.000	0.000	0.000
Sum	6.602	4.297	4.247	22.868	25.358
Sum Sq. Dev.	0.891	0.136	0.183	5.738	5.748
Observations	88.000	88.000	88.000	88.000	88.000

GBP_USD

	Corporate(10A)	Levered(10A)	Unlevered(10A)	Other(10A)	Total(10A)
Mean	0.175	0.105	0.099	0.248	0.320
Median	0.132	0.076	0.075	0.180	0.265
Maximum	0.717	0.450	0.442	1.238	1.511
Minimum	0.008	0.004	0.000	0.002	0.001
Std. Dev.	0.144	0.096	0.092	0.226	0.286
Skewness	1.265	1.543	1.621	1.721	1.401
Kurtosis	4.526	5.187	5.890	6.692	5.650
Jarque-Bera	32.025	52.477	69.139	93.434	54.541
Probability	0.000	0.000	0.000	0.000	0.000
Sum	15.423	9.284	8.753	21.809	28.173
Sum Sq. Dev.	1.804	0.803	0.738	4.458	7.096
Observations	88.000	88.000	88.000	88.000	88.000

GBP_JPY

	Corporate(10A)	Levered(10A)	Unlevered(10A)	Other(10A)	Total(10A)
Mean	0.025	0.014	0.023	0.067	0.075
Median	0.014	0.006	0.011	0.037	0.050
Maximum	0.278	0.220	0.495	0.550	0.546
Minimum	0.000	0.000	0.000	0.002	0.000
Std. Dev.	0.039	0.028	0.056	0.088	0.081
Skewness	4.419	5.174	6.945	3.606	2.962
Kurtosis	26.219	36.594	57.028	18.839	15.709
Jarque-Bera	2263.121	4530.591	11410.260	1110.615	720.981
Probability	0.000	0.000	0.000	0.000	0.000
Sum	2.174	1.269	2.064	5.878	6.613
Sum Sq. Dev.	0.132	0.066	0.277	0.673	0.565
Observations	88.000	88.000	88.000	88.000	88.000

Appendix B7
Descriptive Statistics on actual values of net (buy-sell) order flow - 15 Day Frequency.
(all values * 10^9)

USD_JPY

	Corporate(15)	Levered(15)	Unlevered(15)	Other(15)	Total(15)
Mean	0.022	0.050	0.009	-0.138	-0.058
Median	0.028	0.069	-0.007	-0.151	0.047
Maximum	0.915	0.654	0.960	1.648	2.340
Minimum	-0.764	-0.558	-0.620	-1.598	-2.036
Std. Dev.	0.285	0.221	0.265	0.732	0.904
Skewness	-0.213	-0.209	0.631	0.185	0.026
Kurtosis	4.778	3.627	4.748	2.909	3.041
Jarque-Bera	8.221	1.397	11.436	0.358	0.011
Probability	0.016	0.497	0.003	0.836	0.994
Sum	1.299	2.951	0.507	-8.151	-3.395
Sum Sq. Dev.	4.702	2.844	4.059	31.063	47.406
Observations	59.000	59.000	59.000	59.000	59.000

Euro_USD

	Corporate(15)	Levered(15)	Unlevered(15)	Other(15)	Total(15)
Mean	-0.543	0.054	-0.076	0.370	-0.196
Median	-0.710	0.095	-0.129	0.159	-0.254
Maximum	0.805	0.918	0.940	3.313	2.474
Minimum	-1.717	-0.696	-0.886	-2.074	-2.851
Std. Dev.	0.626	0.329	0.300	1.052	1.157
Skewness	0.428	-0.041	0.315	0.827	0.044
Kurtosis	2.230	3.007	4.430	3.798	2.582
Jarque-Bera	3.264	0.017	6.002	8.298	0.447
Probability	0.196	0.992	0.050	0.016	0.800
Sum	-32.060	3.189	-4.496	21.811	-11.557
Sum Sq. Dev.	22.729	6.267	5.221	64.198	77.580
Observations	59.000	59.000	59.000	59.000	59.000

Euro_GBP

	Corporate(15)	Levered(15)	Unlevered(15)	Other(15)	Total(15)
Mean	0.280	-0.016	0.003	0.239	0.506
Median	0.259	-0.023	0.031	0.162	0.581
Maximum	1.163	0.435	0.289	1.723	1.940
Minimum	-0.595	-0.839	-0.581	-1.915	-1.541
Std. Dev.	0.353	0.220	0.158	0.551	0.683
Skewness	0.306	-1.417	-1.348	-0.133	-0.408
Kurtosis	3.376	7.724	6.340	6.614	3.299
Jarque-Bera	1.265	74.598	45.304	32.275	1.853
Probability	0.531	0.000	0.000	0.000	0.396
Sum	16.523	-0.941	0.172	14.114	29.868
Sum Sq. Dev.	7.232	2.814	1.448	17.582	27.037
Observations	59.000	59.000	59.000	59.000	59.000

Appendix B7 cont/d
Descriptive Statistics on actual values of net (buy-sell) order flow - 15 Day Frequency.
(all values * 10^9)

Euro_JPY

	Corporate(15)	Levered(15)	Unlevered(15)	Other(15)	Total(15)
Mean	-0.016	-0.004	0.010	-0.076	-0.087
Median	-0.004	0.004	-0.001	-0.080	-0.076
Maximum	0.348	0.225	0.293	1.083	1.154
Minimum	-0.492	-0.184	-0.179	-1.266	-1.259
Std. Dev.	0.148	0.075	0.086	0.405	0.438
Skewness	-1.042	0.205	0.725	-0.528	-0.140
Kurtosis	5.727	3.616	3.936	4.884	3.752
Jarque-Bera	28.954	1.346	7.321	11.469	1.581
Probability	0.000	0.510	0.026	0.003	0.454
Sum	-0.943	-0.243	0.582	-4.511	-5.114
Sum Sq. Dev.	1.276	0.331	0.425	9.521	11.127
Observations	59.000	59.000	59.000	59.000	59.000

GBP_USD

	Corporate(15)	Levered(15)	Unlevered(15)	Other(15)	Total(15)
Mean	0.043	0.012	0.041	0.068	0.163
Median	0.031	0.016	0.032	0.069	0.153
Maximum	0.823	0.597	0.584	1.015	1.120
Minimum	-0.521	-0.461	-0.429	-1.485	-1.844
Std. Dev.	0.268	0.184	0.168	0.404	0.514
Skewness	0.158	0.368	0.555	-0.627	-0.743
Kurtosis	3.162	4.550	4.936	5.566	5.422
Jarque-Bera	0.311	7.235	12.236	20.056	19.854
Probability	0.856	0.027	0.002	0.000	0.000
Sum	2.524	0.706	2.424	3.983	9.638
Sum Sq. Dev.	4.151	1.955	1.639	9.459	15.324
Observations	59.000	59.000	59.000	59.000	59.000

GBP_JPY

	Corporate(15)	Levered(15)	Unlevered(15)	Other(15)	Total(15)
Mean	0.011	-0.003	-0.019	-0.027	-0.038
Median	0.001	-0.002	-0.011	-0.011	-0.025
Maximum	0.337	0.084	0.111	0.503	0.309
Minimum	-0.111	-0.201	-0.494	-0.535	-0.512
Std. Dev.	0.062	0.036	0.072	0.133	0.135
Skewness	2.893	-2.591	-4.926	-0.066	-0.665
Kurtosis	15.446	16.614	33.211	9.236	5.680
Jarque-Bera	463.072	521.627	2482.389	95.640	22.005
Probability	0.000	0.000	0.000	0.000	0.000
Sum	0.638	-0.182	-1.106	-1.577	-2.228
Sum Sq. Dev.	0.226	0.077	0.304	1.018	1.063
Observations	59.000	59.000	59.000	59.000	59.000

Appendix B8
Descriptive Statistics on absolute values of net (buy-sell) order flow - 15 Day Frequency.
(all values * 10^9)

USD_JPY

	Corporate(15A)	Levered(15A)	Unlevered(15A)	Other(15A)	Total(15A)
Mean	0.199	0.177	0.196	0.578	0.709
Median	0.123	0.148	0.153	0.408	0.572
Maximum	0.915	0.654	0.960	1.648	2.340
Minimum	0.003	0.001	0.001	0.025	0.047
Std. Dev.	0.203	0.140	0.176	0.464	0.557
Skewness	1.573	1.247	1.745	0.798	1.032
Kurtosis	5.328	4.581	7.572	2.503	3.378
Jarque-Bera	37.655	21.448	81.309	6.863	10.817
Probability	0.000	0.000	0.000	0.032	0.004
Sum	11.755	10.450	11.541	34.077	41.811
Sum Sq. Dev.	2.388	1.141	1.806	12.507	17.972
Observations	59.000	59.000	59.000	59.000	59.000

Euro_USD

	Corporate(15A)	Levered(15A)	Unlevered(15A)	Other(15A)	Total(15A)
Mean	0.716	0.264	0.242	0.766	0.953
Median	0.738	0.210	0.216	0.496	0.763
Maximum	1.717	0.918	0.940	3.313	2.851
Minimum	0.000	0.006	0.007	0.004	0.026
Std. Dev.	0.414	0.200	0.191	0.806	0.672
Skewness	0.159	1.012	1.688	1.509	0.787
Kurtosis	2.340	3.724	6.464	4.539	2.928
Jarque-Bera	1.321	11.356	57.537	28.204	6.107
Probability	0.517	0.003	0.000	0.000	0.047
Sum	42.215	15.582	14.279	45.180	56.245
Sum Sq. Dev.	9.946	2.325	2.108	37.664	26.226
Observations	59.000	59.000	59.000	59.000	59.000

Euro_GBP

	Corporate(15A)	Levered(15A)	Unlevered(15A)	Other(15A)	Total(15A)
Mean	0.353	0.148	0.106	0.396	0.704
Median	0.321	0.097	0.074	0.225	0.630
Maximum	1.163	0.839	0.581	1.915	1.940
Minimum	0.002	0.000	0.005	0.007	0.028
Std. Dev.	0.279	0.163	0.116	0.449	0.472
Skewness	1.115	2.710	2.105	1.761	0.626
Kurtosis	3.949	11.609	7.840	5.447	2.725
Jarque-Bera	14.449	254.397	101.179	45.205	4.036
Probability	0.001	0.000	0.000	0.000	0.133
Sum	20.807	8.715	6.280	23.363	41.542
Sum Sq. Dev.	4.522	1.541	0.780	11.708	12.907
Observations	59.000	59.000	59.000	59.000	59.000

Appendix B8 cont/d
Descriptive Statistics on absolute values of net (buy-sell) order flow - 15 Day Frequency.
(all values * 10^9)

Euro_JPY

	Corporate(15A)	Levered(15A)	Unlevered(15A)	Other(15A)	Total(15A)
Mean	0.094	0.057	0.063	0.297	0.339
Median	0.052	0.048	0.049	0.221	0.282
Maximum	0.492	0.225	0.293	1.266	1.259
Minimum	0.003	0.000	0.001	0.014	0.000
Std. Dev.	0.116	0.049	0.058	0.284	0.287
Skewness	1.949	1.186	1.439	1.986	1.399
Kurtosis	6.164	4.369	5.578	6.596	5.004
Jarque-Bera	61.980	18.446	36.698	70.558	29.129
Probability	0.000	0.000	0.000	0.000	0.000
Sum	5.524	3.361	3.723	17.511	20.007
Sum Sq. Dev.	0.774	0.140	0.196	4.669	4.786
Observations	59.000	59.000	59.000	59.000	59.000

GBP_USD

	Corporate(15A)	Levered(15A)	Unlevered(15A)	Other(15A)	Total(15A)
Mean	0.214	0.135	0.123	0.301	0.412
Median	0.157	0.089	0.086	0.228	0.384
Maximum	0.823	0.597	0.584	1.485	1.844
Minimum	0.018	0.002	0.001	0.007	0.007
Std. Dev.	0.164	0.124	0.121	0.275	0.344
Skewness	1.177	1.754	1.898	1.886	1.597
Kurtosis	4.589	6.031	6.608	7.671	6.759
Jarque-Bera	19.841	52.848	67.445	88.601	59.820
Probability	0.000	0.000	0.000	0.000	0.000
Sum	12.607	7.938	7.238	17.774	24.329
Sum Sq. Dev.	1.565	0.895	0.851	4.373	6.866
Observations	59.000	59.000	59.000	59.000	59.000

GBP_JPY

	Corporate(15A)	Levered(15A)	Unlevered(15A)	Other(15A)	Total(15A)
Mean	0.035	0.020	0.031	0.082	0.096
Median	0.021	0.012	0.012	0.041	0.072
Maximum	0.337	0.201	0.494	0.535	0.512
Minimum	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.053	0.030	0.068	0.107	0.102
Skewness	4.001	4.020	5.655	2.584	2.039
Kurtosis	21.419	23.140	38.058	10.432	7.663
Jarque-Bera	991.393	1156.002	3335.864	201.463	94.356
Probability	0.000	0.000	0.000	0.000	0.000
Sum	2.069	1.205	1.821	4.822	5.691
Sum Sq. Dev.	0.160	0.053	0.268	0.666	0.598
Observations	59.000	59.000	59.000	59.000	59.000

Appendix B9 – Autocorrelation in €/$ Net Flows (Daily)

EUR_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.020	0.020	0.337	0.562
2	0.052	0.052	2.742	0.254
3	0.092	0.090	10.140	0.017
4	0.055	0.050	12.831	0.012
5	0.068	0.058	16.900	0.005
6	0.059	0.045	19.974	0.003
7	0.024	0.008	20.471	0.005
8	0.077	0.060	25.767	0.001
9	0.030	0.013	26.578	0.002
10	0.009	-0.009	26.647	0.003

EUR_USD Uneveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.039	0.039	1.327	0.249
2	0.014	0.013	1.504	0.472
3	-0.002	-0.003	1.508	0.680
4	0.000	0.000	1.508	0.825
5	0.020	0.020	1.856	0.869
6	0.030	0.028	2.651	0.851
7	0.013	0.010	2.799	0.903
8	0.002	0.000	2.802	0.946
9	-0.015	-0.016	3.011	0.964
10	0.000	0.001	3.011	0.981

EUR_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.043	-0.043	1.635	0.201
2	0.001	-0.001	1.635	0.441
3	-0.041	-0.041	3.094	0.377
4	0.010	0.007	3.186	0.527
5	-0.039	-0.038	4.514	0.478
6	-0.041	-0.046	5.994	0.424
7	-0.028	-0.031	6.681	0.463
8	-0.058	-0.065	9.712	0.286
9	-0.036	-0.046	10.879	0.284
10	0.030	0.022	11.656	0.309

EUR_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	0.040	0.040	1.399	0.237
2	0.013	0.011	1.548	0.461
3	0.086	0.085	8.010	0.046
4	0.016	0.009	8.232	0.083
5	0.039	0.036	9.549	0.089
6	0.102	0.092	18.698	0.005
7	0.128	0.120	33.169	0.000
8	0.031	0.017	34.044	0.000
9	-0.010	-0.030	34.142	0.000
10	0.053	0.033	36.653	0.000

EUR_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	0.039	0.039	1.374	0.241
2	0.022	0.021	1.815	0.404
3	0.050	0.049	4.043	0.257
4	0.024	0.020	4.574	0.334
5	0.058	0.054	7.507	0.186
6	0.031	0.024	8.342	0.214
7	0.041	0.036	9.865	0.196
8	-0.006	-0.015	9.895	0.272
9	-0.019	-0.025	10.232	0.332
10	0.038	0.033	11.540	0.317

Appendix B9 – Autocorrelation in €/£ Net Flows (Daily)

EUR_GBP Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.068	0.068	4.069	0.044
2	0.039	0.035	5.427	0.066
3	0.046	0.041	7.299	0.063
4	0.020	0.014	7.668	0.105
5	0.053	0.048	10.124	0.072
6	0.091	0.083	17.524	0.008
7	0.034	0.019	18.554	0.010
8	0.023	0.010	19.005	0.015
9	0.021	0.009	19.399	0.022
10	-0.005	-0.015	19.424	0.035

EUR_GBP Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.020	-0.020	0.366	0.545
2	-0.025	-0.025	0.916	0.632
3	-0.079	-0.080	6.461	0.091
4	0.036	0.033	7.634	0.106
5	-0.006	-0.009	7.671	0.175
6	0.058	0.053	10.620	0.101
7	-0.033	-0.026	11.580	0.115
8	0.014	0.013	11.744	0.163
9	0.007	0.015	11.785	0.226
10	0.013	0.006	11.941	0.289

EUR_GBP Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.005	0.005	0.020	0.889
2	0.001	0.001	0.021	0.989
3	0.022	0.022	0.451	0.930
4	0.007	0.007	0.491	0.974
5	-0.027	-0.027	1.135	0.951
6	-0.034	-0.034	2.159	0.905
7	0.044	0.044	3.841	0.798
8	-0.081	-0.081	9.734	0.284
9	0.052	0.056	12.177	0.204
10	-0.016	-0.019	12.392	0.260

EUR_GBP Other

Lag	AC	PAC	Q-Stat	Prob
1	0.138	0.138	16.817	0.000
2	0.038	0.020	18.119	0.000
3	0.002	-0.006	18.122	0.000
4	-0.021	-0.022	18.524	0.001
5	0.094	0.102	26.417	0.000
6	-0.054	-0.082	29.026	0.000
7	-0.052	-0.041	31.438	0.000
8	-0.002	0.016	31.441	0.000
9	-0.026	-0.021	32.058	0.000
10	-0.042	-0.052	33.600	0.000

EUR_GBP Total

Lag	AC	PAC	Q-Stat	Prob
1	0.136	0.136	16.369	0.000
2	-0.004	-0.023	16.387	0.000
3	0.024	0.028	16.897	0.001
4	0.002	-0.005	16.901	0.002
5	0.091	0.094	24.228	0.000
6	0.000	-0.027	24.228	0.000
7	-0.022	-0.015	24.642	0.001
8	0.010	0.011	24.739	0.002
9	-0.022	-0.024	25.169	0.003
10	-0.026	-0.028	25.784	0.004

Appendix B9 – Autocorrelation in €/¥ Net Flows (Daily)

EUR_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.019	0.019	0.312	0.576
2	-0.059	-0.060	3.397	0.183
3	-0.094	-0.092	11.219	0.011
4	-0.007	-0.007	11.258	0.024
5	0.067	0.057	15.189	0.010
6	0.034	0.023	16.187	0.013
7	0.001	0.006	16.189	0.023
8	-0.056	-0.042	18.945	0.015
9	-0.056	-0.050	21.771	0.010
10	0.018	0.012	22.070	0.015

EUR_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.029	-0.029	0.723	0.395
2	0.045	0.044	2.471	0.291
3	-0.031	-0.029	3.343	0.342
4	-0.005	-0.009	3.369	0.498
5	-0.030	-0.028	4.163	0.526
6	-0.008	-0.010	4.218	0.647
7	0.024	0.026	4.724	0.694
8	-0.003	-0.003	4.731	0.786
9	0.009	0.006	4.809	0.851
10	-0.003	-0.002	4.816	0.903

EUR_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.041	0.041	1.457	0.227
2	0.004	0.003	1.474	0.478
3	-0.026	-0.026	2.078	0.556
4	-0.006	-0.004	2.111	0.715
5	-0.031	-0.031	2.987	0.702
6	0.038	0.040	4.295	0.637
7	-0.039	-0.043	5.670	0.579
8	-0.030	-0.029	6.472	0.595
9	0.007	0.012	6.517	0.687
10	-0.058	-0.062	9.487	0.487

EUR_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.208	0.208	38.285	0.000
2	0.068	0.026	42.387	0.000
3	-0.039	-0.061	43.738	0.000
4	-0.037	-0.019	44.919	0.000
5	-0.035	-0.019	46.027	0.000
6	-0.043	-0.033	47.688	0.000
7	0.015	0.032	47.892	0.000
8	0.012	0.003	48.012	0.000
9	0.017	0.006	48.259	0.000
10	-0.031	-0.038	49.099	0.000

EUR_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.162	0.162	23.050	0.000
2	0.058	0.032	25.990	0.000
3	-0.055	-0.071	28.657	0.000
4	-0.031	-0.013	29.480	0.000
5	-0.017	-0.003	29.727	0.000
6	-0.033	-0.032	30.686	0.000
7	0.017	0.026	30.952	0.000
8	-0.027	-0.033	31.589	0.000
9	0.008	0.011	31.642	0.000
10	-0.036	-0.036	32.809	0.000

Appendix B9 – Autocorrelation in $/¥ Net Flows (Daily)

USD_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.054	0.054	2.577	0.108
2	-0.001	-0.004	2.578	0.276
3	0.032	0.033	3.488	0.322
4	-0.017	-0.020	3.729	0.444
5	-0.022	-0.019	4.139	0.530
6	0.047	0.049	6.136	0.408
7	-0.034	-0.039	7.181	0.410
8	-0.054	-0.049	9.790	0.280
9	-0.025	-0.024	10.366	0.322
10	-0.011	-0.006	10.483	0.399

USD_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.055	0.055	2.642	0.104
2	0.069	0.066	6.799	0.033
3	0.071	0.065	11.313	0.010
4	-0.048	-0.060	13.381	0.010
5	0.029	0.026	14.125	0.015
6	0.049	0.049	16.210	0.013
7	0.045	0.044	17.979	0.012
8	-0.006	-0.024	18.012	0.021
9	0.019	0.012	18.348	0.031
10	-0.029	-0.030	19.099	0.039

USD_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.019	-0.019	0.305	0.581
2	0.011	0.011	0.412	0.814
3	-0.057	-0.057	3.287	0.350
4	-0.004	-0.006	3.301	0.509
5	-0.010	-0.009	3.386	0.641
6	-0.004	-0.007	3.399	0.757
7	-0.030	-0.030	4.177	0.759
8	-0.022	-0.024	4.602	0.799
9	-0.040	-0.041	6.038	0.736
10	0.025	0.020	6.600	0.763

USD_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.067	0.067	3.908	0.048
2	0.033	0.029	4.895	0.086
3	-0.045	-0.049	6.674	0.083
4	0.053	0.059	9.177	0.057
5	0.000	-0.004	9.177	0.102
6	0.062	0.057	12.577	0.050
7	-0.001	-0.004	12.578	0.083
8	0.001	-0.006	12.579	0.127
9	-0.034	-0.028	13.613	0.137
10	-0.007	-0.010	13.658	0.189

USD_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.095	0.095	7.912	0.005
2	0.045	0.036	9.662	0.008
3	-0.043	-0.051	11.294	0.010
4	0.033	0.041	12.283	0.015
5	0.006	0.003	12.317	0.031
6	0.060	0.055	15.558	0.016
7	-0.049	-0.058	17.708	0.013
8	-0.017	-0.013	17.962	0.022
9	-0.040	-0.028	19.397	0.022
10	-0.018	-0.020	19.680	0.032

Appendix B9 – Autocorrelation in £/$ Net Flows (Daily)

GBP_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.047	0.047	1.917	0.166
2	-0.006	-0.008	1.949	0.377
3	0.038	0.039	3.257	0.354
4	-0.028	-0.032	3.962	0.411
5	0.003	0.007	3.972	0.554
6	-0.020	-0.022	4.312	0.635
7	0.011	0.015	4.412	0.731
8	0.042	0.039	5.945	0.653
9	-0.081	-0.083	11.718	0.230
10	-0.016	-0.010	11.949	0.289

GBP_USD Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.010	-0.010	0.080	0.778
2	0.037	0.036	1.257	0.534
3	0.017	0.018	1.526	0.676
4	0.003	0.002	1.534	0.821
5	0.039	0.038	2.869	0.720
6	-0.008	-0.008	2.925	0.818
7	0.029	0.026	3.671	0.817
8	0.015	0.015	3.866	0.869
9	0.031	0.030	4.725	0.858
10	0.004	0.002	4.742	0.908

GBP_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.062	-0.062	3.344	0.067
2	-0.015	-0.019	3.548	0.170
3	-0.018	-0.020	3.823	0.281
4	-0.019	-0.022	4.140	0.387
5	-0.047	-0.050	6.085	0.298
6	0.041	0.034	7.597	0.269
7	0.053	0.055	10.050	0.186
8	0.014	0.020	10.216	0.250
9	-0.011	-0.008	10.328	0.325
10	0.005	0.006	10.352	0.410

GBP_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.044	-0.044	1.702	0.192
2	0.039	0.037	3.025	0.220
3	-0.008	-0.005	3.080	0.379
4	-0.016	-0.018	3.304	0.508
5	0.009	0.008	3.372	0.643
6	0.020	0.022	3.742	0.712
7	0.008	0.009	3.794	0.803
8	0.007	0.006	3.840	0.871
9	0.013	0.014	4.001	0.911
10	0.043	0.045	5.684	0.841

GBP_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.038	-0.038	1.304	0.253
2	-0.016	-0.017	1.525	0.467
3	-0.002	-0.004	1.530	0.675
4	0.003	0.002	1.538	0.820
5	-0.015	-0.015	1.727	0.885
6	0.053	0.052	4.246	0.643
7	-0.008	-0.004	4.299	0.745
8	-0.022	-0.021	4.735	0.786
9	-0.041	-0.042	6.200	0.720
10	0.038	0.033	7.464	0.681

Appendix B9 – Autocorrelation in £/¥ Net Flows (Daily)

GBP_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.005	-0.005	0.019	0.892
2	0.000	0.000	0.019	0.991
3	-0.010	-0.010	0.112	0.990
4	-0.024	-0.024	0.622	0.961
5	0.008	0.008	0.675	0.984
6	0.037	0.037	1.887	0.930
7	-0.002	-0.002	1.889	0.966
8	-0.008	-0.008	1.944	0.983
9	0.010	0.011	2.028	0.991
10	-0.048	-0.046	4.039	0.946

GBP_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.014	0.014	0.161	0.688
2	-0.005	-0.005	0.181	0.914
3	-0.008	-0.008	0.237	0.971
4	-0.005	-0.005	0.261	0.992
5	-0.007	-0.007	0.305	0.998
6	-0.008	-0.008	0.367	0.999
7	-0.019	-0.019	0.689	0.998
8	0.030	0.031	1.499	0.993
9	-0.051	-0.052	3.791	0.925
10	0.010	0.012	3.883	0.952

GBP_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.043	0.043	1.638	0.201
2	0.082	0.081	7.633	0.022
3	-0.034	-0.041	8.628	0.035
4	0.002	-0.002	8.631	0.071
5	0.000	0.006	8.631	0.125
6	-0.011	-0.013	8.740	0.189
7	-0.032	-0.031	9.630	0.211
8	-0.016	-0.012	9.865	0.275
9	0.003	0.009	9.874	0.361
10	-0.014	-0.014	10.040	0.437

GBP_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.033	0.033	0.946	0.331
2	0.016	0.015	1.162	0.559
3	-0.001	-0.002	1.163	0.762
4	0.007	0.007	1.206	0.877
5	0.025	0.025	1.767	0.880
6	-0.013	-0.015	1.911	0.928
7	0.016	0.016	2.124	0.953
8	0.024	0.023	2.623	0.956
9	0.027	0.025	3.284	0.952
10	-0.010	-0.013	3.368	0.971

GBP_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.030	0.030	0.802	0.370
2	0.019	0.018	1.112	0.573
3	-0.010	-0.012	1.209	0.751
4	0.035	0.035	2.271	0.686
5	0.010	0.008	2.355	0.798
6	0.000	-0.002	2.355	0.884
7	0.000	0.001	2.355	0.938
8	0.057	0.056	5.262	0.729
9	0.006	0.002	5.295	0.808
10	-0.022	-0.024	5.721	0.838

Appendix B10 – Autocorrelation in €/$ Net Flows (5 Day)

EUR_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.215	0.215	8.285	0.004
2	0.136	0.094	11.633	0.003
3	0.206	0.169	19.353	0.000
4	0.184	0.111	25.493	0.000
5	0.305	0.243	42.518	0.000

EUR_USD Uneveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.055	0.055	0.540	0.462
2	-0.086	-0.090	1.884	0.390
3	-0.177	-0.169	7.560	0.056
4	-0.058	-0.050	8.175	0.085
5	0.076	0.054	9.231	0.100

EUR_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.245	-0.245	10.779	0.001
2	-0.025	-0.090	10.887	0.004
3	-0.047	-0.081	11.290	0.010
4	0.017	-0.020	11.345	0.023
5	-0.013	-0.022	11.374	0.044

EUR_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	0.236	0.236	9.940	0.002
2	0.103	0.051	11.862	0.003
3	0.180	0.154	17.730	0.001
4	0.333	0.279	37.957	0.000
5	0.198	0.074	45.159	0.000

EUR_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	0.151	0.151	4.091	0.043
2	-0.017	-0.040	4.140	0.126
3	0.073	0.083	5.094	0.165
4	0.300	0.283	21.446	0.000
5	0.106	0.029	23.520	0.000

Appendix B10 – Autocorrelation in €/£ Net Flows (5 Day)

EUR_GBP Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.196	0.196	6.906	0.009
2	0.117	0.081	9.350	0.009
3	0.095	0.061	10.993	0.012
4	-0.011	-0.050	11.014	0.026
5	0.054	0.053	11.551	0.041

EUR_GBP Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.009	0.009	0.013	0.909
2	0.100	0.100	1.823	0.402
3	-0.051	-0.053	2.288	0.515
4	0.137	0.130	5.701	0.223
5	0.050	0.058	6.158	0.291

EUR_GBP Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.141	-0.141	3.565	0.059
2	0.064	0.045	4.294	0.117
3	-0.054	-0.04	4.822	0.185
4	0.029	0.014	4.974	0.29
5	-0.064	-0.054	5.713	0.335

EUR_GBP Other

Lag	AC	PAC	Q-Stat	Prob
1	0.009	0.009	0.015	0.903
2	-0.185	-0.185	6.200	0.045
3	0.025	0.029	6.310	0.097
4	0.019	-0.017	6.374	0.173
5	0.031	0.042	6.549	0.256

EUR_GBP Total

Lag	AC	PAC	Q-Stat	Prob
1	0.079	0.079	1.121	0.29
2	-0.097	-0.104	2.807	0.246
3	-0.036	-0.019	3.036	0.386
4	0.091	0.087	4.553	0.336
5	-0.011	-0.032	4.574	0.47

Appendix B10 – Autocorrelation in €/¥ Net Flows (5 Day)

EUR_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.000	0.000	0.000	0.998
2	-0.067	-0.067	0.816	0.665
3	0.036	0.036	1.054	0.788
4	-0.067	-0.072	1.873	0.759
5	-0.072	-0.068	2.829	0.726

EUR_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.081	-0.081	1.173	0.279
2	-0.010	-0.017	1.191	0.551
3	0.091	0.090	2.694	0.441
4	-0.082	-0.069	3.933	0.415
5	0.012	0.002	3.959	0.555

EUR_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.078	0.078	1.090	0.297
2	-0.200	-0.207	8.289	0.016
3	-0.048	-0.014	8.711	0.033
4	0.076	0.042	9.765	0.045
5	0.009	-0.016	9.779	0.082

EUR_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.127	-0.127	2.902	0.088
2	0.049	0.033	3.333	0.189
3	-0.024	-0.014	3.437	0.329
4	-0.205	-0.214	11.054	0.026
5	0.048	-0.003	11.469	0.043

EUR_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.119	-0.119	2.552	0.110
2	0.011	-0.003	2.576	0.276
3	0.007	0.008	2.584	0.460
4	-0.139	-0.140	6.116	0.191
5	0.030	-0.003	6.279	0.280

Appendix B10 – Autocorrelation in $/¥ Net Flows (5 Day)

USD_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.086	0.086	1.324	0.250
2	-0.097	-0.106	3.033	0.219
3	-0.160	-0.144	7.641	0.054
4	0.185	0.209	13.850	0.008
5	0.020	-0.049	13.923	0.016

USD_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.164	0.164	4.827	0.028
2	-0.037	-0.066	5.078	0.079
3	0.015	0.033	5.118	0.163
4	-0.007	-0.019	5.128	0.274
5	-0.083	-0.079	6.386	0.270

USD_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.154	-0.154	4.260	0.039
2	0.084	0.061	5.516	0.063
3	-0.097	-0.078	7.234	0.065
4	0.002	-0.029	7.235	0.124
5	-0.004	0.004	7.238	0.204

USD_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.179	0.179	5.727	0.017
2	-0.089	-0.125	7.155	0.028
3	-0.141	-0.106	10.748	0.013
4	-0.144	-0.115	14.548	0.006
5	-0.111	-0.096	16.806	0.005

USD_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.100	0.100	1.799	0.180
2	-0.113	-0.125	4.112	0.128
3	-0.077	-0.053	5.197	0.158
4	-0.039	-0.040	5.480	0.241
5	-0.082	-0.092	6.724	0.242

Appendix B10 – Autocorrelation in £/$ Net Flows (5 Day)

GBP_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.031	0.031	0.173	0.677
2	-0.142	-0.144	3.829	0.147
3	-0.044	-0.035	4.172	0.244
4	0.086	0.069	5.512	0.239
5	0.068	0.054	6.37	0.272

GBP_USD Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.044	0.044	0.340	0.56
2	0.083	0.082	1.589	0.452
3	-0.032	-0.039	1.774	0.621
4	0.02	0.016	1.844	0.764
5	-0.029	-0.025	2.001	0.849

GBP_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.013	-0.013	0.031	0.86
2	-0.081	-0.082	1.222	0.543
3	-0.088	-0.09	2.610	0.456
4	-0.061	-0.071	3.279	0.512
5	-0.028	-0.047	3.422	0.635

GBP_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.013	-0.013	0.032	0.858
2	0.032	0.032	0.220	0.896
3	-0.097	-0.096	1.928	0.587
4	-0.104	-0.109	3.903	0.419
5	-0.006	-0.003	3.909	0.563

GBP_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	0.056	0.056	0.565	0.452
2	-0.066	-0.069	1.342	0.511
3	-0.124	-0.117	4.117	0.249
4	-0.049	-0.041	4.562	0.335
5	-0.123	-0.137	7.313	0.198

Appendix B10 – Autocorrelation in £/¥ Net Flows (5 Day)

GBP_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.039	0.039	0.279	0.597
2	-0.068	-0.070	1.118	0.572
3	0.032	0.038	1.303	0.728
4	0.098	0.091	3.053	0.549
5	0.008	0.005	3.066	0.69

GBP_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.040	-0.040	0.290	0.590
2	-0.006	-0.007	0.296	0.862
3	-0.004	-0.004	0.298	0.96
4	0.026	0.025	0.417	0.981
5	0.003	0.005	0.419	0.995

GBP_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.057	-0.057	0.587	0.444
2	-0.08	-0.083	1.737	0.42
3	-0.105	-0.116	3.728	0.292
4	0.004	-0.018	3.731	0.444
5	0.027	0.007	3.862	0.569

GBP_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.105	0.105	1.960	0.162
2	-0.052	-0.064	2.456	0.293
3	0.024	0.037	2.563	0.464
4	-0.027	-0.038	2.699	0.609
5	-0.192	-0.184	9.444	0.093

GBP_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.097	0.097	1.696	0.193
2	-0.050	-0.06	2.142	0.343
3	0.024	0.036	2.250	0.522
4	-0.008	-0.017	2.261	0.688
5	0.070	0.077	3.151	0.677

Appendix B11 – Autocorrelation in €/$ Net Flows (10 Day)

EUR_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.200	0.200	3.626	0.057
2	0.325	0.297	13.340	0.001
3	0.301	0.224	21.768	0.000
4	0.254	0.121	27.830	0.000
5	0.475	0.365	49.359	0.000

EUR_USD Uneveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.169	-0.169	2.603	0.107
2	-0.016	-0.046	2.628	0.269
3	-0.060	-0.073	2.967	0.397
4	-0.120	-0.150	4.335	0.363
5	0.104	0.052	5.360	0.374

EUR_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.089	-0.089	0.721	0.396
2	-0.052	-0.060	0.970	0.616
3	-0.033	-0.044	1.072	0.784
4	-0.129	-0.141	2.637	0.620
5	0.058	0.028	2.959	0.706

EUR_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	0.197	0.197	3.546	0.060
2	0.363	0.337	15.696	0.000
3	0.384	0.316	29.404	0.000
4	0.319	0.183	39.020	0.000
5	0.252	0.028	45.070	0.000

EUR_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	0.095	0.095	0.815	0.367
2	0.354	0.348	12.352	0.002
3	0.212	0.181	16.545	0.001
4	0.190	0.063	19.934	0.001
5	0.238	0.123	25.327	0.000

Appendix B11 – Autocorrelation in €/£ Net Flows (10 Day)

EUR_GBP Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.186	0.186	3.146	0.076
2	0.105	0.073	4.166	0.125
3	0.053	0.022	4.425	0.219
4	0.070	0.052	4.892	0.299
5	0.016	-0.011	4.916	0.426

EUR_GBP Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.127	0.127	1.465	0.226
2	0.120	0.105	2.782	0.249
3	0.204	0.182	6.677	0.083
4	0.021	-0.034	6.716	0.152
5	-0.011	-0.051	6.727	0.242

EUR_GBP Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.130	-0.130	1.533	0.216
2	-0.029	-0.047	1.612	0.447
3	-0.178	-0.192	4.570	0.206
4	0.154	0.107	6.803	0.147
5	0.011	0.029	6.814	0.235

EUR_GBP Other

Lag	AC	PAC	Q-Stat	Prob
1	0.037	0.037	0.122	0.727
2	-0.092	-0.093	0.894	0.640
3	-0.059	-0.053	1.220	0.748
4	-0.055	-0.060	1.503	0.826
5	0.253	0.251	7.603	0.180

EUR_GBP Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.021	-0.021	0.042	0.838
2	0.048	0.047	0.252	0.881
3	-0.070	-0.068	0.708	0.871
4	-0.036	-0.041	0.830	0.934
5	0.117	0.124	2.145	0.829

Appendix B11 – Autocorrelation in €/¥ Net Flows (10 Day)

EUR_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.079	-0.079	0.571	0.450
2	-0.075	-0.082	1.089	0.580
3	0.072	0.060	1.579	0.664
4	0.054	0.060	1.850	0.763
5	-0.013	0.006	1.867	0.867

EUR_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.037	0.037	0.125	0.724
2	-0.051	-0.052	0.364	0.834
3	-0.035	-0.032	0.481	0.923
4	-0.119	-0.120	1.814	0.770
5	-0.076	-0.072	2.363	0.797

EUR_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.079	0.079	0.567	0.451
2	-0.091	-0.098	1.335	0.513
3	0.006	0.022	1.338	0.720
4	0.184	0.176	4.533	0.339
5	-0.155	-0.192	6.822	0.234

EUR_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.005	-0.005	0.002	0.964
2	-0.299	-0.299	8.260	0.016
3	-0.043	-0.051	8.432	0.038
4	0.130	0.043	10.016	0.040
5	0.004	-0.022	10.018	0.075

EUR_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.044	-0.044	0.177	0.674
2	-0.164	-0.166	2.661	0.264
3	-0.042	-0.060	2.826	0.419
4	0.044	0.012	3.010	0.556
5	-0.068	-0.084	3.451	0.631

Appendix B11 – Autocorrelation in $/¥ Net Flows (10 Day)

USD_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.035	-0.035	0.114	0.736
2	0.053	0.051	0.369	0.832
3	-0.024	-0.020	0.422	0.936
4	-0.018	-0.022	0.451	0.978
5	-0.130	-0.129	2.055	0.841

USD_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.034	0.034	0.108	0.743
2	-0.043	-0.044	0.274	0.872
3	-0.145	-0.143	2.245	0.523
4	-0.091	-0.086	3.032	0.553
5	-0.084	-0.094	3.700	0.593

USD_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.000	0.000	0.000	0.999
2	-0.060	-0.060	0.335	0.846
3	-0.086	-0.086	1.027	0.795
4	0.037	0.033	1.153	0.886
5	0.085	0.076	1.848	0.870

USD_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.007	0.007	0.005	0.946
2	-0.296	-0.296	8.048	0.018
3	0.113	0.129	9.241	0.026
4	0.159	0.072	11.618	0.020
5	-0.033	0.032	11.723	0.039

USD_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.058	-0.058	0.309	0.578
2	-0.164	-0.168	2.794	0.247
3	-0.041	-0.064	2.952	0.399
4	-0.028	-0.066	3.026	0.554
5	0.080	0.057	3.638	0.603

Appendix B11 – Autocorrelation in £/$ Net Flows (10 Day)

GBP_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.185	-0.185	3.127	0.077
2	0.222	0.194	7.657	0.022
3	-0.028	0.044	7.731	0.052
4	0.049	0.009	7.957	0.093
5	0.161	0.179	10.437	0.064

GBP_USD Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.007	0.007	0.004	0.950
2	0.042	0.042	0.167	0.920
3	0.055	0.055	0.453	0.929
4	0.041	0.039	0.612	0.962
5	0.182	0.178	3.771	0.583

GBP_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.168	-0.168	2.581	0.108
2	-0.082	-0.113	3.198	0.202
3	-0.115	-0.156	4.433	0.218
4	0.087	0.027	5.151	0.272
5	-0.017	-0.025	5.179	0.394

GBP_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.053	-0.053	0.257	0.612
2	-0.148	-0.152	2.287	0.319
3	-0.021	-0.039	2.329	0.507
4	-0.081	-0.111	2.952	0.566
5	-0.033	-0.058	3.058	0.691

GBP_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.157	-0.157	2.254	0.133
2	-0.094	-0.122	3.072	0.215
3	-0.203	-0.248	6.904	0.075
4	0.057	-0.044	7.207	0.125
5	0.054	0.000	7.482	0.187

Appendix B11 – Autocorrelation in £/¥ Net Flows (10 Day)

GBP_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.001	0.001	0.000	0.994
2	0.142	0.142	1.848	0.397
3	0.086	0.087	2.536	0.469
4	-0.047	-0.068	2.746	0.601
5	0.003	-0.023	2.747	0.739

GBP_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.003	0.003	0.001	0.980
2	0.003	0.003	0.002	0.999
3	0.019	0.019	0.035	0.998
4	-0.038	-0.039	0.175	0.996
5	-0.044	-0.044	0.360	0.996

GBP_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.153	-0.153	2.139	0.144
2	-0.105	-0.131	3.148	0.207
3	0.059	0.022	3.478	0.324
4	0.023	0.024	3.526	0.474
5	-0.087	-0.073	4.253	0.514

GBP_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.001	0.001	0.000	0.994
2	0.069	0.069	0.442	0.802
3	-0.201	-0.203	4.225	0.238
4	0.158	0.164	6.583	0.160
5	-0.011	0.008	6.594	0.253

GBP_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.098	0.098	0.874	0.350
2	0.019	0.009	0.906	0.636
3	0.018	0.016	0.938	0.816
4	-0.012	-0.016	0.952	0.917
5	-0.067	-0.066	1.381	0.926

Appendix B12 – Autocorrelation in €/$ Net Flows (15 Day)

EUR_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.472	0.472	13.815	0.000
2	0.481	0.333	28.437	0.000
3	0.579	0.392	50.004	0.000
4	0.430	0.065	62.122	0.000
5	0.560	0.284	83.056	0.000

EUR_USD Uneveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.155	-0.155	1.485	0.223
2	-0.057	-0.083	1.693	0.429
3	-0.044	-0.069	1.817	0.611
4	0.029	0.006	1.874	0.759
5	-0.073	-0.078	2.228	0.817

EUR_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.175	-0.175	1.905	0.167
2	-0.123	-0.159	2.860	0.239
3	0.029	-0.025	2.914	0.405
4	-0.042	-0.064	3.030	0.553
5	0.103	0.088	3.732	0.589

EUR_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	0.534	0.534	17.684	0.000
2	0.510	0.314	34.076	0.000
3	0.414	0.093	45.087	0.000
4	0.396	0.101	55.347	0.000
5	0.311	-0.011	61.782	0.000

EUR_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	0.398	0.398	9.836	0.002
2	0.397	0.284	19.801	0.000
3	0.320	0.121	26.369	0.000
4	0.343	0.151	34.053	0.000
5	0.249	0.012	38.200	0.000

Appendix B12 – Autocorrelation in €/£ Net Flows (15 Day)

EUR_GBP Corporate

Lag	AC	PAC	Q-Stat	Prob
1	0.206	0.206	2.640	0.104
2	0.025	-0.018	2.679	0.262
3	0.170	0.176	4.532	0.209
4	0.266	0.210	9.174	0.057
5	0.142	0.063	10.526	0.062

EUR_GBP Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.081	-0.081	0.412	0.521
2	0.248	0.243	4.295	0.117
3	0.013	0.051	4.305	0.230
4	0.045	-0.012	4.435	0.350
5	-0.022	-0.038	4.468	0.484

EUR_GBP Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.201	-0.201	2.513	0.113
2	-0.187	-0.237	4.715	0.095
3	0.228	0.148	8.067	0.045
4	-0.308	-0.302	14.294	0.006
5	0.260	0.276	18.796	0.002

EUR_GBP Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.144	-0.144	1.285	0.257
2	-0.159	-0.183	2.878	0.237
3	0.206	0.161	5.597	0.133
4	-0.062	-0.038	5.852	0.211
5	-0.031	0.014	5.915	0.315

EUR_GBP Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.049	-0.049	0.149	0.700
2	-0.132	-0.135	1.251	0.535
3	0.062	0.049	1.502	0.682
4	0.082	0.072	1.940	0.747
5	0.135	0.162	3.159	0.676

Appendix B12 – Autocorrelation in €/¥ Net Flows (15 Day)

EUR_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.140	-0.140	1.219	0.270
2	0.109	0.091	1.971	0.373
3	-0.002	0.026	1.971	0.578
4	0.030	0.024	2.031	0.730
5	0.177	0.187	4.124	0.532

EUR_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.055	0.055	0.191	0.662
2	-0.140	-0.143	1.428	0.490
3	-0.197	-0.184	3.911	0.271
4	0.151	0.159	5.408	0.248
5	0.060	-0.008	5.648	0.342

EUR_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.167	0.167	1.733	0.188
2	-0.015	-0.044	1.746	0.418
3	-0.166	-0.161	3.524	0.318
4	-0.042	0.013	3.641	0.457
5	-0.013	-0.014	3.651	0.601

EUR_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.080	0.080	0.395	0.530
2	-0.345	-0.354	7.930	0.019
3	-0.079	-0.016	8.334	0.040
4	0.128	0.018	9.405	0.052
5	0.179	0.151	11.549	0.042

EUR_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.115	0.115	0.817	0.366
2	-0.253	-0.270	4.860	0.088
3	-0.191	-0.134	7.197	0.066
4	0.081	0.060	7.626	0.106
5	0.144	0.053	9.014	0.109

Appendix B12 – Autocorrelation in $/¥ Net Flows (15 Day)

USD_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.019	-0.019	0.023	0.879
2	0.061	0.061	0.261	0.878
3	-0.193	-0.192	2.656	0.448
4	0.059	0.053	2.883	0.578
5	-0.077	-0.057	3.284	0.656

USD_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.027	-0.027	0.045	0.833
2	-0.216	-0.217	2.994	0.224
3	-0.120	-0.140	3.922	0.270
4	-0.061	-0.129	4.164	0.384
5	0.224	0.168	7.515	0.185

USD_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.123	-0.123	0.946	0.331
2	0.023	0.008	0.979	0.613
3	0.051	0.056	1.147	0.766
4	-0.239	-0.230	4.875	0.300
5	0.012	-0.048	4.884	0.430

USD_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.175	-0.175	1.905	0.168
2	0.106	0.078	2.620	0.270
3	0.042	0.076	2.735	0.434
4	0.023	0.035	2.768	0.597
5	-0.136	-0.145	4.000	0.549

USD_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.156	-0.156	1.505	0.220
2	-0.100	-0.127	2.137	0.343
3	0.018	-0.020	2.159	0.540
4	0.005	-0.009	2.160	0.706
5	-0.029	-0.031	2.218	0.818

Appendix B12 – Autocorrelation in £/$ Net Flows (15 Day)

GBP_USD Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.045	-0.045	0.125	0.723
2	0.037	0.035	0.214	0.899
3	0.273	0.277	4.998	0.172
4	0.098	0.133	5.621	0.229
5	0.038	0.034	5.717	0.335

GBP_USD Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.046	0.046	0.133	0.715
2	-0.088	-0.091	0.625	0.732
3	0.303	0.315	6.537	0.088
4	0.170	0.137	8.422	0.077
5	0.024	0.075	8.459	0.133

GBP_USD Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.252	-0.252	3.956	0.047
2	-0.239	-0.323	7.564	0.023
3	0.259	0.117	11.887	0.008
4	-0.259	-0.266	16.265	0.003
5	0.032	-0.003	16.331	0.006

GBP_USD Other

Lag	AC	PAC	Q-Stat	Prob
1	-0.170	-0.170	1.788	0.181
2	-0.067	-0.098	2.069	0.355
3	-0.039	-0.071	2.165	0.539
4	0.091	0.067	2.702	0.609
5	-0.105	-0.089	3.440	0.633

GBP_USD Total

Lag	AC	PAC	Q-Stat	Prob
1	-0.268	-0.268	4.454	0.035
2	-0.256	-0.353	8.592	0.014
3	0.211	0.029	11.458	0.009
4	-0.042	-0.059	11.576	0.021
5	-0.046	0.003	11.716	0.039

Appendix B12 – Autocorrelation in £/¥ Net Flows (15 Day)

GBP_JPY Corporate

Lag	AC	PAC	Q-Stat	Prob
1	-0.003	-0.003	0.001	0.981
2	0.085	0.085	0.456	0.796
3	-0.049	-0.048	0.607	0.895
4	0.047	0.040	0.749	0.945
5	0.102	0.111	1.443	0.920

GBP_JPY Unleveraged

Lag	AC	PAC	Q-Stat	Prob
1	0.028	0.028	0.048	0.826
2	-0.008	-0.009	0.053	0.974
3	-0.009	-0.008	0.057	0.996
4	-0.080	-0.079	0.473	0.976
5	-0.078	-0.074	0.881	0.972

GBP_JPY Leveraged

Lag	AC	PAC	Q-Stat	Prob
1	-0.212	-0.212	2.791	0.095
2	0.046	0.001	2.923	0.232
3	-0.058	-0.050	3.138	0.371
4	-0.113	-0.142	3.976	0.409
5	-0.093	-0.155	4.548	0.474

GBP_JPY Other

Lag	AC	PAC	Q-Stat	Prob
1	0.050	0.050	0.156	0.693
2	-0.117	-0.120	1.017	0.601
3	0.103	0.117	1.698	0.637
4	0.021	-0.007	1.729	0.786
5	0.137	0.168	2.976	0.704

GBP_JPY Total

Lag	AC	PAC	Q-Stat	Prob
1	0.083	0.083	0.425	0.515
2	0.017	0.010	0.443	0.801
3	-0.055	-0.058	0.638	0.888
4	0.032	0.042	0.707	0.951
5	0.137	0.134	1.952	0.856

Appendix B13
Cross-Correlations Between 4 Customer Categories (Daily)

Dollar_Yen (Daily)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.033585	0.020028	-0.0743
Levered	0.033585	1	0.066389	0.021141
Unlevered	0.020028	0.066389	1	0.021033
Other	-0.0743	0.021141	0.021033	1

Euro_Dollar (Daily)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.02134	0.033697	-0.082674
Levered	0.02134	1	0.05337	-0.079518
Unlevered	0.033697	0.05337	1	-0.010979
Other	-0.082674	-0.079518	-0.010979	1

Euro_Pound (Daily)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.028636	0.098613	-0.058633
Levered	-0.028636	1	0.008186	-0.091329
Unlevered	0.098613	0.008186	1	-0.00942
Other	-0.058633	-0.091329	-0.00942	1

Euro_Yen (Daily)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.007074	0.014434	-0.075561
Levered	-0.007074	1	0.0314	-0.038692
Unlevered	0.014434	0.0314	1	0.02402
Other	-0.075561	-0.038692	0.02402	1

Pound_Dollar (Daily)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.069612	0.040434	-0.114984
Levered	0.069612	1	0.110491	-0.043684
Unlevered	0.040434	0.110491	1	-0.017094
Other	-0.114984	-0.043684	-0.017094	1

Pound_Yen (Daily)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.03427	0.000153	-0.012303
Levered	0.03427	1	0.017379	-0.152988
Unlevered	0.000153	0.017379	1	-0.427347
Other	-0.012303	-0.152988	-0.427347	1

Appendix B14
Cross-Correlations Between 4 Customer Categories (5 Day)

Dollar_Yen (5 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.010279	-0.001814	-0.111217
Levered	0.010279	1	0.221851	0.150471
Unlevered	-0.001814	0.221851	1	0.143993
Other	-0.111217	0.150471	0.143993	1

Euro_Dollar (5 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.042669	-0.027943	-0.197889
Levered	0.042669	1	0.02141	0.077438
Unlevered	-0.027943	0.02141	1	-0.073463
Other	-0.197889	0.077438	-0.073463	1

Euro_Pound (5 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.102523	0.109487	-0.134165
Levered	0.102523	1	0.012074	-0.087151
Unlevered	0.109487	0.012074	1	0.06096
Other	-0.134165	-0.087151	0.06096	1

Euro_Yen (5 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.024491	0.053371	-0.1529
Levered	-0.024491	1	-0.086074	-0.000569
Unlevered	0.053371	-0.086074	1	0.064322
Other	-0.1529	-0.000569	0.064322	1

Pound_Dollar (5 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.105264	-0.140078	-0.159006
Levered	-0.105264	1	0.036503	-0.146528
Unlevered	-0.140078	0.036503	1	0.108266
Other	-0.159006	-0.146528	0.108266	1

Pound_Yen (5 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.037337	-0.020547	0.026934
Levered	0.037337	1	0.007774	-0.147294
Unlevered	-0.020547	0.007774	1	-0.418954
Other	0.026934	-0.147294	-0.418954	1

Appendix B15
Cross-Correlations Between 4 Customer Categories (10 Day)

Dollar_Yen (10 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.027605	-0.136331	-0.077476
Levered	0.027605	1	0.29414	0.020784
Unlevered	-0.136331	0.29414	1	0.253408
Other	-0.077476	0.020784	0.253408	1

Euro_Dollar (10 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.028045	-0.112162	-0.231912
Levered	0.028045	1	-0.038225	0.100619
Unlevered	-0.112162	-0.038225	1	-0.056101
Other	-0.231912	0.100619	-0.056101	1

Euro_Pound (10 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.125922	0.183356	-0.071621
Levered	0.125922	1	0.098155	-0.196348
Unlevered	0.183356	0.098155	1	0.119198
Other	-0.071621	-0.196348	0.119198	1

Euro_Yen (10 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.105018	0.086616	-0.169649
Levered	0.105018	1	-0.030458	-0.087779
Unlevered	0.086616	-0.030458	1	0.155145
Other	-0.169649	-0.087779	0.155145	1

Pound_Dollar (10 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.045202	-0.158873	-0.041328
Levered	-0.045202	1	0.010385	-0.18982
Unlevered	-0.158873	0.010385	1	0.102423
Other	-0.041328	-0.18982	0.102423	1

Pound_Yen (10 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.000745	0.081772	-0.056699
Levered	-0.000745	1	-0.002309	-0.143041
Unlevered	0.081772	-0.002309	1	-0.450744
Other	-0.056699	-0.143041	-0.450744	1

Appendix B16
Cross-Correlations Between 4 Customer Categories (15 Day)

Dollar_Yen (15 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.031434	0.025319	-0.09772
Levered	0.031434	1	0.40654	0.022025
Unlevered	0.025319	0.40654	1	0.154561
Other	-0.09772	0.022025	0.154561	1

Euro_Dollar (15 day)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.048492	-0.094127	-0.254723
Levered	-0.048492	1	-0.003468	-0.001756
Unlevered	-0.094127	-0.003468	1	0.053063
Other	-0.254723	-0.001756	0.053063	1

Euro_Pound (15 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.184829	0.16561	-0.143138
Levered	0.184829	1	0.060902	-0.197671
Unlevered	0.16561	0.060902	1	0.097542
Other	-0.143138	-0.197671	0.097542	1

Euro_Yen (15 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.185824	-0.081088	-0.096458
Levered	0.185824	1	-0.01106	-0.128464
Unlevered	-0.081088	-0.01106	1	0.146499
Other	-0.096458	-0.128464	0.146499	1

Pound_Dollar (15 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	-0.274567	-0.308773	-0.006546
Levered	-0.274567	1	0.204488	-0.101551
Unlevered	-0.308773	0.204488	1	0.192748
Other	-0.006546	-0.101551	0.192748	1

Pound_Yen (15 Day)

	Corporate	Levered	Unlevered	Other
Corporate	1	0.048366	0.014717	0.066424
Levered	0.048366	1	0.044816	-0.186837
Unlevered	0.014717	0.044816	1	-0.498955
Other	0.066424	-0.186837	-0.498955	1

Appendix C – Contemporaneous OLS

Contemporaneous OLS with Aggregated Flows

	Coefficient	p-value	R-Squared
DAILY:			
Euro_USD	0.1100	0.2010	0.0020
Euro_JPY	**1.4280**	0.0000	0.0710
Euro_GBP	**0.2180**	0.0470	0.0050
GBP_USD	**0.4210**	0.0080	0.0110
USD_JPY	**0.5050**	0.0000	0.0350
GBP_JPY	**1.6620**	0.0360	0.0100
5 DAY			
Euro_USD	0.2500	0.1110	0.0130
Euro_JPY	**1.9630**	0.0000	0.1760
Euro_GBP	0.1630	0.4050	0.0040
GBP_USD	-0.0560	0.8670	0.0000
USD_JPY	**0.7070**	0.0000	0.0740
GBP_JPY	0.7780	0.4680	0.0020
10 DAY			
Euro_USD	0.2330	0.3020	0.0140
Euro_JPY	**1.9760**	0.0000	0.1350
Euro_GBP	-0.0410	0.8550	0.0000
GBP_USD	0.4240	0.3190	0.0090
USD_JPY	**1.1440**	0.0000	0.2080
GBP_JPY	2.1750	0.2390	0.0140
15 DAY			
Euro_USD	-0.0500	0.8450	0.0010
Euro_JPY	**1.7360**	0.0000	0.1640
Euro_GBP	-0.1110	0.6670	0.0030
GBP_USD	0.6850	0.2900	0.0240
USD_JPY	**1.0240**	0.0000	0.2060
GBP_JPY	-1.8200	0.4390	0.0160

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t + \varepsilon_t$

where: ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Appendix C2 – Contemporaneous OLS with Disaggregated Flows

Contemporaneous OLS - Disaggregated Order Flow €/$

	Corporate	Unlevered	Levered	Other	R-Squared
Daily:					
Coefficient	***-0.3680***	**0.9860**	**1.1200**	-0.0580	0.0520
p-value	0.0630	0.0050	0.0000	0.5540	
5 DAY:					
Coefficient	**-1.5770**	**1.1350**	0.6940	-0.0320	0.1280
p-value	0.0360	0.0440	0.1320	0.9480	
10 DAY:					
Coefficient	0.0990	**1.5640**	**2.0270**	-0.0580	0.1200
p-value	0.8060	0.0170	0.0060	0.8110	
15 DAY:					
Coefficient	0.4030	1.3440	1.1410	-0.3890	0.1030
p-value	0.4560	0.1930	0.2210	0.1220	

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Contemporaneous OLS - Disaggregated Order Flow €/¥					
	Corporate	**Unlevered**	**Levered**	**Other**	**R-Squared**
Daily:					
Coefficient	-0.1870	**3.9220**	0.0000	**1.5340**	0.0910
p-value	0.7130	0.0000	0.1420	0.0000	
5 DAY:					
Coefficient	-0.5530	3.2335	1.7207	**2.0491**	0.2045
p-value	0.6800	0.1992	0.2621	0.0000	
10 DAY:					
Coefficient	-0.2893	5.5951	-0.1640	**1.9427**	0.1728
p-value	0.8677	0.1491	0.9573	0.0000	
15 DAY:					
Coefficient	2.0407	**5.6433**	-3.4449	**1.5410**	0.2384
p-value	0.2181	0.0351	0.2149	0.0004	

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Contemporaneous OLS - Disaggregated Order Flow €/£					
	Corporate	**Unlevered**	**Levered**	**Other**	**R-Squared**
Daily:					
Coefficient	**-0.4680**	0.3410	**1.0660**	**0.3440**	0.0300
p-value	0.0510	0.5450	0.0000	0.0080	
5 DAY:					
Coefficient	**-0.7868**	-0.5126	**1.4836**	0.3697	0.0629
p-value	0.0094	0.6253	0.0187	0.1779	
10 DAY:					
Coefficient	-0.5857	-2.0005	0.9872	0.4805	0.0709
p-value	0.1196	0.1801	0.1749	0.1670	
15 DAY:					
Coefficient	-0.5985	-0.9312	0.3727	0.1742	0.0437
p-value	0.1016	0.3442	0.4433	0.6666	

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Contemporaneous OLS - Disaggregated Order Flow £/$					
	Corporate	**Unlevered**	**Levered**	**Other**	**R-Squared**
Daily:					
Coefficient	-0.2710	**1.5110**	**2.3110**	0.0300	0.0570
p-value	0.3800	0.0030	0.0000	0.8790	
5 DAY:					
Coefficient	-1.0672	**2.8304**	1.5243	-0.4576	0.0900
p-value	0.1754	0.0034	0.1731	0.2854	
10 DAY:					
Coefficient	-0.5278	***2.4076***	**3.2394**	0.1968	0.1048
p-value	0.6297	0.0546	0.0352	0.7716	
15 DAY:					
Coefficient	-0.2690	**4.3163**	**3.0245**	-0.0598	0.2069
p-value	0.8147	0.0314	0.0335	0.9445	

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Contemporaneous OLS - Disaggregated Order Flow $/¥					
	Corporate	**Unlevered**	**Levered**	**Other**	**R-Squared**
Daily:					
Coefficient	**-0.7280**	**1.5850**	**0.6550**	**0.5420**	0.0700
p-value	0.0120	0.0000	0.0420	0.0000	
5 DAY:					
Coefficient	-1.0272	**3.1299**	0.5296	**0.5313**	0.1721
p-value	0.1353	0.0000	0.3900	0.0160	
10 DAY:					
Coefficient	-0.2613	**3.3253**	1.2013	**0.8622**	0.3042
p-value	0.7685	0.0001	0.1897	0.0019	
15 DAY:					
Coefficient	0.9623	**3.1281**	-0.3358	**0.7385**	0.2727
p-value	0.1790	0.0053	0.7508	0.0443	

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Contemporaneous OLS - Disaggregated Order Flow £/¥					
	Corporate	**Unlevered**	**Levered**	**Other**	**R-Squared**
Daily:					
Coefficient	**-2.0800**	**2.3940**	2.0920	**2.7570**	0.0240
p-value	0.0180	0.0230	0.3330	0.0000	
5 DAY:					
Coefficient	-0.2496	**4.4221**	6.2217	0.2226	0.0327
p-value	0.9122	0.0049	0.2372	0.8385	
10 DAY:					
Coefficient	0.0253	**7.7364**	12.8427	1.5063	0.0777
p-value	0.9946	0.0021	0.1579	0.4282	
15 DAY:					
Coefficient	-3.3089	4.0835	9.1690	-2.1474	0.1154
p-value	0.6520	0.2212	0.2241	0.3765	

Regression specification: $\Delta S_t = \beta_0 + \beta_1 x_t^{Corp} + \beta_2 x_t^{Unlev} + \beta_3 x_t^{Lev} + \beta_4 x_t^{Other} + \varepsilon_t$

ΔS_t : *change* in log spot FX rate

x_t : total net customer order flow

Appendix D – Micro 1 and 2 Forecast Evaluation

RMSE ratio & Directional Ability

Micro 1 Model Forecast Evaluation

Currency: €/$

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.004	1.048	1.037	1.092
2	1.007	1.042	1.042	1.032
3	1.010	1.008	1.047	1.090
4	1.014	1.014	1.053	**0.998**
5	1.017	1.016	1.052	**0.983**
6	-	1.027	1.095	**0.997**
7	-	1.047	1.121	**0.989**
8	-	1.030	1.067	**0.999**
9	-	1.033	1.059	**0.991**
10	-	1.043	1.083	1.020
11	-	-	1.082	**0.998**
12	-	-	1.137	1.024
13	-	-	1.149	1.020
14	-	-	1.196	1.063
15	-	-	1.189	1.127
16	-	-	-	1.121
17	-	-	-	1.145
18	-	-	-	1.122
19	-	-	-	1.085
20	-	-	-	1.074

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Appendix D cont/d

Micro 2 Model Forecast Evaluation

Currency: €/$

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.008	1.205	1.041	1.202
2	1.005	1.048	1.045	1.272
3	1.004	1.007	**0.989**	1.255
4	1.016	1.033	1.013	1.349
5	1.015	1.079	**0.999**	1.408
6	-	1.137	1.030	1.199
7	-	1.190	1.104	1.115
8	-	1.134	1.048	1.028
9	-	1.177	1.128	1.019
10	-	1.150	1.139	1.037
11	-	-	1.167	1.113
12	-	-	1.167	1.113
13	-	-	1.216	1.354
14	-	-	1.331	1.287
15	-	-	1.290	1.373
16	-	-	-	1.224
17	-	-	-	1.141
18	-	-	-	1.174
19	-	-	-	1.150
20	-	-	-	1.140

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Appendix D cont/d

Micro 1 Model Directional Ability

Currency: €/$

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	50.00	38.67	**56.25**	47.06
2	48.17	41.33	43.75	**52.94**
3	47.91	**53.33**	50.00	47.06
4	47.12	48.00	50.00	**58.82**
5	48.95	**52.00**	50.00	**70.59**
6	**-**	**52.00**	50.00	**64.71**
7	**-**	**53.33**	**56.25**	**64.71**
8	**-**	**50.67**	46.88	47.06
9	**-**	49.33	50.00	47.06
10	**-**	**52.00**	40.63	41.18
11	-	-	46.88	**58.82**
12	-	-	46.88	**70.59**
13	-	-	40.63	**58.82**
14	-	-	43.75	47.06
15	-	-	40.63	47.06
16	-	-	-	**52.94**
17	-	-	-	**58.82**
18	-	-	-	41.18
19	-	-	-	**52.94**
20	-	-	-	47.06

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - on the basis of directional ability. i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 2 Model Directional Ability				
Currency: €/$				
History Used:				
	1	**5**	**10**	**15**
Forecast Horizon:				
1	49.87	44.59	**56.25**	43.75
2	**51.31**	40.54	**62.50**	50.00
3	50.00	**55.41**	40.63	37.50
4	47.64	48.65	50.00	50.00
5	50.00	47.30	46.88	**56.25**
6	-	45.95	43.75	50.00
7	-	**52.70**	43.75	50.00
8	-	43.24	34.38	**56.25**
9	-	50.00	46.88	**56.25**
10	-	**51.35**	40.63	50.00
11	-	-	**53.13**	**62.50**
12	-	-	46.88	**56.25**
13	-	-	37.50	50.00
14	-	-	37.50	50.00
15	-	-	37.50	43.75
16	-	-	-	50.00
17	-	-	-	**56.25**
18	-	-	-	43.75
19	-	-	-	43.75
20	-	-	-	**62.50**

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - on the basis of directional ability i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 1 Model Forecast Evaluation

Currency: €/£

History Used:	1	5	10	15
Forecast Horizon:				
1	1.002	1.002	1.163	1.009
2	1.006	1.002	**0.997**	**0.951**
3	1.005	1.000	1.007	1.007
4	1.006	**0.992**	1.04	1.031
5	1.005	1.009	1.115	1.155
6	-	1.037	1.141	1.223
7	-	1.026	1.186	1.193
8	-	1.029	1.162	1.090
9	-	1.062	1.198	1.088
10	-	1.046	1.141	1.099
11	-	-	1.154	1.100
12	-	-	1.107	1.070
13	-	-	1.114	1.114
14	-	-	1.092	1.170
15	-	-	1.094	1.134
16	-	-	-	1.134
17	-	-	-	1.042
18	-	-	-	1.049
19	-	-	-	1.039
20	-	-	-	1.039

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Appendix D cont/d

Micro 2 Model Forecast Evaluation

Currency: €/£

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.002	1.008	1.211	1.310
2	**0.997**	1.038	1.070	1.207
3	**0.993**	1.181	1.095	1.171
4	1.006	1.095	1.231	1.460
5	1.018	1.056	1.244	1.556
6	-	1.008	1.276	1.639
7	-	**0.999**	1.246	1.595
8	-	1.011	1.191	1.496
9	-	1.035	1.221	1.433
10	-	1.013	1.169	1.410
11	-	-	1.164	1.307
12	-	-	1.106	1.171
13	-	-	1.100	1.149
14	-	-	1.098	1.213
15	-	-	1.094	1.224
16	-	-	-	1.169
17	-	-	-	1.081
18	-	-	-	1.060
19	-	-	-	1.031
20	-	-	-	1.025

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Appendix D cont/d

Micro 1 Model Directional Ability

Currency: €/£

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	48.44	**50.67**	37.50	47.06
2	**52.08**	**52.00**	**53.13**	**58.82**
3	**50.52**	**50.67**	**53.13**	35.29
4	**50.13**	**50.67**	46.88	41.18
5	**53.68**	45.33	37.50	29.41
6	-	48.00	34.38	17.65
7	-	**50.67**	37.50	35.29
8	-	**52.00**	40.63	29.41
9	-	38.67	40.63	35.29
10	-	40.00	34.38	29.41
11	-	-	34.38	29.41
12	-	-	40.63	35.29
13	-	-	40.63	35.29
14	-	-	40.63	29.41
15	-	-	40.63	29.41
16	-	-	-	47.06
17	-	-	-	47.06
18	-	-	-	47.06
19	-	-	-	**58.82**
20	-	-	-	**58.82**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - on the basis of directional ability. i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 2 Model Directional Ability

Currency: €/£

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	48.96	47.30	34.38	37.50
2	**51.96**	**54.05**	43.75	37.50
3	**51.05**	50.00	46.88	31.25
4	48.29	**51.35**	40.63	43.75
5	**53.42**	47.30	43.75	31.25
6	-	44.59	34.38	12.50
7	-	50.00	37.50	31.25
8	-	**52.70**	28.13	25.00
9	-	44.59	40.63	31.25
10	-	**54.05**	34.38	31.25
11	-	-	40.63	18.75
12	-	-	40.63	31.25
13	-	-	46.88	50.00
14	-	-	43.75	31.25
15	-	-	**71.88**	37.50
16	-	-	-	43.75
17	-	-	-	43.75
18	-	-	-	43.75
19	-	-	-	**62.50**
20	-	-	-	50.00

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - on the basis of directional ability i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 1 Model Forecast Evaluation

Currency: £/¥

History Used:	1	5	10	15
Forecast Horizon:				
1	1.004	1.048	1.037	1.092
2	1.007	1.042	1.042	1.032
3	1.010	1.008	1.047	1.090
4	1.014	1.014	1.053	**0.998**
5	1.017	1.016	1.052	**0.983**
6	-	1.027	1.095	**0.997**
7	-	1.047	1.121	**0.989**
8	-	1.030	1.067	**0.999**
9	-	1.033	1.059	**0.991**
10	-	1.043	1.083	1.020
11	-	-	1.082	**0.998**
12	-	-	1.137	1.024
13	-	-	1.149	1.020
14	-	-	1.196	1.063
15	-	-	1.189	1.127
16	-	-	-	1.121
17	-	-	-	1.145
18	-	-	-	1.122
19	-	-	-	1.085
20	-	-	-	1.074

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Micro 2 Model Forecast Evaluation

Currency: £/¥

History Used:	1	5	10	15
Forecast Horizon:				
1	1.008	1.205	1.041	1.202
2	1.005	1.048	1.045	1.272
3	1.004	1.007	**0.989**	1.255
4	1.016	1.033	1.013	1.349
5	1.015	1.079	**0.999**	1.408
6	-	1.137	1.030	1.199
7	-	1.190	1.104	1.115
8	-	1.134	1.048	1.028
9	-	1.177	1.128	1.019
10	-	1.150	1.139	1.037
11	-	-	1.167	1.113
12	-	-	1.167	1.113
13	-	-	1.216	1.354
14	-	-	1.331	1.287
15	-	-	1.290	1.373
16	-	-	-	1.224
17	-	-	-	1.141
18	-	-	-	1.174
19	-	-	-	1.150
20	-	-	-	1.140

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Appendix D cont/d

Micro 1 Model Directional Ability

Currency: £/¥

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	50.00	38.67	**56.25**	47.06
2	48.17	41.33	43.75	**52.94**
3	47.91	**53.33**	50.00	47.06
4	47.12	48.00	50.00	**58.82**
5	48.95	**52.00**	50.00	**70.59**
6	**-**	**52.00**	50.00	**64.71**
7	**-**	**53.33**	**56.25**	**64.71**
8	**-**	**50.67**	46.88	47.06
9	**-**	49.33	50.00	47.06
10	**-**	**52.00**	40.63	41.18
11	-	-	46.88	**58.82**
12	-	-	46.88	**70.59**
13	-	-	40.63	**58.82**
14	-	-	43.75	47.06
15	-	-	40.63	47.06
16	-	-	-	**52.94**
17	-	-	-	**58.82**
18	-	-	-	41.18
19	-	-	-	**52.94**
20	-	-	-	47.06

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - on the basis of directional ability. i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 2 Model Directional Ability				
Currency: £/¥				
History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	49.87	44.59	**56.25**	43.75
2	**51.31**	40.54	**62.50**	50.00
3	50.00	**55.41**	40.63	37.50
4	47.64	48.65	50.00	50.00
5	50.00	47.30	46.88	**56.25**
6	-	45.95	43.75	50.00
7	-	**52.70**	43.75	50.00
8	-	43.24	34.38	**56.25**
9	-	50.00	46.88	**56.25**
10	-	**51.35**	40.63	50.00
11	-	-	**53.13**	**62.50**
12	-	-	46.88	**56.25**
13	-	-	37.50	50.00
14	-	-	37.50	50.00
15	-	-	37.50	43.75
16	-	-	-	50.00
17	-	-	-	**56.25**
18	-	-	-	43.75
19	-	-	-	43.75
20	-	-	-	**62.50**

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - on the basis of directional ability i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 1 Model Forecast Evaluation

Currency: $/¥

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.004	1.017	**0.940**	**0.941**
2	1.001	1.041	1.014	**0.921**
3	1.006	1.063	1.094	1.017
4	1.006	1.041	1.008	1.063
5	1.008	1.020	1.033	1.069
6	-	1.017	**0.989**	1.070
7	-	1.019	**0.989**	1.107
8	-	1.033	**0.994**	1.046
9	-	1.021	1.009	1.055
10	-	1.027	1.029	1.052
11	-	-	1.035	1.015
12	-	-	1.039	1.023
13	-	-	1.090	1.040
14	-	-	1.077	1.018
15	-	-	1.086	1.024
16	-	-	-	**0.980**
17	-	-	-	**0.962**
18	-	-	-	1.013
19	-	-	-	1.032
20	-	-	-	**0.984**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Appendix D cont/d

Micro 2 Model Forecast Evaluation

Currency: $/¥

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.005	1.096	**0.836**	1.163
2	1.003	1.091	1.040	1.221
3	1.005	1.166	1.171	1.390
4	1.004	1.133	1.020	1.245
5	1.012	1.080	1.130	1.212
6	-	1.072	**0.965**	1.314
7	-	1.056	**0.961**	1.278
8	-	1.059	**0.973**	1.115
9	-	1.071	1.010	1.340
10	-	1.139	1.075	1.299
11	-	-	1.081	1.225
12	-	-	1.077	1.186
13	-	-	1.145	1.218
14	-	-	1.118	1.188
15	-	-	1.109	1.240
16	-	-	-	1.225
17	-	-	-	1.127
18	-	-	-	1.118
19	-	-	-	1.092
20	-	-	-	1.048

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Appendix D cont/d

Micro 1 Model Directional Ability

Currency: $/¥

History Used:	1	5	10	15
Forecast Horizon:				
1	47.14	48.00	**53.13**	**52.94**
2	48.18	49.33	50.00	**58.82**
3	47.66	**54.67**	43.75	35.29
4	44.79	**53.33**	43.75	**58.82**
5	45.05	**50.67**	43.75	**64.71**
6	-	48.00	43.75	47.06
7	-	41.33	50.00	**58.82**
8	-	45.33	43.75	**52.94**
9	-	**50.67**	**53.13**	**52.94**
10	-	45.33	43.75	**52.94**
11	-	-	43.75	**52.94**
12	-	-	43.75	**52.94**
13	-	-	34.38	47.06
14	-	-	37.50	**52.94**
15	-	-	28.13	41.18
16	-	-	-	47.06
17	-	-	-	**52.94**
18	-	-	-	**52.94**
19	-	-	-	**52.94**
20	-	-	-	**58.82**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - on the basis of directional ability. i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 2 Model Directional Ability

Currency: $/¥

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	49.22	44.59	**62.50**	**68.75**
2	45.83	**54.05**	**53.13**	50.00
3	44.27	47.30	**53.13**	37.50
4	**52.86**	**56.76**	**56.25**	25.00
5	**52.34**	48.65	**53.13**	31.25
6	-	48.65	**59.38**	31.25
7	-	48.65	**59.38**	43.75
8	-	47.30	**62.50**	37.50
9	-	**51.35**	**59.38**	25.00
10	-	**52.70**	**62.50**	31.25
11	-	-	**56.25**	43.75
12	-	-	**56.25**	50.00
13	-	-	43.75	43.75
14	-	-	**53.13**	50.00
15	-	-	**53.13**	37.50
16	-	-	-	37.50
17	-	-	-	50.00
18	-	-	-	50.00
19	-	-	-	31.25
20	-	-	-	50.00

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - on the basis of directional ability i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 1 Model Forecast Evaluation

Currency: €/¥

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.005	**0.989**	1.084	**0.995**
2	1.001	**0.999**	1.010	1.049
3	**0.999**	1.111	1.018	1.041
4	1.002	1.099	1.086	1.029
5	1.001	**0.998**	1.014	1.111
6	-	1.003	1.005	1.011
7	-	1.014	1.002	1.074
8	-	1.037	**0.992**	1.162
9	-	1.028	**0.991**	1.182
10	-	1.046	1.108	1.220
11	-	-	1.028	1.159
12	-	-	1.033	1.142
13	-	-	1.068	1.082
14	-	-	1.073	1.050
15	-	-	1.056	**0.994**
16	-	-	-	**0.988**
17	-	-	-	1.027
18	-	-	-	1.014
19	-	-	-	**0.956**
20	-	-	-	**0.947**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Appendix D cont/d

Micro 2 Model Forecast Evaluation

Currency: €/¥

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.015	1.010	1.419	1.089
2	1.010	1.010	1.231	1.107
3	1.042	1.129	1.144	1.188
4	1.049	1.129	1.063	1.005
5	1.029	1.020	1.111	1.153
6	-	1.023	1.177	1.330
7	-	1.012	1.186	1.290
8	-	1.025	1.069	1.243
9	-	1.039	1.044	1.165
10	-	1.067	1.180	1.213
11	-	-	1.104	1.125
12	-	-	1.072	1.100
13	-	-	1.044	1.073
14	-	-	1.040	1.028
15	-	-	1.039	**0.980**
16	-	-	-	**0.994**
17	-	-	-	1.099
18	-	-	-	1.069
19	-	-	-	**0.974**
20	-	-	-	**0.980**

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Appendix D cont/d

Micro 1 Model Directional Ability

Currency: €/¥

History Used:	1	5	10	15
Forecast Horizon:				
1	**53.03**	**56.76**	29.03	**52.94**
2	**55.94**	**56.76**	**51.61**	**52.94**
3	**58.58**	47.30	48.39	47.06
4	**58.58**	50.00	**51.61**	35.29
5	**59.37**	**62.16**	**64.52**	**58.82**
6	-	**62.16**	**58.06**	**52.94**
7	-	**52.70**	**54.84**	**52.94**
8	-	50.00	**54.84**	47.06
9	-	**59.46**	**58.06**	**52.94**
10	-	**58.11**	45.16	**52.94**
11	-	-	**58.06**	**64.71**
12	-	-	**54.84**	**58.82**
13	-	-	**54.84**	**70.59**
14	-	-	45.16	**64.71**
15	-	-	48.39	**58.82**
16	-	-	-	**58.82**
17	-	-	-	**64.71**
18	-	-	-	**58.82**
19	-	-	-	**64.71**
20	-	-	-	**64.71**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - on the basis of directional ability. i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 2 Model Directional Ability

Currency: €/¥

History Used:	1	5	10	15
Forecast Horizon:				
1	**52.11**	**56.76**	25.81	47.06
2	**52.24**	**55.41**	32.26	**64.71**
3	**56.73**	**51.35**	38.71	**52.94**
4	**52.51**	50.00	**51.61**	**52.94**
5	**55.41**	50.00	48.39	**64.71**
6	**-**	**60.81**	41.94	**58.82**
7	**-**	**54.05**	29.03	**58.82**
8	**-**	**59.46**	**51.61**	41.18
9	**-**	**56.76**	**54.84**	**52.94**
10	**-**	**54.05**	**51.61**	**52.94**
11	**-**	**-**	45.16	**64.71**
12	**-**	**-**	**51.61**	**52.94**
13	**-**	**-**	**51.61**	**64.71**
14	**-**	**-**	41.94	**58.82**
15	**-**	**-**	45.16	**58.82**
16	**-**	**-**	**-**	**58.82**
17	**-**	**-**	**-**	**64.71**
18	**-**	**-**	**-**	**58.82**
19	**-**	**-**	**-**	**64.71**
20	**-**	**-**	**-**	**62.50**

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - on the basis of directional ability i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

Micro 1 Model Forecast Evaluation

Currency: £/$

History Used:	1	5	10	15
Forecast Horizon:				
1	1.930	**0.996**	1.014	1.014
2	1.376	**0.997**	1.024	1.037
3	1.110	**0.991**	1.022	1.009
4	**0.953**	**0.997**	1.036	1.003
5	**0.849**	1.028	1.083	1.079
6	-	1.029	1.076	1.057
7	-	1.016	1.038	1.095
8	-	1.012	1.036	1.046
9	-	1.022	1.028	1.026
10	-	1.047	1.044	1.027
11	-	-	1.073	1.028
12	-	-	1.090	1.005
13	-	-	1.089	**0.971**
14	-	-	1.069	**0.974**
15	-	-	1.080	**0.991**
16	-	-	-	**0.988**
17	-	-	-	**0.979**
18	-	-	-	**0.983**
19	-	-	-	**0.951**
20	-	-	-	**0.944**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the random walk.

Appendix D cont/d

Micro 2 Model Forecast Evaluation

Currency: £/$

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	1.931	1.011	1.015	1.157
2	1.371	1.014	**0.994**	1.176
3	1.108	1.009	1.088	1.007
4	**0.950**	1.030	1.057	**0.976**
5	**0.848**	1.079	1.102	**0.995**
6	-	1.041	1.143	**0.988**
7	-	1.022	1.093	1.052
8	-	1.013	1.039	1.005
9	-	1.016	1.017	**0.979**
10	-	1.049	1.028	1.029
11	-	-	1.053	1.015
12	-	-	1.075	1.010
13	-	-	1.128	**0.995**
14	-	-	1.097	**0.978**
15	-	-	1.106	1.036
16	-	-	-	**0.972**
17	-	-	-	**0.959**
18	-	-	-	**0.938**
19	-	-	-	**0.911**
20	-	-	-	**0.921**

This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - using the RMSE ratio of the model to that of the random walk. A number below 1 (shown in bold) would indicate the that model outperformed the RW.

Appendix D cont/d

Micro 1 Model Directional Ability

Currency: £/$

History Used:	1	5	10	15
Forecast Horizon:				
1	**51.57**	49.33	50.00	**58.82**
2	48.69	**52.00**	34.38	**52.94**
3	50.79	**62.67**	50.00	**58.82**
4	50.00	49.33	43.75	**52.94**
5	50.79	49.33	40.63	47.06
6	-	49.33	37.50	41.18
7	-	45.33	37.50	23.53
8	-	**53.33**	46.88	47.06
9	-	**52.00**	50.00	41.18
10	-	50.67	50.00	47.06
11	-	-	**53.13**	**52.94**
12	-	-	43.75	**52.94**
13	-	-	46.88	**70.59**
14	-	-	43.75	**70.59**
15	-	-	50.00	**58.82**
16	-	-	-	47.06
17	-	-	-	**58.82**
18	-	-	-	47.06
19	-	-	-	**52.94**
20	-	-	-	**70.59**

This table evaluates the Micro 1 model - based on forecasting the FX rate using total order flow - on the basis of directional ability. i.e. Can the model predict direction if not magnitude.

Appendix D cont/d

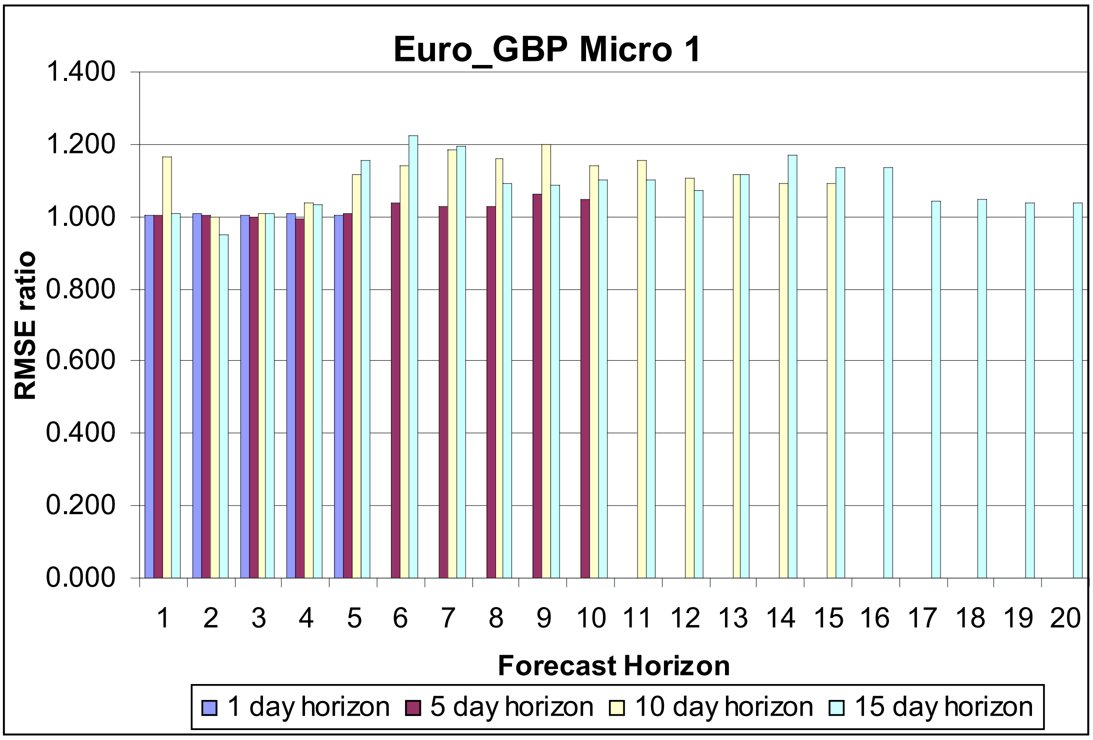
Micro 2 Model Directional Ability

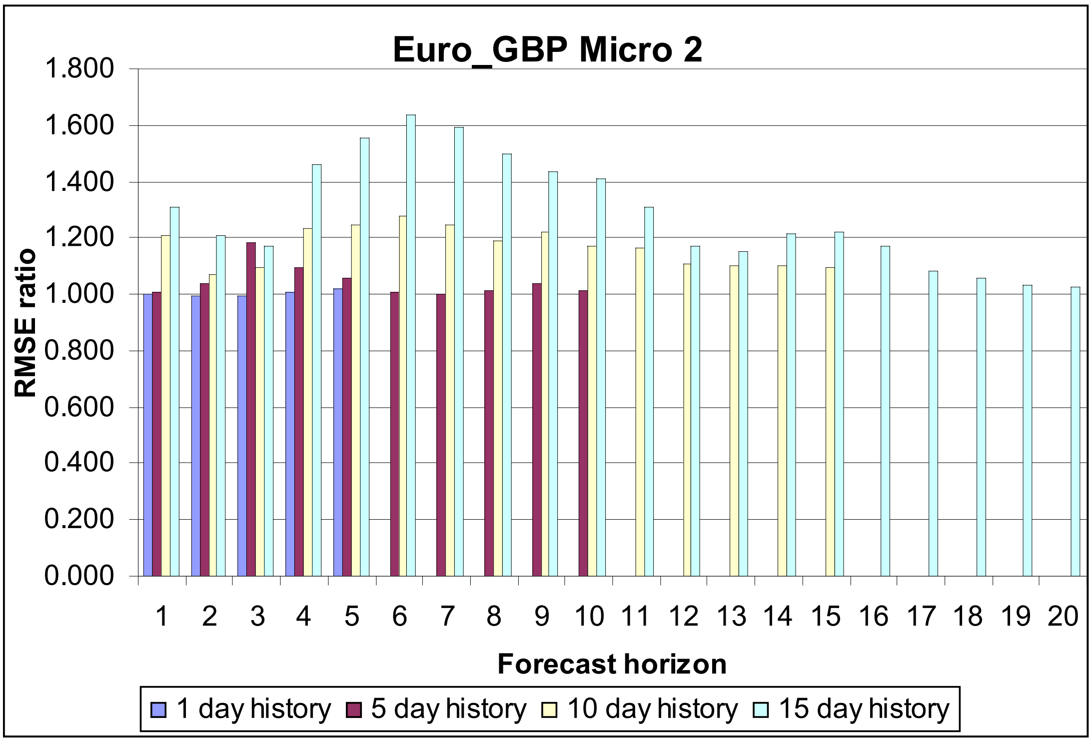
Currency: £/$

History Used:	**1**	**5**	**10**	**15**
Forecast Horizon:				
1	**51.96**	**55.41**	**62.50**	**56.25**
2	48.17	**51.35**	**59.38**	**56.25**
3	**51.05**	**59.46**	50.00	50.00
4	50.52	**54.05**	**62.50**	**56.25**
5	**51.31**	48.65	50.00	50.00
6	-	**52.70**	46.88	**56.25**
7	-	**54.05**	40.63	43.75
8	-	**56.76**	**56.25**	**68.75**
9	-	**55.41**	**59.38**	**56.25**
10	-	45.95	**53.13**	43.75
11	-	-	**53.13**	**56.25**
12	-	-	46.88	**56.25**
13	-	-	50.00	**75.00**
14	-	-	40.63	**68.75**
15	-	-	50.00	**68.75**
16	-	-	-	**68.75**
17	-	-	-	**62.50**
18	-	-	-	**62.50**
19	-	-	-	50.00
20	-	-	-	**62.50**

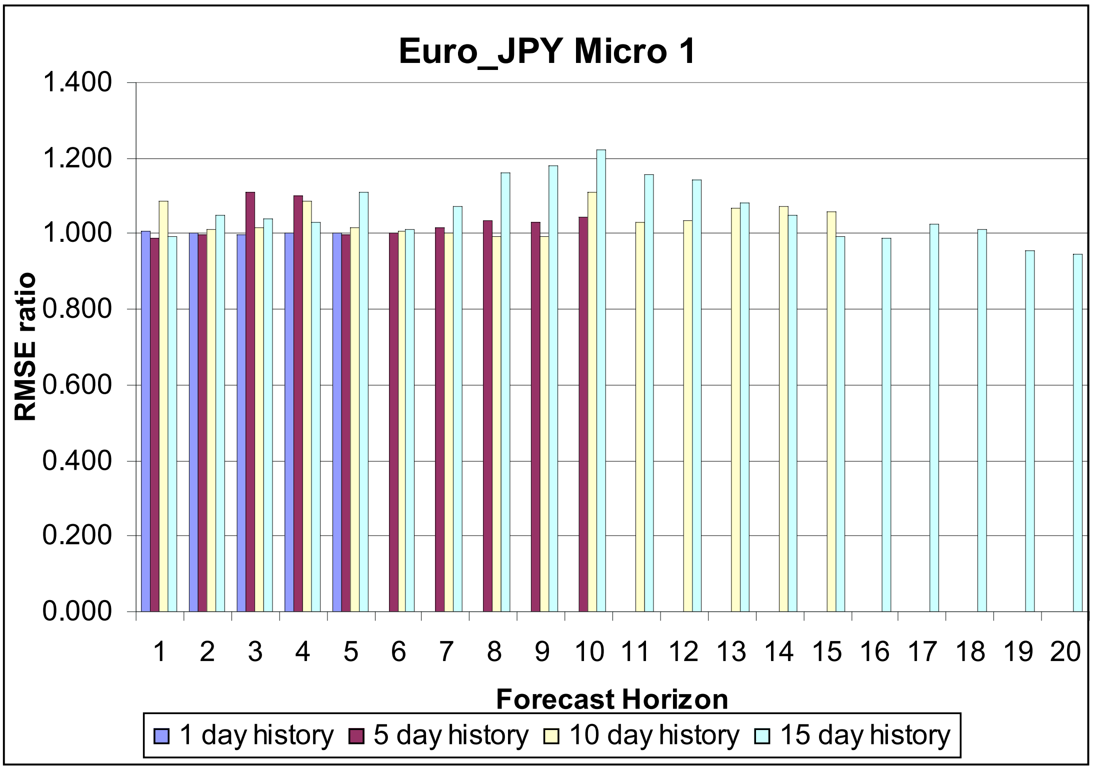
This table evaluates the Micro 2 model - based on forecasting the FX rate using order flow disaggregated by customer type - on the basis of directional ability i.e. Can the model predict direction if not magnitude.

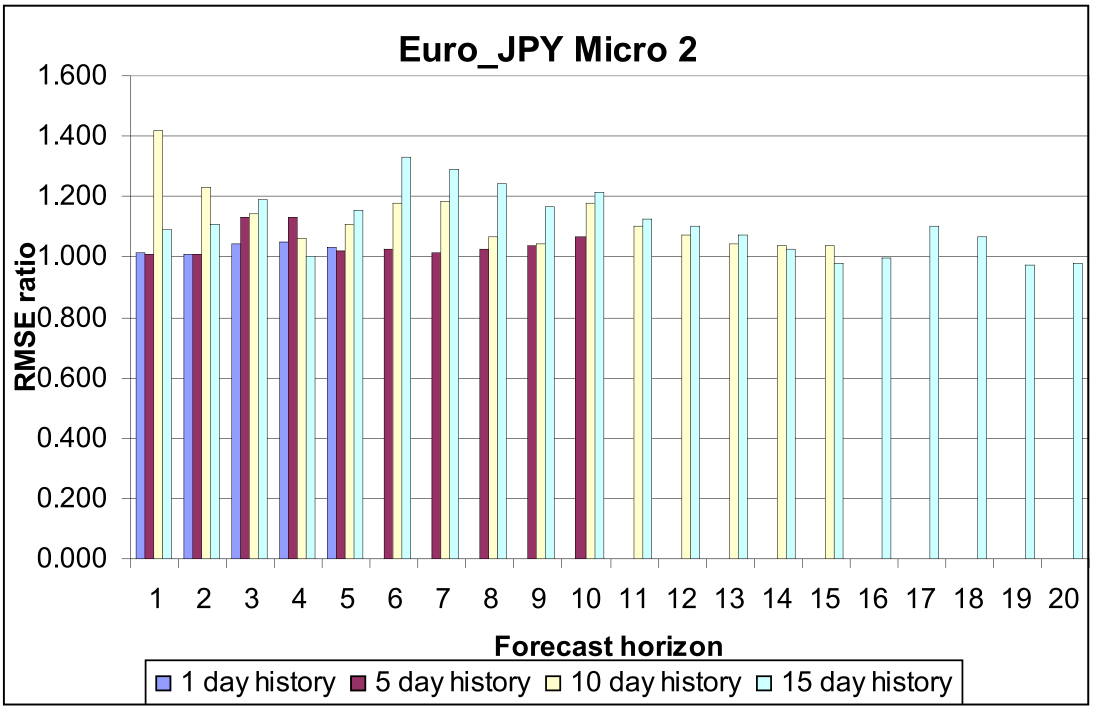
Appendix E - Micro 1 and 2 Graphical Forecast Evaluation



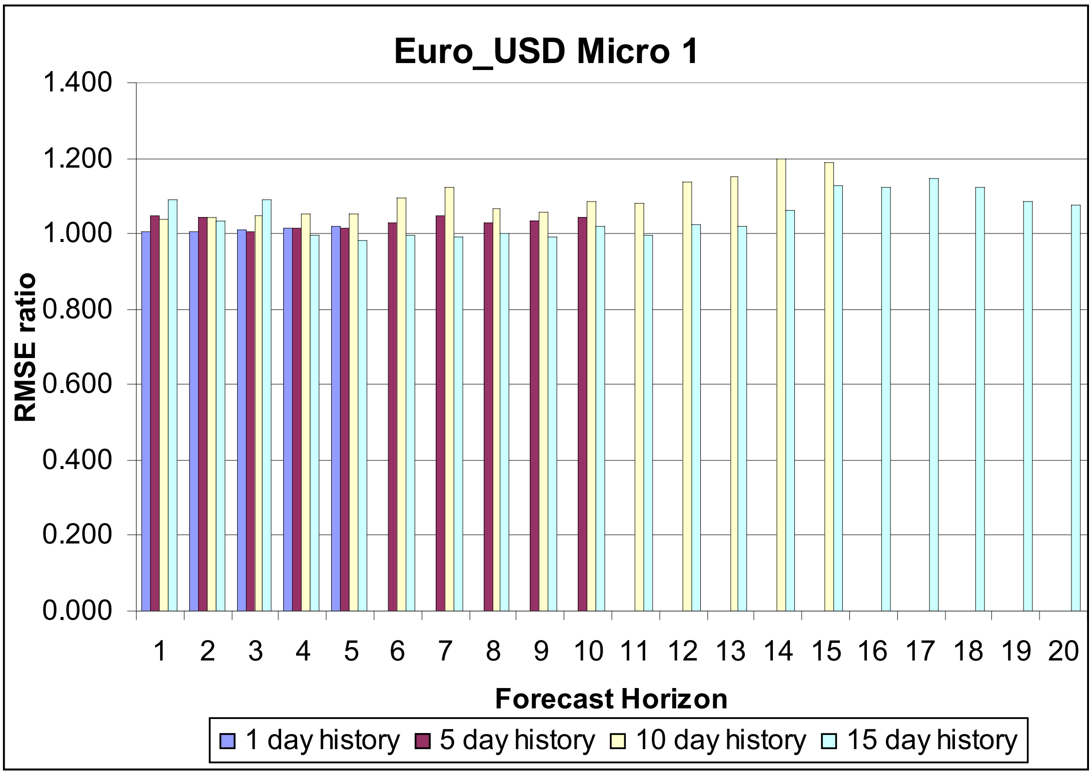


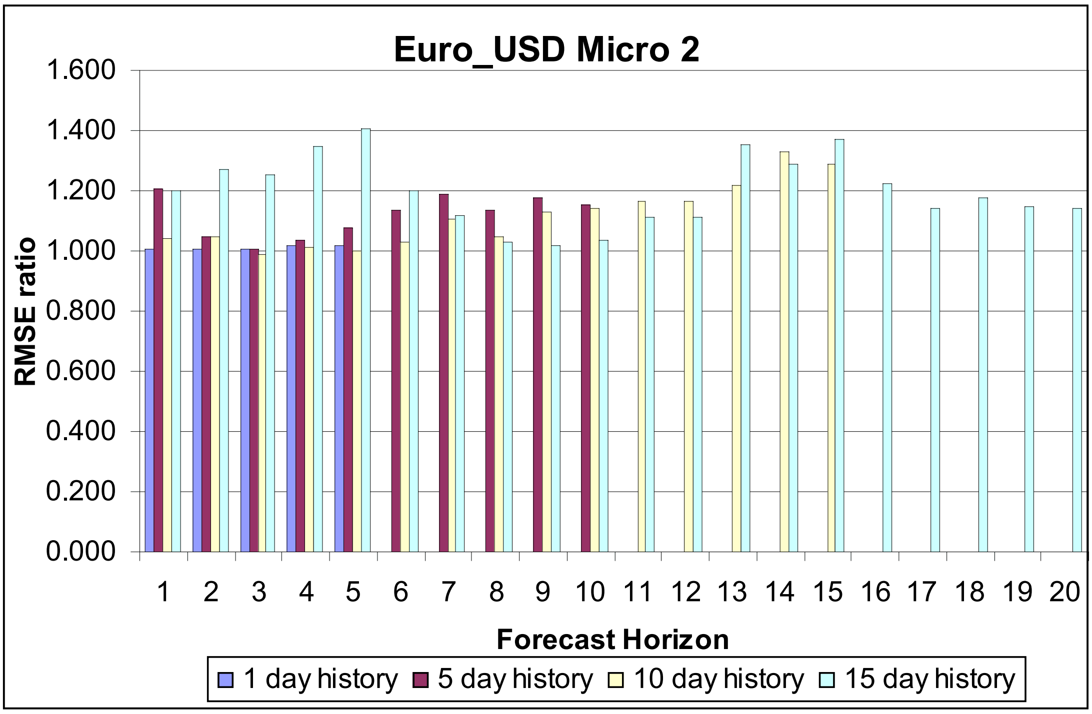
Appendix E cont/d



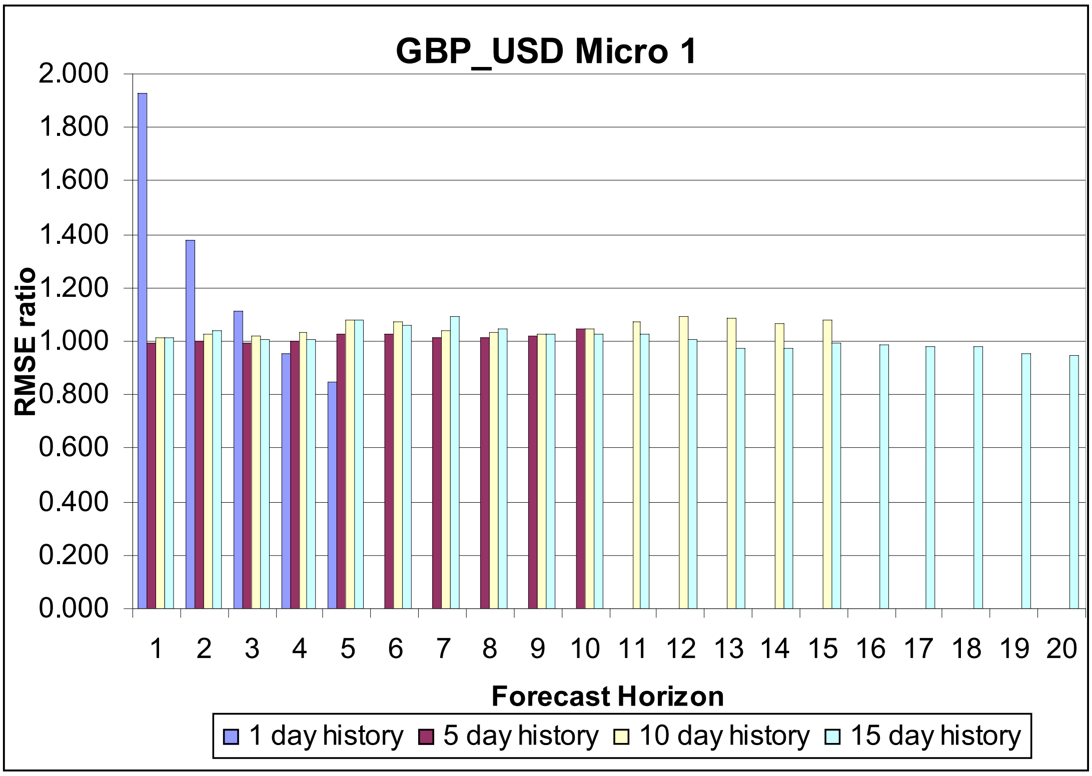


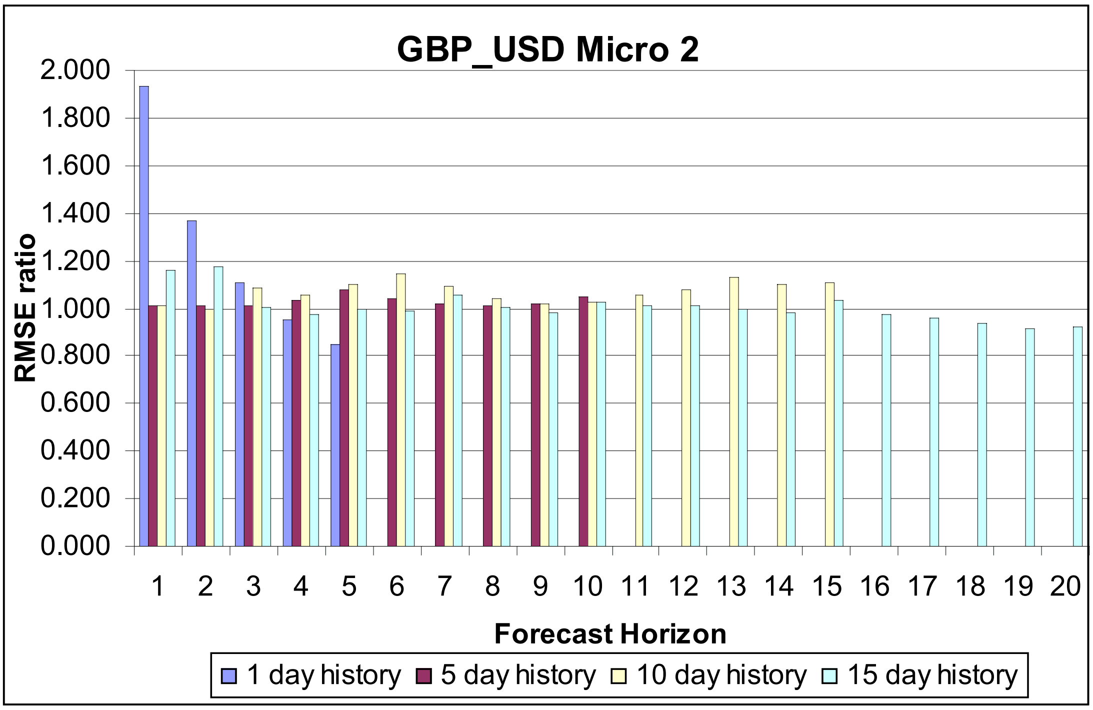
Appendix E cont/d



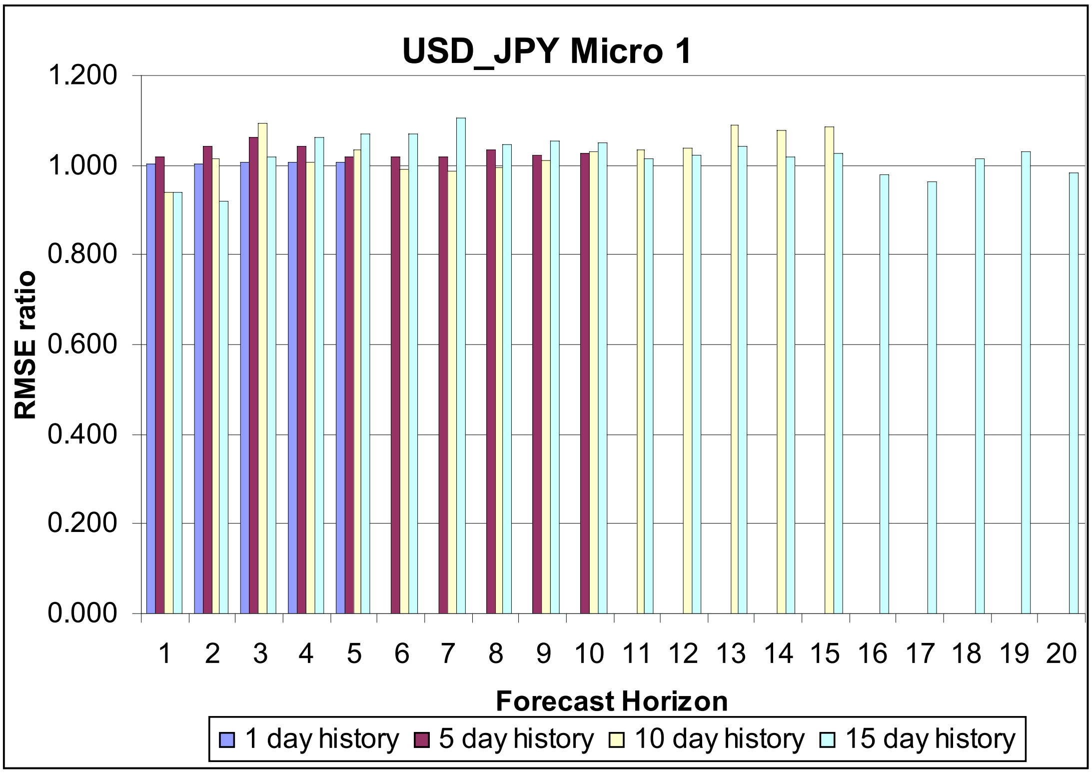


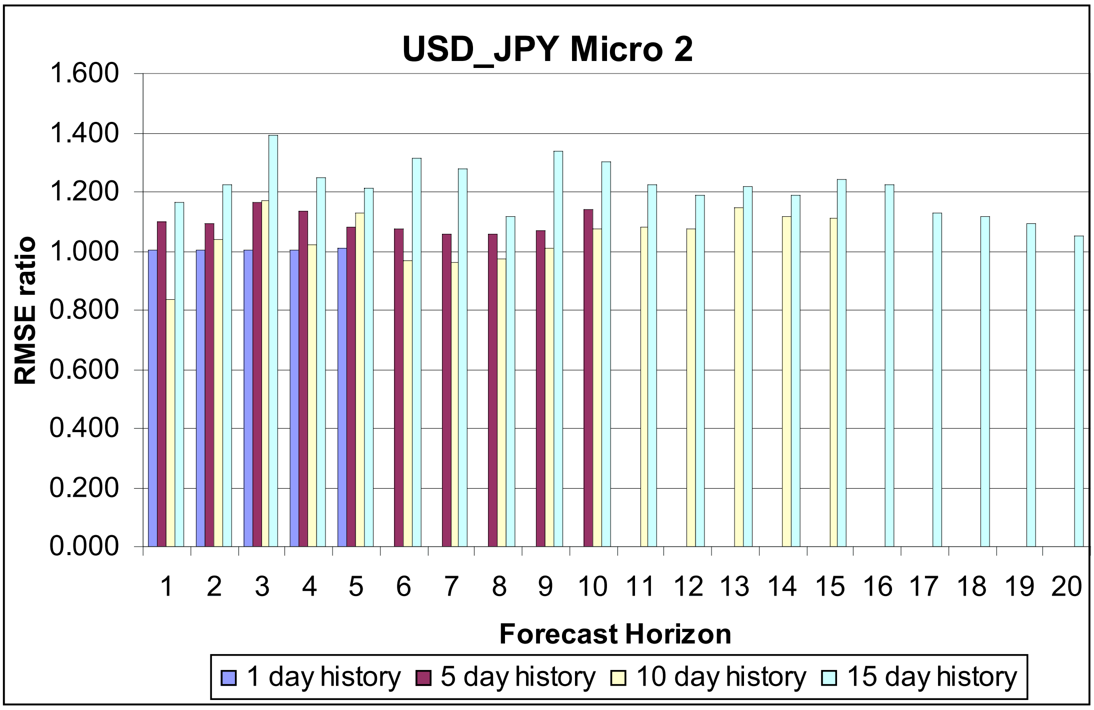
Appendix E cont/d





Appendix E cont/d





Appendix F – Cross-Currency OLS

Cross-Currency Regression

Dependent Variable: €/$
(EURO FLOWS)

	DAILY			5 DAY		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	***-0.316***	***0.093***	0.089	-0.243	0.456	0.184
€/$ Leveraged	**1.081**	**0.000**		**1.886**	**0.000**	
€/$ Unleveraged	**0.947**	**0.007**		**1.332**	**0.017**	
€/$ Other	-0.073	0.446		-0.140	0.395	
€/£ Corporate	**-0.946**	**0.004**		-0.779	0.211	
€/£ Leveraged	***0.672***	***0.063***		0.151	0.890	
€/£ Unleveraged	-0.089	0.849		-0.621	0.558	
€/£ Other	0.247	0.137		0.033	0.926	
€/¥ Corporate	-0.320	0.596		-0.978	0.523	
€/¥ Leveraged	-0.412	0.608		-1.210	0.436	
€/¥ Unleveraged	**2.069**	**0.049**		1.535	0.371	
€/¥ Other	**0.756**	**0.000**		**0.993**	**0.012**	

Cross-Currency Regression

Dependent Variable: €/$
(DOLLAR FLOWS)

	DAILY			5 DAY		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	***-0.355***	***0.070***	0.083	-0.232	0.530	0.174
€/$ Leveraged	**1.067**	**0.000**		**1.725**	**0.000**	
€/$ Unleveraged	**0.947**	**0.005**		**1.315**	**0.024**	
€/$ Other	-0.063	0.515		-0.054	0.776	
£/$ Corporate	-0.544	**0.030**		-0.894	0.133	
£/$ Leveraged	1.185	**0.003**		0.208	0.828	
£/$ Unleveraged	0.990	0.141		***2.454***	***0.096***	
£/$ Other	-0.182	0.368		-0.625	0.172	
$/¥ Corporate	0.188	0.563		0.277	0.713	
$/¥ Leveraged	-0.424	0.238		-0.015	0.986	
$/¥ Unleveraged	**-0.671**	**0.034**		-0.171	0.839	
$/¥ Other	**-0.291**	**0.006**		-0.303	0.247	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}
GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression						
Dependent Variable: €/$						
(EURO FLOWS)						
10 DAY				**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	0.123	0.778	0.18	0.247	0.692	0.182
€/$ Leveraged	**2.182**	0.002		1.101	0.321	
€/$ Unleveraged	**1.784**	0.016		1.624	0.254	
€/$ Other	-0.025	0.922		**-0.536**	0.038	
€/£ Corporate	-0.501	0.5		0.396	0.671	
€/£ Leveraged	-1.303	0.302		-0.075	0.967	
€/£ Unleveraged	0.806	0.666		**-2.936**	0.018	
€/£ Other	-0.766	0.187		-0.532	0.144	
€/¥ Corporate	-1.536	0.454		1.895	0.553	
€/¥ Leveraged	0.642	0.835		-3.287	0.468	
€/¥ Unleveraged	2.757	0.387		3.841	0.388	
€/¥ Other	0.627	0.182		-0.251	0.679	

Cross-Currency Regression						
Dependent Variable: €/$						
(DOLLAR FLOWS)						
10 DAY				**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	0.235	0.581	0.221	0.515	0.408	0.273
€/$ Leveraged	**1.764**	0.031		0.832	0.412	
€/$ Unleveraged	**1.813**	0.006		1.227	0.212	
€/$ Other	0.074	0.715		-0.193	0.451	
£/$ Corporate	0.414	0.656		-0.437	0.702	
£/$ Leveraged	1.135	0.389		-0.314	0.869	
£/$ Unleveraged	1.335	0.424		1.685	0.569	
£/$ Other	-0.72	0.284		-0.86	0.310	
$/¥ Corporate	-1.097	0.372		-0.325	0.709	
$/¥ Leveraged	0.497	0.689		0.984	0.631	
$/¥ Unleveraged	-1.233	0.256		**-2.79**	0.044	
$/¥ Other	-0.521	0.130		-0.589	0.237	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}
GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: €/£
(EURO FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	-0.084	0.433	0.067	-0.065	0.751	0.152
€/$ Leveraged	**0.601**	0.000		**0.976**	0.001	
€/$ Unleveraged	0.263	0.162		***0.842***	0.060	
€/$ Other	-0.012	0.836		0.012	0.897	
€/£ Corporate	***-0.420***	0.074		**-0.679**	0.038	
€/£ Leveraged	**0.988**	0.000		**1.246**	0.042	
€/£ Unleveraged	0.312	0.561		-0.785	0.476	
€/£ Other	**0.332**	0.012		0.283	0.284	
€/¥ Corporate	**-0.721**	0.017		-0.441	0.687	
€/¥ Leveraged	-0.036	0.952		0.637	0.689	
€/¥ Unleveraged	1.172	0.105		0.517	0.620	
€/¥ Other	0.336	0.003		***0.376***	0.077	

Cross-Currency Regression

Dependent Variable: €/£
(GBP FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/£ Corporate	***-0.481***	0.050	0.053	**-0.712**	0.035	0.088
€/£ Leveraged	**1.104**	0.000		**1.447**	0.028	
€/£ Unleveraged	0.353	0.526		-0.503	0.665	
€/£ Other	**0.357**	0.006		***0.442***	0.089	
£/$ Corporate	-0.262	0.250		0.310	0.598	
£/$ Leveraged	**-1.061**	0.001		-1.086	0.113	
£/$ Unleveraged	-0.336	0.423		-0.060	0.956	
£/$ Other	***-0.203***	0.093		-0.129	0.734	
£/¥ Corporate	-0.930	0.115		0.058	0.981	
£/¥ Leveraged	-0.264	0.855		-1.887	0.463	
£/¥ Unleveraged	0.711	0.214		1.453	0.184	
£/¥ Other	-0.198	0.534		0.652	0.437	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}
GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: €/£
(EURO FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	-0.191	0.433	0.151	-0.174	0.617	0.086
€/$ Leveraged	***0.910***	0.059		0.488	0.572	
€/$ Unleveraged	0.853	0.148		0.097	0.912	
€/$ Other	0.034	0.756		-0.121	0.413	
€/£ Corporate	-0.598	0.150		-0.434	0.371	
€/£ Leveraged	0.598	0.404		0.081	0.923	
€/£ Unleveraged	-1.855	0.260		-0.926	0.471	
€/£ Other	0.345	0.303		-0.052	0.897	
€/¥ Corporate	-0.815	0.603		0.742	0.707	
€/¥ Leveraged	-0.515	0.878		-0.047	0.988	
€/¥ Unleveraged	0.132	0.926		2.490	0.300	
€/¥ Other	-0.004	0.992		-0.255	0.634	

Cross-Currency Regression

Dependent Variable: €/£
(GBP FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/£ Corporate	-0.327	0.448	0.184	-0.282	0.414	0.300
€/£ Leveraged	0.665	0.366		0.014	0.981	
€/£ Unleveraged	-2.433	0.111		-1.359	0.190	
€/£ Other	0.403	0.289		0.080	0.774	
£/$ Corporate	0.191	0.797		-0.115	0.886	
£/$ Leveraged	-1.169	0.216		**-1.975**	0.045	
£/$ Unleveraged	-0.560	0.597		-1.250	0.397	
£/$ Other	**-1.107**	0.002		**-1.231**	0.000	
£/¥ Corporate	-3.680	0.226		-2.927	0.606	
£/¥ Leveraged	-0.044	0.992		1.039	0.810	
£/¥ Unleveraged	0.755	0.606		1.742	0.413	
£/¥ Other	0.516	0.646		0.842	0.557	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}
GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: €/¥ (EURO FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	-0.089	0.154	0.109	-0.051	0.878	0.243
€/$ Leveraged	0.520	0.197		**1.000**	0.004	
€/$ Unleveraged	0.454	0.264		0.427	0.341	
€/$ Other	***-0.097***	0.088		0.000	0.997	
€/£ Corporate	-0.157	0.387		0.025	0.966	
€/£ Leveraged	0.141	0.457		-0.636	0.335	
€/£ Unleveraged	-0.465	0.505		***-1.751***	0.055	
€/£ Other	0.197	0.157		0.010	0.968	
€/¥ Corporate	-0.192	0.533		-0.578	0.693	
€/¥ Leveraged	1.161	0.808		2.305	0.118	
€/¥ Unleveraged	3.943	1.091		***4.167***	0.085	
€/¥ Other	1.538	0.144		**2.097**	0.000	

Cross-Currency Regression

Dependent Variable: €/¥ (JPY FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/¥ Corporate	-0.180	0.733	0.118	-0.908	0.524	0.256
€/¥ Leveraged	***1.324***	0.096		1.271	0.402	
€/¥ Unleveraged	**3.859**	0.001		2.524	0.276	
€/¥ Other	**1.424**	0.000		**1.831**	0.000	
$/¥ Corporate	-0.392	0.232		-0.383	0.691	
$/¥ Leveraged	0.076	0.786		-0.188	0.764	
$/¥ Unleveraged	**0.704**	0.044		**1.732**	0.034	
$/¥ Other	**0.164**	0.045		0.129	0.449	
£/¥ Corporate	***-2.083***	0.057		-0.814	0.761	
£/¥ Leveraged	1.576	0.224		4.908	0.180	
£/¥ Unleveraged	**2.701**	0.004		**3.410**	0.025	
£/¥ Other	**2.350**	0.008		0.132	0.891	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: €/¥
(EURO FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	-0.086	0.841	0.264	0.293	0.491	0.362
€/$ Leveraged	**1.963**	0.002		0.585	0.441	
€/$ Unleveraged	-0.017	0.975		-0.177	0.784	
€/$ Other	-0.063	0.730		***-0.318***	0.058	
€/£ Corporate	0.302	0.696		0.556	0.364	
€/£ Leveraged	***-2.287***	0.083		-1.070	0.351	
€/£ Unleveraged	-0.472	0.707		**-3.023**	0.021	
€/£ Other	-0.081	0.859		0.018	0.957	
€/¥ Corporate	-1.251	0.480		2.398	0.309	
€/¥ Leveraged	1.254	0.706		-1.469	0.599	
€/¥ Unleveraged	**6.954**	0.030		**7.865**	0.005	
€/¥ Other	**1.880**	0.000		**1.860**	0.001	

Cross-Currency Regression

Dependent Variable: €/¥
(JPY FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/¥ Corporate	-0.916	0.569	0.293	0.905	0.675	0.413
€/¥ Leveraged	-0.440	0.884		-2.943	0.334	
€/¥ Unleveraged	4.330	0.247		3.821	0.228	
€/¥ Other	**1.658**	0.000		**2.040**	0.000	
$/¥ Corporate	-0.644	0.639		-0.634	0.274	
$/¥ Leveraged	***1.384***	0.092		0.513	0.710	
$/¥ Unleveraged	1.663	0.220		0.261	0.780	
$/¥ Other	0.081	0.772		-0.457	0.118	
£/¥ Corporate	-2.709	0.475		**-8.744**	0.016	
£/¥ Leveraged	9.803	0.124		**12.182**	0.035	
£/¥ Unleveraged	**5.556**	0.031		***4.747***	0.052	
£/¥ Other	1.515	0.455		-0.311	0.766	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: $/¥
(USD FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	***0.244***	0.075	0.098	0.008	0.978	0.279
€/$ Leveraged	**-0.507**	0.008		**-1.123**	0.010	
€/$ Unleveraged	-0.381	0.131		**-0.890**	0.030	
€/$ Other	-0.033	0.696		0.011	0.955	
£/$ Corporate	**0.719**	0.013		**1.340**	0.029	
£/$ Leveraged	**-0.907**	0.035		0.885	0.457	
£/$ Unleveraged	-0.484	0.290		-0.921	0.331	
£/$ Other	***0.270***	0.099		**1.189**	0.004	
$/¥ Corporate	**-0.656**	0.026		-0.903	0.166	
$/¥ Leveraged	**0.620**	0.039		0.160	0.805	
$/¥ Unleveraged	**1.542**	0.000		**3.029**	0.000	
$/¥ Other	**0.495**	0.000		**0.523**	0.004	

Cross-Currency Regression

Dependent Variable: $/¥
(JPY FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/¥ Corporate	0.226	0.606	0.100	0.616	0.573	0.247
€/¥ Leveraged	***1.572***	0.056		***2.962***	0.077	
€/¥ Unleveraged	**2.106**	0.004		2.234	0.176	
€/¥ Other	**0.650**	0.000		0.743	0.111	
$/¥ Corporate	**-0.748**	0.012		-0.737	0.304	
$/¥ Leveraged	**0.637**	0.048		0.815	0.180	
$/¥ Unleveraged	**1.551**	0.000		**2.398**	0.001	
$/¥ Other	**0.550**	0.000		**0.685**	0.002	
£/¥ Corporate	1.794	0.111		**6.730**	0.020	
£/¥ Leveraged	0.931	0.612		2.518	0.464	
£/¥ Unleveraged	0.190	0.825		1.373	0.345	
£/¥ Other	***1.352***	0.060		0.637	0.496	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression						
Dependent Variable: $/¥ (USD FLOWS)						
10 DAY				**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	-0.443	0.126	0.396	-0.262	0.588	0.457
€/$ Leveraged	-0.202	0.716		-0.578	0.536	
€/$ Unleveraged	**-1.788**	0.001		-1.480	0.107	
€/$ Other	-0.085	0.656		0.036	0.872	
£/$ Corporate	0.074	0.927		-0.047	0.967	
£/$ Leveraged	-0.734	0.611		-0.943	0.666	
£/$ Unleveraged	0.047	0.964		***-2.514***	0.055	
£/$ Other	0.610	0.232		***1.177***	0.082	
$/¥ Corporate	0.152	0.849		0.502	0.459	
$/¥ Leveraged	0.856	0.384		-0.099	0.931	
$/¥ Unleveraged	**3.629**	0.000		**3.201**	0.001	
$/¥ Other	**0.834**	0.002		***0.624***	0.082	

Cross-Currency Regression						
Dependent Variable: $/¥ (JPY FLOWS)						
10 DAY				**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/¥ Corporate	0.510	0.676	0.410	0.630	0.634	0.463
€/¥ Leveraged	-0.297	0.912		4.241	0.172	
€/¥ Unleveraged	1.630	0.413		2.266	0.343	
€/¥ Other	0.910	0.190		**1.685**	0.019	
$/¥ Corporate	0.015	0.989		1.071	0.176	
$/¥ Leveraged	***1.718***	0.079		0.106	0.936	
$/¥ Unleveraged	**2.324**	0.002		**2.705**	0.017	
$/¥ Other	**0.942**	0.000		**0.762**	0.008	
£/¥ Corporate	***5.151***	0.062		3.532	0.393	
£/¥ Leveraged	8.734	0.148		7.787	0.207	
£/¥ Unleveraged	5.119	0.121		4.509	0.107	
£/¥ Other	3.729	0.124		3.171	0.151	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£}   USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥}   JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression						
Dependent Variable: £/$ (GBP FLOWS)						
	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/£ Corporate	**-0.460**	0.041	0.077	0.032	0.958	0.116
€/£ Leveraged	-0.305	0.428		-0.631	0.493	
€/£ Unleveraged	-0.426	0.419		0.534	0.735	
€/£ Other	-0.033	0.843		-0.196	0.540	
£/$ Corporate	-0.280	0.329		-1.075	0.197	
£/$ Leveraged	**2.288**	0.000		1.551	0.179	
£/$ Unleveraged	**1.415**	0.005		**2.548**	0.008	
£/$ Other	0.036	0.852		-0.475	0.302	
£/¥ Corporate	**-2.551**	0.012		**-4.159**	0.019	
£/¥ Leveraged	0.385	0.673		3.373	0.351	
£/¥ Unleveraged	**2.256**	0.001		1.489	0.468	
£/¥ Other	**1.638**	0.001		-0.395	0.764	

Cross-Currency Regression						
Dependent Variable: £/$ (USD FLOWS)						
	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	-0.218	0.137	0.090	-0.128	0.680	0.135
€/$ Leveraged	**0.430**	0.014		***0.715***	0.053	
€/$ Unleveraged	**0.652**	0.010		0.652	0.297	
€/$ Other	-0.052	0.527		-0.087	0.673	
£/$ Corporate	-0.279	0.346		-1.029	0.185	
£/$ Leveraged	**2.248**	0.000		1.258	0.246	
£/$ Unleveraged	**1.355**	0.007		**2.700**	0.005	
£/$ Other	0.016	0.931		-0.542	0.222	
$/¥ Corporate	0.139	0.673		0.036	0.959	
$/¥ Leveraged	0.091	0.774		***1.108***	0.063	
$/¥ Unleveraged	**-0.928**	0.001		-0.592	0.378	
$/¥ Other	**-0.212**	0.045		-0.262	0.208	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: £/$
(GBP FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/£ Corporate	0.332	0.644	0.164	1.051	0.136	0.376
€/£ Leveraged	-0.611	0.568		0.161	0.898	
€/£ Unleveraged	2.727	0.331		-1.089	0.460	
€/£ Other	-0.629	0.139		-0.425	0.317	
£/$ Corporate	-0.323	0.781		0.445	0.742	
£/$ Leveraged	***2.624***	0.089		***2.823***	0.081	
£/$ Unleveraged	***2.081***	0.098		***3.898***	0.072	
£/$ Other	0.058	0.939		-0.642	0.456	
£/¥ Corporate	-1.804	0.573		-3.278	0.638	
£/¥ Leveraged	1.206	0.792		10.318	0.191	
£/¥ Unleveraged	1.437	0.662		0.316	0.889	
£/¥ Other	-2.156	0.372		**-5.284**	0.002	

Cross-Currency Regression

Dependent Variable: £/$
(USD FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/$ Corporate	0.476	0.202	0.277	0.624	0.114	0.403
€/$ Leveraged	0.731	0.328		-0.159	0.881	
€/$ Unleveraged	**1.171**	0.044		***1.590***	0.071	
€/$ Other	-0.106	0.561		-0.266	0.284	
£/$ Corporate	0.263	0.786		-0.670	0.544	
£/$ Leveraged	***2.918***	0.091		1.973	0.277	
£/$ Unleveraged	1.963	0.154		3.172	0.204	
£/$ Other	0.512	0.375		0.321	0.708	
$/¥ Corporate	**-2.100**	0.028		-0.178	0.863	
$/¥ Leveraged	1.637	0.128		***2.755***	0.082	
$/¥ Unleveraged	-1.103	0.225		**-2.266**	0.043	
$/¥ Other	**-0.762**	0.011		-0.631	0.149	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: £/¥
(GBP FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/£ Corporate	0.286	0.326	0.054	0.258	0.720	0.100
€/£ Leveraged	**-0.986**	0.014		**-1.614**	0.020	
€/£ Unleveraged	-0.820	0.117		-0.636	0.635	
€/£ Other	-0.172	0.262		***-0.454***	0.082	
£/$ Corporate	0.417	0.174		0.163	0.825	
£/$ Leveraged	**1.284**	0.001		**2.134**	0.041	
£/$ Unleveraged	0.576	0.183		0.729	0.595	
£/$ Other	***0.302***	0.070		***0.697***	0.067	
£/¥ Corporate	**-2.013**	0.038		0.671	0.785	
£/¥ Leveraged	1.949	0.368		6.787	0.153	
£/¥ Unleveraged	**2.428**	0.020		**4.514**	0.003	
£/¥ Other	**2.850**	0.000		1.078	0.324	

Cross-Currency Regression

Dependent Variable: £/¥
(JPY FLOWS)

	DAILY			**5 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/¥ Corporate	0.606	0.253	0.094	0.057	0.952	0.239
€/¥ Leveraged	1.218	0.136		1.298	0.450	
€/¥ Unleveraged	**2.842**	0.005		2.451	0.358	
€/¥ Other	**1.078**	0.000		**1.470**	0.000	
$/¥ Corporate	-0.440	0.185		-0.800	0.266	
$/¥ Leveraged	**0.676**	0.019		**1.259**	0.032	
$/¥ Unleveraged	***0.579***	0.082		***1.309***	0.056	
$/¥ Other	**0.232**	0.020		0.198	0.321	
£/¥ Corporate	-1.315	0.107		0.623	0.779	
£/¥ Leveraged	1.846	0.403		5.997	0.201	
£/¥ Unleveraged	**2.048**	0.044		1.814	0.194	
£/¥ Other	**2.598**	0.001		-0.607	0.461	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£}   USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥}   JPY Flows Equation R= {€/¥, $/¥, £/¥}

Cross-Currency Regression

Dependent Variable: £/¥ (GBP FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/£ Corporate	0.517	0.568	0.174	0.474	0.494	0.196
€/£ Leveraged	**-2.870**	0.003		-1.121	0.254	
€/£ Unleveraged	1.468	0.423		-0.224	0.859	
€/£ Other	-0.121	0.839		0.188	0.683	
£/$ Corporate	0.351	0.787		0.402	0.773	
£/$ Leveraged	1.501	0.446		1.699	0.296	
£/$ Unleveraged	0.938	0.667		0.678	0.683	
£/$ Other	0.894	0.208		0.927	0.148	
£/¥ Corporate	0.802	0.867		-4.575	0.565	
£/¥ Leveraged	10.719	0.195		10.921	0.145	
£/¥ Unleveraged	**8.575**	0.004		4.742	0.238	
£/¥ Other	2.987	0.138		-0.825	0.772	

Cross-Currency Regression

Dependent Variable: £/¥ (JPY FLOWS)

	10 DAY			**15 DAY**		
	Coefficient	p-value	R-Squared	Coefficient	p-value	R-Squared
€/¥ Corporate	-0.207	0.869	0.377	-0.340	0.829	0.421
€/¥ Leveraged	-0.156	0.960		-1.552	0.577	
€/¥ Unleveraged	3.386	0.301		0.866	0.739	
€/¥ Other	**1.800**	0.002		**2.069**	0.002	
$/¥ Corporate	***-1.691***	0.095		-0.144	0.852	
$/¥ Leveraged	**3.347**	0.001		**2.957**	0.006	
$/¥ Unleveraged	1.059	0.369		0.379	0.602	
$/¥ Other	0.073	0.781		-0.068	0.826	
£/¥ Corporate	2.355	0.488		-2.410	0.636	
£/¥ Leveraged	10.719	0.130		**14.846**	0.025	
£/¥ Unleveraged	**3.765**	0.040		**4.450**	0.009	
£/¥ Other	0.220	0.872		-1.991	0.152	

$$\Delta s_t = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_t$$

Euro Flows Equation R= {€/$, €/¥, €/£} USD Flows Equation R= {€/$, £/$, $/¥}

GBP Flows Equation R= {€/£, £/$, £/¥} JPY Flows Equation R= {€/¥, $/¥, £/¥}

Appendix G – Cross-Currency Forecast Evaluation

Cross-Currency Forecast Evaluation
(1 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
Euro Flows			
	EUR_GBP	1	1.0930
	EUR_JPY	1	1.0270
	EUR_USD	1	1.0370
	EUR_GBP	5	1.0670
	EUR_JPY	5	1.0360
	EUR_USD	5	1.0320
GBP Flows			
	EUR_GBP	1	1.0400
	GBP_JPY	1	1.0210
	GBP_USD	1	1.0150
	EUR_GBP	5	1.0430
	GBP_JPY	5	1.0250
	GBP_USD	5	1.0320
USD Flows			
	EUR_USD	1	1.0130
	GBP_USD	1	1.0210
	USD_JPY	1	1.0100
	EUR_USD	5	1.0440
	GBP_USD	5	1.0290
	USD_JPY	5	1.0590
JPY Flows			
	EUR_JPY	1	1.0290
	GBP_JPY	1	1.0360
	USD_JPY	1	1.0300
	EUR_JPY	5	1.0480
	GBP_JPY	5	1.0430
	USD_JPY	5	1.0340

This table evaluates the forecasting performance of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}
GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}

The ratio of RMSE of each model to that of the RW is used.
A ratio smaller than 1 would indicate outperformance of the model.

Cross-Currency Forecast Evaluation
(5 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
Euro Flows			
	EUR_GBP	1	1.0845301
	EUR_JPY	1	1.1391585
	EUR_USD	1	1.3681103
	EUR_GBP	5	1.1765241
	EUR_JPY	5	1.2802852
	EUR_USD	5	1.2518475
	EUR_GBP	10	1.1104942
	EUR_JPY	10	1.2679031
	EUR_USD	10	1.3119487
GBP Flows			
	EUR_GBP	1	1.322841
	GBP_JPY	1	1.3496734
	GBP_USD	1	1.2182404
	EUR_GBP	5	1.1019935
	GBP_JPY	5	1.0671081
	GBP_USD	5	1.3057213
	EUR_GBP	10	**0.7563393**
	GBP_JPY	10	1.0743902
	GBP_USD	10	1.1430048
USD Flows			
	EUR_USD	1	1.1520029
	GBP_USD	1	1.1517757
	USD_JPY	1	**0.916794**
	EUR_USD	5	1.3212485
	GBP_USD	5	1.2463711
	USD_JPY	5	1.3320755
	EUR_USD	10	1.353092
	GBP_USD	10	1.212376
	USD_JPY	10	1.3409301
JPY Flows			
	EUR_JPY	1	1.1113859
	GBP_JPY	1	1.3150872
	USD_JPY	1	**0.954979**
	EUR_JPY	5	1.2903396
	GBP_JPY	5	1.2890728
	USD_JPY	5	1.1104768
	EUR_JPY	10	1.3322198
	GBP_JPY	10	1.2561202
	USD_JPY	10	1.2675815

This table evaluates the forecasting performance of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}
GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}
The ratio of RMSE of each model to that of the RW is used.
A ratio smaller than 1 would indicate outperformance of the model.

Cross-Currency Forecast Evaluation
(10 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
Euro Flows			
	EUR_GBP	1	1.1394727
	EUR_JPY	1	1.9199375
	EUR_USD	1	1.2840386
	EUR_GBP	5	1.2950324
	EUR_JPY	5	2.2467056
	EUR_USD	5	1.5718422
	EUR_GBP	10	1.3158812
	EUR_JPY	10	2.549749
	EUR_USD	10	1.3378496
	EUR_GBP	15	1.164374
	EUR_JPY	15	1.6797717
	EUR_USD	15	1.3340091
GBP Flows			
	EUR_GBP	1	1.0587458
	GBP_JPY	1	1.5422525
	GBP_USD	1	1.4708654
	EUR_GBP	5	1.2757985
	GBP_JPY	5	1.3237869
	GBP_USD	5	1.4703049
	EUR_GBP	10	1.3553845
	GBP_JPY	10	1.2903901
	GBP_USD	10	1.1044557
	EUR_GBP	15	1.1270372
	GBP_JPY	15	1.2804768
	GBP_USD	15	1.1385663

This table evaluates the forecasting performance of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}
GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}

The ratio of RMSE of each model to that of the RW is used.
A ratio smaller than 1 would indicate outperformance of the model.

Cross-Currency Forecast Evaluation

(10 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
USD Flows			
	EUR_USD	1	1.1712163
	GBP_USD	1	1.2008343
	USD_JPY	1	1.2989761
	EUR_USD	5	1.4639385
	GBP_USD	5	1.2965365
	USD_JPY	5	1.6363945
	EUR_USD	10	1.3550047
	GBP_USD	10	1.2335539
	USD_JPY	10	1.2815133
	EUR_USD	15	1.2439114
	GBP_USD	15	1.0971249
	USD_JPY	15	1.281251
JPY Flows			
	EUR_JPY	1	1.3835969
	GBP_JPY	1	1.2648487
	USD_JPY	1	1.2296884
	EUR_JPY	5	2.020479
	GBP_JPY	5	1.2754941
	USD_JPY	5	1.4029943
	EUR_JPY	10	2.1497454
	GBP_JPY	10	1.5363845
	USD_JPY	10	1.3064413
	EUR_JPY	15	1.8618713
	GBP_JPY	15	1.5547793
	USD_JPY	15	1.2747419

This table evaluates the forecasting performance of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}

GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}

The ratio of RMSE of each model to that of the RW is used.

A ratio smaller than 1 would indicate outperformance of the model.

Cross-Currency Forecast Evaluation
(15 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
Euro Flows			
	EUR_GBP	1	1.3004925
	EUR_JPY	1	1.8355834
	EUR_USD	1	1.2996204
	EUR_GBP	5	2.698577
	EUR_JPY	5	2.0235663
	EUR_USD	5	1.2977264
	EUR_GBP	10	2.5608904
	EUR_JPY	10	1.789643
	EUR_USD	10	1.1178823
	EUR_GBP	15	2.4074223
	EUR_JPY	15	1.5654541
	EUR_USD	15	1.8318731
	EUR_GBP	20	2.5640193
	EUR_JPY	20	1.4862095
	EUR_USD	20	1.5641874
GBP Flows			
	EUR_GBP	1	**0.960371**
	GBP_JPY	1	1.361348
	GBP_USD	1	1.1344502
	EUR_GBP	5	1.68297
	GBP_JPY	5	1.2516891
	GBP_USD	5	1.1322788
	EUR_GBP	10	1.7891025
	GBP_JPY	10	1.5048795
	GBP_USD	10	**0.926707**
	EUR_GBP	15	1.3391795
	GBP_JPY	15	1.2641348
	GBP_USD	15	1.0188258
	EUR_GBP	20	1.3485296
	GBP_JPY	20	1.1482976
	GBP_USD	20	1.1959667

This table evaluates the forecasting performance of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}
GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}

The ratio of RMSE of each model to that of the RW is used.
A ratio smaller than 1 would indicate outperformance of the model.

Cross-Currency Forecast Evaluation

(15 day history)

	Currency Pair Forecast	Forecast Horizon	RMSE Ratio
USD Flows			
	EUR_USD	1	1.4164919
	GBP_USD	1	1.7947738
	USD_JPY	1	2.6280048
	EUR_USD	5	1.1629665
	GBP_USD	5	1.6217001
	USD_JPY	5	1.9228272
	EUR_USD	10	**0.8497819**
	GBP_USD	10	**0.9993693**
	USD_JPY	10	1.5962067
	EUR_USD	15	1.4446308
	GBP_USD	15	1.2636344
	USD_JPY	15	1.3030244
	EUR_USD	20	1.3263827
	GBP_USD	20	1.4793126
	USD_JPY	20	1.2216632
JPY Flows			
	EUR_JPY	1	1.1057064
	GBP_JPY	1	**0.9781567**
	USD_JPY	1	2.1748777
	EUR_JPY	5	1.3615651
	GBP_JPY	5	**0.9204176**
	USD_JPY	5	1.1135698
	EUR_JPY	10	1.0035443
	GBP_JPY	10	1.01382
	USD_JPY	10	**0.9533106**
	EUR_JPY	15	1.1144208
	GBP_JPY	15	1.1656059
	USD_JPY	15	1.1156459
	EUR_JPY	20	1.2394552
	GBP_JPY	20	1.3779014
	USD_JPY	20	1.2234308

This table evaluates the forecasting performance of the cross-currency model that uses both own and related flows to forecast:

$$\Delta s_{t+f} = a_0 + \sum_R \left(a_{1R} x_{Rt}^{Corp} + a_{2R} x_{Rt}^{Unlev} + a_{3R} x_{Rt}^{Lev} + a_{4R} x_{Rt}^{Other} \right) + \varepsilon_{t+f}$$

Euro Flows Equation R= {€/\$, €/¥, €/£} USD Flows Equation R= {€/\$, £/\$, \$/¥}
GBP Flows Equation R= {€/£, £/\$, £/¥} JPY Flows Equation R= {€/¥, \$/¥, £/¥}

The ratio of RMSE of each model to that of the RW is used.
A ratio smaller than 1 would indicate outperformance of the model.

Appendix H – Conditional Forecasting Models

Appendix H1
Simple Conditional Model - No threshold - Daily Frequency

	1	2	3	4	5	6	7	8	9	10
	Follow levs	Contrary to corps	Follow unlevs	Follow financials	Follow corps	Contrary to financials	Contrary corps Follow levs	Contrary to corps Follow Financials	Contrary to corps follow financials & other	Contrary to corps & others follow financials
Euro_GBP										
Trading days	385	385	385	385	385	385	385	385	385	385
Trades Triggered	370	384	382	179	384	179	184	82	39	43
Number correct	180	192	190	86	191	92	91	38	23	15
% correct	48.65	50.00	49.74	48.04	49.74	51.40	49.46	46.34	58.97	34.88
Euro_JPY										
Trading days	384	384	384	384	384	384	384	384	384	384
Trades Triggered	370	381	317	147	381	147	182	52	24	28
Number correct	184	197	150	69	183	77	94	27	13	14
% correct	49.73	51.71	47.32	46.94	48.03	52.38	51.65	51.92	54.17	50.00
Euro_USD										
Trading days	387	387	387	387	387	387	387	387	387	387
Trades Triggered	386	386	384	190	386	190	208	97	51	46
Number correct	191	171	197	97	212	91	93	50	30	20
% correct	49.48	44.30	51.30	51.05	54.92	47.89	44.71	51.55	58.82	43.48
GBP_USD										
Trading days	387	387	387	387	387	387	387	387	387	387
Trades Triggered	386	387	384	216	387	216	198	108	51	57
Number correct	196	191	186	107	194	108	99	57	25	32
% correct	50.78	49.35	48.44	49.54	50.13	50.00	50.00	52.78	49.02	56.14
USD_JPY										
Trading days	390	390	390	390	390	390	390	390	390	390
Trades Triggered	389	390	385	178	390	178	164	78	36	42
Number correct	200	195	182	87	194	91	85	35	16	19
% correct	51.41	50.00	47.27	48.88	49.74	51.12	51.83	44.87	44.44	45.24

Appendix H2

Conditional 2 with absolute mean over first 500 days of data as threshold value creating artificial band at + and - value of absolute mean - Daily Frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP	*Trading Days:*	*385*								
#BUYS:	44	35	40	8	66	3	7	1	0	0
#SELLS	46	66	27	3	35	8	13	0	0	0
TOTAL TRADES:	90	101	67	11	101	11	20	1	0	0
#correct:	45	51	35	6	50	4	8	1	0	0
%correct:	**50.00**	**50.50**	**52.24**	**54.55**	**49.50**	**36.36**	**40.00**	**100.00**	**NA**	**NA**
Euro_JPY	*Trading Days:*	*384*								
#BUYS:	93	37	51	12	41	14	10	1	1	0
#SELLS	84	41	47	14	37	12	11	1	0	0
TOTAL TRADES:	177	78	98	26	78	26	21	2	1	0
#correct:	87	38	44	11	39	15	11	2	1	0
%correct:	**49.15**	**48.72**	**44.90**	**42.31**	**50.00**	**57.69**	**52.38**	**100.00**	**100.00**	**NA**
Euro_USD	*Trading Days:*	*387*								
#BUYS:	112	156	44	18	23	18	48	6	4	0
#SELLS	103	23	59	18	156	18	9	1	1	0
TOTAL TRADES:	215	179	103	36	179	36	57	7	5	0
#correct:	111	82	49	15	96	20	27	2	2	0
%correct:	**51.63**	**45.81**	**47.57**	**41.67**	**53.63**	**55.56**	**47.37**	**28.57**	**40.00**	**NA**
GBP_USD	*Trading Days:*	*387*								
#BUYS:	95	81	48	17	105	14	19	3	0	0
#SELLS	75	105	56	14	81	17	16	1	0	0
TOTAL TRADES:	170	186	104	31	186	31	35	4	0	0
#correct:	87	93	57	19	92	12	21	2	0	0
%correct:	**51.18**	**50.00**	**54.81**	**61.29**	**49.46**	**38.71**	**60.00**	**50.00**	**NA**	**NA**
USD_JPY	*Trading Days:*	*390*								
#BUYS:	132	38	46	19	64	14	9	2	0	2
#SELLS	107	64	40	14	38	19	16	4	2	1
TOTAL TRADES:	239	102	86	33	102	33	25	6	2	3
#correct:	119	56	45	21	46	12	16	5	1	3
%correct:	**49.79**	**54.90**	**52.33**	**63.64**	**45.10**	**36.36**	**64.00**	**83.33**	**50.00**	**100.00**

Appendix H3

Conditional 3 with mean over first 500 days of data as threshold value creating artificial band at + and - absolute value of mean - Daily Frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP	*Trading Days:*	*385*								
#BUYS:	188	72	192	94	151	76	43	17	13	3
#SELLS	177	151	170	76	72	94	63	27	10	16
TOTAL TRADES:	365	223	362	170	223	170	106	44	23	19
#correct:	178	109	183	84	113	85	47	21	14	6
%correct:	**48.77**	**48.88**	**50.55**	**49.41**	**50.67**	**50.00**	**44.34**	**47.73**	**60.87**	**31.58**
Euro_JPY	*Trading Days:*	*384*								
#BUYS:	160	174	150	57	170	61	69	15	9	6
#SELLS	163	170	143	61	174	57	74	19	4	11
TOTAL TRADES:	323	344	293	118	344	118	143	34	13	17
#correct:	162	178	137	59	165	59	73	18	8	7
%correct:	**50.15**	**51.74**	**46.76**	**50.00**	**47.97**	**50.00**	**51.05**	**52.94**	**61.54**	**41.18**
Euro_USD	*Trading Days:*	*387*								
#BUYS:	194	273	138	69	87	93	144	53	31	22
#SELLS	177	87	183	93	273	69	46	20	9	11
TOTAL TRADES:	371	360	321	162	360	162	190	73	40	33
#correct:	185	164	160	84	194	76	88	38	23	15
%correct:	**49.87**	**45.56**	**49.84**	**51.85**	**53.89**	**46.91**	**46.32**	**52.05**	**57.50**	**45.45**
GBP_USD	*Trading Days:*	*387*								
#BUYS:	207	179	129	79	207	83	99	34	15	18
#SELLS	178	207	145	83	179	79	98	43	22	21
TOTAL TRADES:	385	386	274	162	386	162	197	77	37	39
#correct:	195	190	137	84	194	77	98	43	18	25
%correct:	**50.65**	**49.22**	**50.00**	**51.85**	**50.26**	**47.53**	**49.75**	**55.84**	**48.65**	**64.10**
USD_JPY	*Trading Days:*	*390*								
#BUYS:	216	184	172	86	190	75	88	37	19	18
#SELLS	168	190	192	75	184	86	66	29	11	18
TOTAL TRADES:	384	374	364	161	374	161	154	66	30	36
#correct:	196	186	175	83	187	78	79	31	14	17
%correct:	**51.04**	**49.73**	**48.08**	**51.55**	**50.00**	**48.45**	**51.30**	**46.97**	**46.67**	**47.22**

Appendix H4

Conditional 4 with mean over first 500 days of data as threshold value - Daily Frequency

	1	2	3	4	5	6	7	8	9	10
	Follow levs	Contrary to corps	Follow unlevs	Follow financials	Follow corps	Contrary to financials	Contrary corps Follow levs	Contrary to corps Follow Financials	Contrary to corps follow financials & other	Contrary to corps & others
Euro_GBP	*Trading Days:*	*385*								
#BUYS:	208	234	192	101	151	86	120	48	33	15
#SELLS	177	151	193	86	234	101	63	30	12	18
TOTAL TRADES:	385	385	385	187	385	187	183	78	45	33
#correct:	186	181	194	91	203	95	83	36	25	11
%correct:	**48.31**	**47.01**	**50.39**	**48.66**	**52.73**	**50.80**	**45.36**	**46.15**	**55.56**	**33.33**
Euro_JPY	*Trading Days:*	*384*								
#BUYS:	221	174	241	139	210	61	102	54	32	22
#SELLS	163	210	143	61	174	139	91	24	6	18
TOTAL TRADES:	384	384	384	200	384	200	193	78	38	40
#correct:	201	197	187	102	186	97	104	41	23	18
%correct:	**52.34**	**51.30**	**48.70**	**51.00**	**48.44**	**48.50**	**53.89**	**52.56**	**60.53**	**45.00**
Euro_USD	*Trading Days:*	*387*								
#BUYS:	194	273	204	110	114	99	144	86	48	38
#SELLS	193	114	183	99	273	110	64	27	13	14
TOTAL TRADES:	387	387	387	209	387	209	208	113	61	52
#correct:	193	176	196	106	208	101	96	56	33	23
%correct:	**49.87**	**45.48**	**50.65**	**50.72**	**53.75**	**48.33**	**46.15**	**49.56**	**54.10**	**44.23**
GBP_USD	*Trading Days:*	*387*								
#BUYS:	207	180	129	79	207	130	99	34	15	19
#SELLS	180	207	258	130	180	79	99	69	34	35
TOTAL TRADES:	387	387	387	209	387	209	198	103	49	54
#correct:	196	191	197	108	194	100	99	56	26	30
%correct:	**50.65**	**49.35**	**50.90**	**51.67**	**50.13**	**47.85**	**50.00**	**54.37**	**53.06**	**55.56**
USD_JPY	*Trading Days:*	*390*								
#BUYS:	216	184	172	86	206	88	88	37	19	18
#SELLS	174	206	218	88	184	86	78	40	16	24
TOTAL TRADES:	390	390	390	174	390	174	166	77	35	42
#correct:	198	193	189	86	196	88	84	34	16	18
%correct:	**50.77**	**49.49**	**48.46**	**49.43**	**50.26**	**50.57**	**50.60**	**44.16**	**45.71**	**42.86**

Appendix H5

Conditional 5 with mean +/- 1st. dev. over first 500 days of data as threshold values - Daily Frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP	*Trading Days:*	*385*								
#BUYS:	10	34	18	1	18	0	3	0	0	0
#SELLS	17	18	13	0	34	1	2	0	0	0
TOTAL TRADES:	27	52	31	1	52	1	5	0	0	0
#correct:	13	22	14	0	30	1	0	0	0	0
%correct:	**48.15**	**42.31**	**45.16**	**0.00**	**57.69**	**100.00**	**0.00**	**NA**	**NA**	**NA**
Euro_JPY	*Trading Days:*	*384*								
#BUYS:	72	8	19	4	10	3	2	0	0	0
#SELLS	54	10	18	3	8	4	4	1	0	0
TOTAL TRADES:	126	18	37	7	18	7	6	1	0	0
#correct:	61	8	20	4	10	3	2	1	0	0
%correct:	**48.41**	**44.44**	**54.05**	**57.14**	**55.56**	**42.86**	**33.33**	**100.00**	**NA**	**NA**
Euro_USD	*Trading Days:*	*387*								
#BUYS:	77	87	16	8	15	3	13	0	0	0
#SELLS	81	15	16	3	87	8	6	0	0	0
TOTAL TRADES:	158	102	32	11	102	11	19	0	0	0
#correct:	85	48	9	2	53	8	11	0	0	0
%correct:	**53.80**	**47.06**	**28.13**	**18.18**	**51.96**	**72.73**	**57.89**	**NA**	**NA**	**NA**
GBP_USD	*Trading Days:*	*387*								
#BUYS:	57	50	16	4	68	5	7	0	0	0
#SELLS	45	68	22	5	50	4	4	0	0	0
TOTAL TRADES:	102	118	38	9	118	9	11	0	0	0
#correct:	51	65	19	6	53	3	7	0	0	0
%correct:	**50.00**	**55.08**	**50.00**	**66.67**	**44.92**	**33.33**	**63.64**	**NA**	**NA**	**NA**
USD_JPY	*Trading Days:*	*390*								
#BUYS:	97	23	25	10	31	4	6	1	0	1
#SELLS	80	31	17	4	23	10	5	1	0	0
TOTAL TRADES:	177	54	42	14	54	14	11	2	0	1
#correct:	85	28	20	7	26	7	7	1	0	1
%correct:	**48.02**	**51.85**	**47.62**	**50.00**	**48.15**	**50.00**	**63.64**	**50.00**	**NA**	**100.00**

Appendix H6
Simple Conditional Model - No threshold - 5Day Frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP										
Trading periods	78	78	78	78	78	78	78	78	78	78
Trades Triggered	75	75	75	34	75	34	36	11	3	8
Number correct	46	29	35	20	46	14	18	4	1	3
% correct	**61.33**	**38.67**	**46.67**	**58.82**	**61.33**	**41.18**	**50.00**	**36.36**	**33.33**	**37.50**
Euro_JPY										
Trading periods	75	75	75	75	75	75	75	75	75	75
Trades Triggered	75	75	75	37	75	37	40	17	11	6
Number correct	41	32	45	24	43	13	19	11	7	4
% correct	**54.67**	**42.67**	**60.00**	**64.86**	**57.33**	**35.14**	**47.50**	**64.71**	**63.64**	**66.67**
Euro_USD										
Trading periods	76	76	76	76	76	76	76	76	76	76
Trades Triggered	76	76	76	40	76	40	32	13	6	7
Number correct	32	41	37	17	34	23	15	7	3	4
% correct	**42.11**	**53.95**	**48.68**	**42.50**	**44.74**	**57.50**	**46.88**	**53.85**	**50.00**	**57.14**
GBP_USD										
Trading periods	76	76	76	76	76	76	76	76	76	76
Trades Triggered	74	73	73	33	74	33	36	21	9	12
Number correct	45	36	36	19	39	13	22	12	5	7
% correct	**60.81**	**49.32**	**49.32**	**57.58**	**52.70**	**39.39**	**61.11**	**57.14**	**55.56**	**58.33**
USD_JPY										
Trading periods	77	77	77	77	77	77	77	77	77	77
Trades Triggered	77	77	77	39	77	39	39	17	11	6
Number correct	40	36	38	20	41	19	19	10	7	3
% correct	**51.95**	**46.75**	**49.35**	**51.28**	**53.25**	**48.72**	**48.72**	**58.82**	**63.64**	**50.00**

Appendix H7

Conditional 2 with absolute mean over first 100 5-day periods of data as threshold value creating artificial band at + and - value of absolute mean - 5Day Frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP	*Trading Periods:*	*75*								
#BUYS:	5	5	10	1	15	1	0	0	0	0
#SELLS	8	15	7	1	5	1	1	1	0	1
TOTAL TRADES:	13	20	17	2	20	2	1	1	0	1
#correct:	11	9	9	1	11	1	0	0	0	0
%correct:	**84.62**	**45.00**	**52.94**	**50.00**	**55.00**	**50.00**	**0.00**	**0.00**	**NA**	**0.00**
Euro_JPY	*Trading Periods:*	*75*								
#BUYS:	24	9	14	5	11	2	4	0	0	0
#SELLS	20	11	7	2	9	5	3	1	0	0
TOTAL TRADES:	44	20	21	7	20	7	7	1	0	0
#correct:	24	9	12	5	11	2	4	0	0	0
%correct:	**54.55**	**45.00**	**57.14**	**71.43**	**55.00**	**28.57**	**57.14**	**0.00**	**NA**	**NA**
Euro_USD	*Trading Periods:*	*76*								
#BUYS:	27	51	5	3	1	2	17	1	0	0
#SELLS	27	1	12	2	51	3	0	0	0	0
TOTAL TRADES:	54	52	17	5	52	5	17	1	0	0
#correct:	22	25	5	2	27	3	7	1	0	0
%correct:	**40.74**	**48.08**	**29.41**	**40.00**	**51.92**	**60.00**	**41.18**	**100.00**	**NA**	**NA**
GBP_USD	*Trading Periods:*	*76*								
#BUYS:	17	10	12	4	24	2	5	2	0	1
#SELLS	16	24	10	2	10	4	2	1	0	1
TOTAL TRADES:	33	34	22	6	34	6	7	3	0	2
#correct:	18	13	12	4	21	2	1	1	0	1
%correct:	**54.55**	**38.24**	**54.55**	**66.67**	**61.76**	**33.33**	**14.29**	**33.33**	**NA**	**50.00**
USD_JPY	*Trading Periods:*	*77*								
#BUYS:	24	7	11	5	14	1	3	0	0	0
#SELLS	14	14	7	1	7	5	1	0	0	0
TOTAL TRADES:	38	21	18	6	21	6	4	0	0	0
#correct:	20	10	8	4	11	2	1	0	0	0
%correct:	**52.63**	**47.62**	**44.44**	**66.67**	**52.38**	**33.33**	**25.00**	**NA**	**NA**	**NA**

Appendix H8

Conditional with mean over first 100 5-day periods of data as threshold value creating artificial band at + and - absolute value of mean - 5Day frequency

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Follow levs	Contrary to corps	Follow unlevs	Follow financials	Follow corps	Contrary to financials	Contrary corps Follow levs	Contrary to corps Follow Financials	Contrary to corps follow financials & other	Contrary to corps & others follow financials
Euro_GBP	*Trading Periods:*	*75*								
#BUYS:	24	8	39	10	22	20	2	0	0	0
#SELLS	46	22	32	20	8	10	15	4	1	3
TOTAL TRADES:	70	30	71	30	30	30	17	4	1	3
#correct:	45	14	32	18	16	12	10	2	0	2
%correct:	**64.29**	**46.67**	**45.07**	**60.00**	**53.33**	**40.00**	**58.82**	**50.00**	**0.00**	**66.67**
Euro_JPY	*Trading Periods:*	*75*								
#BUYS:	33	34	37	17	35	16	16	7	4	3
#SELLS	34	35	36	16	34	17	17	6	4	1
TOTAL TRADES:	67	69	73	33	69	33	33	13	8	4
#correct:	35	29	44	22	40	11	16	9	6	3
%correct:	**52.24**	**42.03**	**60.27**	**66.67**	**57.97**	**33.33**	**48.48**	**69.23**	**75.00**	**75.00**
Euro_USD	*Trading Periods:*	*76*								
#BUYS:	36	67	26	14	3	16	29	11	5	5
#SELLS	38	3	36	16	67	14	1	0	0	0
TOTAL TRADES:	74	70	62	30	70	30	30	11	5	5
#correct:	32	37	29	12	33	18	15	7	3	3
%correct:	**43.24**	**52.86**	**46.77**	**40.00**	**47.14**	**60.00**	**50.00**	**63.64**	**60.00**	**60.00**
GBP_USD	*Trading Periods:*	*76*								
#BUYS:	44	34	24	13	41	11	20	10	5	5
#SELLS	32	41	26	11	34	13	18	6	2	4
TOTAL TRADES:	76	75	50	24	75	24	38	16	7	9
#correct:	45	36	24	15	38	8	22	9	4	5
%correct:	**59.21**	**48.00**	**48.00**	**62.50**	**50.67**	**33.33**	**57.89**	**56.25**	**57.14**	**55.56**
USD_JPY	*Trading Periods:*	*77*								
#BUYS:	44	34	37	21	39	15	20	8	5	3
#SELLS	31	39	38	15	34	21	15	7	4	3
TOTAL TRADES:	75	73	75	36	73	36	35	15	9	6
#correct:	40	33	36	18	40	18	18	10	7	3
%correct:	**53.33**	**45.21**	**48.00**	**50.00**	**54.79**	**50.00**	**51.43**	**66.67**	**77.78**	**50.00**

Appendix H9

Conditional 4 with mean over first 100 5-day periods of data as threshold value - 5Day frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP	*Trading Periods:*	*75*								
#BUYS:	29	53	39	13	22	20	22	8	4	4
#SELLS	46	22	36	20	53	13	15	4	1	3
TOTAL TRADES:	75	75	75	33	75	33	37	12	5	7
#correct:	49	35	33	20	40	13	23	6	2	4
%correct:	**65.33**	**46.67**	**44.00**	**60.61**	**53.33**	**39.39**	**62.16**	**50.00**	**40.00**	**57.14**
Euro_JPY	*Trading Periods:*	*75*								
#BUYS:	41	34	39	21	41	16	20	9	6	3
#SELLS	34	41	36	16	34	21	20	8	5	3
TOTAL TRADES:	75	75	75	37	75	37	40	17	11	6
#correct:	41	32	45	24	43	13	19	10	7	3
%correct:	**54.67**	**42.67**	**60.00**	**64.86**	**57.33**	**35.14**	**47.50**	**58.82**	**63.64**	**50.00**
Euro_USD	*Trading Periods:*	*76*								
#BUYS:	36	67	40	17	9	17	29	13	6	7
#SELLS	40	9	36	17	67	17	2	0	0	0
TOTAL TRADES:	76	76	76	34	76	34	31	13	6	7
#correct:	33	41	34	13	34	21	15	8	3	5
%correct:	**43.42**	**53.95**	**44.74**	**38.24**	**44.74**	**61.76**	**48.39**	**61.54**	**50.00**	**71.43**
GBP_USD	*Trading Periods:*	*76*								
#BUYS:	44	34	24	13	42	21	20	10	5	5
#SELLS	32	42	52	21	34	13	18	10	3	7
TOTAL TRADES:	76	76	76	34	76	34	38	20	8	12
#correct:	45	36	39	21	39	12	22	12	4	8
%correct:	**59.21**	**47.37**	**51.32**	**61.76**	**51.32**	**35.29**	**57.89**	**60.00**	**50.00**	**66.67**
USD_JPY	*Trading Periods:*	*77*								
#BUYS:	44	34	37	21	43	17	20	8	5	3
#SELLS	33	43	40	17	34	21	19	10	5	5
TOTAL TRADES:	77	77	77	38	77	38	39	18	10	8
#correct:	40	34	37	19	43	19	18	10	7	3
%correct:	**51.95**	**44.16**	**48.05**	**50.00**	**55.84**	**50.00**	**46.15**	**55.56**	**70.00**	**37.50**

Appendix H10

Conditional 5 with mean+/- 1st. Dev. over first 100 5-day periods of data as threshold values - 5Day frequency

	1 Follow levs	**2** Contrary to corps	**3** Follow unlevs	**4** Follow financials	**5** Follow corps	**6** Contrary to financials	**7** Contrary corps Follow levs	**8** Contrary to corps Follow Financials	**9** Contrary to corps follow financials & other	**10** Contrary to corps & others follow financials
Euro_GBP	*Trading Periods:*	*75*								
#BUYS:	1	12	5	0	2	0	0	0	0	0
#SELLS	1	2	4	0	12	0	0	0	0	0
TOTAL TRADES:	2	14	9	0	14	0	0	0	0	0
#correct:	2	5	6	0	9	0	0	0	0	0
%correct:	**100.00**	**35.71**	**66.67**	**NA**	**64.29**	**NA**	**NA**	**NA**	**NA**	**NA**
Euro_JPY	*Trading Periods:*	*75*								
#BUYS:	24	4	7	2	4	0	2	0	0	0
#SELLS	14	4	3	0	4	2	2	0	0	0
TOTAL TRADES:	38	8	10	2	8	2	4	0	0	0
#correct:	19	4	6	2	4	0	3	0	0	0
%correct:	**50.00**	**50.00**	**60.00**	**100.00**	**50.00**	**0.00**	**75.00**	**NA**	**NA**	**NA**
Euro_USD	*Trading Periods:*	*76*								
#BUYS:	21	38	1	0	1	0	8	0	0	0
#SELLS	27	1	4	0	38	0	0	0	0	0
TOTAL TRADES:	48	39	5	0	39	0	8	0	0	0
#correct:	20	17	2	0	22	0	4	0	0	0
%correct:	**41.67**	**43.59**	**40.00**	**NA**	**56.41**	**NA**	**50.00**	**NA**	**NA**	**NA**
GBP_USD	*Trading Periods:*	*76*								
#BUYS:	12	7	0	0	18	2	1	0	0	0
#SELLS	12	18	9	2	7	0	0	0	0	0
TOTAL TRADES:	24	25	9	2	25	2	1	0	0	0
#correct:	17	12	4	2	13	0	0	0	0	0
%correct:	**70.83**	**48.00**	**44.44**	**100.00**	**52.00**	**0.00**	**0.00**	**NA**	**NA**	**NA**
USD_JPY	*Trading Periods:*	*77*								
#BUYS:	18	1	8	2	7	0	0	0	0	0
#SELLS	13	7	3	0	1	2	0	0	0	0
TOTAL TRADES:	31	8	11	2	8	2	0	0	0	0
#correct:	17	4	5	2	4	0	0	0	0	0
%correct:	**54.84**	**50.00**	**45.45**	**100.00**	**50.00**	**0.00**	**NA**	**NA**	**NA**	**NA**

Appendix I – Price Impact Model Size Cut-offs

Size Cutoffs - Total and by Counterparty

Total

	cutoffs		# obs	%
q1	**<=1**	**modal**	**12955**	46.51%
q2	**>1 and <=4**	**normal (IQR adjusted up as over 40% data is 1)**	**9062**	32.53%
q3	**>4 and <10**	**large (q3 - 95th percentile)**	**3594**	12.90%
q4	**>=10**	**extremely large**	**2243**	8.05%
Total:			**27854**	100.00%

Financial

	cutoffs	# observations	%	
fq1	**<=1**	**modal**	**3899**	43.77%
fq2	**>1 and <=4**	**normal (IQR adjusted up as +40% is 1)**	**2775**	31.16%
fq3	**>4 and <10**	**large (q3 - 95th percentile)**	**1351**	15.17%
fq4	**>=10**	**extremely large**	**882**	9.90%
Total:			**8907**	100.00%

Corporate

	cutoffs	# observations		%
cq1	**<=1**		**763**	29.51%
cq2	**>1 and <=4**		**844**	32.64%
cq3	**>4 and <=10**		**582**	22.51%
cq4	**>10**		**397**	15.35%
Total:			**2586**	100.00%

Internal

	cutoffs		# observations	%
iq1	**<=1**		**820**	42.89%
iq2	**>1 and <=4**		**550**	28.77%
iq3	**>4 and <10**		**318**	16.63%
iq4	**>=10**		**224**	11.72%
Total:			**1912**	100.00%

Interbank

	cutoffs		# observations	%
ibq1	***<=1***		***7473***	51.72%
ibq2	**<1**		**6976**	48.28%
ibq3	**IGNORE**	**N/A**		
ibq4	**IGNORE**	**N/A**		
Total:			**14449**	100.00%

Appendix J – FX Relevant Data Releases Within HF Sample Period

FX Relevant Data Releases Within Sample Period

DateTimeNY	DateTimeUK	Data Release
2005-10-13 08:30:00	2005-10-13 12:30:00	Export Prices, Import Prices, Initial Claims, Trade Balance
2005-10-14 08:30:00	2005-10-14 12:30:00	Core CPI, CPI, Retail Sales, Retail Sales ex-auto
2005-10-14 09:15:00	2005-10-14 13:15:00	Capacity Utilization, Industrial Production
2005-10-14 10:00:00	2005-10-14 14:00:00	Business Inventories
2005-10-18 08:30:00	2005-10-18 12:30:00	Core PPI, PPI
2005-10-19 08:30:00	2005-10-19 12:30:00	Building Permits, Housing Starts
2005-10-20 08:30:00	2005-10-20 12:30:00	Initial Claims
2005-10-20 10:00:00	2005-10-20 14:00:00	Leading Indicators
2005-10-25 10:00:00	2005-10-25 14:00:00	Consumer Confidence, Existing Home Sales
2005-10-27 08:30:00	2005-10-27 12:30:00	Durable Orders, Initial Claims
2005-10-27 10:00:00	2005-10-27 14:00:00	New Home Sales
2005-10-28 08:30:00	2005-10-28 12:30:00	GDP (adv), Chain deflator (adv), Employment Cost Index
2005-10-31 08:30:00	2005-10-31 12:30:00	Personal Income, Personal Spending
2005-11-01 10:00:00	2005-11-01 14:00:00	Construction Spending
2005-11-03 08:30:00	2005-11-03 12:30:00	Initial Claims, Productivity (prel.)
2005-11-03 10:00:00	2005-11-03 14:00:00	Factory Orders
2005-11-04 08:30:00	2005-11-04 12:30:00	Nonfarm Payrolls, Unemployment Rate, Hourly Earnings, Average Workweek
2005-11-09 10:00:00	2005-11-09 14:00:00	Wholesale Inventories
2005-11-10 08:30:00	2005-11-10 12:30:00	Export Prices (ex-ag), Import Prices (ex-oil), Initial Claims, Trade Balance

Appendix K – Madhavan Smidt Models

Madhavan-Smidt Model With Counterparty and Size Dummies

	Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
CP1 (Financial):				
	q_1Q_t	**-3.6150**	0.0004	0.12665
	q_1D_t	**3.4166**	0.0008	
	q_1D_{t-1}	-0.1040	0.2270	
	q_2Q_t	0.0881	0.3670	
	q_2D_t	-0.0475	0.8614	
	q_2D_{t-1}	**-0.2449**	0.0091	
	q_3Q_t	0.0460	0.6380	
	q_3D_t	-0.0923	0.8674	
	q_3D_{t-1}	-0.1230	0.3512	
	q_4Q_t	-0.0024	0.8862	
	q_4D_t	0.2454	0.4270	
	q_4D_{t-1}	-0.0487	0.7204	
CP2 (Corporate):				
	q_1Q_t	-1.0996	0.4082	
	q_1D_t	1.4415	0.2589	
	q_1D_{t-1}	-0.1564	0.4507	
	q_2Q_t	-0.0613	0.7480	
	q_2D_t	0.7855	0.1352	
	q_2D_{t-1}	**-0.4178**	0.0216	
	q_3Q_t	0.0546	0.5633	
	q_3D_t	-0.0774	0.9163	
	q_3D_{t-1}	0.0353	0.8852	
	q_4Q_t	-0.0152	0.1006	
	q_4D_t	**1.0739**	0.0105	
	q_4D_{t-1}	**-0.6343**	0.0239	
CP3 (Internal):				
	q_1Q_t	***-3.4383***	0.0607	
	q_1D_t	***3.2108***	0.0805	
	q_1D_{t-1}	-0.0703	0.7113	
	q_2Q_t	0.0203	0.9166	
	q_2D_t	-0.1040	0.8475	
	q_2D_{t-1}	-0.2821	0.1658	
	q_3Q_t	0.1668	0.4567	
	q_3D_t	-0.7701	0.5440	
	q_3D_{t-1}	-0.1484	0.5082	
	q_4Q_t	0.0074	0.4810	
	q_4D_t	-0.3608	0.3086	
	q_4D_{t-1}	-0.1426	0.6425	
	MA(1)	**-0.3831**	0.0000	

Model estimated is: $$\Delta P_t = \beta_0 + \sum_{j=1}^{3}\sum_{i=1}^{4} CP_j q_i \left[\beta_1 Q_t + \beta_2 D_t + \beta_3 D_{t-1}\right] + \eta_t$$

$CP1$ - Financial CP2 - Corporate

CP3 - Internal

Size cutoffs are counterparty specific - see Appendix I for details.
D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

Madhavan-Smidt Model with Counterparty, Time and News Dummies

(results for Financial Customers only)

	Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
CP1 (Financial) :				
	TD_1Q_t	**-0.0152**	**0.0163**	0.1255
	TD_1D_t	-0.2132	0.4407	
	TD_1D_{t-1}	-0.1125	0.6776	
	TD_1Q_t	0.0025	0.8905	
	TD_2D_t	0.0013	0.9903	
	TD_2D_{t-1}	*-0.1651*	0.0757	
	TD_3Q_t	-0.0023	0.8699	
	TD_3D_t	-0.0526	0.7156	
	TD_3D_{t-1}	-0.1215	0.3465	
	TD_4Q_t	*0.0173*	0.0993	
	TD_4D_t	0.0007	0.9961	
	TD_4D_{t-1}	-0.0873	0.4735	
	TD_5Q_t	*0.0220*	0.0673	
	TD_5D_t	0.0599	0.6426	
	TD_5D_{t-1}	*-0.2270*	0.0518	
	TD_6Q_t	0.0076	0.7062	
	TD_6D_t	0.2009	0.5600	
	TD_6D_{t-1}	-0.2952	0.3425	
	News $(D_t - D_{t-1})$	-0.0817	0.7389	
	News D_{t-1}	-0.1177	0.6496	
	MA(1)	**-0.3825**	**0.0000**	

$$\Delta P_t = \sum_{j=1}^{6}\sum_{i=1}^{3} TD_j CP_i\left[\beta_1 Q_t + \beta_2 D_t + \beta_2 D_{t-1}\right] + \eta_t$$

*CP*1 - Financial; CP2 - Corporate; CP3 - Internal

*TD*1 - 06:00 - 08:00.TD2 - 08:00 - 10:00

*TD*3 - 10:00 - 12:00. TD4 - 12:00 - 14:00

*TD*5 - 14:00 - 16:00. TD6 - 16:00 - 18:00

D is a directional variable indicating whether the trade was a buy or a sell.

Q represents order flow (signed transaction volume)

The change in price (from trade to trade) is calculated in pips.

Madhavan-Smidt Model with Counterparty, Time and News Dummies

(results for Corporate Customers only)

	Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
CP2 (Corporate) :				
	TD_1Q_t	**-0.0321**	**0.0119**	0.1255
	TD_1D_t	0.3370	0.3843	
	TD_1D_{t-1}	-0.5572	0.1216	
	TD_1Q_t	-0.0132	0.3641	
	TD_2D_t	**0.5420**	**0.0357**	
	TD_2D_{t-1}	-0.1525	0.5099	
	TD_3Q_t	-0.0053	0.6756	
	TD_3D_t	0.3771	0.2249	
	TD_3D_{t-1}	-0.2899	0.2870	
	TD_4Q_t	0.0003	0.9830	
	TD_4D_t	0.1663	0.4802	
	TD_4D_{t-1}	0.1288	0.5615	
	TD_5Q_t	-0.0097	0.5729	
	TD_5D_t	**0.6044**	**0.0189**	
	TD_5D_{t-1}	**-0.4532**	**0.0329**	
	TD_6Q_t	-0.0063	0.8238	
	TD_6D_t	0.9887	0.1106	
	TD_6D_{t-1}	-0.4584	0.4099	
	News $(D_t - D_{t-1})$	**1.5943**	**0.0003**	
	News D_{t-1}	**-0.8396**	0.0542	
	MA(1)	**-0.3825**	**0.0000**	

$$\Delta P_t = \sum_{j=1}^{6}\sum_{i=1}^{3} TD_j CP_i \left[\beta_1 Q_t + \beta_2 D_t + \beta_2 D_{t-1}\right] + \eta_t$$

$CP1$ - Financial; CP2 - Corporate; CP3 - Internal

$TD1$ - 06:00 - 08:00.TD2 - 08:00 - 10:00

$TD3$ - 10:00 - 12:00. TD4 - 12:00 - 14:00

$TD5$ - 14:00 - 16:00. TD6 - 16:00 - 18:00

D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

Madhavan-Smidt Model with Counterparty, Time and News Dummies

(results for Internal Customers only)

	Variable	Coefficient	P-Value (HAC)	Adj. R-Squared
CP3 (Internal) :				
	TD_1Q_t	**-0.0166**	**0.0022**	0.1255
	TD_1D_t	0.2559	0.4059	
	TD_1D_{t-1}	0.1783	0.5778	
	TD_1Q_t	0.0140	0.6119	
	TD_2D_t	-0.3037	0.2259	
	TD_2D_{t-1}	0.2354	0.2865	
	TD_3Q_t	0.0851	0.1572	
	TD_3D_t	-0.2266	0.4733	
	TD_3D_{t-1}	-0.1838	0.4254	
	TD_4Q_t	0.0090	0.3876	
	TD_4D_t	*-0.3736*	0.0901	
	TD_4D_{t-1}	0.0217	0.9158	
	TD_5Q_t	-0.0454	0.3457	
	TD_5D_t	0.1319	0.6372	
	TD_5D_{t-1}	*-0.4468*	0.0539	
	TD_6Q_t	0.0029	0.9351	
	TD_6D_t	0.0061	0.9924	
	TD_6D_{t-1}	-0.8912	0.1221	
	News $(D_t - D_{t-1})$	0.3737	0.2590	
	News D_{t-1}	-0.4310	0.1905	
	MA(1)	**-0.3825**	**0.0000**	

$$\Delta P_t = \sum_{j=1}^{6}\sum_{i=1}^{3} TD_j CP_i\left[\beta_1 Q_t + \beta_2 D_t + \beta_2 D_{t-1}\right] + \eta_t$$

*CP*1 - Financial; CP2 - Corporate; CP3 - Internal

*TD*1 - 06:00 - 08:00.TD2 - 08:00 - 10:00

*TD*3 - 10:00 - 12:00. TD4 - 12:00 - 14:00

*TD*5 - 14:00 - 16:00. TD6 - 16:00 - 18:00

D is a directional variable indicating whether the trade was a buy or a sell.
Q represents order flow (signed transaction volume)
The change in price (from trade to trade) is calculated in pips.

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[3] Links to many of the micro FX papers can be found at :
http://faculty.haas.berkeley.edu/lyons/wpothers.html

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