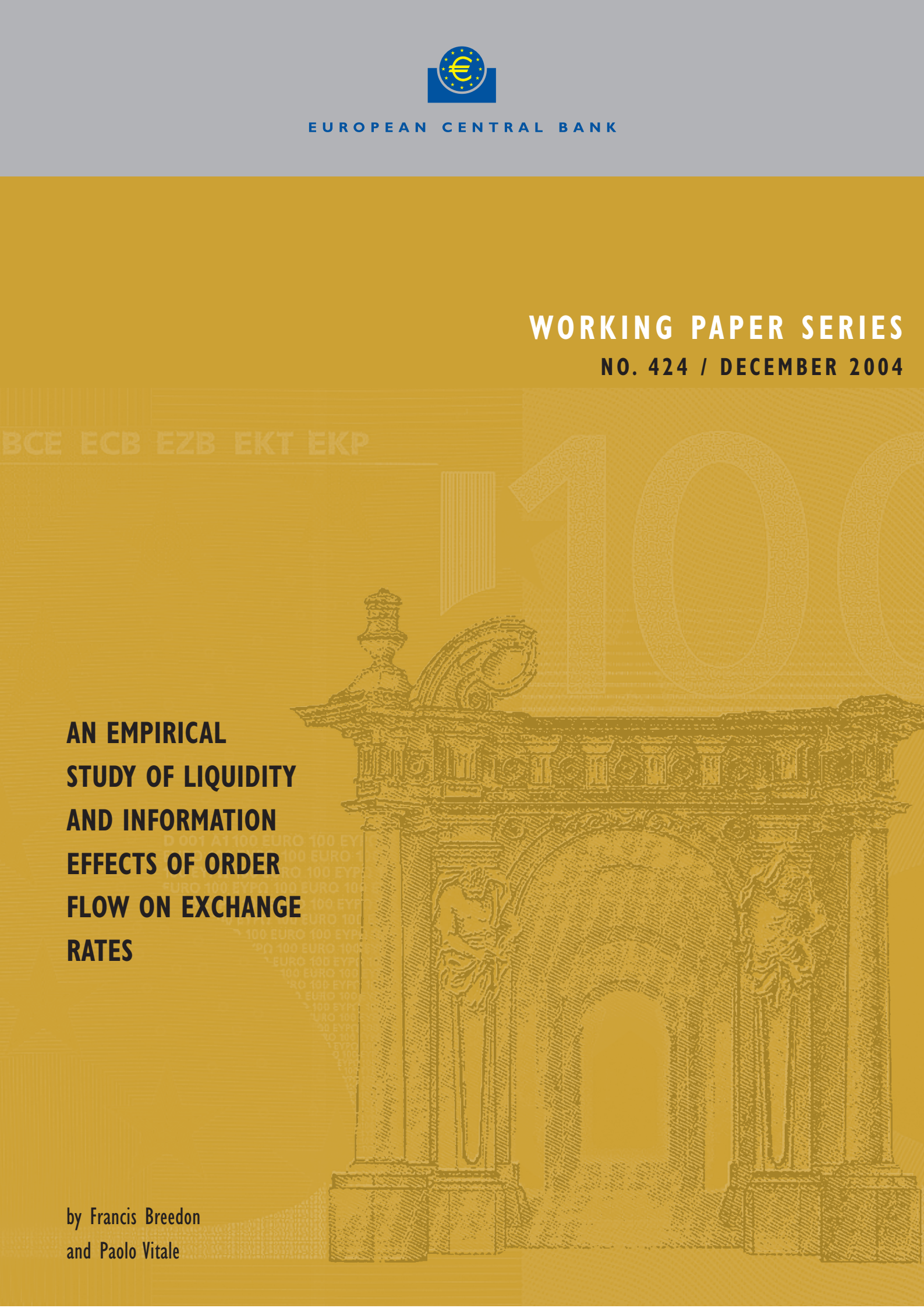

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# AN EMPIRICAL STUDY OF LIQUIDITY AND INFORMATION EFFECTS OF ORDER FLOW ON EXCHANGE RATES

by Francis Breedon
and Paolo Vitale

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by Francis Breedon [2]
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In 2004 all publications will carry a motif taken from the €100 banknote.

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# CONTENTS


Abstract 4
Non-technical summary 5
Introduction 8
1 A simple structural model 11
1.1 Basic set-up 11
1.2 Model interpretation 18
2 Data 20
2.1 Data description and summary statistics 21
2.2 Comparing EBS and Reuters D2000-2 23
2.3 Summary of data properties 25
3 Liquidity and information effects of order flow 25
4 Foreign exchange intervention 31
5 Conclusion 34
References 35
Appendices 37
European Central Bank working paper series 42

**Abstract**

We propose a simple structural model of exchange rate determination which draws from the analytical framework recently proposed by Bacchetta and van Wincoop (2003) and allows us to disentangle the liquidity and information effects of order flow on exchange rates. We estimate this model employing an innovative transaction data-set that covers all direct foreign exchange transactions completed in the USD/EUR market via EBS and Reuters between August 2000 and January 2001. Our results indicate that the strong contemporaneous correlation between order flow and exchange rates is mostly due to liquidity effects. This result also appears to carry through to the four FX intervention events that appear in our sample.

JEL Classification: D82, G14 and G15.
Keywords: Order Flow, Foreign Exchange Micro Structure, Exchange Rate Dynamics.

# NON TECHNICAL SUMMARY

In the past few years students of exchange rate economics have turned their attention to the analysis of transaction data in foreign exchange (FX) markets. Until the late 1990s no detailed data on foreign exchange transactions was available to researchers and it was not possible to conduct any empirical study of micro-structure aspects of FX markets with detailed information on the trading activity of their participants. However, recently the increased competition between trading platforms and data vendors has given researchers and practitioners access to detailed information on individual transactions between FX traders.

The recent interest for the analysis of transaction data in FX markets basically stems from a two-fold argument. On the one hand, the abysmal results of the empirical investigation of the models of exchange rate determination developed in the 1970s questions the validity of the traditional asset market approach. In fact, plenty of empirical evidence shows how asset market models of exchange rate determination completely *fails* to explain exchange rate movements in the short run and can only indicate long-run trends.

On the other hand, the understanding that the organization and regulation of trading activity in financial markets has important implications for the process of price formation has suggested to the international finance community that the analysis of the micro structure of FX markets may guide exchange rate economics out of the "foggy swamp" it has been mired in for the past twenty or more years.

The principal result of the new market micro-structure approach to exchange rate determination is that order flow is an important determinant of exchange rate dynamics in the short term and possibly even in the medium term. Theoretical underpinnings of this empirical result associate the explanatory power of order flow to two different channels of transmission, due respectively to liquidity and information effects. With respect to the former channel, it has simply been suggested that trade innovations perturb the inventories of FX investors which need to be compensated with a shift in expected returns.

With respect to the latter, it has been claimed that the empirical failure of the asset market approach lies with the particular forward looking nature of the exchange rate and with the impact that news on exchange rate fundamentals, such as interest rates, employment levels and so on, have on the value of currencies. When news arrivals condition market expectations of future values of these fundamental variables, exchange rates immediately react anticipating the effect of these fundamental shifts. Since news are hard to observe, it is difficult to control for news effects in the empirical investigation of exchange rate dynamics and hence it is hard to conduct any meaningful analysis of the asset market approach.

However, the analysis of the relation between fundamental values and exchange rates can be bypassed by analyzing buying/selling pressure in FX markets, as the imbalance between buyer-initiated and seller-initiated trades in FX markets, i.e. signed order flow, represents the transmission link between information and exchange rates, in that it conveys information on deeper determinants of exchange rates, which FX markets need to aggregate and impound in currency values. More specifically, as it is typical of rational expectation (RE) models of asset pricing, FX traders collect from various sources information on the fundamental value of foreign currencies and trade accordingly. A general consensus and equilibrium exchange rates are then reached via the trading process, in that information contained in order flow is progressively shared among market participants and incorporated into exchange rates.

So far the new market micro structure approach has not been able to indicate clearly which of these two channels of transmission is at work when trade innovations affect spot rates. Thus, some empirical studies, notably Evans and Lyons (2002a) and Payne (2003), suggest that the impact of order flow on exchange rates is persistent and hence associated to fundamental information; others, notably Froot and Ramadorai (2002), claim instead that order flow is not related to shifts in fundamental variables and hence affect spot rates only via a liquidity effect.

However, these empirical studies estimate simple reduced form models of the link between order flow and exchange rates. On the contrary, we believe that only via the estimation of a structural model of exchange rate determination containing the key micro structural aspects of FX markets it is possible to disentangle the liquidity and information effects of order flow.

In this respect, we present a simple structural model of exchange rate determination, drawn from the analytical framework recently proposed by Bacchetta and van Wincoop (2003), which allows to capture both channels of transmission.

In our version of this analytical framework we modified the original formulation in three important dimensions. Firstly, we assume symmetric information among FX dealers, so that these agents do not have to solve an infinite regress problem when forming their exchange rate expectations. This assumption clearly makes our specification less rich, but also allows to derive a simple, exact closed form solution for the equilibrium value of the exchange rate. Secondly, we assume that private information reaches FX markets via customer order flow, rather than via FX dealers' transactions. This assumption is in line with the commonly held view that FX dealers' ultimate source of private information is given by their customer trade base and is coherent with other market micro-structure models of exchange rate determination (notably Evans and Lyons (2002a)).

Thirdly, in our formulation we explicitly introduce order flow among the determinants of the equilibrium exchange rate, whilst in that of Bacchetta and van Wincoop it is the total holding of

foreign assets on the part of the FX dealers that determines the equilibrium value of the foreign currency. In this way we shift the focus of exchange rate determination from *stocks* to *flows*, consistently with the recent market micro-structure approach.

We estimate this model employing an innovative transaction data-set that covers all direct foreign exchange transactions completed in the USD/EUR market via EBS and Reuters between August 2000 and January 2001. Using GMM techniques we find that order flow explains very little in terms of information or fundamentals. The relationship between order flow and exchange rates seems to be almost totally due to liquidity effects and not to any information contained in order flow. The presence of an important intervention episode in our data-set makes this claim even stronger, as it appears that the large impact of the intervention operations carried out by the ECB in late 2000 is largely brought about via the traditional portfolio-balance channel.

## Introduction

In the past few years students of exchange rate economics have turned their attention to the analysis of transaction data in foreign exchange (FX) markets. Until the late 1990s no detailed data on foreign exchange transactions were available to researchers and it was not possible to conduct any empirical study of micro-structure aspects of FX markets with detailed information on the trading activity of their participants. However, recently the increased competition between trading platforms and data vendors has given researchers and practitioners access to detailed information on individual transactions between FX traders.

The recent interest for the analysis of transaction data in FX markets basically stems from a two-fold argument. On the one hand, the abysmal results of the empirical investigation of the models of exchange rate determination developed in the 1970s questions the validity of the traditional asset market approach. In fact, plenty of empirical evidence shows how asset market models of exchange rate determination completely *fails* to explain exchange rate movements in the short-run and can only indicate long-run trends.[1]

On the other hand, the understanding that the organization and regulation of trading activity in financial markets has important implications for the process of price formation has suggested to the international finance community that the analysis of the micro-structure of FX markets may guide exchange rate economics out of the "foggy swamp" it has been mired in for the past twenty or more years. It has been claimed that the empirical failure of the asset market approach lies with the particular forward looking nature of the exchange rate and with the impact that news on exchange rate fundamentals, such as interest rates, employment levels and so on, have on the value of currencies. When news arrivals condition market expectations of future values of these fundamental variables, exchange rates immediately react anticipating the effect of these fundamental shifts. Since news is hard to observe, it is difficult to control for news effects in the empirical investigation of exchange rate dynamics and hence it is hard to conduct any meaningful analysis of the asset market approach (though a number of recent papers have made significant progress in analyzing the link between news release and exchange rates. See for example Anderson et al (2003).

Nevertheless, it has been suggested that the analysis of the relation between fundamental values and exchange rates could be bypassed by analyzing buying/selling pressure in FX markets. The imbalance between buyer-initiated and seller-initiated trades in FX markets, i.e. signed order flow, may represent the transmission link between information and exchange rates, in that it conveys information on deeper determinants of exchange rates, which FX markets need to aggregate and

[1] See *inter alia* Meese and Rogoff (1983) and Frankel and Rose (1994).

impound in currency values. More specifically, as it is typical of rational expectation (RE) models of asset pricing, FX traders collect from various sources information on the fundamental value of foreign currencies and trade accordingly. A general consensus and equilibrium exchange rates are then reached via the trading process, in that information contained in order flow is progressively shared among market participants and incorporated into exchange rates.

Empirical studies of transaction data and exchange rates, notably Evans and Lyons (2002a) and Payne (2003), show a strong positive correlation between exchange rate returns and signed order flow. Thus, when orders to purchase (sell) a foreign currency exceed orders to sell (purchase) it the corresponding exchange rate increases (falls). The impact of order flow on exchange rates is evident both on the short- and the medium-term, as it is detected using both high frequency data, from 5 minute to daily intervals, and low frequency ones, from weekly to monthly intervals. In addition, the explanatory power of signed order flow is particularly large. If traditional models of exchange rate determination present very low values for the coefficient of multiple determination, when macroeconomic variables, such interest rates and the like, are replaced by signed order flow, this coefficient reaches values close to or even larger than 0.5 (see Vitale (2004) for a review of this literature)

Whilst the information-based interpretation of the explanatory power of order flow is particularly simple and intuitive it is not the only reason that may induce trade innovations in FX markets to move currency values. Evans and Lyons propose an alternative channel of transmission from order flow to exchange rates. According to their portfolio-shift model trade innovations affect exchange rates through a liquidity effect, given that FX dealers are willing to absorb an excess demand (supply) of foreign currency from their customers only if compensated by a shift in the exchange rate.

Of course, it is also possible that the observed correlation between order flow and exchange rate movements comes from the opposite causality, with exchange rates movements causing order flow. Generally speaking most studies in this area reject that possibility arguing that the mechanism through which such causation could occur is unclear or implausible. However, Danielsson and Love (2004). have recently offered a framework under which such feedback trading could be observed. This paper does not pursue this approach as our data set does not contain direct customer order flow through which such feedback trading could be observed. Thus we focus on the prior question of the possible information content of order flow.

Disentangling the information and liquidity effects of order flow on exchange rates is a difficult task. While Evans and Lyons propose a formal model for their portfolio-shift effect, in their empirical investigation they do not directly test it. Instead, they estimate a reduced form specification. Their estimation of a simple linear regression of the exchange rate return on signed order flow is

compatible with other mechanisms of transmission from order flow to exchange rates and hence their analysis is inconclusive.

Payne attempts to separate the information and liquidity effects of order flow on exchange rates following an alternative strategy. Via a simple VAR model he isolates the long-run response of exchange rates to trade innovations. The long-run impact of a trade innovation on exchange rates is usually interpreted as a measure of the information content of order flow, for it is generally presumed that the liquidity effects of buying and selling orders are short-lived. However, as shown by the portfolio-shift model of Evans and Lyons and that we propose here, liquidity shocks in FX markets might also have permanent effects on exchange rates.

In this study we suggest an alternative way to distinguish the information and liquidity effects of order flow based on the direct estimation of a structural model of exchange rate determination, where trade innovations affect exchange rates via both their information content and their impact on the inventories of FX dealers.

The structural model we estimate draws from the analytical framework recently proposed by Bacchetta and van Wincooop (Bacchetta and van Wincoop (2003)) to explain the empirical failure of the traditional asset market models of exchange rate determination. Nevertheless, our specification differs from that chosen by Bacchetta and van Wincoop in three important dimensions.

Firstly, we assume symmetric information among FX dealers, so that, differently from the case studied by Bacchetta and van Wincoop, these agents do not have to solve an infinite regress problem when forming their exchange rate expectations. This assumption clearly makes our specification less rich, but also allows to derive a simple, exact closed form solution for the equilibrium value of the exchange rate. Indeed, in the specification of Bacchetta and van Wincoop the infinite regress of the FX dealers' beliefs implies that the state space presents an infinite dimension and hence the exact solution for the equilibrium exchange rate must be approximated via a truncation of the state space.

Secondly, we assume that private information reaches FX markets via customer order flow, rather than via FX dealers' transactions. This assumption is in line with the commonly held view that FX dealers' ultimate source of private information is given by their customer trade base and is coherent with other market micro structure models of exchange rate determination (notably Evans and Lyons (2002a)).

Thirdly, in our formulation we explicitly introduce order flow among the determinants of the equilibrium exchange rate, whilst in that of Bacchetta and van Wincoop it is the total holding of foreign assets on the part of the FX dealers that determines the equilibrium value of the foreign

currency. In this way we shift the focus of exchange rate determination from *stocks* to *flows*, consistently with the recent market micro-structure approach.

This paper is organised as follows. In Section 1 we present our simplified model of exchange rate determination discussing the economic intuition behind the reduced form equation we eventually derive. In Section 2 we introduce the data-set we employ for our analysis, reporting the typical correlations between signed order flow and excess returns. In the following Section we apply GMM techniques to estimate the parameters of the model. In this way we are able to separate the information and liquidity effects of order flow and to measure their contribution to exchange rate dynamics. In Section 4 we consider possible extensions of our analysis, with a particular focus on the role of foreign exchange intervention. In the last Section we propose some final remarks and a discussion of further research developments.

# 1 A Simple Structural Model

We now present a basic structural model of exchange rate determination which is inspired by the analytical framework proposed by Bacchetta and van Wincoop. However, as already mentioned, our model contains some simplifying assumptions and distinct features which allow to employ our transaction data-set to test the liquidity and information effects of order flow on exchange rates.

## 1.1 Basic Set-Up

In the market for foreign exchange a single foreign currency is traded for the currency of a large domestic economy. Trading in this market is organised according to a sequence of Walrasian auctions. When an auction is called, agents simultaneously submit either market or limit orders for the foreign currency and then a clearing price (exchange rate) for the foreign currency is established.

FX markets are more complex than the simple Walrasian market we envisage here, in that several trading platforms coexist and traders can either complete private bilateral transactions or execute their orders through centralised electronic limit order books, such as the Reuters Dealing 2000-2 and EBS systems. Since a growing share of all FX transactions has been conducted via these centralised trading platforms, our simplification is partially justified.[2] Moreover, our framework will allow to capture the lack of transparency of FX markets, in that all transactions will be anonymous.

In the market for foreign exchange we distinguish two classes of traders: FX dealers and cus-

[2]See the BIS survey of FX markets (BIS (2002)) and Rime (2003).

tomers. Dealers are risk averse investors that absorb any imbalance in the flow of customers' orders. They are rational investors that select optimal portfolios of domestic and foreign assets. They are supposed to be short-sighted in that their investment horizon is just one period long. This assumption is introduced for tractability but also captures a quite well known feature of the behavior of FX dealers, which usually unwind their foreign exchange exposure by the end of any trading day.[3] Bacchetta and van Wincoop assume that all domestic FX dealers share the same CARA utility function of their end-of-period wealth and that at time $t$ they can invest in three different assets: a domestic production technology which depends on the amount of real balances possessed and domestic and foreign bonds that pay period-by-period interest rates $i_t$ and $i_t^*$ respectively.

Under these conditions the optimal demand for the foreign currency on the part of the population of domestic FX dealers is proportional to the *average* expected value of its excess return:

$$x_t \quad = \quad \frac{1}{\gamma\,\sigma^2}\left(\bar{E}_t(s_{t+1}) \,-\, s_t \,+\, (i_t^* \,-\, i_t)\right), \tag{1}$$

where $s_t$ is the log of the spot exchange rate (i.e. the number of units of the domestic currency for one unit of the foreign one), $\bar{E}_t(s_{t+1})$ represents the average of the conditional expectations for next period's spot rate on the part of all domestic FX dealers, $s_{t+1}$, given the information they possess in period $t$, $\sigma^2$ indicates the corresponding conditional variance,[4] and $\gamma$ is the coefficient of risk-aversion of all FX dealers' CARA utility functions. FX dealers' clients provide all the supply of foreign currency. Thus, in equilibrium at time $t$ the total demand for foreign currency on the part of all FX dealers is equal to the total amount of foreign currency supplied by their clients, $z_t$:[5]

$$x_t \quad = \quad z_t. \tag{2}$$

These customers comprise a population of liquidity and informed traders.[6] The amount of foreign currency these customers supply changes over time in order to meet their liquidity needs and/or exploit their private information. If $o_t$ represents the amount of foreign currency liquidity and informed traders collectively desire to sell at time $t$, the total supply of foreign currency changes

[3] See Lyons (1995) and Bjønnes and Rime (2004).

[4] Implicitly it assumed that domestic FX dealers might have different conditional expectations of future exchange rates but always share the same conditional variance. In the presence of asymmetric information this is possible under normality.

[5] We should also consider the supply of foreign currency on the part of foreign FX dealers, which desire to purchase domestic bonds. In any case, since the mass of these FX dealers is infinitesimally small, we can disregard their demand for domestic currency.

[6] As already mentioned, by introducing informed customers we depart from Bacchetta and van Wincoop's original set up. Our assumption allows to directly relates customer order flow to information, while preserving symmetric information among FX dealers.

according to the following expression:

$$z_t \;=\; z_{t-1} \;+\; o_t. \tag{3}$$

Signed *order flow* $o_t$ can be decomposed into the number of units of foreign currency traded respectively by the liquidity, $b_t$, and the informed customers, $I_t$:[7]

$$o_t \;=\; b_t \;+\; I_t. \tag{4}$$

Since order flow presents some evidence of serial correlation we assume that its liquidity component, $b_t$, follows an AR(1) process,

$$b_t \;=\; \rho_b\, b_{t-1} \;+\; \epsilon_t^l, \tag{5}$$

where the liquidity shock $\epsilon_t^l$ is normally distributed, with mean zero and variance $\sigma_l^2$, and is serially uncorrelated (i.e. $\epsilon_t^l \perp \epsilon_{t'}^l$).[8]

At time $t$ the amount of foreign currency offered for sale by the informed traders, $I_t$, is instead correlated with the innovation in the fundamental value, $f_t$, i.e. the variable that in equilibrium determines the value of the foreign currency. This fundamental value is given by $f_t \equiv m_t - m_t^*$, where $m_t$ represents the log of the domestic money supply at time $t$ and $m_t^*$ the equivalent aggregate for the foreign country. We assume that the fundamental value follows a simple AR(1) process with serial correlation coefficient $\rho_f$,[9]

$$f_t \;\;=\;\; \rho_f\, f_{t-1} \;+\; \epsilon_t^f, \tag{6}$$

where the fundamental shock $\epsilon_t^f$ is normally distributed with mean zero and variance $\sigma_f^2$ and is serially uncorrelated ($\epsilon_t^f \perp \epsilon_{t'}^f$).[10]

Whilst the fundamental process is observable, at time $t$ all informed traders possess some private information on its next period shock, $\epsilon_{t+1}^f$, and place a *collective* market order, $I_t$, in order to gain

[7] Differently from the usual convention a positive $o_t$ indicates a net sale of foreign currency. If instead $o_t$ is negative, FX dealers' clients collectively place an order to purchase the foreign currency.

[8] Preliminary analysis of our transaction data suggests a value for $\rho_b$ roughly equal to 0.20 in the USD/EUR spot market.

[9] Unit root tests suggest a value for $\rho_f$ close to 1 in the case of the United States and the euro area. Therefore, we will consider the extreme case of a unit root in the fundamental process, $f_t$.

[10] Clearly, these fundamental shocks are all orthogonal to the liquidity ones (i.e. $\epsilon_t^f \perp \epsilon_{t'}^b$).

speculative profits. We assume that this order is equal to

$$I_t \equiv -\theta\,\epsilon^f_{t+1}, \tag{7}$$

where $\theta$ is a positive constant that measures the intensity of their trading activity. This assumption indicates that some insiders collect information on future shifts in fundamentals before these come into the public domain.[11]

To close the model, equilibrium conditions are imposed for the monetary markets in the domestic and the foreign country. Given the production functions introduced by Bacchetta and van Wincoop, the two following equilibrium conditions in the domestic and foreign country prevail:

$$m_t - p_t = -\alpha\, i_t, \tag{8}$$

$$m^*_t - p^*_t = -\alpha\, i^*_t, \tag{9}$$

where $p_t$ and $p^*_t$ represent respectively the log of the domestic and foreign price level. As in both countries a unique common good is produced, the purchasing parity condition holds:

$$s_t = p_t - p^*_t. \tag{10}$$

Using equations (8), (10), the definition of the demand for foreign currency on the part of domestic FX dealers (equation (1)) and the FX market equilibrium condition (equation (2)) we find that:[12]

$$s_t = \frac{1}{1+\alpha}\sum_{k=0}^{\infty}\left(\frac{\alpha}{1+\alpha}\right)^k\left(\bar{E}^k_t\left(f_{t+k}\right) - \alpha\,\gamma\,\sigma^2\,\bar{E}^k_t(z_{t+k})\right), \tag{11}$$

where $\bar{E}^k_t(f_{t+k})$ is the order $k$ average rational expectation across all FX dealers of period $t+k$ fundamental value, $f_{t+k}$, i.e. $\bar{E}^k_t(f_{t+k}) = \bar{E}_t\bar{E}_{t+1}\ldots\bar{E}_{t+k-1}(f_{t+k})$. Similarly, $\bar{E}^k_t(z_{t+k})$ is the order $k$ average rational expectation across all FX dealers of period $t+k$ supply of foreign currency, $z_{t+k}$.

For simplicity and tractability we assume that: 1) all FX dealers possess symmetric information; 2) all FX dealers at time $t$ can only receive signals over next period fundamental shock, $\epsilon^f_{t+1}$. These two assumptions allow to circumnavigate the infinite regress problem Bacchetta and van

[11] While $\theta$ is a given parameter, it would be relatively simple to endogenise it by assuming that the informed customers form a population of strategic profit maximizers.

[12] Note that in deriving this expression we have assumed that $\text{var}(s_{t+k+1}|\Omega^i_{t+k}) = \sigma^2$, where $\Omega^i_{t+k}$ is FX dealer $i$'s information set at time $t+k$. It can be proved that this condition of time invariance for the conditional variance of the future spot rate holds within the stationary equilibrium we identify. Details of the proof can be obtained from the authors on request.

Wincoop study and hence obtain simple closed form solutions for the exchange rate equation (11).[13] In practice, this amounts to imposing the conditions that $\bar{E}_t^k(f_{t+k}) = E(f_{t+k} \mid \Omega_t)$ and $\bar{E}_t^k(z_{t+k}) = E(z_{t+k} \mid \Omega_t)$, where $\Omega_t$ corresponds to the information set FX dealers possess at time $t$. Thus, the order $k$ average rational expectations of period $t+k$ fundamental value, $f_{t+k}$, and period $t+k$ supply of foreign currency, $z_{t+k}$, are simply equal to all individual FX dealers' conditional expectations of the same variables.

Under the assumption of equation (7) equation (11) presents the following solution:

$$\begin{aligned} s_t \quad = \quad & \frac{1}{1+\alpha(1-\rho_f)} f_t \; + \; \frac{\alpha}{(1+\alpha)} \frac{1}{1+\alpha(1-\rho_f)} E\left(\epsilon_{t+1}^f \mid \Omega_t\right) \\ & - \alpha\,\gamma\,\sigma^2\, z_t \; - \; \gamma\,\sigma^2 \frac{\alpha^2\,\rho_b}{1+\alpha(1-\rho_b)} E\left(b_t \mid \Omega_t\right). \end{aligned} \tag{12}$$

To derive a RE equilibrium and obtain a closed form solution for the spot rate we need to establish how FX dealers formulate their predictions of: 1) the shock to the fundamental value, $\epsilon_{t+1}^f$; and 2) liquidity order flow, $b_t$.

**Fundamental Value.** With respect to the former task we assume that at time $t$ all FX dealers observe the following common signal:

$$v_t \quad = \quad \epsilon_{t+1}^f \; + \; \epsilon_t^v, \tag{13}$$

where once again the signal error $\epsilon_t^v$ is normally distributed with mean zero and variance $\sigma_v^2$. Clearly, the error terms are uncorrelated over time (i.e. $\epsilon_t^v \perp \epsilon_{t'}^v$) and with the fundamental shock (i.e. $\epsilon_t^v \perp \epsilon_{t'}^f$). In practice, the signal $v_t$ represents all the information which FX dealers can readily obtain from various official sources and publicly available data, such newswire services, newsletters, monetary authorities' watchers and so on.

Alongside this signal all FX dealers can observe the flow of transactions that are completed in the market for foreign exchange. This is possible because in centralised platforms such as EBS and Reuters Dealing 2000-2 all transactions are immediately published on the system's computer screens. Therefore, we can assume that in any period $t$ all FX dealers observe the signed order flow, $o_t$. However, given that on these centralised platforms trades are anonymous, the average dealer cannot distinguish between liquidity orders and informative ones, i.e. between $b_t$ and $I_t$.

[13] Besides the loss of generality that these two assumptions bring about, we are not able to reproduce the magnification effect of the liquidity shock on the exchange rate that Bacchetta and van Wincoop find.

Hence, suppose that at time $t-1$ FX dealers have formulated a conditional expectation of the liquidity order flow $E(b_{t-1} \mid \Omega_{t-1})$, where $\Omega_t \equiv v_t, o_t, v_{t-1}, o_{t-1}, \ldots v_{t-k}, o_{t-k} \ldots$. Since this component of order flow is persistent, FX dealers can form the following prediction for the liquidity order flow which will prevail in period $t$:

$$E\left(b_t \mid \Omega_{t-1}\right) = \rho_b E\left(b_{t-1} \mid \Omega_{t-1}\right). \tag{14}$$

Then, applying the projection theorem for normal distributions, under equation (7), the conditional expectation and the conditional variance of the fundamental shock, $\epsilon^f_{t+1}$, are as follows:

$$E\left(\epsilon^f_{t+1} \mid \Omega_t\right) = \frac{\tau_v}{\tau_{\epsilon,t}} v_t - \frac{\tau_{y,t}}{\tau_{\epsilon,t}} \frac{1}{\theta} \left( o_t - E\left(b_t \mid \Omega_{t-1}\right) \right), \tag{15}$$

$$\mathrm{Var}\left(\epsilon^f_{t+1} \mid \Omega_t\right) = 1/\tau_{\epsilon,t}, \tag{16}$$

where $\tau_{\epsilon,t}$ is the conditional precision of the fundamental shock. This precision is equal to

$$\tau_{\epsilon,t} = \tau_f + \tau_v + \tau_{y,t},$$

where $\tau_f = 1/\sigma^2_f$, $\tau_v = 1/\sigma^2_v$, $\tau_{y,t} = \theta^2 \tau_{b,t-1}$, $\tau_{b,t-1} = 1/\sigma^2_{b,t-1}$ and $\sigma^2_{b,t-1}$ is the conditional variance of the liquidity order flow, $b_t$, given the information FX dealers possess at the end of period $t-1$. This conditional variance is equal to

$$\sigma^2_{b,t-1} \equiv \mathrm{Var}\left(b_t \mid \Omega_{t-1}\right) = \rho^2_b \mathrm{Var}\left(b_{t-1} \mid \Omega_{t-1}\right) + \sigma^2_l,$$

where $\mathrm{Var}(b_{t-1} \mid \Omega_{t-1})$ corresponds to the conditional variance of $b_{t-1}$ given the information FX dealers possess at the end of period $t-1$.

**Liquidity Order Flow.** Since the liquidity order flow is persistent, FX dealers can estimate its present and future values. From the projection theorem for normal distributions we conclude that the conditional expectation $E\left(b_t \mid \Omega_t\right)$ respects the following formulation

$$E\left(b_t \mid \Omega_t\right) = E\left(b_t \mid \Omega_{t-1}\right) + \frac{\theta\, \tau_v}{\tau_{\epsilon,t}} v_t + \frac{\tau_f + \tau_v}{\tau_{\epsilon,t}} \left( o_t - E\left(b_t \mid \Omega_{t-1}\right) \right), \tag{17}$$

while the conditional variance is equal to

$$\mathrm{Var}\left(b_t \mid \Omega_t\right) = 1/\tau_{b,t} \quad \text{where}$$

$$\tau_{b,t} = \frac{1}{\theta^2} \tau_{\epsilon,t}. \tag{18}$$

In our analysis we concentrate on steady-state rational expectations equilibria, given that in the limit for $t \uparrow \infty$ $\text{Var}(b_t \mid \Omega_t)$ and $\text{Var}\left(\epsilon^f_{t+1} \mid \Omega_t\right)$ converge to time-invariant values.[14]

Likewise, $\tau_{y,t}$ and $\tau_{b,t-1}$ converge to limit values $\tau_y$ and $\tau_{b,-1}$. In summary, in these steady state equilibria we will have that $\tau_{\epsilon,t}$ and $\tau_{b,t}$ will be replaced by the limit values $\tau_\epsilon$ and $\tau_b$, where

$$\tau_\epsilon = \tau_f + \tau_v + \tau_y, \tag{19}$$

$$\tau_b = \frac{1}{\theta^2}\left(\tau_f + \tau_v + \tau_y\right) \tag{20}$$

and $\tau_y = \theta^2 \tau_{b,-1}$.

Substituting the conditional expectation of the fundamental shock, $E\left(\epsilon^f_{t+1} \mid \Omega_t\right)$, and the liquidity order flow, $E\left(b_t \mid \Omega_t\right)$, into equation (12) we eventually obtain a closed form solution for the exchange rate,

$$s_t = \lambda_{s,-1}\, s_{t-1} + \lambda_f\, f_t + \lambda_{f,-1}\, f_{t-1} + \lambda_z\, z_t + \lambda_{z,-1}\, z_{t-1} + \lambda_o\, o_t + \lambda_{o,-1}\, o_{t-1} + \lambda_v\, v_t, \tag{21}$$

where

$$\lambda_{s,-1} = \rho_b \frac{\tau_y}{\tau_\epsilon},$$

$$\lambda_f = \frac{1}{1+\alpha\left(1-\rho_f\right)},$$

$$\lambda_{f,-1} = -\rho_b \frac{1}{1+\alpha\left(1-\rho_f\right)} \frac{\tau_y}{\tau_\epsilon} = -\lambda_{s,-1}\,\lambda_f,$$

$$\lambda_z = -\alpha\,\gamma\,\sigma^2,$$

$$\lambda_{z,-1} = \alpha\,\gamma\,\rho_b \frac{\tau_y}{\tau_\epsilon}\sigma^2 = -\lambda_{s,-1}\,\lambda_z,$$

[14] It is not difficult to see that the former converges to $\Sigma_b$, where $\Sigma_b$ is the unique positive root of the following quadratic equation: $a_\Sigma \Sigma_b^2 + b_\Sigma \Sigma_b + c_\Sigma = 0$, where $a_\Sigma = \rho_b^2\left(\sigma_f^2 + \sigma_v^2\right)$, $b_\Sigma = \sigma_l^2\left(\sigma_f^2 + \sigma_v^2\right) + \theta^2\sigma_f^2\sigma_v^2\left(1-\rho_b^2\right)$ and $c_\Sigma = -\theta^2\sigma_l^2\sigma_f^2\sigma_v^2$.

$$\lambda_o = -\frac{\alpha}{1+\alpha}\left[\alpha\gamma\sigma^2\left(\frac{\rho_b(1+\alpha)}{1+\alpha(1-\rho_b)}\right)\left(\frac{\tau_f+\tau_v}{\tau_\epsilon}\right) + \frac{\frac{1}{\theta}}{1+\alpha(1-\rho_f)}\frac{\tau_y}{\tau_\epsilon}\right],$$

$$\lambda_{o,-1} = \frac{\alpha}{1+\alpha}\,\rho_b\left(\frac{\frac{1}{\theta}}{1+\alpha(1-\rho_f)}\right)\frac{\tau_y}{\tau_\epsilon},$$

$$\lambda_v = \frac{\alpha}{1+\alpha}\left(\frac{1}{1+\alpha(1-\rho_f)} - \alpha\,\gamma\,\sigma^2\,\theta\,\frac{\rho_b(1+\alpha)}{1+\alpha(1-\rho_b)}\right)\frac{\tau_v}{\tau_\epsilon}.$$

If we take differences, we obtain the following expression for the variation in the exchange rate:[15]

$$s_t - s_{t-1} = \lambda_{s,-1}\,(s_{t-1} - s_{t-2}) + \lambda_f\,(f_t - f_{t-1}) + \lambda_{f,-1}\,(f_{t-1} - f_{t-2}) + \lambda_z\,o_t +$$

$$\lambda_{z,-1}\,o_{t-1} + \lambda_o\,(o_t - o_{t-1}) + \lambda_{o,-1}\,(o_{t-1} - o_{t-2}) + \lambda_v\,(v_t - v_{t-1}), \quad (22)$$

## 1.2 Model Interpretation

From equation (22) we see that eight factors enter into the equilibrium relation for the variation in the exchange rate: the first lag of the spot rate variation, $s_{t-1} - s_{t-2}$, the contemporaneous value and the first lag of the variation in the fundamental variable, $f_t - f_{t-1}$ and $f_{t-1} - f_{t-2}$, the contemporaneous value and the first lag of the order flow, $o_t$ and $o_{t-1}$, the contemporaneous value and the first lag of the variation in the order flow, $o_t - o_{t-1}$ and $o_{t-1} - o_{t-2}$, and the contemporaneous variation in the public signal, $v_t - v_{t-1}$. The signs of the corresponding coefficients deserve some explanation.

Serial correlation in the liquidity component of the order flow, captured by the auto-regressive parameter $\rho_b$, generates serial correlation in the spot rate. Specifically, if liquidity shocks persist in time, i.e $\rho_b > 0$, $\lambda_{s,-1}$ is positive, inducing some positive serial correlation in the value of the foreign currency. Clearly the opposite holds if $\rho_b < 0$.

The sign of the fundamental coefficient $\lambda_f$ is positive. This is not surprising given that an increase in the fundamental value, $f_t$, corresponds to a rise in the relative money supply, i.e. in the interest rate differential $i_t^* - i_t$. In other words, an increase in $f_t$ augments the excess return on the foreign currency and hence determines its appreciation.

Note, however, that positive serial correlation in the liquidity order flow induces some mean reversion in the impact of fundamental shocks on the spot rate, as the coefficient of the first lag

[15] At very high frequencies $s_t - s_{t-1}$ *de facto* corresponds to the exchange rate return.

of the change in the fundamental value, $\lambda_{f,-1}$, is negative, but smaller in magnitude than the corresponding coefficient for the contemporaneous value, $\lambda_f$ ($|\lambda_{f,-1}| < \lambda_f$). On the contrary, in the presence of negative serial correlation the impact of a fundamental shock is magnified over time in that $\lambda_{f,-1}$ is positive as well.

While an increase in the public signal $v_t$ augments the fundamental value perceived by the FX dealers, the sign of the corresponding coefficient, $\lambda_v$, is generally unclear. Nevertheless, when either $\theta$ or $\rho_b$ is small, the public signal coefficient is positive. A positive value for the public signal, $v_t$, induces FX dealers to increase their expectations of current and future realisations of the fundamental process and hence possesses an effect on the spot rate which is similar to that of a positive value for $f_t$.

The total supply coefficients $\lambda_z$ and $\lambda_{z,-1}$ are also quite straightforward to explain. The former is negative because an increase in the supply of foreign currency depresses its value via a liquidity effect. In fact, FX dealers will be willing to hold a larger quantity of the foreign currency only if they are compensated for the increased risk they bear. Thus, a larger $z_t$ forces a depreciation of the foreign currency as this corresponds to a larger excess return FX dealers expect from holding foreign bonds. When $\rho_b > 0$ the latter coefficient is positive, because persistence in the liquidity component of order flow induces mean reversion in the liquidity effect of the total supply of foreign currency. As already seen for the fundamental shock, when $\rho_b$ is negative such mean reversion turns into magnification, in that $\lambda_{z,-1} < 0$.

The order flow coefficients $\lambda_o$ and $\lambda_{o,-1}$ are particularly interesting. The former is negative, because of the aforementioned liquidity effect and because order flow possesses an information content. When some customer orders are informative (i.e. for $\theta > 0$), an excess of sell orders might indicate an impending negative fundamental shock ($\epsilon^f_{t+1} < 0$) and hence induces rational FX dealers to expect an exchange rate depreciation. Consequently, FX dealers will be willing to hold the same amount of the foreign currency only if a reduction in $s_t$ re-establishes the expected excess return foreign bonds yield.

For $\rho_b > 0$ the sign of $\lambda_{o,-1}$ is positive given that persistence in liquidity trading forces mean reversion in the effect of order flow on the spot rate. In fact, FX dealers learn over time the realisations of the fundamental process and can eventually disentangle the informative and the noisy components of order flow. Such mean reversion is in any case only partial, in that $|\lambda_o| > |\lambda_{o,-1}|$, and hence we can conclude that the effect of order flow on exchange rates is *persistent*.

Importantly, this result holds even when customer trades do not carry any information, i.e. when $\theta = 0$, suggesting that the impact of liquidity shocks on exchange rates is not transitory. Such conclusion contrasts with the generally held view that any transitory imbalance between buy

and sell orders possesses only a short-lived effect on exchange rates if order flow does not carry any information. Finally, note that when $\rho_b$ is negative, i.e. in the presence of mean reversion in the liquidity component of order flow, $\lambda_o$ and $\lambda_{o,-1}$ possess the same sign and hence the impact of liquidity shocks on exchange rates is strengthened.

As already mentioned, the existing empirical literature on the relation between order flow and exchange rates has faced difficulties in disentangling the liquidity and information effects. Thus, Evans and Lyons (2002a) estimate a linear relation between exchange rate changes and order flow similar to equation (21) and conclude that the latter moves the former both at high and low frequencies. Whilst the empirical fit of their linear regressions is impressive, their OLS estimates are mired by simultaneity bias. In addition, if it is true that order flow can explain contemporaneous exchange rate variations, it is not useful in predicting future movements in exchange rates.

Payne (2003) follows a different econometric route and estimates a VAR model of exchange rate variation and order flow. His investigation shows that signed order flow presents a positive, significant, and long-lasting effect on exchange rates. Payne interprets such a result as indicating that trades in FX markets carry information. Froot and Ramadorai (2002) employ a different data-set, a longer time horizon and Campbell's variance decomposition technique. Their results reverse Payne's conclusions and suggest that the effect of order flow on exchange rates is not related to fundamental information.

However, since these empirical investigations are not based on any structural model of the relation between order flow and exchange rate their results can only suggest theoretical implications. On the contrary, equation (21) is the result of a formal model and its estimation could shed light on the liquidity-vs-information-effect dilemma. Clearly, a simple direct OLS estimation of this relation would not be enough to run tests of the significance of the deep parameters of the model, i.e. those values which allow isolating the information and liquidity effects of order flow. Therefore, we define a series of moment conditions between observable variables which we employ to apply a GMM estimation technique. Before we turn to this task let us present in some detail the characteristics of our data-set.

## 2 Data

Our core data-set consists of all inter-dealer trades in USD/EUR undertaken through the two major electronic limit order book trading systems employed in the spot FX markets, Electronic Broking Services (EBS) and Reuters Dealing 2000-2 (D2). These two trading platforms represent the dominant mechanism through which inter-dealer trades are mediated and are unusual in FX

markets in the sense that they offer a high degree of pre and post trade transparency. In common with other electronic limit order books, these systems display firm prices (posted by "patient" traders in the form of limit orders) at which other "impatient" traders can trade immediately. Using 2001 data from the BIS triennial survey (BIS (2002)) as a guide we can estimate that these two electronic platforms represent about 60% of all inter-dealer order flow in EUR/USD and perhaps 33% of total order flow.

Customers, on the other hand, do not have access to the data displayed on these two platforms and must usually phone up FX dealers to get trading prices and complete their orders. Thus, customer orders cannot be directly entered into the two electronic limit order books. However, they strongly influence dealers' trading, so that liquidity and information shocks associated to customer order flow is reflected in inter-dealer trading on EBS and D2. We collected bid and ask prices and an indicator of the number of buy and sell transactions from both trading systems at a five minute frequency over the period August 2000 to mid-January 2001. After allowing for public holidays and a few days over which data collection was incomplete, we are left with 128 days of data. We supplement that information both with some daily estimates (on average trade size and euro area and US interest rates) and with five-minute interest rate data collected from the LIFFE 3-month EURIBOR futures contracts.

### 2.1 Data Description and Summary Statistics

Table 1 presents some summary statistics from our data-set at a daily, hourly and five minute frequency. We present data for order flow per period (rather than cumulated order flow), and for the change in the exchange rates and interest rate differentials since the levels of the series all proved to be I(1).

An interesting aspect of our summary table is the consistent pattern of positive auto-correlation we see in the order flow data (particularly for D2). This auto-correlation seems not to be reflected in the other series except at very high frequencies. Evans and Lyons (2002b) ascribe this effect to "hot-potato" trading whereby a large order creates a chain of subsequent smaller orders of the same sign (as dealer pass the hot potato amongst themselves). They also find that this type of order flow has no price impact. In our empirical model we allow for this auto-correlation by assuming that uninformed order flow is auto-correlated.

As a starting point of our analysis Table 2 reports the contemporaneous and first-lag correlations between: i) changes in interest rate differentials, $\Delta(i_t - i_t^*)$; ii) exchange rate returns, $r_t$; and iii) order flow, $o_t$, calculated at the daily frequency (we focus on daily data as this is the frequency that we focus on below). These values show some interesting patterns. In particular, consistently with

Table 1: Summary statistics for order flow, exchange rate and interest rate data.

| | **Mean** | **Std. Dev.** | $\hat{\rho}$**(1)** | **Prob.** |
|---|---|---|---|---|
| | **Daily Frequency** | | | |
| **Order Flow** ($o_t$) | | | | |
| All Transactions | 54 | 270 | 0.19 | 0.04 |
| EBS | 87 | 154 | 0.13 | 0.16 |
| D2 | -33 | 178 | 0.22 | 0.02 |
| **FX Returns** ($r_t$) | 0.0003 | 0.75 | 0.01 | 0.27 |
| **Interest Rates** ($\Delta(i_t - i_t^*)$) | 0.0195 | 0.06 | 0.16 | 0.11 |
| | **Hourly Frequency** | | | |
| **Order Flow** ($o_t$) | | | | |
| All Transactions | 5 | 61 | 0.229 | 0.00 |
| EBS | 8 | 38 | 0.115 | 0.000 |
| D2 | -3 | 47 | 0.092 | 0.001 |
| **FX Returns** ($r_t$) | 0.006 | 0.22 | 0.026 | 0.35 |
| **Interest Rates** ($\Delta(i_t - i_t^*)$) | 0.0003 | 0.0087 | -0.06 | 0.04 |
| | **5-minute Frequency** | | | |
| **Order Flow** ($o_t$) | | | | |
| All Transactions | -0.4 | 13.0 | 0.199 | 0.00 |
| EBS | -0.7 | 10.8 | -0.01 | 0.28 |
| D2 | 0.3 | 11.1 | 0.167 | 0.00 |
| **FX Returns** ($r_t$) | 0.000006 | 0.0007 | -0.035 | 0.00 |
| **Interest Rates** ($\Delta(i_t - i_t^*)$) | 0.00003 | 0.004 | -0.136 | 0.00 |

Notes: Table shows the mean, standard deviation, first-order auto-correlation coefficient and the $p$ value of the Box-Ljung statistic for first-order auto-correlation for a number of series. Order flow $o_t$ is defined as the number of sells minus the number of buys in period $t$. Returns are the percentage change in the USD/EUR exchange rate observed over period $t$, $r_t \equiv 100(\log(S_t) - \log(S_{t-1}))$. Interest rates are the percentage point change in the euro-US interest rate 3-month interest rate differential at the daily frequency and the percentage point change in the Euribor 3-month forward rate (interpolated from the 3 and 6 month Euribor futures contract traded on LIFFE) at higher frequencies, $\Delta(i_t - i_t^*) \equiv 100[(i_t - i_t^*) - (i_{t-1} - i_{t-1}^*)]$. Intra-daily data are shown for the European trading day (7am to 6pm, UK time) excluding the change from the end of one trading day to the beginning of the next.

previous studies, notably Evans and Lyons (2002a), Froot and Ramadorai (2002), and Payne (2003), order flow and exchange rate returns are strongly correlated: when sell orders for the American currency exceed buy ones, $o_t > 0$, the corresponding exchange rate, USD/EUR, depreciates, $r_t < 0$. Interestingly, order flow is also correlated with changes in the interest rate differential. In particular, the first lag in the order flow, $o_{t-1}$, is positively correlated with the innovation in the interest rate differential, $\Delta(i_t - i_t^*)$.

This positive correlation may be read according to an information-based interpretation: investors are able to abandon the US currency, $o_t > 0$, *correctly* anticipating an increase in the interest rate differential between the euro area and the United States, $\Delta(i_t - i_t^*) > 0$, that leads to a depreciation of the US currency, $r_t < 0$, as shown by the negative contemporaneous correlation between the exchange rate return, $r_t$, and the innovation in the interest rate differential, $\Delta(i_t - i_t^*)$. Note that this information-based interpretation could also explain the negative correlation observed between the first lag in the order flow, $o_{t-1}$, and the exchange rate return, $r_t$, as investors anticipate exchange rate movements one period ahead. However, this is of course only one possible interpretation of these correlations

In the next Section we will be able to check this information-based interpretation estimating our structural model of exchange rate determination. Our model explicitly allows for an informative component of order flow that anticipates next period fundamental shift, but also identifies a liquidity-based link between order flow and the exchange rate. By disentangling the information and liquidity effects of order flow on exchange rates we will be able to see whether trade innovations possess an information content, i.e. if investors buy and sell foreign currencies on the basis of fundamental news.

## 2.2 Comparing EBS and Reuters D2000-2

Although it is not the focus of our study, an important aspect of our data-set is the fact that we have comparable data from both major electronic trading platforms. Table 3 shows some evidence on the interaction between the two.

What is clear from Table 3 is that EBS has the dominant position in USD/EUR trading. It share of the total number of trades is about 81% and by value we estimate the share to be around 88%. This trading advantage is also carried though to spreads where, on average, the EBS bid-ask spread is almost one quarter as wide as that of D2. The markets appear to be quite closely linked with the number of potential arbitrage opportunities between the markets (where the ask of one market is below the bid of the other) being only about 4 times greater than arbitrage opportunities within markets (when ask is below bid). Presumably in both cases these arbitrages are very short-lived and arise from the time required to input trade details.

Table 2: Correlation matrix for order flow, exchange rate and interest rate daily data.

| | $\Delta(i_t - i_t^*)$ | $\Delta(i_{t-1} - i_{t-1}^*)$ | $r_t$ | $r_{t-1}$ | $o_t$ | $o_{t-1}$ |
|---|---|---|---|---|---|---|
| $\Delta(i_t - i_t^*)$ | 1.000000 | 0.306376 | -0.260137 | -0.048003 | 0.131069 | 0.072362 |
| $\Delta(i_{t-1} - i_{t-1}^*)$ | | 1.000000 | -0.091724 | -0.251373 | 0.096816 | 0.117978 |
| $r_t$ | | | 1.000000 | 0.085646 | -0.805875 | -0.107502 |
| $r_{t-1}$ | | | | 1.000000 | -0.134207 | -0.798079 |
| $o_t$ | | | | | 1.000000 | 0.220346 |
| $o_{t-1}$ | | | | | | 1.000000 |

Notes: As for Table 1. $\Delta(i_t - i_t^*) = 100[(i_t - i_t^*) - (i_{t-1} - i_{t-1}^*)]$, $r_t = 100(\log(S_t) - \log(S_{t-1}))$, while now $o_t = 1$ means an excess of 1000 sell orders over buy orders for the foreign currency, the US dollar, against the domestic one, the euro, within day $t$.

Table 3: EBS and Reuters Dealing 2000-2 compared.

| | **EBS** | **D2** |
|---|---|---|
| Average number of trades per day | 11020 | 2627 |
| Average trade size | $3.14 million | $1.84 million |
| Average bid-ask spread | 0.014% | 0.051% |
| Occasions when bid-ask spread is zero or less | 5.51% | 2.13% |
| Occasions when bid-ask spread is less than zero | 0.26% | 0.31% |
| Occasions when bid is above ask of other platform | 0.58% | 0.63% |
| Average absolute deviation in mid price | 0.014% | 0.014% |
| Hasbrouck Indicator of information share | 47%-94% | 6%-53% |

Notes: Figures refer to European trading session between 7.00am and 6.00pm. Calculations based on five minute data frequency. Average trade size derived from daily EBS volume data for EBS and Payne (2003) for D2. Hasbrouck Indicator based on identifying contribution to underlying common trend of each set of prices (see Hasbrouck(1995)).

The Hasbrouck Information share statistic (Hasbrouck(1995)) is a measure of a markets contribution to price discovery. Since prices for the same asset in different markets should tend to converge in the long-run but might deviate from one another in the short-run the statistic uses the cointegration between the two prices to derive a measure of the variance of innovations to the long-run price and to decompose it into components, termed information shares, due to each market. But if, as in this case, the price innovations across markets are correlated, the innovations cannot be allocated. Thus, we present a range for this statistic based on the two extreme assumptions; either all the contemporaneous price formation is due to a given market, or none of it is. It is clear in this case the EBS has a far more significant information-leading role the D2 which is in line with its larger market share. Only on the most extreme assumption the all contemporaneous price impact is due to D2 do the markets look comparable.

### 2.3 Summary of Data Properties

Overall, we find that our data share the properties of most other FX transactions based data sets that have been analyzed: i) a strong contemporaneous correlation between FX returns and order flow; and ii) the possibility that order flow may lead FX returns and fundamentals (in the form of interest rates). However, the link between order flow and returns is impossible to identify without a structural model of the type we estimate in the next section. On the comparison between EBS and D2 we find that the two markets are closely linked but that EBS has a dominant position in both turnover and information share. This is of more than passing interest since most studies of liquidity and information effects in USD/EUR (and USD/DEM) have focussed on D2 (i.e. Reuters) data - though of course EBS may not have had such a preeminent position in these earlier samples.

## 3 Liquidity and Information Effects of Order Flow

Having described the data we are now in a position to estimate the model described in Section 1. The estimation process is quite involved and is summarized in the moment conditions contained in Appendix 1. Here we simply outline the procedure.

The key equation we estimate is equation (22), where the $\lambda$'s are defined as above. Note that for estimation we substitute $f_t$ with $-\alpha(i_t - i_t^*)$ throughout. We also split $v_t$ into $(f_{t+1} - f_t)$ and $\epsilon_t^v$ where the latter is subsumed into the residuals of the estimated equation. As well as this equation,

we also have an implicit order flow equation so that:

$$o_t \quad = \quad \rho_b \, o_{t-1} - \theta \, (f_{t+1} - f_t). \tag{23}$$

Between them these equations yield 12 moment conditions for estimating 7 parameters (four coefficients ($\alpha$, $\gamma$, $\rho_b$, $\theta$) and three variances ($\sigma_b^2$, $\sigma_f^2$, $\sigma_v^2$, see appendix for details). It should be noticed that one cannot separate $\gamma$ from $\sigma^2$ in the moment conditions one can obtain from the model and that hence the joint parameter $\gamma\sigma^2$ is estimated. The individual estimates for the two parameter values are then obtained considering that in equilibrium $\sigma^2 = f(\gamma)$.[16]

Since our model is highly non-linear and estimated using a relatively small sample, we undertake a double check of our estimated standard errors through a simple Monte Carlo procedure. This involves taking the estimated model and creating a new data sample by drawing values for the residual term from its estimated distribution to create new values for the endogenous variables. The model is then re-estimated using this new data sample and the estimated parameter values saved. This procedure is then repeated 1000 times so that a distribution of estimated parameter values can be created. As the Tables below show, the estimated distribution of parameter values we derive using this procedure is highly skewed (probably because of the presence of variance terms in the model) so that the estimated standard errors are far larger from the Monte Carlo procedure than from the original GMM estimate while the p-values (probability of the estimated parameter being less than zero) are actually quite comparable. Note also, that since we derive $\gamma$ outside the estimation procedure, the only estimates of standard errors and p-values we have for that parameter are from the Monte Carlo analysis. Tables 4 and 5 report the estimated values of the parameter of the model obtained using GMM for the USD/EUR market. Since preliminary investigation of the interest rate differential between the United States and the euro area shows that this variable is non-stationary, we have restricted the parameter $\rho_f$ to be equal to 1, so that the fundamental value follows a random walk process.

In addition, we have analysed data at the 5-minute, hourly and daily frequencies. In this way, we are able to study the dependence of the liquidity and information effects of order flow on the time horizon of investment decisions. Finally, our transaction data comprise all trades completed via EBS and Reuters Dealing 2000-2 electronic limit order books. Therefore, we are able to estimate the parameters of the model using: i) all the transactions contained in our data-set (Table 4); and ii) those conducted via EBS and Reuters D2 respectively (Table 5). This exercise is quite interesting in that it can shed lights on the relative liquidity and efficiency of the two alternative platforms.

[16] Appendix 2 outlines this procedure.

Table 4: GMM estimates of the model parameters, USD/EUR market (all transactions).

| | **5-minute Interval** | | | | **Hourly Interval** | | | | **Daily Interval** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Parameter** | **Value** | **S.E.(1)** | **S.E.(2)** | $p$**-val** | **Value** | **S.E.(1)** | **S.E.(2)** | $p$**-val** | **Value** | **S.E.(1)** | **S.E.(2)** | $p$**-val** |
| $\rho_b$ | 0.180 | 0.017 | 0.007 | 0.00 | 0.373 | 0.058 | 0.052 | 0.00 | 0.127 | 0.083 | 0.092 | 0.24 |
| $\alpha$ | 0.320 | 0.082 | 0.003 | 0.00 | 0.627 | 0.102 | 3.755 | 0.00 | 1.474 | 0.689 | 1.049 | 0.01 |
| $\gamma$ | 7056.4 | | 1117595 | 0.00 | 187.52 | | 123.854 | 0.00 | 3.957 | | 6.456 | 0.01 |
| $\theta$ | 0.032 | 0.028 | 1.137 | 0.66 | 1.118 | 0.718 | 0.798 | 0.96 | 0.337 | 0.357 | 0.663 | 0.11 |
| $\tau_f$ | 42347.748 | | | | 42715.100 | | | | 137.658 | | | |
| $\tau_y$ | 6.727 | | | | 316.244 | | | | 1.655 | | | |
| $\tau_v$ | 459.225 | | | | 100.730 | | | | 12.987 | | | |
| $\sigma^2$ | 9.089E-05 | | | | 0.0133 | | | | 0.349 | | | |
| | $R^2$ 0.063 | | | | $R^2$ 0.484 | | | | $R^2$ 0.685 | | | |
| | P.O.R. 0.000 | | | | P.O.R. 0.010 | | | | P.O.R. 0.636 | | | |

Notes: The dependent variable is the percentage change in the spot exchange rate, while the signed order flow variable, $o_t$, is normalised to units of 1000 trades. Therefore, a value of $o_t = 1$ corresponds to an excess of 1000 sell orders in period $t$. The fundamental value $f_t$ is equal to the annualised interest rate differential, $\alpha(i_t^* - i_t)$, for the daily data. At higher frequencies $f_t$ is proxied by $-\alpha i_t$. P.O.R. stands for probability value of over-identifying restrictions, The parameter value $\rho_f$ is restricted to be equal to 1. The first set of Standard errors (S.E.(1)) are from GMM estimation whilst the second set of standard errors (S.E.(2)) and $p$-values are from the Monte Carlo procedure described in the text. $p$-values are the probability of parameter values being less than zero.

Table 5: GMM estimates of the model parameters, USD/EUR market (daily data).

| | **EBS Transactions** | | | | **D2 Transactions** | | | |
|---|---|---|---|---|---|---|---|---|
| **Parameter** | **Value** | **S.E.(1)** | **S.E.(2)** | $p$**-val** | **Value** | **S.E.(1)** | **S.E.(2)** | $p$**-val** |
| $\rho_b$ | 0.070 | 0.082 | 0.0932 | 0.37 | 0.208 | 0.071 | 0.090 | 0.12 |
| $\alpha$ | 2.137 | 1.153 | 1.177 | 0.01 | 3.001 | 0.581 | 1.043 | 0.00 |
| $\gamma$ | 6.453 | | 13.548 | 0.01 | 2.752 | | 1.965 | 0.000 |
| $\theta$ | 0.242 | 0.175 | 0.417 | 0.06 | -0.054 | 0.112 | 0.192 | 0.44 |
| $\tau_f$ | 65.485 | | | | 33.062 | | | |
| $\tau_y$ | 2.730 | | | | 0.103 | | | |
| $\tau_v$ | 6.734 | | | | 10.854 | | | |
| $\sigma^2$ | 0.183 | | | | 0.344 | | | |
| | $R^2$ 0.379<br>P.O.R. 0.863 | | | | $R^2$ 0.65<br>P.O.R. 0.288 | | | |

Notes: As for Table 4.

In Table 4 the parameters of major interest are $\alpha$, $\gamma$, $\rho_b$ and $\theta$. Of these four values only $\alpha$ and $\gamma$ are significantly different from zero at all frequencies. Thus, whilst we see strong positive serial correlation in the liquidity component of the order flow at the intra-daily level, in that the parameter $\rho_b$ is positive and strongly significant for the 5-minute and hourly intervals, when we turn to the daily interval such positive serial correlation vanishes, as $\rho_b$ is neither positive nor significant. This is somewhat at odds with significant daily auto-correlation we reported in Table 1 but arises because the model imposes the restriction that all forms of order flow impact the exchange rate and so a significant $\rho_b$ implies auto-correlation in both order flow and FX returns. The latter implication is rejected by the data. Likewise, the information parameter $\theta$, that measures the information content of order flow, is positive and strongly significant only at the 5 minute interval, while it turns insignificant at the lower frequencies. This could be interpreted as evidence that asymmetric information in FX markets is extremely short-lived and that hence it can be detected only when trades are analysed at very high frequencies.

The semi-elasticity of the money demand to interest rates $\alpha$ and the risk-aversion parameter $\gamma$ are instead significantly larger than zero over all frequencies. Nevertheless, their values are not constant over the three different time horizons. Perhaps unsurprisingly $\gamma$ increases with the data frequency. There are two possible causes of this result. First, as also suggested by the values taken by the coefficient of multiple determination, $R^2$, which rises from 5% at the 5-minute frequency to nearly 70% at the daily one, our model is more suited to represent the behaviour of FX markets at the daily level. In particular, in its formulation it is assumed that FX dealers are myopic, i.e. possess a time horizon of just one period. Such an assumption is hard to accept if a period corresponds to five minutes or one hour. On the contrary, normal practice indicates that FX dealers close their accounts on a daily basis, whilst some empirical evidence (Lyons (1995)) shows that FX dealers tend to balance their foreign exchange inventories by the close of any trading day.

Second, since we only use euro interest rates at higher frequencies we miss the contribution of US monetary policy to exchange rate movements. Certainly, when we estimate our daily model excluding US interest rates, gamma rises to over 13 and alpha becomes insignificant. Despite attempting to mitigate that effect by estimating the hourly and five minute model using data from 7am to 1pm European time (before US markets fully open) it is possible we are missing an important element of the fundamentals. Between them the first effect might be expected to decrease $\theta$ and increase $\gamma$ and the second might decrease $\alpha$ and possibly increase $\gamma$. Indeed, the $\chi$-squared test for the over-identifying restriction rejects the specified model both at the five-minute and hourly frequency, while it is accepted at the daily level.

Limiting our analysis at the daily level we have a more precise and conclusive picture of the effect of order flow on exchange rates. Inspection of both Table 4 and Table 5 indicates that order flow presents a positive and significant impact on exchange rates. Anyhow, this is not the consequence

of any informational asymmetry, but rather that of FX dealers' risk aversion, in that $\theta$ is not significantly different from zero, while on the contrary $\gamma$ is positive and significantly so. Indeed, the estimated values for the precision of the fundamental value, $\tau_f$, and the public signal, $\tau_v$, suggest that FX dealers collect a good deal of information from openly available sources rather than from order flow. We see in Table 4 that roughly 10% of the information contained in the fundamental shock $\epsilon^f_{t+1}$ is anticipated by the public signal $v_t$, in that $\tau_v/\tau_f \cong 0.09$.[17] Note that our finding of a strong role for risk aversion in determining exchange rate movements, whilst unusual in the overall macro literature on FX markets, is quite standard for microstructure models. This suggests that it is may be in this area that microstructure is likely to make one of its most important contributions to understanding exchange rates.

When comparing the two competing trading platforms we detect some differences. While the values taken by $\alpha$, $\gamma$, $\rho_b$ and $\theta$ are not significantly different when estimated using respectively transactions completed via EBS and D2, we detect a larger precision of the public information observed by FX dealers which operate on the Reuters D2 platform. In fact, our measure of the information content of the public signal, $\tau_v/\tau_f$, is close to 0.10 for the transactions completed via EBS, while it is larger than 0.33 for those conducted via D2. Perhaps this is due to the different time of the day during which trading is concentrated on EBS and D2, given that the former is dominant in the Far East and North American whilst the use of the latter is more widespread in Europe. Then, if news realises at different times of the day have a different information content, our measure of the information content of the public signal, $\tau_v/\tau_f$, will differ across the two platforms.

Moreover, deriving the coefficients $\lambda$'s associated to the estimated values of the model parameters it is possible to estimate the impact of trade innovations on exchange rates and derive simple measures of liquidity. In the Table 6 we report the immediate impact of order flow and the cost of a round trip for different trade sizes. These values indicate that liquidity is very high and transaction costs are very small on both platforms. In addition, as commonly presumed, EBS turns out to be slightly more liquid, in that the immediate impact of a trade innovation and its round trip cost are smaller.

Note that our estimates of the transaction costs on the two platforms are not very distant from those of Evans and Lyons (2000). They estimate in 5 basis points the immediate impact of $100 million trade innovations in USD/DEM market, while we estimate a 18 basis points impact (for D2, 9 basis points for EBS) for a similar size trade in the USD/EUR market. The somewhat higher trade impact per dollar in our sample seems plausible given that Evans and Lyons estimate a surprisingly large average trade size on D2 of $4 million perhaps indicating that market liquidity was significantly higher in their sample.

[17] An alternative explanation is that FX traders collect information on fundamental shifts which materialize in the distant future, i.e. after several days, weeks or months, and trade accordingly. To investigate this possibility one would need estimating a more complicated structural models, with more moment conditions and observable variables.

Table 6: Trade impact on EBS and Reuters D2.

| | Trade Impact | | Round Trip Cost | |
|---|---|---|---|---|
| **Trade Size** | EBS | D2 | EBS | D2 |
| 1000 | 2.746 | 3.339 | 2.970 | 3.823 |
| $1 Billion | 0.875 | 1.815 | 0.946 | 2.078 |

Notes: Size equal to 1000 means an excess of 1000 sell orders on buy orders, while size equal to $1 billion indicates an excess of sell orders on buy orders for the value of $1 billion. The impact of a $1 billion order is estimated using average trade sizes derived from daily EBS volume data for EBS and Payne (2003) for D2. See Table 3.

# 4 Foreign Exchange Intervention

Another interesting facet of our data is that it contains a significant intervention episode. One important policy issue that can possibly be addressed by order flow models is the efficacy of official foreign exchange intervention. Certainly, microstructure models seem to have the potential to offer significant insights into intervention episodes (see for example, Dominguez (2003)). Our data-set is of particular interest in this regard since it contains the only intervention episode aimed at influencing the value of the euro. However, since the intervention episode consisted of only four individual events, there is a limited amount of detailed analysis we can undertake — even using our detailed data-set.

Using our data we can address two key questions concerning the transmission of intervention. The first question concerns the extent to which large scale interventions translate into order flow imbalance. Evans and Lyons (2000) implicitly assume that every dollar of intervention translates into an equivalent dollar of order flow imbalance such that the inter-dealer market is left "holding" all the intervention trades. It is possible, however, that the order imbalance generated by intervention is rapidly translated into customer orders such that the inter-dealer market effectively passes the intervention on to customers and is left with little or no imbalance to trade amongst themselves. Since we know approximately the scale of the intervention trades and the scale of the order imbalance, we can give some insight into the relationship between the two.

The second question we can partially address is the extent to which intervention trades are different to normal trading. A number of studies have highlighted the signalling role of interven-

Table 7: Impact of euro interventions.

| | **22 Sep.** | **3 Nov.** | **6 Nov.** | **10 Nov.** | **Average** |
|---|---|---|---|---|---|
| **Size of Intervention** | -$8.7bn | -$2.3bn | -$2.3bn | -$1.2bn | -$3.625bn |
| **Actual Impact:** | | | | | |
| on Exchange Rate | -2.413% | -0.653% | 0.834% | -0.568% | -0.700% |
| on Order Flow | -800 | -289 | -141 | -227 | -364 |
| on Order Flow ($) | -$2.3bn | -$0.835bn | -$0.407bn | -$0.656bn | -$1.05bn |
| on Interest Rates | -0.1bp | -0.7bp | -4bp | 2.2bp | -0.7bp |
| **Predicted Impact:** | | | | | |
| of Order flow on Exchange Rate | -1.685% | -0.474% | -0.188% | -0.416% | -0.691% |
| of Interest Rates on Exchange Rate | -0.003% | -0.068% | -0.155% | 0.100% | -0.032% |
| Total | -1.688% | -0.542% | -0.343% | -0.316% | -0.722% |

Notes: Actual impacts are the difference between levels predicted by the model had intervention not occurred, and the actual changes that did occur. Predicted impacts on the exchange rate shows how the actual impact of the intervention on order flow and interest rates should have impacted the exchange rate according to the model. Order flow is the estimated order imbalance created by the intervention expressed both as a number of trades and as a dollar value using the estimates in Table 3. Exchange rate effects are expressed as the percentage change in the dollar vs. the euro and interest rate changes are the change in US interest rates relative to euro rates expressed in basis points.

tion,[18] suggesting that there may be channels through which intervention influences the exchange rate which are distinct from the conventional order flow impact discussed above. Our model can to some extent directly describe the signalling channel since we have an independent role for monetary policy in our description of fundamentals (this method of identifying the signalling channel is similar to that used by Fatum and Hutchinson (1999)).

Note that we only use the daily version of our model to address these questions. This is for two reasons. First, the ECB does not give out detailed information on the timing of its interventions and so although we know which days the interventions took place, we cannot pin down the precise hour, let alone 5 minutes. Second, as was noted above the high frequency versions of the model suffer from a number of theoretical and empirical drawbacks and so are probably not appropriate, even for the cursory policy analysis conducted here.

In Table 7 we report the estimated *actual* impact of intervention on the spot rate, order flow and the interest rate differential. These values are calculated as the *difference* between the values for the spot rate, $s_t$, order flow, $o_t$, and the interest rate differential, $i_t - i_t^*$, observed during any intervention day, $t$, and those predicted by the estimated model using all information preceding the intervention episode, i.e. all information up to day $t-1$. The actual impact of intervention on order flow is then used to calculate, via the estimated model, the *predicted* impact of order flow innovations on the spot rate. This figure represents an estimate of the effect of intervention on exchange rates via the traditional portfolio-balance channel. Likewise, the actual impact of intervention on the interest rate differential is used to derive, via the estimated model, the *predicted* impact of fundamental innovations on the spot rate, a measure of the effect of intervention on currency values via the signalling channel. Finally, the sum of these two predicted impacts gives an estimate of the *total* effect of foreign exchange intervention on exchange rates.

Table 7 gives a detailed analysis of the four intervention days in our sample. The first interesting pattern it reveals is that large scale intervention generates an order imbalance that is only a fraction of size. Thus, for the September 22nd intervention, nearly $9 billion of intervention generated an estimated overall imbalance of just over $2 billion.

Looking at the effect of intervention on exchange rates via the innovation in the interest rate differential, there seems to be little evidence in favor of a strong signalling channel. Although most of the interventions are associated with a rise in euro interest rates relative to US ones, as the signalling channel predicts, the changes are generally too small to have a significant impact on the exchange rate.[19]

[18] Mussa (1981) firstly suggested that foreign exchange intervention can be an effective way to signal future changes in monetary policy, as the monetary authorities put at stakes their foreign exchange reserve in support of their signal. Several empirical studies, notably Dominguez and Frankel (1993), Lewis (1995), Kaminsky and Lewis (1996) and Payne and Vitale (2003), have shown that foreign exchange intervention has a persistent effect on currency values supporting the signalling hypothesis put forward by Mussa. See also Edison (1993).

[19] Though, it may be that interest rate expectations beyond the 3 month horizon used in our model were influenced. Then, our model would under-estimate the information content of official intervention.

As for the effect of intervention via the innovation in order flow, it seems that exchange rates movements on intervention days are largely consistent with that predicted by our model. So despite the fact that the intervention on September 22nd had a larger than predicted impact and that the intervention on November 6th had a smaller than predicted impact, the average of the four events leaves the actual and predicted impacts fairly close, and all four events are well within the 95% forecast confidence interval. Overall, this implies that we can potentially explain most of the impact of intervention on the exchange rate through a simple portfolio balance channel.

Overall, although it is difficult to draw general conclusion for four observations, the evidence from the ECB's intervention episode in late 2000 suggests that the effect of intervention comes mainly through its impact on order flow imbalance. Additionally, it seems not to be the case that every dollar of intervention generates a dollar of order flow imbalance.

# 5 Conclusions

Order flow based models seem to offer a promising route to understanding the dynamics of exchange rates. Certainly, $R^2$'s of nearly 70% as we have found here are likely to dazzle even the most estimation-weary exchange rate economist. Nevertheless, disentangling the information and liquidity effects that may underlie the explanatory power of order flow is a challenging task. With respect to previous studies based on the analysis of reduced form models we propose an improvement in that our analysis is based on the estimation of a structural model of exchange rate determination.

While a first look at the correlations between order flow, exchange rate returns and innovations in the interest rate differential can suggest an information-based interpretation of the effect of trade innovations on the exchange rate, our investigation indicates that order flow explains very little in terms of information or fundamentals. The relationship between order flow and exchange rates seems to be almost totally due to liquidity effects and not to any information contained in order flow. The presence of an important intervention episode in our data-set makes this claim even stronger, as it appears that the large impact of the intervention operations carried out by the ECB in late 2000 is largely brought about via the traditional portfolio-balance channel.

These results outline possible lines of future research. *In primis*, it would be very useful to have access to longer and more detailed data-sets. Likewise, direct observation of customer order would allow us to: i) investigate feed-back effects of the pricing behaviour of FX dealers on customer

trading, as recent results suggest that these may be quite important;[20] and ii) analyse a richer structural model of exchange rate determination.

Another important direction of research to follow is suggested by the intense intervention activity of the Bank of Japan (BoJ). In the 1990s and early 2000s the BoJ has intervened heavily and constantly in the FX markets to alter the value of the yen, so that access to transaction data for the Japanese FX markets would allow to carry out a more fruitful investigation of the information and liquidity effects of official intervention in FX markets.

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[20] See Danielsson and Love (2004).

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# APPENDICES

## A Moment Conditions

### A.1 Moment Conditions in the Non-stationary Case ($\rho_f = 1$, $\rho_b = 0$)

This appendix outlines the moment conditions that can be employed to estimate the parameters of the model. In the simplest version, under the hypothesis that the fundamental process follows a random walk and net order flow does not present serial correlation (i.e. for $\rho_f = 1$ and $\rho_b = 0$), we can derive the following unconditional moments:[21]

$$\mathrm{Var}\left(o_t\right) = \theta^2 \sigma_f^2 + \sigma_b^2, \tag{24}$$

$$\mathrm{Var}\left(f_t - f_{t-1}\right) = \sigma_f^2, \tag{25}$$

$$\mathrm{cov}\left(f_t - f_{t-1}, s_t - s_{t-1}\right) = \left[\left(1 - \lambda_v\right) + \theta\,\lambda_o\right]\sigma_f^2, \tag{26}$$

$$\mathrm{cov}\left(o_t, f_{t+1} - f_t\right) = -\theta\,\sigma_f^2, \tag{27}$$

$$\mathrm{cov}\left(o_t, s_t - s_{t-1}\right) = -\theta\left[\lambda_v - \theta\left(\lambda_z + \lambda_o\right)\right]\sigma_f^2 + \left(\lambda_z + \lambda_o\right)\sigma_b^2, \tag{28}$$

$$\mathrm{cov}\left(s_t - s_{t-1}, f_{t+1} - f_t\right) = \left[\lambda_v - \theta\left(\lambda_z + \lambda_o\right)\right]\sigma_f^2, \tag{29}$$

$$\mathrm{cov}\left(o_t, s_{t+1} - s_t\right) = -\theta\left[\left(1 - \lambda_v\right) + \theta\,\lambda_o\right]\sigma_f^2 - \lambda_o\,\sigma_b^2, \tag{30}$$

$$\begin{aligned}\mathrm{Var}\left(s_t - s_{t-1}\right) = {} & \left[\left(\lambda_z + \lambda_o\right)^2 + \lambda_o^2\right]\sigma_b^2 + 2\,\lambda_v^2\,\sigma_v^2, \\ & \left(\left[\left(\lambda_z + \lambda_o\right)^2 + \lambda_o^2\right]\theta^2 + 2\left[\lambda_o - \left(\lambda_z + 2\,\lambda_o\right)\lambda_v\right]\theta \right. \\ & \left. + \left(1 - \lambda_v\right)^2 + \lambda_v^2\right)\sigma_f^2.\end{aligned} \tag{31}$$

[21] Notice that we calculate moments only for stationary variables: $s_t - s_{t-1}$, $f_t - f_{t-1}$, $o_t$.

These eight moment conditions are over-identifying restrictions to estimate six parameters ($\alpha$, $\gamma$, $\sigma_b^2$, $\sigma_f^2$, $\sigma_v^2$, $\theta$). In particular, moment conditions (24), (25) and (27) allow to identify $\sigma_b^2$, $\sigma_f^2$ and $\theta$. The remaining four moment conditions can then be employed to estimate the other 3 parameters of the model. More precisely, from moment conditions (26), (28), (29), (30) and (31) it is possible to pin down the coefficients $\lambda_o$, $\lambda_z$ and $\lambda_v$ and hence, given these, the values of the deep parameters $\alpha$, $\gamma$ and $\sigma_v^2$.

Notice, however, that equations (24) to (31) are very difficult to sign. In particular, one can easily sign only moment conditions (27) and (29).

### A.2 Moment Conditions in the Non-stationary Case ($\rho_f = 1$, $\rho_b \neq 0$)

Let us see how these moment conditions change when net order flow presents serial correlation, $\rho_b \neq 0$. Clearly, moments (25), (27) and (29) remain unchanged. On the other hand, the others change as follows:

$$\mathrm{Var}\left(o_t\right) = \theta^2 \sigma_f^2 + \frac{1}{1-\rho_b^2}\sigma_b^2, \tag{32}$$

$$\mathrm{cov}\left(f_t - f_{t-1}, s_t - s_{t-1}\right) = \left[1 - \left(1 - \lambda_{s,-1}\right)\lambda_v + \theta\left(\left(1 - \lambda_{s,-1}\right)\lambda_o - \lambda_{o,-1}\right)\right]\sigma_f^2, \tag{33}$$

$$\begin{aligned}\mathrm{cov}\left(o_t, s_t - s_{t-1}\right) = & -\theta\left[\lambda_v - \theta\left(\lambda_z + \lambda_o\right)\right]\sigma_f^2 + \frac{1}{1-\rho_b^2}\frac{1}{1-\rho_b\lambda_{s,-1}} \\ & \left(\lambda_z + \rho_b\lambda_{z,-1} + \left(1-\rho_b\right)\lambda_o + \rho_b\left(1-\rho_b\right)\lambda_{o,-1}\right)\sigma_b^2,\end{aligned} \tag{34}$$

$$\begin{aligned}\mathrm{cov}\left(o_t, s_{t+1} - s_t\right) = & \theta\left[\left(1-\lambda_{s,-1}\right)\lambda_v - 1 + \theta\left(\lambda_{o,-1} - \left(1-\lambda_{s,-1}\right)\lambda_o\right)\right]\sigma_f^2 + \\ & \frac{1}{1-\rho_b^2}\frac{1}{1-\rho_b\lambda_{s,-1}}\left[-\left(\left(1-\rho_b\right) - \left(1-\rho_b^2\right)\lambda_{s,-1}\right)\lambda_o + \right. \\ & \left.\rho_b\left(1-\rho_b\lambda_{s,-1}\right)\lambda_z + \left(1-\rho_b\right)\lambda_{o,-1}\right]\sigma_b^2.\end{aligned} \tag{35}$$

We also need some more moment conditions:

$$\operatorname{cov}(o_t, o_{t-k}) = \frac{\rho_b^k}{1-\rho_b^2}\,\sigma_b^2, \tag{36}$$

$$\begin{aligned}\operatorname{cov}\left(o_t, s_{t-1}-s_{t-2}\right) &= \frac{1}{1-\rho_b^2}\,\frac{\rho_b}{1-\rho_b\lambda_{s,-1}}\Big(\lambda_z + \rho_b\,\lambda_{z,-1} + \\ &\quad (1-\rho_b)\,\lambda_o + \rho_b\,(1-\rho_b)\lambda_{o,-1}\Big)\,\sigma_b^2, \end{aligned}\tag{37}$$

$$\begin{aligned}\operatorname{cov}\left(o_t, s_{t+2}-s_{t+1}\right) &= \theta\,(1-\lambda_{s,-1})\Big[\lambda_{s,-1}\lambda_v - \theta\Big(\lambda_{o,-1} + \lambda_{s,-1}\lambda_o\Big)\Big]\,\sigma_f^2 + \\ &\quad \frac{1}{1-\rho_b^2}\,\frac{1}{1-\rho_b\lambda_{s,-1}}\Big[\rho_b^2\,(1-\rho_b\lambda_{s,-1})\,\lambda_z + \Big\{\rho_b^2\,(1-\rho_b\lambda_{s,-1}) \\ &\quad -(1-\lambda_{s,-1})\Big(\lambda_{s,-1} + \rho_b\,(1-\rho_b\lambda_{s,-1})\Big)\Big\}\lambda_o + \\ &\quad \Big\{\rho_b\,(1-\rho_b\lambda_{s,-1}) - (1-\lambda_{s,-1})\Big\}\,\lambda_{o,-1}\Big]\,\sigma_b^2, \end{aligned}\tag{38}$$

$$\operatorname{cov}\left(f_t - f_{t-1}, s_t - s_{t-1}\right) = \Big\{1 - (1-\lambda_{s,-1})\,\lambda_v + \theta\Big[(1-\lambda_{s,-1})\,\lambda_o - \lambda_{o,-1}\Big]\Big\}\,\sigma_f^2, \tag{39}$$

$$\operatorname{cov}\left(f_t - f_{t-1}, s_{t+k+1} - s_{t+k}\right) = -\lambda_{s,-1}^k\,(1-\lambda_{s,-1})\Big[\lambda_{s,-1}\,\lambda_v - \theta\,(\lambda_{s,-1}\,\lambda_o + \lambda_{o,-1})\Big]\,\sigma_f^2. \tag{40}$$

These twelve moment conditions are over-identifying restrictions to estimate seven parameters ($\alpha$, $\gamma$, $\rho_b$, $\sigma_b^2$, $\sigma_f^2$, $\sigma_v^2$, $\theta$). In particular, moment conditions 25), (27), (32) and (32) allow to over-identify $\sigma_b^2$, $\rho_b$, $\sigma_f^2$ and $\theta$. The remaining eight moment conditions can then be employed to estimate the other 3 parameters of the model. More precisely, from moment conditions 29), (33) to (35) and (37) to (40) it is possible to pin down the coefficients $\lambda_o$, $\lambda_{o-1}$, $\lambda_z$ $\lambda_{z,-1}$ and $\lambda_v$ and hence, given these, the values of the deep parameters $\alpha$, $\gamma$ and $\sigma_v^2$.

Notice, however, that equations (25), (27), (29) and (32) to (40) are also very difficult to sign. In particular, one can easily sign only moment conditions (27) and (29).

## B Spot Rate Conditional Variance

Since the moment conditions do not allows to determine $\gamma$ separately from $\sigma^2$ we need to discuss the determination of $\sigma^2$, the conditional variance of the spot rate $s_{t+1}$ given the information the average FX dealer possesses in period $t$. This is not an exogenous value and therefore we need to calculate it. Moreover, we have to check that it is actually time invariant as we have assumed. From equation (21), we have that:

$$\begin{aligned}\operatorname{Var}(s_{t+1} \mid \Omega_t) \;=\; & \lambda_f^2 \operatorname{Var}(f_{t+1} \mid \Omega_t) \;+\; \lambda_v^2 \operatorname{Var}(v_{t+1} \mid \Omega_t) \;+\; (\lambda_o + \lambda_z)^2 \operatorname{Var}(o_{t+1} \mid \Omega_t) + \\ & 2\,\lambda_f\,\lambda_v \operatorname{cov}(f_{t+1}, v_{t+1} \mid \Omega_t) \;+\; 2\,\lambda_f\,(\lambda_o + \lambda_z) \operatorname{cov}(f_{t+1}, o_{t+1} \mid \Omega_t) \;+ \\ & 2\,\lambda_v\,(\lambda_o + \lambda_z) \operatorname{cov}(v_{t+1}, o_{t+1} \mid \Omega_t). \end{aligned} \tag{41}$$

Calculating the conditional variances and covariances in the right hand side of (41) we find that:

$$\operatorname{Var}(s_{t+1} \mid \Omega_t) \;=\; \frac{\lambda_f^2}{\bar{\tau}_\epsilon} \;+\; \frac{\lambda_v^2}{\tau_v} \;+\; \frac{(\lambda_o + \lambda_z)^2}{\tau_{b,-1}} \;+\; \left[\lambda_v \;-\; \theta\,(\lambda_o + \lambda_z)\right]^2 \frac{1}{\tau_f}.$$

We can conjecture an equilibrium value for the conditional variance $\operatorname{Var}(s_{t+1} \mid \Omega_t) = \sigma^2_{\text{cong}}$ and substitute $\sigma^2$ with $\sigma^2_{\text{cong}}$ into the coefficients $\lambda_f$, $\lambda_v$ and $\lambda_z$. Under our assumptions, $\sigma^2 = \operatorname{Var}(s_{t+1} \mid \Omega_t)$ solves the following equation:

$$\sigma^2 \;=\; a_\sigma\,\sigma^4_{\text{cong}} \;+\; b_\sigma\,\sigma^2_{\text{cong}} \;+\; c_\sigma, \tag{42}$$

where:

$$a_\sigma \;=\; \alpha^2\,\gamma^2 \left( \theta^2\,\frac{1}{\tau_f} \;+\; \left[1 \;+\; 2\,\alpha\,\frac{\rho_b}{\Delta_b} \;+\; \alpha^2 \left(\frac{\rho_b}{\Delta_b}\right)^2 \left(\frac{\tau_f \;+\; \tau_v}{\bar{\tau}_\epsilon}\right)\right] \frac{1}{\tau_{b,-1}} \right), \tag{43}$$

$$b_\sigma \;=\; 2\,\alpha \left(\frac{\alpha}{1+\alpha}\right) \gamma\,\theta\,\frac{1}{\Delta_f} \left(1 \;+\; \alpha\,\frac{\rho_b}{\Delta_b}\,\frac{\tau_f}{\bar{\tau}_\epsilon}\right) \frac{1}{\tau_f}, \tag{44}$$

$$c_\sigma \;=\; \left(\frac{1}{\Delta_f}\right)^2 \left[1 \;+\; \left(\frac{\alpha}{1+\alpha}\right)^2 \left(\frac{\tau_v \;+\; \tau_y}{\tau_f}\right)\right] \frac{1}{\bar{\tau}_\epsilon}. \tag{45}$$

where $\Delta_b = 1 + \alpha(1 - \rho_b)$ and $\Delta_f = 1 + \alpha(1 - \rho_f)$.

Equation (42) possesses two real solutions if $(1-b_\sigma)^2 > 4a_\sigma c_\sigma$ is positive. These two roots,

$$\sigma^2 = \begin{cases} \frac{1}{2\,a_\sigma}\left((1-b_\sigma) - \Delta_\sigma\right) \\ \\ \frac{1}{2\,a_\sigma}\left((1-b_\sigma) + \Delta_\sigma\right) \end{cases} \tag{46}$$

with $\Delta_\sigma^2 \equiv (1-b_\sigma)^2 - 4a_\sigma c_\sigma$, will either be both positive (if $1-b_\sigma > 0$) or both negative (if $1-b_\sigma < 0$). Clearly, only the former case is economically meaningful and prevails if $\theta$ is small enough. If this condition is met, only the smaller root of equation (42) is stable and consequently will be the preferred value.

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