An Empirical Study of Portfolio-Balance and Information Effects of Order Flow on Exchange Rates*

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October 2005

*We would like to thank Lehman Brothers in general and Tom Grant and Giovanni Pillitteri in particular for their help on acquiring data. We also thank Reuters and EBS for permission to use this data. We wish to thank participants at seminars at the the Central Bank of Iceland, the European Central Bank, the Luigi Einaudi Research Centre in Rome, the Bicocca University in Milan, the Guido Carli (LUISS) University in Rome, the London School of Economics, the Norges-Bank in Oslo, the Sacro Cuore (Cattolica) University in Milan, the Queens University in Belfast, the Stockholm School of Economics, the University of Pompeu Fabra, the University of Pavia and the University of Tor Vergata. We received particularly useful comments by Geir Biønnes, Kathryn Dominguez, Andreas Fischer, Philipp Hartmann, Ryan Love, Richard Lyons, Ian Marsh, Andrew Patton, Dagfinn Rime and Haakon Solheim. This research was undertaken whilst Francis Breedon was a research visitor at the ECB. Any errors remain our responsibility.

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ABSTRACT

We propose a simple structural model of exchange rate determination which draws from the analytical framework recently proposed by Bacchetta and van Wincoop (2005) and allows us to disentangle the portfolio-balance and information effects of order flow on exchange rates. We estimate this model employing an innovative transaction data-set that covers all indirect 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 largely due to portfolio-balance effects. This result also appears to carry through to the four FX intervention events that appear in our sample.

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

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. More recently, however, improved data capture by trading platforms and data vendors has given researchers and practitioners access to detailed information on individual transactions between FX traders.

As well as improved data availability, the recent interest in the analysis of transaction data in FX markets 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 *fail* 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.

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, ie. 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 impound in currency values. More specifically, as it is typical of rational expectations models of asset pricing, FX traders collect from various sources information on the fundamental value of

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

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. As shown by Evans and Lyons (2002a), Payne (2003), Biønnes and Rime (2005), Froot and Ramadorai (2005), if traditional models of exchange rate determination that normally deliver very low values for the coefficient of multiple determination are augmented by signed order flow, this coefficient reaches values close to or even larger than 0.5.

Whilst this *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 (2002a) 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 portfolio-balance 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.

Disentangling the information and portfolio-balance 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 portfolio-balance 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 portfolio-balance 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, portfolio shocks in FX markets might also have long term effects on exchange rates.

In this study we suggest an alternative way to distinguish the information and portfolio-balance 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 investors.

The structural model we estimate draws from the analytical framework recently proposed by Bacchetta and van Wincooop (2005) 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 investors, 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 investors' 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.

Secondly, Bacchetta and van Wincoop assume that FX investors' collect private signals on exchange rate fundamentals, so that fundamental information is disseminated through FX markets via FX investors' transactions. On the contrary, we assume that such information reaches FX markets via order flow. In particular, we suppose that in FX markets, beside the group of *rational* investors, there exists a population of FX customers. We assume that while these agents are *unsophisticated* their trades may present an information content.

This assumption is in line with the commonly held view that in FX markets the ultimate source of private information is customer trades, as suggested by other market micro structure models of exchange rate determination (notably Evans and Lyons (2002a), Evans and Lyons (2004)), and is coherent with some recent empirical evidence (Evans and Lyons (2005) and Marsh and O'Rourke (2004)) which indicates how customer order flow can anticipate shifts in exchange rate fundamentals. In particular, given that in our data-set order flow is positively correlated with future changes in interest rates, we allow for the possibility that some customers anticipate future variations in interest rates.

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 *uniquely* the total holding of foreign assets on the part of the rational investors 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, and obtain a specification where, in line with the data, the spot rate is a nonstationary variable.

We estimate this model employing an innovative transaction data-set that covers all indirect FX transactions completed between August 2000 and January 2001 in the USD/EUR market via the two major trading platforms employed in spot FX markets, EBS and Reuters. While researchers have recently gained access to transaction data in FX markets, our is the first study to employ information from both trading platforms. This means that we are able to offer a comprehensive analysis of the functioning of the USD/EUR market, alongside a novel investigation of the differences which exist between the two trading platforms.

In a nutshell the results of the GMM estimation of this model are as a follows. Firstly, we confirm that order flow is a powerful determinant of exchange rate dynamics, as it has a large and significant impact on exchange rates. Secondly, while we find some evidence that order flow moves exchange rates via the information channel, we see that it affects currency values primarily via the portfolio-balance effect. Thirdly, this result is also reinforced by the fact that the large impact of the intervention operations carried out by the European Central Bank in late 2000 is consistent with our estimates of the traditional portfolio-balance channel. Fourthly, whatever the channel of transmission, our estimates also suggests that the impact of order flow on exchange rates is persistent. Finally, insofar the comparison between EBS and Reuters is concerned, we conclude that the former trading platform is more liquid, in that its transaction costs are somewhat smaller, and has a more important role in price formation.

This paper is organised as follows. In Section 1 we introduce the data-set used for our analysis and outline some of its key statistical properties. We then use this empirical evidence to guide the formulation of our simplified model of exchange rate determination. In Section 2 we present our model discussing the economic intuition behind the reduced form equation for the spot rate we eventually derive. 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 portfolio-balance effects of order flow and to measure their contribution to exchange rate dynamics. In Section 4 we consider the role of foreign exchange intervention given that a small number of intervention events occur in our data sample. In the last Section we offer some final remarks and a discussion of further research developments.

1. Data

Our core data-set consists of 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. Additionally as a trade takes place, the price and direction of the trade is revealed to all users of the system (though not the counter-parties nor the size of the trade). In fact, it is from this datafeed that our data is derived. 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.

We collected bid and ask prices and an indicator of the number of buy and sell transactions from both trading systems at the daily 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 with daily observations of euro area and US short-term interest rates.

1.1. Data Description and Summary Statistics

Table 1 presents some summary statistics for daily observations of order flow (rather than cumulated order flow), changes in the exchange rate and interest rate differentials, since the levels of the series all proved to be I(1).

An interesting aspect of our summary Table is that there is some evidence of positive auto-correlation in the order flow data (particularly for D2). This auto-correlation seems less pronounced in the other series. 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 FX dealers pass the hot potato amongst themselves).

Table 1

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

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 day t. Returns are the percentage change in the USD/EUR exchange rate observed over day 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, $\Delta(i_t - i_t^*) \equiv 100[(i_t - i_t^*) - (i_{t-1} - i_{t-1}^*)]$.

	Mean	**Std. Dev.**	$\hat{\rho}(1)$	**Prob.**
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

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. These values show some interesting patterns. In particular, consistent with previous studies, notably Evans and Lyons (2002a), Payne (2003) and Froot and Ramadorai (2005), 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, $r_t < 0$. Even more significantly, 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: some 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.

Table 2

Correlations for order flow, exchange rate and interest rate daily data.

$\Delta(i_t - i_t^*) = 100[(i_t - i_t^*) - (i_{t-1} - i_{t-1}^*)]$, $r_t = 100(\log(S_t) - \log(S_{t-1}))$, 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.

	$\Delta(i_t - i_t^*)$	$\Delta(i_{t-1} - i_{t-1}^*)$	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

In Section 2 we formulate a simple structural model of exchange rate determination which will replicate these particular features of our data-set. Indeed, the findings outlined in Table 2 have inspired the formulation of the model presented in Section 2. This model explicitly allows for an informative component of order flow that anticipates next period fundamental shift, but also identifies a portfolio-balance link between order flow and the exchange rate. By disentangling the information and portfolio-balance 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.

1.2. 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.

Table 3

EBS and Reuters Dealing 2000-2 compared.

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)).

	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%

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). In both cases these arbitrages are very short-lived and presumably arise from the time required to input trade details.

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 that 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.

1.3. 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 (ie. Reuters) data - though of course EBS may not have had such a preeminent position in these earlier samples.

2. A Simple Structural Model

We now present our 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 us to employ our transaction data-set to test the portfolio-balance and information effects of order flow on exchange rates. More precisely, in the formulation of this model our objective is twofold: on the one hand, we have to meet the constraints of our data-set and derive a model which can be estimated at high frequencies with a limited set of observable variables; on the other, we require a specification which captures the specific correlation structure of our data-set outlined in Table 2.

2.1. 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 are conducted via these centralised trading platforms, our simplification is partially justified.[2] Moreover, our framework allows us 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: rational investors and unsophisticated customers. Rational investors, such as FX dealers, managers of currency funds, hedge funds and of other actively traded funds, are risk averse agents which select optimal portfolios of domestic and foreign assets. They are supposed to be short-sighted in that their investment horizon is just one day long. This assumption is introduced for tractability but also captures a quite well known feature of the behavior of many professional traders in FX markets, which usually attempt to unwind their foreign exchange exposure by the end of any trading day.[3] Bacchetta and van Wincoop assume that the population of rational investors is given by a continuum of agents which share the same CARA utility function of their end-of-day wealth and that in day t can invest in three different assets:[4] a domestic production technology which depends on the amount of real balances possessed and domestic and foreign bonds that pay day-by-day 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 rational investors 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 (ie. 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 day's spot rate, s_{t+1}, on the part of all rational investors given the information they possess in day t, σ^2 indicates the corresponding conditional variance,[5] and γ is the coefficient of risk-aversion of all rational investors' CARA utility functions.

[2]See the BIS survey of FX markets (BIS (2004) and Rime (2003)).

[3]See Lyons (1995) and Biønnes and Rime (2005).

[4]This assumption implies that all rational investors will be price takers. This is reasonable given the large number of professional traders in FX markets.

[5]Implicitly it assumed that these investors 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.

The unsophisticated customers provide all the supply of foreign currency. Thus, in day t the total demand for foreign currency on the part of all rational investors is in equilibrium equal to the total amount of foreign currency supplied by the unsophisticated customers, z_t,[6]

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

These customers comprise a population of noise and informed traders.[7] 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 noise and informed customers collectively desire to sell in day t, the total supply of foreign currency changes according to the following expression

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

Signed *order flow* o_t can be decomposed into the number of units of foreign currency traded respectively by the noise, b_t, and the informed customers, I_t,[8]

$$o_t \;=\; b_t \;+\; I_t.$$

Since, as shown in Table 1, order flow presents some evidence of serial correlation we assume that its noise trading component, b_t, follows an AR(1) process,

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

where the noise trading shock ϵ_t^n is normally distributed, with mean zero and variance σ_n^2, and is serially uncorrelated (ie. $\epsilon_t^n \perp \epsilon_{t'}^n$). We may interpret the population of noise customers as formed by the financial arms of industrial corporations and by other unsophisticated financial traders, whose portfolios of foreign assets are subject to persistent shifts. Such shifts may be associated

[6]Combining the optimal demand for the foreign currency on the part of the population of rational investors with the equilibrium condition for the spot rate, ie. combing equations (1) and (2), one can confirm that in the presence of risk averse investors the uncovered interest parity does not hold, as the interest rate differential between domestic and foreign bonds is equal to the sum of the average expected rate of devaluation of the domestic currency and a risk premium proportional to the total supply of the foreign currency,

$$i_t \,-\, i_t^* \;=\; (\bar{E}_t(\tilde{s}_{t+1}) \,-\, s_t) \,-\, \gamma\, \sigma^2\, z_t.$$

[7]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, as suggested by the preliminary analysis of our data-set, while preserving symmetric information among rational investors.

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

with current account transactions or with capital movements, such as foreign direct and portfolio investment, which are not motivated by current movements in exchange rates.

In day t the amount of foreign currency offered for sale by the informed customers, I_t, is instead correlated with the innovation in the fundamental variable, f_t, ie. the variable that in equilibrium determines the value of the foreign currency. To identify this fundamental variable consider that by definition we can write the spot rate as follows

$$s_t = p_t - p_t^* + q_t, \tag{3}$$

where p_t and p_t^* represent respectively the log of the domestic and foreign price level, while q_t is the log of the *real* exchange rate, $q_t \equiv \ln(S_t P_t^*/P_t)$. In addition, consider that equilibrium conditions exist 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

$$m_t - p_t = -\alpha\, i_t, \tag{4}$$

$$m_t^* - p_t^* = -\alpha\, i_t^*, \tag{5}$$

where m_t and m_t^* represent respectively the log of the domestic and foreign money supply. Combining (3) with (4) and (5) we then conclude that

$$s_t = \alpha\,(i_t - i_t^*) + f_t, \tag{6}$$

where f_t denotes the exchange rate *fundamental* variable, $f_t \equiv m_t - m_t^* + q_t$.

We assume that this variable follows an AR(1) process with serial correlation coefficient ρ_f,

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

where the fundamental shock ϵ_t^f is normally distributed with mean zero and variance σ_f^2 and is serially uncorrelated ($\epsilon_t^f \perp \epsilon_{t'}^f$).[9] Given the definition of f_t the fundamental shock ϵ_{t+1}^f can be divided into two components, ϵ_{t+1}^m and ϵ_{t+1}^q,

$$\epsilon_{t+1}^f = \epsilon_{t+1}^m + \epsilon_{t+1}^q,$$

[9] Clearly, these fundamental shocks are all orthogonal to the noise trading ones (ie. $\epsilon_t^f \perp \epsilon_{t'}^n$).

where ϵ^m_{t+1} can be interpreted as a monetary innovation, directly influenced by the domestic and foreign monetary authorities, while ϵ^q_{t+1} pertains to real perturbations, associated with demand and supply shocks, such as technological innovations, fiscal stimuli and so on. For consistency we need to assume that both the monetary and the real components of the fundamental shock follow independent white noise processes, so that $\epsilon^m_t \sim N(0, \sigma^2_m)$, $\epsilon^q_t \sim N(0, \sigma^2_q)$, where $\forall\, s \neq t$ $\epsilon^m_t \perp \epsilon^m_s$, $\epsilon^q_t \perp \epsilon^q_s$, whereas $\forall\, s$ and t $\epsilon^m_t \perp \epsilon^q_s$. This clearly implies that $\epsilon^f_t \sim N(0, \sigma^2_f)$ where $\sigma^2_f = \sigma^2_m + \sigma^2_q$.

Whilst the fundamental process is observable, on day t all informed customers possess some private information on its next day shock, ϵ^f_{t+1}, and place a *collective* market order, I_t, in order to gain speculative profits. We assume that this order is equal to

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

where θ 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.

Using equation (6), the definition of the demand for foreign currency on the part of the rational investors (equation (1)) and the FX market equilibrium condition (equation (2)) we find that[10]

$$s_t \quad = \quad \frac{1}{1+\alpha} \sum_{k=0}^{\infty} \left(\frac{\alpha}{1+\alpha} \right)^k \; \left(\bar{E}^k_t\,(f_{t+k}) \;-\; \alpha\,\gamma\,\sigma^2\,\bar{E}^k_t(z_{t+k}) \right), \tag{8}$$

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

Equation (8) suggests that differently from traditional monetary models of exchange rate determination, the fundamental variable f_t does not exhaust all the factors which underpin the equilibrium value for the spot rate. Thus, the term f_t denotes the "traditional" fundamental variable of the monetary approach, pertaining to nominal, $m_t - m^*_t$, and real macroeconomic factors, q_t, which influence exchange rates, while the total supply z_t indicates a "new" fundamental value which

[10]Note that in deriving this expression we have assumed that $\mathrm{var}(s_{t+k+1}|\Omega^i_{t+k}) = \sigma^2$, where Ω^i_{t+k} is investor i's information set in day $t+k$. 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.

captures the impact of portfolio shifts on exchange rates induced by risk-aversion and exchange rate risk.

For simplicity and tractability we assume that all rational investors: i) possess symmetric information; and ii) observe in day t the current value of the fundamental variable, f_t, while receiving a public signal over next day fundamental shock, ϵ^f_{t+1}. These two assumptions allow us to circumnavigate the infinite regress problem Bacchetta and van Wincoop study and hence obtain simple closed form solutions for the exchange rate equation (8).[11] In practice, this amounts to imposing the conditions that $\bar{E}^k_t(f_{t+k}) = E(f_{t+k} \mid \Omega_t)$ and $\bar{E}^k_t(z_{t+k}) = E(z_{t+k} \mid \Omega_t)$, where Ω_t corresponds to the information set FX dealers possess in day t. Thus, the order k average rational expectations of day $t+k$ fundamental value, f_{t+k}, and day $t+k$ supply of foreign currency, z_{t+k}, are simply equal to all individual FX dealers' conditional expectations of the same variables.

Given equation (7), equation (8) presents the following solution

$$\begin{aligned} s_t \quad &= \quad \frac{1}{1+\alpha(1-\rho_f)}\, f_t \;+\; \frac{\alpha}{(1+\alpha)}\,\frac{1}{1+\alpha(1-\rho_f)}\, E\,(\epsilon^f_{t+1} \mid \Omega_t) \\ &\quad -\,\alpha\,\gamma\,\sigma^2\, z_t \;-\; \gamma\,\sigma^2\,\frac{\alpha^2\,\rho_b}{1+\alpha(1-\rho_b)}\, E\,(b_t \mid \Omega_t). \end{aligned} \tag{9}$$

To derive a rational expectations equilibrium and obtain a closed form solution for the spot rate we need to establish how the rational investors formulate their predictions of: i) the shock to the fundamental value, ϵ^f_{t+1}; and ii) the noise trading component of the order flow, b_t.

Fundamental Value. With respect to the former task we assume that in day t all FX dealers observe the following common signal

$$v_t \quad = \quad \epsilon^f_{t+1} \;+\; \epsilon^v_t,$$

where once again the signal error ϵ^v_t is normally distributed with mean zero and variance σ^2_v. Clearly, the error terms are uncorrelated over time (ie. $\epsilon^v_t \perp \epsilon^v_{t'}$) and with the fundamental shock (ie. $\epsilon^v_t \perp \epsilon^f_{t'}$). In practice, the signal v_t represents all the information which the rational investors can readily obtain from various official sources and publicly available data, such newswire services, newsletters, monetary authorities' watchers and so on.

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

Alongside this signal, all rational investors 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. In addition, while in the past only FX dealers could operate on these centralised platforms, nowadays other professional traders, as currency and hedge fund managers, have gained access to such electronic limit order books. Therefore, we can assume that in any day t all rational investors observe the signed order flow, o_t. However, the average rational investor cannot distinguish between the orders of the noise and informed traders, ie. between b_t and I_t.

Hence, suppose that in day $t-1$ the rational investors have formulated a conditional expectation of the noise trading component of the order flow $E(b_{t-1} \mid \Omega_{t-1})$, where $\Omega_t \equiv v_t, o_t,\ v_{t-1}, o_{t-1}, \ldots$ $v_{t-k}, o_{t-k} \ldots$. Given the persistency of the noise trading component of the order flow, in day $t-1$ the rational investors formulate the following prediction

$$E\,(b_t \mid \Omega_{t-1}) \;=\; \rho_b\, E\,(b_{t-1} \mid \Omega_{t-1}).$$

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

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

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

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 noise order flow, b_t, given the information the rational investors possess at the end of day $t-1$. This conditional variance is equal to

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

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

Noise Trading Order Flow. Since the noise trading component of the order flow is persistent, the rational investors 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

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

while the conditional variance is equal to

$$\mathrm{Var}\left(b_t \mid \Omega_t\right) \quad = \quad 1/\tau_{b,t} \quad \text{where} \quad \tau_{b,t} \; = \; \frac{1}{\theta^2} \, \tau_{\epsilon,t}.$$

In our analysis we concentrate on steady-state rational expectations equilibria, given that in the limit for $t \uparrow \infty$ $\mathrm{Var}(b_t \mid \Omega_t)$ and $\mathrm{Var}\left(\epsilon^f_{t+1} \mid \Omega_t\right)$ converge to time-invariant values.[12] Likewise, $\tau_{y,t}$ and $\tau_{b,t-1}$ converge to limit values τ_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 τ_ϵ and τ_b, where

$$\tau_\epsilon \; = \; \tau_f \; + \; \tau_v \; + \; \tau_y, \quad \tau_b \; = \; \frac{1}{\theta^2} \left(\tau_f \; + \; \tau_v \; + \; \tau_y \right) \quad \text{with} \quad \tau_y \; = \; \theta^2 \tau_{b,-1}.$$

Substituting the conditional expectation of the fundamental shock, $E\left(\epsilon^f_{t+1} \mid \Omega_t\right)$, and of the noise trading component of the order flow, $E\left(b_t \mid \Omega_t\right)$, into equation (9) we eventually obtain a closed form solution for the exchange rate,

$$s_t \; = \; \lambda_{s,-1} \, s_{t-1} \; + \lambda_f \, f_t \; + \; \lambda_{f,-1} \, f_{t-1} \; + \; \lambda_z \, z_t \; + \; \lambda_{z,-1} \, z_{t-1} \; + \; \lambda_o \, o_t \; + \; \lambda_{o,-1} \, o_{t-1} \; + \; \lambda_v \, v_t, \tag{10}$$

where

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

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

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

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

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

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

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

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

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

If we take differences, we obtain the following expression for the variation in the exchange rate

$$s_t - s_{t-1} = \lambda_{s,-1}(s_{t-1} - s_{t-2}) + \lambda_f(f_t - f_{t-1}) + \lambda_{f,-1}(f_{t-1} - f_{t-2}) + \lambda_z o_t +$$
$$\lambda_{z,-1} o_{t-1} + \lambda_o(o_t - o_{t-1}) + \lambda_{o,-1}(o_{t-1} - o_{t-2}) + \lambda_v(v_t - v_{t-1}). \quad (11)$$

2.2. Model Interpretation

From equation (11) 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 noise trading component of the order flow, captured by the autoregressive parameter ρ_b, generates serial correlation in the spot rate. Specifically, if shifts in the portfolios of customers 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 λ_f is positive. This is not surprising given that an increase in the fundamental value, f_t, typically corresponds to a rise in the relative money supply and in the interest rate differential $i_t^* - i_t$. Then, an increase in f_t corresponds to a rise in the excess return on the foreign currency and hence determines its appreciation.

Note, however, that positive serial correlation in the noise trading component of the order flow induces some mean reversion in the impact of fundamental shocks on the spot rate, as the coefficient of the first lag of the change in the fundamental value, $\lambda_{f,-1}$, is negative, but smaller in magnitude than the corresponding coefficient for the contemporaneous value, λ_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 rational investors, the sign of the corresponding coefficient, λ_v, is generally unclear. Nevertheless, when either θ or ρ_b is small, the public signal coefficient is positive. A positive value for the public signal, v_t, induces rational investors to increase their expectations of current and future realisations of the fundamental process and hence has an effect on the spot rate which is similar to that of a positive value for f_t.

The total supply coefficients λ_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, the rational investors 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 the rational investors expect from holding foreign bonds. When $\rho_b > 0$ the latter coefficient is positive, because persistence in the noise trading component of order flow induces mean reversion in the portfolio-balance effect of the total supply of foreign currency. As already seen for the fundamental shock, when ρ_b is negative such mean reversion turns into magnification, in that $\lambda_{z,-1} < 0$.

The order flow coefficients λ_o and $\lambda_{o,-1}$ are particularly interesting. The former is negative, because of the aforementioned portfolio-balance effect and because order flow possesses an information content. When some customer orders are informative (ie. for $\theta > 0$), an excess of sell orders might indicate an impending negative fundamental shock ($\epsilon_{t+1}^f < 0$) and hence induces the rational investors to expect an exchange rate depreciation. Consequently, the rational investors 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 noise trading forces mean reversion in the effect of order flow on the spot rate. In fact, the rational investors 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, ie. when $\theta = 0$, suggesting that the impact of portfolio shifts on exchange rates is not transitory. Such a 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 ρ_b is negative, ie. in the presence of mean reversion in the noise trading component of order flow, λ_o and $\lambda_{o,-1}$ possess the same sign and hence the impact of portfolio shifts on exchange rates is strengthened.

2.3. Review of Related Literature

As already mentioned, the existing empirical literature has faced difficulties in disentangling the portfolio-balance and information effects of order flow on exchange rates, in that these empirical investigations are not based on structural models of exchange rate determination. However, recently several structural models of exchange rate determination, based on the market microstructure approach, have been formulated.

Thus, Hau and Rey (2005) consider a model in which exchange rate dynamics is linked to equity returns and portfolio flows. In particular, in the face of constant risk-free interest rates, dividend innovations influence the portfolio holdings of international investors and hence affect capital flows and exchange returns. Carlson and Osler (2005) on the other hand develop a model where exchange rate dynamics is linked to shifts in interest rates and current account flows. In fact, in this model the demand for foreign currency of risk averse speculators meets the supply of non-speculative traders. While the former reflects shifts in the interest rate differential, which modify expected currency returns, the latter is price sensitive and reflects current account transactions.

While these two models differ in various aspects, they share an important feature which differentiate them from our formulation. In these models there exists *no* asymmetric information between FX traders, so that, unlike our formulation, order flow cannot have any information content. Evans and Lyons (2004) instead propose a very rich micro-founded model, which, combining a market microstructure component based on the analytical framework originally proposed by Lyons (1997) with a general equilibrium set up derived from the recent new open macroeconomics literature, assigns an informative role to order flow.

Two important features of their model are worth noticing. Firstly, for tractability Evans and Lyons assume that the FX dealers, ie. those agents which in their model set the equilibrium spot rate, can at the end of any trading day unwind their foreign exchange exposure with the national central bank. This implies that, unlike our formulation, order flow cannot affect exchange rates via the portfolio-balance channel. Secondly, consumption enters into the specification of the fundamental process which governs exchange rate dynamics. This implies that the model they formulate cannot be directly tested at high frequencies. Rather, in Evans and Lyons (2005) they derive some empirical implications which they can then test.

We have chosen a different approach, in that we have formulated a rather simpler model but one that can be conveniently estimated and tested. In this way we are able to give a precise answer to the important question of the origin of the impact of order flow on exchange rates. That is exactly what we now go on to do.

3. Results

The estimation of equation (10) can shed light on the portfolio-balance-vs-information-effect dilemma. Clearly, a simple direct OLS estimation of this relation is not enough to run tests of the significance of the deep parameters of the model, ie. those values which allow isolating the information and liquidity effects of order flow. Therefore, we need to define a series of moment conditions between observable variables which we can then employ to apply the GMM technique.

3.1. Estimation Restrictions

However, before we turn to the implementation of the GMM technique we need to impose two restrictions on the model, in that daily observations of the real exchange rate, q_t, are not available. First, we suppose that the sort of private information which informed customers may possess at the beginning of any trading day *only* pertains to the monetary component of the fundamental shock, ϵ^m_{t+1}. Thus, equation (7) changes to

$$I_t \quad \equiv \quad -\,\theta\,\epsilon^m_{t+1}.$$

Second, we assume that the real exchange rate component of the fundamental process, f_t is *constant*. In this way it is possible to proxy the fundamental variable, f_t, with the interest rate differential, $i_t^* - i_t$.

Our assumption that private information concerns only shifts in monetary aggregates, or equivalently in interest rates, may seem a very special one. Indeed, FX traders may collect information on several macro variables which affect the fundamental value of a foreign currency. Thus, on the one hand, studies of the impact of macro announcements on exchange rates, notably Ito and Roley (1987), Andersen *et al* (2003), indicate that news releases on several macro aggregates, such as industrial production, trade balance, employment level, etc., condition currency values. On the other hand, as suggested by some empirical evidence outlined by Love and Payne (2003), the information content of these news releases may be transferred into exchange rates via the trading process they generate.

Since high frequency data on most macro aggregates are not available, we cannot *directly* test any existing relation between order flow and these macro variables employing our high-frequency data-set. Likewise, using a daily data-set we are not able to estimate a model in which private information concerns future perturbations to the real exchange rate.

However, news releases on macro aggregates *typically* influence short term interest rates and hence our model should be able to capture *indirectly* the effect of most news releases on exchange rates. In addition, the same empirical studies listed above suggest that usually news items with the biggest impact on currency values concern monetary aggregates. Finally, one recall that, as reported in the Table 2, in our data-set we have identified some positive correlation between the first lag of the order flow variable and the variation in the interest rate differential. This correlation suggests how some FX traders actually anticipate shifts in interest rates and trade accordingly.

Plenty of empirical evidence suggests that purchasing power parity (PPP) does not hold over the short horizon, so that imposing a constant real exchange rate in the estimation of our model is potentially problematic. However, while the inability to observe daily values of the real exchange rate does not permit us to consider explicitly q_t among the determinants of the exchange rate, deviations from PPP can still be captured by adding an ARMA component into the error term of the equilibrium condition for the spot rate in equation (10). Whilst we do not explicitly model such an ARMA component, the GMM technique we employ is robust with respect to serial correlation and heteroscedasticity any deviation from PPP may induce in the error term.

Having described the data and the restrictions we need to apply to be able to estimate and test the model, we are now in a position to employ a GMM technique. Let us see the outline of this technique.

3.2. The Estimation Method

The key equation we estimate is equation (11), where the λ'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 ϵ_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:

$$o_t = \rho_b \, o_{t-1} - \theta \, (f_{t+1} - f_t) + \rho_b \theta \, (f_t - f_{t-1}). \tag{12}$$

Between them these equations yield 12 moment conditions for estimating 7 parameters (four coefficients (α, γ, ρ_b, θ) and three variances (σ_b^2, σ_f^2, σ_v^2).These moment conditions comprise $\mathrm{Var}\,(f_t - f_{t-1})$, $\mathrm{Var}\,(o_t)$, $\mathrm{Var}\,(s_t - s_{t-1})$, $\mathrm{cov}\,(f_t - f_{t-1}, s_{t+1} - s_t)$, $\mathrm{cov}\,(f_t - f_{t-1}, s_t - s_{t-1})$, $\mathrm{cov}\,(f_{t+1} - f_t, s_t - s_{t-1})$, $\mathrm{cov}(o_t, o_{t-1})$, $\mathrm{cov}\,(o_t, f_{t+1} - f_t)$, $\mathrm{cov}\,(o_t, s_{t-1} - s_{t-2})$, $\mathrm{cov}\,(o_t, s_t - s_{t-1})$, $\mathrm{cov}\,(o_t, s_{t+1} - s_t)$ and $\mathrm{cov}\,(o_t, s_{t+2} - s_{t+1})$.

It should be noticed that one cannot separate γ from σ^2 in the moment conditions one can obtain from the model and so the joint parameter $\gamma\sigma^2$ is estimated. The individual estimates for the two parameter values are then obtained considering that in equilibrium $\sigma^2 = h(\gamma)$.[13]

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.

[13] Indeed, for any choice of the model's parameters there always exist two sets of coefficients λ's, and correspondingly two different values for the conditional variance σ^2, which identify a steady-state rational expectations equilibrium for the model. However, of the two steady-state equilibria only one is *stable* and hence only for this there is certainty of convergence in the long run. Our estimation procedure employs this steady-state equilibrium.

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 ρ_f to be equal to 1, so that the fundamental value follows a random walk process.

3.3. Portfolio-Balance and Information Effects of Order Flow

As Table 4 shows, 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 γ outside the estimation procedure, the only estimates of standard errors and p-values we have for that parameter are from the Monte Carlo analysis.

Table 4 reports the estimated values of the parameter of the model obtained using GMM for the USD/EUR market. Since our transaction data comprise all trades completed via EBS and Reuters Dealing 2000-2 electronic limit order books, we are able to estimate the parameters of the model using: i) all the transactions contained in our data-set; and ii) those conducted via EBS and Reuters D2 respectively. This exercise is quite interesting in that it can shed light on the overall functioning of the USD/EUR market and on the relative liquidity and efficiency of the two alternative platforms.

Inspection of Table 4 indicates that over the three sets of transactions we consider: i) the model specification is always supported, as the over-identification restrictions are never rejected; ii) order flow has a positive, large and significant impact on exchange rates, with the coefficient of multiple determination, R^2, ranging between 0.38 and 0.68; and iii) the parameters of major interest, α, γ, ρ_b and θ, mostly take the expected sign.

Notice, however, that of these four values only α and γ are significantly different from zero in all estimations. In particular, θ is significantly larger than zero (at the 10% level) only for the transactions completed on EBS, while on the contrary γ is positive and significantly so for all three sets of transactions. This seems to suggest that the impact of the order flow on exchange rates is mostly due to the FX dealers' risk aversion, rather than to any informational asymmetry.

Even the estimated values for the precision of the fundamental value, τ_f, and the public signal, τ_v, point in the same direction, as they indicate that investors in the USD/EUR market collect a

Table 4:
GMM estimates of the model parameters, USD/EUR market.

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 day t. The fundamental value f_t is equal to the annualised interest rate differential, $\alpha(i_t^* - i_t)$, for the daily data. P.O.R. stands for probability value of over-identifying restrictions, The parameter value ρ_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.

	All Transactions				**EBS Transactions**				**D2 Transactions**			
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**
ρ_b	0.127	0.083	0.092	0.24	0.070	0.082	0.0932	0.37	0.208	0.071	0.090	0.12
α	1.474	0.689	1.049	0.01	2.137	1.153	1.177	0.01	3.001	0.581	1.043	0.00
γ	3.957		6.456	0.01	6.453		13.548	0.01	2.752		1.965	0.00
θ	0.337	0.357	0.663	0.11	0.242	0.175	0.417	0.06	-0.054	0.112	0.192	0.44
τ_f	137.658				65.485				33.062			
τ_y	1.655				2.730				0.103			
τ_v	12.987				6.734				10.854			
σ^2	0.349				0.183				0.344			
	R^2	0.685			R^2	0.379			R^2	0.650		
	P.O.R.	0.636			P.O.R.	0.863			P.O.R.	0.288		

good deal of information from openly available sources rather than from order flow. Specifically, we see in the left and centre panels of Table 4 that roughly 10% of the information contained in the fundamental shock ϵ_{t+1}^{f} is anticipated by the public signal v_t, in that $\tau_v/\tau_f \cong 0.09$.

Finally, whilst in the preliminary analysis of our data-set we found positive serial correlation in the order flow, in Table 4 we see that the parameter ρ_b, which captures the degree of serial correlation in the noise trading component of the order flow, is positive but insignificant in all estimations. Hence, to check the robustness of our results we have re-run our GMM estimation of the model under the restriction that $\rho_b = 0$. We do not report the corresponding results, but they are not substantial dissimilar from those shown in Table 4.

Even if the information parameter θ does not appear to be significantly larger than zero across all sets of transactions we have considered, our estimated model maintains an appealing property of Bacchetta and van Wincoop's framework, ie. that the spot rate is a weak predictor of the fundamental process. It is possible, in fact, to simulate the spot rate, s_t, and the fundamental process, f_t within our model specification using the parameters derived from the daily estimates reported in Table 4. From the simulated series it is then possible to regress leads of the fundamental shock, $f_{t+k} - f_t$, over the contemporaneous spot rate return, $s_{t+1} - s_t$. Results of this exercise indicate a coefficient of multiple determination, R^2, in the 10-15% range for leads varying between 1 and 20 days. Such a property is an appealing one, as recent empirical evidence (Engel and West (2005) and Froot and Ramadorai (2005)) shows how this is borne out by the data.

In truth, an insignificant value for θ does not preclude some sort of informed trading in FX markets. On the one hand, FX traders may collect information on fundamental shifts which materialize in the distant future, ie. after several days, weeks or months, and trade accordingly. In this respects Evans and Lyons (2005) propose some supportive empirical evidence. In fact, their study confirms that customer order flow is a good predictor of *future* money growth rates, but also finds that such predictability is stronger over medium-run horizons than short ones.

On the other hand, FX traders may collect information on movements in fundamental variables other than interest rates or monetary aggregates. Once again Evans and Lyons (2005) offer some supportive evidence as they find that customer order flow is a good predictor of *future* values of output levels and inflation rates. Furthermore, Froot and Ramadorai (2001) propose some empirical evidence indicating that cross-border institutional equity flows, which are eventually reflected into FX order flow, are good predictors of *future* equity markets returns, while according to the portfolio re-balancing effect outlined by Hau and Rey (2004, 2005) equity markets returns and exchange rate returns should be negatively correlated.

Finally, one should also consider the possibility that informed FX trading is concentrated on the *direct* section of the inter-dealer FX market, as its lower degree of transparency facilitates anonymity and the preservation of private information. To investigate such a possibility one should employ data on the direct inter-dealer transactions we do not have access to. However, our discussions with spot dealers suggests that this does not occur in practice.

3.4. Liquidity and Efficiency Conditions on EBS and Reuters D2000-2

When comparing the two competing trading platforms we detect some important differences. While the values taken by α, γ, and ρ_b are not significantly different when estimated using transactions completed on EBS and D2 separately, we see that the information parameter θ takes opposite values. In particular, the value obtained for the transactions completed on D2 is not significantly different from zero, while the same parameter appears to be significantly positive for the transactions completed on EBS. Interestingly, this suggests that some private information is brought to the market via the latter platform.

In the same direction points the 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, τ_v/τ_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 such differences are 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. Thus, if news releases at different times of the day have a different information content, our measure of the information content of the public signal, τ_v/τ_f, will differ across the two platforms. Similarly, if investors with different access to private sources of information on American and European monetary policies operate on the two platforms, it is possible that evidence of asymmetric information appears only on one platform.

Deriving the coefficients λ's associated to the estimated values of the model parameters it is also possible to estimate the impact of trade innovations on exchange rates and derive simple measures of liquidity. In the Table 5 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.

Table 5

Trade impact on EBS and Reuters D2.

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.

	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

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.

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 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 so FX dealers are 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.

Table 6

Impact of euro interventions.

A positive value for the intervention variable indicates a sell of US dollars on the part of the ECB. 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 (sell minus buy orders) 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.

	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%

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 intervention,[14] 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)).

In Table 6 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, ie. 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 6 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 the 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.[15]

As for the effect of intervention via the innovation in order flow, it seems that exchange rate movements on intervention days are largely consistent with those predicted by our model. So

[14] 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).

[15] 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.

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 portfolio-balance 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.

A first look at the correlations between order flow, exchange rate returns and innovations in the interest rate differential suggests an information-based interpretation of the effect of trade innovations on the exchange rate. However, our investigation proposes weak support in favour of this information-based interpretation. Indeed, while we find some evidence that order flow moves exchange rates via the information channel, we also see that order flow affects currency values primarily via the portfolio-balance channel. 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, as this would permit studying low frequency relations between order flow and exchange rate fundamentals that we have not been able to identify. Likewise, direct observation of customer order flow 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;[16] 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 portfolio-balance effects of official intervention in FX markets.

References

Andersen, T., T. Bollerslev, F. Diebold, and C. Vega, 2003, Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange, American Economic Review, 93, 38–62.

Bacchetta, P., and E. van Wincoop, 2005, Can Information Heterogeneity Explain the Exchange Rate Determination Puzzle?, American Economic Review, forthcoming.

Biønnes, G. H., and D. Rime, 2005, Dealer Behavior and Trading Systems in Foreign Exchange Markets, Journal of Financial Economics, 75, 571–605.

BIS, 2002, Triennal Central Bank Survey: Foreign Exchange and Derivatives Market Activity in 2001. Bank of International Settlement, Basel.

——— , 2004, Triennal Central Bank Survey: Foreign Exchange and Derivatives Market Activity in 2004. Bank of International Settlement, Basel.

Carlson, A. J., and C. L. Osler, 2005, Short-Run Exchange Rate Dynamics: Evidence, Theory, and Evidence, mimeo.

Danielsson, J., and R. Love, 2004, Feedback Trading, London School of Economics mimeo.

Dominguez, K. M., 2003, The Market Microstructure of Central Bank Intervention, Journal of International Economics, 59, 25–45.

Dominguez, K. M., and J. A. Frankel, 1993, "Foreign Exchange Intervention: An Empirical Assessment". In J.A. Frankel: *On Exchange Rates*, Mit Press, Cambridge, MA.

Edison, H. J., 1993, The Effectiveness of Central-Bank Intervention: A Survey of the Literature After 1982, Special paper 18, Princeton University.

[16] See Danielsson and Love (2004).

Engel, C., and K. D. West, 2005, Exchange Rates and Fundamentals, Journal of Political Economy, 113, 485–517.

Evans, M. D., and R. K. Lyons, 2000, The Price Impact of Currency Trades: Implications for Interventions", University of California at Berkeley mimeo.

——— , 2002a, Order Flow and Exchange Rate Dynamics, Journal of Political Economy, 110(1), 170–80.

——— , 2002b, Time Varying Liquidity in Foreign Exchange, Journal of Monetary Economics, 49, 1025–51.

——— , 2004, A New Micro Model of Exchange Rate Dynamics, NBER Working Paper 10379.

——— , 2005, Exchange Rate Fundamentals and Order Flow, University of California at Berkeley mimeo.

Fatum, R., and M. Hutchison, 1999, Is Intervention a Signal of Future Monetary Policy? Evidence from the Federal Funds Futures Market, Journal of Money, Credit, and Banking, 31, 54–69.

Frankel, J. A., and A. K. Rose, 1994, A Survey of Empirical Research on Nominal Exchange Rates, NBER Working Paper 4865.

Froot, K., and T. Ramadorai, 2001, The Information Content of International Portfolio Flows, NBER Working Paper 8472.

——— , 2005, Currency Returns, Intrinsic Value, and Institutional Investor Flows, Journal of Finance, 60, 1535–1566.

Hasbrouck, J., 1995, One Security, Many Markets: Determining the Contributions to Price Discovery, Journal of Finance, 50, 175–99.

Hau, H., and H. Rey, 2004, Can Portfolio Rebalancing Explain the Dynamics of Equity Returns, Equity Flows and Exchange Rates?, American Economic Review, Papers and Proceedings, 93, 126–133.

——— , 2005, Exchange Rates, Equity Prices and Capital Flows, Review of Financial Studies, forthcoming.

Ito, T., and V. V. Roley, 1987, News from the U.S. and Japan: Which Moves the Yen/Dollar Exchange Rate?, Journal of Monetary Economics, 19, 255–277.

Kaminsky, G. L., and K. K. Lewis, 1996, Does Foreign Exchange Intervention Signal Future Monetary Policy?, Journal of Monetary Economics, 37, 285–312.

Lewis, K. K., 1995, Are Foreign Exchange Intervention and Monetary Policy Related and Does It Really Matter?, Journal of Business, 68, 185–214.

Love, R., and R. Payne, 2003, Macroeconomic News, Order Flow and Exchange Rates, London School of Economics mimeo.

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

——— , 1997, A Simultaneous Trade Model of the Foreign Exchange Hot Potato, Journal of International Economics, pp. 275–298.

Marsh, I. W., and C. O'Rourke, 2004, Customer Order Flow and Exchange Rate Movements: Is There Really Information Content", Cass Business School mimeo.

Meese, R., and K. Rogoff, 1983, Empirical Exchange Rate Models of the Seventies: Do They Fit Out of the Sample?, Journal of International Economics, 13, 3–24.

Mussa, M., 1981, The Role of Official Intervention. Group of Thirty, New York, NY.

Payne, R., and P. Vitale, 2003, A Transaction Level Study of the Effects of Central Bank Intervention on Exchange Rates, Journal of International Economics, 61, 331–352.

Rime, D., 2003, "New Electronic Trading Systems in Foreign Exchange Markets". In: *New Economy Handbook*, Elsevier Science, USA.