Sources of Private Information in FX Trading

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Abstract

This paper examines the information content of trades by different participants via different trading channels in the spot foreign exchange market. Using spot FX transactions of a major Australian bank, we find that central banks have the greatest price impact, followed by non-bank financial institutions such as hedge funds and mutual funds. Trades by non-financial corporations have the least impact on dealer pricing. In the interbank market, dealers with greater private information appear to choose direct trading which has lower post-trade transparency, while indirect trading via brokers has little price impact. Furthermore, the price impact from each group largely comes from dealers or customers in the top quartile of trading volume. Overall the study presents an information hierarchy across different types of players and the choices of trading mechanisms in the FX market.

VERY PRELIMINARY

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I. INTRODUCTION

A fundamental difference between the foreign exchange (FX) market and equity markets is the nature and the sources of private information. In equity markets, private information is primarily on the fundamental value of equities. With centralized order flows and disclosure, private information on order imbalance is short lived. There is a well-recognized information hierarchy from corporate insiders to institutional investors to individuals. Such an information hierarchy is critical to the standard models of price discovery where market makers do not have private information and they learn from trading against insiders [e.g. Kyle (1985)]. It also motivates the study of the behavior and market impact of differentially informed investor groups such as insiders and institutional investors.

In the FX market, however, the existence of private information on macro fundamental variables such as interest rates is yet to be established. It is well known that macro variables have limited explanatory power for exchange rate movements. FX trading is decentralized and opaque, making short-term order flow imbalance private information of individual dealers. Recent studies, e.g. Evans and Lyons (2002a), show that such order flow imbalance is an important determinant of exchange rate movements. Therefore FX dealers are not uninformed market makers as in Kyle (1985), but rather insiders with private information or non-fundamental speculators as in Madrigal (1996). Their private information comes from trading with their customers and other dealers. Unlike equity markets, the FX market is overwhelmingly dominated by institutional participants. The existence and the structure of an information hierarchy across institutions are yet to be examined. A study of heterogeneous information across market participants will shed light on the sources of information for FX dealers, and in turn, the nature of private information in the FX market.

This paper is an empirical examination of the price impact from different participants in the FX market. The price impact reflects the information content of trades from different investor groups thus reveals the sources of private information in FX trading. There are two reasons for order flows to have different price impact. First, although the existence of private information on macro fundamentals is yet to be established, market participants, particularly financial institutions, often hold interest-rate sensitive assets with different currency denominations and have speculative views on future changes in interest rates and inflations in different countries. These views in turn affect their reactions to macroeconomic announcements [Evans and Lyons (2003)]. By differentiating investor groups, FX dealers are able to extract and aggregate these speculative views through trading. Second, order flows also reflect changes in net demand for a currency. Such changes may affect exchange rates through the portfolio balancing effect [see Lyons (2001, chapter 2) and Evans and Lyons (2002b)]. By itself, each trade affects portfolio balancing by its size, not its origin. However, if some order flows convey more information about their own future flows or market-wide order flows, then these orders may have greater price impact than others.

The importance of differentiating investors has long been recognized in studies of financial markets. There is a large body of literature on the behavior and market impact of corporate insiders, large institutions, and individuals. However, due to data limitation, we are not aware of any study of equity trading that jointly estimates the price impact of different investor groups in real time. Recent studies of FX microstructure also examine heterogeneous groups in the FX market. Wei and Kim (1997) find trades by big players are a major source of FX volatility but do not have significant information content. But Froot and Ramadorai (2002) find institutional order flows carry information on future excess currency returns. Lyons (2001, chapter 9) reports that leveraged and unleveraged financial institutions have different market impact in different currency markets. Bjonnes and Rime (2001, 2002) show customer trading has greater price impact than interbank trading.

Our study is in the same spirit as Lyons (2001) and Bjonnes and Rime (2001, 2002), with several distinct features. Using monthly data from Citibank, Lyons demonstrates differential price impacts from three customer groups: leveraged and unleveraged financial institutions, and non-financial corporations. We use tick-by-tick data and examine the relationship between the dealer's pricing and his current and previous trades. The results show a direct link between transactions by different market participants and subsequent price changes, and add granularity to Lyons' analysis. While Lyons' data contain only customer trades, we estimate the joint impact of interbank trades as well as customer trades. Unlike Bjonnes and Rime, we further break down customer trades into subgroups based on their institutional characteristics and constraints. A detailed partition of customers is essential for differentiating the information content of order flows. For interbank trades, we separate direct trades from indirect trades where the levels of pre- and post-trade transparency are different. Post-trade transparency affects informed traders' choice of trading channels, as demonstrated by dealers on the London Stock Exchange [Reiss and Werner (1999)]. Bjonnes and Rime (2001) partition direct interbank trades based on the perception of being "informed" or "uninformed", but fail to find any significant differences in price impact and subsequent trades by the receiving dealers.

Our empirical analyses are based on spot FX transactions of a major Australian bank in AUD/USD and EUR/USD exchange rates over a period of 45 days in 2002. The sample is longer than most previous intraday FX trading data, and includes a customer code to allow for classification. Customers are separated into central banks, non-bank financial institutions which have no direct access to the interbank market, and non-financial corporations. We find that the Reserve Bank of Australia (RBA) was actively selling AUD into a rising market, and their trades have the greatest price impact in the AUD/USD market. On the other hand, central banks in the EUR/USD market during our sample period are classified as "Overseas Central Banks – non OECD" and their trades have no market impact. Non-bank financial institutions include managed funds, insurance companies, brokering services, etc. They have cross-currency asset holdings and often are significant players in the FX market. Our results show that non-bank financial institutions have significant price impact in both markets. Trades by non-financial corporations reflect international trade in goods and services which accounts for about one percent of all currency transactions. We find non-financial corporations have the least impact on dealer pricing. In the interbank market, dealers with greater private information appear to choose direct trading which has low post-trade transparency. Indirect trading via voice or e-brokers is often partially revealed to the market and has little price impact. Furthermore, the price impact from each group largely comes from dealers or customers in the top quartile of trading volume. Overall the study presents an information hierarchy across different types of players and the choices of trading mechanisms in the FX market.

The structure of this paper is organized as follows. Section II discusses the institutional characteristics of customer groups and interbank trading channels. It provides a basis for the partition of order flows and for understanding the role and impact of different customer groups. Section III describes the data set and the sample construction. Section IV discusses model specification and estimation. Section 5 reports the estimation results, followed by a summary and conclusion in section VI.

II. MARKET PARTICIPANTS AND TRADING MECHANISMS

Spot FX trading is conducted in a two-tier market. At the center is the interbank market where interdealer trading occurs. It allows dealers to pass unwanted inventory to others and to provide liquidity to each other. Most importantly, the interbank market digests and impounds information from disparate sources into exchange rates. The second tier of the market involves customer-dealer trades, which are often the cause for the "sound and fury" in interbank trading [Lyons (1996)]. These trades are not observed by the market. Any information imbedded in customer trades becomes private information of the dealer involved. Indeed dealers with significant customer order flows are regarded as having a competitive advantage in the interbank market [see dealer surveys by Cheung, Chinn and Marsh (2000) and Cheung and Chinn (2001)]. On average, customer trades have greater price impact than interbank trades.

Customers include central banks and small banks who are not members of the interbank market, managed funds, insurance companies, non-financial corporations, and individuals. They differ in their level of risk aversion, hedging and liquidity needs. Most FX trading banks have a regular customer base, and make a concerted effort to attract customers and understand customer order flows. Banks have designated dealers, called distributors, who specialize in customer trades. They play a crucial role in gathering information for trading decisions. Through frequent customer contact, often in social situations, distributors achieve a good understanding of large customers, their motivation for trading, level of information acquisitions, trading horizons and institutional constraints. This knowledge allows distributors to extract information from customer order flows, which is relayed to interbank dealers to form price expectation in real time trading.

In this section, we discuss the characteristics of different customer groups and the information content of their trades. Customers are classified into three groups: central banks, non-bank financial institutions, and non-financial corporations. We ignore trades by individuals which have no information content. While there is a large body of literature on central bank intervention in the FX market [e.g. Pasquariello (2001) and references therein], relatively little is known about trades by other institutions. We then examine the choice of trading channels by dealers and the information content of their interbank trades.

A. Central Banks

Central banks play a unique role in the FX market. They are the monopoly suppliers of national currencies. They have a significant impact on long-term exchange rates through monetary policy. They are perceived to be "informed" about any exchange rate misalignment. Most central banks have some mandate to maintain the short-term stability of the currency, through direct intervention and monetary policy. A significant portion of their trading is aimed at influencing the direction of exchange rate movements. These institutional features give central banks greater power in the FX market than any other institutions.

Early studies [e.g. Taylor (1982) and Obstfeld (1990)] find intervention to be ineffective. Currency crises in the 1990s also reflect the limited market power of central banks. Recent surveys [Cheung and Chinn (2001)] indicate most FX dealers do not believe interventions have a substantial effect except increasing market volatility. However, recent microstructure studies show the effect of intervention to be significant but short lived. Peiers (1997) and Dominguez (2003) report that the interbank market begins to move in the direction of central bank intervention one hour prior to newswire reports of intervention. Using intraday transaction data by the Swiss central bank (SNB), Payne and Vitale (2002) report that the market impact of intervention concentrates during the 15-minute interval before and after the transaction, and a purchase of USD50 million by SNB has an immediate impact of nearly 30 basis points on the exchange rate. Pasquariello (2002) examines SNB trades under different market conditions and show SNB trades induce greater uncertainty. Evans and Lyons (2000) estimate a lower bound of 5 basis points in the hour following a USD100 million intervention in the DEM/USD market, while Kearn and Rigobon (2002) show that a \$US100 million purchase by the Reserve Bank of Australia (RBA) will appreciate the Australian dollar by 1.35 to 1.81 per cent on the day of intervention. The full effects of intervention appear to be reflected in the exchange rate within a matter of hours.

B. Non-Bank Financial Institutions

Non-bank financial institutions are hedge funds, mutual funds, superannuation funds, insurance companies, and brokering services. These institutions trade currencies to access foreign asset markets or to speculate on fluctuations in exchange rates. They have strong reputation in the collection and analysis of financial information, and have considerable short-term market power through asset holding. With worldwide financial liberalization and technological development, foreign investment and cross-border capital flows have grown exponentially. These capital flows, particularly portfolio flows, tend to occur in herds as reported in Froot, O'Connell and Seasholes (1998). Such concentrated demand and supply can have significant impact on exchange rates and carry information regarding future excess currency returns [Froot and Ramadorai (2002)]. Some institutions within this segment, particularly hedge funds, use substantial leverage to achieve greater market power. Given the large amounts of capital afforded by high gearing, coupled with the absence of governmental regulation in the FX market, these institutions are able to employ trading strategies, illegal in more regulated markets, to ensure that their trading has a maximum impact. For example, the Reserve Bank of Australia has noted that "a key feature of [hedge funds'] strategy was to concentrate sales into periods of thin trading (such as lunchtime in the Sydney market and the shoulder periods between Sydney and London trading)" [Rankin (1999, p154)]. When asked what causes exchange rates to deviate from fundamental values, 68% of US dealers surveyed in Cheung and Chinn (2001) blame institutional customers/hedge fund manipulations.

C. Non-Financial Corporations

Non-financial corporations do not engage in short-term currency speculations. Their currency transactions represent international trade in goods and services, foreign direct investment and repatriation of profits from foreign subsidiaries, and as such, reflect a country's trade surplus and balance of payment. Surveys of dealers indicate macroeconomic information do not affect short-term exchange rate movements. Indeed researchers have long been puzzled by the lack of explanatory power of macroeconomic variables.

While international trade has been growing in absolute term, its share in currency trading has dropped. International trade accounts for only about one percent of all currency transactions and about 11% of spot transactions; see Euromoney (2002) and BIS (2002). Foreign direct investment and cross-border mergers and acquisitions have become an increasingly important component of FX flows, so much so that they have been credited with causing a number of significant trends in exchange rates in recent years.[1] However, most transactions of this type are intermediated by financial institutions such as investment banks and are not reflected in the retail order flows of the corporations involved. Overall we expect trades by non-financial corporations have limited impact on FX dealer's short-term pricing.

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[1] For example, in its 2000 Annual Report, BIS (2000) identified acquisitions of US targets by European companies as a key source of weakness in the Euro.

D. Direct and Indirect Interdealer Trading

Direct interdealer trading is conducted via Reuters Dealing 3000 Direct[2] or over the telephone. Indirect trading is intermediated by voice or electronic brokers[3]. A key difference between direct and indirect trading is the level of pre- and post-trade transparency. Direct trading involves bilateral negotiation that is not observed by anyone else except the dealers involved. In indirect trading, while the initiating dealer remains anonymous, his order is publicized and trades are partially revealed to the entire market.[4] Microstructure theory suggests that informed traders will try to hide their trades and disguise their private information. Therefore we would expect dealers with private information to prefer direct trading with lower level of transparency.

The difference in pre-trade transparency is similar to interdealer trading on the London Stock Exchange, where a dealer can trade by telephone or anonymously through interdealer broker (IDB). Reiss and Werner (1999) show that LSE dealers are likely to choose telephone instead of IDB when they have private information. LSE dealers also show preference towards the lower level of post-trade transparency, as demonstrated by the debate on post-trade announcement [Gemmill (1996)]. We estimate the price impact of direct and indirect trades, and the spread charged by the receiving dealer. If direct trading is associated with more informed trades, then the receiving dealer would charge a bigger spread. Indeed Reiss and Werner (1999) report larger spreads for direct trading on the LSE.

III. DATA AND SAMPLE CONSTRUCTION

This study employs a data set consisting of all external FX transactions from the Australian office of one bank that occurred between 1st May and 3rd July 2002, covering a period of 45 trading days. Australia has an active FX market, ranked 8th globally in terms of FX trading [BIS (2002)]. The data set is similar to other proprietary data used in Lyons (1995), Yao (1998ab), and Bjønnes and Rime (2001), with two distinct features. First, each

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2 Reuters Dealing 3000 Direct is the successor of Dealing 2000-1 referred in previous studies. It allows FX dealers to initiate a bilateral conversation similar to a private Internet chat room. The initiating dealer is able to solicit a two-way quote from the targeted dealer. The quote is valid for several seconds. The system allows contacts with up to twenty-six dealers simultaneously while each conversation remains bilateral.

3 There are two main electronic broking systems in the FX market, Reuters Dealing 3000 Spot Matching which is the successor of Dealing 2000-2, and the Electronic Brokering Service (EBS).

4 Electronic broker systems provide a record of trades conducted through the system, showing currency pair, time, rate, and whether it was "paid" or "given" (i.e. whether the aggressor was buying or selling respectively). Voice brokers also indicate a transaction has taken place when the best bid or ask is cleared.

counterparty has a unique customer code, which allows us to classify customers according to their codes and trading frequencies. In Lyons' study, the dealer has no customer order flow and earns profits by continually "shading" his quotes to induce interbank trades. Bjønnes and Rime (2001) separate customer trading from interbank trading, but do not differentiate among customers. Second, the length of the sample is much longer than that of Lyons (5 days), Yao (25 days), and Bjønnes and Rime (5 days). One drawback of the data is that we are unable to calculate the bank's inventory position across dealers.

A. Data Sources and Structure

The data used in this study has been compiled from several sources. The transaction data are obtained from the bank's front-office risk management system. Each trade record contains the following information:

1. Currency pair;
2. Deal sequence (DSEQ, a chronologically ordered unique identifier which also links the spot and forward legs of swaps);
3. Date and time stamp of the trade (to the minute);
4. Settlement date;
5. Transaction price;
6. Quantity traded;
7. Trading Channel
8. Dealer ID;
9. Customer ID.
10. Interbank Trade Identifier

Transaction data are supplemented with Reuters FXFX quote data obtained from Olsen and Associates. The quote data include time stamp to the second, bid, ask, and Olsen credibility index ranging from 0 to 1. The credibility index identifies incorrectly entered quotes and other errant data points that appear in the raw Reuters FXFX quote series. In keeping with the recommendations of Müller (2001), observations with credibility indices below 0.5 are removed from the sample. The best bid and best ask from each minute are used to calculate the midpoint of the market = (Bid + Ask)/2.[5] As shown by Hasbrouck (1991), assuming transaction costs are symmetric for purchases and sales, the effects of new information can be summarized as the subsequent revision in the quote midpoint. Over time, the quote midpoint converges in expectation to the market clearing price. Therefore we use the midpoint as an approximation for the market clearing price. Goodhart, Ito, and Payne

(1996) show that while FXFX spreads are substantially larger than those available in the interbank market, the returns of the actual transaction price series on the Dealing 2000-2 system and the returns of the Reuters midpoint series are almost perfectly correlated.

The bank also provides a list of industry classifications for the counterparties appearing in the sample, as well as identifying each of the bank's dealers as either a trader in the interbank market or a distributor dealing with customer trades. Using the customer IDs and interbank trade identifier, trades are classified into customer trades and interbank trades. Customers are divided into three groups: central banks, non-bank financial institution, and non-financial corporation. Interbank trades are further segmented into direct and indirect trades in order to assess the differences in private information across trading channels.

B. Sample Construction

While a large cross-section of currencies appear in the raw data, we examine the most active currency pairs traded by the bank, AUD/USD and EUR/USD. AUD is the home currency of the bank where it has a large customer base. In EUR, the bank has a smaller customer base but is active in interbank trading.

Spot Transactions

We focus on spot trading where the majority of innovations in exchange rates occur [see Lyons (2001)]. A two-step filtering is used to remove non-spot transactions in the raw data. First, we remove small trades less than USD10,000[6], trades settled outside the spot settlement dates, and trades by known options/swap dealers in the bank. This results in a sample of trades settling on or before the spot date[7]. Second, using the minute-by-minute market midpoint (obtained from the Reuters quotes) as an approximation of the market clearing price at a given time, we apply outlier filters to interbank and customer trades. For interbank trades, we calculate the standard deviation of 50 Reuters quote midpoints prior to the trade. The choice of a moving average window 50 roughly corresponds to ten minutes in both the AUD and EUR samples. The average moving standard deviation is 1.32 basis points

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[5] For minutes with no quotes recorded, the last quote submitted is used. This was, however, seldom required since the median time between Reuters quotes is five seconds or under across both currencies.

[6] These trades generally represent accounting adjustments or error corrections and do not play a role in dealers trading decisions in a market where the median trade size is well over USD 1 million.

[7] Some spot trades are settled before the spot settlement date and are referred to as "value today and value tomorrow" trades.

for the AUD series and 1.61 basis points[8] for the EUR over the sample period. Centered on the market midpoint in each minute, interbank trades occurred more than six moving standard deviations away are removed from the sample. For customer trades, all trades that occur on the wrong side of the spread are deleted.[9] In addition, we calculate the standard deviation of customer trade prices in the hour prior to the trade. Centered on the market midpoint in each minute, customer trades occurring more than two standard deviations away are removed from the sample. Table 1 provides an overview of the results of the filtering procedures used in the sample selection process. Ignoring small trades, spot trades account for approximately half of the total trades in AUD and EUR, which is consistent with BIS survey of FX trading.

Incoming and Outgoing Trades

Outgoing trades are trades initiated by our dealer. They are executed at prices set by other dealers and do not reflect the pricing decision of our dealer. Therefore we need to remove outgoing trades from the sample. All customer trades are incoming trades initiated by customers. The dealer will always be the supplier of liquidity. For interbank trades, the dealer may either provide liquidity to other dealers, or demand liquidity by requesting quotes from other dealers or submitting market orders to brokers.

In order to identify the initiator of the trade a modified version of the tick-test is used, in conjunction with whether the bank is the buyer or seller in a particular transaction. The first transaction of every minute is matched with the first Reuters FXFX quote of the same minute if the quote occurred within the first fifteen seconds of the minute, or alternatively, with the last quote prior to the minute of the transaction. Similar to the identification of the prevailing quote in Lee and Ready (1991), the midpoint of this quote is used to calibrate the first trade of each minute, by referencing the trade to where the market is currently trading. This is particularly important in reliably signing transactions after periods where the bank has not had any trades, but the market has nevertheless moved to a new price, as opposed to using a simple application of the tick-test. If the first trade of the minute occurs above the market midpoint, then the trade occurred at the ask. If the bank is the seller at the ask, then that trade is classified as *incoming*, since it is the other bank that is demanding liquidity. Alternatively, if the trade is classified as an ask price, but the bank is the buyer, then the transaction is

[8] Note that 1 basis point is equivalent to USD 0.0001 for both AUD and EUR.
[9] Since customers are exclusively the demanders of liquidity, they will always buy at the ask and sell at the bid, therefore transaction prices that occur on the other side of the midpoint are not spot transactions.

classified as an *outgoing* trade. The reverse is true for trades occurring at the bid. Once the first trade of each minute has been identified as occurring at the bid or the ask, the tick-test is then used to identify whether trades occurring within the same minute occur at the bid or the ask, and in turn, whether they are *incoming* or *outgoing*.

Consistent with existing literature, the calculation of order flow variables is undertaken from the perspective of the trade initiator, where *incoming* buy orders have a positive sign, and *incoming* sell orders have a negative sign. For *outgoing* trades, since the bank in the sample is the trade initiator, trades will have a positive sign when the bank is a buyer and a negative sign when the bank is a seller.

Spot Inventory

The calculation of spot inventory involves the aggregation of spot transactions across dealers and over time. If a dealer trades both AUD/USD and JPY/USD, then we cannot calculate his USD inventory from AUD/USD transactions. Therefore an accurate measure of the bank's spot inventory in a currency requires the aggregation of spot trades across many currency pairs. In addition, spot inventory is also affected by swap transactions or exercising options. As such we are unable to construct a reliable measure of spot inventory. We will discuss the implication on model specification in the next section.

C. Descriptive Statistics

Figures 1 shows the interbank transaction rates traded by the bank over the 45-day period for AUD and EUR. There are overnight jumps in prices from European and North American trading. In later analyses, all overnight changes are removed from the sample, so that all price effects are related to intraday order flow transacted by the bank. AUD had an upward trend in the first half of the sample, while EUR was rising for the full sample. Figure 2 presents the daily volume (in USD) and the number of trades across the sample period. The average daily volume of the bank is USD 213 million for AUD and USD 73 million for EUR. The difference in volumes reflects the bank's Australian customer base, which in turn gives the bank a natural advantage in the interbank AUD market.

Table 2 presents the composition of the bank's trading by counterparty for AUD and EUR. For AUD, 65 percent of the bank's trades are with other interbank dealers, whereas for EUR, the number is 94 percent. Consequently, the AUD dealer in this study is similar to the dealer in Yao (1998ab), who had considerable customer order flow, while the EUR dealer is similar to the one in Lyons (1995), albeit with substantially less volume. The average trade same varies across different counterparties. In the case of AUD the mean trade size of central banks[10] is four times that of the mean across all counterparty types, while the mean trade size of non-financial corporations is approximately a quarter the mean of trade size of all counterparties. Insofar as trade size is indicative of relative informativeness of a trader [see Easley and O'Hara (1987)], this provides preliminary evidence of central bank trades being more informative than those of other trader types.

Table 3 further disaggregates interbank trades into incoming and outgoing, and according to the trading channel used. For both direct and indirect trading, electronic trading dominates phone or voice-brokered trading. Electronic broker is the favourite trading channel by the bank, accounting for around 60% of AUD trades and over 75% EUR trades. Voice-brokered trades have the largest trading size. Reinforcing the validity of the method used to assign trades as *incoming* and *outgoing*, there does not appear to be any unreasonable bias toward either *incoming* or *outgoing* trades in the case of either AUD or EUR. The vast majority of both dealers' interbank trading activity is transacted through electronic brokers.

IV. MODEL SPECIFICATION AND ESTIMATION

Previous studies of dealer behaviour in the FX market [see Lyons (1995), Yao (1998a), Bjønnes and Rime (2001)] build upon the theoretical framework developed by Madhavan and Smidt (1991). The Madhavan-Smidt model considers the pricing decision of a specialist on the NYSE as a Bayesian learning problem, in which price P_t is determined by the dealer's expectation μ_t, his current (I_t) and desired (I_d) inventory, and a competitive spread based on buyer ($D_t = 1$) or seller ($D_t = -1$) initiated trades: $P_t = \mu_t - \gamma(I_t - I_d) + \varphi D_t$. In each period t a trader arrives to the market and chooses an optimal trading volume Q_t based on his private information and liquidity needs. The dealer uses the Bayse rule to extract the information component in Q_t and to form his post-trade expectation. His price adjustment process is given by

$$\Delta P_t = \beta_0 + \beta_1 Q_t + \beta_2 I_t + \beta_3 I_{t-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_t$$

[10] The average trade size by central banks is considerably smaller than the daily intervention size reported in Kim and Sheen (2001) and Kearn and Rigobon (2002), which include some large intervention trades by the RBA in 1998. The central banks may also trade with several dealers to implement intervention.

where the innovation term ε_t is driven by public information. Madhavan and Smidt find strong information effect in β_1 but no inventory effect: $\beta_2 = \beta_3 = 0$. Lyons (1995) expands the model by separating Q_t into trades involving his dealer and trades between other dealers conducted through voice brokers, and reports strong information and inventory effects. However, using Lyons' data, Romeu (2001) reports that both effects disappear after allowing for structural breaks during the sample period. Bjønnes and Rime (2001) separate Q_t into interbank and customer trades. They find greater price impact from customer trades but no inventory effect.

This study aims to identify differential price impact from different customers. Therefore we decompose customer trades into trades with central banks CB_t, non-bank financial institutions FIN_t, and non-financial corporations $CORP_t$. Interbank trades include incoming and outgoing trades. We exclude outgoing trades since their prices are set by other dealers. Incoming trades are separated into direct (DIR_t) and indirect (IND_t) trades, with two trade indicator variables, $D_{DIR,t}$ and $D_{IND,t}$. Therefore we specify $Q_t = \{CB_t, FIN_t, CORP_t, DIR_t, IND_t\}$, and $D_t = \{D_{DIR,t}, D_{IND,t}\}$. As discussed before, we are unable to construct a reliable measure of spot inventory; therefore we do not include inventory variables in our analysis. Given the lack of inventory effects found in both equity and FX studies, this is unlikely to bias our results. The lack of inventory effect is consistent with dealers' preference towards trading away his inventory, instead of shading his own quotes.[11] The growth of liquid electronic broker markets has further subordinated the need to shade quotes as a means of inventory control. Dealers can quickly and efficiently hit limit orders posted in the electronic broking systems in order to adjust inventory toward a desired level. The price adjustment process for our dealer is given by

$$\text{(1)} \qquad \Delta P_t = \beta_0 + \beta_{CB}CB_t + \beta_{FIN}FIN_t + \beta_{CORP}CORP_{,t} + \beta_{DIR}DIR_t + \beta_{IND}IND_t \\ + \lambda_{DIR}D_{DIR,t} + \delta_{DIR}D_{DIR,t-1} + \lambda_{IND}D_{IND,t} + \delta_{IND}D_{IND,t-1} + \varepsilon_t$$

The structural model of Madhavan and Smidt (1991) dictates that $\{\beta_{CB}, \beta_{FIN}, \beta_{CORP}, \beta_{DIR}, \beta_{IND}, \lambda_{DIR}, \lambda_{IND}\} > 0$, $\{\delta_{DIR}, \delta_{IND}\} < 0$, $\lambda_{DIR} > |\delta_{DIR}|$, and $\lambda_{IND} > |\delta_{IND}|$. The absolute values of the coefficients for the lagged trade indictors, $|\delta_{DIR}|$ and $|\delta_{IND}|$, are the estimated half-spread for direct and indirect trading. In addition, the discussion in section II predicts that central banks have the greatest price impact, followed by financial institutions and non-financial corporations: $\beta_{CB} > \beta_{FIN} > \beta_{CORP}$. Direct trading has greater price impact, $\beta_{DIR} > \beta_{IND}$, and larger spread, $|\delta_{DIR}| > |\delta_{IND}|$.

The error term ε_t represents innovations in dealer pricing not captured by order flows. In particular it may reflect information such as quote revisions by voice or electronic brokers, or brokered trades between other dealers. As such it is related to the market-wide order flow and trade intensity, which are serially correlated and have well known intra-day patterns [e.g. Bollerslev and Domowitz (1993), Lyons (1996)]. We propose to link the variance of the error term ε_t with the market-wide volatility $\sigma_{m,t}$:

(2) $$\varepsilon_t^2 = \alpha_0 + \alpha_1\sigma_{m,t} + \alpha_2\sigma_{m,t-1} + \eta_t.$$

Baysian learning suggests that for a dealer with substantial customer order flows, therefore significant private information, his price expectation will be based more on his private order flows, less on public information such as market-wide price changes. On the other hand, a dealer with no customer order flow will form expectation based entirely on market price movements. In our case, we would expect that AUD order flows have greater explanatory power on price changes, i.e. $R^2_{AUD} > R^2_{EUR}$, and EUR price changes have greater correlation with the market: $\alpha_{1,EUR} > \alpha_{1,AUD}$.

The market-wide volatility $\sigma_{m,t}$ is measured by the mean absolute change in the Reuters mid-quote between incoming interbank trades. Specifically,

(3) $$\sigma_{m,t} = \frac{1}{n_t}\sum_{k=1}^{n_t}\left|mq_k - mq_{k-1}\right|$$

where mq_k is the Reuters' mid-quote at time k, k is any minute occurring between trades t-1 and t and n_t is the duration in minutes occurring between trade t-1 and t. Müller et al (1997) note that mean absolute price change is not statistically dominated by extreme observations, a particular concern for FX returns with fat-tailed unconditional distributions.

In order to estimate the model outlined above, a time series of incoming interbank trades is constructed from the data sets of all trades over the 45-day period, for both AUD and

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[11] Indeed, the dealer in Lyons (1995) recognises the impact of quote 'shading'. He notes, "When I shade my price it gives the caller a sense of my position" [Lyons (1995, p.344)].

EUR. First, outgoing trades are removed from the samples, leaving series consisting of 6,349 and 1,411 incoming trades (both customer and interbank trades) for AUD and EUR respectively. Each incoming interbank trade is indexed with a time t. All customer trades occurring between interbank trades at time t-1 and t are aggregated and incorporated into the tth observation according to their counterparty type. Finally, the first observation of each day is deleted to remove overnight price changes. The median time between incoming interbank transactions is 3 minutes in the AUD sample, compared to 6 minutes in the EUR sample.

The model is estimated with the Generalised Method of Moments (GMM). GMM has a number of well-known advantages that make it attractive. It makes no distributional assumptions regarding the error term. GMM estimators and their standard errors are consistent, even when the error terms in the moment equations are subject to heteroscedasticity and serial correlation. GMM is flexible in the choice of instruments and moment restrictions, which is particularly useful for this model. The variance function can be easily incorporated into the estimation by imposing a restriction on the second moment. In addition, central bank trades may be endogenous to exchange rate movements[12]. Kearns and Rigobon (2002) note that failing to account for this endogeneity will result in a downward bias to the impact of central bank intervention. To correct for this problem, we need to control for pre-existing market conditions prior to central bank intervention. We use an instrument given by the product of central bank order flow at time t, and market-wide volatility at time t-1, $CB_t \times \sigma_{m,t-1}$. This instrument plus the remaining regressors comprise the set of instruments, resulting in a system that is exactly identified.

V. ESTIMATION RESULTS

We first present the estimation results for the baseline model of equations (1) and (2). The price impact of customer and interbank trades are discussed. Comparisons are made between AUD and EUR. The analysis is then extended to lagged effects and the impact of large and small customers. As the focus of this study is the information contained in customer order flow, the extended analysis is restricted to AUD, where the bank has substantial customer order flows.

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[12] Central banks' decisions to intervene are the results of exchange rate movements. The timing of intervention trades also depends on intraday volume and volatility [see Dominquez (2003)].

A. Baseline Results

Table 4 presents the parameter estimates for the baseline model of equations (1) and (2) for both AUD and EUR. Table 5 reports Wald tests of the predicted relationships among coefficients. In the case of AUD, central bank trades have the greatest impact on the exchange rate. The coefficient indicates an increase in the AUD exchange rate of 3.2 basis points for a purchase of AUD 10 million. This is similar to that estimated by Kearns and Rigobon (2002), which is equivalent to 4.1 to 5.5 basis points for a purchase of AUD 10 million, assuming an AUD rate of 0.5500. Note that Kearns and Rigobon results reflect the change in price over the days following intervention (although most of the impact occurs during the day of the intervention), whereas this model considers the price impact in the minutes directly following the intervention trade.

The central bank coefficient for EUR is not significant. This can be explained upon closer inspection of the underlying trades. For AUD there are thirteen central bank transactions, eleven of which are from the Reserve Bank of Australia. Nine out of the eleven trades are sales of AUD into a rising market, with an average sell value of USD 5.25 million, approximately five times the average trade size of the entire sample. These trades are highly indicative of intervention by the RBA. For EUR, the twelve central bank trades are all classified as "Overseas Central Bank – non OECD", which indicates that these transactions are not from either the European Central Bank or the U.S. Federal Reserve. In addition, the average size of Central Bank trades in the EUR is USD 2.95 million with no significant order flow imbalance. Therefore, the finding of an insignificant Central Bank coefficient does not contradict the prediction of central bank order flow being the most informative.

The price impact of trades by non-bank financial institutions is correctly signed and significant for both AUD and EUR. The dealer adjust his prices in the direction of the order flow (that is, upwards for a buy and downwards for a sell) after trading with a non-bank financial institutions. Non-financial corporations have the smallest price impact relative to other participants, and only in the case of EUR is the impact significant. Lyons (2001, chapter 9) find that non-financial corporations have a negative price impact, whereas leveraged and unleveraged financial institutions, categories subsumed by the non-bank financial institutions used in this study, both have significantly positive price impacts at monthly frequencies.

The direct interbank coefficients are positive and significant. The dealer widens his spread to interbank counterparties as the quantity requested increases. The coefficients for the indirect interbank trades are insignificant, which is consistent with the nature of indirect trading. Remember that in the case of incoming direct trading, the dealer is obliged to quote a competitive two-way price to the requesting counterparty. With indirect trading, however, the dealer has to first submit a limit order to brokers. Therefore, in some ways, incoming indirect trades are closer in nature to outgoing trades, than incoming direct trades[13].

All of the trade indicator variables are significant and have the correct sign. The inequalities posited by the model also hold. The estimated base spreads in the AUD market are approximately 3.1 basis points (1.55 x 2) in direct trading and 1.6 basis points in indirect trading. In the EUR the estimated base spreads are approximately 2.5 basis points and 2 basis points for the direct and indirect trading respectively. These spreads are quite plausible relative to spreads observed in the interbank market. The base spread in the direct trading is larger. The dealer is likely to face adverse selection problem in direct trading. He must also be compensated for standing ready to quote two-way prices, whereas the spread in the indirect trading reflects the difference between limit orders of the most optimistic buyer(s) and the most pessimistic seller(s).[14] Reiss and Werner (1999) also find larger spreads in direct trading on the LSE.

Finally, the explanatory power of this dealer pricing model is a function of the dealer's access to customer order flow. For the AUD dealer, customer order flow comprises 35.1 percent of trades and 10.6 percent of volume, compared to the EUR dealer's composition of 5.8 percent and 4.6 percent respectively. The R^2 of the model in the case of AUD is 0.24 compared to 0.10 for EUR. In the variance equation, α_1 is significant across both currency pairs, with a larger coefficient for EUR.

B. Price Impact over Time

The decentralized and low-transparency structure of the FX market means that private information contained in customer order flow may be valuable to the dealer beyond a single trade. To examine the lagged effects of order flow, a number of lagged order flow variables

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[13] The coefficient for the indirect interbank trades can be negative depending on the dealer's strategy. If the dealer wants to buy AUD, he can submit limit orders to brokers and waits to be hit by other dealers' market orders. As market demand is exhausted at each level where he has left a limit order, he incrementally increases his bid price to continue buying AUD. In this case the order flow variable would be negative, since other dealers are selling to him, and he is buying AUD, even though the change in price between trades is positive, resulting in a negative coefficient for the indirect interbank order flow variable.

are introduced into the model. Base on Aikaike information criteria, the final model uses two lags of central bank order flow, two lags of non-bank financial institution order flow and one lag of non-financial corporation order flow. The analysis is based on AUD only, as customer trades account for only 5% of EUR trades. The results are presented in Table 6.

There are number of noteworthy points relating to central bank and non-bank financial institution order flow. Consistent with expectations, the informative order flow of central banks and non-bank financial institutions have price impacts beyond the current period. Indeed, in the case of receiving a buy order for AUD 10 million from a central bank (most likely the Reserve Bank of Australia in this sample), the dealer would increase his price by a total of 5.25 basis points over the three interdealer periods following a central bank trade. Similarly, the price impact of non-bank financial institutions is distributed over time, with the aggregate price update over the three interdealer periods following a transaction equivalent to 3.25 basis points for a trade of AUD 10 million. The findings of multi-period price impacts are corroborated by Yao (1998a), who finds evidence of lagged price response by conducting impulse response analysis of price and inventory variables after a shock resulting from a customer trade. Non-financial corporations have no contemporary or lagged price impact. The estimates of the remaining coefficients are in line with the baseline results for AUD, and consistent with the predictions of the model.

C. Heterogeneity within Counterparty Segments

As a final test of heterogenous impacts of different types of order flow, the non-bank financial institutions, non-financial corporations and direct interbank segments are separated into two groups, based on the volume transacted by counterparties within each group over the sample period. Counterparties with total traded USD volume at or above the 75th percentile for their segment are placed in a high volume subcategory, whereas the remaining counterparties within each segment are placed in their respective low volume subcategories.[15] The 75th percentile breakpoints are USD 5.1 million for non-bank financial institutions, USD 0.32 million for non-financial corporations, and USD 14 million for direct interbank trading.

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[14] Refer to Chung, Van Ness and Van Ness (2002) for further discussion of the difference in spreads between dealer markets and electronic limit order books.

[15] Bjønnes and Rime (2001) attempt a similar test by examining the price impacts of different groups of interbank counterparties. The interbank counterparties are segmented using the dealers' perceptions of how well informed each individual interbank counterparty is, relative to the bank in their study.

Indirect interbank trading is not segmented further since these trades are ex ante anonymous, and therefore, counterparty identity will not play a role in the dealer's pricing decision.

Table 7 presents the results from further segmenting counterparty types based on the volume transacted with the bank in this study over the sample period. The results clearly show that there are substantial differences in the price impact of order flow within individual counterparty segments. The price impact of non-bank financial institutions comes from the high-volume group, which are likely to be regular customers. Although non-financial corporations as a group do not have price impact, dealers do react to trading by the top 25% of the group. The contrast between the high and low groups of the interbank segment is even more striking. Our dealer moves his prices with trades by his regular/major interbank counterparties, but against trades by those who trade less frequently with him. The relative impact across different customers remains the same. The results reflect the role played by distributors in understanding their major clients, those in the high volume group. Customer order flow consists of both information and liquidity components. Distributors, with knowledge of their major clients' business operation and trading motivation, are able to extract more precise private signals from customer trades, which in turn help interbank dealers updating their expectation of price. As a result, the trades of high volume customers have the greatest impact on price.

VI. CONCLUSION

By extending existing FX microstructure models to account for different types of order flow this study is able to identify heterogeneous price impacts across different counterparty types, consistent with the hypothesis that not all trades are equally informative. Further, it is found that price impacts of what is considered informative order flow (central bank and non-bank financial institutions) are distributed across time. This finding reflects dealers not adjusting their quotes instantaneously after receiving informative customer flow, but rather taking advantage of the private information by trading at other dealers' prices, and thus impounding their information into interbank market rates. Finally, the model identifies heterogeneously informed counterparties within each group, with the larger players dominating the price discovery process. This finding is also consistent with the greater precision of signals contained in this type order flow due to a greater understanding of these customers motives for trading and their institutional constraints.

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Table 1: Sample Selection Process

This table reports the number of observations remained after filtering. "Settlement Date" is the results of removing trades settled after the spot dates. "Trade Size" shows the results of removing trades < USD10,000. "Market Midpoint" is the result of matching with Reuters midquotes.

		Filter		
Currency Pair	**Raw Data**	**Settlement Date**	**Trade Size**	**Market Midpoint**
AUD	24,733	15,175	10,408	9,131
EUR	5,013	3,731	3,329	2,280

Table 2: Trading Activity by Counterparty Type

This table provides an overview of the bank's trading activity over the 45-day period. Trade and Volume data have been disaggregated into four counterparty types, namely, interbank, non-bank financial institution*s*, non-financial corporation and central bank*s*. The sample period covered 1st May 2002 to 3rd July 2002. All volume and size figures are in million USD.

Counterparty Type	Interbank	Non-bank Financial Institutions	Non-financial Corporations	Central Banks	Total
Panel A: AUD / USD					
#Trades	5925	203	2990	13	9131
%Total	64.9%	2.2%	32.7%	0.1%	100.0%
Total Volume	8,557	221	740	55	9,572
% Total Volume	89.4%	2.3%	7.7%	0.6%	100.0%
Mean Trade Size	1.44	1.09	0.25	4.25	1.05
Median Trade Size	1.08	0.57	0.045	2.3	0.56
25% Size	0.56	0.1	0.02	1.61	0.1
75% Size	1.67	1.14	0.11	7.0	1.13
Panel B: EUR / USD					
#Trades	2148	11	109	12	2280
%Total	94.2%	0.5%	4.8%	0.5%	100.0%
Total Volume	3,133	7.49	109	35	3,285
% Total Volume	95.4%	0.2%	3.3%	1.1%	100.0%
Mean Trade Size	1.46	0.68	1.00	2.95	1.44
Median Trade Size	0.97	0.90	0.94	2.90	0.97
25% Size	0.92	0.23	0.90	1.82	0.92
75% Size	1.88	1.04	0.98	4.26	1.88

Table 3: Interbank Trading Channels and Incoming and Outgoing Trades

This table presents the results of assigning interbank trades as *Incoming* and *Outgoing* according to the modified tick-test. In addition it provides a summary of direct and indirect interbank trading channels and their components. Consistent with overall market trends, the bank's interbank trading is dominated by the use of electronic brokers. All volume and size figures are in million USD.

	Incoming					Outgoing				
	Direct		Indirect			Direct		Indirect		
	Reuters 3000 Direct	Phone	Electronic Broker	Voice Broker	ALL	Reuters 3000 Direct	Phone	Electronic Broker	Voice Broker	ALL
Panel A: AUD / USD										
# Trades	584	126	2078	327	3115	318	82	2149	263	2812
% Total	18.7%	4.0%	66.7%	10.5%	100%	11.3%	2.9%	76.4%	9.4%	100%
Volume	970	196	2,449	813	4,427	722	95	2,611	701	4,129
% Total	21.9%	4.4%	55.3%	18.4%	100%	17.5%	2.3%	63.2%	17.0%	100%
Average Size	1.66	1.55	1.18	2.48	1.42	2.27	1.16	1.22	2.67	1.47
Median Size	0.55	0.88	1.07	2.29	1.08	1.08	0.57	0.58	2.68	1.08
Panel B: EUR / USD										
# Trades	148	70	1013	47	1278	127	42	648	53	870
% Total	11.6%	5.5%	79.3%	3.7%	100%	14.6%	4.8%	74.5%	6.1%	100%
Volume	116	99	1,490	173	1,878	148	50	915	142	1,255
% Total	6.2%	5.3%	79.4%	9.2%	100%	11.8%	4.0%	72.9%	11.3%	100%
Average Size	0.78	1.42	1.47	3.67	1.47	1.17	1.18	1.41	2.68	1.44
Median Size	0.50	0.99	0.97	2.26	0.97	0.49	0.95	0.97	1.92	0.97

Table 4: Price Impact of Heterogeneous Trader Types

This table presents the GMM estimation of the following dealer pricing model:

$$\Delta P_t = \beta_0 + \beta_{CB}CB_t + \beta_{FIN}FIN_t + \beta_{CORP}CORP_{,t} + \beta_{DIR}DIR_t + \beta_{IND}IND_t + \lambda_{DIR}D_{DIR,t} + \delta_{DIR}D_{DIR,t-1} + \lambda_{IND}D_{IND,t} + \delta_{IND}D_{IND,t-1} + \varepsilon_t$$

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\sigma_{m,t} + \alpha_2\sigma_{m,t-1} + \eta_t.$$

The dependent variable ΔP_t is the change in price between time *t-1* and time *t,* and is in units of one basis point. The order flow variables are in AUD 1 million and EUR 1 million respectively. T-statistics in parentheses are calculated with robust standard errors. The asterisks *,** and *** represent significance at the 10%, 5% and 1% level respectively.

Variable	Model Coefficient	Expected Sign	Currency: AUD / USD	Currency: EUR / USD
Constant	β_0	(?)	-0.0085 (-0.054)	0.556 (1.37)
Central Bank Impact	β_{CB}	(+)	0.3214 (5.089)***	-0.629 (-0.802)
Non-bank Financial Institution Impact	β_{FIN}	(+)	0.1531 (2.504)**	4.199 (4.431)***
Non-financial Corporation Impact	β_{CORP}	(+)	0.0059 (0.148)	0.815 (1.917)*
Direct Incoming Interdealer Impact	β_{DIR}	(+)	0.0810 (2.648)***	0.643 (1.706)*
Indirect Incoming Interdealer Impact	β_{IND}	(+)	-0.0365 (-1.524)	0.139 (0.892)
Direct Trade Indicator Dummy	λ_{DIR}	(+)	1.9714 (12.066)***	1.519 (2.053)**
Direct Lag Trade Indicator Dummy	δ_{DIR}	(-)	-1.5545 (-10.034)***	-1.253 (-2.409)**
Indirect Trade Indicator Dummy	λ_{IND}	(+)	1.6503 (15.763)***	1.722 (4.804)***
Indirect Lag Trade Indicator Dummy	δ_{IND}	(-)	-0.7839 (-10.574)***	-1.027 (-4.849)***
Constant Variance	α_0	(+)	0.1074 (0.414)	0.038 (1.312)
Market Volatility	α_1	(+)	0.6007 (9.928)***	1.150 (7.409)***
Lagged Market Volatility	α_2	(+)	0.1748 (4.203)***	0.022 (0.258)
Adjusted R^2			0.24	0.10
Durbin-Watson			2.08	2.08
Observations			3,069	1,232

Table 5: Wald Tests of Differences in Model Coefficients

This table presents the hypothesis test results for the baseline model. (1) tests for total order flow having no impact on price. (2) tests customer order flow having no impact on price. (3) tests for *Non-bank financial Institutions* and *Non-financial corporation* having the same impact on price. (4) tests for *Non-bank financial Institutions* and central bank*s* having the same impact on price. (5) tests for the same price impact across interbank trading channels, while (6) to (8) test relative spreads. P-values are in parentheses. # Indicates that the inequality is in the direction predicted by the model.

Test	Null	Alternate	Currency	
			AUD/USD	EUR/USD
(1)	$\beta_{DIR}=\beta_{IND}=\beta_{CENT}=\beta_{FIN}=\beta_{CORP}=0$		43.01 (0.000)	25.97 (0.000)
(2)	$\beta_{CENT}=\beta_{FIN}=\beta_{CORP}=0$		32.49 (0.000)	23.33 (0.000)
(3)	$\beta_{FIN}=\beta_{CORP}$	$\beta_{FIN}>\beta_{CORP}$	4.07 (0.044)#	10.99 (0.001)#
(4)	$\beta_{CENT}=\beta_{FIN}$	$\beta_{CENT}>\beta_{FIN}$	3.66 (0.056)#	15.61 (0.000)
(5)	$\beta_{DIR}=\beta_{IND}$	$\beta_{DIR}>\beta_{IND}$	9.15 (0.002)#	1.47 (0.225)#
(6)	$\lvert\delta_{DIR}\rvert = \lvert\delta_{IND}\rvert$	$\lvert\delta_{DIR}\rvert > \lvert\delta_{IND}\rvert$	19.65 (0.000)#	0.15 (0.694)#
(7)	$\lambda_{DIR} = \lvert\delta_{DIR}\rvert$	$\lambda_{DIR} > \lvert\delta_{DIR}\rvert$	3.70 (0.054)#	0.09 (0.765)#
(8)	$\lambda_{IND} = \lvert\delta_{IND}\rvert$	$\lambda_{IND} > \lvert\delta_{IND}\rvert$	85.82 (0.000)#	4.87 (0.027)#

Table 6: Lagged Impacts of Order Flow

This table presents the results for the lagged impact of order flow. Two lags are included for central bank*s* and non-bank financial institution*s*, while one lag is included for non-financial corporation*s*. The remainder of the coefficients are identical to the baseline model. T-statistics in parentheses are calculated with robust standard errors. The asterisks *,** and *** represent significance at the 10%, 5% and 1% level respectively.

	AUD / USD		
Variable	**Model Coefficient**	**Estimate**	**T-value**
Constant	β_0	0.025	(0.51)
Central Bank Contemporary	β_{CB}	0.258	(3.68)***
Central Bank Lag 1	β_{CB_LAG1}	0.241	(9.874)***
Central Bank Lag 2	β_{CB_LAG2}	0.026	(1.444)
Non-bank Financial Institution Contemporary	β_{FIN}	0.136	(2.439)**
Non-bank Financial Institution Lag 1	β_{FIN_LAG1}	0.185	(2.945)***
Non-bank Financial Institution Lag 2	β_{FIN_LAG2}	0.004	(0.095)
Non-financial Corporation Contemp.	β_{CORP}	0.004	(0.122)
Non-financial Corporation Lag 1	β_{CORP_LAG1}	0.007	(0.417)
Direct Incoming Interdealer	β_{DIR}	0.078	(2.332)**
Indirect Incoming Interdealer	β_{IND}	-0.034	(-1.413)
Direct Trade Indicator Dummy	λ_{DIR}	1.961	(12.22)***
Direct Lag Trade Indicator Dummy	δ_{DIR}	-1.574	(-9.987)***
Indirect Trade Indicator Dummy	λ_{IND}	1.640	(16.006)***
Indirect Lag Trade Indicator Dummy	δ_{IND}	-0.773	(-10.407)***
Constant Variance	α_0	4.770	(6.748)***
Volatility of Reuters' Midpoint	α_1	0.565	(6.14)***
Lagged Volatility of Reuters' Midpoint	α_2	0.042	(1.155)
Adjusted R^2		0.24	
Durbin Watson stat		2.08	
Observations		2,979	

Table 7: Volume Segmented Counterparties

This table presents the results of further segmenting customers according to the volume they transacted with the bank over the sample period. NBFI - non-bank financial institution*s*, NFC – non-financial corporation*s,* and direct interbank are segmented into *High* and *Low* volume categories. The remaining variables are the same as those in the previous models. T-statistics in parentheses are calculated with robust standard errors. The asterisks *,** and *** represent significance at the 10%, 5% and 1% level respectively.

	AUD / USD		
Variable	**Model Coefficient**	**Estimate**	**T-value**
Constant	β_0	0.023	(0.483)
Central Bank Impact	β_{CB}	0.245	(3.007)***
High Volume NBFI	β_{FIN_HIGH}	0.140	(2.278)**
Low Volume NBFI	β_{FIN_LOW}	0.125	(0.713)
High Volume NFC	β_{CORP_HIGH}	0.066	(2.71)***
Low Volume NFC	β_{CORP_LOW}	0.980	(0.309)
High Volume Direct Interbank	β_{DIR_HIGH}	0.081	(2.403)**
Low Volume Direct Interbank	β_{DIR_LOW}	-0.110	(-2.065)**
Indirect Interbank	β_{IND}	-0.025	(-1.065)
Direct Trade Indicator	λ_{DIR}	2.049	(12.778)***
Direct Lag Trade Indicator	δ_{DIR}	-1.566	(-9.996)***
Indirect Trade Indicator	λ_{IND}	1.633	(16.152)***
Indirect Lag Trade Indicator	δ_{IND}	-0.807	(-10.972)***
Constant Variance	α_0	4.595	(6.867)***
Volatility of Reuters' Midpoint	α_1	0.584	(6.334)***
Lagged Volatility of Reuters' Midpoint	α_2	0.065	(1.635)
Adjusted R^2		0.25	
Durbin-Watson stat		2.08	
Observations		3,069	

Figure 1: Interbank Transaction Rates
May 1 to July 3, 2002

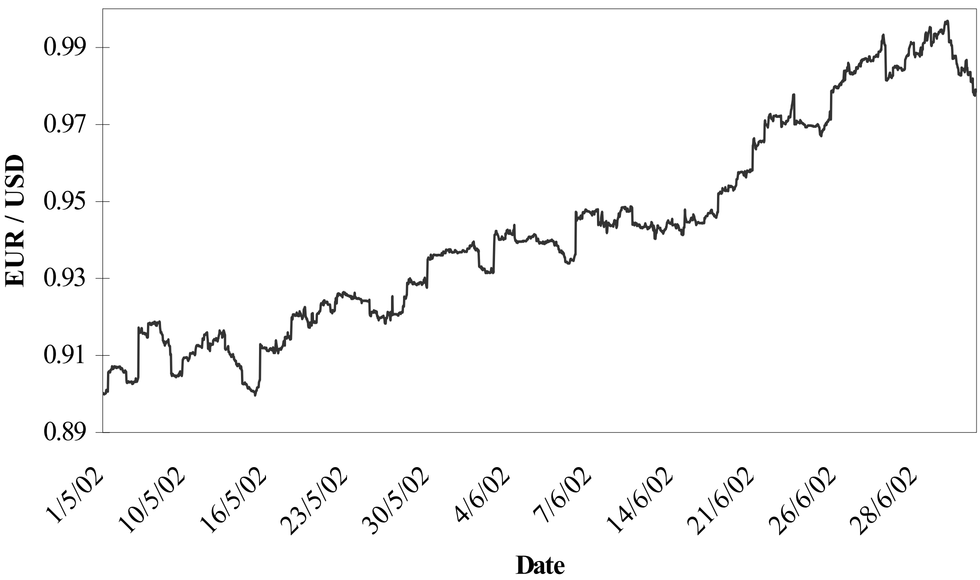
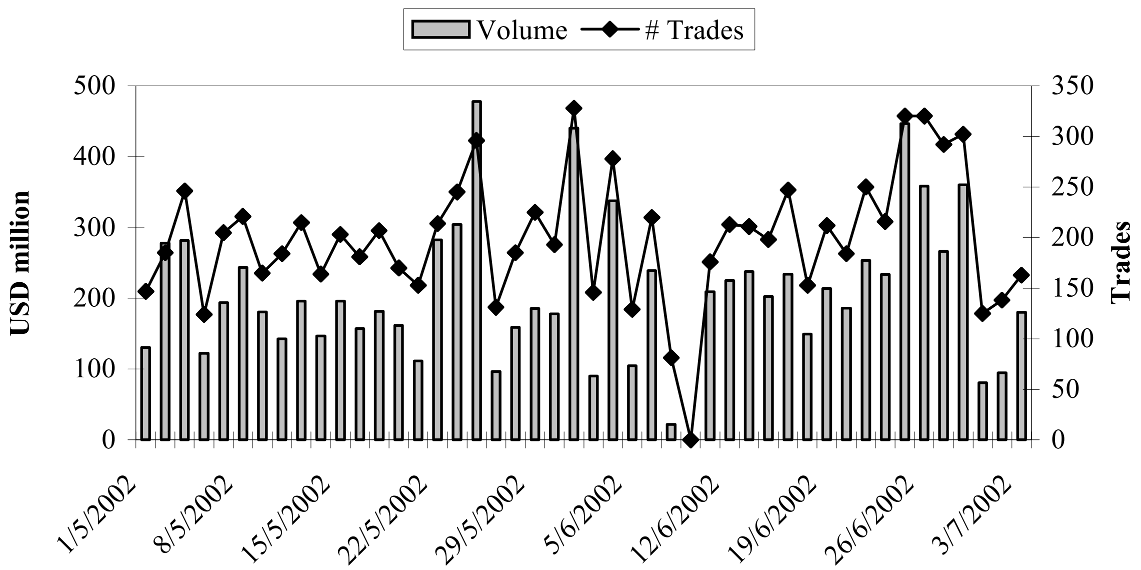


Figure 2: Daily Volume and Number of Trades

May 1 to July 3, 2002

A. AUD/USD



B. EUR/USD