Market Making in the

Interbank Foreign Exchange Market

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Abstract

This paper studies the market making behavior of FX dealers in the interbank market which is characterized by high trade volume and decentralized market structure. The dataset for my empirical estimation is based on the complete trade records of a FX dealer at a major commercial bank over 25 trading days. The dealer is among the five largest DM/$ dealers in the world, and the composition of his trades (customer trades, inter-dealer trades, etc.) is representative of the industry.

I find evidence that incoming trades have information effects. However, I do not find evidence of price-shading as a tool for inventory control in inter-dealer trades. This is consistent with the view that quote shading signals a dealer's position, and further reveals information from his proprietary order flows. A representative FX dealer instead lays off most undesired inventories through outgoing trades against other dealers' quotes. Price impacts of such outgoing trades are minimized because the depth and low transparency of this market, together with the electronic dealing systems, allow a dealer to search effectively for the best prices. A dynamic analysis indicates that large trades have significant lagged price impacts, and that FX dealer often strategically delays quote revision to take advantage of low market transparency while working off inventory shocks. My study also suggests that dealers with diverse market positions might prefer different trading strategies. For example, an uninformed dealer with little customer business is likely to shade quotes for inventory control.

1. Introduction

Foreign exchange (FX) markets are characterized by short-term price fluctuations which researchers in international finance have long agreed can not be explained by long-term economic fundamentals. However, little research has been done to study the question of how trading mechanisms in FX markets affect the price formation process at the market microstructure level. The interbank FX market is of great interest in particular because it is the world's most active financial market and because it is where most FX trading takes place[1]. Moreover, the interbank market is unique because of its largely unregulated and decentralized dealership market structure.

This paper studies the market making behavior of FX dealers who are subject to adverse selection arising from private information, and who have to manage inventory shocks from order flows. A unique dataset of complete trade records of one of the most active \$/DM dealers in the interbank market allows me to address several market microstructure hypotheses. Because the interbank FX market is basically unregulated and free from market friction such as high liquidity costs, this paper focuses on the dealer's inventory management behavior in the presence of traders with heterogeneous information. Since I have all the information on each trade of this dealer, I can examine the dealer's market making behavior testing whether he takes advantage of the low order transparency in the FX market. In particular, I study the transient versus persistent price impacts from order flows, as well as the dealer's joint management of inventory shocks and information impacts. Using data on trade counterparty identity, I examine different types of

[1] According to Bank of International Settlements 1996 survey, global foreign exchange turnover reached a daily average of \$1.2 trillion in April 1995, an increase of 45% from 1992. The US market alone had a daily turnover of \$244 billion in April 1995. To put this number in perspective, Frankel and Froot (1990) estimate that the annualized FX turnover in US market alone in *1989* equals about twice world GDP. On the other hand, trade volume on FX futures market is only a small percentage of that on the spot market. For example, Lyons (1995) estimates that in

trades (such as customer versus inter-dealer trades) and provide insights into the dealer's strategic behavior under different circumstances as the dealer attempts to optimize inventory control and protection against adverse selection.[2]

The most comparable study of FX dealer behavior in the literature is Lyons (1995), which represents the first attempt to use proprietary dealer inventory and trade data. However, Lyons' results are limited by certain aspects of his dataset. The most significant limitation is that there is no customer trade data in his 5-day sample. Customer trades are important because they are the major source of private information in the FX market. As a result, his study focuses primarily on incoming inter-dealer trades, and fails to address a broader range of issues such as the possibility of different strategies for customer and inter-dealer trades. In contrast, the dataset in this study comprises the complete trading records of a major market maker at one of the five largest $/DM dealing banks. The dealer has substantial customer flows over the entire 25-day sample period. Most importantly, the composition of his trades (customer trades, direct and brokered inter-dealer trades, etc.) is representative of the industry as depicted in market-wide surveys by the Bank of International Settlements (1993, 1996). Because of the dealer's status as a major market maker and of the representative composition of his trades, his activities offer a reasonable proxy for market making activities in the FX market. The complete records of his dealing activities thus allow me to examine market microstructure issues with respect to some of the most unique and interesting aspects of this market.

1992 the average daily volume on all IMM $/DM contracts was less than $5 billion, one tenth of the daily spot volume in the U.S. during the same period.

[2] Yao (1997) further exploits the dataset to examine FX dealer trading profits from different sources and market making costs. One interesting finding is that although customer trades account for less than 14% of the dealer's total trade volume, they represent about 75% of his total profits over the 25-day sample period.

There are three major findings in this paper along with some other results. First, there is little evidence of quote-shading (raising quotes when the dealer is short relative to his desired position and lowering quotes when he is long) as a tool for inventory control in inter-dealer trades. This is consistent with the view that quote shading signals a dealer's position to other dealers, and further reveals information from his proprietary order flows. Because the concern of revealing information which the counterparty can capitalize on is mitigated in customer trades, data suggests that the dealer in my study shades prices quoted to customers. Second, I find that instead of shading quotes in hope of eliciting trades of a desired sign, the FX dealer lays off most inventory shocks through outgoing trades by hitting other dealers' quotes. The high liquidity, tight spreads[3] and low transparency of the FX interbank market, together with the electronic dealing systems, allow a dealer to search effectively for the best prices for his outgoing trades and hence minimize price impacts. Third, while incoming trades have information effects in general, large trades have particularly significant lagged price impacts. A dynamic analysis indicates that the FX dealer often strategically delays quote revision subsequent to incoming trades to take advantage of low market transparency while working off inventory shocks.

The paper is organized as follows: Section 2 briefly reviews the literature on market microstructure and its application to foreign exchange markets. Section 3 develops an integrated framework for studying the price impact from the dealer's incoming and outgoing trades. Section 4 describes the data and reports some descriptive statistics. Section 5 discusses the test

[3] For \$/DM, a bid-ask spread of 3 - 5 pips is typical for transactions less than \$20 million (the mean and median transaction size in my sample is \$8.4 million), where 1 pip, the smallest increment in quotes, equals one hundredth of a pfennig, or 0.0001 DM versus US dollar. This amounts to only about 0.02 - 0.04% of transaction price. Using daily closing quotes from Reuters, Bessembinder (1994) reports that mean spot FX spreads range from 0.049% for \$/DM to 0.079% for \$/SF. By comparison, Amihud and Mendelson (1986) report spreads for NYSE stock portfolios ranging from .5% to 3.2%, and Stoll (1989) reports that spreads for OTC stocks range from 1.2% for the largest decile to 6.9% for the smallest decile.

specifications and empirical methods, and presents the results of model estimation. Section 6 provides a dynamic VAR analysis of price, trade and inventory. Finally section 7 concludes.

2. Literature Overview

The literature on market microstructure is well developed as it pertains to the centralized market structure of NYSE specialists. There are two principal approaches to modeling market making behavior. First, inventory control models (e.g. Garman, 1976; Amihud and Mendelson, 1980; O'Hara and Oldfield, 1986; among others) consider the pricing problem faced by risk-averse dealers to keep their inventories within bounds. For specialists, the only tool is to adjust price, or shade quotes, to offset order flow fluctuations. Ho and Stoll (1983) extend the study of dealer pricing-setting to markets with multiple dealers. Second, asymmetric information models (e.g. Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988; among others) focus on adverse selection problems when there are traders with heterogeneous information. In these models, dealers set spreads to guard against informed traders, and update their own price expectations from trades. In reality, dealers are likely to confront both problems. However, since both models predict that buyer-initiated trades push up prices and seller-initiated trades push them down, disentangling the two effects presents a challenge to empirical studies. Hasbrouck (1988) suggests that the two effects can be separated through dynamic analyses. The inventory control component of price change is transient while the information component is permanent, reflecting the impounded new information. Madhavan and Smidt (1991, 1993) develop theoretical models that incorporate both effects and test them using inventory and trade data. The earlier (1991) paper analyzes intraday trades and finds that price changes reflect significant information effects but weak inventory control effects.

Extending the theoretical models of centralized specialist markets to FX market poses the challenge of modeling a decentralized, multiple-dealer environment with such additional features as low market transparency. Among the few attempts, Lyons (1996) provides a model of risk-averse FX dealers who prefer ex-ante low market transparency because it gives them time to manage inventories and reduce market-making risk inherent in price discovery . Although not related directly to the FX market, a multi-period, multiple-dealer model developed by Hansch, Naik and Viswanathan (1993) posits that relative inventory differences determine dealer behavior. Their model is supported by tests using London Stock Exchange (a dealership market) data and provides useful implications for FX market microstructure studies.

As for empirical work on FX market microstructure, efforts are hampered by the difficulty in obtaining detailed data. Dealers' inventory and trade data are proprietary information of their respective banks, and are not generally available to the public. Recently a body of research on FX market microstructure has emerged using Reuters indicative quotes. The research focuses mostly on dealer bid-ask spreads (e.g. Huang and Masulis,1995) and FX price volatilities (e.g. Anderson and Bollerslev,1996). Since indicative quotes from Reuters screens are not transaction prices and do not provide any measure of order flow, these studies fail to address FX dealer market making behavior directly. In a study of dealer inventories and spreads, Bessembinder (1994) finds that FX spreads increase with forecasts of price risk, with interest rates, and before weekends. Although these results are consistent with an inventory cost model, the study provides no insight on intraday inventory swings and quote adjustments because it uses only daily closing quotes.

Lyons (1995) is the first study that utilizes dealer intraday inventory and trade data in FX markets. His data supports both asymmetric information and inventory control models. However, generalization of his findings is subject to questions because of the following two aspects of his data. First, his dataset spans only 5 trading days (August 3-7, 1992), and it is not clear whether these days or the dealer are representative of the overall FX market. Second, during those 5 trading days, there are virtually no customer trades in the sample. Customer trades are important in the FX market because they represent the major source of asymmetric information, and because they often generate a significant portion of dealer profits.

This paper studies the market making behavior of a representative FX dealer who is a major player in the market and whose trade composition (customer flows, inter-dealer trades, etc.) is representative of the industry. The study uncovers unique dealer behavior arising from the interbank FX market's tremendous trade volume and liquidity, as well as its decentralized market structure.

3. The Model

I start with some institutional background of the interbank FX market, which is essential to the model below. Figure 1 outlines the two major types of transactions in this market, customer-dealer trades and inter-dealer trades, as well as the major channels through which these trades are conducted.

Figure 1 Here

Although customer trades account for only 10 - 15% of total trade volume in the inter-bank FX market, dealers emphasize the importance of customer trades because without them their view and understanding of the market will be limited. Moreover, customer trades generate the majority of trading profits for most FX dealers. In this market, each FX dealer has a different level of access to customers, who trade with dealers through banks' sales staff[4]. Because of lack of trade reporting requirement, a FX dealer has no direct information about other dealers' customer trades. Therefore, knowledge of customer order flow is a major source of asymmetric information in the interbank FX market.

In inter-dealer trades, a FX dealer lays off inventory shocks from customer trades. In the meantime, he also provides liquidity to other dealers. Inter-dealer trades are conducted through either brokers (both voice and electronic brokers) acting only as intermediaries, or inter-bank direct markets where all participating dealers are linked to each other by Reuters 2000-1 electronic dealing system. Such multiple trading channels equipped with fast electronic communication and dealing systems allow a FX dealer to request quotes and execute trades in a matter of seconds. Because of their immediacy and execution certainty, and because of the tight bid-ask spreads in this market, outgoing trades at other dealers' quotes (also called active trades throughout this study) become a viable alternative to the traditional "quote-shading" strategy for managing inventory.

The model, which is closest in spirit to Lyons (1995) and Madhavan and Smidt (1991), extends the existing frameworks by incorporating these important features of the interbank FX market. First, my model provides a framework to include the dealer's outgoing active trades and to study the order flow impact on active trade prices. Second, while Lyons (1995) studies only inter-dealer trades, incoming trades in my study includes both inter-dealer trades and customer-

[4] Members of a bank's FX sales staff are also called corporate traders. They are located worldwide and linked to the bank's dealers through phone and electronic dealing systems. A well-organized and capable FX sales staff is vital to the dealer (and the bank) because of the customer order flow it generates provides not only informational advantage but also steady trading profits for the dealer (see Yao (1997) for an analysis of FX dealer's profits). Note also that wholesale customers do not have access to FX brokers for trading, so that dealing banks are the only place where they can trade.

dealer trades. I will show that the presence of customer trades, which are the major source of asymmetric information in the interbank FX market, has significant impact on a FX dealer's trading strategies in *inter-dealer* trades.

Consider a multi-period economy with two assets: a riskless bond (the numeraire) and a risky asset representing FX. FX is traded in a decentralized dealership market with n dealers. In this study, I focus on a representative dealer i. His counterparty, denoted as trader j, can be a market maker at a competing bank or sometimes a corporate customer. FX is traded in either a passive trade or an active trade at times $t = 1,2,...,T$. A passive trade, such as a customer trade or a Reuters incoming trade, is an incoming trade effected at dealer i's quote. An active trade, such as a Reuters outgoing trade, is an outgoing trade initiated by dealer i against other dealers' quotes.

The full information price of FX at termination time T, denoted by m, is the summation of each period's innovation, $\tilde{m} = \sum_{t=0}^{T} \tilde{d}_t$, where $d_0 > 0$ is a known constant. Each increment d_t is realized after a trade in period t. Therefore, the FX value at time t is given by $m_t = \sum_{i=0}^{t} d_i$. Just before the trade at time t, m_t is a random variable. In a market without transaction costs and private information, the FX price at time t, denoted by P_t, is m_{t-1}, the expected value of FX given current information.

At the outset of each period t, all dealers observe a noisy public signal y_t concerning the full-information value at t:

$$\tilde{y}_t = m_t + \tilde{\varepsilon}_t \tag{1}$$

where $\tilde{\varepsilon}_t$ is an independently normally distributed error term with a mean of zero and variance of σ_ε^2. The dealer's prior distribution over the FX value m_t is thus normal with mean y_t, the realization of $\tilde{y}_t$, and variance σ_ε^2. There are several sources of information for the public signal y_t. The first is a public announcement, such as newswire story. Second is the brokered trades effected at either bid or ask prices broadcast through the FX broker boxes. The open box system consists of a microphone in front of a FX broker which transmits continuously everything he says down the direct phone lines to the speaker boxes in the banks. This way, dealers at all banks can hear the deals being executed through brokers as the only *indication* for market wide order flow.[5]

Also at the beginning of period *t* that coincides with the occurrence of an incoming passive trade, trader *j* receives a private signal W_{jt}. One major source of such a private signal is a customer deal, which is only known to trader *j*. Based on this private information, trader *j* updates his conditional expectation concerning the FX value. He requests quotes from dealer *i*, and decides a trade quantity Q_{jt} according to his demand schedule. Upon observing Q_{jt} which provides a signal of W_{jt} received by trader *j*, dealer *i* updates his expectation for period *t*. It is likely that in subsequent periods dealer *i* will conduct several active trades by hitting other dealers' quotes to lay off the inventory from trade Q_{jt} if the inventory is deemed undesirable. Figure 2 highlights the sequencing of the aforementioned events of the model.

<u>Figure 2 Here</u>

[5] However the broker box signal is noisy in several ways. First, brokered trades only account for a fraction of total turnover. Second, only brokered trades that clear at the bid or offer are broadcast. Lyons (1995) provides an estimate that 50-75% of all brokered trades clear at the bid or offer. Third, the trade amount is not announced, although a typical brokered trade averages $5 million. The last shortcoming is overcome by the emerging electronic brokered/matching system (such as EBS, MINEX, etc.) which displays the trade quantity. Despite all these shortcomings, brokered boxes and matching systems are the only source for indications of market wide order flows. For a story on recent growth of electronic brokered/matching system, see Blitz (1993).

In the model, a FX dealer's quotes are assumed to be ex post "regret free" in the sense of Glosten and Milgrom (1985). Therefore, a dealer takes into account the fact that his post-trade belief concerning the FX value depends on the order flow, and sets prices that he believes to be fair given the trade observed.

3.1 Price determination

In reality, prices deviate from expected FX values because of microstructure elements such as inventory effects and transaction costs. Such deviations from expectations are modeled here for passive and active trades separately. First consider passive trades which are effected at dealer *i*'s quotes. In the prototypical inventory control model, price is linearly related to a dealer's current inventory level as follows:

$$P_{it} = \mu_{it} - \gamma(I_{it} - I_i^*) + \psi D_t \qquad (2)$$

where μ_{it} is dealer *i*'s expectation of $\tilde{m}_t$ conditional upon his information at time *t*, I_{it} is dealer *i*'s current inventory, I_i^* is his desired long-run inventory level, and $\gamma > 0$ is the parameter that measures the inventory response effect. D_t is an indicator variable with value +1 for trader *j*'s purchase (buyer-initiated passive trade) and -1 for trader *j*'s sale (seller-initiated passive trade). The constant $\psi > 0$ is interpreted as fixed transaction cost, and ψD_t provides a measure for (half of) the baseline quote spread. Hence trader *j* always buys at dealer *i*'s offer and sells at dealer *i*'s bid in a passive trade.

Next consider active trades in which dealer *i* hits other dealers' quotes. Active trades resulting in inventory decumulation and accumulation are depicted differently, although in both types of trades dealer *i* will *pay* the spread. Decumulating trades can be written assuming a linear relation to inventory:

$$P_{it} = \mu_{it} - \gamma_D (I_{it} - I_i^*) - \psi_A D_t \tag{3}$$

Notice that eq. (3) is quite similar to (2). A key difference is the negative sign before the quote spread $\psi_A D_t$. D_t is defined in the same way as before, +1 for counterparty dealer *j*'s purchase (or a sell by dealer *i*, the aggressor) and -1 for dealer *j*'s sale (or a buy by dealer *i*, the aggressor). In any case, D_t always takes on value +1 for a counterparty buy and value -1 for a counterparty sell. In eq. (3) ψ_A reflects the fixed transaction cost of dealer *j*, or a representative of other dealers, and therefore may not be equal to ψ in (2) which measures the fixed cost of dealer *i*. Since $\psi_A >$ 0, (3) indicates that dealer *i* will buy at dealer *j*'s offer and sell at dealer *j*'s bid in an active trades, which is exactly the opposite of the situation in a passive trade. Also the inventory response coefficient γ_D might be in general different from γ in (2).

There are several situations in which a dealer may resort to accumulating active trades. He may be building up a speculating position. Or, his sales staff just informs him of a firm customer interest, and the dealer is simply building up a position in anticipation of the impending customer trade. In either case, the price for such a trade can be expressed as

$$P_{it} = \mu_{it} + \gamma_A' (I_{it}^* - I_{it}) - \psi_A D_t \tag{4}$$

Again, as in eq. (3) for decumulating active trades, dealer *i* will have to pay the spread. The difference comes in the inventory term. Notice the difference between I_{it}^* , the short-term position target which is a function of time *t*, and I_i^* in eq. (2) and (3), the long-term inventory level which is time-invariant and assumed close to zero for most FX dealers. I_{it}^* can be thought of as the quantity of an anticipated customer trade, or dealer *i*'s targeted speculating position size. I_{it}^* - I_{it} then measures the gap between the target I_{it}^* and the current inventory I_{it}. For example, if dealer *i* is long ($I_{it} > 0$) but wishes to get longer ($I_{it}^* > I_{it} > 0$), he will pay up and buy aggressively to reach his short-term target, given $\gamma_A' > 0$. The converse is true if he wants to get short. Since the linearity assumption of $\gamma_A'(I_{it}^* - I_{it})$ is somewhat stringent and since I_{it}^* is not observable in general, I introduce the following indicator variable in place of $I_{it}^* - I_{it}$: T_t = sign(I_{it}), since for an accumulative active trade sign($I_{it}^* - I_{it}$) = sign(I_{it}). Such a simplification allows for the rewriting of (4) as follows

$$P_{it} = \mu_{it} + \gamma_A T_t - \psi_A D_t \tag{5}$$

where γ_A is not equal to γ_A' in (4).

Introducing two indicator variables allows me to combine eq. (2), (3) and (5) as

$$\begin{aligned} P_{it} = {} & \mu_{it} - \gamma(I_{it} - I_i^*)\Theta_t - \gamma_D(I_{it} - I_i^*)(1-\Theta_t)\Omega_t \\ & + \gamma_A T_t(1-\Theta_t)(1-\Omega_t) + \psi D_t \Theta_t - \psi_A D_t(1-\Theta_t) \end{aligned} \tag{6}$$

where Θ_t equals 1 for passive trade and 0 for active trade, and Ω_t equals 1 for decumulating active trades and 0 for accumulating active trades. In eq. (6), the second, third and fourth terms combined describes the deviation from conditional expectation due to inventory considerations. The fifth and sixth terms together describes the deviation due to fixed transaction costs.

3.2 Revision of Expectations

Now I turn to the formulation of expectation revisions following order flows. In a passive trade, the signed trade quantity Q_{jt} provides a signal to dealer *i* about the private information received by his counterparty trader *j*, and dealer *i* will update his own expectation conditional upon observing Q_{jt}. However, in an active trade initiated by dealer *i*, dealer *i* would not gain any additional information from the trade concerning the FX value. Hence, passive and active trades have different impacts on dealer *i*'s expectation revision process.

First consider a passive trade, which is initiated by trader j who has time-t private information W_{jt}. The private signal takes the form of $\tilde{W}_{jt} = m_t + \tilde{\omega}_{jt}$, where $\tilde{\omega}_{jt}$ is independently and identically normally distributed with mean zero and variance σ_ω^2. Trader j's posterior mean then can be written as:

$$\mu_{jt} = \theta W_{jt} + (1-\theta) y_t \tag{7}$$

where $\theta = \sigma_\varepsilon^2 / (\sigma_\varepsilon^2 + \sigma_\omega^2)$.

Trader j's trade demand is determined by the deviation between his posterior expectation and price schedule quoted by dealer i, plus an idiosyncratic liquidity demand X_{jt} uncorrelated with m_t:

$$Q_{jt} = \alpha(\mu_{jt} - P_{it}) - X_{jt} \tag{8}$$

where α is a positive constant. Since X_{jt} is also only known to trader j, Q_{jt} will only provide a noisy signal concerning the FX value.

Following Glosten and Milgrom (1985), Dealer i sets prices that are ex post regret-free, i.e. his quote schedule incorporates expectations conditional on information at t, including the current trade Q_{jt}. Specifically, given a order size Q_{jt}, dealer i forms the following statistic:

$$\hat{V}(Q_{jt}) = \frac{P_{it} + Q_{jt} / \alpha - (1-\theta) y_t}{\theta} = m_t + \omega_{jt} - \frac{1}{\alpha\theta} X_{jt} \tag{9}$$

where eqs. (7) and (8) are used to derive the second equality. From (9), $\hat{V}(Q_{jt})$ is also normally distributed with mean m_t and variance $\sigma_{\hat{V}}^2$ which is equal to the variance of the last two terms, both of which are orthogonal to the prior mean, y_t. Hence, $\hat{V}(Q_{jt})$ is also orthogonal to y_t. Dealer i's posterior mean is then updated as follows:

$$\mu_{it} = \varsigma y_t + (1-\varsigma)\hat{V}(Q_{jt}) \tag{10}$$

where $\varsigma = \sigma^2_{\hat{V}} / (\sigma^2_{\varepsilon} + \sigma^2_{\hat{V}})$. Using the first equality in (9), μ_{it} can be written as:

$$\mu_{it} = \pi y_t + (1-\pi)(P_{it} + \alpha^{-1} Q_{jt}) \tag{11}$$

where $\pi = (\varsigma + \theta - 1)/\theta$. Substituting (11) into (2) and collecting terms yields:

$$P^P_{it} = y_t + \frac{1-\pi}{\alpha\pi} Q_{jt} - \frac{\gamma}{\pi}(I_{it} - I^*_i) + \frac{\psi}{\pi} D_t \tag{12}$$

In eq. (12), the superscript of $P_{it}{}^P$ indicates a passive trade at time *t*.

Next consider active trade in which dealer *i* trades at other dealers' quoted prices. Since in the model a private signal arrives only in an incoming trade (either dealer *i*'s own non-dealer flows or an incoming inter-dealer trade), an active trade initiated by dealer *i* does not provide a new signal to him, and his posterior mean remains the same as the prior mean, i.e. $\mu_{it} = y_t$. Then eq. (3) and (5) can be combined and re-written as

$$P^A_{it} = y_t - \gamma_D (I_{it} - I^*_i)\Omega_t + \gamma_A T_t (1-\Omega_t) - \psi_A D_t \tag{13}$$

where Ω_t equals 1 for decumulating active trades and 0 for accumulating active trades. The superscript of $P_{it}{}^A$ indicates a active trade at time *t*.

Since the prior mean y_t is not observable to the econometrician, it is assumed that the prior mean is equal to last period's posterior mean plus an expectational error term representing public information announcements between trades, i.e. $y_t = \mu_{it-1} + \eta_t$ in both eq. (12) and (13). Next, substituting in (6) for μ_{it-1} as a function of trade variables at time *t*-1 yields a price return equation between trades at *t-1* and *t*. Such a price return equation involves trade variables all available from the dataset, which I turn to next.

4. Data

The dataset employed in this study consists of complete trading records of a spot $/DM dealer[6] at a major New York City commercial bank over the 25 trading day period from November 1 to December 8, 1995. Each trading day of the dealer in my study starts informally at 12:30 Greenwich Mean Time (GMT) and ends at around 21:00 GMT (corresponding to 7:30 EST and 16:00 EST, respectively). My dealer is one of the most active $/DM market makers with substantial customer order flow. His average daily volume of $1.5 billion puts him among the top five $/DM dealers. More importantly, as I will show below, the composition of his trades is representative of the industry as depicted in market-wide surveys by BIS (1993, 1996).

The quality and scope of my dataset is similar to that in Lyons (1995). It includes transaction prices, quantities and dealer inventories over the whole sample period. Lyons (1995), who was the first to employ such a dataset, provides a summary of advantages of such a dataset over other FX data alternatives, mostly Reuters indicative quotes (see Goodhart and Gigliuoli, 1991; Bollerslev and Domowitz, 1993). The advantages are transaction prices, tighter spreads and realistic prices when trading intensity is high. Also dealer inventory data would allow a direct test of inventory models and the investigation of trading strategies.

Because of the rarity of such datasets, it is useful to highlight some of the differences between my dataset and Lyons'. Probably the most significant difference is the inclusion of customer trades in my dataset. Customer transactions are considered important because they represent the major source of asymmetric information and because they generate a significant

[6] My dealer makes market only in *spot* $/DM (transactions for delivery in two business days). Like most other banks, my dealer's bank has a separate dealer making markets in $/DM outright forwards and swaps. Unlike spot currency dealers, the major price exposure for forward dealers is not the direction of a currency pair, but rather the differential of the two interest rates involved. Outright forward and swap transactions account for 53.2% of the total volume of all FX transactions (including spot, futures and options) in April 1995 (BIS 1996).

portion of dealer profits. For the dealer in this study, customer trades account for 13.9% of total trade volume, and about 75% of total (gross) trading profits.[7] In contrast, Lyons (1995) reports no customer trades during his entire sample period. Also, my sample spans a much longer period of 25 trading trades, as opposed to Lyons' 5 trading days.

The raw data consists of two components: the dealer's trade blotters and copies of the dealer's conversations (including trades as well as non-dealt quotes) over the widely-used Reuters 2000-1 interbank direct dealing system.

4.1 Dealer's Trade Blotters

Trade blotters are hand-written records of all trades done by dealers. A dealer starts a blotter with his overnight open position (mostly close to flat in my sample), and enters his deals as the day goes along. With an average daily turnover of about 180 deals, my dealer has about 8 - 10 blotters per day. Each entry on the trade blotter includes the following information:

(1) The counterparty of each trade;

(2) Trade channel by which the trade is executed, e.g. Reuters 2000-1 dealing system ("direct"), voice broker, electronic broker, or bank's sales staff (by name);

(3) The quantity traded;

(4) The transaction price;

(5) Dealer's inventory immediately after the transaction.

Figure 3 provides an example of a typical trade blotter by my $/DM dealer.

[7] Total trading profits are reported on a daily basis by the bank's back office. For each customer trade, I compute the trade profits by identifying offsetting trades surrounding the customer trade. Denote the trade quantity and price pair for *i*th customer trade as ($Q_{i,c}$, $p_{i,c}$) and those for unwinding trades as ($Q_{i,j}$, $p_{i,j}$), j = 1, 2, ..., n, where n is the number of unwinding trades. Then the trade profit for the *i*th customer trade is computed as (see Yao (1997) for more details)

Figure 3 Here

While this component alone includes three key data series, i.e. transaction prices, trade quantities and dealer inventories, which are sufficient for some microstructure tests, there are two elements missing. First, the bid-offer quote at the time of each transaction is not recorded. Therefore, brokered trades and Reuters 2000-1 trades cannot be signed using blotters alone. Reuters direct trade will be signed (i.e. determining incoming or outgoing) with the aid of the second component. The sign of a brokered trade has to be estimated using either quote-based inference (e.g. Lee and Ready, 1991) or a tick test. The second drawback of trade blotters is that entries are generally not time-stamped. These two drawbacks are overcome at least for a subset of the dataset, i.e. Reuters direct trades.

4.2 Reuters 2000-1 direct quotes and trades

The Reuters 2000-1 dealing system is the most widely used electronic dealing system among FX dealers. This direct dealing system is based on trading reciprocity; what a dealer expects, and is expected to provide in turn, is a fast quote with a tight spread. The system provides more discretion as compared to the brokers market. Through a terminal, a dealer can request or handle four quotes with four different counterparties at the same time. Since $10 million relationships are common among major market participants, this set-up allows a dealer to lay off undesirable inventories very quickly. This contrasts with a median deal size of $5 million in the electronic or brokered market. Moreover, brokered trades, especially voice-brokered trades, often take place only sequentially. All Reuters conversations, including trade

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$$\Pi_{i,C} = \sum_{j=1}^{n} (Q_{i,j} p_{i,j}) + Q_{i,C} p_{i,C}$$

confirmations, are printed out on hardcopy, which is the source of the second component of my dataset.

For each Reuters direct trade, the following information is obtained from the hardcopy record:

(1) The time the conversation is initiated (to the minute);

(2) The counterparty;

(3) Which of the two dealers is seeking the quote;

(4) The quote quantity;

(5) The two-sided quote;

and if the quote results in a trade,

(6) The quantity traded;

(7) The transaction price.

Figure 4 provides an example of a Reuters dealing 2000-1 communication. Since a Reuters conversation is usually very short, transaction time to the minute is virtually the same as the time the conversation is initiated.[8]

Figure 4 Here

For Reuters incoming trade, the median trade size is $10 million for my dealer versus $3 million for Lyons' (1995) dealer (the median sizes for brokered trades are both around $4 million). I offer several reasons why my dealer has a larger Reuters trade size. First, although Reuters direct trades capture only inter-dealer trading, the larger trade size reflects the

[8] The exception occurs when the counterparty is requesting a transaction of large size (e.g. over $100 million). The communication will remain open while the dealer is working (to get an average price) to fill the order. This working process could take as long as 1-2 minutes, and therefore in this case the transaction time cannot be pinned down exactly. Also, in some trades of large size, the requesting dealer might identify himself as a buyer or seller (of US$), and hence only one-sided quote is given.

importance of my dealer who has significant customer order flow, whereas Lyons' dealer has no customer trade and merely provides liquidity in the inter-dealer markets.[9] Without access to customer order flow, a dealer's view and understanding of the market are severely limited. Because dealers emphasize customer order flow, the importance of Lyons' dealer in the inter-dealer market is also limited. Second, my dealer is affiliated with a commercial bank which is one of the largest and most influential FX dealing banks compared to Lyons' dealer's investment bank which is not traditionally known for its strength in FX trading. Finally, the three years between the two sample periods (1992 and 1995) saw a 45% increase in overall FX trading volume (BIS, 1996), which also contributed to the rise in inter-dealer trade size.

The following three data fields allow me to match Reuters direct trades in the two data components: counterparty, traded quantity and transaction price. They produce exact matches for all the Reuters direct trades in my sample. This in turn allows me (1) to determine whether a Reuters direct trade is incoming (passive) or outgoing (active) and (2) to time stamp at least some trades on the trade blotter. Since Reuters direct trades are the only trades that my dealer has time stamps on, I have to use interpolation to obtain an estimate of inter-transaction time for all trades. The estimated mean inter-transaction time for all trades is 2.1 minutes, with a standard deviation of 2 minutes. The estimated median inter-transaction time is 1.6 minutes.

Although Reuters direct trade records provide the most complete information for investigation, they account for less than 25% of total volume in our sample, compared with about 50% in Lyons (1995). The reasons seem to be two fold. First, my dealer has many non-dealer trades such as customer trades and internal deals. As pointed out by Hansch, Naik and

[9] The fact that my dealer has more non-dealer trades, such as customer trades and internal deals, suggests that his inter-dealer trade volume as a percentage of his total trade volume is smaller than Lyons's dealer. For example, my

Viswanathan (1995) in a study of dealership market of London Stock Exchange, dealers with large flows of non-dealer trades engage in less inter-dealer trading as a fraction of total trades. This is because such dealers expect a shorter waiting time before obtaining an offsetting non-dealer trade, and hence face much less risk of carrying inventory over time. The second reason has to do with the fast growth of electronic broker/matching systems which seizes considerable market share from both traditional voice brokers market and Reuters direct market.

4.3 Classify active versus passive trades

The model in this study requires the classification of whether a trade is active (in which my dealer initiates the trade) or passive (in which the counterparty initiates the trade), so as to determine the value for dummy variable Θ. Except for brokered trades, electronic and voice, all other trades can be classified as active or passive by examining their counterparties and/or the channels by which the trades are executed. Active trades include IMM trades and Reuters outgoing trades. Passive trades include customer trades, limit and stop loss orders, Reuters incoming trades and internal deals.

Now I turn to the signing of brokered trades. A brokered trade takes place when a dealer hits a posted quote or when his own posted quote with a broker is hit by other dealers. For example, if a dealer wishes to purchase US$ against DM and the posted quote is 1.4402 - 1.4407 DM/$, he can take the offer at 1.4407, join the bid at 1.4402 and face some waiting time and transaction uncertainty, or improve the bid anywhere between 1.4402 and 1.4407. Lyons (1995) estimated that about 50-75% of all brokered trades actually clear the posted bid or offer prices. Since the dealer trade blotters do not indicate explicitly the aggressor in a brokered trade, it has to

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dealer's Reuters direct trades account for only 25% of his total volume, compared with about 50% for Lyons' dealer.

be inferred from other information in the dataset whether the brokered trade is initiated by a buyer or a seller.

The traditional tick test compares the current price with the most recent price; trades with uptick or zero-uptick (downtick or zero-downtick) are assumed to be initiated by buyers (sellers). However, I use an alternative methodology (See Lee and Ready (1991), Madhavan and Smidt (1991)) that compares the trade price with the prevailing quotes. Since the prevailing broker quotes are not available at the dealer level and are difficult to compile from brokerage houses because of lagging time-stamps and numerous broker sources as reported by Lyons (1995), I have to use non-broker quotes as prevailing quotes. I compile the prevailing quotes from three sources: time-stamped *dealt* and *non-dealt* quotes from Reuters 2000-1 communication records, and constructed quotes based on internal deals. A brokered trade is then classified as a buy if the price is greater than or equal to the prevailing ask, or closer to the ask than the bid, and as a sell if the price is less than or equal to the prevailing bid, or closer to the bid than the ask. The appendix provides the details of signing the brokered trades.

After a brokered trade is determined as initiated by a buyer or seller, I determine whether it is passive or active as follows: if a brokered trade is signed as initiated by a buyer (seller) and if it is a buy (sell) by my dealer, it is classified as an active trade, and if it is a sell (buy) by my dealer, it is classified as a passive trade. A value of 1 is then assigned for Θ for all passive trades, including other non-brokered trades, and a value of 0 for Θ for all active trades. Next I determine whether an active trade is accumulating or decumulating. By definition, when the dealer is long (short), if the trade is a buy (sell) by my dealer, it is classified as an accumulating active trade; if the trade is a sell (buy), it is classified as a decumulating active trade. Then a value of 1 for Ω_t is

The less importance of Reuters direct trades is also a result of recent growth of electronic dealing system.

assigned for all decumulating active trades, and a value of 0 for Ω_t for accumulating active trades.

4.4 Descriptive Statistics

Table 1 reports some statistics on my $/DM dealer's daily activities over the sample period.[10] There are considerable daily variations in turnover. The busiest day has as much as three times the turnover in the slowest day in the sample. The average daily volume of about $1.5 billion puts this dealer among the top five $/DM dealers in the North America. He has a so-called "$10 million dollar relationship" with other major dealers such that quotes without specified quantities are understood to be good for $10 million worth of DM. The dealer is representative in terms of the composition of different types of trades such as customer flows and inter-dealer trades. Table 2 presents descriptive statistics about my dealer's different types of trades, as well as the market-wide statistics based on BIS (1996) surveys. For example, over the entire sample period, customer trades account for 13.9% of total volume, compared with about 16% for the market as a whole. Voice and electronic brokered trades combined account for 43.3% of total volume, compared with around 39% for the market as a whole. Interbank direct trades conducted via Reuters 2000-1, including Reuters incoming, outgoing and aggregate[11], account for 23.3% of

[10] The sample covers an otherwise continuous trading period for the dealer, except for (1) weekends and (2) Thanksgiving Day (11/23) when the U.S. operation is closed, and the day before (11/22) and after (11/24), both days on which the dealer, like many other dealers in the United States, did not quote or trade in the interbank direct (i.e. Reuters 2000-1) markets. Dealers at other financial centers, such as London and Frankfurt, did quote in the direct market during their hours overlapping with the U.S.

[11] Reuters aggregate trades are outgoing trades by nature. They take place when the dealer's inventory is significantly in imbalance from his desired level, most often resulting from large trades above $50 million. In this case, aside from requesting quotes (Recall that the Reuters 2000-1 enable the handling of four quotes at a time) himself, the dealer also asks other dealers such as $/Stg and $/Aus dealers on the desk to call out as well for $/DM quotes. Deals done by various dealers are fed into a computer that figures out an average price. On the $/DM dealer's blotter, though, all these deals are recorded as one trade, with the rate equal to the average price. Note that the average and median trade size of Reuters aggregate trades are $75.3 and $70.0 millions respectively.

total volume, compared with a market-wide 25%. Note that IMM trades, mostly concentrated around the beginning and end of trading days when interbank trades are light, account for only 1.4% of total volume.

<u>Table 1 and 2 Here</u>

Figure 5 and 6 present two plots. The first is the transaction price for all passive trades over the entire 25-day sample period, Nov. 1 -- Dec. 8, 1995. Note that there is a price discontinuity surrounding the Thanksgiving Day (Nov. 23). In figure 6, the top graph plots the dealer inventories at the time of all passive trades. The maximum long position is $198 million, and the maximum short position is $158.7 million. The bottom graph, using the same scale, plots the dealer's daily closing positions, which are fairly small compared to his intraday inventories. Figure 7 then plots the combined price and inventory series for November 17, the day with median turnover.

<u>Figure 5, 6 and 7 Here</u>

Table 3A and 3B present the classification of active and passive trades. First, Table 3A reports the signing of brokered trades, following the quote-based methodology described above. Results in panel (I) for voice brokers and panel (II) for electronic brokers suggest that roughly 70% of both types of brokered trades combined are active trades, i.e. trades in which the dealer acts as an aggressor. Trades other than brokered trades are directly classified either by trade channels through which they are executed (such as customer and internal trades) or by communication records (such as direct trades via Reuters 2000-1 system). Table 3B presents the results for all trades in the sample, including brokered trades. The statistics are quite similar in terms of number of trades or volume. In volume terms, passive trades constitute 60% of total volume, decumulating active trades 30% and accumulating active trades 10%.

Table 3A and 3B Here

5. Model Estimation

5.1 Empirical specification

In Section 3, I present a framework for studying price impacts of both passive and active trades. Because not all trades in my sample are time-stamped in the dataset, price impacts in such a framework have to be measured based on trade time as opposed to clock time. Then, the distinction between a passive and an active trade becomes important due to the following considerations. First is the variation of information intensity. Presumably, public signals occur at times of all trades, passive and active. However, private signals, associated with either customer deals or incoming inter-dealer trades, arrive only with passive trades. The second and related consideration arises from the endogeneity of trade.[12] Passive trade, originating from private information arrival, is considered exogenous, at least relative to active trade, such that inter-passive-trade time is assumed to be close to identically and independently distributed exponential random variables (i.e. a Poisson trade arrival process). In contrast, active trade has more time endogeneity in the sense that dealers essentially control the timing of its occurrence.

This motivates me to compute price returns for passive trade from the previous *passive* trade. In particular, let t index all trades, and τ index passive trades only. Suppose a trade double-indexed by (t, τ), is a passive trade, and another trade double-indexed by $(t - n_\tau - 1, \tau - 1)$ is the previous passive trade, where n_τ is the number of active trades between τ-1 and τ. Then

[12] Although previous work (e.g. Hausman, Lo, and MacKinlay, 1992) has rejected the assumption of exogenous inter-transaction time, modeling data in trades is the prevalent methodology, especially when the trade price impacts are the focus of investigation. This is partly because that (trade) time formation results from variation of information intensity, the rate at which the informational signals evolve.

$$
\begin{aligned}
y_\tau = y_t &= \mu_{it-1} + \eta_t \\
&= y_{t-1} + \eta_t \\
&= \mu_{it-2} + \eta_{t-1} + \eta_t \\
&= \cdots \; \cdots \\
&= \mu_{i\tau-1} + \eta_\tau \\
&= P_{i\tau-1} + \gamma(I_{i\tau-1} - I_i^*) - \psi D_{\tau-1} + \eta_\tau
\end{aligned}
\tag{14}
$$

where $\eta_\tau = \sum_{k=0}^{n_\tau} \eta_{t-k}$, representing the sum of public announcement of FX increments between τ-1 and τ. Eq. (14) utilizes the fact that $\mu_{it-k} = y_{t-k}$, for the n_τ active trades k = 1,2, .. n_τ . Eq. (2) is used to arrive at the last equality in eq. (14). Substituting (14) for the prior mean in (12) yields

$$
\Delta P_{i\tau} = \kappa + \lambda Q_{j\tau} - \frac{\gamma}{\pi} I_{i\tau} + \gamma I_{i\tau-1} + \frac{\psi}{\pi} D_\tau - \psi D_{\tau-1} + \eta_\tau \tag{15}
$$

where $\kappa = \kappa_1 - \kappa_2 = -\gamma(1 - 1/\pi) I_i^*$, τ indexes passive trade only , and $\Delta P_{i\tau}$ measures the price change between two successive passive trades. From an empirical viewpoint, computing price change between two passive trades as in eq. (15) has the advantage of breaking down the perfect collinearity between inventory and trade. Since eq. (15) is similar to the estimation equation in Madhavan and Smidt (1991) for NYSE stocks and the core model in Lyons (1995) for Reuters incoming trades, my estimation results based on eq. (15) are directly comparable to theirs.

As for active trade, I compute the price impact as the change from the immediately preceding trade indexed by time t. More specifically, I can write the prior mean for an active trade as:

$$
\begin{aligned}
y_t &= \mu_{it-1} + \eta_t \\
&= P_{it-1} + \gamma(I_{it-1} - I_i^*)\Theta_{t-1} + \gamma_D(I_{it-1} - I_t^*)(1-\Theta_{t-1})\Omega_{t-1} \\
&\quad - \gamma_A T_{t-1}(1-\Theta_{t-1})(1-\Omega_{t-1}) - \psi D_{t-1}\Theta_{t-1} + \psi_A D_{t-1}(1-\Theta_{t-1}) + \eta_t
\end{aligned}
\tag{16}
$$

where the second equality utilizes eq. (6) since the last trade at t-1 can be either passive or active trade.

Substituting (16) for y_{it} in (13) yields the price returns for active trades:

$$\begin{aligned} \delta P_{it} &= -\gamma I_i^* \Theta_{t-1} + \gamma_D I_i^* (\Omega_t - (1-\Theta_{t-1})\Omega_{t-1}) \\ &\quad + \gamma I_{it-1}\Theta_{t-1} - \gamma_D (I_{it}\Omega_t - I_{it-1}(1-\Theta_{t-1})\Omega_{t-1}) \\ &\quad + \gamma_A (T_t(1-\Omega_t) - T_{t-1}(1-\Theta_{t-1})(1-\Omega_{t-1})) \\ &\quad - \psi D_{t-1}\Theta_{t-1} - \psi_A (D_t - D_{t-1}(1-\Theta_{t-1})) + \eta_t \end{aligned} \tag{17}$$

where δP_{it} measures the price change between the time-t active trade and the immediate preceding (t -1) trade, passive or active.

Equations (15) and (17) are the basis of my empirical estimation:

$$\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \eta_t \tag{18}$$

for passive trades. The model predicts that $\{\beta_1, \beta_3, \beta_4\}>0$, $\{\beta_2, \beta_5\}<0$, $|\beta_2| > \beta_3$, and $\beta_4 > |\beta_5|$ where the latter inequalities derive from that fact that $0 < \pi < 1$. For active trades,

$$\begin{aligned} \delta P_{it} &= b_{01}\Theta_{t-1} + b_{02}(\Omega_t - (1-\Theta_{t-1})\Omega_{t-1}) \\ &\quad + b_1 I_{it-1}\Theta_{t-1} + b_2 (I_{it}\Omega_t - I_{it-1}(1-\Theta_{t-1})\Omega_{t-1}) \\ &\quad + b_3 (T_t(1-\Omega_t) - T_{t-1}(1-\Theta_{t-1})(1-\Omega_{t-1})) \\ &\quad + b_4 D_{t-1}\Theta_{t-1} + b_5 (D_t - D_{t-1}(1-\Theta_{t-1})) + \eta_t \end{aligned} \tag{19}$$

The model predicts that $\{b_1, b_3\} > 0$, $\{b_2, b_4, b_5\} < 0$.

Table 4 and 5 report sample moment statistics for passive trades and active trades respectively. Although the statistics in Table 4 are quite similar to those in Lyons (1995), it should be noted that passive trades, as broadly defined in this paper, include not only Reuters incoming trades, the only type described in Lyons descriptive statistics, but also other passive trades such as customer trades, internal deals and passive brokered trades. One consequence of including a broad range of passive trades is that inter-transaction time can not be measured precisely in calendar time since most of them are not time-stamped. Hence, inter-passive-trade time is measured in transaction time. On average, there is close to one intervening active trade between two successive passive trades. Since inter-transaction time for all trades is estimated as

2.1 minutes on average, the mean inter-passive-trade is about 4 minutes (1.8 x 2.1). This is considerably longer than the 1.8 minute mean inter-transaction time Lyons (1995) reports for Reuters incoming trades alone. As for active trades, since price impacts are calculated from the immediate proceeding trade, passive or active, the mean inter-active-trade time is the same as the mean inter-transaction time for all trades, i.e. about 2 minutes.

Table 4 and 5 Here

5.2 Estimation methods

I use the generalized method of moments (GMM) approach of Hansen (1982) to estimate the models for passive trade as well as active trade. GMM has several important advantages that make it particularly appropriate here. First, GMM does not require the usual normality assumption. In the estimation of price impacts, normality is not a good assumption because of the unusually large number of outliers. Second, Newey and West (1987) show that the weighting matrix used in GMM procedure can be adjusted to account for conditional heteroskedasticity and serial correlation. Consider the estimation equation (18) for passive trade, where the error term has the interpretation of the sum of public signals between two successive passive trades. Assuming that public signal occurs at all trade periods and that the number of intervening active trades between two successive passive trades is random, the error term in eq. (18) is likely to be conditionally heteroskedastic, and is likely to be serially correlated. Finally, GMM has been used in other empirical microstructure studies by Bessembinder (1994) and Madhavan and Smidt (1993). For most of results in this study, the set of instruments is identical to the set of regressors, resulting in systems that are exactly identified and parameter estimates that are identical to OLS results.[13] However, standard errors are corrected for conditional heteroskedasticity and autocorrelation following Newey and West (1987).

5.3 Results for passive trades

Table 6 presents the GMM estimation results for passive trades. There are 2447 observations, excluding 25 overnight price changes, over the 25-day sample period. Since the model for the estimation is very similar to those in Lyons (1995) on FX and others such as Glosten and Harris (1988) and Madhavan and Smidt (1991) on stock markets, the results are directly comparable to their findings.

Table 6 Here

There are several noteworthy results. First, the coefficient for order quantity Q_{jt}, reflecting information effects, is significant and properly signed. The coefficient estimate indicates that the dealer widens spreads by 0.9 pips (0.44 doubled) per \$10 million to guard against adverse selection arising from private information. The magnitude of my estimate is smaller than the 2.8 pips per \$10 million estimated by Lyons (1995). However, I will argue later (in Section 6) that full information content of a trade is not reflected instantaneously, but with protracted lagged, especially in the FX market with low market transparency.

The coefficients β_2, which is related to the inventory-control effects, has the right sign, but is not significant at the conventional confidence level. Moreover, the coefficient estimate of -0.11 pips per \$10 million is only about one-tenth of the estimate in Lyons (1995)[14], suggesting much weaker evidence for inventory control effects on transaction prices. The other inventory

[13] For both passive and active trade models, I do experiment by including lagged variables as additional instruments. However, these tests produce coefficient estimates of little change and χ^2 test statistics below 5% p-value.

related coefficient β_3 has the wrong sign, but is also insignificant at the conventional confidence level. Overall, the data provides very weak evidence that quote shading is practiced intraday as a tool for inventory control in response to passive trades. A weak inventory control effect via quote shading is often found in previous works on equity market such as Madhavan and Smidt (1991). Madhavan and Smidt (1991) suggests that the statistically weak finding may arise from increased estimation standard errors due to the multicollinearity between trades and inventories. However, by using only passive trades as in Lyons (1995), I am able to disentangle such multicollinearity in the estimation.

One possibility that may hamper the successful detection of quote shading effects on prices is that I have aggregated various types of bid-ask bounces which may well differ across different trade channels. More specifically, the variable D_t could be replaced by several indicator variables, representing the different fixed transaction costs (or the baseline bounces) of Reuters direct, brokered and customer trade separately. However, such refined estimation would only make a difference when inter-passive-trade time is sufficiently short. Guillaume et al. (1995) and Bollerslev and Melvin (1994) indicate that 5 minutes seem to be the cut-off time interval within which the bid-ask bounce effect becomes dominant. In other words, bid-ask bounce should not mask the significance of statistics constructed by sampling periods close to 5 minutes.[15] Recall that in the data section I estimate the mean inter-passive-trade time to be about 4 minutes. Thus, it is not likely to detect new significance if a more refined bid-ask bounce representation is used. This argument notwithstanding, I experiment by including three trade indicator variables, with value +1 for buyer-

[14] The estimate for β_2, is -0.98 pips per $10 million (with a t-statistic of -3.59) in Lyons (1995). The other coefficient β_3 has an estimated value of 0.79 pips per $10 million (with a t-statistic of 3.00), suggesting that Lyons' dealer shades his DM price of dollars by about 0.8 pips for every $10 million of net open position.

[15] For example, Anderson and Bollerslev (1996) use 5-minute returns for $/DM exchange rates to study the intraday volatility process and news announcement effects.

initiated passive trade and value -1 for seller-initiated passive trade, representing Reuters direct, brokered, and customer trades respectively in the estimation. Such a refined specification does not produce any results regarding information and inventory effects that are significantly different from those reported in table 6.

One explanation for the findings that one $/DM dealer shades quotes (as in Lyons's study) and another does not (as in this study) arises from the fact that quote shading by a dealer sends a signal, albeit noisy at times, to other dealers about his position. For example, in studying time-of-day effects Lyons (1995) finds that inventory effects via quote shading by his dealer are muted at the end of day. His dealer accounts for the absence of quote shading at the end of day as follows:

> "*...... so when I shade my price it gives the caller a sense of my position. At the end of my trading day it is important to keep my position to myself, since other dealers are also getting rid of positions in order to go home flat*."

Hence signaling one's position through quote shading is costly because it makes it harder to manage a position. Moreover, it provides essentially free information to other dealers who request quotes and yet have no obligation to trade. Quote shading would further reveal a dealer's private information if his order flows are informative. The amount of private information revealed through quote shading depends on the degree of private information a dealer has. As mentioned earlier, the major source of asymmetric information among FX dealers is their customer order flow. Therefore a dealer with customer flow, like the one in my sample, has substantial private information and thus is less likely to shade quotes. Since the dealer in Lyons (1995) has no customer trades over his 5-day sample period, it is not surprising that Lyons' dealer is not concerned about signaling his position via quote shading until the end of the day. In summary, a dealer with informative flows is unlikely to shade quotes because it would otherwise reveal his position and, as a result, (1) make his inventory control more difficult and (2) give other dealers a free ride on his private information.

To investigate the above idea further, I estimate the price impact model for passive trade using two subsets of the overall data used in table 6. The first subset consists of time-*t* customer trades only, and the second consists of time-*t* dealer trades (both Reuters direct and brokered) only. Time *t*-1 trade can be any type of passive trade. The objective is to see whether β_2 associated with inventory effects behaves differently when the dealer trades with customers and with other dealers. I also conduct a Chow test to determine whether the coefficient β_2 is the same across the two subsets. Regression results are presented in Table 7.

<u>Table 7 Here</u>

The key result is that the coefficient β_2 is significant and has the right sign for time-*t* customer trades, but not significant and has the wrong sign for time-*t* dealer trades. My dealer actually shades quotes by less than 0.5 pips per $10 million open position (recall that β_2 equals the inventory response parameter γ divided by a parameter $\pi < 1$.) when he deals with customers. However, he does not shade quote at all when he trades with dealers (directly or through brokers). This is consistent with the view that avoidance of quote shading is out of the concern of signaling positions to the market. Note that the coefficient β_3 associated with lagged inventory is not significant in either case because the time *t*-1 trade can be any type of passive trade. Also the information effect coefficient β_1 has the right sign but is not statistically significant at the conventional level. Part of the reason for the large estimation standard error for customer trades is that customer trades, which have much larger trade size, have significant price impacts not fully reflected by contemporaneous changes. I demonstrate later in VAR analysis that large trades tend to have pronounced price impacts at protracted lags. Finally, the Chow test can not reject the null hypothesis that the inventory coefficient β_2 is the same across customer trades and dealer trades. This is likely due to the low power of the test, however, since customer trades are rare (190 observations) compared to dealer trades (1291 observations).

The investigation above suggests that the FX dealer reacts differently to customer trades and inter-dealer trades. He shades quotes in customer trades because his fear of revealing information that the counterparty can capitalize on is mitigated. On the other hand, he does not shade quotes in inter-dealer trades to avoid revealing his position and further his information. This is especially true if the dealer has substantial customer flows which generate both high degrees of private information and the majority of trading profits.

Yao (1997) shows that 75% of my dealer's total trading profits during the 25-day sample period are derived from customer trades. In a survey of trading room profits around the world, Braas and Bralver (1990) examine over forty trading desks around the world and find that customer business represents a significant portion of trading revenues --- generally between 60 and 150 percent (in which case positioning or proprietary trading loses money) of total revenue. For dealers without much customer business, they may have to adopt a "jobber" style of trading to make money on the bid-ask spread. For a "jobber", since signaling position (which is not as informative to begin with) is secondary to spread retention, quote shading which increases spread retention is preferred to active trading. Thus, the choice of shading quotes or actively trading at others' quotes for inventory control purpose does not seem arbitrary, but rather arises from different market positions of dealers such as penetration of customer market. In this sense, the absence of quote shading here does not contradict Lyons's findings. It rather complements his results, and supports the view that dealers with diverse market positions might prefer different trading strategies. Unfortunately, testing such a conjecture in a rigorous fashion here is impossible because of data limitations.

Finally, the coefficients on both the current and lagged trade indicator variables, D_t and D_{t-1}, are significant and of the correct signs. The condition $\beta_4 > |\beta_5|$ as predicted by the model is also satisfied. The baseline bid-ask bounce is 2.4 pips (i.e. two times 12.2 divided by 10), assuming no information and inventory effects.

5.4 Results for active trades

Table 8 presents the GMM estimation results for active trades. The sample consists of active trade price changes from their immediate preceding trades, passive or active, for a total of 2040 observations. Over the 25-day sample period, six trading days start with active trades. Hence I have excluded the 6 overnight price changes.

Table 8 Here

The central results are that all coefficients except for the baseline spread bounce terms are not statistically significant at the conventional confidence level. The coefficient b_1 related to the time (t-1) passive trade is not correctly signed, again suggesting the lack of quote-shading. The coefficient b_2 related to decumulating active trades is not properly signed either. The coefficient b_3 related to accumulative active trades is correctly signed, yet is not significant at the conventional confidence.[16] These results suggest that after accounting for baseline spreads, there is no significant price impact associated with active trades. Since the estimation equation depends on the somewhat stringent assumptions about active trades, I experiment with different

[16] Note that the magnitude of b_3 coefficient estimate is much greater than those of both b_1 and b_2. This has to do with the fact that data series associated with b_1 and b_2 use actual inventory levels, while the data series associated with b_3

specifications of variables associated with b_2 and b_3. However I am not able to obtain any different results with significance.

The results above indicate that a dealer who is short (long) will be able to cover (unwind) the position at prices not any higher (lower) than his conditional expectation after paying a tight (see below) spread. The dealer is able to minimize the price impacts of a active trade because of several factors. First, since Reuters direct trade is bilateral and only a fraction of all brokered trades are reported, price discovery in the dealer market is slow enough to give the dealer time to work off his undesired inventories under normal circumstances. Second, the depth of the interbank FX market allows a dealer to trade a large amount of currency through a broad range of channels without much price impacts. Also, a North American dealer can also trade with dealers in Europe during the overlapping hours when both markets are active. Last but not least, advanced computer systems (Reuters 2000-1, EBS, etc.) allow a dealer to search effectively and quickly for the best prices in the market. For example, Reuters 2000-1 allows a dealer to handle four quotes at the same time, and it is commonplace that he trades $40 million within 30 seconds.

The results of baseline spreads are correctly signed and very significant. According to the model, b_4 is associated with my dealer's own quoted baseline spreads, and b_5, associated with my dealer's active trades, provides a measure of baseline spreads of other dealers that he deals with. Following the discussions above, because active trades measure price changes from the immediate preceding trades and because the mean inter-transaction time is estimated as 2.1 minutes (much shorter than the cut-off 5 minute interval), aggregation of spreads across different trading channels may mask the statistical significance of other coefficients. Thus I use three refined bounce variables, D_t^R, D_t^B, and D_t^C for spreads of Reuters direct, brokered interbank, and

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use only an indicator variable with a value of +1 for accumulating long positions and a value of -1 for accumulating customer trades respectively. There are three spread coefficients, b_4^R, b_4^B, and b_4^C for my dealer, and yet only two, b_5^R and b_5^B, for his dealer counterparties since there is no customer trade between two dealers. Estimates indicate that my dealers' baseline spreads (coefficient estimate for b_4^R, b_4^B, and b_4^C multiplied by 2 and divided by 10) are 2.1 pips, 3.3 pips, and 4.3 pips for Reuters direct, brokered interbank, and customer trades, respectively. Not surprisingly, customer trades are quoted at the widest baseline spread. Since the baseline spreads reflect the fixed transaction cost such as order processing cost, which should not be different for a customer or inter-dealer trade, the wider baseline spread for customer trades suggests that it includes a price mark-up on customer trades by the dealer.[17] The dealer's brokered trade spread of 3.3 pips is the same as those of his dealer counterparties, estimated at 3.2 pips (b_5^B times 2 and divided by 10) as well. However, his Reuters direct trade baseline spread is almost 1 pip tighter than the 2.9 pip spread (b_5^R times 2 and divided by 10) quoted by his dealer counterparties.

6. A VAR analysis of price, trade, and inventory

So far, my analysis has been limited to a static, or single equation framework. The results are a measure of instantaneous price response to order flows. However, previous research suggests that the full impact of a trade on the security price is not felt instantaneously but with protracted lags (See Hasbrouck 1991, 1993, and 1995, among others). Hasbrouck (1991) proposes a bivariate trade/quote vector autoregression (VAR) representation and provides a good example that demonstrates the advantage of VAR modeling by allowing for impacts from lagged

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short positions. Details see section 3 of the paper.

[17] Note that all customer trades are conducted via the intermediary of a in-house corporate salesperson. The price for customer trade in my sample is the price quoted to the in-house sales staff. Therefore, although it suggests a mark-up on the part of *the dealer*, it does NOT include the possible further mark-up to customers by *the sales staff*.

variables. Hasbrouck (1993) studies the dynamic behavior of NYSE prices using a VAR model of quotes, trades and inventories. The specification of using both trades and inventories allows him to analyze the distinctions with and without the specialist participation. In this section, I consider a VAR application to the interbank FX market to study the dealer's joint management of price impacts and inventory shocks from order flows, and the significant impacts of low market transparency on such strategic behavior.

The VAR empirical specification is based on the following framework.[18] Trade periods are defined as the occurrences of passive trades. At period t, public signal arrives, quotes are set, and a passive trade with quantity Q_t occurs (the subscript of j is suppressed here.). As before, Q_t is positive if it is buyer-initiated, and negative if it is seller-initiated. The trade leads to a transaction price $p_{t,}$ from which price changes Δp_t from last period t-1 is computed. Following the trade, the new efficient price of FX is set to reflect the information innovation contained in the trade. The FX dealer's inventory at the close of period t is n_t, net of trade Q_t. The dealer inventories are related between two periods as follows:

$$n_t = n_{t-1} - x_t - Q_t \tag{20}$$

where x_t is the aggregate amount of active trades that take place between period t-1 and t. Let D_t=sign(Q_t) denotes the indicator variable that captures the baseline bounce. The column vector of four variables included in the VAR system is $z_t = [\Delta p_t,\ n_t,\ Q_t,\ D_t]'$. An eight-lag structure is adopted and the VAR system is summarized as:

$$z_t = C_0 z_t + C_1 z_{t-1} + C_2 z_{t-2} + \cdots + C_8 z_{t-8} + u_t \tag{21}$$

[18] The VAR framework deviates from the model in Section 2, which is closest in spirits to Madhavan and Smidt (1991) and Lyons (1995). The reason is the earlier model allows for the interaction between inventory and information effects. A simple, additive model of these two effects are appropriate for the VAR representation.

where u_t is the column vector of residuals and the C_i's are conformable coefficient matrices. The contemporaneous term $C_0 z_t$ reflects the fact that in this market Q_t occurs prior to Δp_t and n_t.[19] The system is estimated for all passive trades over the entire 25-day sample period.

A key feature of this specification is that it includes both signed trade quantities and inventory levels. Hasbrouck (1993) uses such a specification to study the specialist participation since only a small portion of NYSE trades actually involve the specialist. Here, since time is indexed by passive trade, such a specification of passive trade quantity and inventory level determines the aggregate active trade quantity between two successive passive trades. Further inference can be drawn as to the extent to which active trades are used to lay off inventory shocks following a trade innovation.[20]

Asymmetric information effects suggest that inventory shocks should affect trade prices. If a dealer shade quotes to elicit trades of desired sign, prices should also affect inventories. Tests of Granger-Sims causality indicates that such causality runs from inventories to trade prices, but not the reverse.[21] This again lends support to the view that the FX dealer does not shade quotes to manage inventories.

A more refined picture of price impacts from order flows can be obtained form the impulse response functions of the system. The above VAR(8) system can be re-written as

$$z_t = (1 - C_0)^{-1} C_1 z_{t-1} + \cdots + (1 - C_0)^{-1} C_8 z_{t-8} + (1 - C_0)^{-1} u_0 \tag{22}$$

[19] Since Δp_t is the first equation in the system, the first nonzero element of C_0 are in the first rows, $[C_0]_{1,2}$ through $[C_0]_{1,4}$. The second nonzero elements of C_0 are in the second rows, $[C_0]_{2,3}$ through $[C_0]_{2,4}$, reflecting contemporaneous determination of *inventory innovation*, which is only a fraction of *trade innovation* due to contemporaneous inventory build-up by active trades during period t.

[20] An alternative to this specification is to use active trade variable and inventory. Because of significant time endogeneity of active trades, the alternative is likely to produce results that are less robust. This argument notwithstanding, I estimate the VAR system of this alternative trade and inventory specification and arrive at the same conclusion that active trades lay off the majority of inventory shocks.

where u_0 has the economic interpretation of the initial order flow. Taking all lagged values as zero, I calculate the initial impact of the initial shock u_0 as $E[z_0|u_0] = (1-C_0)^{-1}u_0$. The expectation of each following period's realization can be calculated by recursively substituting in this for z_0, and so on. The first element of z_t is price change Δp_t, inventory n_t the second, and passive trade Q_t the third. I also calculate two cumulative measures. First is the expected cumulative price changes through incoming trade m:

$$\alpha_P(u_0) = \sum_{t=0}^{m} E[\Delta p_t | u_0]$$

The second is the expected amount of subsequent cumulative incoming trade:

$$\alpha_Q(u_0) = \sum_{t=1}^{m} E[{}_t Q_t | u_0]$$

Thus, the difference between inventory innovation, n_0, and $\alpha_Q(u_0)$ provides a measure of expected cumulative active trades throughout subsequent incoming trade m. I use $m = 30$ to compute the impulse response functions.

Figure 8, 9 and 10 plot the impulse response functions of price change, inventory and cumulative passive trade, respectively. Four schedules are plotted in each figure that represent respectively \$10, \$20, \$50, and \$100 million incoming US\$ *purchases* against DM. (The impulse response functions for US\$ sells will be similar due to the symmetry of the VAR system.) Of these four, a trade size of \$20 million corresponds to the 90th percentile of all passive trades, and a trade size of \$50 million corresponds to the 97.5th percentile.

<u>Figure 8, 9 and 10 Here</u>

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[21] Using NYSE intraday data, Hasbrouck (1993) find bidirectional Granger-Sims causality between inventory levels and quote revisions. However, using NYSE daily data, Madhavan and Smidt (1993) find Granger-Sims causality running from quote revisions to inventories, but not the reverse.

As shown in Figure 8, the DM/$ price experiences a contemporaneous jump following an initial US$ purchase. The size of this initial jump consists of an information component that is proportional to initial trade size and a fixed half-spread of about 1.2 pips. At time $t = 1$ (recall that time is defined as the occurrence of incoming passive trade), the price drops by a half spread because it is almost equally likely for a US$ buy or sell at $t = 1$,[22] plus a small reversion of price change. At $t = 2$, the dealer basically maintains his quote. However, during these two periods ($t = 1, 2$), he is busy working off inventories via outgoing active trades. To see this, the inventory response function in fig. 9 indicates that the trade innovation of US$ purchase leaves the dealer with an short inventory innovation which is 72.4% of the size of trade innovation. The difference between trade and inventory innovations is due to contemporaneous offsetting inventory build-up by active trades. By the end of trade at $t = 1$, he is only short about 26% of the trade innovation. And by the end of trade at $t = 2$, he cuts down his short position to just 12% of the trade innovation. From figure 10, by the end of $t = 2$, incoming passive trades cumulatively offset only about 1% of trade innovation. The majority of inventory reduction, about 59% of trade innovation, during the two periods have to be accounted for by outgoing active trades.

During the following two incoming trades at $t = 3$ and 4[23], prices increase again by an amount that is in close proportion to the size of the trade innovation. Price retreats a bit thereafter and finally stabilizes at a level that fully reflects the information content of trade innovation. For

[22] As a result, the spread indicator variable D_t has a value of close to zero at $t = 1$. From this point on, signed incoming trades are small in size compared to the trade innovation, and D_t is very close to zero throughout trade m. Hence the spread bounce is no longer a major factor in price changes

[23] From t = 3, the inventory series in fig. 9 and the subsequent incoming passive trade series in fig. 10 start to diverge across different initial trade sizes. The divergence in both cases is caused by the trade sign indicator D_t's in the VAR system. With a value of +1 for buys and -1 for sells regardless of the trade size, they introduce a nonlinear effects in both series which are plotted as percentages of the initial trade sizes. The lag in the divergence effects reflect the three-trade lagged effects estimated by the VAR system.

trades of small to median size (i.e. less then $20 million, which is about ninety-five percentile trade size for interbank trades in my sample), the full price impact is not much different than the initial impact. For larger trades (e.g. $50 or $100 million trade in fig. 8), the full price impact is much greater than the initial impact.

The delayed quote revision until after substantial inventory shock reduction illustrates the FX dealer's strategic joint management of inventory shocks and price impacts facilitated by low market transparency. It is consistent with the view that low market transparency is preferred ex ante so that a FX dealer has time to manage inventory shocks. In the FX market, trade, especially customer trade which represents the major source of asymmetric information, is mostly bilateral and is observable only by the participating dealer(s). The discovery of this asymmetric information by other dealers occurs entirely through the subsequent interbank dealing. The dealer involved in a customer trade does not have anything to gain but all to lose by signaling with quotes that fully reflect his private information while he is stuck with an undesired inventory. This is because dissemination of private information via quote shading would be much faster than through volume dealing,[24] and would in turn increase the risk of unwinding positions at less favorable prices. While the dealer is laying off inventories mostly by hitting other dealers' quotes, information is disseminated to the extent that the market price gradually incorporates the dealer's private information. Then, the dealer can adjust the quote further which now fully reflects the price impact of a trade innovation, likely in tandem with those dealers who learn about his trade innovation when their quotes are hit in his active unwinding trades.

Finally, the cumulative passive trade and inventory response functions provide an estimate as to the percentage of inventory innovation that is laid off by passive trades and active trades, respectively. According to fig. 10, the percentage of inventory innovation that is laid off by passive trades is inversely related to the initial trade size. Because of the contemporaneous inventory build-up of about 27.6% of the size of *trade innovation*, the dealer has a short (long) *inventory innovation* of US$ amounting to 72.4% of trade innovation of US$ buy (sell). Subsequent to the trade innovation, the percentage of trade innovation that is laid off by incoming passive trades is about 10% (between 9% - 13%) for a trade innovation of small to median size (i.e. less then $20 million), and about 5% for larger trades (e.g. $50 or $100 million trade in fig. 8). Put differently, including the contemporaneous offsetting inventory build-up by active trades, active trades lay off at least 90% of trade innovation, rising to about 95% for large trade innovations. The remaining 5-10% of trade innovations are offset by incoming trades. This is largely due to short-run information heterogeneity (and likely an information advantage on the part of the dealer with proprietary informative flows). For example, a dealer who was hit with a large customer buy order, is more likely to lead the market in raising prices, although the price increase is likely to be spread over time and small to exclude arbitrage. Such short term price leadership in a heterogeneous informational environment is studied by Peiers (1995). She shows that Deutsche Bank, the largest German bank and an active $/DM dealer, has price leadership for up to 25 minutes during Bundesbank (the German central bank) interventions due to the close working relationships between the two banks.

7. Conclusion

This paper studies the market making behavior of a FX dealer who is subject to adverse selection arising from private information, and who has to manage inventory shocks from order

[24] See Lyons (1996) for a model of FX market transparency. As noted rightfully in his study, quote signaling is also

flows. The FX dealer in this study appears to be representative in terms of both trade volume and composition of different types of trades. The findings in this paper emphasize three elements that are important to understand a FX dealer's market making behavior: customer order flow as a major source of private information, outgoing active trades as a primary tool for inventory control, and low market transparency as a important factor in shaping dealer's trading strategy.

Although in the FX market private information is not significant in the usual sense, three types of private information exist. First, although very rare, is private information about the fundamental value of foreign exchange. One example is certain dealer's superior knowledge about central bank intervention (Peiers, 1995). Second, although FX dealers usually project their expectations on the same public information set, they often process this information differently and arrive at a wide dispersion of expectations. The third, and the most prevalent type of private information is order flow. Among all different types of order flow, dealer's customer order flow is the most important and informative order flow, reflecting demands from international trade and capital flow. Because of low order transparency, dealers with different customer trades have asymmetric information, and can only deduce from inter-dealer trades the order flows of others in the market. However, I find that any private information exists only for a very short period of time (less than 30 minutes). Therefore, dealers have only a small window of opportunity to capitalize on such short-lived private information.

I find little evidence of inventory effects on transaction prices. Shading quotes signals a dealer's position. In interbank dealing, such signals can be free to dealers requesting quotes because they do not have the obligation to trade. Quote shading may also be costly because it makes unwinding a position more expensive. The dealer in my study has substantial customer

limited by no-arbitrage condition which is significant given the tight spread in FX market.

flows and moreover derives the majority of his trading profits from such customer trades. Since customer trades represent a major source of asymmetric informative in the FX market, the dealer has substantial private information and hence does not shade quote to avoid revealing such information. This finding complements Lyons' (1995) description of the quote-shading behavior of a FX dealer with no customer transaction and relatively low degree of private information. This is consistent with the view that dealers with diverse market positions might prefer different trading strategies.

The alternative to quote-shading for managing inventory is actively hitting other dealers' quotes. Such active trade is appealing because the benefit of immediacy often outweighs the cost of paying a fairly tight spread in fast-moving markets. The price impacts of active trades are minimized because the great depth and low transparency of the FX interbank market, together with the computerized dealing systems, allow a dealer to search effectively for the best prices. A dynamic analysis indicates that the majority of FX inventory shocks (about 90% on average and as much as 95% for innovations over $50 million) are laid off by active trades.

The vector time series model in this paper uncovers significant price impacts at protracted lags. Large trades have price impacts at prolonged lags reflecting ultimately impounded information that is not captured by static models. The lagged price dynamics are particularly interesting. After a contemporaneous transaction price change in response to a trade, the dealer will delay further quote revision through several incoming trades, while in the meantime quickly laying off inventory shocks by active trades. He is able to do so because of the low market transparency; trades are almost always bilateral, and the impounded information is only found out by other market participants through subsequent interbank dealing. Once the dealer almost balances his position while at the same time the market digests the flow, he adjusts price to the level that ultimately incorporates the full information content of the trade. The dealer's strategic joint management of inventory shocks and price impacts calls for a FX market structure model that incorporates both low market transparency and game theoretic behavior on the part of the FX dealer.

Appendix

Signing brokered trades using quote-based methods, Section 4 "Data"

To sign brokered trades, voice/traditional and electronic, I use a quote based methodology (See Lee and Ready (1991), Madhavan and Smidt (1991) among others) that compares the trade price with the prevailing quotes. Since the prevailing broker quotes are not available at the dealer level and are difficult to compile from brokerage houses because of lagging time-stamps and numerous broker sources as reported by Lyons (1995), I have to use non-broker quotes as prevailing quotes. I compile the prevailing quotes from three sources:

1. Time-stamped *dealt* quotes from Reuters 2000-1 communication records of Reuters incoming and outgoing trades, which together account for about 10% of total number of trades in my sample.

2. Time-stamped *non-dealt* quotes from Reuters 2000-1 communication records, since the records include all inter-dealer conversations (such as early morning greetings). There are about 100 recorded incoming and outgoing non-dealt quotes on average every trading day in my sample. The drawback with non-dealt quotes are that some portion of them are quite clustered, in real time, around large trades.

Recall that brokered trades are not time-stamped. Thus, interpolation is used to time stamp a brokered trade which is bracketed by two time-stamped Reuters quotes. By comparing the estimated time of a brokered trade to the time-stamp of adjacent dealt and non-dealt quotes, prevailing quote is chosen as the one that is the closest in real time. However, in the fast pace FX market, any quotes that are 5 minutes or 2 trades old (recall that the mean inter-transaction time is estimated as 2.1 minutes) are stale. According to this criteria, dealt and non-dealt Reuters quotes combined do not provide adequate prevailing quotes for the large number of brokered trades in my sample, accounting for 60% of total number of trades. I have to resort to the following third source.

3. Constructed quotes from internal deals. Since large banks' FX operations include spots, forwards/swaps and options, there are in-house demands for a major currency such as \$/DM for hedging a European Monetary System (EMS) cross currency (e.g. FF/DM, Lira/DM), a forward/swap contract, or an option position. These traders, and possibly the in-house proprietary trading desk, would often come to the chief \$/DM dealer who has far better access to and reading of the market. The transaction between the chief \$/DM dealer and other in-house traders are referred to as internal deals. In my sample, internal deals account for 20.5% of total number of trades (16.1% of total \$ volume). One thing unique about internal deals, at least in the case of my \$/DM dealer, is that there is no markup by the chief \$/DM dealer; if his colleague wants to buy (sell) US\$ versus DM, he simply go to the brokered and/or Reuters direct markets to buy (sell) the same amount of US\$ and pass on the rate(s) to his colleague. Thus, quotes constructed from internal deals as follows should serve as a good proxy for prevailing quotes: If the internal deal is a buy (sell), the offer (bid) price is equal to the transaction price, and the bid (offer) price is equal to the transaction price minus (plus) a spread. The spread is determined by the following schedule:

if trade size is less than \$10mm, the spread = 3 pips;

if trade size if between \$10mm and \$30mm, the spread = 5 pips;

if trade size is greater than \$30mm, the spread = 10 pips;

The spread schedule is estimated based on spreads of Reuters direct quotes in my sample. Note that the 3 pip spread for trades less than \$10mm is consistent with that in Lyons (1995).

The three quote sources above allow me to sign almost all the brokered trades using prevailing quotes that are within two trades or about 5 minutes in real time. I use the following rules recommended by Lee and Ready (1991) and used as well by Madhavan and Smidt (1991): A brokered trade is classified as a buy if the price is greater than or equal to the prevailing ask, or closer to the ask than the bid, and as a sell if the price is less than or equal to the prevailing bid, or closer to the bid than the ask. There is a very small number (less than 1% of total brokered trades) of brokered trades that are in the middle of the spread. (Note that most prevailing quotes has odd-number spreads (3 or 5 pips) except for large trades.) They are classified using the tick test.

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Table 1

Overview Statistics, Nov. 1 -- Dec. 8, 1995

The overall daily trade data are from trade blotters of a $/DM dealer at a major New York City commercial bank. The sample covers a continuous trading period for the dealer, except for (1) weekends and (2) Thanksgiving Day (11/23) when the U.S. operation is closed, and the day before (11/22) and after (11/24), both days on which the dealer, like most other North American dealers, did not quote or trade on the interbank direct (i.e. Reuters 2000-1) markets. Volume and size of trade are in $US million.

#	date	day of week	#trades	volume	mean size
1	11/01	W	207	1737	8.4
2	11/02	Th	157	1320	8.4
3	11/03	F	195	2253	11.6
4	11/06	M	138	1031	7.5
5	11/07	Tu	147	1244	8.5
6	11/08	W	148	931	6.3
7	11/09	Th	289	2746	9.5
8	11/10	F	198	1406	7.1
9	11/13	M	179	1479	8.3
10	11/14	Tu	223	1928	8.6
11	11/15	W	194	1635	8.4
12	11/16	Th	151	1170	7.7
13	11/17	F	177	1346	7.6
14	11/20	M	174	1624	9.3
15	11/21	Tu	110	841	7.6
16	11/27	M	232	2120	9.1
17	11/28	Tu	165	1188	7.2
18	11/29	W	220	1758	8.0
19	11/30	Th	237	1868	7.9
20	12/01	F	129	1154	8.9
21	12/04	M	120	1038	8.6
22	12/05	Tu	171	1675	9.8
23	12/06	W	117	930	7.9
24	12/07	Th	197	1621	8.2
25	12/08	F	243	2175	9.0
total			4518	38217	
Minimum			110	841	6.3
maximum			289	2746	11.6
average			181	1529	8.4
median			177	1479	8.4

* The median trade size of each and every trading day in the sample is around $5 millions.

Table 2

Descriptive Statistics: Types of Trades

This table lists all different types of trades, in terms of trade venues, of my $/DM dealer over the sample period of Nov. 1 -- Dec. 8, 1995. For definitions of different types of trades, refer to the text of the paper. All volume and trade size statistics are in US$ millions.

	(1) customer	(2) voice broker	(3) electronic broker	(4) Reuters incoming	(5) Reuters outgoing	(6) Reuters aggregate	(4+5+6) Reuters direct	(7) internal	(8) IMM	(9 limit/stop order	(10) misc.	total
# trades	194	1480	1283	312	130	29	471	928	101	54	7	4518
% total	4.3%	32.8%	28.4%	6.9%	2.9%	0.6%	10.4%	20.5%	2.2%	1.2%	0.2%	100.0%
volume	5299	9913	6649	5248	1500	2185	8933	6169	516	678	59	38217
% total	13.9%	25.9%	17.4%	13.7%	3.9%	5.7%	23.3%	16.1%	1.4%	1.8%	0.2%	100.0%
market-wide*	16%	21%	18%				25%	-	-	-	-	
average size	27.6	6.7	5.2	16.9	11.5	75.3		6.6	5.1	12.6	7.4	
median size	20	5	4	10	10	70		5	4.3	10	4	
25% size	12.25	5	2	10	10	40		3	2.6	8.5	0.5	
75% size	40	8.5	6	19	10	100		9.7	8.5	12	10	

***** Sources for market-wide statistics: Bank of International Settlements surveys, 1993 and 1996.

Table 3A

Signing the Brokered Trades

This table presents the results of determining the aggressor of brokered trades, voice and electronic (EBS, etc.), using quote-based methodology. Sample period: Nov. 1 -- Dec. 8, 1995.

(I) Voice Brokers

	active trades	passive trades	total
number of trades	934	546	1480
% of total number of active trades	63.1%	36.9%	100%
volume ($mm)	6401	3512	9913
% of total active trade volume	64.6%	35.4%	100%

(II) Electronic Brokers (EBS,etc.)

	active trades	passive trades	total
number of trades	846	437	1283
% of total number of active trades	65.9%	34.1%	100%
volume ($mm)	4671	1978.3	6649.3
% of total active trade volume	70.2%	29.8%	100%

Table 3B

Determining Active vs. Passive Trades

(all trades, Nov.1 -- Dec. 8, 1995)

This table presents the results of determining the aggressor of all types of trades. Most trades are classified as passive or active simply by trade channels. Passive trades thus classified include customer trades, internal deals, limit and/or stop-loss orders, and Reuters incoming trades. Active trades thus classified include Reuters outgoing trades and IMM trades. Brokered, both voice/traditional and electronic (EBS, etc.), trades and miscellaneous trades (such as trades done over the phone without a broker) are classified using quote-based methodology (details see text of the paper).

	accumulating active trades	decumulating active trades	Subtotal: active trades	passive trades	total
number of trades	617	1429	2046	2472	4518
% of total number of all trades	13.7%	31.6%	45.3%	54.7%	100%
volume ($mm)	3842.8	11452.4	15295.2	22921.6	38216.8
% of total volume of all trades	10.0%	30.0%	40.0%	60.0%	100%

Table 4

Passive Trades: Sample Moments

Std denotes standard deviation. 25% and 75% denote the 25th and 75th percentile values, respectively. ΔP_{it} is the price change, measured in pips (i.e. 0.0001DM/$), between two successive passive trades. Inventory I_{it} and transaction amount Q_{jt} are both in US$ millions. Q_{jt} is positive for a buyer-initiated trade (my dealer's sell) and negative for a seller-initiated trade (my dealer's buy). Δt measures inter-transaction time, where t indexes all trades (not calender time). For example, Δt = 1 indicates that a passive trade is immediately followed by another passive trade, Δt = 2 indicates that there is one intervening active trades between two passive trades. The estimated mean time between two successive trades of all types in the sample is 2.1 minutes with a standard deviation of 2 minutes (median 1.6 minutes). Sample: Nov. 1 -- Dec. 8, 1995, 2447 observations.

	mean	Std	median	25%	75%
ΔP_{it}	0.2	8.1	0.0	-3.0	3.0
$\lvert \Delta P_{it} \rvert$	5.0	6.3	3.0	1.0	7.0
Q_{jt}	-0.3	15.7	-1.0	-5.0	5.0
$\lvert Q_{jt} \rvert$	9.3	12.7	5.0	4.0	10.0
I_{it}	-1.3	17.7	-1.2	-9.0	6.1
$\lvert I_{it} \rvert$	11.0	13.9	7.6	3.4	13.6
Δt	1.8	1.2	1.0	1.0	2.0

.

Table 5

Active Trades: Sample Moments

Std denotes standard deviation. 25% and 75% denote the 25th and 75th percentile values, respectively. δP_{it} is the price change, in pips (i.e. 0.0001DM/$), from the immediate preceding trade. Inventory I_{it} and transaction amount Q_{jt} are both in US$ millions. For active trades, Q_{jt} is positive for a buy by the counterparty or a sell by my dealer (an aggressor), and negative for a sell by the counterparty or a buy by my dealer (an aggressor), The estimated mean time between two successive trades of all trades in the sample is 2.1 minutes with a standard deviation of 2 minutes (median 1.6 minutes). Sample: Nov. 1 -- Dec. 8, 1995, 2040 observations. Of the total 2040 (t-1) trades, 1163 are passive trades, 700 are decumulating active trades, and 177 are accumulating active trades.

	mean	SD	median	25%	75%
δP_{it}	0.0	4.9	0.0	-2.0	2.0
$\lvert \delta P_{it} \rvert$	2.9	4.0	2.0	0.0	4.0
Q_{jt}	0.4	13.3	0.6	-5.0	5.0
$\lvert Q_{jt} \rvert$	7.5	10.9	5.0	3.0	10.0
I_{it}	-1.2	15.7	-1.3	-8.5	5.2
$\lvert I_{it} \rvert$	10.0	12.2	7.0	3.2	12.5

Table 6

GMM Coefficient Estimates for Passive Trades

The model to be estimated is:

$$\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \eta_t$$

where ΔP_{it} is the price change in pips (i.e. 0.0001DM/\$) from t-1 to t. I_{it} and I_{it-1} are dealer i's inventories at period t and $t-1$, respectively. Q_{jt} is the transacted quantity effected at dealer i's quote, positive for buyer-initiated trade (at dealer i's offer) and negative for seller-initiated trade (at dealer i's bid). I_{it} , I_{it-1} , and Q_{jt} are all measured in US\$ millions. D_t is an indicator variable with value 1 for buyer-initiated trade, and value -1 for seller-initiated trade. The model is estimated using GMM and standard errors are heteroskedasticity- and autocorrelation- consistent. All coefficient estimates, with t-statistics in parentheses, are multiplied by a factor of 10. Sample: Nov. 1 -- Dec. 8, 1995. 2447 observations.

	β_0	β_1	β_2	β_3	β_4	β_5	R^2
Estimated	0.14 (0.95)	0.44 (3.61)	-0.11 (-0.91)	-0.08 (-0.65)	15.62 (8.34)	-12.20 (-7.51)	0.09
Predicted		>0	<0	>0	>0	<0	

Table 7

Quote shading: Customer trades vs. dealer trades

The model to be estimated is:

$$\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \eta_t$$

The model is estimated for two subsets of passive trades, time-*t* customer trades only and time-*t* dealers trades (Reuters direct and brokered) only. ΔP_{it} is the price change measured in pips (i.e. 0.0001DM/$) from *t*-1 to *t*. I_{it} and I_{it-1} are dealer *i*'s inventories at period *t* and *t-1*, respectively. Q_{jt} is the transacted quantity effected at dealer i's quote, positive for buyer-initiated trade (at dealer *i*'s offer) and negative for seller-initiated trade (at dealer *i*'s bid). I_{it} , I_{it-1} , and Q_{jt} are all measured in US$ millions. D_t is an indicator variable with value 1 for buyer-initiated trade, and value -1 for seller-initiated trade. The model is estimated using GMM and standard errors are heteroskedasticity- and autocorrelation- consistent. All coefficient estimates, with *t*-statistics in parentheses, are multiplied by a factor of 10. Sample: Nov. 1 -- Dec. 8, 1995.

(1) time-*t* customer trades only:
(190 observations)

	β_0	β_1	β_2	β_3	β_4	β_5	R^2
Estimated	-0.87	0.37	-0.47	0.16	15.53	-11.95	0.09
	(-1.40)	(1.64)	(-2.29)	(0.60)	(2.08)	(-2.09)	
Predicted		>0	<0	>0	>0	<0	

(2) time-*t* dealers trades (Reuters direct and brokered) only:
(1291 observations)

	β_0	β_1	β_2	β_3	β_4	β_5	R^2
Estimated	0.38	0.34	0.15	-0.32	24.34	-10.84	0.15
	(1.94)	(2.04)	(0.79)	(-1.64)	(10.16)	(-5.22)	
Predicted		>0	<0	>0	>0	<0	

Table 8

GMM Coefficient Estimates for Active Trades

The model to be estimated is:

$$\delta P_{it} = b_{01}\Theta_{t-1} + b_{02}(\Omega_t - (1-\Theta_{t-1})\Omega_{t-1}) + b_1 I_{it-1}\Theta_{t-1} + b_2(I_{it}\Omega_t - I_{it-1}(1-\Theta_{t-1})\Omega_{t-1})$$
$$+ b_3(T_t(1-\Omega_t) - T_{t-1}(1-\Theta_{t-1})(1-\Omega_{t-1})) + b_4 D_{t-1}\Theta_{t-1} + b_5(D_t - D_{t-1}(1-\Theta_{t-1})) + \eta_t$$

where δP_{it} is the price change, measured in pips (i.e. 0.0001DM/$), from the immediate preceding trades at *t*. I_{it} and I_{it-1}, in US$ millions, are dealer *i*'s inventories at period *t* and *t-1*, respectively. Θ_t is an indicator variable with value of 1 for passive trades, and value of 0 for active trades. Ω_t is an indicator variable with value of 1 for decumulating active trade, and value of 0 for accumulating active trade. T_t is also an indicator variable for accumulating active trade, with value of 1 when dealer *i* is long, and value of -1 when dealer *i* is short. (For definition of types of trades, please refer to the text.) D_t is an indicator variable with value 1 for dealer *i*'s sell, and value of -1 for dealer *i*'s buy. The model is estimated using GMM and standard errors are heteroskedasticity- and autocorrelation-consistent. All coefficient estimates, with *t*-statistics in parentheses, are multiplied by a factor of 10. Sample: Nov. 1 -- Dec. 8, 1995, 2040 observations

	b_{01}	b_{02}	b_1	b_2	b_3	b_4^R	b_4^B	b_4^C	b_5^R	b_5^B	R^2
Estimated	0.72	-1.19	-0.20	0.05	5.67	-10.36	-16.49	-21.55	-14.29	-16.10	0.12
	(0.29)	(-0.45)	(-1.80)	(0.67)	(1.84)	(-3.29)	(-9.07)	(-4.98)	(-3.13)	(-8.06)	
Predicted			>0	<0	>0	<0	<0	<0	<0	<0	

(1) Customer-dealer trades:

(2) Inter-dealer trades:

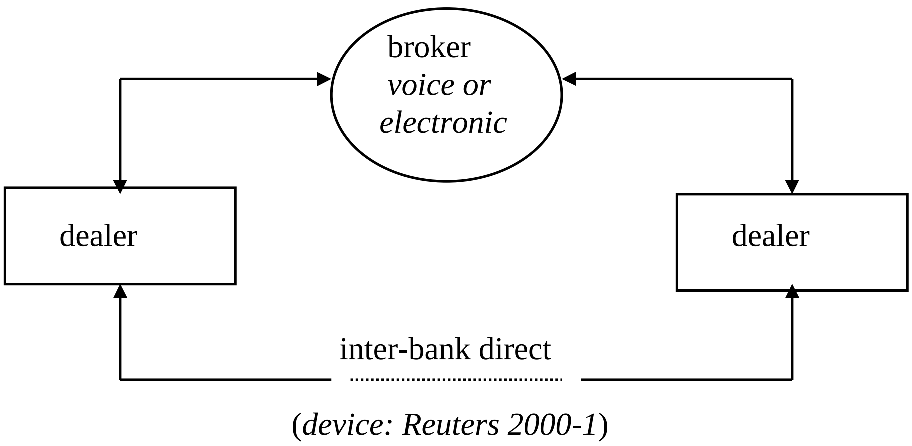


Fig. 1 Major participants and trade channels in the interbank FX market

This figure provides a simple outline of the structure of the interbank FX market. There are two major types of transactions, customer-dealer trade and inter-dealer trade. Customers, who do not have access to brokers, rely on currency dealing banks' sales staff to trade with banks' dealers. Dealers engage in inter-dealer trades through brokers or Reuters direct dealing systems to lay off inventory shocks as well as to provide liquidity to each other.

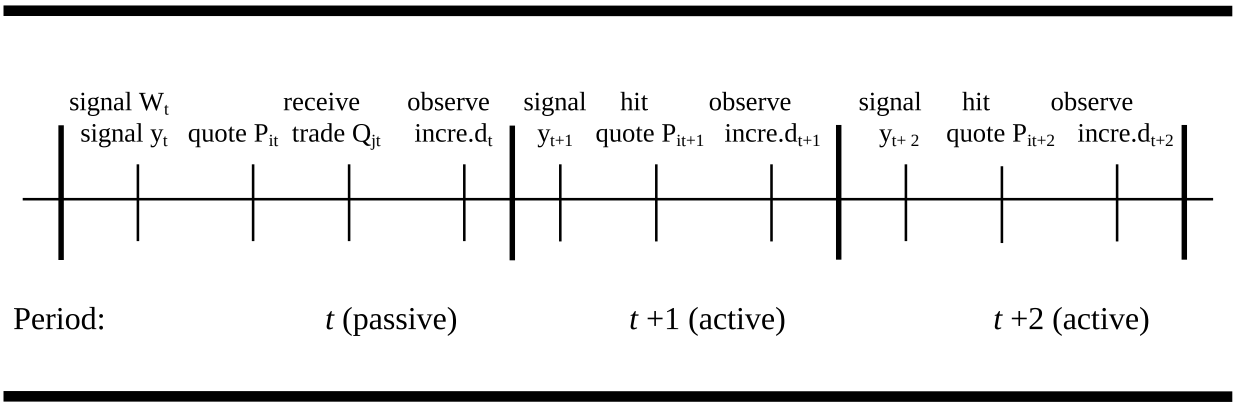


Fig. 2 Time indexing of trades and sequencing of events

This figure depicts the time/event sequence of the model. At time t = 1,2,..., T, it can be either a passive trade effected at dealer *i*'s quote, or an active trade which is initiated by dealer *i* and is effected at other dealer's quote. The figure depicts three trades: a passive trade at time *t*, followed by two active trades at *t*+1 and *t*+2. Public signal arrives in each time period; private signal W_t is only present with a passive trade. Thus, information increment d_t to FX fundamental value incorporates revelation of both public and private information subsequent to a passive trade, but only public information subsequent to an active trade.

Date	11/7	Currency: DM/$		Dealer Name	Value Date	11/9
CUSTOMER		BUY	SOLD	RATE	NET POSITION	AVERAGE
		($ mil.)	($ mil.)	(DM/US$)	($ mil.)	(DM/US$)
Previous balance					-22.6	
BANK 1	B	5		1.4151	-17.6	
BANK 2	B	8		51	-9.6	
BANK 3	Q		2	50	-11.6	
COLLEAGUE 1		5		48	-6.6	
IMM	50	(6.25)	4.4	48	-11.0	
BANK 4	Q		3	47	-14.0	1.4151
CUSTOMER 1	S	17.22	(24.375)	53		
BANK 5	Q		10	53		
BANK 6	B		5	54	-12.0	
BANK 7 **	R	10		50	-2.0	
...	...	...	...	...	...	...

Fig. 3. Example: one of my dealer's actual trading blotters on November 7, 1995.

This figure provides an example of one of many trade blotters recorded by my DM/US$ dealer every day. Each page starts with a balance from the previous page, or previous day if it is the first blotter of a trading day. The first column is the counterparty identity of each trade, such as the name of a corporation in a customer trade, the name of a bank in an inter-dealer trade, or the name of the dealer's colleague in an internal deal. The second column indicates the trade channels, where B stands for voice broker (by name of the broker), Q for electronic broker, S for the name of the salesperson involved in a customer trade, and R for Reuters direct trade. A number in the second column associated with an entry of "IMM" in the first column indicates the number of contracts traded on the IMM futures market. Entries in the "BUY" and "SELL" columns are in millions of U.S. dollars. When the original trade amount is in DMs, such as an IMM trade with contract size denominated in DMs or a trade involving a customer with a DM invoice, my dealer enters the DM amount as well in parentheses, and then convert the DM amount to U.S. dollars at the corresponding DM/US$ trade price for position keeping.

** For this Reuters direct trade, I match up with Reuters 2000-1 records and identify the time as 14:41 GMT, and the quoted spread 50-55. Since the dealer is buying at the bid, this trade is identified as an incoming trade.

```
From  CODE  BANK NAME            * 1441GMT  071195 */4260
Our terminal:  CODE           Our user:  DEALER NAME
        DM 10
#  5055
        I  SELL
#  VAL  09NOV95
#  TO  CONFIRM  AT  1.4150  I  BUY  10  MIO  USD
#  MY  USD  TO  USD  DIRECT
#  THANKS  AND  BYE
        VAL  09NOV95
        MY  DEM  TO  BANK  NAME  FRANKFURT
        TO  CONFIRM  AT  1.4150  I  SELL  10  MIO USD
#
        # INTERRUPT #

        # END REMOTE #

( 239 CHARS)
```

Fig 4. Example of an actual Reuters Dealing 2000-1 communication at 14:41 Greenwich Mean Time (GMT) on November 7, 1995.

The example in this figure describes an incoming trade in which another dealer requests a quote for $10 million worth of DMs from my dealer, and hit my dealer's bid price of 1.4150 DM/US$ (The offer side of the two-way quote is 1.4155 DM/US$). Such a $10 million trade is considered normal among major DM/US$ dealers who maintain "$10 million relationship" with each other. Note that the bid-ask spread of 0.0005 DM/US$ (or 5 pips) is only 3.5 basis points of the trade size. Coded information in the first two lines (in italics) indicates the identities of the two parties (actual names disguised) involved in this inter-dealer direct trade. The conversation is very concise, often in pre-programmed Reuters language, so that a trade can be completed in just a few seconds. The Reuters 2000-1 dealing system allows a FX dealer to conduct such conversations with four dealers simultaneously.

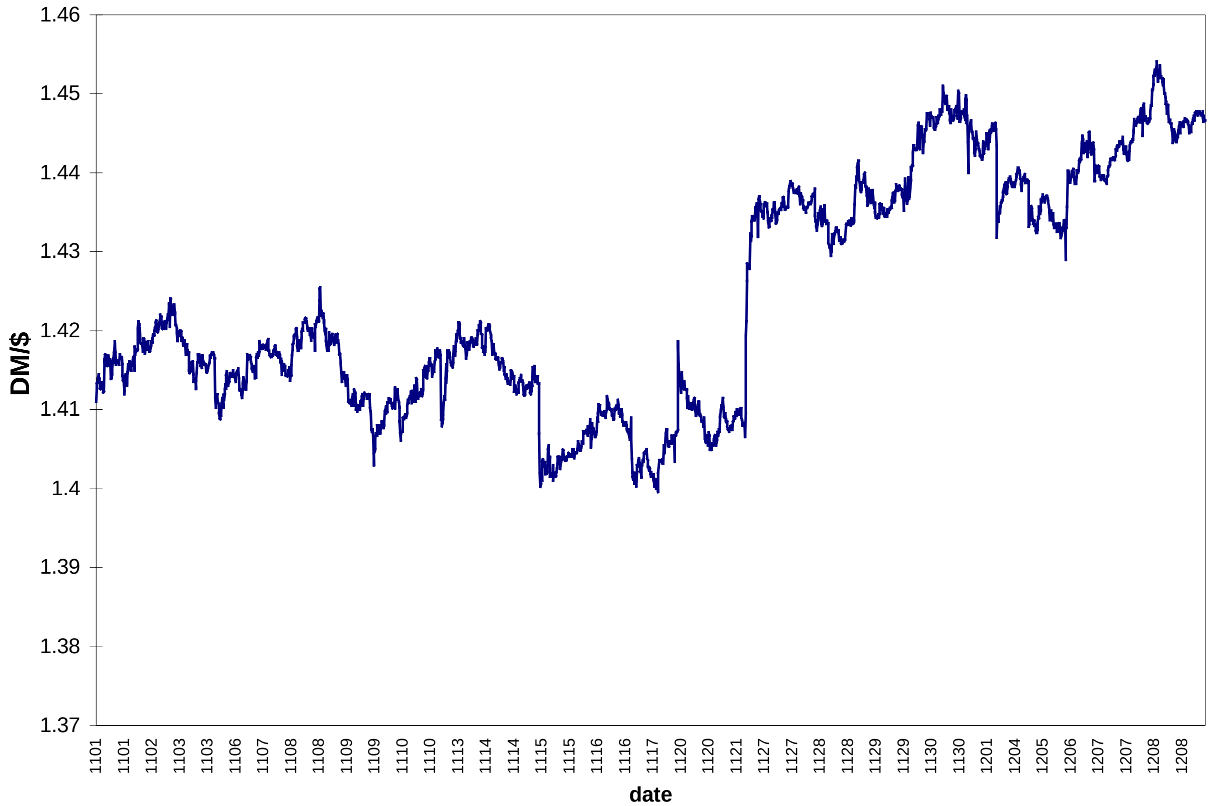
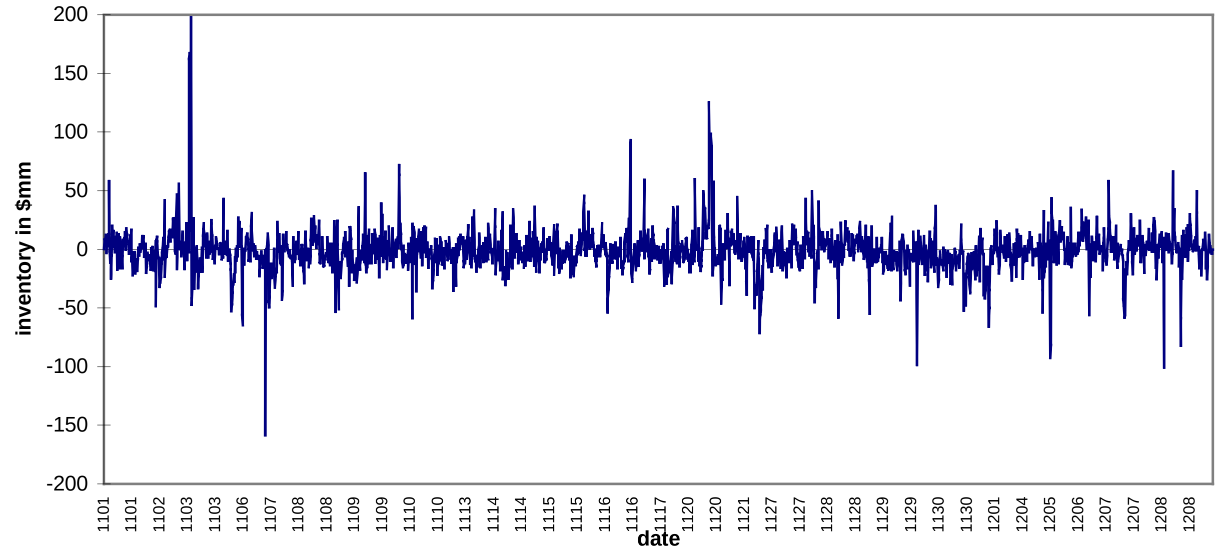


Fig. 5 Transaction price: DM/$, *Nov. 1 - Dec. 8, 1995*.

The figure plots the transaction price of DM/$ of each incoming passive trade over the entire 25-day sample period. The sample period, Nov. 1 - Dec. 8, 1995, covers 25 continuous trading days except for (1) weekends and (2) Thanksgiving Day (11/23) when the U.S. operation is closed, and the day before (11/22) and after (11/24) when the dealer, like most other North American dealers, did not quote or trade in the Reuters 2000-1 direct interbank market. Passive trades include customer trade, internal deal, limit order, Reuters incoming trade, and brokered trade which is signed by quote-based methodology and determined as incoming passive trades. Note that the date (x-axis) tick mark is not evenly distributed, indicating different trade volume (in terms of numbers of passive trades) across trading days.



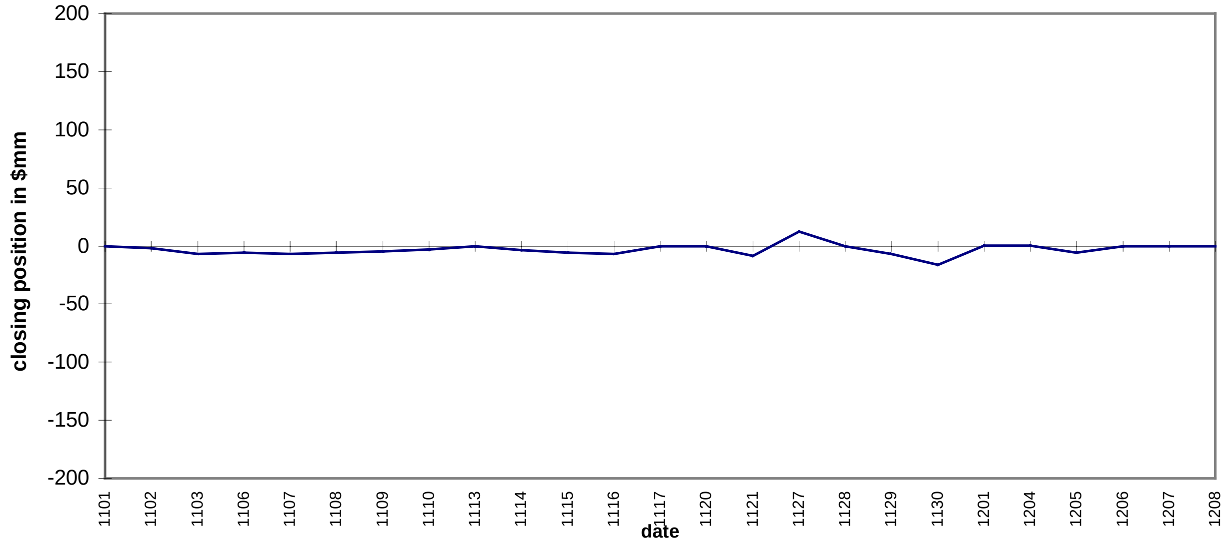


Fig. 6 Net inventory and daily closing position in millions of US$, *Nov. 1 - Dec. 8, 1995*.

The chart at the top plots the $DM dealer's net position in millions of US$ at the time of each incoming passive trade over the entire 25-day sample period. Note that the date (x-axis) tick mark is not evenly distributed, indicating different trade volume (in terms of numbers of passive trades) across trading days.

The chart at the bottom plots the dealer's daily closing inventory in millions of US$ over the 25-day sample period. The chart has the same scale as the one at the top.

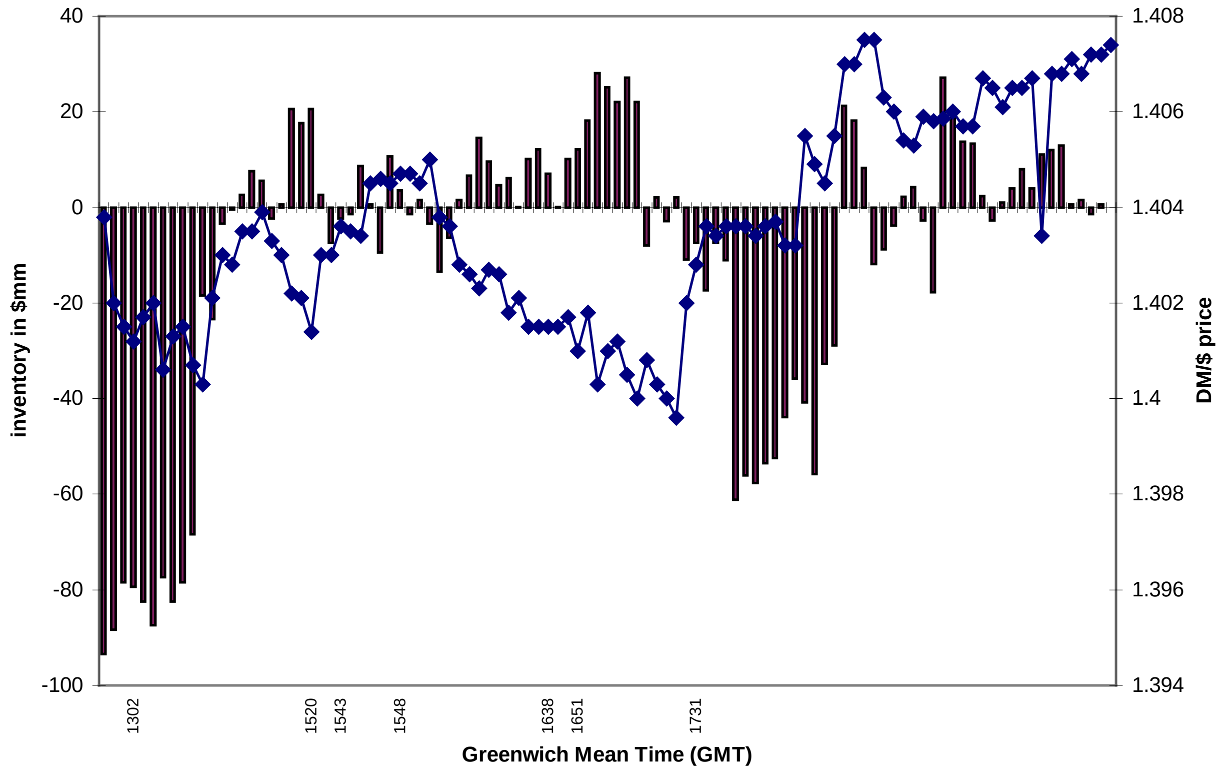


Fig. 7 Transaction price and inventory for all passive trades on Nov. 17, 1995.

The figure depicts both transaction price and inventory for all incoming passive trades on Nov. 17, 1995, the day with median turnover in the sample of 25 trading days, Nov. 1 - Dec. 8, 1995. Passive trades include customer trade, internal deal, limit order, Reuters incoming trade, and brokered trade which is signed by quote-based methodology and determined as incoming passive trade.

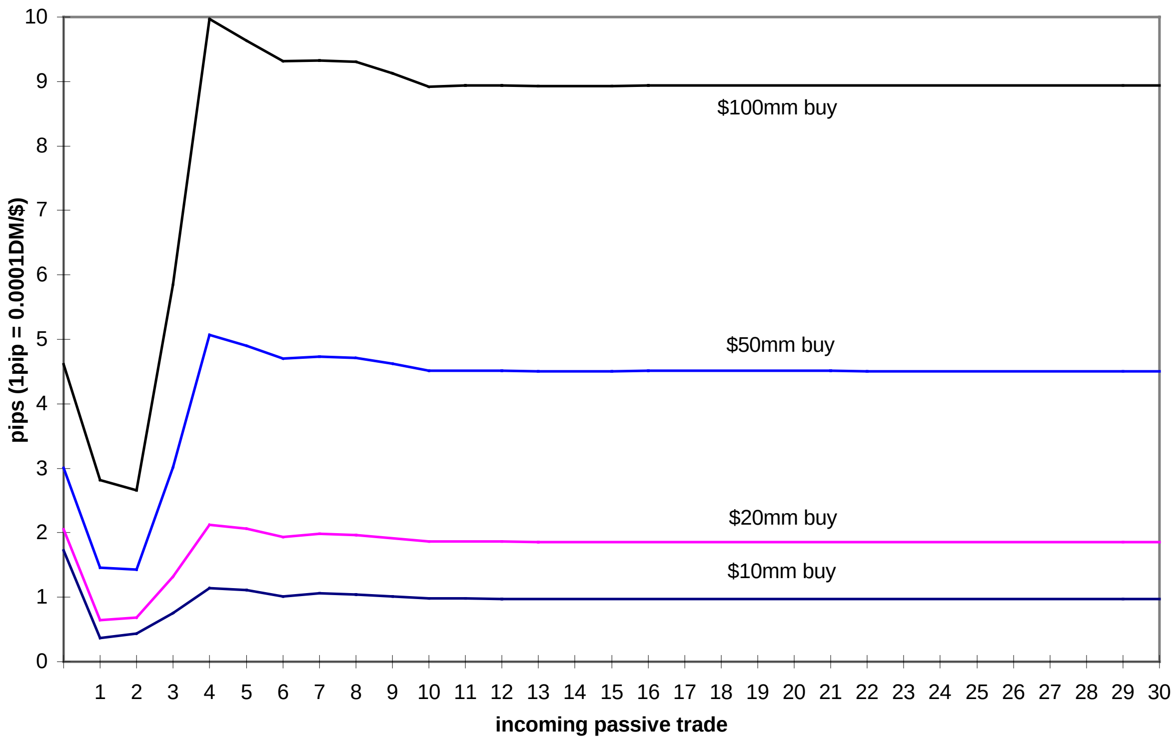


Fig. 8 Price response process following an initial $US buy order against DM.

The figure depicts the price response process according to a VAR (8) system of price, inventory and passive trade, subsequent to initial $US buy orders of the indicated sizes.

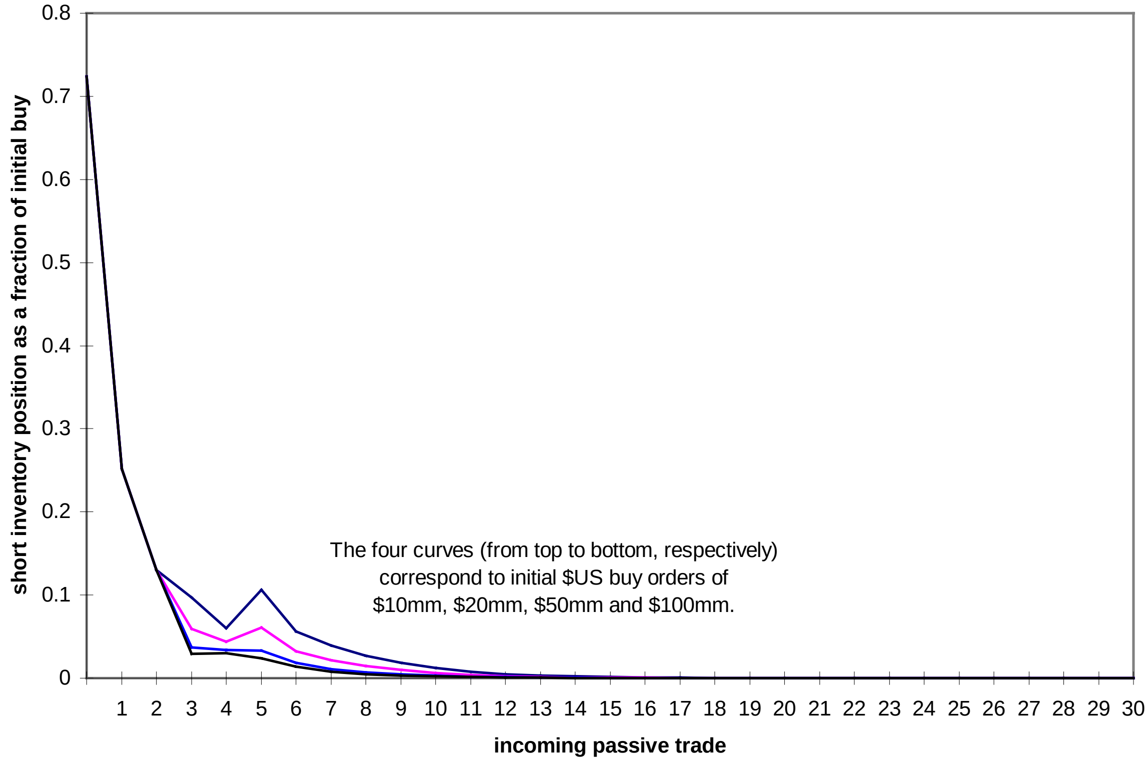


Fig. 9 Inventory adjustment process following an initial $US buy order against DM.

The figure depicts the inventory adjustment process according to a VAR(8) system of price, inventory and passive trade, subsequent to initial $US buy orders of the indicated sizes. Immediately following a initial $US buy, the dealer has a short position in $US amounting to only about 72.4% of the size of initial buy order because of anticipatory inventory build-up in advance.

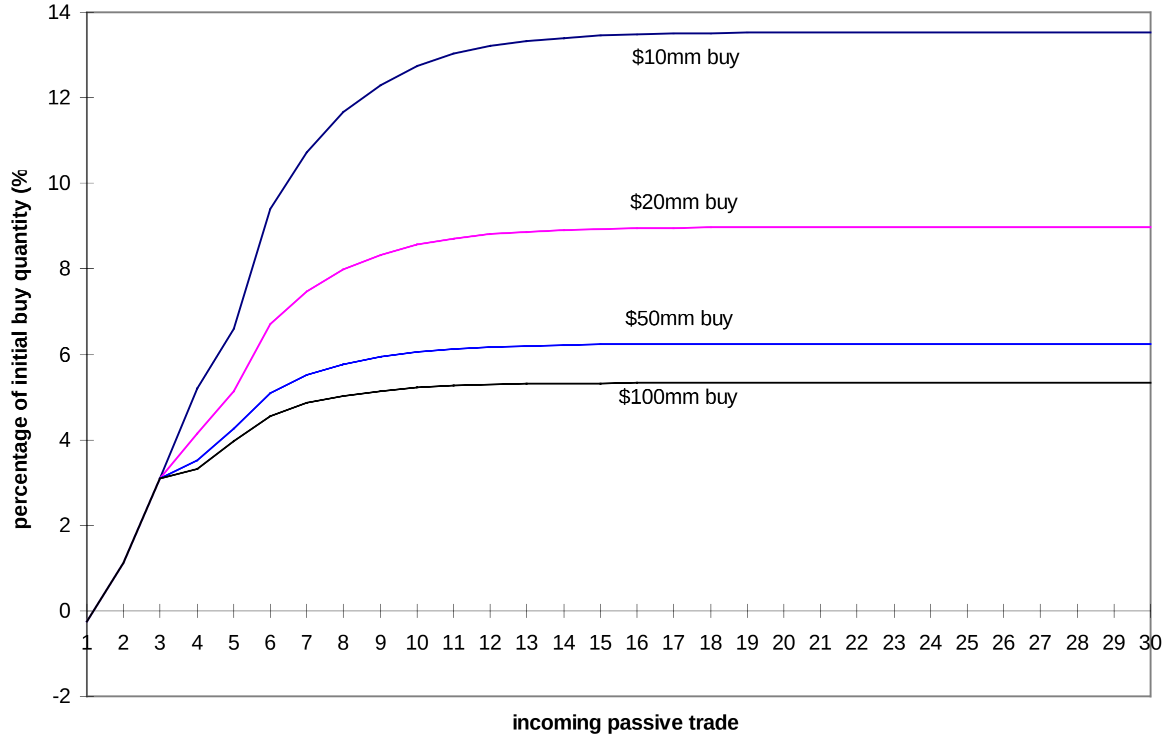


Fig. 10 Cumulative incoming passive sells following an initial $US buy order against DM.

The figure depicts the cumulative passive *sells* according to a VAR(8) system of price, inventory and passive trade, throughout 30 incoming passive trades subsequent to initial $US buy orders of the indicated sizes. Such incoming sells allow the dealer to cover part of his short $US position, whose size immediately following the initial buy order is equal to about 72.4% of the initial buy order.