Customer Trading and Information in Foreign Exchange Markets*

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Abstract

Recent research point to the possible existence of private information in foreign exchange markets. Dealers claim that customer orders are their most important source of private information, and that banks with a large customer base have a competitive advantage. In this paper we test hypotheses on effects of private information using observations on customer trades, and the identity of the counterparties the dealers trade with. We find that customer trades influence the trading decision. Neither customer trades nor counterparty identity affect pricing decisions. Dealers do not price discriminate between dealers, but they do price discriminate customers. Spreads to customers are wider than to other dealers.

Keywords: Foreign Exchange; Microstructure; Customer trading; Private information

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1 Introduction

Recently there has been several papers addressing the possibilty of private information in the foreign exchange market, e.g. Lyons (1995), Yao (1998a), and Bjønnes and Rime (2000). Dealers operating in the interbank foreign exchange market regard trading with customers of the bank to be their most important source of private information (Lyons, 1995). Hence, banks with access to a large customer pool are also expected to be better informed about exchange rate movements (see several recent surveys, Cheung and Chinn (2000, 1999b,a), Cheung et al. (2000), and Cheung and Wong (2000)).

We empirically study two related questions concerning the importance of private information in the foreign exchange market: First, how customer trades (private information) influence trading strategy. Second, how (nonanonymous) counterparties perceived to be well informed affect affect trading strategies.

With trading strategies we here mean the dealer's pricing decisions (i.e. market making), and the placement of orders. It is important to analyze both, since in a multiple dealership market like the interbank foreign exchange market, a dealer will typically function in both roles. He may place orders at other dealers quotes, and other dealers may contact him and request quotes.

Hence, private information is approached from four viewpoints. The studies mentioned above only consider pricing decisions, and only the case where only the counterpart has access to private information. Moreover, they do not distinguish between different counterparts.

We are able to approach the issue of private information from these four viewpoints due to a unique data set with complete transactions for two dealers during one week in March 1998. The dealers both give quotes and trade at other dealers' quotes. Furthermore, we have all trades with customers, their alleged private information, and coded information on all interbank counterparts in direct trading.

Since customer orders are claimed to be the most important source of private information in foreign exchange, studying the effect of customer trades is to study the behavior of an informed dealer. Most models of dealer behavior only consider that the initiating dealer has private information, not the Market Maker (e.g. Kyle, 1985). However, since dealers in foreign exchange functions as both market makers and dealers, this makes an artificial asymmetry between the market making decision and the order placement decision. Most interbank dealers receive some private signals from customer order flows. A dealer cannot choose when this information arrives. Therefore, a Market Maker may have private information while he gives quotes. Furthermore, a dealer with private information does not wait for other dealers to initiate trades. If the information is sufficiently precise, he acts upon it and places his own orders with other dealers.

In the theoretical literature it is common to assume that the Market Maker only knows the distribution of informed dealers, not whether he is actually trading with an informed dealer. In the foreign exchange market, dealers see the identity of their counterparty in direct trades, and through experience get a noisy signal on whether it is an informed dealer or not. Through interviews with the dealers, we have observations on whether the dealers view their counterparties in direct interbank trading to be worse, equally or better informed than themselves. This allows us to directly test how dealers protect themselves against the possibility of trading with better informed dealers. To the best of our knowledge, these two questions have not previously been addressed in the literature.

We find that customer trades do not influence the dealers interbank pricing decisions. The dealers do not utilize their private information to price different from the rest of the market. This may be due to a strategy of not revealing the private information, since there is high price transparency in the interbank foreign exchange market. The dealers do however price discriminate against the customers. We find that the spreads quoted to customers are significantly wider than interbank spreads. The estimated baseline spread is 3 and 4 times wider for customers in DEM/USD and NOK/DEM trades, respectively.

Customer trades influence the order-placing strategy, so that a customer purchase leads to subsequent purchases by the dealer in excess of inventory control. Instead of using the private information in the pricing strategy, which is very transparent, they use their private information in their order placement strategy, which is much less transparent.

The identity of counterparties and their perceived level of informativeness do not influence pricing strategy. This is somewhat surprising given the weight in the literature on protection against better informed dealers. Spreads do widen with the size of the trade, but whether the counterparty is perceived to be well informed or not does not matter for spreads. Consequently, the dealers do not price discriminate in interbank trading. This is probably due to the high degree of transparency with respect to prices. An informed dealer that feels he is being price discriminated, only turns to another dealer and obtains a better spread. That spreads do not react to counterparty identity is however in line with surveys showing that spreads are determined by norms.

It has been suggested that trading with better informed counterparties would lead a dealer to revise his view of the market. Trading with informed counterparties do not influence the order-placing strategy. The dealers do not take the same positions as their informed counterparties.

The rest of the paper is organized as follows: In the next section (2) we describe the foreign exchange market in relation to customer trading and private information, drawing on some recent surveys. In section 3 we adapt the Madhavan and Smidt (1991) model to incorporate customer trading and different precision of information. Section 4 presents the data set that we use for our empirical analysis (section 5). We conclude in section 6.

2 Customer orders and private information in foreign exchange

We first describe the role of customer trades in foreign exchange markets in more detail (section 2.1). In section 2.2, we then describe the trading environment of dealers in the interbank foreign exchange market. The trading environment has implications both for identification of counterpart, and for trading strategy.

2.1 The importance of customer orders

A customer is an industrial corporation, non-dealer financial institution or a professional speculator that demands the dealer's services in the foreign exchange market. Banks functions as intermediaries for customers, and executes the customers' orders in the interbank market.

The spot market has about 40% of the average daily total turnover of USD 1.4 trillion. Customer trading account for only 20–30% of total spot trading, while the interbank market account for the remaining 70–80% (see BIS, 1993, 1996, 1998). In this paper we study a DEM/USD Market Maker and a NOK/DEM Market Maker operating in the Norwegian currency market. The dealers have 4% and 31% of their trading with customers respectively, and both perceive customer trades as very important.[1]

The importance that dealers attach to customer trading may seem at odds with customer orders' low share of total volume. However, the trading of customers is the underlying source of demand for currency. The "hot-potato-trading" story (see Lyons, 1997) may shed some light on why interbank trading is so much larger than customer trading is. Imagine that a dealer initially is holding his preferred positions when a large customer order arrives at his desk. Since customer orders usually are larger than ordinary interbank trades, the dealer split the order in several smaller orders which are passed on to other interbank dealers. These dealers do not wants this position either, and the initial customer trade is passed on further to other dealers as a "hot potato." The resulting interbank trading volume ends up being much larger than the initial customer order.

There are two reasons for why customer trading is important in the foreign exchange market. First, dealers can quote a wider spread on these trades than what is normal in interbank trading (Yao, 1998b). Yao studies a large New York based dealer with 13% customer order flow. Out of total profits, 75.9% came from trading with customers. Dealers are able to quote wider spreads to customers since customers do not have access to the more liquid interbank market where spreads are tighter. Furthermore, the customers are in

[1] In case of the NOK/DEM Market Maker, this only reflects NOK/DEM-trading. This dealer has substantial customer trading in NOK/USD as well.

a bad bargaining position vs. the banks due to the low transparency of foreign exchange markets. Customers can not see any of the interbank trading flow or the prices that dealers quote to each other.[2]

Second, customer order flows are the most important source of private information in foreign exchange markets. In what sense are customer trades informative? Order flow may be seen as expectations backed by money: the "voting" of the market (Lyons, 2000). By observing customer order flow, the dealers obtain a signal of the customers' expectations. Customer order flow may be informative about fundamental values through three channels. These three may work simultaneously: (*i*) Customers may have private information (see different signals) on fundamental value; (*ii*) customers may use different "models" to evaluate new information; or (*iii*) customers may use different probability distributions to evaluate new information.

All three may be a valid description of the foreign exchange market. Some customers may have better capabilities for collecting, analyzing, and interpreting information. Furthermore, new public information of a given kind may be interpreted differently by the customer sector at different points in time. Customer trading may then give a dealer information on how the customer sector evaluate a new piece of public information, or in the words of the dealers — information on the "market sentiment".

A empirical result supporting the importance of customer trades is found in Rime (2000). Rime study how trading by different sectors in the Norwegian market affect weekly exchange rate changes. He finds that the strongest effect comes from the trading of customers, and that this effect is permanent. The interviews with London based dealers reported in Heere (1999) confirm that large customers' views on the market is valuable information.

However, even if we take the extreme view that customer trades are completely unrelated to any fundamental value of the currency, these trades may still be useful for the dealer in forecasting prices. In Cao and Lyons (1998), dealers speculate based on customer flow that is uncorrelated with the fundamentals by using the customer order to predict whether there will be a buyer-pressure or seller-pressure in interbank trading later on. A buyer-pressure, in this model, will push prices up. In the model demand is not perfectly elastic due to risk aversion. The risk aversion, together with an assumption that the customer trade is sufficiently large and not observed by the rest of the market, drives the result.

Table 1 states sources of competitive advantage of the large players in the foreign exchange market, as reported in a series of surveys by Cheung and collaborators (Cheung

[2]Although customers have less information about the intra day movements of the interbank market, compared to the dealers, their trading may still be regarded as informative if they either have better information about longer-term movements, or helps the dealers in predicting intra day movements in the interbank market. See below.

Table 1: The most important sources for competitive advantage for the large players in the Foreign exchange market? (In %)

	UK	US	Hong Kong	Tokyo	Singapore
Large customer base	33	33	27	27	30
Better information	22	23	22	21	22
Can deal in large volumes	16	15	17	15	12
Can influence exchange rates	14	9	12	12	9
Access to global trading network	4	5	8	9	11

Source: Cheung and Wong (2000); Cheung and Chinn (1999b); Cheung et al. (2000). The table reports the answers that dealers gave to the question "Select the 3 (or fewer) most important sources of competitive advantage for the large players in the FX market?" Table shows percentages of all answers within each country

and Wong, 2000; Cheung and Chinn, 1999b; Cheung, Chinn, and Marsh, 2000). At the top, we find "Large customer base." However, also the second and third most important advantage may be related to customer trading. Since customer trades are regarded as private information, banks with larger customer base may also be better informed. Furthermore, since customer orders typically are larger than the ordinary inter-bank trade, it also enables them to trade more and in larger volumes. In fact, many dealers base their trading strategy on customer orders. According to Cheung et al.'s surveys of dealers, between 22% (US) and 37% (UK) base their trading on customer orders. Trading based on customer orders is equally popular as using technical or fundamental analysis.

2.2 Trading channels in the interbank market

When dealers turn to the interbank market, they have four trading options available, as shown in figure 1. Dealers can trade directly with another dealer through telephone or the bilateral electronic system Reuters D2000-1, or indirectly with a broker, either a traditional voice-broker or the electronic brokers Reuters D2000-2 and EBS (rows). In each trade the dealer can either set a price (quote) at which other dealers can trade (incoming trade), or the dealer can trade at other dealers' quotes (outgoing trade) (columns). The advantage with incoming trades is that the (quoting) dealer trade at the most favorable side of the bid-ask spread. In case the initiating dealer wants to buy, the quoting dealer sells at the ask, the highest price. The advantage with outgoing trades is more control with time of execution.

Figure 1: Trading options

	Incoming (Nonaggressor)	Outgoing (Aggressor)
Direct	Trade at own quotes	Trade at other dealers' quotes
Indirect	Dealer give quote(s) to a broker	Dealer trade at quotes given by a broker

The direct trading channel D2000-1 allows a dealer to contact a specific dealer, at the cost of identifying oneself and revealing information to the other dealer. However, for larger trades this system may be more suitable than the electronic brokers since a dealer only contacts other dealers that he knows are willing to trade these volumes at reasonable prices. Market Makers are expected to give competitive two-way quotes to another dealer at request.

A typical D2000-1 conversation starts by a dealer contacting another dealer. The contacting dealer usually requests for bid and ask quotes for a certain amount, for instance USD one million.[3] When seeing the quotes, the contacting dealer states whether he wants to buy or sell. In some cases, he may ask for better quotes, or end the conversation without trading. However, most conversations result in a trade. All D2000-1 transactions in the data set take place at the quoted bid or ask.

In general, the three most important aspects of any kind of foreign exchange broker, traditional "voice" brokers or electronic brokers, are that (i) the initiating part stay anonymous, (ii) dealers can enter one-way prices (bid or ask) without being worried about revealing their position, and (iii) the quoting party chooses when to place a quote, opposed to direct trading. The execution is still decided by the "hitting" dealer, of course. In case of electronic brokers, we could add higher speed of execution, compared to voice brokers, to the list.

An important feature of the foreign exchange market, distinguishing it from stock markets, is the decentralized multiple dealership structure, and the low transparency of trading. Transparency has implications for how fast new information dissipates in the market. Customer trades are only observed by the dealer, so customer trades are private information. All direct trades are unknown except to the two parties in a trade. In indirect trades with voice-brokers, a small subset of the trades is communicated to the market via intercoms. On electronic broker systems, all trades are shown in a "trade window."[4]

Traditionally, direct trading through D2000-1 and indirect trading through voice-brokers have been the most popular trading channels. Lately the new electronic brokers D2000-2 and EBS have increased their shares of the market, while the share of voice-brokers has gone down.

3 A theoretical framework

There exist no coherent model to analyze the effects of customer trades and counterparty identity together. In stead, we will use the Madhavan and Smidt (1991) model as a framework. In section 3.1 we address the effects of customer trades on pricing strategy (section

[3]In some few cases, the contacting dealer also tells whether he wants to buy or sell.

[4]To be precise, they observe the time, the price, and the direction of all trades. Most trades on electronic brokers are between 1 and 5 million.

3.1.1) and order placement strategy (section 3.1.2). Then, in section 3.2, we address the effects of counterparty identity. First however, we introduce the framework that is common to the analysis of both problems.

To be a Market Maker a dealer must be willing to give both sell and buy quotes to any other dealer interested in trading a particular currency pair. A Market Maker has two particular considerations: First, he utilizes all available information to quote a reasonable price. This is his information aggregation problem, which in the context of asymmetric information is studied by Kyle (1985) and Glosten and Milgrom (1985). Second, since a Market Makers' inventory rarely will be equal to his desired due to the obligation to accept any trade on his quoted price, he have to manage his inventory so that he does not carry excessive risk. This is his inventory control problem (see Ho and Stoll, 1981).

To handle the information problem the Market Maker will try to learn the motives for trade from an initiative from another dealer. If the contacting dealer buys, the Market Maker interprets this as a signal that the true value can be (if informed) higher than the current price.

The Market Maker has four options available for inventory control. He can trade at other dealers' quotes (outgoing trades), or by giving quotes so that he induces a trade in his preferred direction (incoming trades). Both alternatives can be used in either a direct trade, e.g. through D2000-1, or in indirect trades, e.g. through electronic brokers.

The information and inventory problem have not yet been satisfactory integrated in one model. We use the model developed in Madhavan and Smidt (1991) as a framework, where the two effects are incorporated through postulated equations. We extend the model so that both dealers observe private signals, and address how differences in precision of these signals may influence pricing decisions.

Consider a pure exchange economy with a risk free and a risky asset. The risky asset represents currency. There are n dealers, and T periods (the whole trading day). The basic model focus on the pricing decision of a representative Market Maker, dealer i, so each period is characterized by one incoming order at dealer i's quote. Incoming means that the bilateral contact was initiated by dealer i's counterparty, denoted j (aggressor). At time T the true value of the currency, $\tilde{V}$, is revealed. The value in period 0 is known and equal to r_0. After trading in period t, there arrives some new public information $r_t \sim IID\left(0, \sigma_r^2\right)$ on the increment to currency value. Private information is short-lived in the sense that when r_t arrives at time t agents know that the true value is described as $V_t = \sum_{\iota=0}^{t} r_\iota$. In other words, private information is a signal on r_t.

Information and inventory effects are incorporated through two postulated behavioral equations

$$Q_{jt} = \theta\left(V_{t-1} + \mu_{jt} - P_{it}\right) + X_{jt}, \tag{1}$$

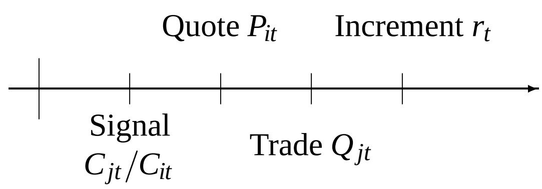
$$P_{it} = V_{t-1} + \mu_{it} - \alpha\left(I_{it} - I_i^*\right) + \gamma D_t, \tag{2}$$

where $\mu_{\ell t}$ $(\ell = i, j)$ are the dealers' conditional expectation of this period's increment, so $V_{t-1} + \mu_{\ell t}$ is the conditional expectation of V_t. Dealer j decides on his demand Q_{jt} conditional on the quoted price P_{it}, while the Market Maker, dealer i, decides on a price P_{it}.

The demand of the contacting dealer j, (1), is optimal when dealers maximize exponential utility over end-of-period wealth, added a stochastic element X_{jt} for inventory shocks which is unobservable for dealer i. The coefficient θ is equal to the inverse of the absolute risk aversion parameter and the variance of dealer j's conditional expectation. The inventory adjustment trading X_{jt} is assumed to be uncorrelated with r_t. If dealer j's conditional expectation of V_t is above (below) dealer i's price P_{it}, he will tend to buy (sell) dollars. As a convention, Q_{jt} is positive for sales of dealer i to dealer j and negative for purchases. Since X_{jt} is only known to trader j, Q_{jt} will only provide a noisy signal to dealer i of dealer j's information on V_t.

Equation (2) is typical for inventory models, where price P_{it} is linearly related to the dealer's current inventory (I_{it}). I_i^* is i's desired inventory position, and α (> 0) measures the inventory response effect. The inventory effect is negative because the dealer may want to "shade" (reduce) his price to induce a sale if the inventory is above the preferred level. D_t is a direction-dummy that takes the value 1 if it is a sale and -1 if it is a buy.[5] Since the quoted spread is expected to widen with quantity to protect against adverse selection, captured by the conditional expectation, we can think of γD_t as half of the spread for quantities close to zero. The price is set such that it is ex post regret-free, in the sense of Glosten and Milgrom (1985), after observing the trade Q_{jt}.

Figure 2: Information structure within period t



At the beginning of each period all information is public. Before trading in the period both dealers observe a private signal through a customer trade. Then dealer j "ask" dealer i for a quote P_{it}. The trade Q_{jt} is then realized. In the end of the period all information is made public, hence private information is only short-lived.

[5] Buy and sell are from the perspective of the Market Maker, that is, the Market Maker sells at the high price (ask), and buys at the low price (bid).

Figure 2 summarizes the information structure, as seen from the perspective of the Market Maker dealer i. Without any new information, the dealers' expectation of V_t equals V_{t-1}. At the beginning of each period t, the dealers receive a customer trade $C_{\ell t}$ ($\ell = i, j$) which is their private signal of r_t. This signal is given by

$$\tilde{C}_{\ell t} = r_t + \tilde{\omega}_{\ell t}, \tag{3}$$

where the noise term, $\tilde{\omega}_{\ell t}$, is independently normally distributed around zero with variance $\sigma^2_{\omega \ell}$.For dealer i, the quantity actually traded with dealer j, Q_{jt}, gives dealer i a signal of dealer j's private information C_{jt}. Similarly, for dealer j the price he receives may give him a signal of C_{it}.[6] We derive the price-schedule by inserting for the expectations in (2) and (1).

To address the two issues at hand, Customer trading and Counterparty informativeness, we will consider two different formulations for the basis of dealer i's formation of expectations: The first is a simple extension of the standard Madhavan-Smidt framework by including customer trading in the posterior expectation as a private signal. In the second, we let the counterparty to trade matter in the sense that counterparts have different precision in their private signals and market makers consider this when giving quotes. The first one will be used to discuss the importance of customer trading as part of the dealers' information set, while in the other we address the importance of counterpart identity.

Since the Market Maker receives a private signal, and gives quotes based on his conditional expectation, the contacting dealer might use the quoted price to learn about the Market Maker's private information. This was the argument in Lyons (1995) for why the dealer did not shade prices at the end of the day, namely that initiating dealer might learn from the price. Therefore, in general, when both dealers have private information, both dealers may use the action of their counterparty to learn about their private signal.

We will however not consider this problem here. Our main reason is to simplify the discussion. We also believe that the present framework is not very useful in this respect because it is a postulated model, not the result of full optimization. The model therefore does not allow the strategic consideration that would be natural to model if both dealers learn from each other. The simplification may be valid if the Market Maker (myopically) does not take into account that the contacting dealer may learn about the Market Maker's private information through his pricing behavior. Alternatively, one may take the view that the initiating dealer, aware of the informativeness of the dealer he contacts, already has conditioned on the possible signal from alternative quotes. This is more in line with rational expectations, and there is nothing that the Market Maker can do to influence this.

[6]We do not pursue the learning problem of dealer j any further. See below.

3.1 Customer trading as part of dealers' information set

We let the customer trade of dealer i enter his conditional expectation as a private signal, and model the implication for the two parts of his trading strategy: Pricing and order placement. In the next section, we extend the Madhavan and Smidt framework described above, so that the Market Maker uses the customer trade to update his conditional expectation. In other words, we derive a pricing strategy were both dealers may have private information. Next, in section 3.1.2, we show how private information influences the order placement strategy, using an analog to equation (1).

3.1.1 Customer trading and pricing strategy

The modelling implication of a private signal to dealer i, when dealer i does not take account of dealer j's possible learning from dealer i's action, is that dealer i will receive two private signals. These signals will be the trade with the customer, and the trade with dealer j, which is a signal on dealer j's private signal. Dealer j, seen from dealer i's perspective, only observes his own customer trade as private information. Of course, the demand of dealer j is still described by equation (1), so he conditions on the price in his demand. To simplify we abstract from different precision of private signals, which is considered in section 3.2.

After observing the customer trade C_{jt}, dealer j's posterior (μ_{jt}) can be expressed as

$$\mu_{jt} = (1-\lambda)C_{jt} \tag{4}$$

where $\lambda = \sigma_\omega^2/(\sigma_r^2+\sigma_\omega^2)$. Similarly, dealer i will have the following expectation after observing his customer trade:

$$\mu_{it}' = (1-\lambda)C_{it}, \tag{5}$$

The weight on private signals $C_{\ell t}$ is the same for the two dealers since the signals have the same precision. Upon observing Q_{jt} dealer i extracts as much information about C_{jt} as possible, so to include in his expectation for his quote decision. More specifically, dealer i forms the sufficient statistic Z_{jt} given by

$$Z_{jt} = \frac{Q_{jt}/\theta + P_{it} - V_{t-1}}{1-\lambda} \equiv C_{jt} + \frac{1}{\theta(1-\lambda)}X_{jt}. \tag{6}$$

Equations (1) and (4) are used to derive the second equality. Z_{jt} is normally distributed with mean V_t and variance σ_{Zj}^2 (equal to the variance of C_{jt} and X_{jt}). Furthermore, Z_{jt} is statistically independent of V_{t-1}. Dealer i's posterior belief (μ_{it}) is a weighted average of μ_{it}' and Z_{jt},

$$\mu_{it} = \kappa\mu_{it}' + (1-\kappa)\,Z_{jt}, \tag{7}$$

where $\kappa = \sigma^2_{Zj}/(\sigma^2_{\mu'} + \sigma^2_{Zj})$. Using the first equality in (6), we see that dealer i's posterior belief can be expressed as a function of Q_{jt},

$$\mu_{it} = \kappa(1-\lambda)C_{it} + (1-\phi)\left(\frac{Q_{jt}}{\theta} + P_{it} - V_{t-1}\right), \tag{8}$$

where $\phi = (\kappa - \lambda)/(1-\lambda) \in (0,1)$ since $\kappa > \lambda$.

Inserting (8) into (2) gives

$$P_{it} = V_{t-1} + \kappa(1-\lambda)C_{it} + (1-\phi)\left(\frac{Q_{jt}}{\theta} + P_{it} - V_{t-1}\right) - \alpha(I_{it} - I_i^*) + \gamma D_t.$$

Collecting all terms containing P_{it} on the left hand side gives,

$$P_{it} = V_{t-1} + \frac{\kappa(1-\lambda)}{\phi}C_{it} + \frac{1-\phi}{\phi\theta}Q_{jt} - \frac{\alpha}{\phi}(I_{it} - I_i^*) + \frac{\gamma}{\phi}D_t. \tag{9}$$

To test this equation, we need to replace V_{t-1}, which is unobservable to the econometrician. We replace V_{t-1} with last periods conditional expectation of currency value, and add an expectational error term ε_{it} that represents public information that arrives between trades. Hence,

$$V_{t-1} = V_{t-2} + \mu_{it-1} + \varepsilon_{it} = P_{it-1} + \alpha(I_{it-1} - I_i^*) - \gamma D_{t-1} + \varepsilon_{it}. \tag{10}$$

Substituting this expression for V_{t-1} into (9), gives

$$\begin{aligned}\Delta P_{it} = \left(\frac{\alpha}{\phi} - \alpha\right)I_i^* + \frac{\kappa(1-\lambda)}{\phi}C_{it} + \left(\frac{1-\phi}{\phi\theta}\right)Q_{jt} \\ - \left(\frac{\alpha}{\phi}\right)I_{it} + \alpha I_{it-1} + \left(\frac{\gamma}{\phi}\right)D_t - \gamma D_{t-1} + \varepsilon_{it}.\end{aligned} \tag{11}$$

The model we use to test for effects from customer trades on pricing strategy, is then given by

$$\Delta P_{it} = \beta_0 + f(C_{it};\boldsymbol{\beta}_C) + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it}. \tag{12}$$

The coefficients β_1 and β_3 measure the information effect and inventory effect, respectively, while β_4 measure the transaction costs for small quantities. The model predicts that $\{\beta_1,\beta_3,\beta_4\} > 0, \{\beta_2,\beta_5\} < 0, \mid \beta_2 \mid > \beta_3, \beta_4 > \mid \beta_5 \mid$. The latter inequalities derive from the fact that $0 < \phi < 1$. We let the function $f(C_{it};\boldsymbol{\beta}_C)$, with coefficient vector $\boldsymbol{\beta}_C$, capture the effect from customer trades, since we in the empirical implementation do not only considered one-period effects. In the model of Madhavan and Smidt and Lyons, this part falls out since they do not allow for private signals to the market maker. The model predicts that the effect from customer trades will be positive for customer purchases and negative for customer sales.

3.1.2 Customer trading and order placement strategy

If a dealer have good information due to customer trades, it will be natural to utilize this information in his own position taking. After receiving a customer trade, the dealer may choose to place his own orders with other dealers, rather than to wait for others to contact him. This is important in foreign exchange markets, where the multiple dealership structure allows the dealers to trade actively in addition to function as market makers. If private information may live longer than only one period (trade), the dealer may use the information from the customer trade in subsequent order placements as well.

We use ideas from Lyons (1997) to incorporate customer trading's effect on order placement strategy. A trade τ_{it} can be decompose into three parts,

$$\tau_{it} = I^*_{it} - I_{it-1} + E\left[\tau'_{it}|\Omega_{it}\right]. \tag{13}$$

The dealer wants to have an inventory of I^*_{it}, and prior to the period t trade he already have I_{it-1} of this preferred inventory. In addition he buys a hedge against the expected inventory shocks that the dealer may receive from other dealers, $E\left[\tau'_{it}|\Omega_{it}\right]$. We will assume that this expectation is zero (see Lyons, 1997). This trading strategy can be used to analyze informed demand through the preferred inventory I^*_{it}.

Following Lyons (1997), the preferred inventory can be determined from an optimization of a negative exponential utility over final wealth. It is well known from Grossman and Stiglitz (1980) that this gives us

$$I^*_{it} = \theta\left(V_{t-1} + \mu_{it} - P_t\right), \tag{14}$$

where $V_{t-1} + \mu_{it}$ represent the conditional expectation of currency value (μ_{it} is the expectation for increment in currency value), and θ equals the inverse of the coefficient of risk aversion and the variance of the conditional expectation.

Similar to the treatment in section 3.1.1 there is a customer trade C_{it} which gives dealer i a private signal on this periods increment to currency value, r_t. Conditionally on observing the customer trade, the expected increment μ_{it} is

$$\mu_{it} = (1-\lambda)\, C_{it}, \tag{15}$$

where $\lambda = \sigma^2_\omega / \left(\sigma^2_\omega + \sigma^2_r\right)$ and σ^2_ω and σ^2_r as before. We proxy for the unobservable currency value from previous trade V_{t-1} in a very simple way: We simply subtract the half-spread from the prices in last trade, $P_{t-1} - \gamma D_{t-1}$, and add a noise term for new information that may have arrived in the meantime. The conditional expectation of V_t can the be expressed as

$$V_{t-1} + \mu_{it} = P_{t-1} - \gamma D_{t-1} + (1-\lambda) C_{it} + \varepsilon_{it}.$$

When we insert this into (14), let the more general $f(C_{it}; \boldsymbol{\beta}_C)$ represent $(1-\lambda) C_{it}$, and insert for I^*_{it} into (13), the testable equation becomes

$$\tau_{it} = \beta_0 + f(C_{it}; \boldsymbol{\beta}_C) + \beta_2 P_{t-1} + \beta_3 D_{t-1} + \beta_4 P_t + \beta_5 I_{t-1} + \varepsilon_{it} \tag{16}$$

where $f(C_{it}; \boldsymbol{\beta}_C) + \beta_2 P_{t-1} + \beta_3 D_{t-1}$ represents $V_{-1} + \mu_{it}$. Notice that the customer trade also will be included in I_{t-1} so that the effect from C_{it} is net of inventory control after a customer trade. The expected sign on the coefficients are $\beta_2 > 0$, $(\beta_3, \beta_4, \beta_5) < 0$, and positive effects from customer trades. We use the function $f(C_{it}; \boldsymbol{\beta}_C)$ to represent the information from a customer trade since we do not want to be constrained to a linear static implementation as $(1-\lambda) C_{it}$.

3.2 Different precision of dealers' private signals

In the model above, we assumed that the precision of the private signal is the same for all dealers. However, larger banks see more customer order flow. Thus, the assumption of equal precision may not hold. Since dealers know the identity of the counterparty in a bilateral trade, they may also have some knowledge of their precision. In broker trades, the counterparty is anonymous when trading, so counterparty identity is only relevant for direct bilateral trading through the Reuters D2000-1 system.

In this section we will only consider how different precision of dealers' private signals influences the pricing strategy in (9). The effect of a trade with an informed counterparty on subsequent order placement strategy is completely analogous to the case described in section 2.1, we will therefore not go further into that here. It is enough to see that any trade with an initiator is a signal of his private information, and can be treated similar to a signal through own customer orders. If information is long-lived (more than one trade), it can be useful for subsequent order placement. The only difference from the order placement strategy derived in section 2.1 is that the weight the dealer gives information from a direct trade, will be higher for trades with informed counterparties.

To address the issue of different counterparties we allow for different precision of their private signal, so that their conditional expectation of period increment to currency value after observing the customer trade is

$$\mu_{jt} = \left(1 - \lambda_j\right) C_{jt}, \tag{17}$$
$$\mu'_{it} = (1 - \lambda_i)\, C_{it} \tag{18}$$

where $\lambda_\ell = \sigma^2_{\omega\ell} / \left(\sigma^2_r + \sigma^2_{\omega\ell}\right)$, $\ell = i, j$. We continue to abstract from the contacting dealer's learning problem, so it is only dealer i that learn from the trade. Dealer j does condition his demand on the quoted price, but does not update his expectation after observing the quote. The change in price will be as in (11), except that the weight on new information in the conditional expectation μ_{it} expressed in (8) now have a subscript j, where $\phi_j = \left(\kappa - \lambda_j\right) / \left(1 - \lambda_j\right)$. Notice that λ_j depends on $\sigma^2_{\omega j}$, while κ depends on both $\sigma^2_{\omega i}$ and $\sigma^2_{\omega j}$.

We are particularly interested in how the coefficient on the trade Q_{jt} depends on the precision of the private information. All coefficients to present period variables are inversely related ϕ_j, while the coefficient on the trade Q_{jt} itself, cf. equation (9), now becomes

$$\frac{1}{\theta}\frac{1-\phi_j}{\phi_j} = \frac{1}{\theta}\frac{1-\kappa}{\kappa - \lambda_j}.$$

The effect of $\left(1 - \phi_j\right) / \theta\phi_j$ of a change in $\sigma^2_{\omega j}$ is

$$\frac{\partial \left[\left(1-\phi_j\right)/\theta\phi_j\right]}{\partial \sigma^2_{\omega j}} = \frac{\partial (1/\theta)}{\partial \sigma^2_{\omega j}}\frac{1-\phi_j}{\phi_j} + \frac{1}{\theta}\frac{\partial \left[\left(1-\phi_j\right)/\phi_j\right]}{\partial \sigma^2_{\omega j}}. \tag{19}$$

There is no unambiguous result for the effect of $\sigma^2_{\omega j}$ on this coefficient. In the appendix we argue that for reasonable values on the variances, the second derivative term in the expression above, $\partial \left[\left(1-\phi_j\right)/\phi_j\right] / \partial \sigma^2_{\omega j}$, is negative. In other words, $\left(1-\phi_j\right)/\phi_j$ will increase as the counterparty gets better informed (lower $\sigma^2_{\omega j}$). A buy order from a well informed counterparty will receive a larger weight in the updating of expectations, and lead to a larger price increase (for a given θ, see below) to protect against private information. This is also the most intuitive case.

The parameter θ is the parameter in the demand function of the contacting dealer,

$$Q_{jt} = \theta \left(V_{t-1} + \mu_{jt} - P_{it}\right) + X_{jt}.$$

This parameter equals

$$\theta = \frac{1}{\rho \sigma^2_{\mu j}}, \tag{20}$$

where

$$\sigma^2_{\mu j} = \lambda_j^2 \sigma^2_r + \left(1 - \lambda_j\right)^2 \sigma^2_{\omega j} = \frac{\sigma^2_r \sigma^2_{\omega j}}{\sigma^2_r + \sigma^2_{\omega j}} \tag{21}$$

and ρ is the coefficient of risk aversion. When $\sigma^2_{\omega j}$ decreases there is a direct negative effect on the variance $\sigma^2_{\mu j}$ through lower $\sigma^2_{\omega j}$, an indirect positive effect through the weight $\left(1-\lambda_j\right)$ on the noisy signal C_{jt}, and an indirect negative effect through the weight λ_j on the prior information. It turns out that the two indirect effects cancel out, so when dealer j receives signals that are more precise the θ-parameter increases and he trades more aggressively. The expression is given by

$$\frac{\partial\left(1/\theta\right)}{\partial\sigma^2_{\omega j}} = \rho\left(1-\lambda_j\right)^2.$$

Since $\sigma^2_{\mu j}$ is concave in $\sigma^2_{\omega j}$, $1/\theta$ will also be concave in $\sigma^2_{\omega j}$. This implies that for a relatively well informed dealer (low $\sigma^2_{\mu j}$, and high θ), changes in $\sigma^2_{\omega j}$ will only lead to small changes in θ. Furthermore, since $\left(1-\lambda_j\right)$ is between zero and 1, and in cases where dealer i gives higher weight to his own information than to the signal from trading with dealer j $\left(\phi_j > 1-\phi_j\right)$, the first term in (19) will most likely be small and positive.

If the private information signal is more precise than the public information signal, which most likely will be the case for well informed dealers, then we can feel rather confident that (19) will be decreasing in $\sigma^2_{\omega j}$ since the second term in (19) is negative. This means that the Market Maker put more weight on a trade with a well informed dealer than on a trade with a uninformed.

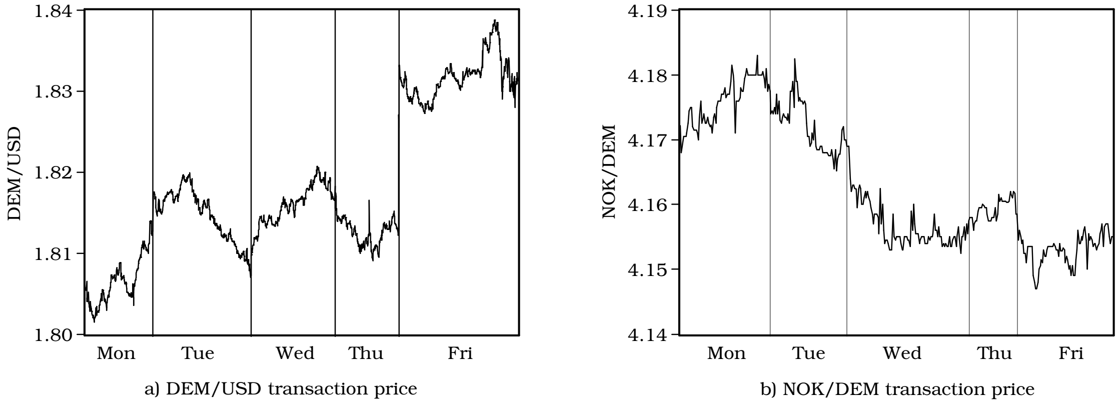
We cannot observe the precision of other dealers' signals, but we can observe how well informed the market makers perceive their counterparties are. We have interviewed the dealers about how well informed they perceive their counterparties in direct trading are compared to themselves, using a scale from 1 to 5, where 3 was equally well informed and 5 was superiorly informed. The results from the interviews are presented below.

4 Data

The data set employed in this study consists of the complete trading records for two spot dealers over a five-day period in March 1998. Both dealers work in the same Scandinavian commercial bank.[7] The dealers trade in different currency pairs and represent different trading styles. Both are experienced dealers. The first dealer is a medium-sized Market Maker in DEM/USD, while the other dealer is the largest Market Maker in NOK/DEM. The DEM/USD Market Maker has some customer order flow, while the NOK/DEM Market Maker has large customer order flows. In figure 3 transaction prices for the two exchange rates are presented, based on the trading of the whole Foreign Exchange Department in the bank.

[7]For the time being, both the period and the name of the bank will remain confidential. Both will be published in the final version of the paper.

Figure 3: Transaction prices



Transaction prices during the week. The source is all the spot transactions conducted electronically by the whole Foreign Exchange department of the bank, a total of 2108 DEM/USD transactions and 377 NOK/DEM transactions. The horizontal axis is in "transaction"-time. Vertical lines indicate end of day.

The data set consists of two components: (*i*) the dealers' record from an internal system used for controlling inventory positions and dealer profits, and (*ii*) information from electronic trading systems. Our data allows a direct test of inventory models and the investigation of trading strategies, since it contains the complete records of the dealers' trading actions.

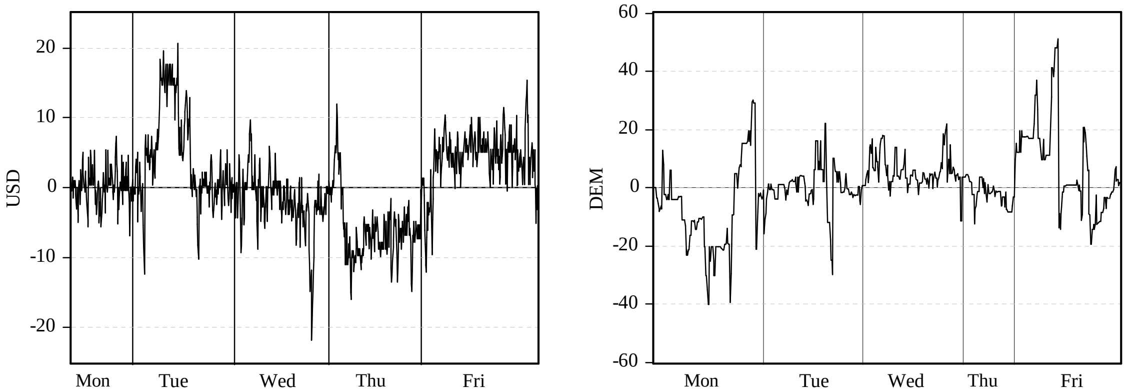
The first component of the data set consists of all trades, including trades with "voice" brokers, direct trades completed by telephone, internal trades and customer trades. Trades executed by electronic systems, the bilateral system Reuters D2000-1 and the two electronic brokers Reuters D2000-2, and EBS, are electronically entered into the record. Other trades must be entered manually. This part contains all exchanges, so we can track the dealers' inventory position.

The second part of the data set consists of all trades executed on the three electronic trading systems, Reuters Dealing 2000-1, Reuters Dealing 2000-2 and EBS. When we match the two parts, we obtain a data set with information on (*i*) the type of transaction (D2000-1, D2000-2, EBS, Voice broker, customer trade, or internal transfer); (*ii*) time of transaction; (*iii*) exact inventories in all currencies; (*iv*) transaction price; (*v*) whether the dealer bought or sold; and in the case of electronic transactions, we have information on (*vi*) initiator of the trade; and (*vii*) counterparty to the trade (see Bjønnes and Rime, 2000).

Figure 4 present inventory positions of the two dealers. The inventories follow similar patterns. The DEM/USD Market Maker trades only in DEM/USD. The maximum long position in dollar was USD 21 million, the maximum short dollar position USD 22 million. He ends each day with a position close to zero. The NOK/DEM Market Maker has a maximum long DEM position of DEM 51 million and a maximum short position of DEM

40 million.[8] He has significant trading in several currency crosses, most important is interbank trading in NOK/USD related to customer trading in NOK/USD. The NOK/DEM Market Maker ends his day with a slightly higher average absolute value of inventory, DEM 2.43 million against the DEM/USD Market Maker's USD 0.2 million.

Figure 4: Dealer inventory



a) DEM/USD Market Maker b) NOK/DEM Market Maker

The evolution of the inventory of the two dealers over the week. The horizontal axis is in "transaction"-time. Vertical lines indicate end of day. Panel *a* shows the USD-inventory of the DEM/USD Market Maker, while panel *b* shows the DEM-inventory of the NOK/DEM Market Maker.

Table 2 reports statistics on the dealers' daily activity during the sample period. The DEM/USD Market Maker has an average daily trading volume of USD 443 million, and average trade size of USD 2.2 million. The NOK/DEM Market Maker's average daily trading volume in NOK/DEM is DEM 292 million, with an average trade size of DEM 4.4 million. The total daily average NOK/DEM trading in the Norwegian market in April 1998 was USD 656 million (BIS, 1998).[9] Compared to this the NOK/DEM Market Maker has approximately 25% of the average daily total in the Norwegian market. The NOK/DEM Market Maker is certainly a major player in this market. From table 2 we can see that there is considerable daily variations in volume. For the NOK/DEM Market Maker the busiest day in NOK/DEM has as much as five times the volume compared with the slowest day.

Table 2 also presents numbers on customer trades. For the DEM/USD Market Maker customer trades account for only 4% of total trading. Customer trading is very important for the NOK/DEM Market Maker. About 31% of his trading in NOK/DEM are with customers. In addition, he has considerable customer trading in other currency crosses, as evident by the difference in the line with number of all customer trades and the number of customer trades in NOK/DEM only. Most important is trading in NOK/USD.

[8]We have deleted a internal trade at the end of Friday. This gave a spike up to 153 million DEM, making the graph difficult to read.

[9]This number reflects NOK/DEM trading with at least one Norwegian bank as counterpart. Taking account of some NOK/DEM trading executed outside of Norway the share will be somewhat lower.

Table 2: Trading volumes and number of trades

			Mon.	Tue.	Wed.	Thu.	Fri.	Total
DEM/USD Market Maker	All DEM/USD	Amount	302	491	464	395	562	2214
		Number	133	221	192	206	240	992
	Customer trades	Amount	23	27	18	2	15	86
		Number	6	5	6	3	5	25
NOK/DEM Market Maker	All NOK/DEM	Amount	373	304	325	79	377	1458
		Number	73	71	87	31	70	332
	Customer trades in NOK/DEM	Amount	142	74	79	10	138	449
		Number	16	16	20	2	11	66
	All customer trades	Number	43	30	32	16	41	163
	All trades	Number	135	123	127	66	134	585

Total absolute volume traded in the specified exchange rates each day, and the number of trades in the same exchange rates. The DEM/USD Market Maker trade only in DEM/USD, while the NOK/DEM Market Maker trade in several exchange rates where NOK/DEM is the most important one. "All trades" represent all trades executed by the dealer. The "amount" figures are in USD and DEM for the DEM/USD Market Maker and the NOK/DEM Market Maker, respectively.

The distribution of signed customer order flow, positive for a customer purchase and negative for a sale, is shown in table 3. The DEM/USD Market Maker has a few medium sized customer trades of USD 10 and 15 million, but most are small. Most of the customers bought DEM when trading with the NOK/DEM Market Maker. Although the two Market Makers have different access to customer trades, both regard their customer trades as important. We do not know whether this particular week was especially quiet when it comes to customer trades. The market as a whole however, was quiet this week.

Table 3: Customer trading

	DEM/USD Market Maker		NOK/DEM Market Maker	
$[-30,-25)$			1	(1.5%)
$[-20,-15)$			1	(1.5%)
$[-15,-10)$	2	(8%)		
$[-10,-5)$	2	(8%)	5	(7.6%)
$[-5,0)$	14	(56%)	9	(13.6%)
$[0,5)$	4	(16%)	27	(40.9%)
$[5,10)$	2	(8%)	12	(18.2%)
$[10,15)$	1	(4%)	7	(10.6%)
$[15,20)$			1	(1.5%)
$[20,25)$			1	(1.5%)
$[50,55)$			1	(1.5%)
$[65,70)$			1	(1.5%)
Total	25	(100%)	66	(100%)
Aver(Q_t^{CUS})	-1.53		2.99	
Aver(abs(Q_t^{CUS}))	3.43		6.80	

Distribution of the dealers customer transactions. Negative numbers indicate that the customers sold to the market maker, while positive indicate a customer purchase. The intervals measure USD-amounts for the DEM/USD Market Maker, and DEM-amounts for the NOK/DEM Market Maker.

The relevant trading channel for the testing of pricing behavior when the counterparty is known is direct trading through D2000-1. This is the traditional channel for market making, i.e. giving quotes on request. Both dealers use direct trading, but to a smaller extent than what they used to before the introduction of electronic brokers. They never use outgoing direct trades. This was regarded as expensive. The NOK/DEM Market Maker was also concerned by not signalling his inventory position. For the DEM/USD Market Maker direct trading account for 6% of total volume, while for the NOK/DEM Market Maker direct trading account for 23% of total volume (30% of interbank trading in case of the NOK/DEM Market Maker). Both dealers regard direct trading as an obligation following being a "Market Maker." They also see their presence on this system as a way to attract trades from other dealers. As we see below, they generally trade with counterparties that in their own views are less informed than themselves.

Since none of the Market Makers use direct trading for outgoing trades, the order placement strategies are related to the electronic brokers. The DEM/USD Market Maker primarily uses electronic broker systems. These account for 77% of his total volume. The NOK/DEM Market Maker also uses electronic broker systems, but only for 28% of total volume.[10]

To study the importance of counterparty identity in direct trading, without revealing the actual identity of the counterparty, we made a questionnaire to each of the most active spot dealers in the department. Each dealer was asked to give scores with respect to informativeness, from 1 to 5, to the banks they had been trading directly with during the week. A score of 3 indicated that the dealer expected the bank to be equally well informed as him, while 5 indicated superiorly informed and 1 were for those banks the dealer regarded as very badly informed compared to him.

Table 4: Dealer perceptions of counterparty's information

	DEM/USD Market Maker	NOK/DEM Market Maker	Dealer 2	Dealer 4	Dealer 5
(1) Inferiorly	12	26	1	36	
(2) Worse	3		7		3
(3) Equally	5	8	5	7	2
(4) Better			4		3
(5) Superiorly	4	5	4	13	1
Total	24	39	21	56	9
Average	2.2	1.9	3.1	2.2	3.2

The table reports the number of replies in each category in the questionnaire.

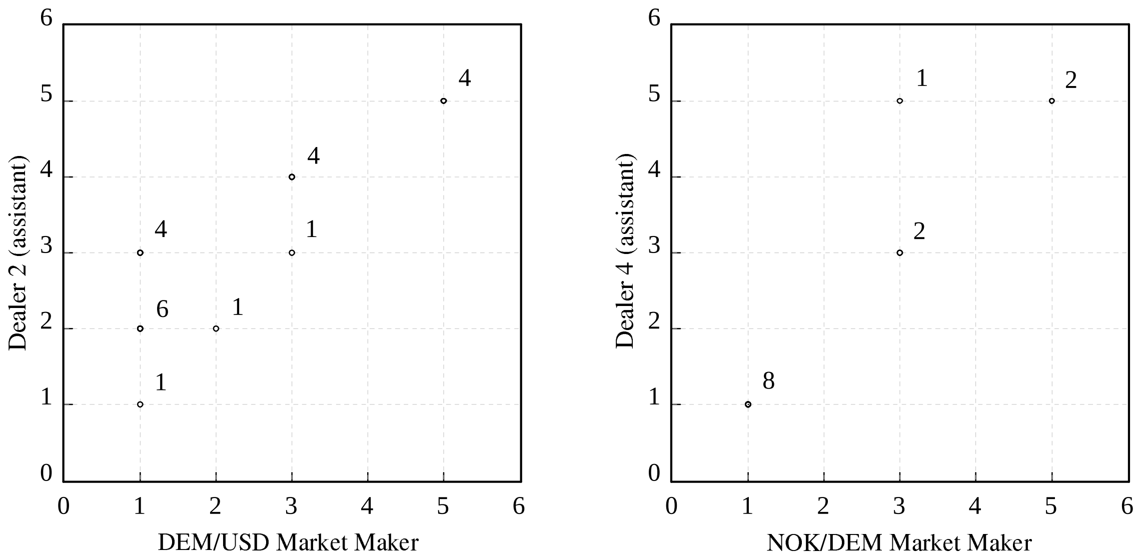
The results of the questionnaire are reported in table 4, where the two dealers in the present study are presented together the other dealers answering the questionnaire. The

[10] Both dealers also use traditional voice brokers. For the DEM/USD Market Maker voice-broker trades account for 11% of total volume, while for the NOK/DEM Market Maker the number is 8% (10% of interbank trades in case of the NOK/DEM Market Maker).

other dealers in the table are as follows: Dealer 2 and 4 are the same dealers as in Bjønnes and Rime (2000). Dealer 2 is a DEM/USD dealer working as assistant for the DEM/USD Market Maker, and Dealer 4 is a DEM/USD and SEK/DEM dealer that was also working as an assistant for the NOK/DEM Market Maker. Dealer 5 is a JPY-dealer that was not very active this particular week.

The DEM/USD Market Maker and the NOK/DEM Market Maker traded directly with 24 and 39 different banks respectively. We can see that they traded mainly with banks they regarded as worse informed than themselves. Figure 5 presents scatter plots of the cases where the Market Makers and their assistants, Dealer 2 and 4 respectively, traded with the same bank, and how they regarded the bank's informativeness. We can see that the assistants entries are either on or above the 45-degree line, showing that they were somewhat less confident than the Market Makers.

Figure 5: Bank counterparty informativeness



Scatter plot of how the dealers agree on counterparty informativeness. Each dot represent a bank that both dealers had traded with, and the position of the dot reflects how they regarded this bank. The number next to each dot gives the numbers of banks in each combination.

Table 5 confirms the picture in figure 5. The table shows the correlation between the dealers in the cases where they both had traded with the same bank. We see that they seem to agree to a large extent, which may be taken as a sign of reliability of the results. However, in some cases there are very few banks they share, as can be seen from the numbers in parenthesis.

Table 5: Correlation matrix of dealer perceptions

	DEM/USD Market Maker	NOK/DEM Market Maker	Dealer 2	Dealer 4	Dealer 5
DEM/USD Market Maker	1				
NOK/DEM Market Maker	(4)	1			
Dealer 2	0.90 (21)	(3)	1		
Dealer 4	0.92 (7)	0.95 (13)	0.94 (7)	1	
Dealer 5	0.94 (4)	1 (2)	1 (4)	(1)	1

Correlations between the dealers replies in cases where they have traded with the same bank. Numbers in parenthesis indicate the number of banks. In some cells it was not possible to calculate a correlation coefficient.

5 Results

In section 5.1 we test the importance of customer trades, and in section 5.2 test the importance of counterparty identity. In both cases we test the effect on both pricing strategy (sections 5.1.1 and 5.2.1), and order placement strategy (sections 5.1.2 and 5.2.2). In all regressions, except the ones testing for effects on the spread, we will use the event study method that is commonly applied in corporate finance (see Thompson, 1995). In short, in the corporate finance applications, event studies are used to measure the impact of new information on stock prices. In the present setting, we measure the impact of new information from customer trades and counterparty identity on the dealers trading strategy. Since dealers regard customer trades as private information, we use the event study methodology to study the effect of these trades as new information. We also regard a trade with particularly well informed banks as information events.

In an event study it is important to identify the event itself and define a period ("event window") where the event is allowed to have effect. In our case, the identification of the event is easy since we have an exact timing of the trades with both customers and informed counterparties. In most cases, we let the event window be the event itself and the two or three following trades. With a median intertransaction time for the DEM/USD and NOK/DEM Market Maker in incoming trades of 2.3 and 7.6 minutes, respectively, this should be sufficient to capture the potentially abnormal effect following the new information. We implement the events with dummies.

5.1 Customer trading

5.1.1 Customer trading and pricing strategy

In equation (12) we incorporate customer trades as private information to the Madhavan and Smidt model. The equation we test is the following,

$$\Delta P_{it} = \beta_0 + \sum_{\ell=0}^{3} \beta_{\ell 1}^{B} d_{\ell t} Q_{t-\ell}^{CUS} + \sum_{\ell=0}^{3} \beta_{\ell 2}^{S} d_{\ell t} Q_{t-\ell}^{CUS} + \beta_3 Q_{jt} + \beta_5 I_{it} + \beta_6 I_{it-1} + \beta_5 D_t + \beta_4 D_{t-1} + \varepsilon_t, \quad (22)$$

where the dummies $d_{\ell t}^{j}$, $j = \{B, S\}$, takes the value 1 in period ℓ after the customer trade (the event), and zero otherwise. We have implemented the effect from customer trades, the $f(C_{it}; \boldsymbol{\beta}_C)$-function in (12), as a linear function with three lags. The results for testing on the pricing strategy are shown in table 6.

The results for whether the dealers utilize their private information in pricing are somewhat ambiguous. Several of the coefficients are positive, as predicted, and significant. However, we also have cases with negative and significant coefficient. The effect on the change in the price is countered by a opposite sign in the next quote. This may be due to that using private information to give quotes different from the rest of the market may neither be a preferable strategy, due to high transparency of prices, nor a viable strategy for a Market Maker supposed to give competitive quotes.

We do not find any inventory effects through quote shading. This is line with previous results in Bjønnes and Rime (2000). The baseline spread variables D_t are significant and correctly signed.

When we add a specific baseline spread variable (direction-variable, D_t^{CUS}) for the customer trades to take account of the possibility that dealers give wider spreads to customers than in interbank trading, some of the effects disappear. However, the coefficient on the customer baseline spread is significantly larger than the interbank baseline spread. The baseline spread to customers is three to four times larger than the interbank baseline spread. This shows that customers receive wider spreads than interbank dealers do. Wider spreads to customers have been highlighted as one of the main benefits with customer order flow by Yao (1998b). One reason why it is possible to discriminate between customers and interbank dealers is that the customers do not have access to the electronic trading systems in the interbank market.

5.1.2 Customer trading and order placement strategy

To explore the order-placing strategy we take equation (16) as our starting point. We implement the effect from customer trades, i.e. the $f(C_{it}; \boldsymbol{\beta}_C)$ function in (16), as a lin-

Table 6: Customer trade as event in estimation of the pricing strategy ΔP_{it}

	DEM/USD Market Maker		NOK/DEM Market Maker	
Constant	0.147	0.246	1.274	1.066
	(0.49)	(0.82)	(1.11)	(0.95)
Customer purchase: $d^B_{0t}Q^{CUS}_t$ $(+)$	1.447	0.895	0.462	-0.770
	***(2.93)	*(1.79)	*(1.83)	(-1.46)
Customer purchase: $d^B_{1t}Q^{CUS}_{t-1}$ $(+)$	-0.242	0.792	-0.555	0.636
	*(-1.79)	**(2.10)	*(-1.90)	(0.99)
Customer purchase: $d^B_{2t}Q^{CUS}_{t-2}$ $(+)$	4.971	-4.991	-0.087	-0.058
	**(2.11)	**(-2.13)	(-0.36)	(-0.36)
Customer purchase: $d^B_{3t}Q^{CUS}_{t-3}$ $(+)$	1.219	1.375	-0.884	-0.233
	(1.27)	*(1.70)	(-1.32)	(-0.43)
Customer sale: $d^S_{0t}Q^{CUS}_t$ $(+)$	0.277	-0.274	0.962	-3.101
	**(2.21)	(-1.19)	(1.32)	***(-3.69)
Customer sale: $d^S_{1t}Q^{CUS}_{t-1}$ $(+)$	0.021	-0.352	-1.870	2.607
	(0.26)	(-1.44)	***(-3.72)	***(3.41)
Customer sale: $d^S_{2t}Q^{CUS}_{t-2}$ $(+)$	-0.380	-0.360	0.510	0.315
	*(-1.82)	*(-1.71)	(0.24)	(0.13)
Customer sale: $d^S_{3t}Q^{CUS}_{t-3}$ $(+)$	0.011	-0.051	0.872	-0.650
	(0.06)	(-0.40)	(0.63)	(-0.89)
Interbank trade Q_{jt} $(+)$	-0.058	-0.104	0.092	-0.018
	(-0.21)	(-0.39)	(0.25)	(-0.06)
Inventory I_{it} $(-)$	0.158	0.145	0.117	-0.201
	(1.19)	(1.07)	(0.58)	(-1.30)
Lagged inventory, I_{it-1} $(+)$	-0.143	-0.119	-0.252	0.079
	(-1.17)	(-0.96)	(-1.15)	(-0.60)
Direction D_t $(+)$	1.614	1.713	7.081	5.551
	***(3.18)	***(3.42)	***(4.52)	***(4.21)
Direction lagged D_{t-1} $(-)$	-0.567	-0.511	-5.506	-4.014
	*(-1.80)	(-1.62)	***(-3.06)	**(-2.53)
Customer direction D^{CUS}_t $(+)$		5.103		21.931
		**(2.34)		***(7.08)
Customer dir lagged D^{CUS}_{t-1} $(-)$		3.628		-24.717
		(1.44)		***(-5.68)
AR(1) $(-)$	-0.081	-0.078	-0.360	-0.290
	***(-3.46)	***(-3.23)	***(-4.57)	***(-2.99)
Adjusted R^2	0.20	0.22	0.18	0.43
Durbin-Watson stat	1.92	1.92	2.02	2.08

Estimation by GMM and Newey-West correction. t-values are in parenthesis, and ***, ** and * indicates significance at the 1%, 5% and 10%-level respectively. All coefficient except the AR-term are multiplied by 10^4. Number of included observations are 452 and 191 for the DEM/USD Market Maker and the NOK/DEM Market Maker, respectively. Overnight price changes are deleted.

ear function with three lags, so we allow the customer trade to have effect on the three following trades. The following equation is used to test customer trades effect on order placement strategy:

$$\tau_{it} = \beta_0 + \sum_{\ell=0}^{3} \beta_{\ell 1}^{B} d_{\ell t}^{B} Q_{t-\ell}^{CUS} + \sum_{\ell=0}^{3} \beta_{\ell 2}^{S} d_{\ell t}^{S} Q_{t-\ell}^{CUS} + \beta_3 P_{t-1} + \beta_4 D_{t-1} + \beta_5 P_t + \beta_6 I_{t-1} + \varepsilon_t \quad (23)$$

with event-dummies d inserted for the new information contained in customer trades. The $\beta_{\ell 1}^{B}$-coefficients measures the abnormal effect on trading strategy in trade ℓ after a customer purchase. The S-superscript indicates coefficients capturing the effect from a customer sale. Notice that the customer trade is captured in the lagged inventory, so inventory control related to the customer trade will therefore be picked up by this variable. Hence, the effect through the $\beta_{\ell 1}^{B}$ and $\beta_{\ell 2}^{S}$ coefficients from a customer trade may be interpreted as a speculative demand. We include both current and lagged price variables. Both are non-stationary, but a linear combination of the two is stationary. Replacing the two with the change in price, and thereby constraining the β_3 and β_5 coefficients to be equal, does not alter the results.

We are interested in how the customer trade influences the dealer's subsequent trading. Hence, in τ_{it} we include all deliberate purchases and sales on behalf of the dealer. This means that we include all outgoing trades (irrespective of choice of trading system), and all incoming trades on electronic brokers. Incoming trades on electronic brokers are often placed as a one-way quote so the dealer controls the direction of trade. We let a purchase by dealer i be a positive trade, and a sale be a negative trade. The predicted sign on the coefficients are $\left(\beta_{\ell 1}^{B}, \beta_{\ell 2}^{S}\right) > 0, \beta_3 > 0, (\beta_4, \beta_5, \beta_6) < 0$. Notice that both $\beta_{\ell 1}^{B}$ and $\beta_{\ell 2}^{S}$ will be positive since we weight each event with the customer trade, which will be positive for customer purchases and negative for customer sales. In this way we let the effect from a large customer trade be larger than from a small one, in line with the presumption that a large trade leads to a larger change in conditional expectation.

The results are reported in table 7. Since the NOK/DEM Market Maker has so few transactions where the customer sells, it is difficult to evaluate an implementation where these are included. We see that customer purchases of currency tend to make the dealer purchase currency. The effect after customer sales is weaker. The results are most evident for the DEM/USD Market Maker, which probably is in a more favorable position to take advantage of customer trades since he operates in a more liquid sub-market than the NOK/DEM market. We also see that both dealers use several trades to follow up on a customer trade. One should keep in mind that the customer trade also is contained in the inventory, so that the effect measured by the $\beta_{\ell 1}^{B}$ and $\beta_{\ell 2}^{S}$ coefficients are in excess of inventory control. This is in line with the speculation that occurs in the model of Cao and Lyons (1998). An example may clarify: If a customer buys 10 million USD from

Table 7: Customer trade as event in estimation of the order placement strategy τ_{it}

	DEM/USD Market Maker	NOK/DEM Market Maker
Constant	-17.322	407.227
	(-0.98)	(1.33)
Customer purchase: $d^B_{0t}Q^{CUS}_t$ $(+)$	0.141	0.409
	**(2.08)	**(2.60)
Customer purchase: $d^B_{1t}Q^{CUS}_{t-1}$ $(+)$	-0.154	0.328
	(-0.96)	(1.02)
Customer purchase: $d^B_{2t}Q^{CUS}_{t-2}$ $(+)$	0.289	0.385
	***(9.05)	**(2.33)
Customer purchase: $d^B_{3t}Q^{CUS}_{t-3}$ $(+)$	0.180	0.017
	***(10.99)	(0.20)
Customer sale: $d^S_{0t}Q^{CUS}_t$ $(+)$	-0.279	
	*(-1.69)	
Customer sale: $d^S_{1t}Q^{CUS}_{t-1}$ $(+)$	0.087	
	(0.68)	
Customer sale: $d^S_{2t}Q^{CUS}_{t-2}$ $(+)$	-0.005	
	(-0.05)	
Customer sale: $d^S_{2t}Q^{CUS}_{t-2}$ $(+)$	0.176	
	*(1.75)	
Lagged price P_{t-1} $(+)$	12.479	653.551
	(0.11)	**(2.03)
Direction lagged D_{t-1} $(-)$	0.033	-0.632
	(0.35)	(-1.51)
Price P_t $(-)$	-2.925	-751.142
	(-0.03)	**(-2.25)
Inventory I_{t-1} $(-)$	-0.034	0.002
	**(-2.27)	(0.05)
AR(1)	-0.213	0.224
	***(-5.04)	(1.32)
Adjusted R^2	0.06	0.18
Durbin-Watson stat	2.08	1.60

Estimation by GMM and Newey-West correction. t-values are in parenthesis, and ***, ** and * indicates significance at the 1%, 5% and 10%-level respectively. Dependent variable is trade τ_{it}. Number of included observations are 808 for the DEM/USD Market Maker and 106 for the NOK/DEM Market Maker. Inventory is USD-inventory in case of the DEM/USD Market Maker, and DEM inventory in case of the NOK/DEM Market Maker.

the DEM/USD Market Maker, he will in the next four deliberate trades buy a total of 6 million USD $(0.14+0.28+0.18)$. When a customer buys 10 million DEM from the NOK/DEM Market Maker, he will buy almost 8 million DEM during the next four trades $(0.41+0.38)$.[11]

The coefficients on lagged price should be positive, since it is part of the dealers' expectations, and this is confirmed for the NOK/DEM Market Maker. Impact of current price should be negative for a profit maximizing dealers. This coefficient is negative for both dealers, but significantly so only for the NOK/DEM Market Maker. The coefficient on lagged inventory should be negative due inventory control, and this is confirmed for the DEM/USD Market Maker. A large positive inventory in the previous trade, leads the DEM/USD Market Maker to sell currency so to control inventory.

5.2 Counterparty informativeness

5.2.1 Counterparty informativeness and pricing strategy

A dealer can relate to trading with potentially better informed dealers in two ways: He can widen his spread to discourage trade, and he can update his beliefs based on the trade and hence influence subsequent trades. In this section we first analyze spread determination, and then regard a trade with an informed dealer as an information event.

Table 8 reports the relation between the absolute size of trades in direct trading, and the dealers' perception of their counterparties' informativeness. The picture from earlier that the dealers generally regard their counterparties in direct trading as worse informed than themselves are confirmed. A majority of the trades is small.

Table 8: Absolute size of direct trade and informativeness of counterparty

		Inferiorly Informed	Worse Informed	Equally Informed	Superiorly Informed	Total Total
DEM/	[0, 5)	45 (58%)	6 (8%)	19 (24%)	3 (4%)	73 (94%)
USD	[5, 10)			4 (5%)		4 (5%)
Market	[10, 15)				1 (1%)	1 (1%)
Maker	Total	45 (58%)	6 (8%)	23 (29%)	4 (5%)	78 (100%)
NOK/	[0, 5)	47 (52%)		10 (11%)	7 (8%)	64 (71%)
DEM	[5, 10)	1 (1%)			4 (4%)	5 (6%)
Market	[10, 15)	2 (2%)		6 (7%)	8 (9%)	16 (18%)
Maker	[15, 20)	1 (1%)			1 (1%)	2 (2%)
	[20, 25)				2 (2%)	2 (2%)
	[40, 45)				1 (1%)	1 (1%)
	Total	51 (57%)		16 (18%)	23 (26%)	90 (100%)

The table shows the absolute value of direct trade in groups, together with how the two dealers regarded their counterparts in the same trades. We see that a majority of the inferiorly informed banks also trade smaller volumes.

[11] Here we only consider significant coefficients.

The spread of the dealers in direct trading on D2000-1 is reported in table 9. With an exchange rate of 1.8 for DEM/USD and 4.16 for NOK/DEM, the minimum spread of 0.0001 DEM in DEM/USD is worth 0.000416 Kroner. The minimum spread in NOK/DEM is 0.0005 Kroner, only slightly higher.

Table 9: Spread from D2000-1 trading

DEM/USD Market Maker			NOK/DEM Market Maker		
Spread	Number	Percent	Spread	Number	Percent
1	8	(10.3%)	5	6	(6.7%)
2	48	(61.5%)	10	25	(27.8%)
3	5	(6.4%)	15	15	(16.7%)
4	1	(12.8%)	20	1	(1.1%)
			30	14	(15.6%)
NA	16	(20.5%)	NA	29	(32.2%)
Total	78	(100%)	Total	90	(100%)

The spread is measured "pips," which is the fourth decimal of the exchange rate, e.g. 0.0001 DEM.

We test two different formulations for how counterparty information influences the spread. In the first we simply let the slope coefficient of a trade differ for different groups of counterparties, while in the second we also address the possibility that it is only large trades that really add to the spread. The two regressions are

$$Spread_{it} = \alpha_0 + \sum_{\ell \in L} \alpha_\ell d_{\ell t} \text{abs}\left(Q_{jt}\right) + \varepsilon_{it}, \tag{24}$$

$$Spread_{it} = \alpha_0 + \sum_{k \in K} \sum_{\ell \in L} \alpha_{k\ell} \delta_{kt} d_{\ell t} \text{abs}\left(Q_{jt}\right) + \varepsilon_{it}, \tag{25}$$

where the two summations differ for the two dealers. In case of the DEM/USD Market Maker, $K = \left\{\text{abs}\left(Q_{jt}\right) < 1, \text{abs}\left(Q_{jt}\right) \geq 1\right\}$ and $L = \{INFO < 3, INFO \geq 3\}$. For the NOK/DEM Market Maker the two sets are $K = \left\{\text{abs}\left(Q_{jt}\right) < 5, \text{abs}\left(Q_{jt}\right) \geq 5\right\}$ and $L = \{INFO < 3, INFO = 3, INFO > 3\}$. We split the counterparties into a "informed" and "uninformed" group in this way in order to have enough observations for estimation in each group.

In table 10 the results for the DEM/USD Market Maker is reported, while the results for the NOK/DEM Market Maker is reported in table 11.

From the two tables we can see that the most significant coefficient is the constant term, which may be interpreted as the normal spread. We also see that it is the size of the trade, and not the counterparty information, which contributes to the spread. When we distinguish between trade size and counterparty, it is only the large trades that are significant, irrespective of the counterpart. This result is in line with recent survey results by Cheung and collaborators. To a question of what is the main determinant of the bid-ask spread, most dealers replied "Market convention" to an alternative of "Potential cost of

Table 10: DEM/USD Market Maker: Spread in direct trading

Constant	1.722	1.750
	***(17.95)	***(11.94)
Uninformed $d_t^{INFO<3}\text{abs}(Q_{jt})$	0.172	
	**(2.00)	
Informed $d_t^{INFO\geq 3}\text{abs}(Q_{jt})$	0.132	
	***(3.91)	
Uninformed, small trade $\delta_t^{abs(Q)\leq 1} d_t^{INFO<3}\text{abs}(Q_{jt})$		0.113
		(0.58)
Uninformed, large trade $\delta_t^{abs(Q)>1} d_t^{INFO<3}\text{abs}(Q_{jt})$		0.168
		*(1.91)
Informed, small trade $\delta_t^{abs(Q)\leq 1} d_t^{INFO\geq 3}\text{abs}(Q_{jt})$		0.250
		*(1.71)
Informed, large trade $\delta_t^{abs(Q)>1} d_t^{INFO\geq 3}\text{abs}(Q_{jt})$		0.125
		***(3.26)
Adjusted R^2	0.19	0.17
Durbin-Watson stat	2.52	2.52

t-values are in parenthesis, and ***, ** and * indicates significance at the 1%, 5% and 10%-level respectively.

Table 11: NOK/DEM Market Maker: Spread in direct trading

Constant	10.427	11.976
	***(17.50)	***(16.00)
Uninformed $d_t^{INFO<3}\text{abs}(Q_{jt})$	1.196	
	***(3.07)	
Equally informed $d_t^{INFO=3}\text{abs}(Q_{jt})$	1.913	
	***(29.63)	
Informed $d_t^{INFO>3}\text{abs}(Q_{jt})$	1.500	
	***(3.93)	
Uninformed, small trade $\delta_t^{abs(Q)<5} d_t^{INFO<3}\text{abs}(Q_{jt})$		-1.376
		(-0.90)
Uninformed, large trade $\delta_t^{abs(Q)\geq 5} d_t^{INFO<3}\text{abs}(Q_{jt})$		1.082
		***(2.81)
Equally, small trade $\delta_t^{abs(Q)<5} d_t^{INFO=3}\text{abs}(Q_{jt})$		-1.394
		(-1.49)
Equally, large trade $\delta_t^{abs(Q)\geq 5} d_t^{INFO=3}\text{abs}(Q_{jt})$		1.802
		***(24.08)
Informed, small trade $\delta_t^{abs(Q)<5} d_t^{INFO>3}\text{abs}(Q_{jt})$		-5.380
		**(-2.02)
Informed, large trade $\delta_t^{abs(Q)\geq 5} d_t^{INFO>3}\text{abs}(Q_{jt})$		1.366
		***(3.44)
Adjusted R^2	0.72	0.74
Durbin-Watson stat	2.15	2.23

t-values are in parenthesis, and ***, ** and * indicates significance at the 1%, 5% and 10%-level respectively.

quoting." The shares of the dealers giving this reply ranged from 69% in the US, 70% for U.K. and Tokyo, 71% for Singapore, and 77% for Hong Kong.

That spreads do not widen abnormally when trading with informed counterparties is an indication that the dealers do not price discriminate between each other. The condition for doing price discrimination is not present in a market where the transparency with regard to prices is so high as in the foreign exchange market. A contacting dealer being price discriminated would not be willing to trade, and rather turn to another dealer, e.g. through a electronic broker, that were offering better terms.

In table 12 we test if trading with an expected well-informed counterparty influences subsequent pricing behavior with the following adoption of the Madhavan and Smidt model:

$$\Delta P_{it} = \beta_0 + \sum_{\ell=0}^{3} \beta_{\ell 1} \delta_{t-\ell} d_{t-\ell} Q_{t-\ell} + \beta_3 Q_{jt} + \beta_5 I_{it} + \beta_6 I_{it-1} + \beta_5 D_t + \beta_4 D_{t-1} + \varepsilon_t, \quad (26)$$

where d_t equals one if the counterpart is perceived to be well informed. This formulation allows us to test whether there is an extra protection against adverse selection, and if subsequent trading is affected.

The first and the second lagged informed trade are significant for the DEM/USD Market Maker while the third lag is significant for the NOK/DEM Market Maker. The sign of the coefficients are however not intuitive. The model's prediction is that at least one of the coefficients on the events should be positive, i.e. that a purchase from an informed dealer should tend to increase expectations about currency value. The negative coefficients in both equations suggest that we are picking up some other dynamics in pricing strategy.

There is no sign of extra protection in the price quoted to well informed dealers. This confirms the previous result of no price discrimination in interbank trading. With high transparency of prices it is difficult to quote a price different from the rest of the market based on private information. Again, this is in line with the previously mentioned survey result.

5.2.2 Counterparty informativeness and order placement strategy

The dealer may want to use the information that a well informed counterpart traded in a particular direction as a signal of the dealers' information, and thereby influence his own expectations and strategy. Heere (1999) reports that in interviews with dealers in London they say that as important as protecting against adverse selection when trading with a well informed dealer, is to use the trade as a basis for own trading. After a trade with a "trustworthy" informed dealer, the dealers take the same position as the informed dealers.

In table 13 we adapt equation (16) to the case where the information event is that an

Table 12: Counterparty information as an event in the pricing strategy ΔP_{it}

	DEM/USD Market Maker	NOK/DEM Market Maker
Constant	-0.043	-0.187
	(-0.13)	(-0.23)
Informed direct trading $\delta_t^{\text{Direct}_t} d_t^{INFO_t \geq 3} Q_{jt}$ $(+)$	0.224	-0.292
	(0.41)	(-0.90)
Informed direct, lagged 1 $\delta_{t-1}^{\text{Direct}_{t-1}} d_{t-1}^{INFO_{t-1} \geq 3} Q_{jt-1}$ $(+)$	-0.415	0.284
	**(-2.47)	(0.81)
Informed direct, lagged 2 $\delta_{t-2}^{\text{Direct}_{t-2}} d_{t-2}^{INFO_{t-2} \geq 3} Q_{jt-2}$ $(+)$	0.719	0.140
	**(2.14)	(0.65)
Informed direct, lagged 3 $\delta_{t-3}^{\text{Direct}_{t-3}} d_{t-3}^{INFO_{t-3} \geq 3} Q_{jt-3}$ $(+)$	0.012	-0.509
	(0.04)	***(-4.04)
Other trades $\left(1 - \delta_t^{\text{Direct}_t} d_t^{INFO_t \geq 3}\right) Q_{jt}$ $(+)$	-0.089	-0.136
	(-0.52)	(-0.49)
Inventory, I_{it} $(-)$	0.060	-0.008
	(0.51)	(-0.04)
Lagged inventory, I_{it-1} $(+)$	-0.024	-0.152
	(-0.22)	(-0.80)
Direction, D_t $(+)$	1.859	9.998
	***(3.67)	***(7.31)
Lagged direction, D_{t-1} $(-)$	-0.207	-8.959
	(-0.63)	***(-4.83)
AR(1)	-0.092	-0.324
	***(-3.35)	***(-3.59)
Adjusted R^2	0.05	0.32
Durbin-Watson stat	1.98	2.04

Estimation by GMM. t-values are in parenthesis, and ***, ** and * indicates significance at the 1%, 5% and 10%-level respectively. All coefficient except the AR-term are multiplied by 10^4.

informed counterparty bought or sold in the previous transaction. The hypothesis from the interviews by Heere is that a purchase of currency by a dealer perceived to be well informed will lead the dealer to trade in the same directions.

Table 13: Informed direct trade as an event in the order placement strategy τ_{it}

	DEM/USD Market Maker	NOK/DEM Market Maker
Constant	-18.410	281.165
	(-1.02)	(1.08)
Informed purchase $(+)$	-0.201	-0.392
	(-0.97)	(-1.57)
Informed purchase $(+)$	0.172	-0.185
	(0.73)	(-0.91)
Informed purchase $(+)$	0.188	-0.382
	(1.15)	***(-3.86)
Informed sale $(+)$	0.392	-0.142
	***(2.67)	(-0.44)
Informed sale $(+)$	0.156	0.009
	(0.57)	(0.06)
Informed sale $(+)$	0.052	-0.010
	(0.24)	(-0.06)
Lagged price P_{t-1} $(+)$	30.880	797.423
	(0.30)	*(1.79)
Direction lagged D_{t-1} $(-)$	0.005	-0.546
	(0.05)	(-1.41)
Price P_t $(-)$	-20.720	-864.519
	(-0.20)	*(-1.93)
Inventory I_{t-1} $(-)$	-0.035	-0.020
	**(-2.34)	(-0.37)
AR(1)	-0.198	-0.056
	***(-4.39)	(-0.73)
Adjusted R-squared	0.05	0.09
Durbin-Watson stat	2.11	1.25

Estimation by GMM and Newey-West correction. t-values are in parenthesis, and ***, ** and * indicates significance at the 1%, 5% and 10%-level respectively. Number of included observations are 808 and 106 for the DEM/USD Market Maker and the NOK/DEM Market Maker, respectively. Inventory is USD-inventory in case of the DEM/USD Market Maker, and DEM inventory in case of the NOK/DEM Market Maker.

The lack of any conclusive results may be because there are few trades where the dealers perceive the counterparty to be well informed. It may of course also be that these dealers do not follow the positions of informed counterparties. Especially in a less liquid markets as the Norwegian market, taking the same positions as informed counterparties in previous trades may be difficult.

6 Conclusion

We investigate empirically two aspects of private information in spot interbank foreign exchange markets. First, we study how dealers react to customer trades, which is claimed to be their most important source for private information, and second, how they react to trading with dealers they regard to be better informed than themselves. We study how these two aspects of private information influence the two elements of their trading strategy, namely pricing and order placement.

To the best of our knowledge, none of these two aspects of private information in foreign exchange has been studied before. We are able to address these issue through a unique data set covering the complete trading of two market makers during one week in March 1998. Our data includes the trading with customers. We have collected observations on the dealers perceptions of how well informed their counterparties in direct interbank trading are compared to themselves through a questionnaire.

We do not find any consistent effect from customer trades on the pricing strategy of the market makers. This leads us to conclude that dealers do not use their private information from customer trades in pricing. The reason might be that even if they end up giving quotes different from their conditional expectation, they gain from not revealing their private information. In the foreign exchange market the transparency with regard to prices is very high, so prices away from the rest of the market would either not be traded at or would be taken as a signal of new information, which then would be transferred to the market price extremely fast.

Interbank dealers do however price discriminate against the customers. We find that the spreads quoted to customers are three to four times wider than the interbank spreads. The dealers are able to price discriminate the customers since the customers can not participate in the more liquid interbank market. Furthermore, they do not see the prices traded at in the interbank market, only prices directly intended for the customers through the Reuters FXFX system. Larger spreads to customers have been emphasized as a main advantage with large customer order flow by Yao (1998b).

Instead of using their private information in their pricing strategy, the dealers use their information in formation of order placement strategy. We find that the trading with customers influence the dealers' order-placing strategy. After a purchase of currency by the customers, the dealers buy currency in the interbank market. We do control for inventory adjustment in the trading strategy, so the trading by the dealers following the customer trade may be interpreted as speculative position taking. The dealers ride herd on the customers.

One might expect that the dealers would let the identity of the counterpart influence their trading strategy, e.g. protecting even stronger against adverse selection when trading with a perceived well informed dealer. When we investigate the spread in direct trading, we find that it is the size of the transaction, and not the identity of the initiator, that explains the spread. Consequently, dealers do not discriminate between well informed and less informed dealers. This is also in line with surveys showing that spreads are determined by "market norms," and not by the actual cost of the specific transaction.

It has been suggested that dealers in foreign exchange markets adopts the position taking of their counterparts when trading with better informed dealers. We do not find this for our dealers. Trading with informed counterparties do not influence their order-placing strategy.

In this paper we have empirically investigated aspects of private information in foreign exchange markets without addressing the strategic issues arising when several dealers have private information and trade with each other. With the structure of multiple dealership markets in mind, such as the foreign exchange market, we believe there is a need for such models to help understanding the issues at hand. Hopefully the results from the present study may prove useful in such an attempt.

A Q_{jt}-coefficient when dealers have different precision

We are interested in the effect on the coefficient on Q_{jt} in (11) of a change in the precision of the counterparties' private information. We are interested in how

$$\frac{1-\phi_j}{\theta\phi_j} = \frac{1}{\theta}\frac{1-\kappa}{\kappa-\lambda_j} \tag{A.1}$$

depends on $\sigma^2_{\omega j}$. We have the following relations:

$$\phi_j = \frac{\kappa-\lambda_j}{1-\lambda_j},\ 1-\phi_j = \frac{1-\kappa}{1-\lambda_j} \tag{A.2}$$

$$\kappa = \frac{\sigma^2_{Zj}}{\sigma^2_{\mu'}+\sigma^2_{Zj}},\ 1-\kappa = \frac{\sigma^2_{\mu'}}{\sigma^2_{\mu'}+\sigma^2_{Zj}} \tag{A.3}$$

$$\lambda_j = \frac{\sigma^2_{\omega j}}{\sigma^2_r+\sigma^2_{\omega j}},\ 1-\lambda_j = \frac{\sigma^2_r}{\sigma^2_r+\sigma^2_{\omega j}} \tag{A.4}$$

$$\sigma^2_{\mu'} = \lambda_i^2\sigma_r^2 + (1-\lambda_i)^2\sigma^2_{\omega i} = \frac{\sigma_r^2\sigma^2_{\omega i}\left(\sigma_r^2+\sigma^2_{\omega i}\right)}{\left(\sigma_r^2+\sigma^2_{\omega i}\right)^2} = \frac{\sigma_r^2\sigma^2_{\omega i}}{\sigma_r^2+\sigma^2_{\omega i}} \tag{A.5}$$

$$\sigma^2_{Zj} = \sigma^2_{\omega j} + \left[\frac{1}{\theta(1-\lambda_j)}\right]^2\sigma^2_{Xj} = \sigma^2_{\omega j} + \left[\frac{\sigma_r^2+\sigma^2_{\omega j}}{\theta\sigma_r^2}\right]^2\sigma^2_{Xj} \tag{A.6}$$

The ϕ_j, κ and λ_j are weights in the dealer's updating formulas for conditional expectations. θ is the inverse of the absolute risk aversion and the variance of the conditional expectation.

The easiest way to investigate the coefficients dependence on $\sigma^2_{\omega j}$ is to begin with investigating $1-\phi_j$.

$$\frac{\partial(1-\phi_j)}{\partial\sigma^2_{\omega j}} = \frac{(1-\kappa)'(1-\lambda_j)-(1-\kappa)(1-\lambda_j)'}{(1-\lambda_j)^2}$$

where prime indicate the derivative with respect $\sigma^2_{\omega j}$. The derivatives can be written as

$$\begin{aligned}
(1-\kappa)' &= \frac{-\sigma^2_{\mu'}}{\left(\sigma^2_{\mu'}+\sigma^2_{Zj}\right)^2}\left[1+2\sigma^2_{Xj}\left(\frac{\sigma_r^2+\sigma^2_{\omega j}}{\theta\sigma_r^2}\right)\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma^2_{\omega j}\right)\sigma_r^2\theta'}{(\theta\sigma_r^2)^2}\right] \\
&= -\frac{(1-\kappa)}{\sigma^2_{\mu'}+\sigma^2_{Zj}}\left[1+2\sigma^2_{Xj}\left(\frac{\sigma_r^2+\sigma^2_{\omega j}}{\theta\sigma_r^2}\right)\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma^2_{\omega j}\right)\sigma_r^2\theta'}{(\theta\sigma_r^2)^2}\right] \\
(1-\lambda_j)' &= \frac{-\sigma_r^2}{\left(\sigma_r^2+\sigma^2_{\omega j}\right)^2} = -\frac{1-\lambda_j}{\sigma_r^2+\sigma^2_{\omega j}}
\end{aligned}$$

In the second line we use that $(1-\kappa) = \sigma^2_{\mu'}/\left(\sigma^2_{\mu'}+\sigma^2_{Zj}\right)$. Above θ' represent the derivative of θ with respect $\sigma^2_{\omega j}$, and are more closely investigated below.

We insert these two into the expression above, and switch the sequence of the two to get the positive first, to obtain

$$
\begin{aligned}
\frac{\partial\left(1-\phi_j\right)}{\partial\sigma_{\omega j}^2} &= \frac{(1-\kappa)\left(1-\lambda_j\right)}{\left(1-\lambda_j\right)^2}\left\{\frac{1}{\sigma_r^2+\sigma_{\omega j}^2}\right. \\
&\quad \left. -\frac{1}{\sigma_{\mu'}^2+\sigma_{Zj}^2}\left[1+2\sigma_{Xj}^2\left(\frac{\sigma_r^2+\sigma_{\omega j}^2}{\theta\sigma_r^2}\right)\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma_{\omega j}^2\right)\sigma_r^2\theta'}{\left(\theta\sigma_r^2\right)^2}\right]\right\} \\
&= \frac{1-\kappa}{\left(1-\lambda_j\right)\left(\sigma_r^2+\sigma_{\omega j}^2\right)\left(\sigma_{\mu'}^2+\sigma_{Zj}^2\right)}\left\{\sigma_{\mu'}^2+\sigma_{Zj}^2-\sigma_r^2-\sigma_{\omega j}^2\right. \\
&\quad \left. -2\sigma_{Xj}^2\left(\frac{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2}{\theta\sigma_r^2}\right)\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma_{\omega j}^2\right)\sigma_r^2\theta'}{\left(\theta\sigma_r^2\right)^2}\right\} \\
&= \frac{1-\kappa}{\sigma_r^2\left(\sigma_{\mu'}^2+\sigma_{Zj}^2\right)}\left\{\lambda_i^2\sigma_r^2+\left(1-\lambda_i\right)^2\sigma_{\omega i}^2+\sigma_{\omega j}^2+\left[\frac{\sigma_r^2+\sigma_{\omega j}^2}{\theta\sigma_r^2}\right]^2\sigma_{Xj}^2-\sigma_r^2-\sigma_{\omega j}^2\right. \\
&\quad \left. -2\sigma_{Xj}^2\left[\frac{\sigma_r^2+\sigma_{\omega j}^2}{\theta\sigma_r^2}\right]^2\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma_{\omega j}^2\right)\sigma_r^2\theta'}{\theta\sigma_r^2}\right\}
\end{aligned}
$$

In the second equality we get a common denominator, and resolve the square-bracket. In the third equality we use that $\left(1-\lambda_j\right)=\sigma_r^2/\left(\sigma_r^2+\sigma_{\omega j}^2\right)$, $\sigma_{\mu'}^2=\lambda_i^2\sigma_r^2+\left(1-\lambda_i\right)^2\sigma_{\omega i}^2$, and $\sigma_{Zj}^2=\sigma_{\omega j}^2+\left[\frac{\sigma_r^2+\sigma_{\omega j}^2}{\theta\sigma_r^2}\right]^2\sigma_{Xj}^2$. Finally we collect terms to obtain,

$$
\begin{aligned}
\frac{\partial\left(1-\phi_j\right)}{\partial\sigma_{\omega j}^2} &= \frac{1-\kappa}{\sigma_r^2\left(\sigma_{\mu'}^2+\sigma_{Zj}^2\right)}\left\{\left(1-\lambda_i\right)^2\sigma_{\omega i}^2-\left(1-\lambda_i^2\right)\sigma_r^2\right. \\
&\quad \left. +\left[\frac{\sigma_r^2+\sigma_{\omega j}^2}{\theta\sigma_r^2}\right]^2\sigma_{Xj}^2\left(1-2\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma_{\omega j}^2\right)\sigma_r^2\theta'}{\theta\sigma_r^2}\right)\right\}
\end{aligned}
\tag{A.7}
$$

In order to evaluate the sign of the first two terms in the curly braces, let $\sigma_r^2=\alpha\sigma_{\omega i}^2$. If $\alpha=1$, they are equal to $-\sigma_{\omega i}^2/2$ and if $\alpha=2$ they equal $-2\sigma_{\omega i}^2$, the general expression being

$$
\frac{-\sigma_{\omega i}^2}{\left(1+1/\alpha\right)^2}\left(1+\alpha\right).
$$

The last parenthesis in the equation above can be written as

$$
1-2\frac{\theta\sigma_r^2-\left(\sigma_r^2+\sigma_{\omega j}^2\right)\sigma_r^2\theta'}{\theta\sigma_r^2}=-1+\frac{2\left(\sigma_r^2+\sigma_{\omega j}^2\right)\theta'}{\theta},
$$

which is negative if θ' is small or negative. Below we show that θ' indeed is negative, so then the whole derivative will be negative. If $\partial\left(1-\phi\right)/\partial\sigma_{\omega j}^2<0$, then $\partial\phi/\partial\sigma_{\omega j}^2>0$, hence $\left(1-\phi_j\right)/\phi_j$ will decrease when $\sigma_{\omega j}^2$ increases. Higher precision, lower $\sigma_{\omega j}^2$, will then increase this part of the coefficient on Q_{jt}.

Now we investigate the effect on θ, given by

$$
\theta=\frac{1}{\rho\sigma_{\mu j}^2},
$$

where ρ is the coefficient of risk aversion, and

$$\sigma_{\mu j}^2 = \lambda_j^2\sigma_r^2 + (1-\lambda_j)^2\sigma_{\omega j}^2 = \frac{\sigma_r^2\sigma_{\omega j}^2\left(\sigma_r^2+\sigma_{\omega j}^2\right)}{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2}.$$

The derivative of $1/\theta = \rho\sigma_{\mu j}^2$ with respect to $\sigma_{\omega j}^2$ is

$$\frac{\partial(1/\theta)}{\partial\sigma_{\omega j}^2} = \rho\left[2\lambda_j\lambda_j'\sigma_r^2 + (1-\lambda_j)^2 + 2(1-\lambda_j)(1-\lambda_j)'\sigma_{\omega j}^2\right]$$

where prime indicate the derivative with respect $\sigma_{\omega j}^2$. The derivatives can be written as

$$\lambda_j' = \frac{\sigma_r^2+\sigma_{\omega j}^2-\sigma_{\omega j}^2}{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2} = \frac{\sigma_r^2}{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2}$$
$$(1-\lambda_j)' = -\frac{\sigma_r^2}{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2}$$

When inserted into the expression for the derivative above, we get

$$\begin{aligned}\frac{\partial(1/\theta)}{\partial\sigma_{\omega j}^2} &= \rho\left[2\lambda_j\lambda_j'\sigma_r^2 + (1-\lambda_j)^2 + 2(1-\lambda_j)(1-\lambda_j)'\sigma_{\omega j}^2\right]\\ &= \rho\left[2\lambda_j\sigma_r^2\frac{\sigma_r^2}{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2} + (1-\lambda_j)^2 - 2(1-\lambda_j)\sigma_{\omega j}^2\frac{\sigma_r^2}{\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2}\right]\\ &= \rho\left[2\lambda_j(1-\lambda_j)^2 + (1-\lambda_j)^2 - 2(1-\lambda_j)^2\frac{\sigma_{\omega j}^2}{\sigma_r^2+\sigma_{\omega j}^2}\right]\\ \frac{\partial(1/\theta)}{\partial\sigma_{\omega j}^2} &= \rho(1-\lambda_j)^2 > 0 \qquad \text{(A.8)}\end{aligned}$$

In the third equality we use that $(1-\lambda_j) = \sigma_r^2/\left(\sigma_r^2+\sigma_{\omega j}^2\right)$ and $(1-\lambda_j)^2 = \sigma_r^4/\left(\sigma_r^2+\sigma_{\omega j}^2\right)^2$. This is intuitive; when dealer j receives more precise signals (lower $\sigma_{\omega j}^2$), he will trade more aggressively (θ increases).

Notice that this implies that

$$\frac{\partial\theta}{\partial\sigma_{\omega j}^2} = -\frac{1}{\rho\sigma_{\mu j}^2}\frac{(1-\lambda_j)^2}{\sigma_{\mu j}^2} = -\theta\frac{(1-\lambda_j)^2}{\sigma_{\mu j}^2} < 0.$$

The change of $(1-\phi_j)/\theta\phi_j$ from change in $\sigma_{\omega j}^2$ is equal to

$$\frac{\partial[(1-\phi_j)/\theta\phi_j]}{\partial\sigma_{\omega j}^2} = \frac{\partial(1/\theta)}{\partial\sigma_{\omega j}^2}\frac{1-\phi_j}{\phi_j} + \frac{1}{\theta}\frac{\partial[(1-\phi_j)/\phi_j]}{\partial\sigma_{\omega j}^2}. \qquad \text{(A.9)}$$

The term $\partial(1/\theta)/\partial\sigma_{\omega j}^2$ is likely to be less than one since $1-\lambda_j$ is between zero and one. If $\rho = 2$ then the weight on the private signal C_{jt} has to be above 0.7 for the whole derivative to be above 1. The multiplicative term $(1-\phi_j)/\phi_j$ will be less than 1 if dealer i puts higher weight on his own information than the signal from the interbank trade, making the first term even smaller. We know that the second term is negative. We will proceed with assuming that (A.9) is negative.

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