Different Counterparties in a Small Bank's FX Trading

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Abstract

This study examines the USD/EUR-trading of a small bank in Germany over a four-month period and thereby complements previous analyses of large market makers. Our data comprehensively differentiates deal-by-deal trading information between other banks, commercial customers and the increasingly important financial customers. Results reveal that these differences play an insignificant role for inventory control. However, information levels between groups clearly differ. Correspondingly, cumulative order flows of incoming interbank and financial customer trades are informative, even at the small bank. Spreads and profits increase for trading with less informed counterparties. Proprietary trading seems to be profitable.

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1. Introduction

The microstructure research in foreign exchange is largely motivated by the failure of traditional exchange rate modeling (see e.g. Frankel and Rose, 1995; Taylor, 1995; Faust, Rogers and Wright, 2003). In particular, the analysis of order flows has become a promising avenue of research, as aggregated flows seem to be related to exchange rates (Evans and Lyons, 2002, 2003). This recently uncovered fact about order flows is thus an additional motivation, beyond the goal of extending finance approaches to the FX market (Madhavan, 2000), to examine the decision-making of FX dealers. Empirical work on dealers' behavior is scarce, however, as private information on the single transactions is necessary. We analyze a new data set of this kind, which is the first from a small bank and the first in comprehensively differentiating trading information between other dealers, commercial customers and the increasingly important financial customers. Our results reveal differences which seem to reflect informational levels and thus affect trading behavior and profits. Moreover, order flows from interbank and financial customer trades are informative even at the low frequency and limited order volume of a small bank, highlighting the explanatory power of the order flow approach in foreign exchange.

The pioneering research in this field is Lyons (1995), who examined the trading behavior of a very large US dealer over one week in 1992. He established the existence of an inventory as well as an information effect in FX trading, in accordance with earlier findings for stock markets, such as Hasbrouck (1991), Madhavan and Smidt (1991) and Hasbrouck and Sofianos (1993). The single dealer, however, is particular, as he trades only with other banks. Yao (1998) is thus the first study analyzing customer dealing separately from interbank dealing, finding smaller differences. Bjønnes and Rime (2001) introduce two facts into the literature: diversity in trading style found from their analysis of four dealers and the consideration of the new electronic brokerage systems. Separating traditional deals from electronically brokered deals reveals that the latter bring about a full disappearance of the inventory and information effect in the form detected by Lyons (1995). Related effects can be found in a new form, however. Finally, Carpenter and Wang (2003) analyze different participants' orders (as we do) with respect to their price impact on the dealer's pricing, subsequent price changes and preferred trading channel. They find that the central bank has greatest impact, followed by non-bank financial institutions. Dealers with greater private information seem to prefer direct trading. These findings raise questions which are organized according to three typical determinants in the price equations of the microstructure literature, i.e. inventory, information and spread:

First, can findings for the dealer's *inventory* control mechanisms be confirmed for a small bank and for different counterparties? Second, is the dealers' *information* in relation to different counterparties the same or do the increasingly important financial customers in particular differ from the traditional commercial customers? Third, how do *spreads* behave towards the different counterparties and what can be inferred about sources of *profitability*? These three research questions are addressed in this study.

According to our knowledge, there are only the four above-mentioned data sets of Lyons (1995), Yao (1998), Bjønnes and Rime (2001) and Carpenter and Wang (2003) to analyze banks' deal-by-deal FX transactions. In comparison with these studies our data is unique in three respects: first, from a technical point of view, the data is quite recent, i.e. from the electronic brokerage environment of the year 2001, it spans the longest period so far, includes the relatively highest share of customer transactions and alone includes forward trades. Second, it covers a very different dealer, i.e. a participant whose FX trading volume is small in relation to the so far considered market makers – the small bank. Third, the data distinguishes three trading counterparties: we examine interbank versus customer business and we differentiate for the first time in this literature comprehensively between commercial and financial customers (Carpenter and Wang, 2003, disaggregate in the same way with their more recent data, including also the central bank).

Our findings support the result of Bjønnes and Rime (2001), namely that the new electronic trading systems may have changed dealers' behavior in interbank trading in a way that contradicts results from Lyons (1995) and Yao (1998). Inventory control still exists, as can be recognized from the strong mean reversion in the trading position, but the mechanism works by using outgoing trades. In contrast to earlier studies, the information effect in our sample is masked by the many small trades with inverse sign, which reflects a simple cost effect. Regarding the information level of counterparties, price setting slightly indicates better informed financial customers. The cumulative order flows support this supposition: only incoming interbank flows and financial customer flows seem to carry information whereas commercial customers behave like liquidity traders. Moreover, spreads seem to reflect these different levels of information too, as commercial customers pay more even after controlling for size. Finally, we propose a calculus to decompose sources of profitability. It reveals that commercial customer business dominates profits, but that proprietary trading may also contribute.

Overall, the results suggest that the size of a trading bank and in particular the kind of counterparty play a significant role. The small bank mostly acts as an intermediary for its customers whereas much of the interbank business serves to clear customer orders. The bank treats other banks and tentative financial customers as informed counterparties. Finally, it seems to make some money from proprietary trading, whose sources cannot be identified in the customer business. Bringing findings to the macro level of exchange rate determination, incoming interbank and financial customer order flows are informative even at the low frequency and comparatively low volume that is characteristic of small banks. Thus, our disaggregated and high-frequency data is consistent with the findings of Fan and Lyons (2003; see also Lyons, 2001), namely that financial customers may be very important for understanding shorter-term exchange rate movements.

The paper proceeds as follows: Section 2 develops three hypotheses based on a selective literature review, which are going to be tested later. Section 3 describes the data. Examination results are reported in Section 4 and Section 5 presents conclusions.

2. Literature and hypotheses

The empirical literature on foreign exchange market microstructure received a most important impulse by Lyons' (1995) study on transaction determinants of a large US dealer in the spot DEM/USD market. This study was the first to show the importance of order flows for decision making in foreign exchange trading and thus the first to introduce a new category of "order flow information". Several studies have demonstrated the usefulness of this concept: Ito, Lyons and Melvin (1998) or Covrig and Melvin (2001) use flows in an event study environment. Questionnaire surveys, such as Cheung and Chinn (2001) and Cheung, Chinn and Marsh (2000) revealed the importance of flows for FX dealers. Gehrig and Menkhoff (2002) tested more detailed hypotheses on the character of flow information. Finally, recent work aims to apply flow information to exchange rate explanations, e.g. Evans and Lyons (2002, 2003), Evans (2002), Killeen, Lyons and Moore (2001) or Froot and Ramadorai (2002), or uses order flow characteristics to explain the forecasting power of technical analysis (Osler, 2003).

Whereas these kinds of studies show the power of "order flow information" in understanding foreign exchange markets, studies directly following Lyons' approach are comparatively rare (see Lyons, 2001, and Sarno and Taylor, 2001, for surveys on FX microstructure). Their focus is on grasping the dealers' decision-making, which requires a command of the relevant pieces of information. This information has, of course, proprietary nature and is thus difficult to get. Other studies on transaction data in foreign exchange have been based on indicative quotes (such as Peiers, 1997; Andersen and Bollerslev, 1998; Danielsson and Payne, 2002; Dominguez, 2003) or aggregated flows (Lyons and Evans, 2002). However, these kinds of data are not comprehensive enough – and thus not used – to analyze dealers' behavior in detail. For this purpose, one needs more information, for example, about the inventory position of the dealer or about all sources of FX business.

In this line of research, there are, to our best knowledge, the four earlier studies mentioned above, i.e. Lyons (1995), Yao (1998), Bjønnes and Rime (2001) and Carpenter and Wang (2003)(related aspects based on the same data sets have been analyzed e.g. in Lyons 1998, Yao, 1998a, Bjønnes and Rime, 2001a). Their common theoretical background is the market microstructure literature – in particular Madhavan and Smidt (1991) – postulating that pricing decisions will be influenced, among other things, by three interesting effects: first, an asset's own inventory will influence price setting by promoting deals, leading to a mean-reversion of the inventory, in short the *inventory effect*.[1] Second, dealers acknowledge asymmetric information among market participants in the sense that they assume private information when they set prices for a larger potential deal. They protect themselves against this assumed information disadvantage by setting larger spreads for larger orders; in short, the *information effect*. Finally, traders live from buying low and selling high, so that a *spread* is to be expected. The examination of the existence of these three effects is at the core of the earlier studies. We come to our research questions by reviewing respective literature results.

[1] The inventory information is missing in Carpenter and Wang (2003).

Several important differences between the studies can be directly recognized from obvious design features. Starting with Lyons (1995) as the benchmark, he analyzes one very large US dealer in the DEM/USD spot market over one week. Yao (1998) also focuses on a large US dealer, but the coverage is over five weeks and this dealer is not only concerned with interbank trading but has a customer share of his trading volume of 13.9%. Bjønnes and Rime (2001) observe foreign exchange dealings at a Norwegian bank that is characterized as a major player in these markets. They analyze four dealers over one week of trading: dealer 1 mostly resembles Lyons' dealer, as he is the bank's main spot dealer in DEM/USD, although the volume is clearly smaller compared to Lyons' or Yao's market leaders. The Norwegian dealer is a "medium-sized market maker in DEM/USD". Dealer 3 is the "largest market maker in NOK/DEM". Dealers 2 and 4, by contrast, command smaller volumes and are mainly active in the DEM/USD market. Carpenter and Wang (2003) analyze an Australian bank's external spot trading in AUD/USD and EUR/USD over 45 days. The customer volume share is about 10.6% and 4.6% respectively. More information on characteristics of the core DEM/USD (EUR/USD) dealers and their trading activity as well as market wide "benchmarking" information from the survey of the BIS (2002) is compiled in Table 1. Our own study is mentioned there for comparative purposes.

Referring to the BIS turnover data in Table 1, it becomes obvious that previous studies on transaction data focus on extremely large dealers trading about 10 to 30 times of the median dealer (see Annex 1 for a derivation of median size). Our bank, with a relevant volume of 39 mill. USD, is tiny by contrast but appears to be a good representation of a typical bank in this market. The same applies to the structure of counterparties. Whereas the dealers covered in other studies focus on a market maker's interbank trading, our bank has a customer share which is more normal when compared to the total market. Seen from this angle, our study – covered in Table 1 for comparative purposes – thus provides hitherto missing evidence of a small bank, complementing earlier work.

This difference between our sample and earlier studies thus compels the first research objective, i.e. to check robustness of earlier findings. In his seminal study, Lyons (1995) tests the explanatory power of several price determinants derived from the Madhavan and Smidt (1991) model of a market maker's behavior. He finds that price setting for incoming non-brokered interdealer trades, in the sense of a price change in relation to the earlier trade Δp_{it}, is indeed systematically influenced by three determinants: first, there is an inventory effect as the dealer shows a clear mean reversion of his open position over time by "quote-shading", being caught by the terms I_{it} and I_{it-1}. If he has, for example, a large open long position in foreign currency, he sets prices more attractive to other buyers than to sellers in order to balance his portfolio. There is thus a larger probability of reducing the open position. Second, the dealer shows an information effect in the sense that he reacts carefully to large orders as he may suspect superior knowledge – private information – on the other market-side. The order volume is the term Q_{jt}. Third, in order to earn a spread from his transaction, there is an asymmetry in price-setting as the price for purchases is slightly lower than for sales, i.e. the "direction" expressed by the terms D_t and D_{t-1} is important. Whereas this third determinant seems to be a necessary ingredient of trading, and is thus regularly found in empirical studies, the two other determinants – I and Q – are open to discussion. The baseline equation (1) is thus:

$$\Delta p_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it} \quad (1)$$

Yao (1998) does not confirm the inventory effect for interbank trading. He argues that his dealer has a large customer business which provides him with an information advantage that the dealer does not want to signal unintentionally to others by quote shading. The existent inventory effect in customer trading (Yao, 1998, Table 7) mirrors the discussion of the missing inventory effect in the interdealer market as quote shading does not play a significant role in the customer business.

The Bjønnes and Rime (2001) study on interbank trading does not find an inventory effect in interbank trading either. It provides convincing evidence that the changing market structure plays a role. In 1992, when Lyons' data was compiled, interbank trading was mainly executed by direct interdealer communication and to a lesser extent by voice brokered trades, whereas nowadays electronic broker systems dominate. The latter systems, such as EBS and Reuters Dealing 2000-2 or its successors, offer convenient ways for inventory control and are much more transparent than the former interbank market. Thus, we do not expect our small bank which effectively trades in the electronic brokerage world to behave as a Lyons' dealer would.

However, the economic task of inventory control still exists and is addressed. The three earlier studies have unanimously shown that banks tightly control inventory in the sense that open positions in the respective currencies are restricted to certain limits and may be reversed several times during a trading day. The microstructure literature on stock markets, which had been confronted with weak inventory effects too, suggests the existence of alternative ways of inventory control (e.g. Madhavan and Sofianos, 1997). Trading with other market participants, i.e. in particular outgoing trade, is an obvious means. It may be interesting to note that Madhavan (2000) explicitly mentions the (minor) use of this instrument in Lyons (1995) as a clear sign of its existence. It is Bjønnes and Rime (2001) who show that outgoing trades indeed serve as a systematic instrument to balance inventory. A small bank can be even more strongly expected to perform inventory control in the same way as a market maker.

H1 Inventory control: Inventory control of a small bank in an electronic brokerage environment refers to all kinds of incoming trades and is mainly conducted via outgoing trades.

A possibly even more interesting aspect in trading decisions than inventory control is the role of information. Lyons (1995) established an asymmetric information effect in interbank trading, just as in stock markets. This has been confirmed by Yao (1998) although not for customer business. Here, the coefficient of the information effect is rightly signed, but comes with a t-value of only 1.63. Yao argues that the insignificance may be due to the fact that the full price impact of a large customer order develops over several periods. Bjønnes and Rime (2001) confirm the effect for direct interbank trades of their bank but do not find it in the electronic brokerage anymore. This difference may be no surprise, as the microstructure literature finds that informed dealers prefer less transparent trading channels and would thus rather prefer direct to electronically brokered trades. That is indeed what Carpenter and Wang (2003) find in their study for the large interbank trades. This implies for our small bank that we do not expect an asymmetric information effect, neither for interbank nor for customer trades.

However, the analyses of order flows have shown their relation with exchange rates, indicating an informative role of cumulative order flows for the whole market (Evans and Lyons, 2002, Rime, 2001) or for a large bank (Fan and Lyons, 2003). Does the order flow at a small bank reveal any information, too? Will even the findings for disaggregated flows by Lyons (2001) and Fan and Lyons (2003) – showing that financial customer orders are highly correlated with shorter-term exchange rate movements – show up again? Both mentioned studies use the data of a large bank which is aggregated per day for all the trading of three differentiated customer groups each. This flow information is thus still much more representative and thus more robust than our transaction data at a small bank. If there is any effect, it could show up in the incoming interbank trades, reflecting order flows of large participants but, again, the comparatively small customer base does not promise too much.

H2 Information effects: There is no asymmetric information effect expected in the small bank's trading. Cumulative incoming interdealer trades may carry private information but the customer business of a small bank does not.

The third microstructure element being examined here is the spread as a basis for understanding sources of profits from FX trading. For a small bank, we would expect that profits are even more clearly based in the customer business than for potentially better informed large market making banks. As the profit share from proprietary trading is estimated to be about only 15 per cent in Lyons (1998), the expectation for the small bank may tend towards zero. Regarding the differentiation of customer groups, which is possible from the data here, one might plausibly assume that better informed counterparties are less profitable for the bank.

H3 Spreads and profitability: The bank does not make money from proprietary trading. Regarding counterparties, the least informed counterparties – possibly commercial customers – may be most profitable.

In summary, the new data allows us to test the three hypotheses as described above. Regarding hypothesis 1 on inventory control, the idea is to confirm the existence of other instruments than quote shading. Regarding hypothesis 2 on information effects, we do not expect to find asymmetric information in the new environment. Due to the small size of the bank, any information from cumulative order flows seems to be highly questionable ex ante. Finally, possible differences in spreads may translate into the heterogeneous profitability of counterparties in trading. The data to test these hypotheses is described in the next section.

3. Data

The data set employed in this study consists of the complete USD/EUR trading record of a bank in Germany. The record covers 87 trading days, beginning on Wednesday, the 11th of July 2001, and ending on Friday, the 9th of November 2001.[2]

Compared with the other microstructure data sets mentioned, this is the longest observation period to date. Due to the size of the bank as a marginal market making participant with a limited customer base, the transaction frequency is comparatively low. The bank realizes about 40-50 USD/EUR trades per day, including all kinds of transactions, whereas the big market makers covered earlier perform about five times as many transactions per day. The data set includes transaction prices, quantities, information about the initiator of each trade and a time stamp. The information on the bank's inventory position can be designed by cumulating the successive transactions. These kinds of calculations are performed for the bank and not for a single dealer. However, due to the comparatively small size of our institution, there is only one dealer responsible for the bank's USD/EUR inventory position and trading policy – although he may be supported by other dealers when required – so that there is no de facto difference to earlier studies covering dealers.

In order to obtain a broad data set, we include outright-forward trades in an adjusted manner, i.e. by correcting for the forward points. In our opinion, these trades should not be disregarded, as we especially focus on customer trading, and outright-forward trades account for a large portion of customer business. Moreover, outright-forward trades influence the inventory position in "our" small bank, as this trading is also conducted by, and accounted for, the same dealer as the spot trading. However, to make our findings more comparable to the literature, we have also performed the examinations without these outright-forward trades. Results mostly do not differ from each other and are thus not reported, although statistical measures tend to be better when more data is considered.

3.1 Deals blotter

The FX dealings of the bank are split into two segments: (i) trading with other dealers takes place on the "trading floor", and (ii) customer trades are transacted by the "sales staff". While dealers on the trading floor can choose between different trading channels, the sales staff generally communicates by telephone with the custom-

[2] We could not find any enduring change in trading behavior due to a possible "September-11th-effect".

ers and their colleagues from the trading floor respectively. Each member of the sales staff is responsible for a certain group of customers, e.g. financial institutions or commercial customers. The dealers are notified of customers' requests by the sales staff via voice-box or phone. Because they are not informed about the direction of the upcoming trade (buy or sell), they always place bid/offer quotes at market conditions. Figure 1 illustrates the communication structure and the process of FX trading. Dealers told us that they almost solely use the electronic brokerage system EBS, because communication and transactions require less time than in any other interdealer trading channel. Moreover, spreads are very advantageous – around one or two pips only.

The data set consists of all trades, including indirect trades executed by voice-brokers or electronic brokerage systems such as EBS, direct trades completed by telephone or electronically, internal trades and customer trades. All trades are entered manually into the "deals blotter" by the back-office without differentiating between the several trading channels of each transaction. Bid-offer quotes at the time of each transaction are not recorded, either, but we can easily identify bid-offer prices afterwards by means of the trade-initiating party. For each trade, the following information is obtained from the hardcopy record:

(1) the type of each trade;
(2) the date and time of the trade[3];
(3) the counterparty;
(4) the quantity traded;
(5) the transaction price;
(6) the forward points if applicable[4];
(7) the initiator of the trade.

Identifying the initiator of each trade allows for distinguishing between incoming (passive) and outgoing (active) trades. Similar to the finding by Yao (1998, Table 3b), approximately 53% of all trades are signed as incoming or passive.

[3] The time stamp indicates the time of data entry and not the moment of trade execution which will differ slightly. Nevertheless there is no allocation problem because all trades are entered in a strict chronological order.

[4] On the basis of the forward points it is possible to transform each outright-forward trade into a "spot-like" trade. This requires that the covered interest parity holds, which is a stylized fact for the market under consideration.

3.2 Inventory position

The bank performs a clearly risk-averse policy regarding its open USD/EUR inventory position. The maximum long position is EUR 73.1 million, and the maximum short position is EUR 49.1 million. These extreme values are misleading, however, as the average absolute open position during the day is just EUR 3.4 million. The day always ends with a position close to zero. As we have no information about a possible overnight position change, we follow Lyons (1995) and set the daily starting position to zero. Figure 2 presents this inventory position measured in EUR.

The findings on our bank's inventory policy is consistent with Lyons (1995), Yao (1998) and Bjønnes and Rime (2001). Also, the absolute size of the inventory does not differ significantly from those observed in the three former studies, which is noteworthy, as our bank trades less often and with less volume. Obviously, the balancing of the inventory position is an important feature of dealers' behavior regardless of the bank's size.

3.3 Types of trade

Table 2 presents some statistics about the different types of trade. The structure of the interdealer trades is very similar to the ones observed by Bjønnes and Rime (2001, Table 2). Mean, median and standard deviation indicate that most transactions are in fact executed via EBS, as the dealers told us.[5]

Of more interest are the customer trades. The share of customer trading volume, amounting to nearly 40% (23% spot trades only), is striking. Moreover, our data set allows us to distinguish between three different groups of customers according to the bank's classification: financial business, commercial business and preferred commercial business. Whereas preferred and commercial customers mostly trade small positions in foreign exchange, financial customers transact larger amounts. The latter, however, trade less often with our bank than commercial customers. Outright-forward trades seem to play a major role in customer business where they make up for 30 to 40% of all trades. Despite their numerical importance, they do not have an effect on the statistical structure of the data set (see Panel A and B in Table 2). The

[5] When working with the EBS system dealers can only transact trades of the size of one, two or five million EUR/USD. Trades of the size of 10 million EUR/USD are pretty uncommon. There is only one single trade above that.

share of outright-forward trades does not differ significantly between the three customer groups, either.

3.4 Descriptive statistics of regression variables

Descriptive statistics for the relevant variables used in the estimations and intertransaction times are reported in Table 3. According to the above reasoning we will include outright forward transactions when it comes to the regression analysis. We will neglect, however, the preferred commercial business in the following, as these customers are attended to individually, each with specific conditions, possibly reflecting cross-selling arrangements. Moreover, some cases are deleted from the final data set due to extreme price changes of more than 100 basis points or tiny volumes of less than 1,000 USD, as both characteristics may overly influence the relations of interest.

The final data set is thus composed of all incoming and outgoing spot and outright-forward trades of the interdealer, the financial and the commercial customer business (see Table 3). When reproducing Lyons' (1995) baseline model, we also consider only incoming trades. It might be interesting to compare the absolute values of these variables with the ones of the former studies.

One thing that catches the eye is the absolute change in transaction price between two periods Abs(Δp_{it}). Mean, median and standard deviation are by far higher – though not beyond means – than in the other studies mentioned. This can be explained by the fact that the trading records contain transactions of very different counterparties and by the comparatively long intertransaction time Δt. Whereas the average intertransaction time in Lyons (1995) and Yao (1998) is only 1 minute and 46 seconds, and in Bjønnes and Rime (2001) approximately 5 minutes, almost 13 minutes pass between two trades in our study and as long as 25 minutes between two incoming trades. In the foreign exchange business this is a huge time gap. The question arises whether the regression equation of Lyons' baseline model, which tries to map the dealer's reaction, is still an appropriate way of modeling this kind of trading behavior, as a lot can happen within 25 minutes! We help ourselves by trimming the data set to transactions and price changes of up to five minutes only and we use this "adjusted" data set for confirmatory estimations.[6] Although we lose a lot of observations, explanatory power sometimes tends to increase.

The statistics of the absolute values of order flow Abs(Q_{jt}) and inventory Abs(I_{it}) are very similar to those observed in Bjønnes and Rime (2001, Table 4, dealer 1), but clearly smaller than in Lyons (1995, Table 2) or Yao (1998, Table 4), which is compatible with the differences in the dealers' sizes.

4. Results

This section presents results in the order of the three hypotheses derived above. Within each section the different counterparties in foreign exchange trading are addressed. Section 4.1 focuses on inventory control, Section 4.2 examines information effects and Section 4.3 concentrates on spreads as a basis for profits. In order to check the robustness of findings all analyses discussed below have been repeated for spot trades only, for subsamples with different intertransaction times, for subperiods and with OLS regressions where appropriate. These changes do not systematically influence results and are thus usually not reported here.

The examination of microstructure effects in foreign exchange interdealer trading was pioneered by Lyons (1995). However, the changing trading environment and to some degree the different positioning of traders makes the earlier findings seem too specific (i.e. not general enough), as Bjønnes and Rime (2001) show. For the purpose of comparison, we have nevertheless repeated Lyons' regressions but do not find surprising effects. What can still be recognized is a clear "bounce" effect seen in the significant direction variables, but neither an inventory nor an information effect – just as expected (see Table 4).[7]

4.1 Inventory control

The picture becomes very different when we turn to confirm the fact of inventory control and to identify another instrument for inventory control. One approach to test inventory control is to regress the inventory position in t-1 on the change in inventory

[6] We also cut down the data set after a 10, a 15 and a 20 minutes interval. The results do not differ significantly. As a tendency one can recognize that the smaller the time interval, the better the fit of the model.

[7] In order to better identify the unexpected component of order flow, Romeu (2003) suggests a modification which we have applied and which indeed brings about a correctly signed and statistically significant order flow term, indicating an asymmetric information effect. In our regression, however, the inventory terms now become "wrongly" and significantly signed. So, we do not follow this approach in our case.

from t-1 to period t. The coefficient of interest would be zero if inventory changed randomly. If there were inventory control, however, the expected mean reversion in inventory would be revealed by a negatively signed coefficient. Table 5 gives a "correctly" signed and statistically significant coefficient showing that inventories tend to be reduced in the next trade by 21%. The size of this coefficient indicates a higher risk aversion in holding inventories than for the market maker examined by Bjønnes and Rime (2001) with a parameter size of 11%. However, the holding period is longer, so both effects tend to compensate each other.

If we apply this approach to measure an inventory effect for different counterparties, we do find that inventories are basically adjusted in the same way as when considering interbank business alone. It may be interesting to note, however, that financial customer orders are most cautiously treated in the sense that the mean reversion term is the comparatively highest.

The supposed instrument to perform inventory control is outgoing trades. We provide two approaches supporting the role of this instrument. Table 6 shows that for a regression approach proposed by Bjønnes and Rime (2001), the choice for an outgoing trade is independent of the inventory size (Abs I_{it-1}), negatively related to the trade size (Abs Q_{jt}) but positively determined by the fact that a customer trade was foregoing.

Another test of the particular role of outgoing interbank trades can be conducted by regressing cumulative customer order flow on different forms of cumulative interbank flows. If customer trades would indeed be squared by outgoing interbank trades – and not by appropriate positioning of limit orders – the exclusive relation should become obvious. The cointegration test shown in Table 7 and the graphical presentation of the relation in Figure 3 clearly supports the importance of outgoing interbank trades as an instrument of inventory control.

4.2 Information effects

Regarding the examination of information effects in FX trading, we examine three possible effects: first, the traditional asymmetric information assumption, second, counterparty-dependent information levels, and, third, the information content of disaggregated cumulative order flows.

Regarding asymmetric information in interbank trading, we have learnt that dealers do not regard this as a core issue anymore, as the electronic brokerage system provides sufficient liquidity to square less welcomed incoming trades, too. The empirical examination in Table 4 above is largely consistent with this view.

In another attempt to find out a possible asymmetric information effect, Bjønnes and Rime (2001) suggest to re-estimate the Madhavan and Smidt equation without the insignificant inventory terms. Calculations with our data show that the size of an incoming trade can then become a significant determinant of the bank's pricing behavior. Table 8, Panel A gives a statistically significant but surprisingly signed coefficient for the overall sample as the coefficient is negative, indicating that larger customer orders receive better prices. The explanation is straightforward, however: in contrast to earlier studies, our small bank is characterized by many small-sized customer orders below one million USD that were unimportant in other studies. These small orders are handicapped by two effects. First, banks have to cover fixed administrative costs for each deal and, second, small orders are more often given by small customers who can be expected to be less informed.

We thus run the same exercise for the different counterparties and find that the comparatively small commercial customers are indeed the driving force whereas neither financial customers nor interbank trading generate a significant negative coefficient (not reported here). The importance of size also becomes obvious from a regression considering only deals of one million USD and more which lead to an insignificant coefficient (not reported here). It is interesting, however, that a sample considering only incoming interbank trades results in a positive coefficient that is significant (Table 8, Panel B). Even though significance is fragile, the positive sign seems to be robust and indicates the problematic informative position of a small bank in the interbank market where the large market makers may be regarded as better informed.

We further explore this indication of counterparty-dependent levels of information by running the same type of regression as in Table 8 Panel A but including dummies for the three different counterparties (see Table 9). The significantly negative size effect is found again. New is, however, that the change in price is significantly lower for interbank trades and higher for commercial customer trades when compared to others. As there is some control for size, the counterparty effects – leading to differentiated prices – may cautiously indicate respective levels of information: other dealing banks, i.e. mainly big market makers, are comparatively best informed, followed by financial customers and, lastly, commercial customers. We dig deeper into this field in Section 4.3.

Finally, possible information in cumulative trades is examined. Evans and Lyons (2002) found that the cumulative order flow in the market is positively related to the exchange rate movement on the basis of daily aggregation. Fan and Lyons (2003) confirmed this kind of relation even for customer groups of a large market maker, again, for daily aggregated data. We test the same kind of idea but use deal-by-deal data for the different counterparties. As formulated in Hypothesis 2, a translation of findings from market wide data to a small bank does not seem to be very realistic. Many idiosyncratic shocks have to be expected, which might distort any relation. Findings for our data are given as cointegration tests documented in Table 10 and as graphical presentation in Figure 4 (see also Bjønnes and Rime, 2001).

It can be seen that two kinds of flows may contain information, i.e. incoming interbank trades and financial customer orders. Regarding the interbank market, the distinction between incoming and outgoing deals is necessary because outgoing trades largely serve as an instrument to balance inventory. They may thus be informative to other banks, but information about the market can only be gained from incoming trades. Less clear-cut is the case for the two customer groups. Even though the Fan and Lyons (2003) finding might suggest the informative content in financial customer orders, the sample of a small bank is really tiny when compared to the market and the findings thus rather surprising.

Reflecting these information effects, they may seem trivial from a demand and supply perspective but are a challenge for an asset market view. Traditional macro-models of foreign exchange markets consider fundamentals, possibly a risk premium and assume that any news is instantaneously incorporated into prices. Information contained in order flows may thus be seen as a vehicle of time-consuming information flows, either about news or risk perceptions. The case of the order flow view of foreign exchange is thus not self-evident and needs empirical support. Our data fits into the new literature but is remarkable in the respect that it stems from a small bank. A smaller bank, by definition, does not receive as many and as large flows as a market maker. That a small bank can recognize anything at all from incoming orders indicates that orders are widely and quickly disseminated in the market. The foreign exchange market is in this sense an efficient means of distributing "information" and the order flow view gains support from our study.

4.3 Spreads and profits

The last element to be examined is the spread component. It seems ex ante logical that a positive spread should be in the data, as banks do not charge fees to their counterparties in foreign exchange. Banks have to cover their administrative and capital costs and aim for earning a risk premium. It is thus comforting to note that a positive spread is a very consistent and robust finding in all kinds of specifications. For example, it can be found in the above presented "baseline estimation" (see Table 4), even though other aspects of this approach seem to be dependent on the type of trader and the trading environment. In the following, we proceed in four steps: first, we document the very clear size dependent price effect. Second, after controlling for size, different spreads are still observable. Third, profits are statistically explained by customer business and other variables. Fourth, estimating the impact from proprietary trading, profit sources are calculated from different angles. At the beginning, there is the objective to better understand the determination of spreads, as this is the basis of understanding the sources of profits.

Spreads do quite clearly depend on the size of the transaction, in particular when the sizes differ as much as in our sample. Figure 5 provides a plot of the absolute volume of a trade and the absolute price change. Considering that price changes vary significantly due to various unsystematic shocks, it is only the "average" that informs about the systematic volume dependent component. A regression where we take the log of the absolute size, plus the absolute size of transactions as explanatory variables, generates the regression line given in Figure 5. The fit of this approach is not very good, even though it is better than that of many other approaches we have tried.[8] Due to the low explanatory power, a disaggregation of this approach considering different counterparties does not help much either (not reported here).

We thus follow a different path and extend the reduced baseline equation as used in Section 4.2 by considering different spreads for the three counterparties being differentiated. Table 11 shows that coefficients have the expected signs and are indeed statistically significant. Moreover, the extension increases interpretive reliability. Assessing the spreads for different counterparties, we find very different sizes of spreads and an ordering that resembles an earlier finding from Section 4.2, where we had applied counterparty dummies. Table 11 reveals that the spread in interbank

[8] The rationale for this specification is to grasp two effects, i.e. the cost effect dominating small orders and the weak asymmetric information effect for very large orders.

trading is small and in this specification even not significantly different from zero (see also Carpenter and Wang, 2003, Table 4, electronic brokerage). Financial customers get a higher spread but it is commercial customers that clearly pay most (although this does not say anything about the competitiveness of the pricing). We interpret findings up to this point as a sign of group-specific spreads, even being different when taking into account the different trade sizes. This may cautiously indicate that groups with highest spreads are most important for profitability.

The crucial question for any profitability calculation is whether the bank only makes profit from customer trading or whether it earns from its own proprietary trading as well. The supposition from the scarce literature is quite clear: customer trading, or more generally, the income from spreads, seems to be the dominant profit base (Lyons, 1998, Yao, 1998a). In our case one may speculate that the small bank predominantly acts as intermediary and much less as a market maker. One may even question whether it can successfully participate in the interbank market due to its small size and the correspondingly small flows.

The suggested methods to investigate profitability of proprietary trading cannot be reproduced here. Lyons (1998) uses the information from non-dealt quotes to infer about speculative position-taking and thus proprietary trading. Yao (1998a) makes reasonable assumptions about interbank trades that follow incoming order flow with the aim of closing unwanted positions – the remaining position is then of a rather speculative nature. Unfortunately, we neither have information on quotes nor a stable pattern following incoming trades. Nevertheless, we generate almost perfect information about actual income per day, have information about relative spreads of counterparties and roughly know fixed total costs per trade – this frame ensures that calculations about income and profits should be useful. Moreover there is the methodological advantage – due to the comparatively long period covered here – that regressions can be run on daily income data.

According to the data used in this study, one can calculate the total income by subtracting value-weighted total purchases from total sales. In addition, we assume the average income margin resulting from this calculation applies to the open position at the end of the day – this yields an income of approximately 966 thousand Euros. Inflating this figure to a full year makes roughly 3 mill. EUR income from spot and forward USD trading. Further sources of income for the total FX department come from swap trades, future and option trades and from trading in other currencies. In comparison to this "hard" income figure, profit figures are more questionable. We basically assume for our calculations that there are fixed administrative costs per trade of 100 EUR. Reliable information on this issue is difficult to get and not easy to interpret, as it would require insight into the internal cost accounting of a bank. We just take this figure – which may be a rough guess of full transaction costs – and later provide some robustness considerations.

Income determinants cannot be calculated exactly, as this would require information on alternative market prices simultaneously – the true spread would then be the difference between the price realized with the counterparty and the market price. This information is not included in our data and cannot be constructed from available sources. We have to rely on approximations based on different available data. Spread income from trading is plausibly estimated by trading volume and can be divided into groups of counterparties. The difficult analytical problem is proprietary trading: even though the bank is tentatively closing open positions that have been received due to incoming order flow, the bank usually does not directly and fully close open positions during the day. A proxy for this kind of position-taking is the daily average of absolute values of inventory from trade to trade. Again, in a frictionless market, a non-speculative approach would result in a zero inventory, even though customer orders are intermediated. Other proxies for possible gains from proprietary trading are volatility in the market or possible trends over the day.

Putting these variables into univariate regressions explaining income for 87 trading days shows that volume and inventory have clear explanatory power, but that the other variables, such as price trend and price volatility, do not (not reported here). Testing several multivariate regressions always leads to a similar finding: volume and inventory are significant. Of course, both have a common component. The resulting regression in Table 12 thus considers the volume of three counterparties as well as the inventory component going beyond volumes. Standardized coefficients for this approach give a rough picture about the relative importance of these variables for income. Commercial customers are first in this respect, proprietary trading second and financial customers third, whereas a positive income effect from interbank trading is questionable.

As an alternative way of investigating the possible impact of proprietary trading on income, the structure of spreads over time is informative. We thus follow the reduced baseline equation approach from Table 8 and calculate the change in spread depending on the intertransaction time. As can be seen from Table 13, there is a recognizable trend that spreads become larger over time (the level of "spreads" is not of interest here but rather its time structure). As the estimation includes the direction of the trade, the finding does not just reflect increasing volatility with lower data frequency. If we assume that trades within one-minute intervals come closest to the notion of frictionless intermediation, the time-dimension of increasing spreads indicates profitable decisions to hold positions. Then the difference between shortest-term trades and long-term trades serves as a proxy for proprietary trading. It follows from this procedure that the "share" of proprietary trading to overall income would be in the order of up to 18% (for overall spread vs. 1 minute spread). Less clear is the origin of this income: we cannot identify any trading strategy that would systematically react on customer orders (not reported here).

Translating 18% into Euros means that the bank generated an income of about 174 thousand Euros with proprietary trading during the sample period. The remaining 792 thousand Euros are distributed according to the structure of spreads with counterparties (see Table 11) times their respective volumes. Table 14 Panel A gives the results. Not surprisingly, commercial customers generate most income according to this calculation. More interesting – but unfortunately also quite debatable – is the next step from income to profits.

As a first assumption, we set administrative costs to be fixed costs per trade of 100 Euros and we neglect other kinds of costs. As a second assumption, we allocate interbank trading to the three other groups by conducting two things: commercial customer trades are followed by interbank trades in 34% of cases, financial customer trades in 64%. The costs of these interbank trades are allocated to the respective customer trades. All remaining interbank trades, i.e. 1,269 trades, are assumed to be caused by proprietary trading. As a third assumption, the small amount of interbank income is allocated according to the just described trading shares. These calculations result into a "profit" that is about 612 thousand Euros, of which more than 80% is generated by commercial customers, 10% by proprietary trading and less than 10% by financial customers (see Panel B in Table 14).

Of course, the assumptions that we have made explicit can be debated. In particular, three questions arise: first, is the rough estimation of an 18% income share from proprietary trading justified? Second, is the fixed cost of 100 Euros possibly too low, and, third, is the interbank trading correctly allocated? Regarding the 18% share, the argument is not that it is exactly this value, but also the regression approach (see Table 12) shows that proprietary probably generates income. Regarding fixed costs, higher figures would in particular reduce the profit share of the small-sized commercial customers. A different allocation of interbank trading might, for example, argue that the participation of the small bank is not only necessary to conduct own account trading but also to attract larger customers. This might justify a redistribution of costs from proprietary trading to customer trading with respective consequences for profitability.

In summary, there is evidence that commercial customers of this small bank pay higher spreads due to smaller volumes per trade – covering fixed costs – and due to less information – reflecting their avoidance of costs for information acquisition. The opposite end of the spectrum of counterparties is marked by banks in the interdealer market where the small bank hardly generates income and does not seem to be too well informed. Financial customers are in between, but clearly come closer to the interbank market than to commercial customers. Profitability calculations reflect relative information levels: the bank mainly relies on trading income from commercial customers. There are indications of income from proprietary trading but its source can neither be related to an information advantage in the interbank market nor to private information from customer orders.

5. Conclusions

This study examines all of the single transactions of a bank in Germany in USD/EUR-trading over a four-month period. The purpose is to learn about the behavior of this bank and about possible differences of the counterparties in the trading process. We complement and extend the rare earlier literature in three respects: first, we examine inventory effects for three different counterparties in the new environment of electronic brokerage. Evidence supports hypothesis 1, confirming the findings of Bjønnes and Rime (2001), namely that inventory control is important and that its main instrument is outgoing trades. Second, we apply several approaches to test information effects. In contrast to earlier literature, asymmetric information effects are rather small; trade size does matter but inversely to findings in earlier studies, i.e. trade size is related to decreasing price changes, as the small bank conducts small trades. What is surprising from our point of view is, however, that cumulative order flows of incoming interbank and financial customer trades are informative even at the low business frequency and low trading volume of a small bank. In summary, there is much more information identified even at the small bank than was expected ex ante. Thus, hypothesis 2 is not really supported. Thirdly, spreads are found to reflect not only different amounts of trades but also differences in information level. These differences can be shown to tentatively translate into profits for our bank, thereby backing hypothesis 3. Moreover, we find, without explanation, that the small bank generates profits in proprietary trading. Our expectation in this respect was more skeptical – so hypothesis 3 is not supported.

Overall, the order flow approach to foreign exchange as pioneered by Lyons (1995) proves to be a fruitful avenue (see early Goodhart, 1988). It is comforting that the advances made by Bjønnes and Rime (2001) hold at a different time and for a different type of bank, too. It is encouraging, moreover, that the findings for the interbank business can for the most part be extended to customer business (see earlier Yao 1998). Finally, the microstructure approach's supposition that heterogeneity matters is confirmed by the different roles played by the different counterparties. The key towards understanding the behavior of the small bank towards these counterparties seems to be the relative information level of each group. Other market makers may be even better informed than the small bank, financial customers are treated cautiously and only commercial customers are clearly less informed. It fits into this interpretation that the last group may be the main source of profitability.

In particular, the findings on the differences in customer groups impel us to speculate on possible links with the macro exchange rate literature. Our results strengthen the hypothesis that the theoretically and empirically hardly explainable shorter-term exchange rate movements are connected to the behavior of financial customers, such as fund managers. Moreover, the analysis of order flows may provide a useful approach to studying the behavior of this group in particular and thus to learning about the true dynamic forces in the foreign exchange market. As these results point in the same direction as the study of Fan and Lyons (2003), although applying more disaggregated data of a different kind of bank, further research along these lines may promise high rewards.

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Table 1 Comparison of daily spot USD/EUR (USD/DEM) trading volumes, average numbers of trades per day and customer shares for several studies

Study	Lyons (1995)	Yao (1998)	Bjønnes/Rime (2001), dealer 1	Carpenter/Wang (2003), AUD/USD	This paper	BIS (2002) per bank
Data period	08/03/92 – 08/07/92, 5 trading days	11/01/95 – 12/08/95, 25 trading days	03/02/98 – 03/06/98, 5 trading days	05/01/02 – 07/03/02, 45 trading days	07/11/01 – 11/09/01, 87 trading days	-
Volume per day (mill. USD)	1,200	1,529	443	213	39 (52)*	50 - 150 (mean)
Trades per day	267	181	198	203	40 (51)*	-
Volume per trade (mill. USD)	4.5	8.4	2.2	1.1	1.0	-
Customer share	0%	13.9%	3.3%	10.6% (incl. central bank trades)	22.5% (39.2%)*	25.0% GER 32.5% world

*The values in parentheses refer to the data set including outright-forward transactions.

Figure 1 Participants and trade channels in the FX market

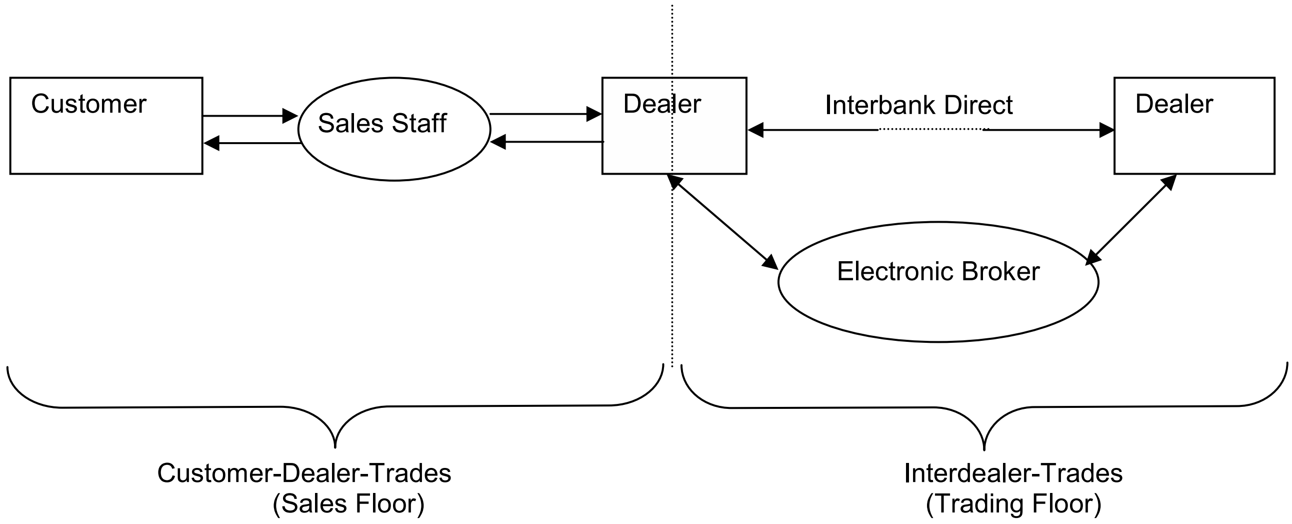
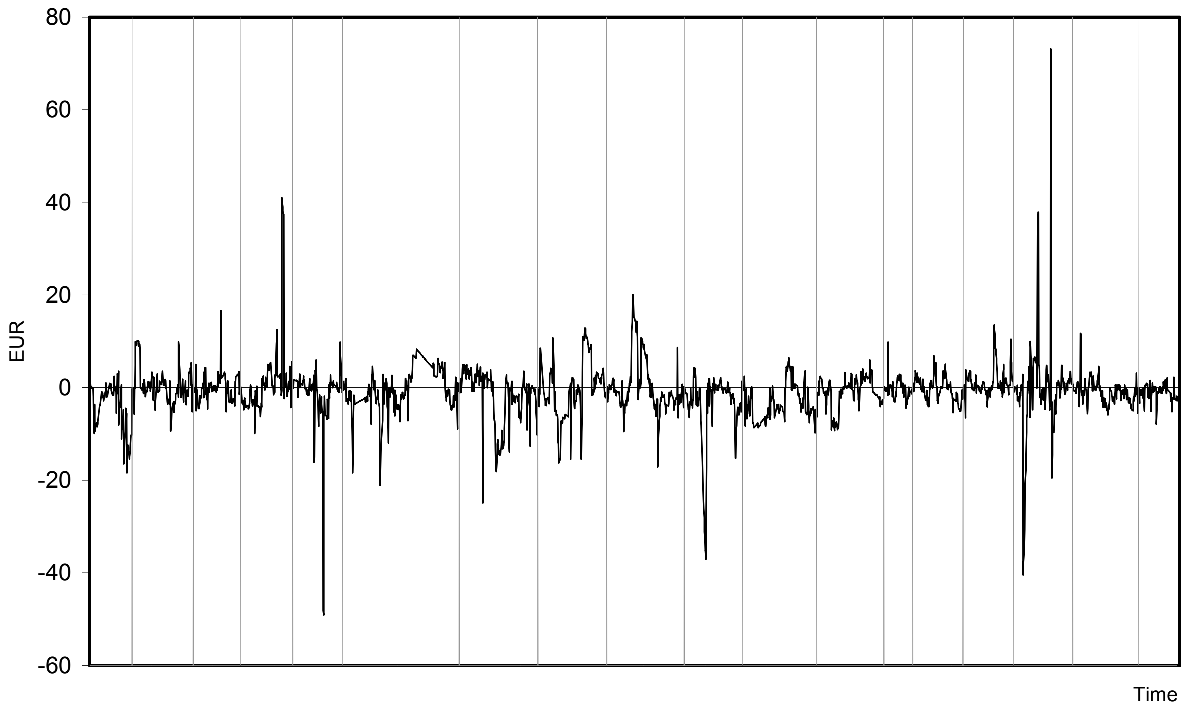


Figure 2 Overall inventory position (in EUR millions)



Plot shows the evolution of the dealer's inventory position in EUR millions over the whole sample period (07/11/01 – 11/09/01). The horizontal axis is in transaction-time. Vertical lines indicate the end of each calendar week.

Table 2 **Types of trades**

A Spot and outright forward trades

	Interbank	Customers	Preferred commercial business	Financial business	Commercial business	Total
No. of trades	1,919	2,491	801	171	1,519	4,410
% total	43.51%	56.49%	18.16%	3.88%	34.44%	100.00%
Volume	2,726	1,755	146	405	1,204	4,481
% total	60.83%	39.17%	3.25%	9.04%	26.87%	100.00%
Average size	1.42	0.70	0.18	2.37	0.79	
Median size	1.00	0.08	0.05	0.76	0.08	
St. dev.	1.42	3.50	0.74	4.92	4.08	
Min.	0.00	0.00	0.00	0.02	0.0	
Max.	16.42	76.43	7.29	41.68	76.43	

B Spot trades only

	Interbank	Customers	Preferred commercial business	Financial business	Commercial business	Total
No. of trades	1,805	1,703	545	111	1,047	3,508
% total	51.45%	48.55%	15.54%	3.16%	29.85%	100.00%
Volume	2,639	767	70	179	518	3,406
% total	77.49%	22.51%	2.04%	5.25%	15.22%	100.00%
Average size	1.46	0.45	0.13	1.61	0.49	
Median size	1.00	0.06	0.05	0.43	0.07	
St. dev.	1.43	2.80	0.49	4.40	3.22	
Min.	0.00	0.00	0.00	0.02	0.00	
Max.	16.42	76.32	7.06	41.68	76.32	

The table shows the trading activity of the four different types of counterparties over the sample period, i.e. interbank, preferred commercial, financial and commercial business respectively. All volume and trade size statistics are in EUR millions. Panel A contains spot as well as outright forward trades, whereas Panel B contains spot trades only.

Table 3 Descriptive statistics on regression variables (adjusted data set)
A Spot and outright forward trades

	Δp_{it}	Abs(Δp_{it})	Q_{jt}	Abs(Q_{jt})	I_{it}	Abs(I_{it})	Δt
Mean	-0.05	10.71	0.02	1.17	-0.90	3.39	12:56
Median	0.00	6.00	0.05	0.58	-0.60	2.08	3:47
Maximum	99.70	99.70	76.43	76.43	73.12	73.12	3:47:49
Minimum	-91.00	0.00	-76.32	0.00	-49.10	0.00	00:00
Std. Dev.	17.30	13.58	3.28	3.07	5.77	4.76	20:31
Observations	3449	3449	3535	3535	3535	33535	3449

B Spot trades only

	Δp_{it}	Abs(Δp_{it})	Q_{jt}	Abs(Q_{jt})	I_{it}	Abs(I_{it})	Δt
Mean	-0.09	10.95	-0.06	1.09	-0.85	3.21	15:44
Median	0.00	7.00	0.05	1.00	-0.53	1.92	5:55
Maximum	91.00	91.00	16.46	76.32	73.12	73.12	3:47:49
Minimum	-91.00	0.00	-76.32	0.00	-49.10	0.00	00:00
Std. Dev.	17.19	13.25	2.64	2.41	5.76	4.85	23:02
Observations	2808	2808	2895	2895	2895	2895	2808

Δp_{it} is the change in price between two successive trades in pips. Abs(Δp_{it}) is the absolute value of this change. Q_{jt} is the quantity transacted in millions of EUR from the perspective of the dealer's counterparty, positive for a purchase and negative for a sale. Abs(Q_{jt}) is the absolute value of Q_{jt}. I_{it} is the inventory at the end of period t and Abs(I_{it}) its absolute value. Δt is intertransaction time between two successive trades. Panel A contains spot as well as outright forward trades, whereas Panel B only shows spot trades.

Table 4 Lyons' baseline model

A Overall sample (spot and forward trades)

Dependent Variable: Δp_{it}
Included observations: 3449

Variable	Coefficient	t-Statistic
Constant	***-0.703	-3.53
Order flow Q_{jt}	0.387	0.55
Inventory I_{it}	0.737	1.06
Lagged inventory I_{it-1}	-0.811	-1.17
Direction D_t	***6.504	18.40
Lagged direction D_{t-1}	***-5.030	-16.04
Adjusted R^2	0.12	
D-W stat	2.47	

B Incoming interbank trades (spot trades only)

Dependent Variable: Δp_{it}
Included observations: 1087

Variable	Coefficient	t-Statistic
Constant	***-2.661	-5.45
Order flow Q_{jt}	0.519	1.51
Inventory I_{it}	-0.083	-0.61
Lagged inventory I_{it-1}	0.045	0.34
Direction D_t	***1.993	2.85
Lagged direction D_{t-1}	***-1.829	-3.73
Adjusted R^2	0.01	
D-W stat	2.12	

The dependent variable is Δp_{it}, the change in price between two successive trades. In Panel B we use incoming interbank spot trades only. Q_{jt} is order flow measured in millions, positive for a purchase by another dealer or customer, and negative for a sale. I_{it} is inventory at the end of period t. D_t is an indicator variable picking up the direction of the trade, positive for purchases (at the ask) and negative for sales (at the bid). Estimation uses GMM and Newey-West correction. t-values in the third column, and "***", "**" and "*" indicate significance at the 1%, 5% and 10%-level respectively.

Table 5 Inventory management: mean reversion in dealer's EUR/USD inventory, results for $I_{it} - I_{it-1} = \alpha + \beta I_{it-1} + \varepsilon_t$

A Interbank trades

β	-0.21
Test statistic	***(-10.51)
Implied half-life (mean)	47:58
Implied half-life (median)	14:02
Observation	1875

B Incoming interbank trades

β	-0.27
Test statistic	***(-9.26)
Implied half-life (mean)	37:32
Implied half-life (median)	10:59
Observation	1268

C Commercial business

β	-0.35
Test statistic	***(-7.82)
Implied half-life (mean)	29:50
Implied half-life (median)	8:44
Observation	1491

D Financial business

β	-0.47
Test statistic	***(-4.39)
Implied half-life (mean)	23:27
Implied half-life (median)	6:52
Observation	170

The dependent variable is the change in dealer's inventory between two successive (incoming) interbank, commercial or financial customer trades, respectively. The explanatory variable is lagged inventory. The first row reports the mean reversion coefficient β. The second row shows the test statistic from an Augumented Dickey-Fuller unit root test. "***" indicate that the null hypothesis of a unit root is rejected at a 1%-significance level. The implied half-life is calculated as mean or median intertransaction time multiplied with $\ln(2)/\ln(1+\beta)$ (see Lyons 1998, p.109). The regression contains spot and outright forward trades. Results for β and the significance remain stable when we use spot trades only.

Table 6 Probit-regression of choice of incoming/outgoing trade

Dependent Variable: Trade-choice
Included observations: 3533 (spot and outright forward trades)

Variable	Coefficient	z-Statistic
Constant	***-0.611	-13.89
Abs(Q_{jt})	**-0.018	-2.49
Forgoing customer trade	***0.505	10.84
Abs(I_{it-1})	0.003	0.62
Trade-choice(-1)	***0.529	11.99
McFadden's R^2	0.07	

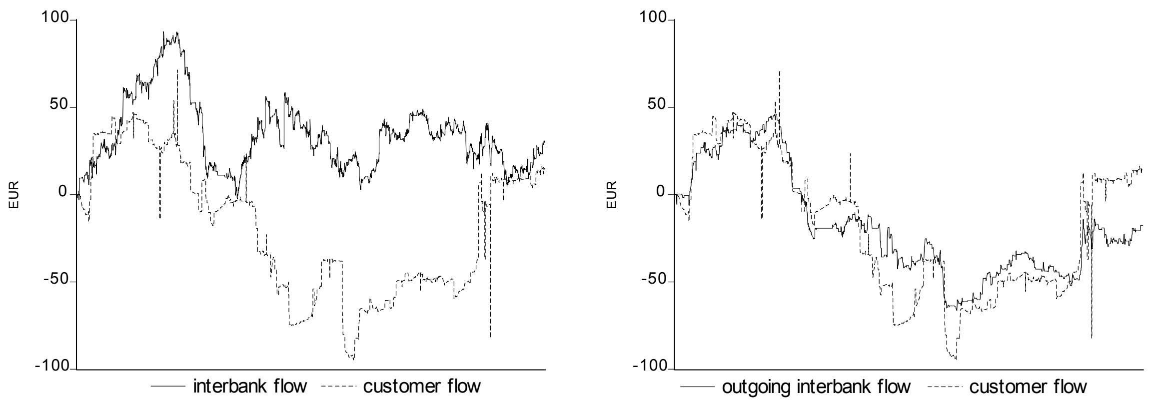
Probit regression of incoming/outgoing interbank trade decision. Incoming trades are coded 0, while outgoing trades are coded 1. The dummy "Forgoing customer trade" equals 1 if previous trade was with a customer. R^2 is McFadden's analog to ordinary R^2-measures.

Table 7 Tests of cointegration between cumulative customer order flow and interbank order flow

	Customer vs. interbank	Customer vs. incoming interbank	Customer vs. outgoing interbank
Constant	44.40	33.06	13.16
Cumulative flow (cum Q_{jt})	0.08	-0.50	0.56
Trend	-0.00	0.01	-0.02
ADF-test	***(-3.00)	***(-3.32)	***(-3.97)
PP-test	***(-2.94)	***(-3.49)	***(-4.59)
Observations	3535	2929	2269

The parameters are estimated using ordinary least squares. Since the null hypotheses of a unit root are not rejected when testing for the variables, t-values for each coefficient are not reported here. The dependent variable is interbank order flow, incoming or outgoing respectively. Cumulative order flow is created using the direction and size of all executed trades, incoming and outgoing respectively. ADF-test is a standard augmented Dickey-Fuller test on the regression residuals. PP-test is a Phillips-Perron test on the regression residuals. The tests do not include a constant since a constant is included in the original regression equation. So "***", "**" and "*" indicate significance of the whole model at the 1%, 5% and 10% level respectively.

Figure 3 Movement of cumulative customer order flow and interbank order flow



Plots show the evolution of cumulative customer order flow and cumulative (outgoing) interbank order flow measured in EUR millions.

Table 8 Microstructure effects in FX trading: Information effect

A Overall sample (spot and forward trades)

Dependent Variable: Δp_{it} Included observations: 3449		
Variable	Coefficient	t-Statistic
Constant	***-0.608	-3.14
Order flow Q_{jt}	***-0.380	-4.03
Direction D_t	***6.433	18.44
Lagged direction D_{t-1}	***-5.012	-16.02
Adjusted R^2	0.12	
D-W stat	2.47	

B Incoming interbank trades (spot trades only)

Dependent Variable: Δp_{it} Included observations: 1087		
Variable	Coefficient	t-Statistic
Constant	***-2.603	-5.58
Order flow Q_{jt}	*0.577	1.69
Direction D_t	***1.975	2.81
Lagged direction D_{t-1}	***-1.813	-3.70
Adjusted R^2	0.01	
D-W stat	2.12	

The dependent variable is Δp_{it}, the change in price between two successive trades. In Panel B we use incoming interbank spot trades only. Q_{jt} is order flow measured in millions, positive for a purchase by another dealer or customer, and negative for a sale. D_t is an indicator variable picking up the direction of the trade, positive for purchases (at the ask) and negative for sales (at the bid). Estimation uses GMM and Newey-West correction. t-values in the third column, and "***", "**" and "*" indicate significance at the 1%, 5% and 10%-level respectively.

Table 9 Microstructure effects in FX trading: Interbank vs. customer trades

A Interbank-Dummy

Dependent Variable: Δp_{it} Included observations: 3449		
Variable	Coefficient	t-Statistic
Constant	**0.719	2.33
Order flow Q_{jt}	***-0.364	-4.04
Interbank	***-2.612	-5.05
Direction D_t	***6.227	17.60
Lagged direction D_{t-1}	***-5.008	-16.16
Adjusted R^2	0.12	
D-W stat	2.46	

B Customer-Dummies

Dependent Variable: Δp_{it} Included observations: 3449		
Variable	Coefficient	t-Statistic
Constant	***-1.889	-5.64
Order flow Q_{jt}	***-0.362	-4.09
Commercial	***2.949	5.52
Financial	-1.097	-0.82
Direction D_t	***6.165	17.34
Lagged direction D_{t-1}	***-5.021	-16.15
Adjusted R^2	0.12	
D-W stat	2.45	

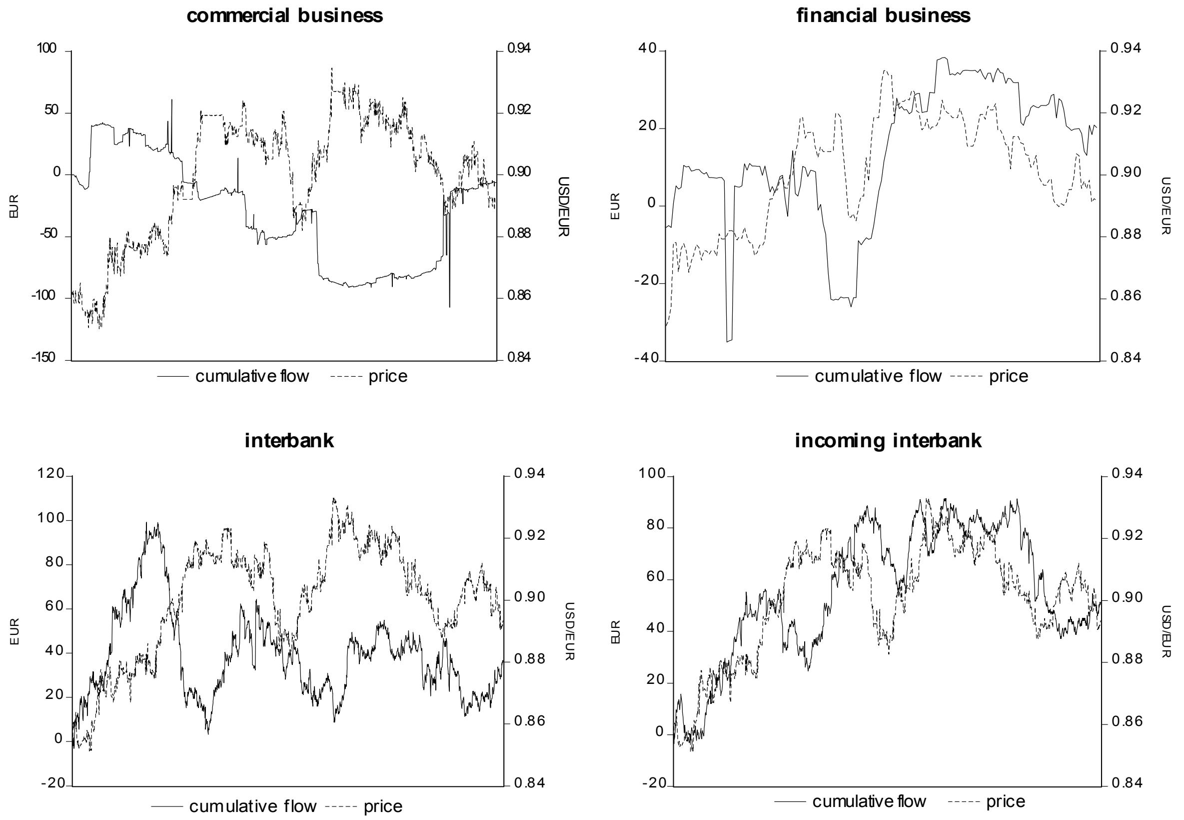
The dependent variable is Δp_{it}, the change in price between two successive trades. Q_{jt} is order flow measured in millions, positive for a purchase from another dealer or customer, and negative for a sale. In Panel A the dummy-variable "Interbank" equals 1 if the counterparty is another dealer, 0 otherwise. In Panel B the dummy-variable "Commercial" equals 1 if the counterparty is a commercial customer, 0 otherwise. The dummy-variable "Financial" equals 1 if the counterparty is a financial customer, 0 otherwise. D_t is an indicator variable picking up the direction of the trade, positive for purchases (at the ask) and negative for sales (at the bid). Estimation uses GMM and Newey-West correction. t-values in the third column, and "***", "**" and "*" indicate significance at the 1%, 5% and 10%-level respectively.

Table 10 Test of cointegration between price and cumulative order flows

	Commercial business	Financial business	Interbank	Incoming interbank	Outgoing interbank
Constant	0.884	0.884	0.885	0.871	0.891
Cumulative flow (cum Q_{jt})	-0.291	0.152	-0.029	0.417	-0.438
Trend	0.008	0.167	0.017	0.010	0.001
ADF-test	***(-3.02)	**(-2.31)	*(-1.78)	**(-2.40)	***(-2.88)
PP-test	***(-3.77)	**(-2.45)	**(-2.14)	***(-2.67)	***(-3.11)
Observations	1492	171	1876	1269	606

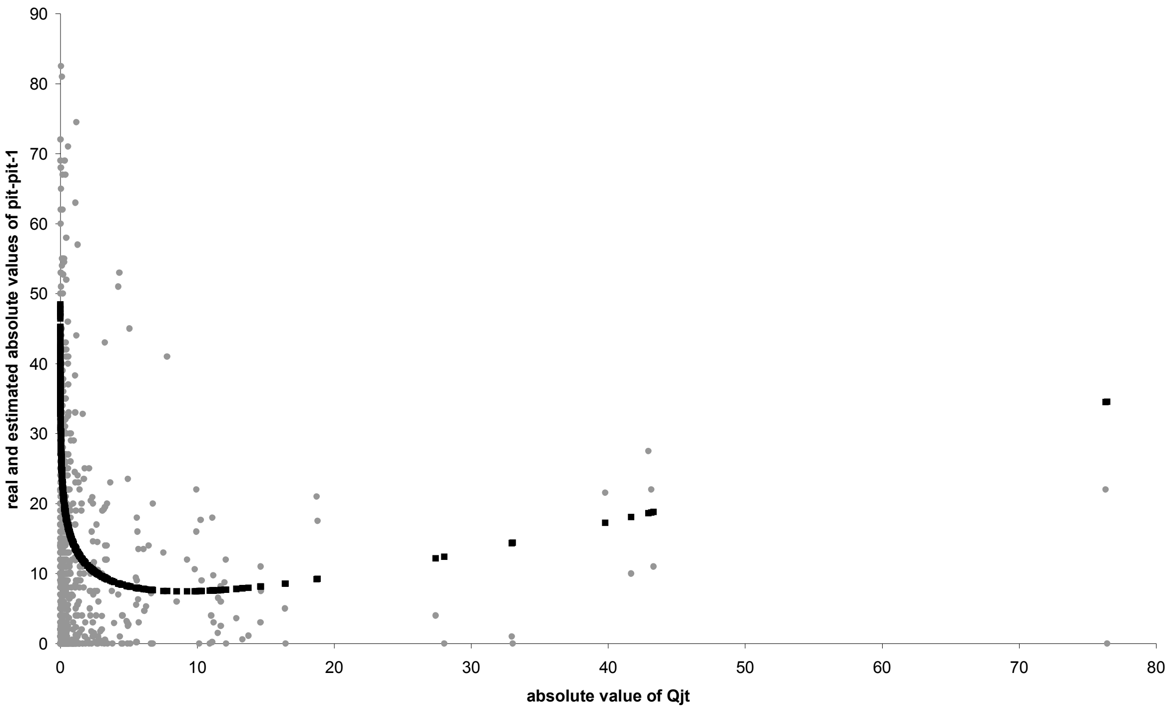
The parameters are estimated using ordinary least squares. Since the null hypotheses of a unit root are not rejected when testing for the variables, t-values for each coefficient are not reported here, because they are unreliable as they depend on the sample's size. The dependent variable is price, the exchange rate respectively. Cumulative order flows are created using the direction and size of all executed trades, incoming and outgoing respectively. ADF-test is a standard augmented Dickey-Fuller test on the regression residuals. PP-test is a Phillips-Perron test on the regression residuals. The tests do not include a constant since a constant is included in the original regression equation. So "***", "**" and "*" indicate significance of the whole model at the 1%, 5% and 10% level respectively. The flow and trend coefficients are multiplied by 10^3.

Figure 4 Price movements and cumulative order flows



Plots show the evolution of price movements and cumulative order flows for different counterparties, i.e. commercial and financial customers, interbank and incoming interbank respectively, measured in EUR millions.

Figure 5 Economies of scale in FX trading: Transaction size, real and estimated price changes in customer trades



Plot shows the relationship between the absolute values of customer orders Q_{jt} measured in EUR millions and the absolute values of change in price between two successive trades Δp_{it} (grey). The black dotted line is generated by a regression where we take the log of the absolute values of Q_{jt} plus the absolute value itself as explanatory variables.

Table 11 Microstructure effects in FX trading: Different baseline spreads in interbank, commercial and financial customer trades

Dependent Variable: Δp_{it} Included observations: 3449		
Variable	Coefficient	t-Statistic
Constant	**-0.430	-2.24
Order Flow Q_{jt}	***-0.313	-4.03
Commercial direction D_t	***12.751	25.30
Lagged commercial direction D_{t-1}	***-12.210	-23.94
Financial direction D_t	***5.872	4.45
Lagged financial direction D_{t-1}	***-3.885	-3.71
Interbank direction D_t	***2.595	6.27
Lagged interbank direction D_{t-1}	-0.595	-1.57
Adjusted R^2	0.26	
D-W stat	2.41	

The dependent variable is Δp_{it}, the change in price between two successive trades. Q_{jt} is order flow measured in millions. D_t is an indicator variable picking up the direction of the trade, positive for purchases (at the ask) and negative for sales (at the bid) multiplied with a dummy variable for each counterparty group, i.e. other dealers, commercial or financial customers respectively. Estimation uses GMM and Newey-West correction. t-values in the third column, and "***", "**" and "*" indicate significance at the 1%, 5% and 10%-level respectively.

Table 12 Earnings in daily FX trading: Trading volumes and average inventory position

Dependent Variable: Daily trading profit in EUR Included observations: 87			
Variable	Coefficient	t-Statistic	Standardized β-coefficients
Constant	1,713.83	0.79	1,713.83
Interbank trading volume in EUR	*0.00017	1.68	0.19156
Financial customer trading volume in EUR	***0.00035	3.91	0.24075
Commercial customer trading volume in EUR	**0.00021	2.48	0.34009
Residuals of "absolute value of average daily inventory = a_0 + a_1 (trading volume)"	**0.00254	2.39	0.29250
Adjusted R^2	0.34		
D-W stat	2.07		

The dependent variable is daily trading profit in EUR calculated from the overall purchases and sells of USD/EUR each day. We average out daily buy and sell rates weighted by the volume of each trade and the according exchange rate. Trading volume is the absolute value of daily amounts of EUR sold and purchased, separated for individual trading groups such as interbank, financial and commercial customers respectively. The absolute value of average daily inventory is the average EUR position during each trading day. To extract the partial correlation between trading volume and average inventory position, we here use the residuals of an OLS-estimation regressing trading volume on absolute value of average daily inventory. Estimation uses OLS and Newey-West correction for heteroskedasticity and autocorrelation. t-values are reported in the third columns, "***", "**" and "*" indicate significance at the 1%, 5% and 10%-level respectively. Standardized β-coefficients report the influence of the exogenous variables independent of their dimensions.

Table 13 Development of the direction variables (spread) over time

Dependent Variable: Δp_{it}	overall	< 1 min.	< 2 min.	< 3 min.	< 5 min.	< 10 min.	< 40 min.
Constant	***-0.61	-0.17	0.07	-0.10	-0.11	-0.14	*-0.37
Order Flow Q_{jt}	***-0.38	-0.06	*-0.19	**-0.23	***-0.21	***-0.23	***-0.32
Direction D_t	***6.43	***4.61	***4.89	***4.95	***5.25	***5.46	***6.33
Lagged direction D_{t-1}	***-5.01	***-4.12	***-4.36	***-4.44	***-4.57	***-4.69	***-4.71
Baseline spread 2x $\|D_{t-1}\|$	10.02	8.24	8.73	8.89	9.14	9.37	9.42
Share of overall baseline spread	100%	82%	87%	89%	91%	93%	94%
Adjusted R^2	0.12	0.11	0.13	0.14	0.16	0.15	0.13
Included observations	3449	1081	1421	1617	1854	2249	3153

The dependent variable is Δp_{it}, the change in price between two successive trades. Q_{jt} is order flow measured in millions. D_t is an indicator variable picking up the direction of the trade, positive for purchases (at the ask) and negative for sales (at the bid). Estimation uses GMM and Newey-West correction. "***", "**" and "*" indicate significance at the 1%, 5% and 10%-level respectively.

Table 14 Estimated income and profits in FX trading
A Incomes from different counterparties and proprietary trading

EURO	Income	%	Income/Day	Income/Trade	Income/Volume	Volume
Total	966,289.62	100.0%	11,106.78	273.35	0.023%	4,138,353,779
Proprietary	173,932.13	18.0%	1,999.22	49.20	0.004%	4,138,353,779
Interbank	21,805.96	2.3%	250.64	11.62	0.001%	2,552,087,693
Financial	72,423.54	7.5%	832.45	423.53	0.018%	405,290,330
Commercial	698,127.98	72.2%	8,024.46	467.91	0.059%	1,180,975,756

B Profits from different sources

EURO	Profit	%	Profit/Day	Profit/Trade	Profit/Volume	Volume
Total	612,389.62	100.0%	7,038.96	173.24	0.015%	4,138,353,779
Interbank/Proprietary	61,763.84	10.1%	709.93	48.66	0.001%	4,138,353,779
Financial	47,104.72	7.7%	541.43	178.43	0.012%	405,290,330
Commercial	503,521.05	82.2%	5,787.60	251.03	0.043%	1,180,975,756

Total income has been calculated on a daily basis: For every day we average out a buy and a sell rate (amount of EUR/amount of USD) for all trades weighted by the volume of each trade, e.g. "daily volume of USD sold in EUR" divided by "daily volume of USD sold" = average daily exchange rate at the bid. Then we approach the income due to the trading activity within each counterparty group and the income that stems from proprietary trading. The share of proprietary trading income is estimated by the gap between the overall baseline-spread and the overall spread within an intertransaction time of less than 1 minute (see Table 13). We estimate spreads and generated trading income for each single trade and for each single counterparty group by using the regression in Table 11. The estimated income shares for each trading group are then attached to the total income minus proprietary income. For an approximation of profits we assume average transaction costs of EUR 100 per trade. Interbank trading income is broken down as follows: Costs are split between commercial and financial customer trades depending on the average offsetting activity within each group, the share of offsetting interbank trades and the number of trades itself, i.e. costs of commercial business = (1,492 commercial business trades + 34% interbank offsetting trades)*EUR 100 and costs of financial business = (171 financial business trades + 64% interbank offsetting trades)*EUR 100. Remaining interbank trades are assumed to be proprietary based (costs of proprietary trading = 1,269*EUR 100).