Knowing Me, Knowing You: Trader Anonymity and Informed Trading in Parallel Markets[*]

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Abstract:

In this paper we empirically analyze whether the degree of trader anonymity is related to the probability of information-based trading. We use data from the German stock market where non-anonymous traditional floor based exchanges co-exist with an anonymous computerized trading system. We extend the model of Easley / Kiefer / O'Hara / Paperman (1996) to allow for simultaneous estimation for two parallel markets. We find that the probability of informed trading is significantly lower in the floor based trading system. We further document that the size of the spread and the adverse selection component are positively related to the estimated probabilities of information-based trading.

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1 Introduction

The coexistence of multiple markets for the same asset is a pervasive phenomenon. To a certain extent it has historical roots. This is likely to be the reason for the coexistence of regional exchanges with the main market. In the last one or two decades, however, we have witnessed the development of new, and in most cases electronic, markets for assets that were already traded on existing markets. Examples comprise, but are not limited to, the advent of proprietary trading systems like Instinet, the development of Tradepoint in the UK and the introduction of a fully computerized trading system as a complement to existing floor-based exchanges in Germany.

The coexisting markets usually differ along a variety of dimensions. One striking observation is that they often differ with respect to the degree of anonymity they offer. Particularly, most electronic crossing networks are completely anonymous whereas the New York Stock Exchange (NYSE) is not. On the other hand, the upstairs market for block trades is less anonymous than the trading floor of the NYSE. NASDAQ's anonymous Small Order Execution System (SOES) coexists with the less than perfectly anonymous NASDAQ dealer market. The electronic trading system in Germany is completely anonymous whereas the floor trading system, organized similar to the NYSE, is not.

The degree of trader anonymity is a potentially important determinant of market quality. Institutional traders are often said to prefer an anonymous environment because they do not want to publicly disclose their trading needs (Economides / Schwartz 1995, Schwartz / Steil 1996). On the other hand, however, anonymity allows informed traders to remain unidentified and may thus aggravate the adverse selection problem. This view is supported by the theoretical analysis of Benveniste / Marcus / Wilhelm (1992).[1] They model the interaction between a specialist and brokers who may have information about the trading motives of their customers. Due to the ongoing relation with the specialist, the brokers have an incentive to share this information with the specialist in order to maintain a reputation as fair traders. The incentive to do so derives from the fact that the specialist in a non-anonymous market can price discriminate against brokers that have previously exploited their informational advantage.[2]

The coexistence of markets with differing degrees of anonymity raises the question of which traders prefer which market. This is an important question because it has immediate implications for the design of trading systems. The arguments outlined above suggest that informed traders have a preference for the anonymous markets. The main objective of the present paper is to test this hypothesis empirically.

Our paper is related to previous research on trading in parallel markets and on trader anonymity. Most theoretical models of multimarket trading (e.g. Pagano 1989, Bhushan 1991, Chowdhry / Nanda 1991, Subrahmanyam 1991, Grossman 1992, Hendershott / Mendelson 1999) offer little guidance as to whether informed traders prefer anonymous markets because the markets in these models do not differ with respect to the degree of anonymity. Among the exceptions are the papers by Seppi (1990) and Rhodes-Kropf (1998). Seppi (1990) models the coexistence of an anonymous trading floor and a non-anonymous upstairs market for block transactions. He finds that the upstairs market attracts only uninformed traders because be-

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1 The issue of trader anonymity is also implicitly addressed in the dual trading models of Röell (1990) and Fishman / Longstaff (1992). In both models, a broker has information about the trading motives of his customers. The market itself, however, is anonymous. In Forster / George (1992) strategic traders and the price-setting market makers may have information about either direction or magnitude of liquidity trading. This knowledge about the composition of the order flow is, however, qualitatively different from the ability to obtain information about the trading motives of individual investors or brokers.

2 Chan / Weinstein (1993) make a similar point. A further argument suggesting that adverse selection costs may be higher in anonymous markets rests on the observation that it is more difficult for uninformed traders to credibly signal their uninformed trading motives, e.g. in the sense of „sunshine trading“ (Admati / Pfleiderer 1991).

havioral constraints that informed traders do not want to comply with can be enforced in the non-anonymous setting. Rhodes-Kropf (1998) examines the coexistence of an anonymous and a non-anonymous dealer market. Customers in the non-anonymous market can negotiate with the dealers and thus obtain execution at prices inside the quoted spread. This feature is absent in the anonymous market.

Previous empirical research is generally consistent with the notion that anonymity is associated with higher adverse selection costs. Harris / Schultz (1997) find that market makers loose on trades with the „SOES bandits“ which are executed in the anonymous SOES system. Madhavan / Cheng (1997) find that, consistent with the model of Seppi (1990), the upstairs market is used by traders who can credibly signal that they trade for liquidity reasons. De Jong / Nijman / Röell (1996) show that trades that are negotiated bilaterally (and thus non-anonymously) and are then executed through the Paris Bourse's CAC system have a lower price impact than regular CAC trades. Garfinkel / Nimalendran (1998) document that NYSE stocks exhibit larger increases in the bid-ask spread on insider trading days[3] than NASDAQ stocks and conclude that the trading system of the NYSE is less anonymous. In a paper that is closely related to ours, Heidle / Huang (1999) document that, consistent with the results of Garfinkel / Nimalendran (1998), the probability of informed trading is higher on NASDAQ than on the NYSE or AMEX.

The present paper's potential to offer new insights rests on two distinguishing features. First, our research design makes use of the fact that in Germany an anonymous electronic market and a non-anonymous floor trading system coexist. Our sample stocks are traded in both systems and both markets are open to all traders, thus making the choice of the trading location to

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[3] An insider trading day is a day on which officers or directors have traded in shares of their firm. Such trades are published by the SEC.

a large part endogenous.[4] This unique institutional setting comes close to an experimental design.

Second, we extend the empirical method proposed by Easley / Kiefer / O'Hara / Paperman (1996). The method is based on a structural sequential trade model along the lines of Easley / O'Hara (1987, 1992). It allows to estimate the intensity of informed and uninformed order flow and thus permits a direct assessment of the probability of informed trading.[5] We extend this method to allow for simultaneous estimation for two parallel markets This allows us to directly compare the probability of informed trading and to test our main hypothesis that this probability is higher in the anonymous market.

Our results provide strong support for this hypothesis. The probability of informed trading is significantly lower on the floor of the Frankfurt Stock Exchange than in the anonymous screen trading system. We further document that the size of the bid-ask spread, and particularly the size of the adverse selection component of the spread, is positively related to the probability of informed trading. Finally, we provide evidence on the validity of our empirical method.

The paper is organized as follows. In section 2 we provide background information about the organization of trading in the German stock market. Section 3 describes our data set. The empirical method is developed in section 4. Results are reported in section 5. It includes a subsection that presents extensions and robustness checks. Section 6 discusses the implications of the results and concludes.

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4 This is an exception rather than the rule. For example, only large blocks are traded in the upstairs market. Orders for more than 1000 shares cannot be executed in SOES. Access to proprietary trading systems is limited to institutional investors.

5 Easley / Kiefer / O'Hara / Paperman (1996) estimate their model using NYSE data. They find that the probability of informed trading is negatively related to firm size. The methodology has subsequently been adopted to address a variety of issues. These comprise (but are not limited to) the practice of payment for order flow (Easley / Kiefer / O'Hara 1996), the information content of the time between trades (Easley / Kiefer / O'Hara 1997a), the importance of trade size (Easley / Kiefer / O'Hara 1997b), analyst coverage (Easley / O'Hara / Paperman 1998), the order flow in an electronic market (Brown / Thomson / Walsh 1999) and differences between dealer and auction markets (Heidle / Huang 1999).

2 Market Structure

As already outlined, the German stock market offers investors the choice between two trading systems. Since April 1991 an anonymous electronic trading system operates parallel to the floor. It was introduced to facilitate institutional investors' trading activities in the most liquid German stocks. All stocks that are traded electronically are also traded on the floor.

Floor trading takes place at the Frankfurt Stock Exchange and seven smaller regional stock exchanges. The former is by far the most important German exchange in terms of trading volume and number of officially listed firms. Therefore, our analysis of floor trading concentrates on the Frankfurt Stock Exchange. The daily trading period starts and ends with a batch auction. Between these auctions continuous trading, interrupted by a third batch auction at noon, takes place. Trading on the floor of the Frankfurt Stock Exchange is organized in a way that is similar to the trading protocol of the NYSE. Order matching is conducted by a Kursmakler whose position resembles that of the NYSE specialist. The Kursmakler has exclusive access to the information in the limit order book. He may trade for his own account, but is not obliged to do so. It has, however, been found that the Kursmakler participation rates are higher than comparable rates for the NYSE specialists.[6] The Kursmakler continuously quotes bid and ask prices which either represent orders in the limit order book or his willingness to trade for his own account. The quotes are publicly displayed on the floor (next to a screen displaying the quotes from the electronic trading system) and also entered into the electronic order routing and information system BOSS-CUBE. Therefore, access to the quotes is not limited to the market participants on the floor. During our sample period the trading hours of the Frankfurt Stock Exchange extended from 10.30 a.m. to 1.30 p.m.[7] The minimum order

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6 See Freihube/Kehr/Krahnen/Theissen (1999) and Madhavan/Sofianos (1998).
7 Trading hours have been extended in July 1998.

size was (with the exception of the noon auction) 50 or 100 shares, depending on the nominal value of a stock.[8] Odd-lot orders could only be submitted to the noon auction.

Besides any profits they may earn on their market making activities the Kursmaklers receive a commission called *Courtage*. Both buyers and sellers have to pay 0.04% of the trading volume for stocks included in the DAX index and 0.08% for all other stocks. Floor brokers (Freimakler) pay only a reduced commission. Since (institutional) investors may execute their orders through a Freimakler,[9] the rates given above are only upper bounds of the amount effectively paid.

The electronic trading system IBIS, replaced by XETRA in November 1997,[10] was operated parallel to the floor. It was an anonymous open limit order book system. In 1997 about 100 of the most liquid German stocks were quoted in IBIS. In that year the IBIS trading volume for the 30 stocks which constitute the DAX index accounted for about 39.5% of the total DM trading volume in these stocks on all German exchanges. The IBIS trading hours extended from 8.30 a.m. to 5.00 p.m. All member banks of the regional stock exchanges as well as Kursmaklers and Freimaklers were allowed to participate in IBIS. Some participants acted as "voluntary market makers" in IBIS, i.e., they continuously quoted bid and ask prices. They were, however, not obliged to do so and did not have any privileges.

The trading screens displayed the best bid and ask prices as well as the quoted depth. Trading in IBIS was completely anonymous. No broker identification codes were displayed on the screen and the identity of the counterparty in a transaction was only revealed in the settlement note. The minimum order size for an IBIS transaction in 1997 was either 100 or 500 shares,

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8 In June 1999 this minimum order size requirement was abolished.

9 By doing so investors may economize on transaction costs. On the other hand, however, employing the Freimakler introduces an additional layer of intermediation and may thereby cause agency problems, e.g. front running.

depending on the liquidity of the stocks. Although the minimum order size in IBIS was larger than on the floor, the average transaction size for 29 of the 30 stocks we analyze was larger on the floor. The lower minimum order size on the floor is, therefore, unlikely to be an important issue.

Dual capacity trading, i.e., trading on behalf of customers and principal trading by the same institution, was allowed in both systems. Also, both systems were subject to the same insider trading legislation and the same level of enforcement. Different levels of informed trading can, therefore, not be explained by differing legal environments.

The coexistence of the two trading systems raises the question of why both markets are viable. First, the electronic trading system is likely to exhibit a higher degree of operational efficiency that may compensate for higher adverse selection costs. Theissen (1999) presents evidence consistent with this view. Second, some traders are likely to have a natural preference for one of the markets. For example, futures and options are also traded in an electronic market. It is therefore likely that traders in the derivatives markets will use the electronic trading system for their spot market transactions rather than rooting their orders to the floor. Foreign institutions can access the electronic trading system via remote access but would have to incur much higher costs in order to establish a presence on the floor (see Hau 1999 for an analysis of the relation between trader location and trading profits in XETRA).

3 Data

Our analysis concentrates on the three hours in which the floor and the screen trading systems operate parallel. The data set comprises time-stamped transaction prices for the 30 stocks which constitute the DAX index. These stocks account for more than 80% of the total trading

[10] Xetra is also an anonymous continuous auction system. Unlike IBIS it includes batch auctions and offers

volume in domestic stocks. The sample period spans the 44 trading days in June and July 1997. Two days (July 21st and July 23rd) had to be removed from the sample. On both days heavy trading caused a breakdown of the exchange's computer facilities. Trading had to be suspended several times.

The floor data comprise time-stamped transaction prices, volume data and the quotes entered by the Kursmaklers. Batch auction prices were removed from the data set because they do not have a counterpart in IBIS. Quote data from the floor do not include information about the quoted depth. The IBIS data include time-stamped best-bid, best-ask and transaction prices, trading volume and volume at the best-bid and best-ask.

The descriptive statistics presented in Table 1 document that the sample stocks differ considerably with respect to market capitalization and trading activity. The number of transactions (the central variable in our empirical model) of the most liquid stock is more than 8 times (floor) and 10 times (IBIS) as high as the number of transactions for the least liquid stock. The differences are even more pronounced when the DM trading volume is considered. The volume of the most liquid stock is more than 14 times the volume of the least liquid stock. Therefore, although our sample includes only the 30 stocks which constitute the DAX index, these stocks nevertheless exhibit a wide range in terms of liquidity.

Insert Table 1 about here

IBIS was a "hit and take" system according to the taxonomy of Domowitz (1992). Therefore, buy and sell orders were not automatically matched by the system. Rather, traders willing to buy shares had to explicitly accept sell orders submitted by others and vice versa. A trader wishing to buy or sell a large number of shares had to accept several standing orders. From an economic point of view, this may be considered as one trade. In our data set, however, one

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some additional features, e.g. special order types.

transaction is recorded for each of the accepted orders. Since these transactions do not have identical time stamps, we cannot identify the component transactions to a large trade with certainty. We therefore used the following algorithm to bundle transactions. All transactions that occurred within at most x seconds from the previous transaction within a sequence of transactions at either non-increasing or non-decreasing prices where considered as one large trade. This algorithm thus treats a sequence of buyer-initiated transactions that occurred with a delay of no more than x seconds between two consecutive transactions as one large trade, and similarly for seller-initiated transactions. We chose two values for x, one second and five second. We refer to the algorithms as the 1-second aggregation rule and the 5-second aggregation rule. A third rule is the no aggregation rule. It simply uses the raw data as provided by the exchange. To assure the robustness of our results we re-estimated our model using all three aggregation rules.

4 Methodology

Easley / Kiefer / O'Hara / Paperman (1996) have developed and empirically implemented a structural model that builds on Easley / O'Hara (1987, 1992). In this section we describe an extension of this model that accounts for parallel trading in two markets.[11] In anticipation of our empirical implementation we denote the two markets as the screen trading system and the floor, respectively.

During a period T (a trading day) a risky asset is traded in both markets. In each market a risk neutral competitive market maker quotes bid and ask prices for one unit of the risky asset.

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[11] Heidle / Huang (1999) also use the Easley / Kiefer / O'Hara / Paperman (1996) method to compare the probability of informed trading across trading venues. They do, however, not analyze parallel trading but rather construct a sample of stocks that switched their trading location (e.g. from NASDAQ to NYSE). They then estimate the probability of informed trading separately for the pre- and post-switch period and compare the resulting estimates using t-tests and non-parametric tests. In contrast, we estimate the model jointly for both markets and draw inferences by imposing appropriate restrictions and testing whether they are binding.

Trades arise from market buy and sell orders submitted by a large number of traders. A fraction of these traders is potentially informed.

Time within the trading day is indexed by $t \in [0,T]$, trading days are indexed by $i \in [1,I]$. Prior to the beginning of the trading day, nature determines whether an information event takes place. Information events are assumed to be independent across days and to occur with probability α.[12] If no information event takes place the asset value is V_i^*. If an information event occurs, the asset value is $\underline{V}_i < V_i^*$ with probability δ and $\overline{V}_i > V_i^*$ with probability 1-δ. The asset value is revealed at the end of the trading day. Information events on different days are assumed to be independent.

There are two groups of traders. Uninformed traders do not know the asset value nor do they observe whether an information event occurred. They trade for liquidity reasons. Informed traders know whether an information event took place and observe the true asset value. They buy assets when the value (to be publicly revealed at T) is high and sell when the value is low. This implies that they do not trade when there was no information event. We do not model traders' market choice. We rather assume that the arrival rates of uninformed and informed traders in both markets are given. We do, however, allow these arrival rates to be different in the two markets.

Following Easley / Kiefer / O'Hara / Paperman (1996) we model the order arrival processes as independent Poisson processes. We denote the arrival rate of uninformed buy and sell orders in the screen trading system by ε_S and the corresponding rates for the floor by ε_F.[13] The arrival rates of informed traders on days with information event are μ_S (screen) and μ_F (floor)

[12] For ease of notation we suppress the index for the asset under consideration. We estimate the model for each stock separately, thereby allowing the probability α to vary across stocks.

and zero on days without information event. Figure 1 shows the composition of the order flow in both trading systems on days with good news, bad news and no news.

<u>insert Figure 1 about here</u>

The market makers do not observe whether an information event occurred or not, but they do know the unconditional probabilities of the information events and the order arrival rates. Throughout the trading day they use Bayes' rule to update their beliefs. For example, after a buyer-initiated transaction they will revise the probability assigned to a positive information event upwards.

For the updating process and the resulting bid and ask prices it is of importance whether a market maker observes only the trades in her market or the trades in both markets. This is inconsequential, however, for the estimation of the parameters of our structural model. This follows from the assumption of independent order arrival rates in both markets.

Consider the market maker on the floor.[14] At time zero, the beginning of the trading day, her beliefs about the probabilities for a "no news" (n) "bad news" (b) and "good news" (g) event correspond to the unconditional probabilities, i.e., $P_F(0) = \left(1-\alpha, \alpha\delta, \alpha\left(1-\delta\right)\right)$.[15] After each trade these probabilities are updated using Bayes' rule. Let $P_F(t) = \left(P_{F,n}(t), P_{F,b}(t), P_{F,g}(t)\right)$ denote the vector of the subjective probabilities conditional on the trade history in the market prior to time t. The expected asset value, conditional on the trade history, is then

$$E_F(V_i \mid t) = P_{F,n}(t) \cdot V_i^* + P_{F,b}(t) \cdot \underline{V}_i + P_{F,g}(t) \cdot \overline{V_i} \tag{1}$$

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[13] As in Easley / Kiefer / O'Hara / Paperman (1996) we make the simplifying assumption that the arrival rates of uninformed buy and sell orders are equal.

[14] The derivation for the electronic trading system is identical.

[15] We dropped the subscript i for the trading day.

The market maker sets bid and ask prices $b_F(t)$ and $a_F(t)$ equal to the conditional expectation of the asset value, given that the next trade is seller-initiated and buyer-initiated, respectively. The resulting bid-ask spread is given by

$$s_F(t) = a_F(t) - b_F(t) = PI_{F,Buy}(t) \cdot \left(\overline{V_i} - E\left[V_i \mid t\right] \right) + PI_{F,Sell}(t) \cdot \left(E\left[V_i \mid t\right] - \underline{V_i} \right) \tag{2}$$

where $PI_{F,Buy}(t)$ [$PI_{F,Sell}(t)$] are the conditional probabilities that the next buyer-initiated [seller-initiated] trade is information-motivated. The spread at time *t* is thus equal to the probability that a buy is information based times the expected loss to an informed buyer, plus a symmetric term for sells. The probability that any trade that occurs at time *t* is information-based is the average of the probability of an information-based sell and the probability of an information based buy, weighted by the probability that the next transaction is buyer- or seller-initiated, respectively.

$$PI_F(t) = \text{Prob}(buy) PI_{F,Buy}(t) + \text{Prob}(sell) PI_{F,Sell}(t) = \frac{\mu\left(P_{F,g}(t) + P_{F,b}(t)\right)}{2\varepsilon + \mu\left(P_{F,g}(t) + P_{F,b}(t)\right)} \tag{3}$$

At the opening we have, using the unconditional probabilities,

$$PI_F \equiv PI_F(0) = \frac{\alpha \cdot \mu_F}{\alpha \cdot \mu_F + 2 \cdot \varepsilon_F} \tag{4}$$

Easley / Kiefer / O'Hara / Paperman (1996) propose a method to estimate the model parameters α, δ, ε and μ for one market. These parameters can be used to obtain an estimate of the unconditional probability *PI*(0) to encounter an informed trader. Our objective is to estimate the parameters for two markets and to test the hypothesis that the probability PI_S to encounter an informed trader in the anonymous screen trading system is higher than the corresponding probability PI_F on the floor. We have to take into account the inherent linkage between the two markets. Since the same stocks are traded, both the probability α that an information event occurs and the probability δ that new information is negative should be equal. Our estimation is, therefore, based on the joint likelihood of observing a given trade history in both markets. In constructing the likelihood function we impose (and test) the restriction that α and δ are equal in the two markets.

Under the assumptions stated above, the likelihood of observing $S_{S,i}$ sells and $B_{S,i}$ buys in the screen trading system and $S_{F,i}$ sells and $B_{F,i}$ buys on the floor on a "no news" day *i* is

$$l_{n,i} = \exp\left(-2(\varepsilon_S + \varepsilon_F)T\right) \cdot \frac{(\varepsilon_S T)^{B_{S,i}} \cdot (\varepsilon_S T)^{S_{S,i}} \cdot (\varepsilon_F T)^{B_{F,i}} \cdot (\varepsilon_F T)^{S_{F,i}}}{B_{S,i}!S_{S,i}!B_{F,i}!S_{F,i}!} \tag{5}$$

Note that (5) equals the product of the densities of the four independent Poisson processes that determine the arrival of uninformed sellers and buyers in the two trading systems. On a "bad news day" and a "good news day", the corresponding likelihoods are given by

$$\begin{aligned} l_{b,i} = {} & \exp\left(-(2\varepsilon_F + 2\varepsilon_S + \mu_F + \mu_S)\cdot T)\right) \\ & \cdot \frac{(\varepsilon_S T)^{B_{S,i}} \cdot \left[(\varepsilon_S + \mu_S)T\right]^{S_{S,i}} \cdot (\varepsilon_F T)^{B_{F,i}} \cdot \left[(\varepsilon_F + \mu_F)T\right]^{S_{F,i}}}{B_{S,i}!S_{S,i}!B_{F,i}!S_{F,i}!} \end{aligned} \tag{6}$$

$$\begin{aligned} l_{g,i} = {} & \exp\left(-(2\varepsilon_F + 2\varepsilon_S + \mu_F + \mu_S)\cdot T)\right) \\ & \cdot \frac{(\varepsilon_S T)^{S_{S,i}} \cdot \left[(\varepsilon_S + \mu_S)T\right]^{B_{S,i}} \cdot (\varepsilon_F T)^{S_{F,i}} \cdot \left[(\varepsilon_F + \mu_F)T\right]^{B_{F,i}}}{B_{S,i}!S_{S,i}!B_{F,i}!S_{F,i}!} \end{aligned} \tag{7}$$

The likelihood of observing $\Omega_i = \left\{S_{S,i}, B_{S,i}, S_{F,i}, B_{F,i}\right\}$ on a day of unknown type is the weighted average of equations (5)-(7).

$$l_i = (1-\alpha)\cdot l_{n,i} + \alpha\cdot\delta\cdot l_{b,i} + \alpha\cdot(1-\delta)\cdot l_{g,i} \tag{8}$$

Because the news events are assumed to be independent across days, the likelihood of observing the data $\mathrm{M} = \{\Omega_\mathrm{i}\}_{\mathrm{i}=1}^{\mathrm{I}}$ over I days is

$$L(M \mid \theta) = \prod_{i=1}^{I} l_i \tag{9}$$

Maximization of (9) with respect to the parameter vector θ yields maximum likelihood estimates of the parameters of interest. Since the probabilities α and δ are defined on a scale from 0 to 1 we estimate unrestricted parameters and convert them via a logit transform into economically interpretable probabilities. Standard errors of the transformed coefficients are calculated using the delta method.[16]

The model just outlined restricts the probabilities α and δ to be equal across markets whereas the estimated order arrival rates ε and μ are allowed to be different. This is our base model, denoted model 1. We estimate three other models. Model 2 allows all parameters to be different across markets. We compare models 1 and 2 using likelihood ratio tests to test whether the restriction on α and δ imposed by model 1 is binding. This provides a useful check of the validity of the empirical model.

Model 3 restricts all parameters to be equal across markets. We perform likelihood ratio tests of model 3 against model 1 to test for differences in the trading intensity. Model 3 imposes the joint restrictions $\varepsilon_S = \varepsilon_F$ and $\mu_S = \mu_F$. Rejection of this restriction does not generally allow conclusions about whether the probability of informed trading is higher in one of the markets. We therefore estimate a model 4 where we impose the nonlinear restriction

$$PI_S = \frac{\alpha \cdot \mu_S}{\alpha \cdot \mu_S + 2 \cdot \varepsilon_S} = PI_F = \frac{\alpha \cdot \mu_F}{\alpha \cdot \mu_F + 2 \cdot \varepsilon_F} \tag{10}$$

that the probability of informed trading is equal in the two trading systems. The likelihood ratio test of model 4 against model 1 serves as the test of our main hypothesis.

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[16] We estimated the model in GAUSS. The procedures make use of the Constrained Maximum Likelihood library and are available upon request.

5 Empirical Results

5.1 Parameter estimates and tests of significance

Table 2 reports the parameter estimates and robust standard errors of the base model. All results are based on the 5-second aggregation rule for IBIS transactions defined in section 3. Results for the no aggregation rule are similar and are shown in a table in the appendix.[17]

The standard errors of the estimated parameters are small. This is particularly true for the order arrival rates ε and μ. The probabilities α that an information event occurs lie between 0.16 and 0.55. The probabilities δ that an information event is negative is smaller than 0.5 for the majority of the stocks. This is consistent with the observation that the return on the DAX was positive during the sample period. The order arrival rates are generally higher in the electronic trading system. This reflects the fact that IBIS has a higher market share than the Frankfurt Stock Exchange.

The probability of informed trading in trading system *j* is given by

$$PI_j = \frac{\alpha \cdot \mu_j}{\alpha \cdot \mu_j + 2 \cdot \varepsilon_j} \tag{11}$$

We find that, consistent with our main hypothesis, this probability is higher in the anonymous electronic trading system for 29 of the 30 stocks. Figure 2 depicts the point estimates of PI_j and their 90 % confidence intervals for both trading systems. Visual inspection of the figure yields two conclusions. First, the differences of the *PI* point estimates are large for the majority of stocks and, second, there is either no or only a small overlap of the confidence intervals.

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[17] Results for the 1-second aggregation are available upon request. They are very similar to both the no aggregation and the 5-second aggregation case. Note that the parameter estimates for the floor are not the same for the different aggregation rules because we estimated the model for the floor and IBIS jointly. The differences in the estimated parameters for the floor are, however, negligible.

Hence, figure 2 clearly suggests economically significant differences in the amount of informed trading. A more formal test of this hypothesis will be presented below.

Insert Figure 2 here

An important issue is whether the probability of informed trading is systematically related to the firm size or the liquidity of the stocks. The results reported in Easley / Kiefer / O'Hara / Paperman (1996) suggest the existence of a negative relation. This is confirmed in our data set. We regressed the *PI* estimates on the log of the number of transactions. The results for the 5-second aggregation rule and the no aggregation case, presented in Table 3, document that the probability of informed trading is negatively related to the overall liquidity of the stock. The slope coefficients are negative and are significantly different from zero at better than the 5% level.

Insert Table 3 about here

In Section 4 we have proposed a set of likelihood ratio tests that serve to test the validity of our model specification and the parameter restriction implied by our main hypothesis. Table 4 reports the results. As outlined above, our base model (model 1) can be interpreted as a restricted version of the most flexible model 2. In this model, all parameters, including the probabilities α and δ, are allowed to differ between the floor and screen trading system. Model 2 is the least restrictive model, but it is also an implausible specification since one would expect the probabilities α and δ to be equal. Hence, a rejection of model 1 in favor of model 2 would clearly indicate misspecification. The results reported in column 2 of Table 4 are, however, encouraging. At the 5% significance level model 1 is rejected only for 4 out of the 30 stocks (BASF, Commerzbank, Karstadt and Siemens). At the 1% level only the model for one stock (Karstadt) is rejected.

Model 3 restricts both the probabilities α and δ and the order arrival rates ε and μ to be equal in both trading systems. Visual inspection of Table 2 suggests already that the order arrival rates tend to be higher in IBIS. It is therefore not surprising that the restrictive model 3 is rejected in favor of model 1. The likelihood ratio tests indicate rejection at the 5% level for all stocks and at the 1% level for all but two stocks. The test thus provides clear evidence that the trading intensities in the two trading system are significantly different.

Insert Table 4 about here

We now turn to the formal test of our main hypothesis that the probability of informed trading is larger in the anonymous screen trading system. In Table 2 we already documented that the probability PI_S in IBIS exceeds its counterpart on the floor, PI_F, for 29 of the 30 stocks. A formal test of this hypothesis is provided by the likelihood ratio test of model 1 against model 4. The last column of Table 4 contains the p-values that correspond to this test. The specification of model 4 imposes the nonlinear restriction (10), i.e., it restricts the (unconditional) probability of informed trade to be equal in both trading systems. The null hypothesis of equal *PI* is rejected at the 5 % significance level for 25 of the 29 stocks for which we documented a higher *PI* in IBIS.

To check the robustness of this result we also followed Heidle / Huang (1999) and tested the null hypothesis of equal mean *PI* in both trading systems using a cross-sectional t-test. Similarly, we tested the hypothesis of equal median *PI* using a non-parametric Wilcoxon test. The results are summarized in Table 5. The null hypothesis is rejected at the 1% level in all cases. Therefore, the results of the formal statistical tests confirms the conclusions drawn from inspection of Figure 2.

Insert Table 5 here

5.2 Probability of informed trading and the bid-ask spread

In this section we provide supplementary results that serve to provide additional evidence on the validity of the empirical model. We make use of the fact that the probability of informed trading, *PI*, is directly related to the adverse selection risk that suppliers of liquidity face. This adverse selection risk should be incorporated into the bid-ask spread. Note that the structural model underlying the estimation of the *PI*'s implies that the spread at the beginning of the trading day is

$$s_j(0) = PI_j\left(\overline{V} - \underline{V}\right).$$

It is thus positively related to the probability of informed trading and to $\left(\overline{V} - \underline{V}\right)$, which has a natural interpretation as a measure of volatility. We therefore expect stocks with higher *PI* to have higher bid-ask spreads. To test this hypothesis we ran the cross-sectional regression[18]

$$s_{j,k,l} = \gamma_0 + \gamma_1 PI_{j,l} + \varepsilon_{j,k,l}$$

where l indexes the sample stocks. Separate regressions are estimated for the two trading systems j (j = floor, screen) and for three different measures of the bid-ask spread, indexed by k. We used the quoted bid-ask spread, the effective bid-ask spread and the adverse selection component of the spread. All spread measures are expressed as a percentage of the quote midpoint. Calculation of the adverse selection component is based on a two-way decomposition of the spread similar to the one used by Huang / Stoll (1996).[19] Table 6 shows the results ob-

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18 We also included the standard deviation of daily closing midquote returns as an additional explanatory variable. It was insignificant in each case.

19 We classified, using the method proposed by Lee / Ready (1991), each transaction as being buyer-initiated or seller-initiated. We then matched each transaction with the next transaction at the opposite side of the market (i.e., we matched each buyer-initiated transaction with the next seller-initiated transaction and vice versa). The prices of the two transactions are then used to calculate the realized spread which directly measures the profit of the suppliers of immediacy. The difference between the average effective and the average realized spread is our measure of the adverse selection component.

tained when the *PI*'s estimated using 5-second aggregation are used as the independent variable. Results based on the no aggregation and 1-second aggregation rules are very similar.

Insert Table 6 here

As hypothesized, the spread is positively related to the probability of informed trading. The slope coefficients are significantly different from zero at the 5% level in all but one case. In this one case (quoted spreads for the floor) the coefficient is significant at the 10% level. The probability of informed trading is, as is evidenced by the R^2, most closely related to the adverse selection component of the spread. This is what one would expect to find given that the *PI* is a direct measure of the adverse selection risk.

Consistent with the larger *PI* estimates, the adverse selection component of the spread is generally higher in IBIS than on the floor. The average over all stocks is 0.238% in IBIS as compared to 0.183% on the floor.[20] Our model predicts that the differences in the adverse selection component are positively related to the differences in the *PI* measure. To test this conjecture we estimate the following regression:

$$\left(s_{S,l}^{a} - s_{F,l}^{a}\right) = \gamma_0 + \gamma_1 \left(PI_{S,l} - PI_{F,l}\right) + \varepsilon_l$$

The results are (for the 5-second aggregation):

$$\left(s_{S,l}^{a} - s_{F,l}^{a}\right) = \underset{(0.15)}{0.003} + \underset{(3.35)}{0.605}\left(PI_{S,l} - PI_{F,l}\right)$$

The regression R^2 is 0.29. The cross-sectional differences in the *PI*'s are, as hypothesized, positively related to the cross-sectional differences in the adverse selection component of the spread. We interpret this as evidence of the validity of our empirical model.

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[20] See Theissen (1999) for detailed results.

6 Conclusion

In the present paper we address the issue of trader anonymity empirically. We make use of a unique institutional feature of the German stock market, namely, the co-existence of an anonymous electronic trading system and a non-anonymous floor-based exchange. Our main objective is to analyze whether informed traders have a preference for the anonymous trading system. We extend the empirical method developed in Easley / Kiefer / O'Hara / Paperman (1996) to allow for simultaneous estimation for two parallel markets. This allows us to formally test the null hypothesis of equal probabilities of informed trading. This hypothesis is strongly rejected. Our results thus provide evidence that informed traders prefer the anonymous electronic trading system. We further confirm findings by others that the probability of informed trading is negatively related to measures of the overall liquidity of the sample stocks.

Supplementary analysis supports our conclusions. We document that the estimated probabilities of informed trading are positively related to the bid-ask spread and, particularly, to the adverse selection component of the spread. We further document that cross-sectional differences in the probability of informed trading on the floor and in IBIS are directly related to differences in the adverse selection component.

The results clearly support the notion that anonymity matters. A higher degree of anonymity is associated with a higher probability of informed trading. Combining this results with the observation that asymmetric information is a more severe problem for less liquid stocks yields implications for the design of trading systems. Whereas anonymous trading mechanisms may be well suited for liquid stocks, they may be much less appropriate for small caps. Our results thus provide an explanation for the fact that the market share of the anonymous electronic trading system in Germany is very high for the most liquid stocks but declines quickly with decreasing liquidity.

Electronic trading systems undeniably offer many advantages and may serve to reduce trading costs. They are, however, in a certain sense inherently anonymous because it is difficult to reveal the identity of those demanding liquidity before a transaction occurs. Devising an electronic trading protocol that reduces the degree of anonymity and may, therefore, be better suited to trade less liquid stocks is a challenging yet promising task for the future.

The extension of the Easley / Kiefer / O'Hara / Paperman (1996) model proposed in the present paper may be used to address a variety of important issues. For example, estimating the model for equity or index options that differ with respect to their moneyness may reveal whether informed traders prefer at-the-money or out-of the money options. Further, the model could be adopted to compare the probability of informed trading in equity versus index futures or index option markets. Finally; it is straightforward to extend the model to the case of more than two markets. Such an extension may prove to be useful to compare trading in the different ECNs or to investigate into the nature of the emerging internet trading systems. These are promising areas for future research.

Appendix: Estimation results for the no aggregation case

	α	δ	ε		μ		PI	
			floor	screen	floor	screen	floor	screen
ALV	0.271	0.306	0.147	0.227	0.115	0.494	0.096	0.228
	(0.052)	(0.107)	(0.004)	(0.004)	(0.012)	(0.021)	(0.019)	(0.035)
BAS	0.315	0.646	0.187	0.338	0.125	0.374	0.095	0.148
	(0.060)	(0.099)	(0.004)	(0.006)	(0.015)	(0.024)	(0.018)	(0.024)
BAY	0.395	0.434	0.340	0.352	0.143	0.335	0.077	0.158
	(0.061)	(0.094)	(0.006)	(0.006)	(0.014)	(0.020)	(0.013)	(0.022)
BHW	0.293	0.362	0.124	0.129	0.115	0.312	0.120	0.261
	(0.053)	(0.105)	(0.003)	(0.003)	(0.012)	(0.016)	(0.021)	(0.036)
BMW	0.375	0.340	0.044	0.117	0.056	0.208	0.191	0.250
	(0.063)	(0.091)	(0.002)	(0.003)	(0.008)	(0.012)	(0.031)	(0.034)
BVM	0.312	0.320	0.067	0.113	0.072	0.310	0.144	0.301
	(0.060)	(0.104)	(0.003)	(0.004)	(0.008)	(0.022)	(0.027)	(0.041)
COB	0.383	0.284	0.165	0.300	0.124	0.568	0.126	0.266
	(0.058)	(0.090)	(0.004)	(0.005)	(0.011)	(0.020)	(0.019)	(0.031)
DAI	0.173	0.349	0.170	0.464	0.109	0.892	0.053	0.143
	(0.049)	(0.140)	(0.004)	(0.006)	(0.016)	(0.039)	(0.014)	(0.035)
DBK	0.369	0.495	0.315	0.470	0.199	0.714	0.104	0.219
	(0.057)	(0.089)	(0.006)	(0.006)	(0.015)	(0.024)	(0.015)	(0.027)
DEG	0.184	0.326	0.049	0.080	0.040	0.189	0.069	0.179
	(0.061)	(0.154)	(0.002)	(0.003)	(0.016)	(0.015)	(0.024)	(0.049)
DRB	0.392	0.318	0.110	0.178	0.097	0.267	0.148	0.227
	(0.059)	(0.090)	(0.003)	(0.004)	(0.010)	(0.016)	(0.023)	(0.028)
DTE	0.486	0.370	0.143	0.309	0.087	0.309	0.129	0.203
	(0.076)	(0.085)	(0.004)	(0.019)	(0.012)	(0.019)	(0.021)	(0.025)
HEN3	0.455	0.635	0.047	0.064	0.017	0.105	0.074	0.271
	(0.086)	(0.108)	(0.002)	(0.003)	(0.009)	(0.008)	(0.037)	(0.040)
HFA	0.196	0.528	0.213	0.302	0.124	0.715	0.054	0.188
	(0.050)	(0.134)	(0.005)	(0.005)	(0.016)	(0.034)	(0.013)	(0.040)
KAR	0.443	0.425	0.051	0.076	0.057	0.129	0.200	0.273
	(0.076)	(0.095)	(0.002)	(0.003)	(0.009)	(0.009)	(0.032)	(0.037)
LHA	0.339	0.501	0.084	0.155	0.076	0.173	0.133	0.160
	(0.076)	(0.117)	(0.003)	(0.004)	(0.016)	(0.013)	(0.025)	(0.030)
LIN	0.363	0.445	0.039	0.043	0.039	0.079	0.154	0.253
	(0.097)	(0.109)	(0.002)	(0.003)	(0.007)	(0.011)	(0.037)	(0.048)
MAN	0.238	0.446	0.051	0.059	0.056	0.097	0.115	0.162
	(0.065)	(0.129)	(0.002)	(0.003)	(0.011)	(0.014)	(0.030)	(0.036)
MEO	0.301	0.322	0.044	0.118	0.048	0.293	0.141	0.273
	(0.065)	(0.108)	(0.002)	(0.003)	(0.007)	(0.018)	(0.030)	(0.044)
MMW	0.426	0.236	0.120	0.093	0.086	0.200	0.133	0.314
	(0.066)	(0.080)	(0.004)	(0.003)	(0.009)	(0.015)	(0.021)	(0.035)
MUV2	0.490	0.153	0.061	0.057	0.063	0.133	0.203	0.365
	(0.065)	(0.068)	(0.003)	(0.002)	(0.007)	(0.008)	(0.028)	(0.035)
PRS	0.444	0.154	0.075	0.093	0.076	0.184	0.184	0.306
	(0.069)	(0.067)	(0.003)	(0.004)	(0.008)	(0.012)	(0.027)	(0.035)
RWE	0.487	0.300	0.069	0.110	0.062	0.120	0.180	0.209
	(0.077)	(0.081)	(0.003)	(0.004)	(0.008)	(0.009)	(0.028)	(0.029)
SAP3	0.553	0.296	0.161	0.191	0.090	0.214	0.134	0.237
	(0.068)	(0.074)	(0.004)	(0.005)	(0.011)	(0.011)	(0.018)	(0.025)
SCH	0.373	0.232	0.151	0.118	0.076	0.221	0.086	0.259
	(0.070)	(0.097)	(0.004)	(0.003)	(0.011)	(0.014)	(0.017)	(0.037)
SIE	0.383	0.386	0.267	0.448	0.256	0.419	0.155	0.152
	(0.055)	(0.089)	(0.005)	(0.007)	(0.021)	(0.017)	(0.021)	(0.019)
THY	0.456	0.448	0.047	0.113	0.040	0.198	0.161	0.286
	(0.072)	(0.092)	(0.002)	(0.003)	(0.007)	(0.011)	(0.030)	(0.034)
VEB	0.460	0.264	0.125	0.252	0.040	0.288	0.069	0.208
	(0.075)	(0.094)	(0.004)	(0.005)	(0.011)	(0.014)	(0.019)	(0.028)
VIA	0.321	0.366	0.068	0.119	0.044	0.161	0.094	0.178
	(0.086)	(0.119)	(0.003)	(0.004)	(0.010)	(0.017)	(0.025)	(0.037)
VOW	0.401	0.471	0.192	0.348	0.082	0.415	0.079	0.193
	(0.076)	(0.103)	(0.005)	(0.008)	(0.011)	(0.036)	(0.017)	(0.027)

The table reports the estimation results for model 1 which restricts the probabilities α and δ to be equal in both markets. Standard errors obtained using the delta method are given in parentheses.

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Table 1: Descriptive statistics

Firm	Ticker symbol	Trading volume (daily average, Mio DM)	Market capitalization (billion DM)	No. of transactions on the floor, daily average	Number of transactions in IBIS, daily average
Deutsche Bank	DBK	132.83	51.14	129.45	205.76
Daimler	DAI	128.01	73.11	65.93	186.10
Siemens	SIE	119.02	57.27	108.64	198.52
Volkswagen	VOW	101.82	41.11	76.45	148.95
Allianz	ALV	72.61	83.75	59.71	100.79
Bayer	BAY	69.47	48.54	135.00	145.17
VEBA	VEB	66.95	48.39	48.33	115.55
BASF	BAS	64.29	39.83	74.02	143.93
Commerzbank	COB	61.70	21.31	69.83	139.62
Hoechst	HFA	59.11	43.50	82.93	123.93
Deutsche Telekom	DTE	47.92	42.00	57.88	137.50
Dresdner Bank	DRB	46.85	29.65	46.55	82.26
Mannesmann	MMW	44.02	28.64	50.83	46.36
SAP Vz.	SAP3	38.04	15.39	65.98	92.29
Münchener Rückv.	MUV2	32.15	78.22	27.50	32.29
BMW	BMW	31.48	26.56	19.93	55.50
Bayer. Vereinsbank	BVM	30.20	21.68	28.62	55.21
Bayer. Hypobank	BHW	29.19	13.41	50.76	62.38
Thyssen	THY	28.50	14.17	20.74	56.29
RWE	RWE	26.33	24.78	30.02	50.43
Schering	SCH	25.99	12.74	59.64	56.55
VIAG	VIA	23.46	21.06	27.10	52.02
Metro	MEO	21.43	24.25	18.69	55.64
Preussag	PRS	19.84	7.79	33.55	47.00
Lufthansa	LHA	18.49	12.76	33.95	68.69
Karstadt	KAR	14.30	5.22	21.74	39.95
Degussa	DEG	11.25	8.50	18.83	36.24
Linde	LIN	10.61	11.22	16.48	20.50
Henkel Vz.	HEN3	9.57	5.88	18.38	31.86
MAN	MAN	9.11	5.92	20.90	25.86
average		46.48	30.59	50.61	87.10

Stocks are sorted by trading volume. Figures on market capitalization are for end of June 1997. Figures on trading volume and number of transactions are for the sample period, June and July 1997 and are calculated from the three hours of daily parallel trading analyzed in this paper.

Table 2: Estimation results (5-second aggregation)

	α	δ	ε		μ		PI	
			floor	screen	floor	screen	floor	screen
ALV	0.271	0.306	0.147	0.191	0.115	0.378	0.096	0.211
	(0.052)	(0.107)	(0.004)	(0.004)	(0.012)	(0.019)	(0.019)	(0.034)
BAS	0.262	0.605	0.188	0.298	0.129	0.325	0.083	0.125
	(0.063)	(0.116)	(0.005)	(0.006)	(0.016)	(0.029)	(0.018)	(0.025)
BAY	0.410	0.420	0.340	0.299	0.143	0.264	0.079	0.153
	(0.062)	(0.092)	(0.006)	(0.005)	(0.014)	(0.018)	(0.013)	(0.021)
BHW	0.283	0.374	0.124	0.115	0.115	0.262	0.116	0.244
	(0.053)	(0.108)	(0.003)	(0.003)	(0.012)	(0.017)	(0.021)	(0.036)
BMW	0.386	0.344	0.044	0.102	0.055	0.157	0.195	0.229
	(0.065)	(0.091)	(0.002)	(0.003)	(0.008)	(0.011)	(0.031)	(0.032)
BVM	0.300	0.325	0.067	0.100	0.072	0.245	0.139	0.269
	(0.061)	(0.112)	(0.003)	(0.003)	(0.008)	(0.021)	(0.027)	(0.040)
COB	0.355	0.259	0.166	0.256	0.125	0.436	0.118	0.233
	(0.058)	(0.093)	(0.004)	(0.005)	(0.011)	(0.021)	(0.019)	(0.030)
DAI	0.251	0.364	0.169	0.369	0.103	0.404	0.071	0.121
	(0.060)	(0.119)	(0.004)	(0.006)	(0.015)	(0.035)	(0.016)	(0.024)
DBK	0.369	0.498	0.315	0.404	0.198	0.501	0.104	0.187
	(0.057)	(0.077)	(0.006)	(0.006)	(0.015)	(0.022)	(0.016)	(0.024)
DEG	0.163	0.334	0.050	0.074	0.043	0.181	0.066	0.166
	(0.057)	(0.159)	(0.002)	(0.002)	(0.017)	(0.016)	(0.024)	(0.048)
DRB	0.359	0.288	0.110	0.163	0.098	0.227	0.138	0.201
	(0.072)	(0.095)	(0.003)	(0.006)	(0.010)	(0.028)	(0.026)	(0.028)
DTE	0.425	0.316	0.143	0.316	0.090	0.255	0.117	0.177
	(0.063)	(0.087)	(0.004)	(0.049)	(0.012)	(0.014)	(0.019)	(0.023)
HEN3	0.508	0.619	0.047	0.055	0.015	0.081	0.077	0.270
	(0.098)	(0.106)	(0.003)	(0.003)	(0.009)	(0.007)	(0.041)	(0.041)
HFA	0.369	0.516	0.210	0.239	0.112	0.287	0.090	0.181
	(0.065)	(0.101)	(0.005)	(0.005)	(0.014)	(0.017)	(0.016)	(0.027)
KAR	0.444	0.423	0.051	0.069	0.057	0.105	0.201	0.252
	(0.076)	(0.095)	(0.002)	(0.003)	(0.009)	(0.008)	(0.032)	(0.036)
LHA	0.308	0.490	0.085	0.141	0.080	0.138	0.127	0.130
	(0.079)	(0.114)	(0.003)	(0.004)	(0.018)	(0.013)	(0.025)	(0.029)
LIN	0.388	0.437	0.038	0.039	0.038	0.068	0.161	0.253
	(0.086)	(0.106)	(0.002)	(0.002)	(0.007)	(0.008)	(0.035)	(0.044)
MAN	0.212	0.491	0.052	0.056	0.058	0.098	0.106	0.157
	(0.057)	(0.126)	(0.002)	(0.002)	(0.011)	(0.013)	(0.027)	(0.037)
MEO	0.309	0.340	0.043	0.105	0.047	0.221	0.144	0.245
	(0.066)	(0.106)	(0.002)	(0.003)	(0.007)	(0.015)	(0.030)	(0.041)
MMW	0.444	0.221	0.120	0.084	0.086	0.158	0.137	0.295
	(0.062)	(0.076)	(0.004)	(0.003)	(0.009)	(0.010)	(0.021)	(0.033)
MUV2	0.506	0.163	0.061	0.051	0.063	0.116	0.208	0.364
	(0.064)	(0.067)	(0.003)	(0.002)	(0.007)	(0.008)	(0.028)	(0.035)
PRS	0.423	0.094	0.075	0.084	0.077	0.147	0.178	0.269
	(0.086)	(0.102)	(0.003)	(0.005)	(0.009)	(0.016)	(0.032)	(0.038)
RWE	0.489	0.322	0.069	0.097	0.062	0.100	0.181	0.201
	(0.079)	(0.083)	(0.003)	(0.004)	(0.008)	(0.009)	(0.028)	(0.029)
SAP3	0.550	0.302	0.161	0.164	0.090	0.160	0.134	0.212
	(0.066)	(0.074)	(0.004)	(0.004)	(0.011)	(0.010)	(0.018)	(0.023)
SCH	0.407	0.330	0.150	0.103	0.075	0.169	0.092	0.251
	(0.069)	(0.095)	(0.004)	(0.003)	(0.011)	(0.011)	(0.017)	(0.035)
SIE	0.374	0.381	0.267	0.383	0.256	0.289	0.152	0.124
	(0.056)	(0.095)	(0.005)	(0.006)	(0.021)	(0.016)	(0.021)	(0.017)
THY	0.506	0.481	0.047	0.099	0.039	0.141	0.173	0.264
	(0.075)	(0.087)	(0.002)	(0.003)	(0.006)	(0.009)	(0.031)	(0.032)
VEB	0.469	0.260	0.125	0.223	0.040	0.225	0.070	0.191
	(0.077)	(0.093)	(0.004)	(0.005)	(0.011)	(0.013)	(0.020)	(0.027)
VIA	0.304	0.312	0.068	0.103	0.044	0.120	0.090	0.151
	(0.083)	(0.118)	(0.003)	(0.003)	(0.010)	(0.014)	(0.025)	(0.033)
VOW	0.433	0.498	0.192	0.289	0.081	0.264	0.084	0.165
	(0.071)	(0.082)	(0.005)	(0.006)	(0.010)	(0.019)	(0.016)	(0.023)

The table reports the estimation results for model 1 which restricts the probabilities α and δ to be equal in both markets. Standard errors obtained using the delta method are given in parentheses.

Table 3: Regression results: probability of informed trading and liquidity

	Floor			IBIS		
	γ_0	γ_1	R^2	γ_0	γ_1	R^2
5-second aggregation rule	0.263 (4.67)	-0.029 (-2.48)	0.18	0.451 (6.21)	-0.051 (3.34)	0.29
no aggregation	0.268 (4.60)	-0.030 (2.50)	0.18	0.437 (5.90)	-0.044 (2.83)	0.22

The table reports the results of the regression

$$PI_l = \gamma_0 + \gamma_1 Log\left(n_l\right) + \varepsilon_l$$

where *l* indexes the stocks in the sample and n_l is the daily average number of transactions. Results for the floor and IBIS and for the 5-second aggregation rule and the no aggregation case are presented separately. t-values are given in parentheses.

Table 4: P-values of likelihood ratio tests

	Model 1 vs. Model 2	Model 1 vs. Model 3	Model 1 vs. Model 4
BAS	0.0154	0.0000	0.0097
ALV	0.3295	0.0000	0.0000
BAY	0.1715	0.0000	0.0000
BHW	0.8780	0.0000	0.0000
BMW	0.7387	0.0000	0.2212
BVM	0.3512	0.0000	0.0000
COB	0.0205	0.0000	0.0000
DAI	0.2690	0.0000	0.0002
DBK	0.0734	0.0000	0.0000
DEG	0.3202	0.0000	0.0048
DRB	0.0842	0.0000	0.0005
DTE	0.5416	0.0000	0.0005
HEN3	0.5815	0.0000	0.0000
HFA	0.0472	0.0000	0.0000
KAR	0.0093	0.0000	0.1111
LHA	0.0531	0.0000	0.8808
LIN	0.9714	0.0108	0.0082
MAN	0.9280	0.0272	0.0423
MEO	0.3110	0.0000	0.0001
MMW	0.2408	0.0000	0.0000
MUV2	0.9372	0.0000	0.0000
PRS	0.1496	0.0000	0.0001
RWE	0.8010	0.0000	0.4393
SAP3	0.3557	0.0000	0.0001
SCH	0.6029	0.0000	0.0000
SIE	0.0200	0.0000	0.0232
THY	0.1841	0.0000	0.0026
VEB	0.4681	0.0000	0.0000
VIA	0.5260	0.0000	0.0115
VOW	0.0643	0.0000	0.0000

The table reports the results of likelihood ratio tests that test the base model 1 against alternative specifications. These are described in detail in section 4. The table reports the p-values of the tests. Because model 1 is more restrictive than model 2 but less restrictive than models 3 and 4, a value larger than 0.05 in column 2 and values smaller than 0.05 in columns 3 and 4 support the specification of model 1.

Table 5: Comparison of the probability of informed trading

Aggregation	Mean *PI* floor	Mean *PI* IBIS	t-value	Median *PI* floor	Median *PI* IBIS	z-value
no	0.123	0.229	8.06	0.128	0.227	5.79
5-second	0.124	0.210	6.51	0.118	0.206	5.06

The table reports the results of a test of the null hypothesis that the PIs estimated for the floor and IBIS have the same mean (columns 2-4) and the same median (columns 5-7). Results for the 5-second aggregation rule and the no aggregation case are presented separately.

Table 6: Regression results: spread and probability of informed trading

	Floor			IBIS		
	γ_0	γ_1	R^2	γ_0	γ_1	R^2
Quoted spread	0.184 (2.49)	1.045 (1.85)	0.109	0.002 (0.02)	1.507 (3.63)	0.319
Effective spread	0.096 (2.25)	0.779 (2.39)	0.170	0.022 (0.34)	1.039 (3.47)	0.301
Adverse selection component	0.042 (0.85)	1.139 (3.02)	0.245	-0.039 (0.64)	1.319 (4.70)	0.441

The table reports the results of the cross-sectional regression

$$s_{j,k,l} = \gamma_0 + \gamma_1 PI_{j,l} + \varepsilon_{j,k,l}$$

where *l* indexes the sample stocks. Separate regressions are estimated for the two trading systems *j* (results for the floor are in columns 2-4, results for IBIS in columns 5-7) and for the three different measures of the bid-ask spread, indexed by *k* and listed in column 1. All spread measures are expressed as a percentage of the quote mid-point. Calculation of the adverse selection component is based on a two-way decomposition similar to the one used by Huang / Stoll (1996).

Figure 1: Parallel trading in the floor and screen trading systems

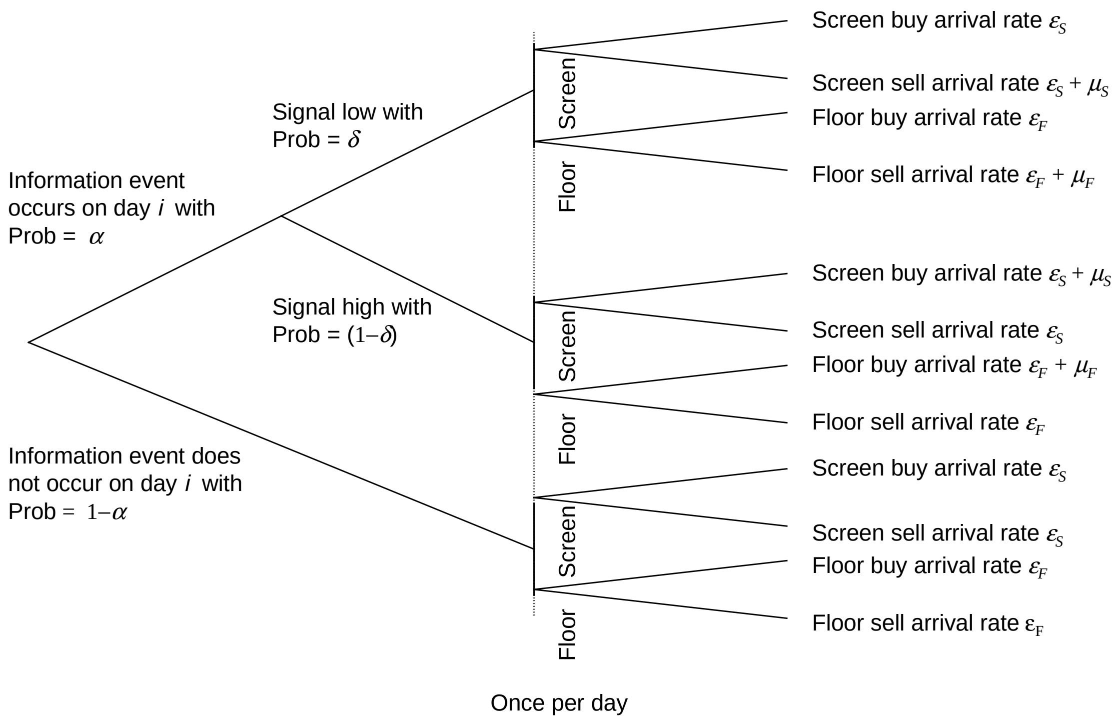
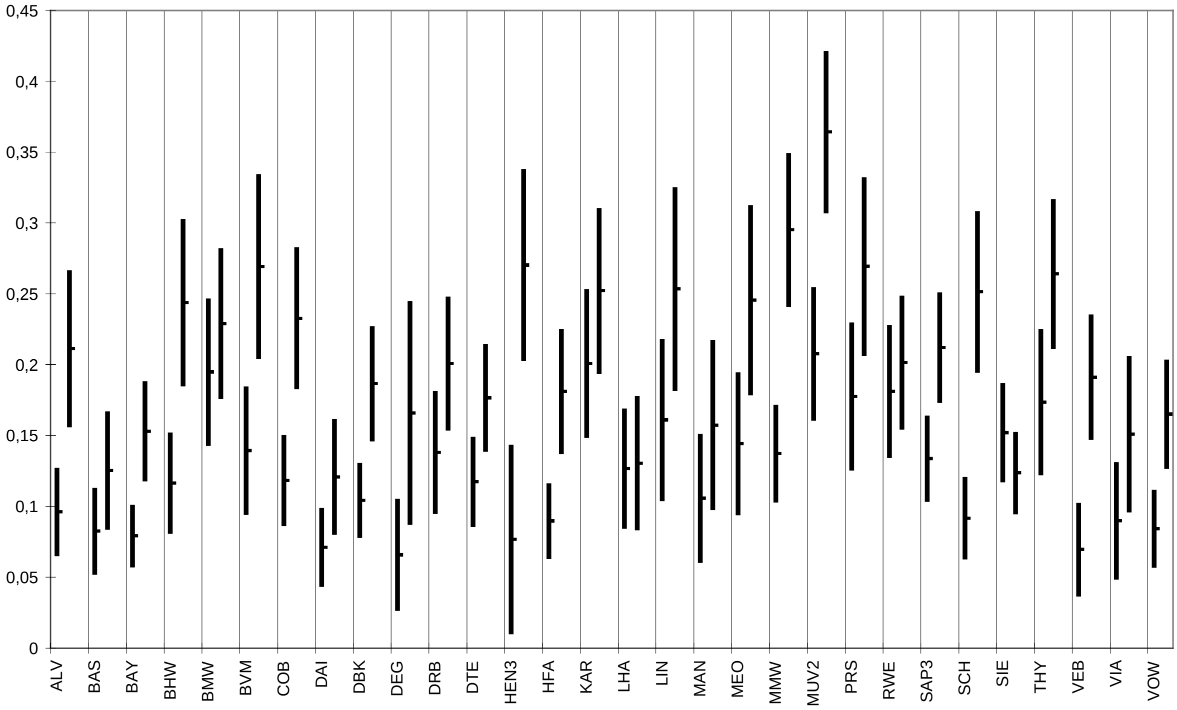


Figure 2: Confidence intervals for the probabilities of informed trading



The figure shows the estimated probabilities of informed trading and their 90% confidence intervals. They are based on the 5-second aggregation rule. The standard errors used to calculate the confidence intervals were obtained by the delta method. The left-hand entry for each stock represents the estimate for the floor, the right-hand entry the estimate for IBIS.