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**understanding the limit order book:
conditioning on trade informativeness**

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Understanding the Limit Order Book: Conditioning on Trade Informativeness

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Abstract

Electronic limit order books are ubiquitous in markets today. However, theoretical models for limit order markets fail to explain the real world data well. Sandas (2001) tests the classic Glosten (1994) model for order book equilibrium and rejects it. We reconfirm this result for one of the largest European stock markets. We then relax one of the model's assumptions and allow the informational content of trades to change over time. Adapting Hasbrouck's (1991a,b) methodology to estimate time varying trade informativeness we find that it is a slowly mean reverting process. By conditioning on trade informativeness, we find support for the Glosten model's implication that books are more shallow during times of informative market orders. However, a high level of liquidity supply is committed up to an economically significant trade size volume, even when trade informativeness is high. This can be seen as a vindication of the open order book design which dispenses with dedicated market makers. We also find evidence for a market order trader population which is quite heterogenous with respect to price sensitivity.

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1 Introduction

An increasing number of financial assets trade in limit order markets the world over. In such markets, traders can submit market and limit orders. A market order trades at the best available price posted by previously submitted limit orders that make up the limit order book. A limit order is a conditional buy or sell at a pre-specified price and is stored in the book until canceled or hit by an incoming market order.¹

In this paper, we aim to understand order book depth by estimating and testing the Glosten (1994) model directly, as in Sandas (2001), and indirectly through a dynamic setting that allows for a time-varying level of private information in order flow. In the indirect test, we estimate the level of private information of the trade, hereafter referred to as trade informativeness, using the vector autoregressive approach advocated in Hasbrouck (1991a,b). As theory predicts that the level of private information is a key determinant of the limit order book equilibrium, we study the state of the book and the trading activity for a cross section of stocks and condition on the level of trade informativeness.

Theoretical and empirical papers dealing with the behavior of agents and the evolution of prices in limit order markets abound in the literature. The economic modeling centers around an allegedly simple trade-off situation. A limit order trades at a better price than a market order. However, there are two types of costs to submitting a limit order. First, the order may fail to execute. Second, the order may execute against a market order that is based on private information. In this case, limit orders trade at the wrong side of the market. This is referred to as picking-off risk. Various models have been proposed that formalize this trade-off between prices, execution probability, and picking-off risk. They essentially take either of two fundamentally different approaches. The first treats the arrival of traders at the market exogenously and models their decision to submit a limit or market order and, potentially, conditions on the state of the book (see, e.g., Cohen, Maier, Schwartz, and Whitcomb (1981), Foucault (1999), Harris (1998), Parlour (1998), Hollifield, Miller, and Sandas (2004), and Goettler, Parlour, and Rajan (2004)). These models have a rich set of predictions for the state of the order book at each point in time. The second approach, essentially, endogenizes trader arrivals, as it retrieves the state of the book from a zero-profit condition on the marginal limit order. In other words, at each point in time profit opportunities in the book can only be short-lived as they attract traders who exploit them immediately. Market orders arrive exogenously in time, consume liquidity, and potentially leave profit opportunities in the book that are, again, immediately exploited (see, e.g., Glosten (1994), Seppi (1997), and Parlour

¹If a limit order is submitted at a price such that it executes immediately (a *marketable* limit order), we consider it a market order.

and Seppi (2003)).

The distinction in the theoretical literature carries over to the empirical literature. Many recent studies focus on whether an arriving trader chooses a market or limit order and how market conditions affect this choice (see, e.g., Biais, Hillion, and Spatt (1995), Griffiths, Smith, Turnbull, and White (2000), and Rinaldo (2004)). Most of them condition on the best bid and ask quotes and depth offered at these quotes. Relatively few studies, however, focus on explaining the state of the order book beyond these quotes. This is surprising as the best quotes only partially reflect overall liquidity. A nice illustration is the sequential tick size reduction in the U.S. that led to a 20% reduction in quoted spreads, but, at the same time, reduced aggregate depth in the order book (see, e.g., NYSE (2000), Goldstein and Kavajecz (2000)). Sandas (2001) tests the celebrated Glosten (1994) model and rejects it for a sample of Swedish stocks. Coppejans, Domowitz, and Madhavan (2003) study order book resiliency to shocks in volatility and returns for the Swedish stock index future.

We contribute to the literature in two ways. First, we consider the state of limit order books in a dynamic setting with time-varying order informativeness. This, essentially, allows us to test the importance of “picking-off” risk, a key ingredient to limit order book models. If the market can expect very informative order flow, the book should be shallow. We adapt the standard Hasbrouck (1991a) methodology to estimate trade informativeness. Second, we use a new dataset with full order book data for arguably one of the largest fully electronic markets, the German stock exchange. We perform our tests based on market event data for the thirty stocks that constitute the DAX30 index, the leading German stock market index. The data are rich as they contain real time limit order book information. The sample runs from January 2, 2004 through March 31, 2004. We consider this an ideal laboratory for a test of the Glosten model, as the market runs off of a fully electronic consolidated limit order book and therefore closely resembles the idealized set-up studied by Glosten. The current experiment compares favorably to the NYSE order book, as the latter allows for ex-post quote improvement by the specialist or floor brokers. This seriously undermines the Glosten framework, as the probability of limit order execution critically depends on the full market order being executed against the order book.²

The main results can be summarized as follows: Although, consistent with Sandas’ (2001) findings, we reject, on statistical grounds, Sandas version of the Glosten (1994) model, we find evidence that “picking-off” risk is important for order book depth in our dynamic set up. When the market can expect informative market orders, given all history, depth in the book is considerably lower. These effects are also economically significant, since order book liquidity, as measured by immediate price impact, is 1.5 times lower at times of high informativeness. We find that trade informativeness can be described as a stationary and slowly mean-reverting process. In addition to the state of the book, we study market order

²We refer to Parlour and Seppi (2003) for an excellent analysis of the two market structures: a fully electronic market and a hybrid market.

sizes and trade durations conditional on order informativeness. We find evidence of larger market order sizes and slightly shorter durations at times when upcoming market orders are expected to be less informative. We also find evidence for a heterogeneous market order trader population. Part of the market order traders is very price sensitive in that they adapt market order volumes to the liquidity state of the book. However, another part of the market order traders do not reduce trade sizes in response to a reduction of liquidity supply. An important result regarding the assessment of market quality is that a high level of liquidity supply is committed up to an economically significant trade size volume, even during periods when trades are allegedly informative. The fact that this conclusion is also valid for smaller capitalized, less frequently traded stocks is a vindication of the limit order book trading design and its viability without dedicated market makers.

The remainder of the paper is structured as follows. Section 2 introduces the Xetra open book and the data used in this paper. In section 3.1 we present a direct test of the Glosten (1994) model based on Sandas' (2001) framework. The following section is devoted to explain the methodology that we employ to estimate the time-varying level of trade informativeness and its relation to the order book. Section 3.3 presents and discusses the results and section 4 concludes.

2 Market structure and the data

2.1 The Xetra open order book

Xetra is an open order book system developed by the German Stock Exchange.³ It has operated since 1997 as the main trading platform for German blue chip stocks at the Frankfurt Stock Exchange. Between an opening and a closing call auction - and interrupted by another mid-day call auction - trading is based on a continuous double auction mechanism with automatic matching of orders based on the usual rules of price and time priority. During pre- and post-trading hours it is possible to enter, revise and cancel orders, but order executions are not conducted (even if possible). Trading hours extend from 9 a.m. CET to 5.30 p.m. CET For the DAX30 stocks there are no designated market makers. Traders have access to the full order book, except hidden shares coming from so-called iceberg orders. An iceberg or 'hidden' order is similar to a limit order in that it has pre-specified limit price and volume. The difference is that a portion of the volume is kept hidden from the other traders. The visible portion of the iceberg order, called the 'peak', enjoys full price and time priorities (as any limit order). The hidden portion only gets price priority. All disclosed volumes are executed first, even if those volumes entered the book after the iceberg order submission. When a market order hits the hidden portion, a new portion of the iceberg order (equal to the peak size) is revealed to the market participants and is granted time priority over subsequent order

³See Deutsche Börse AG (1999) for a detailed description of the Xetra system.

submissions. Consequently, a trader submitting a market order may receive an unexpected price improvement if her market order is executed against a hidden order. Iceberg orders are convenient for some market participants as they provide a tool to hide investment decisions. Whether those decisions are liquidity-motivated or informed remains an open question. In the realm of limit order book markets, the Xetra system is thus very close to the Euronext trading system (at the time of this writing, the Euronext trading system encompasses the Amsterdam, Brussels, Lisbon and Paris stock exchanges), see e.g. Biais, Hillion, and Spatt (1995). Xetra is also very close to the trading system used at the Hong Kong stock exchange, which has been recently studied by Ahn and Cheung (1999), Brockman and Chung (1999) or Ahn, Bae, and Chan (2001). A Xetra market design feature which makes the data for the purpose of our study preferable is that market orders exceeding the volume at the best quote are allowed to ‘walk up the book’. In other words, market orders are guaranteed immediate full execution, at the cost of incurring a higher price impact on the trades. The liquidity measure used in the present chapter and discussed in the next subsection implicitly assumes that a ‘walk up the book’ is possible.

2.2 Data

The German Stock Exchange granted access to a database containing complete information about Xetra order book events (entries, cancelations, revisions, expirations, partial-fills and full-fills of market, limit, and iceberg orders) that occurred during the first quarter of 2004 (January 2, 2004 - March 31, 2004). The data encompasses the 30 stocks belonging to the DAX30 index. Based on the event histories we perform a real time reconstruction of the order book sequences. Starting from an initial state of the order book, we track each change in the order book implied by entry, partial or full fill, cancelation and expiration of market, limit, and iceberg orders. This is done by implementing the rules of the Xetra trading protocol in a GAUSS program. Although running an exhaustive battery of consistency checks no errors occur during the reconstruction process. From the resulting real-time sequences of order books, snapshots of the book during the continuous trading hours were taken each time a trade takes place (just *before* its matching with the book). For each snapshot, the order book entries were sorted on the bid (ask) side in price descending (price ascending) order. As iceberg orders are not fully disclosed to market’s participants, we reconstruct, at each point in time, two limit order books. First, we have the visible order book, which contains all limit orders as well as the visible portion of the iceberg orders. Second, we study the complete order book that features all orders, including the hidden portions.

Table 1 presents some characteristics of the DAX30 stocks. Liquidity supply for these stocks is indeed quite active, as on average 13,000 (11,000) non-marketable limit orders per stock are submitted (canceled) each day. Implicit transaction costs are relatively small with relative spreads ranging from 0.04 to 0.14%. On average, 2,100 trades per stock are executed

each day and on average 15.2% of these walk up the book (i.e. they are matched by standing limit orders beyond the best bid and ask prices). We refer to those events as ‘aggressive trades’.

We adopt a classification of the 30 DAX stocks in four groups based on trading activity. Indeed, the analysis centers on the impact of trades on liquidity; it is then natural to group stocks by the number of trades executed each day (on average). The first group is then composed by the 7 stocks more frequently traded stocks whereas the 7 less frequently traded stocks are in group 4. The second and third group contain 8 stocks each.⁴

3 Methodology and Results

3.1 A direct test of the Glosten model

Sandas (2001) presents a variant of Glosten’s (1994) limit order book model with discrete price ticks and price priority rules. The model delivers an equation that predicts that order book depth and adverse selection effects are inversely related. The associated empirical methodology is closely based on economic theory and permits the quantification of the relation of adverse selection effects and order book depth we are after. Since the Xetra trading protocol is quite close to the idealized framework assumed in Sandas (2001), adopting the approach for the present paper seems a natural starting point.

In the following we will briefly describe the key ingredients of the Glosten/Sandas framework. The fundamental asset value v_t is described by a random walk with innovations depending on an adverse selection parameter α , which gives the informativeness of a signed market order of size X_t . The price impact of a trade is linear, immediate and not state-dependent, viz

$$v_t = c_v + v_{t-1} + \alpha X_t + \eta_{v,t}. \quad (1)$$

Negative values of X_t denote sell orders, positive values buy orders. Furthermore, it is assumed that $E(X_t) = 0$. $\eta_{v,t}$ is an innovation orthogonal to v_{t-1} and X_t . c_v gives the expected change in the fundamental value. Market buy and sell orders are assumed to arrive with equal probability with a two-sided exponential density describing the distribution of order sizes X_t :

$$f(X_t) = \begin{cases} \frac{1}{2\lambda} e^{-\frac{X_t}{\lambda}} & \text{if } X_t > 0 \text{ (market buy)} \\ \frac{1}{2\lambda} e^{\frac{X_t}{\lambda}} & \text{if } X_t < 0 \text{ (market sell)}. \end{cases} \quad (2)$$

Risk neutral limit order traders face a fixed order submission cost γ and have knowledge about the distribution of market order size and how informative market orders are, that is, they know α . They do not know the true value of the security, but estimate it conditional on market order size. They choose limit order prices and quantities such that the expected

⁴The classification by trading activity is very similar to a classification by market capitalization.

profit is maximized. If the last unit at any discrete price tick exactly breaks even, i.e. has expected profit equal to zero, the order book is in equilibrium.

Denote the ordered discrete price ticks on the ask (bid) side by p_{+k} (p_{-k}) with $k = 1, 2, \dots$ and the associated volumes at these prices by q_{+k} (q_{-k}). Given these assumptions and setting $q_{0,t} \equiv 0$, the equilibrium order book at time t can recursively be constructed as follows:

$$\begin{aligned} q_{+k,t} &= \frac{p_{+k,t} - v_t - \gamma}{\alpha} - \sum_{i=+1}^{+k-1} q_{i,t} - \lambda \quad k = 1, 2, \dots \quad (\text{ask side}) \\ q_{-k,t} &= \frac{v_t - p_{-k,t} - \gamma}{\alpha} - \sum_{i=-1}^{-k+1} q_{i,t} - \lambda \quad k = 1, 2, \dots \quad (\text{bid side}). \end{aligned} \quad (3)$$

Equation (3) gives the theoretical model's answer to the question that motivates the present paper: order book depth and adverse selection component are inversely related. If the model provides a good description of the real world trading process, and if we can provide consistent estimates of the model parameters, we can use equation (3) to predict the evolution of the order book for a given stock and quantify adverse selection effects on order book depth. Sandas (2001) proposes to employ GMM for parameter estimation and specification testing. Assuming mean zero random deviations from the order book equilibrium at each price tick, the following unconditional moment restrictions, referred to as break-even conditions, can be used for GMM estimation:

$$E \left(p_{+k,t} - p_{-k,t} - 2\gamma - \alpha \left(\sum_{i=+1}^{+k} q_{i,t} + \sum_{i=-1}^{-k} q_{i,t} + 2\lambda \right) \right) = 0 \quad k = 1, 2, \dots \quad (4)$$

A second set of moment conditions, referred to as updating restrictions, relate the expected changes in the order book to the market order flow:

$$\begin{aligned} E \left(\Delta p_{+k,t} - \alpha \left(\sum_{i=+1}^{+k} q_{i,t+1} - \sum_{i=+1}^{+k} q_{i,t} \right) - c_v - \alpha X_t \right) &= 0 \quad k = 1, 2, \dots \\ E \left(\Delta p_{-k,t} + \alpha \left(\sum_{i=-1}^{-k} q_{i,t+1} - \sum_{i=-1}^{-k} q_{i,t} \right) - c_v - \alpha X_t \right) &= 0 \quad k = 1, 2, \dots \end{aligned} \quad (5)$$

where $\Delta p_{j,t} = p_{j,t} - p_{j,t-1}$. An obvious moment condition to identify the expected market order size is given by

$$E(|X_t| - \lambda) = 0. \quad (6)$$

Using the DAX30 order book data we estimate the model parameters exploiting the break-even conditions (4) and the updating conditions (5) along with (6). To construct the moment conditions we use the respective first four best quotes, i.e. $k = 1, \dots, 4$ on the bid and the ask side of the order book. This yields 13 moment conditions, four break-even conditions, eight update conditions plus the moment condition (6). For convenience, order sizes X_t are

expressed in 1000 shares. Table 2 contains the first stage GMM results for the 4 groups. We report parameter estimates, t -statistics and the value of the GMM J -statistic with associated p -values. Under the null hypothesis that the moment conditions are correctly specified, the J -statistic is asymptotically χ^2 with degrees of freedom equal to the number of moment conditions minus the number of estimated parameters. We also report a standardized adverse selection component computed as $\alpha^S = \frac{\alpha \cdot 50,000}{P^2}$, where P is the sample average of the midquote of the respective stock. The parameter α measures the absolute impact on prices of a buy of one share while the standardized measure α^S measures the impact on prices in basis points of a 50,000-euro buy. This standardization ensures comparability of the adverse selection component across stocks.⁵

To conserve space and highlight the central findings table 2 presents first stage GMM estimation results summarized for four stock groups. The thirty stocks are sorted according to their trading frequency. The first group contains the most frequently traded stocks, the fourth group the least frequently traded stocks. The information which stock belongs to which group is presented in table 1. The first stage GMM estimation results are in line with the central findings reported in Sandas (2001).⁶ For only one out of thirty stocks the model is not rejected at 1 % level of significance (in Sandas' application the model was rejected for all stocks). Like in Sandas' (2001) application, the transaction cost estimates (γ) are significantly negative for all stocks, a result that is difficult to reconcile with the underlying theoretical model. From an economic point of view, the drift parameter (c_v) estimates are small, and not significantly different (at 1 %) from zero for half of the stocks. This is not surprising given the high trading frequency. There is a considerable variation in the standardized adverse selection component α^S across stocks. Less frequently traded and small cap stocks tend to have larger adverse selection components: the Spearman rank correlations of α^S and the daily number of trades and the market capitalization both amount to -0.92. This confirms previous results which have shown that adverse selection effects are more severe for less frequently traded, smaller capitalized stocks. In itself, these are interesting results, yet with considerable amounts of grains of salt given the unsatisfactory empirical performance reported above. This is a familiar trade-off. Although a formal model like the Sandas/Glosten framework delivers economically interpretable parameter estimates, some assumptions required to provide closed form moment conditions for parameter estimation may be too restrictive and responsible for the disconcerting performance when the model is confronted with real world data. Specifically, it could be argued that the linearity, state-independence and immediacy of the price impact of trades implied by equation (1) is incompatible with a dynamic order book. Sandas (2001) dealt with this issue by introducing state variables that describe the time dependence of the model

⁵One share costs $1/P$ euros, therefore a trade of 50,000 euros amounts to $50,000/P$ shares. α/P measures the impact on prices in basis points of a one-share buy. We also computed a standardized α based on the (stock-specific) average trade size; the results presented below were not affected.

⁶Second stage and iterated GMM results are qualitatively identical and lead to the same conclusions.

parameters. The advantage of this approach is that one can stay within the GMM estimation and testing framework. However, the choice of plausible state variables is rather ad hoc and not guided by theory. In the following we will pursue an alternative approach to investigate the relation of the informational content of the order flow and order book variation. For this purpose we reconsider a classic approach developed by Hasbrouck (1991a,b) and adapt it for our purpose.

3.2 Allowing for time-varying trade informativeness

In the previous section a series of restrictive assumptions have been made to obtain estimable equations and estimates of trade informativeness derived from order book equilibrium conditions. As argued above, the assumption that the trade informativeness parameter α is time-invariant seems restrictive. Some restrictions are already planted in Glosten's basic theoretical framework. Specifically, variations in the book caused by non-informationally motivated agents who choose strategically between limit and market orders (as e.g. in Foucault, Kadan, and Kandel (2003)) are explicitly not accounted for. Although these two streams in the theoretical literature - the one focussing on adverse selection effects, the other on strategic trading - are antinomic, it is reasonable to assume that both explain important aspects of the trading processes in real world limit order markets.

We deal with these shortcomings in an alternative econometric framework. To estimate trade informativeness, we reconsider the classic approach introduced by Hasbrouck (1991a,b) and adapt this methodology to allow for time varying trade informativeness. The resulting estimates are then used to study the relation of trade informativeness and the state of the order book. Unlike in the direct test of the Glosten model, no prior assumption is imposed on the trade informativeness-book relation. Furthermore, the possibility of changes in the book originating from non-informationally induced, serially correlated liquidity shocks is not ruled out. We will briefly review Hasbrouck's methodology and show how it is adapted for the present paper. The basic idea is to estimate trade informativeness by the long-run impact of a trade on the prices computed from a two variable vector autoregression (VAR). This methodology offers a straightforward way to disentangle short term microstructure effects from permanent information. Inventory management and lagged price adjustments do not prevent prices to ultimately incorporate the informational content of a trade.

Hasbrouck's VAR contains two variables. The first is the midquote difference, $r_t = q_t - q_{t-1}$, where $q_t = (p_{1,t} + p_{-1,t})/2$. The second variable X_t denotes, as above, the signed market order size. The subscript t refers to event time, i.e. every time there is a trade or a midquote update, t is incremented by one. r_t is zero if at time t there is a trade without any change in the midquote. When the midquote changes at time t without a trade event then $X_t = 0$.

Setting up the VAR as

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \dots + b_0 X_t + b_1 X_{t-1} + b_2 X_{t-2} + \dots + v_{1,t} \\ X_t &= c_1 r_{t-1} + c_2 r_{t-2} + \dots + d_1 X_{t-1} + d_2 X_{t-2} + \dots + v_{2,t}, \end{aligned} \quad (7)$$

contemporaneous causality from trades to prices is accounted for. In a pure order book this effect could be truly contemporaneous as trades frequently walk up the book and consume the liquidity available at the best quotes and thus induce an immediate change of the midquote.

The Vector Moving Average (VMA) representation of the VAR 7 is given by

$$\begin{aligned} r_t &= v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} + \dots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \dots \\ X_t &= c_1^* v_{1,t-1} + c_2^* v_{1,t-2} + \dots + v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} \dots \end{aligned} \quad (8)$$

The parameter b_0^* gives the immediate impact of an unexpected buy of one share on the midquote, The permanent impact of an one unit (buy) trade innovation is given by $\alpha^* = \sum_{i=0}^{\infty} b_i^*$. While short-lived inventory or microstructure effects may move the midquote away from the efficient price, α^* serves a natural measure of the permanent effect of trade related information on the asset price. It is the counterpart of the Glosten/Sandas- α (see equation 1) and directly comparable in levels.

Traders are likely to update their beliefs about the information content of trades continuously. Ideally, an econometrician would update her estimate of trade informativeness whenever there is an update in traders' beliefs. This is of course impossible. As a feasible approximation we fix the number of trade events N that have to occur before a new VAR estimation is conducted, and a new measure of trade informativeness is computed. This produces a sequence of trade informativeness measures $\{\alpha_j^*\}(j = 1, \dots, J)$, each estimated from data on N successive trade events. We also retrieve a sequence of estimated immediate impacts $\{b_{0,j}^*\}(j = 1, \dots, J)$.⁷ α_j^* can be interpreted as the average of the true, but non observable time varying trade informativeness over the j th estimation period. As long as the updates on trade informativeness are smooth, this approximation seems not overly restrictive.

Table 3 reports some details about the specifications. For the group of less frequently traded stocks we choose $N = 100$ trades. This implies that on average a new estimate of α_j^* is computed every 60 minutes. For the group of most frequently traded stocks, we use $N = 250$. In this case a new trade informativeness measure is computed on average every 30 minutes. Sensitivity tests which involved changing the number of trades events N were conducted, but the results do not change substantially. The number of lags in the VARs is 10 for all stocks which ensures serially uncorrelated residuals. We follow Hasbrouck and truncate the infinite

⁷An alternative would be to fix the number of quotes or events. However, quote updates are quite frequent in the order book market that we study. One can observe hundreds of quote updates without any trade event. By setting a fixed number of trades instead of a fixed number of events, we avoid estimating trade informativeness with only few number of trade events.

sum over the VMA parameters at 40 steps, i.e. $\alpha^* = \sum_{i=0}^{40} b_i^*$ (omitting the j subscript). We do not regress today's trades and quotes on yesterday's. Instead, we re-initialize the VARs at the start of each trading day. To ensure cross sectional comparability, we standardize α_j^* in the same fashion as the Glosten/Sandas- α viz,

$$\alpha_j^H = \frac{\alpha_j^* \cdot 50,000}{P^2}. \quad (9)$$

Thus, α_j^H is the long-term impact in basis points of an (unexpected) 50,000-euro buy. The sample average $\alpha^H = J^{-1} \sum \alpha_j^H$ can be directly compared to the standardized trade informativeness measure α^S which has been used in the Glosten/Sandas framework. The immediate impact $b_{0,j}^*$ can be standardized in the same fashion. The resulting sequence will be denoted by $\{b_j^H\} (j = 1, \dots, J)$. Computing $b^H = J^{-1} \sum b_j^H$ allows to compare the levels of the average short run effect of trades on prices with the average permanent impact α^H and the Sandas/Glosten measure of trade informativeness, α^S .

3.3 Cross sectional and time series properties of trade informativeness

Table 4 summarizes the time series properties of the estimates of the standardized trade informativeness measures α_j^H and the standardized immediate price impacts b_j^H as well as the corresponding cross sectional variation of the sample averages α^H and b^H . In line with the results discussed in section 3.1 we find that trade informativeness estimates tend to be smaller for frequently traded stocks and higher for less frequently traded stocks. The group specific averages of α^H are strikingly similar to the GMM estimates of the trade informativeness measures α^S in the Glosten/Sandas framework (compare the first column of table 4 and the last column of table 2). On the other hand, the group averages of the α^H estimates (and of α^S) are almost two times larger than the average of the estimated immediate impacts b^H . Hence, the GMM estimates of α^S seem to capture the long-term impact of a trade. At first sight this may seem surprising, since equation (1) postulates an immediate impact of signed trades. However, the immediate effect is exerted on the unobservable fundamental asset value. The VAR in equations (7), however, is estimated on observable midquote changes. The midquote arguably serves as a proxy for the fundamental value, but, as discussed above, it may deviate from the fundamental value due to microstructure effects. In fact, it turns out that in Sandas' GMM setting framework the (static) break-even order book conditions are the most important moment restrictions to infer the trade informativeness estimate parameter α .⁸ Sandas' theory based, yet restrictive GMM approach to estimate trade informativeness is quite different from the agnostic yet less restrictive VAR approach. The result the trade informativeness estimates delivered by both methodologies are quite similar indicates that

⁸As in Sandas (2001) the update conditions do not help greatly for the identification of α . The standard errors of the α estimates are very large if only update conditions are used for GMM estimation. The update restrictions are more important to identify the drift parameter c_v .

the formal Glosten/Sandas framework is not as much at odds with the data as the rejection based on statistical tests suggests.

While this can be interpreted as a vindication of the Sandas/Glosten theoretical framework the results reported in table 4 and the time series plots in figure 1 also show that the trade informativeness sequences $\{\alpha_j^H\}$ exhibit a considerable variation. Figure 1 plots the estimated $\{\alpha_j^H\}$ sequence for selected stocks, one from each of the four groups sorted by trade-frequency. From time series perspective one may describe these data as being generated by a mean reverting process. Table 4 reports the minimum and maximum of the α_j^H estimates averaged over the stocks in the respective group. Figure 2 which plots time-of-day averages of α_j^H for half hour intervals shows that the trade informativeness estimates exhibit a distinct intra-day (diurnal) pattern. Trade informativeness is (on average) highest at the beginning of the trading day, but drops to a lower level during the two hours or so after the opening. For the more frequently traded stocks trade informativeness increases during the overlap period with NYSE trading. It seems that the beginning of US trading of the respective stock initiates another trade informative period. All the stocks belonging to the group of most frequently traded stocks and half of the stocks belonging to the second group are cross-listed in an US market (mostly as ADRs at NYSE). The third and the fourth group do not contain any US cross-listed stock. To some extent, these time-of-day patterns are in line with findings of studies which used different methodologies to analyze time-of-day variations of trade informativeness in other markets.⁹ The variation of estimated α_j^H over time corroborates the conjecture that part of the rejection of the Sandas specification originates in the neglected variation of the adverse selection parameter α .

To study the serial dependence of the trade informativeness measures in greater detail, we de-seasonalize the data by subtracting the stock specific time-of-day (half-hour) average from α_j^H . Table 4 reports the serial correlation, inter-day correlation, and intra-day correlation of the diurnally adjusted sequence $\{\alpha_j^H\}$. Figure 3 plots the autocorrelation functions (ACFs) averaged across the four stock groups. The first order autocorrelation of the seasonally adjusted trade informativeness measure ($\rho_{\alpha_j^H}$) ranges from 0.28 to 0.38. This means that trade-informative periods are clustered. A period where trade informativeness is high (more precisely higher than the time-of-day average) tends to be followed by another informative period. Intra-day serial dependence of trade informativeness is stronger than inter-day dependence. This can be seen by comparing the correlation between the last estimate of α_j^H for a trading day and the first estimate of the following trading day ($\text{inter-}\rho_{\alpha_j^H}$) with the pure intra-day correlation ($\text{intra-}\rho_{\alpha_j^H}$) which excludes successive observations that do not belong to the same trading day. Table 4 shows that the inter-day correlation is considerably lower than the intra-day serial correlation. This implies that informative periods do not tend to extend across trading days. The intra-day serial correlation of the trade informativeness measure

⁹Ahn, Cai, Hamao, and Ho (2002) decompose the spread in a pure limit order book market (Tokyo Stock Exchange) and found that the adverse selection component of the spread exhibits a U-shape.

does not vary greatly between stock groups. It lies between 0.40 (average of first group, most frequently traded) and 0.31 (average of third group).

3.4 Book liquidity, trading activity, and trade informativeness

Figures 4 to 8 illustrate graphically the relation of book liquidity measures and trading activity on the one hand and the degree of informativeness of trades on the other. Each figure consists of four panels which display the results for the four groups of stocks sorted by the trading frequency (trade frequency quartiles). In each of the graphs, the values on the horizontal axis are the deciles of the standardized adverse selection component α_i^H . To compute the deciles, we pool all observations of the stocks belonging to the same trading frequency group. The observations are trade events for which we measure trading volume (in euros), the duration since the last trade, and the prevailing relative inside spread (best bid minus best bid offer divided by midquote) prior to the trade. To each trade event we assign the α_j^H of the estimation window to which the respective trade event belongs to.

In an open limit order book market it is especially interesting to study how liquidity beyond the best quotes responds to informed order flow. For this purpose, we employ a pre-trade book liquidity measure similar to those proposed in Irvine, Benston, and Kandel (2000) and Gomber, Schweickert, and Theissen (2004). The basic idea is to compare the per-share price of a time t buy or sell order of volume v with the prevailing best ask or bid price, respectively. The per-share price obtained when selling v shares at time t can be computed as

$$b_t(v) = \frac{\sum_k b_{k,t} v_{k,t}}{v}, \quad (10)$$

where v is the volume executed at k different unique bid prices $b_{k,t}$ with corresponding volumes $v_{k,t}$ standing in the limit order book at time t (this takes into account that the order can 'walk up the book'). The unit price $a_t(v)$ of a buy of size v at time t can be computed analogously. To ensure comparability across stocks, we relate the per-share prices to the best quotes, viz

$$ap_t(v) = \frac{a_t(v) - a_t(1)}{a_t(1)} \cdot 100 \quad (11)$$

and

$$bp_t(v) = \frac{b_t(1) - b_t(v)}{b_t(1)} \cdot 100. \quad (12)$$

We refer to $ap_t(v)$ as the ask price impact and to $bp_t(v)$ as the bid price impact. These price impacts serve as natural liquidity measures for an open order book system. They account for the bi-dimensionality of liquidity supply (price and volume), and are comparable across stocks.¹⁰ To generate the values on the vertical axes of figures 4 to 8, we proceed as follows:

¹⁰In fact, the German Stock Exchange employs a closely related concept (denoted XLM, short for Xetra Liquidity Measure) to monitor and report the quality of liquidity in the Xetra system, both across stocks and over time.

each trade event with corresponding order book snapshot immediately prior to the trade is assigned to its α^H decile. We then compute decile specific means, medians, and 0.75-quantiles of the trade related variables (volume and duration) and of the variables describing liquidity displayed in the order book, inside spread as well as the bid and ask price impacts, $ap_t(v)$ and $bp_t(v)$. We set v equal to an 'average' volume, $v = 50,000$ euros, and a 'large' volume, $v = 250,000$ euros, respectively. A trade of 50,000 euros roughly corresponds to the average trade size computed over all thirty stocks, while a trade of 250,000 euros can be considered a large trade for any of the stocks. Figure 4 shows that the inside spread tends to be higher (smaller) when trade informativeness is high (low). This is most pronounced for the two groups of less frequently traded stocks (two lower panels in figure 4). For the group of least frequently traded stocks the average spread increases from 0.07% to 0.11 % when comparing the 0.1 α^H -decile with the .9-decile. Figures 5 and 6 show that liquidity supply beyond the best quotes, as measured by price impacts, $ap_t(v)$ and $bp_t(v)$, is sensitive towards informational order flow. Limit order traders demand liquidity premiums for taking the counterpart in large transactions during times of informational order flow. Both bid and ask side results support this conclusion. It holds true especially for less frequently traded stocks (see the lower panels of figure 5 and 6). For example, the average ask price impact for the large volume, $ap_t(250,000)$, increases from 0.13 % (0.1 decile) to 0.33 % (0.9 decile). Therefore, both in relative and in absolute terms, price impacts increase considerably more than inside spread. The result that book liquidity beyond the best quotes reacts to informed order flow concerns also the frequently traded/large capitalized stocks. While the response is comparable in relative terms, it is smaller in absolute terms. For example $ap_t(250,000)$, increases from 0.02 % to 0.05 % in the group of most frequently traded stocks (see upper left panel of figure 5). Measuring liquidity for the 'average' volume $v = 50,000$, the inverse relation of liquidity supply and trade informativeness is still discernable, but it is weaker. Figures 5 and 6 show that a relative high level of liquidity supply is committed up to a economically significant trade size volume, even during periods when trades are allegedly informative. The fact that this conclusion is also valid for smaller capitalized, less frequently traded stocks can be interpreted as a vindication of the limit order book trading design and its viability without dedicated market makers.

Figure 7 shows that trade sizes and trade informativeness are inversely related, with a considerable decrease of average trading volumes during times of informed order flow. The finding holds true for all four trade frequency quartiles. For example, in the group of least frequently traded stocks, the average trade size decreases from 35,000 euros in the 0.1 α^H -decile to 20,000 euros in the 0.9 α^H -decile. In the group of most frequently traded stocks, the average trade size in the 0.1 α^H -decile amounts to 80,000 euros while in the 0.9 decile the average trade size is 50,000 euros. Previous studies have already documented that market order submissions in open order book markets are clearly timed (see Coppejans, Domowitz, and Madhavan (2002) and Gomber, Schweickert, and Theissen (2004)). Large order sizes are

submitted when committed liquidity in the book is high, while at times of reduced liquidity supply, trade order sizes are smaller. Our results point in the same direction, but they also highlight an important background variable which affects both book liquidity and order sizes, namely the degree of informed order flow. We have seen above that adverse selection effects reduce liquidity supply beyond the best quotes, especially for large volumes.

The considerable reduction of trade sizes during periods of informed order flow suggests that market order traders (be they informed or not) are very price sensitive and that they adapt their market order volumes to the liquidity state of the book. We have seen that liquidity supply is reduced during periods of informed order flow (especially for large trading volumes and less frequently traded stocks and to a lesser extent for moderate trading volumes and frequently traded, large cap stocks). However, the average trade sizes are noticeably smaller during times of informed order flow. This holds true also for frequently traded stocks, for which the markups and discounts demanded by limit order traders during periods of informed order flow are moderate even for large volumes. This result suggests a high price sensitivity of market order traders. Accordingly, the result that the median trade size does not change with trade informativeness can be interpreted as evidence for a heterogeneous market order trader population. One group of traders does not reduce trade sizes in response to a (allegedly informationally induced) reduction of liquidity supply. In line with the reasoning, these agents may either be impatient informed or price-insensitive traders who are willing to conduct buy and sell transactions even with some markup or discount on the per share price. On the other hand, the trader population also seems to contain highly price sensitive traders who closely monitor the book, time their trades, and who adjust their trade sizes according to the liquidity state of the book.

While the sensitivity of average trade sizes towards informed order flow is considerable, trade durations are only marginally affected. Although figure 8 shows a positive relation of trade informativeness and trade durations, the increase of average trade durations when comparing the 0.1 α^H -decile with the 0.9 decile seems small in terms of economic significance. Average trade duration increases by only about 5 seconds even when the informational content of the order flow is highest. Since the interest in the role of trade durations and their relation with adverse selection effects has surged (spurred by the papers by Engle and Russell (1998) and Engle (2000)), this result rewards some further discussion. Dufour and Engle (2000) have pointed out that the theoretical model of Easley and O'Hara (1992) implies a testable hypothesis about the relation of trading intensity and informed order flow. In a nutshell it works as follows. During informative periods, traders possessing superior information split their orders in order to prevent the market maker from identifying their trades as being informationally motivated. The informed agents submit smaller volumes, albeit more frequently. One would therefore expect shorter trade durations and smaller volumes during informational periods. To test this prediction, Dufour and Engle (2000) propose another adaptation of the Hasbrouck (1991a,b) framework which accounts for the alleged relation of trading frequency and trade

informativeness. Estimating their model on NYSE data, they find a strong relation between trade durations and trade informativeness, and interpret this as empirical support for the validity of the Easley and O’Hara (1992) model. Our results show that this conclusion cannot be readily transferred to an automated auction system. While the reduction of average trade sizes during informative periods is compatible with the predictions implied by the Easley and O’Hara (1992) model, the weak relation of trade informativeness and trade durations is not. We interpret this result as an outcome of the different market structures. Unlike the NYSE trading process analyzed by Dufour and Engle (2000), the Xetra automated auction system employs no central market makers endowed with discretionary pricing power. The NYSE specialist can grant price improvements over the quoted spreads and is (relatively) free to set prices for volumes that exceed depth at the best quotes. In the automated auction system, however, the per share price for a given trading volume is fixed *ex ante* and also *ex post*.¹¹ In other words, liquidity suppliers, unlike the NYSE specialist, do not have the opportunity to discriminate prices between allegedly informed and uninformed order arrivals. Instead, they have to take trade informativeness into account prior to the arrival of the market orders. And in fact, this is what is reflected in our data. We have seen that liquidity committed to the book does react to trade informativeness. So do the sizes of market orders, as both informed and uninformed trader population contain price sensitive agents. However, the inverse relation of trade informativeness and trade durations predicted by the Easley and O’Hara (1992) seems to be confined to specialist systems.

4 Conclusion and outlook for further research

In this paper we have analyzed how the state of the limit order book and trade informativeness interact. Following Sandas (2001) we have performed a direct test of the Glosten (1994) model which provides a closed form expression for the relation of order book depth and trade informativeness. However, like in Sandas (2001) analysis, the Glosten model is rejected based on the grounds of formal statistical tests despite the fact that the data generating process fits the theoretical framework set up by Glosten much better. Given this disconcerting result we develop a more flexible approach based on an adaption of Hasbrouck’s (1991a, 1991b) methodology and study the relation of trade informativeness and the state of the order book, market order sizes and trade durations. The main results can be summarized as follows:

- The level of trade informativeness varies greatly and can be described as a slowly mean reverting process. This result may explain why the theory-based Sandas (2001) model with time invariant trade-informativeness parameter fails to explain order book data well.

¹¹For the ask side these prices are given by equation (10).

- As predicted in the Glosten/Sandas limit order book model, our methodology confirms that the book is shallower when trade informativeness is high. Limit order traders demand liquidity premiums for taking the counterpart in large transactions during times of informational order flow. This result is most pronounced for less frequently traded stocks.
- The inside (quoted) spread tends to be larger when trade informativeness is high (low). However, the effect of an increase of trade informativeness on the inside spread is smaller than the effect on liquidity beyond the best quotes.
- Average trade sizes are noticeably smaller during times of informed order flow. However, while the sensitivity of average trade sizes towards informed order flow is considerable, the effects on trade durations are much smaller. This result indicates the presence of a heterogeneous market order trader population. Part of the market order traders is quite price sensitive in that they adapt their market order volumes to the liquidity state of the book. However, another group does not reduce trade sizes in response to an informationally induced reduction of liquidity supply. Whether these traders are informed or merely price insensitive and impatient remains an open point.
- Contrary to findings for specialist markets we show that trade durations do not react in an economically significant way towards trade informativeness. Thus, care should be taken when applying the conclusions regarding the validity of predictions from theoretical models of specialist market microstructure to automated auction systems.
- In the open order book market that we have studied, a high level of liquidity supply is committed up to a economically significant trade size volume, even during periods when trades are allegedly informative. The fact that this conclusion is also valid for smaller capitalized, less frequently traded stocks is a vindication of the limit order book trading design and its viability without dedicated market makers.

Avenues for further research stretch in various directions. First, the investigation how book liquidity reacts to informativeness of trades could be placed in a multivariate empirical analysis. The objective of this exercise is to assess to which degree order book variation is attributable to adverse selection effects. We hope that such an analysis will shed light on the empirical relevance of those two parallel streams in the theoretical literature that explain limit order book evolution. Second, a drawback of our analysis is that so far we use fixed windows to estimate the trade informativeness measure. A greater flexibility would be obtained if the trade informativeness measure would be updated after each trade. Third, we believe that the methodology presented in this paper could be fruitfully applied to assess issues of market design in open order book markets. The market structures of the leading European exchanges are subject to a permanent redesign process. The empirical tools presented in this

paper could be used to quantify how the balance of liquidity supply and demand is affected by these design measures. Furthermore, the favorable conclusion regarding the viability of the open limit order book market without dedicated market makers are valid for a sample of stocks in which even the least frequently traded stock was still quite actively traded and had a rather liquid book. Whether the same conclusion also holds for stocks which do not belong to a major stock market index is an open question for further research. Finally, it would be interesting to study liquidity supply for internationally cross listed stocks using the methodology presented in this paper. The NYSE open book program allows to estimate and compare the effect of trade informativeness on the liquidity supply of internationally cross listed stocks.

References

- AHN, H., K. BAE, AND K. CHAN (2001): “Limit orders, depth and volatility: evidence from the stock exchange of Hong Kong,” *Journal of Finance*, 56, 767–788.
- AHN, H., J. CAI, Y. HAMAOKA, AND R. HO (2002): “The components of the bid-ask spread in a limit order market: evidence from the Tokyo stock exchange,” *Journal of Empirical Finance*, 9, 399–430.
- AHN, H., AND Y. CHEUNG (1999): “The intraday patterns of the spread and depth in a market with market makers: the Stock Exchange of Hong Kong,” *Pacific-Basin Finance Journal*, 7, 539–556.
- BIAIS, B., P. HILLION, AND C. SPATT (1995): “An empirical analysis of the limit order book and the order flow in the Paris Bourse,” *Journal of Finance*, 50, 1655–1689.
- BROCKMAN, P., AND D. CHUNG (1999): “An analysis of depth behavior in an electronic, order-driven environment,” *Journal of Banking and Finance*, 23, 1861–1886.
- COHEN, K., S. MAIER, R. SCHWARTZ, AND D. WHITCOMB (1981): “Transaction Costs, Order Placement Strategy and Existence of the Bid-Ask Spread,” *Journal of Political Economy*, 89, 287–305.
- COPPEJANS, M., I. DOMOWITZ, AND A. MADHAVAN (2002): “Liquidity in an automated auction,” Mimeo.
- (2003): “Dynamics of Liquidity in an Electronic Limit Order Book Market,” Discussion paper, Department of Economics, Duke University.
- DEUTSCHE BÖRSE AG (1999): “Xetra Market Model Release 3 Stock Trading,” Technical Report.
- DUFOUR, A., AND R. ENGLE (2000): “Time and the impact of a trade,” *The Journal of Finance*, 55, 2467–2499.
- EASLEY, D., AND M. O’HARA (1992): “Time and the Process of Security Price Adjustment,” *Journal of Finance*, 47, 577–605.
- ENGLE, R., AND J. RUSSELL (1998): “Autoregressive conditional duration; a new model for irregularly spaced transaction data,” *Econometrica*, 66, 1127–1162.
- ENGLE, R. F. (2000): “The econometrics of ultra-high frequency data,” *Econometrica*, 68, 1–22.
- FOUCAULT, T. (1999): “Order flow composition and trading costs in a dynamic limit order market,” *Journal of Financial Markets*, 2, 99–134.

- FOUCAULT, T., O. KADAN, AND E. KANDEL (2003): “Limit order book as a market for liquidity,” *Forthcoming, Review of Financial Studies*.
- GLOSTEN, L. (1994): “Is the electronic open limit order book inevitable?,” *Journal of Finance*, 49, 1127–1161.
- GOETTLER, R., C. PARLOUR, AND U. RAJAN (2004): “Equilibrium in a Dynamic Limit Order Market,” *Forthcoming, Journal of Finance*.
- GOLDSTEIN, M., AND K. KAVAJECZ (2000): “Eights, Sixteenths, and Market Depth: Changes in Tick Size and Liquidity Provision on the NYSE,” *Journal of Financial Economics*, 1(56), 125–149.
- GOMBER, P., U. SCHWEICKERT, AND E. THEISSEN (2004): “Zooming in on Liquidity,” EFA 2004 Working Paper, University of Bonn.
- GRIFFITHS, M., B. SMITH, D. TURNBULL, AND R. WHITE (2000): “The Costs and Determinants of Order Aggressiveness,” *Journal of Financial Economics*, 56, 65–88.
- HARRIS, L. (1998): “Optimal Order Submission Strategies in Some Stylized Trading Problems,” *Financial Markets, Institutions, and Instruments*, 7(2).
- HASBROUCK, J. (1991a): “Measuring the information content of stock trades,” *Journal of Finance*, 46(1), 179–207.
- (1991b): “The Summary Informativeness of Stock Trades: An Econometric Analysis,” *Review of Financial Studies*, 4(3), 571–595.
- HOLLIFIELD, B., R. MILLER, AND P. SANDAS (2004): “Empirical Analysis of Limit Order Markets,” Discussion paper, *Forthcoming, Review of Economic Studies*.
- IRVINE, P., G. BENSTON, AND E. KANDEL (2000): “Liquidity beyond the inside spread: measuring and using information in the limit order book,” Mimeo, Goizueta Business School, Emory University, Atlanta.
- NYSE (2000): “Presentation at SEC Roundtable discussion on Decimalization, December 11, 2000,” Discussion paper.
- PARLOUR, C., AND D. SEPPI (2003): “Liquidity-Based Competition for Order Flow,” *Review of Financial Studies*, 16(2), 301–343.
- PARLOUR, C. A. (1998): “Price Dynamics in Limit Order Markets,” *Review of Financial Studies*, 11, 789–816.
- RANALDO, A. (2004): “Order aggressiveness in limit order book markets,” *Journal of Financial Markets*, 7, 53–74.

SANDAS, P. (2001): “Adverse Selection and Competitive Market making: Empirical Evidence from a Limit Order Market,” *Review of Financial Studies*, 14(3), 705–734.

SEPPI, D. J. (1997): “Liquidity provision with limit orders and a strategic specialist,” *Review of Financial Studies*, 10, 103–150.

Ticker	Company Name	Daily Turnover	Market cap. (mill.)	Trade size	% agg. trades	Daily nb. trades	Daily nb. subm.	Daily nb. cancel.	Price Spread	Spread (%)	Group	
ALV	ALLIANZ	289980556	33805	64114	21.4	4523	29791	25882	100.1	0.05	0.05	1
DTE	DEUTSCHE TELEKOM	350627866	34858	78884	5.0	4445	14498	11009	15.7	0.01	0.07	
SIE	SIEMENS	321704299	52893	72831	16.7	4418	23659	19920	64.0	0.03	0.05	
DBK	DEUTSCHE BANK	309282831	38228	78083	19.3	3961	23169	19772	67.2	0.03	0.05	
MUV2	MUENCH.RUECKVERS	207353230	16396	60534	20.7	3425	20154	16894	93.9	0.06	0.06	
DCX	DAIMLERCHRYSLER	187737846	30316	56736	14.5	3309	18722	15919	36.4	0.02	0.06	
EOA	E.ON	160625983	33753	55950	13.6	2871	18899	16468	52.5	0.03	0.06	
SAP	SAP	184628162	27412	65795	21.9	2806	19733	17095	131.5	0.08	0.06	2
IFX	INFINEON	146462315	4790	52331	8.6	2799	10320	7744	11.6	0.01	0.10	
BAS	BASF	124434537	25425	48236	13.8	2580	18211	15898	43.3	0.03	0.06	
VOW	VOLKSWAGEN	104249843	9688	40963	16.0	2545	13474	11273	39.2	0.03	0.07	
BAY	BAYER	88776121	15911	36994	12.4	2400	15258	12988	23.1	0.02	0.08	
RWE	RWE	97655566	12653	42203	13.0	2314	14438	12355	33.8	0.03	0.08	
BMW	BMW.BAY.MOTOREN WERKE	87854358	12211	41639	14.4	2110	14736	12764	34.7	0.02	0.07	
HVM	BAY.HYPO-VEREINSBK	98351090	6629	50783	15.0	1937	10204	8293	18.7	0.02	0.11	
SCH	SCHERING	51413053	7055	33756	16.2	1523	9111	7669	40.8	0.04	0.09	3
CBK	COMMERZBANK	53171668	7569	36659	12.6	1450	11922	10476	15.4	0.02	0.11	
LHA	LUFTHANSA	43946809	4548	32504	11.9	1352	8079	6780	14.2	0.02	0.12	
DPW	DEUTSCHE POST	43836617	6806	33330	11.0	1315	6861	5666	18.2	0.02	0.11	
TKA	THYSSENKRUPP	37892493	6450	30017	11.3	1262	7864	6672	15.9	0.02	0.13	
MEO	METRO	38874669	5018	31480	15.7	1235	7975	6702	35.0	0.04	0.12	
ALT	ALTANA	30985416	3338	28310	18.9	1095	7718	6609	48.6	0.05	0.10	
TUI	TUI	26281175	2025	24723	17.6	1063	6767	5714	18.7	0.03	0.14	
MAN	MAN	27685031	2434	26189	13.0	1057	7214	6235	27.7	0.03	0.12	4
CONT	CONTINENTAL	25627638	4060	25574	13.5	1002	8036	7052	31.6	0.04	0.11	
DB1	DEUTSCHE BOERSE	35696903	4847	36359	18.4	982	6598	5698	46.9	0.04	0.10	
ADS	ADIDAS-SALOMON	31976047	4104	32635	20.1	980	8057	7105	92.6	0.08	0.09	
LIN	LINDE	22378772	3448	24971	15.8	896	8342	7454	43.6	0.05	0.11	
HEN3	HENKEL	18174548	3682	25904	16.6	702	7989	7306	65.9	0.07	0.10	
FME	FRESENIUS.MEDICAL CARE	12850947	1944	20680	16.7	621	5764	5195	54.0	0.07	0.13	
Average		108683880	14076	42972	15.2	2099	12785	10887	44.5	0.04	0.09	

Table 1: **Characteristics of the stocks in the sample (DAX30 stocks)** The table reports characteristics of the stocks constituting the DAX30 index and our sample. The statistics are computed based on the data on the market events during the sample period January 2, 2004 to March 31, 2004 except for the column *Market cap.* which gives the market capitalization of the respective stock in million euros at the end of December 2003. *Daily turnover* is the total average turnover (in euros) per trading day. *Trade size* is the average trade size, and *% agg. trades* is the percentage of total trading volume that has been executed beyond the best quotes (aggressive trades). *Daily nb. trades* is the average daily number of trades. *Daily nb. subm.* is the average number of order submissions per day, market orders excluded. *Daily nb. cancel.* is the average number of order cancelations per day. *Price, Spread* and *Spread (%)* denote to the average midquote, spread and relative spread over the 3 months sample period. The stocks sorted into four groups according to their trading frequency, i.e. by the column *Daily nb. trades*. The horizontal lines separate the four groups.

stock group	$\alpha \cdot 1000$	γ	λ	c_v	$J(9)$	no reject	α^S
1	0.0085 (-438.9)	-0.0059 (73.7)	1.6082 (298.6)	0.0000 (2.5)	2904.6	0	0.00009 [0.00004 0.00012]
2	0.0080 (298.5)	-0.0077 (80.2)	1.7630 (235.5)	0.0001 (2.1)	787.0	0	0.00019 [0.00011 0.00024]
3	0.0075 (251.3)	-0.0095 (79.9)	1.5088 (178.5)	-0.0001 (2.2)	136.7	0	0.00047 [0.00032 0.00077]
4	0.0293 (185.4)	-0.0176 (67.9)	0.6049 (150.3)	0.0001 (2.3)	67.3	1	0.00056 [0.00032 0.00078]

Table 2: **Estimation results of the Sandas/Glosten model using 2×4 quotes from the complete book (visible book).** The table reports the aggregated estimation results for the four groups of stocks ordered by trading frequency. Group one contains the most frequently traded stocks while group four the least frequently traded stocks. See table 1 for the assignment of stocks into trade frequency groups. The table reports first stage GMM estimates of α , γ , λ , and c_v which are averaged across the stocks in the groups. The values in parentheses are the parameter t -values which are also group averages. The $J(9)$ column is the group average of the GMM J - statistic (with 9 degrees of freedom). In the column labeled *no reject* we report the number of stocks in the respective group for which the specification is not rejected at 1 % significance level. The last column reports the group averages of the standardized trade informativeness measure $\alpha^S = \alpha/P^2 \cdot 50,000$ where P denotes the sample average of the midquote. The values in brackets are the smallest and the largest α^S estimates within the respective group.

Group	N	Daily estimates	Time interval (min.)
1	250	14.9	34.3
2	200	11.6	42.8
3	150	8.1	60.7
4	100	8.4	59.7
all	-	10.7	49.6

Table 3: **Number of trades and daily number of VAR estimates.** The table reports the number of trades N that are required to estimate a new VAR and compute the implied trade informativeness measure α_j^H . Stocks are sorted into four groups which are ordered by trading frequency. Group one contains the most frequently traded stocks while group four contains the least frequently traded stocks. See table 1 for the assignment of stocks into trade frequency groups. For each group the same number N is chosen. The table reports the group averages of the daily number of VAR estimates (column *Daily estimates*) implied by the choice of N . The average duration before N successive trades are observed is reported in column *Time interval (min.)*.

Group	α^H	$\min(\alpha_j^H)$	$\max(\alpha_j^H)$	$\rho_{\alpha_j^H}$	$\text{inter-}\rho_{\alpha_j^H}$	$\text{intra-}\rho_{\alpha_j^H}$	b^H
1	0.00008 (0.00002)	0.00001 (0.00000)	0.00028 (0.00006)	0.38 (0.05)	0.16 (0.17)	0.40 (0.06)	0.00004 (0.00001)
2	0.00015 (0.00004)	-0.00001 (0.00003)	0.00065 (0.00026)	0.36 (0.10)	0.17 (0.18)	0.39 (0.11)	0.00009 (0.00003)
3	0.00034 (0.00009)	-0.00001 (0.00001)	0.00128 (0.00039)	0.28 (0.08)	0.16 (0.19)	0.31 (0.07)	0.00020 (0.00006)
4	0.00041 (0.00012)	-0.00006 (0.00007)	0.00164 (0.00042)	0.30 (0.05)	0.17 (0.09)	0.33 (0.06)	0.00022 (0.00007)
all	0.00024	-0.00002	0.00096	0.33	0.16	0.36	0.00014

Table 4: **Cross sectional and time series properties of estimated trade informativeness measures α_j^H and immediate impacts b_j^H .** The table reports the aggregated results for the four groups sorted by trading frequency. Group one contains the most frequently traded stocks while group four contains the least frequently traded stocks. See table 1 for the assignment of stocks into trade frequency groups. The table reports averages of α_j^H (column α^H) and b_j^H (column b^H) over the observations of all stocks in the same group. The numbers in parentheses are standard deviations computed in the same way. The columns labeled $\min(\alpha_j^H)$ and $\max(\alpha_j^H)$ report the group averages of the smallest and largest α_j^H estimate for each stock in the respective group. $\rho_{\alpha_j^H}$ is the first order autocorrelation of the de-seasonalized $\{\alpha_j^H\}$ sequence. $\text{inter-}\rho_{\alpha_j^H}$ is the inter-day correlation of the de-seasonalized α_j^H , i.e. the correlation between the last α_j^H estimate of a day and the first α_j^H estimate of the following day. $\text{intra-}\rho_{\alpha_j^H}$ is the intra-day serial correlation of the de-seasonalized α_j^H , two observations of different trading days are excluded for the computation of the correlations. All reported correlations are group averages.

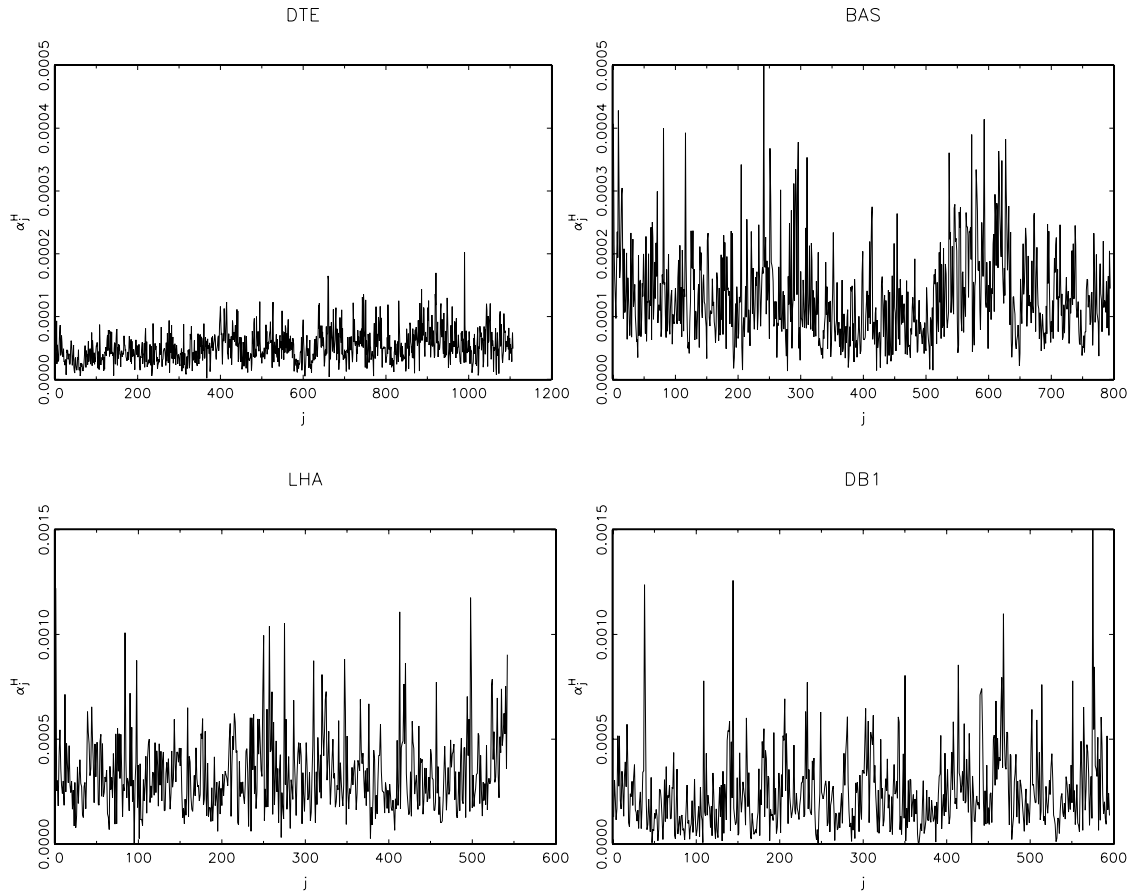


Figure 1: **Time series of estimated time-varying trade informativeness measures α_j^H for four selected stocks.** The four panels depict the sequences of the estimated trade informativeness measures $\{\alpha_j^H\}$ for four selected stocks. Stocks are classified in four groups according to their trading frequency and one representative stock per group is selected. The top left panel shows the Deutsche Telekom series (DTE, group one, most frequently traded stocks), the top right is the BASF series (BAS, group two), the bottom left is the Lufthansa series (LHA, group three) and the bottom right is the Deutsche Börse series (DB1, group four, least frequently traded stocks).

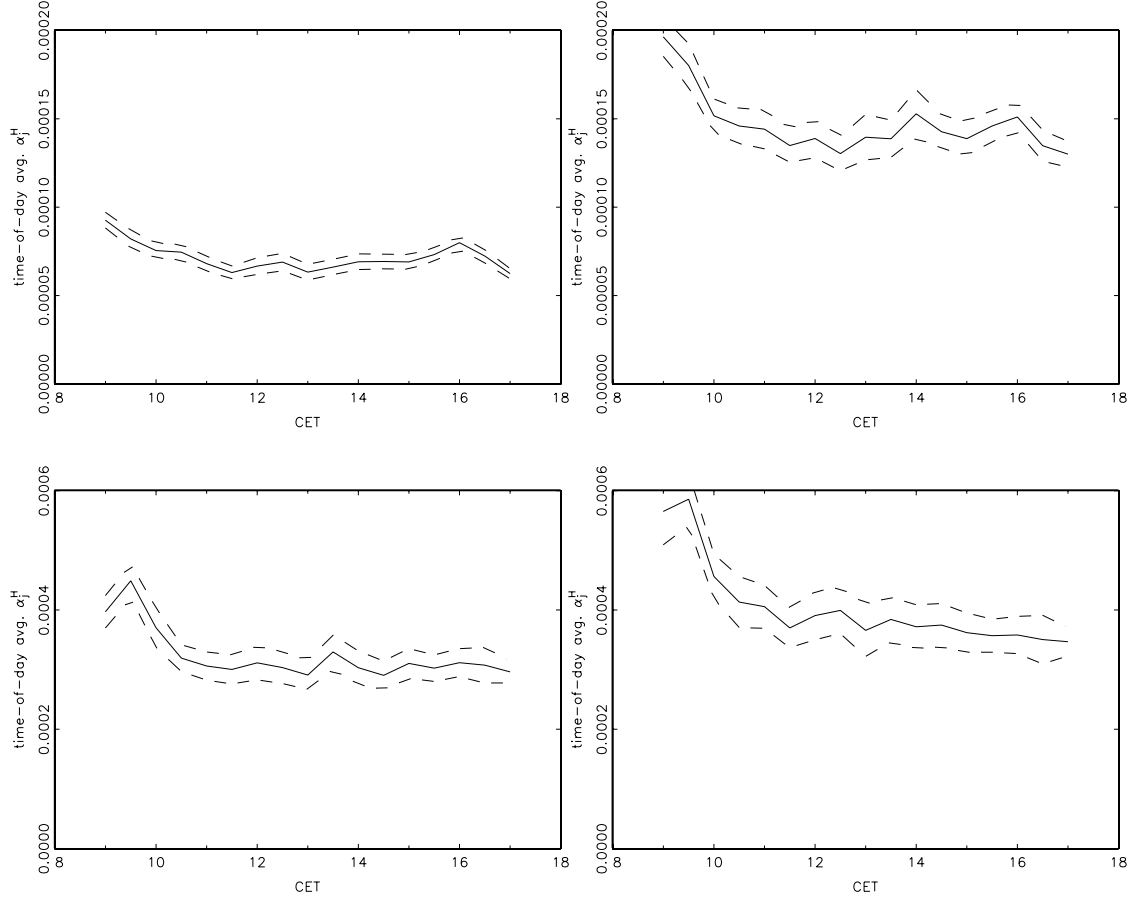


Figure 2: **Time-of-day patterns of the trade informativeness measure α_j^H .** The four panels of the figure show half hour averages of the estimated trade informativeness measures α_j^H . The averages are computed over all α_j^H estimates in the same half hour bin and over all stocks belonging to the same group. Stocks are classified into four groups according to their trading activity. See table 1 for the assignment of stocks into trade frequency groups. The top left panel displays the results for group one (most frequently traded), the top right panel for group two, the bottom left panel for group three, and the bottom right panel for group four (least frequently traded stocks). The dashed lines are bounds of the 95% confidence interval.

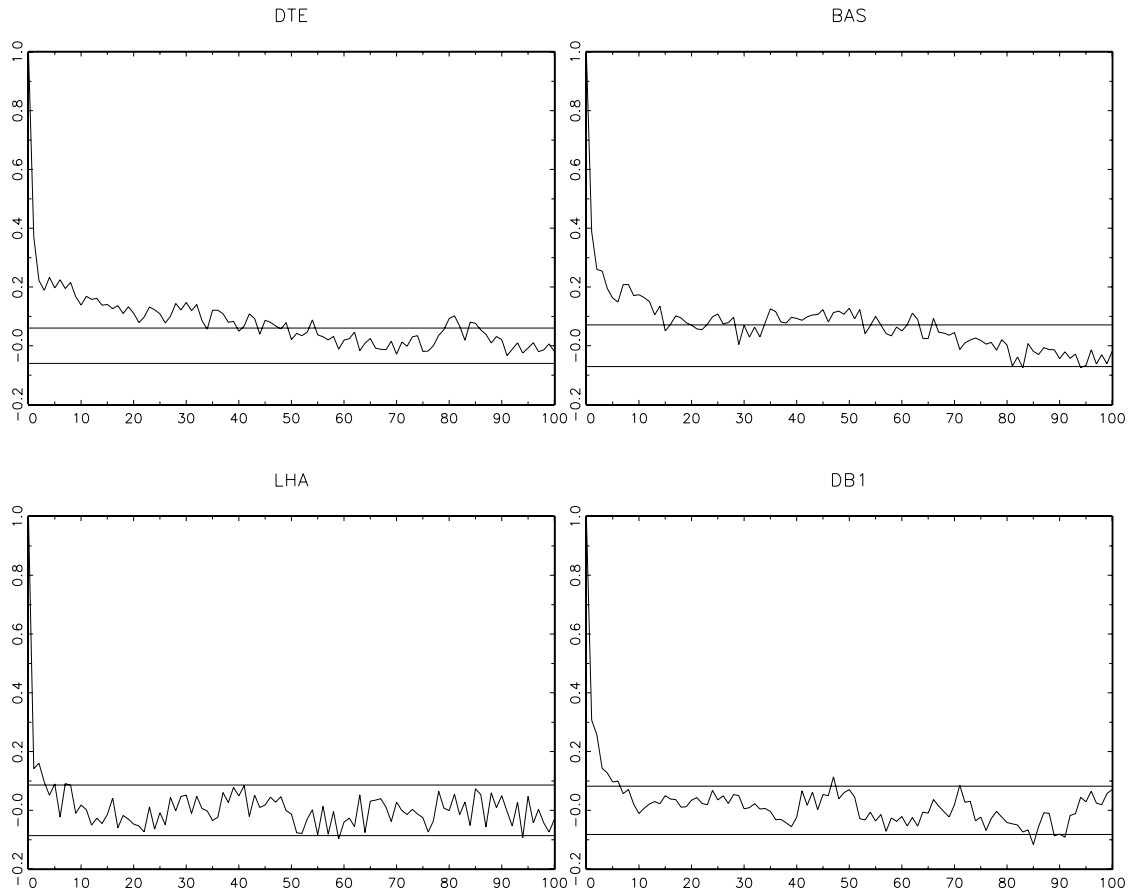


Figure 3: **Autocorrelograms of de-seasonalized trade informativeness estimates.** The figure depicts the autocorrelograms (ACFs) of the sequence of de-seasonalized estimates of $\{\alpha_j^H\}$ for four selected stocks. Stocks are classified into four groups according to their trading frequency. The figures show the results for one representative stock per group. The top left panel depict the results for Deutsche Telekom (DTE, group one, most frequently traded stocks), the top right the results for BASF (BAS, group two), the bottom left panel displays the results for Lufthansa (LHA, group three), and the bottom right panel the results for Deutsche Börse (DB1, group four, least frequently traded stocks). The straight lines are the bounds of the 95% confidence intervals.

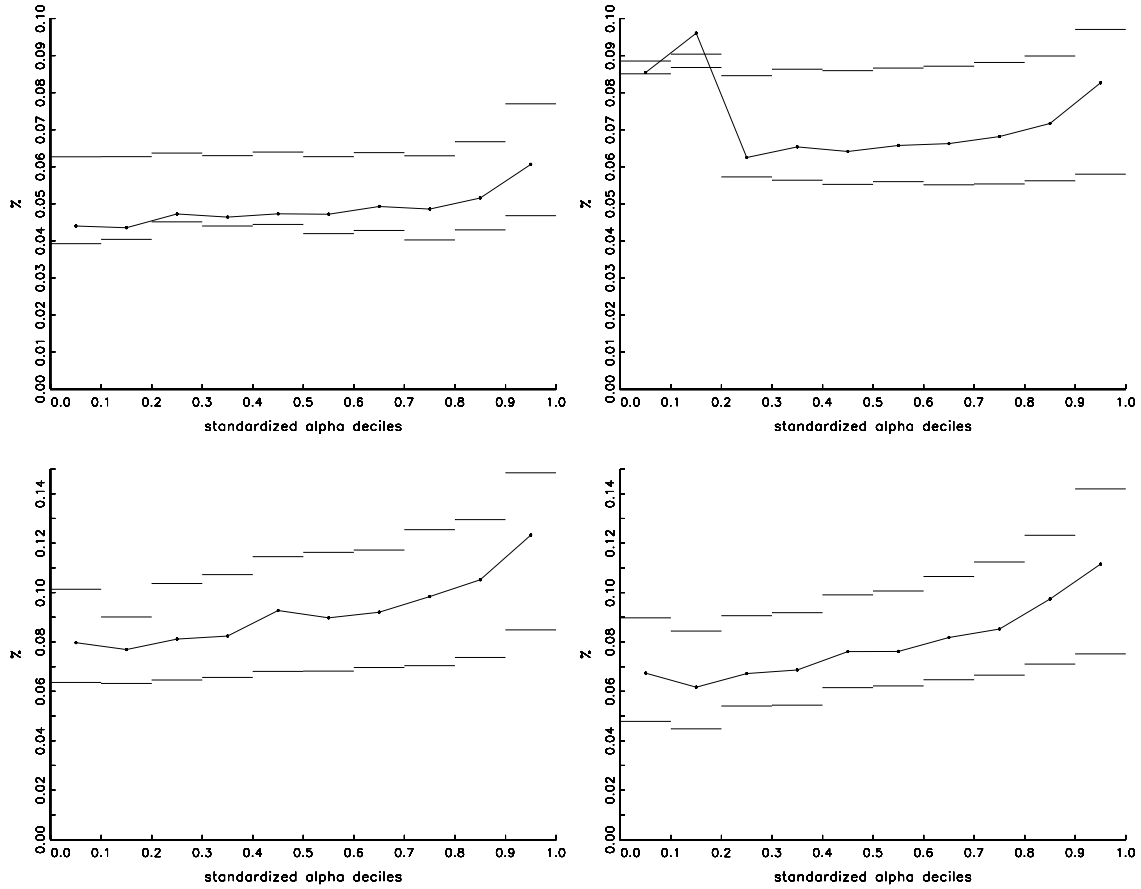


Figure 4: **Inside spread versus trade informativeness.** The figures depict means, medians, and 0.75-quantiles of the inside spread versus deciles of the standardized adverse selection component α_j^H . The panels display the results for four groups of stocks which are ordered according to their daily trading frequency. The top left corner displays the results for the group of most frequently trades stocks, the top right panel shows the results for the second trade frequency group. The lower left panel depicts the results for the third group. The lower right panel presents the results for the least frequently traded stocks. We pool all observations of stocks belonging to the same group to compute the mean and median spread as well as the 0.75 quantile for each standardized α^H -decile. Median spread and 0.75-quantile are displayed with horizontal lines. The decile means are connected with corresponding line types.

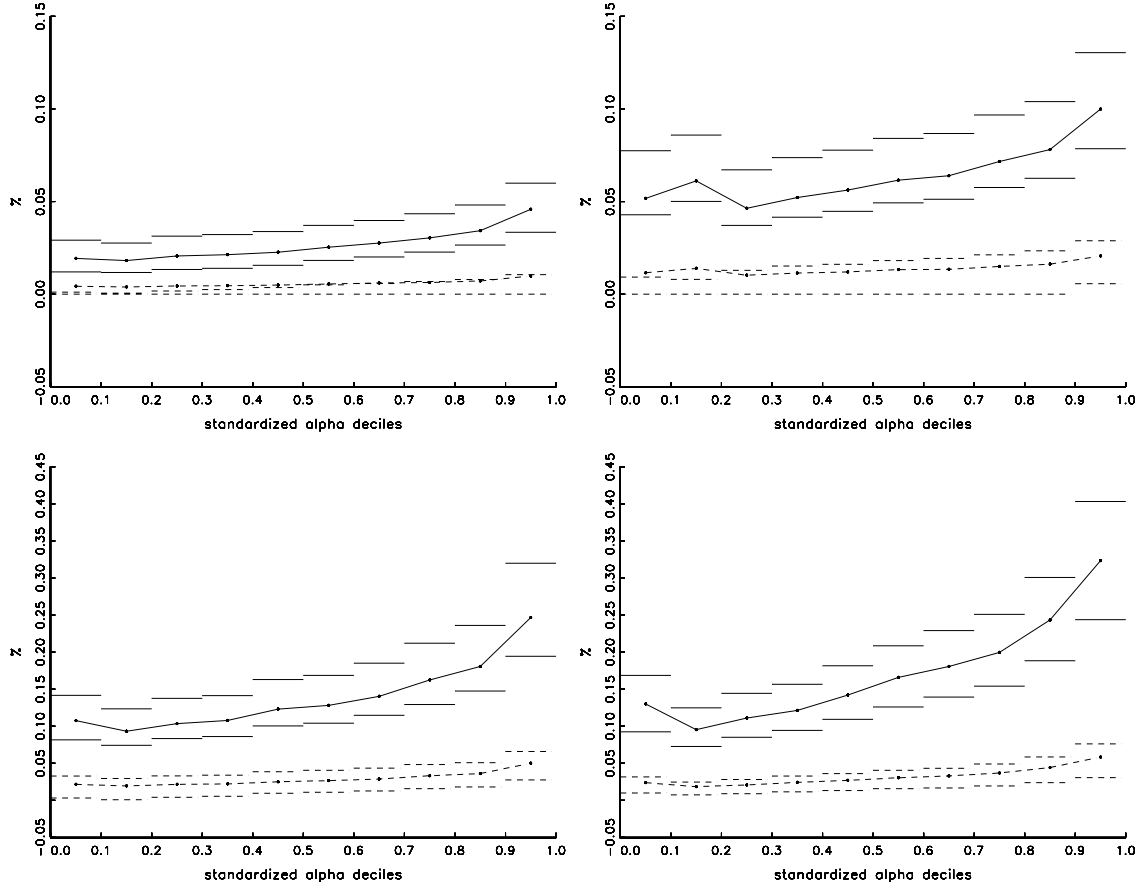


Figure 5: **Book liquidity beyond the best quotes (sell side) versus trade informativeness.** The figures depict means, medians, and 0.75-quantiles of ask price impacts $ap_i(v)$ versus deciles of the standardized adverse selection component α_j^H . The panels display the results for four groups of stocks which are ordered according to their daily trading frequency. The top left corner displays the results for the group of most frequently trades stocks, the top right panel shows the results for the second trade frequency group. The lower left panel depicts the results for the third group. The lower right panel presents the results for the least frequently traded stocks. We pool all observations of stocks belonging to the same group to compute the mean and median price impacts as well as the 0.75 quantiles for each standardized α^H -decile. The dashed lines correspond to the $v = 50,000$ price impact and the solid lines to the $v = 250,000$ euro price impact. Median and 0.75-quantile price impacts are displayed with horizontal lines. The decile means for each price impact are connected with corresponding line types.

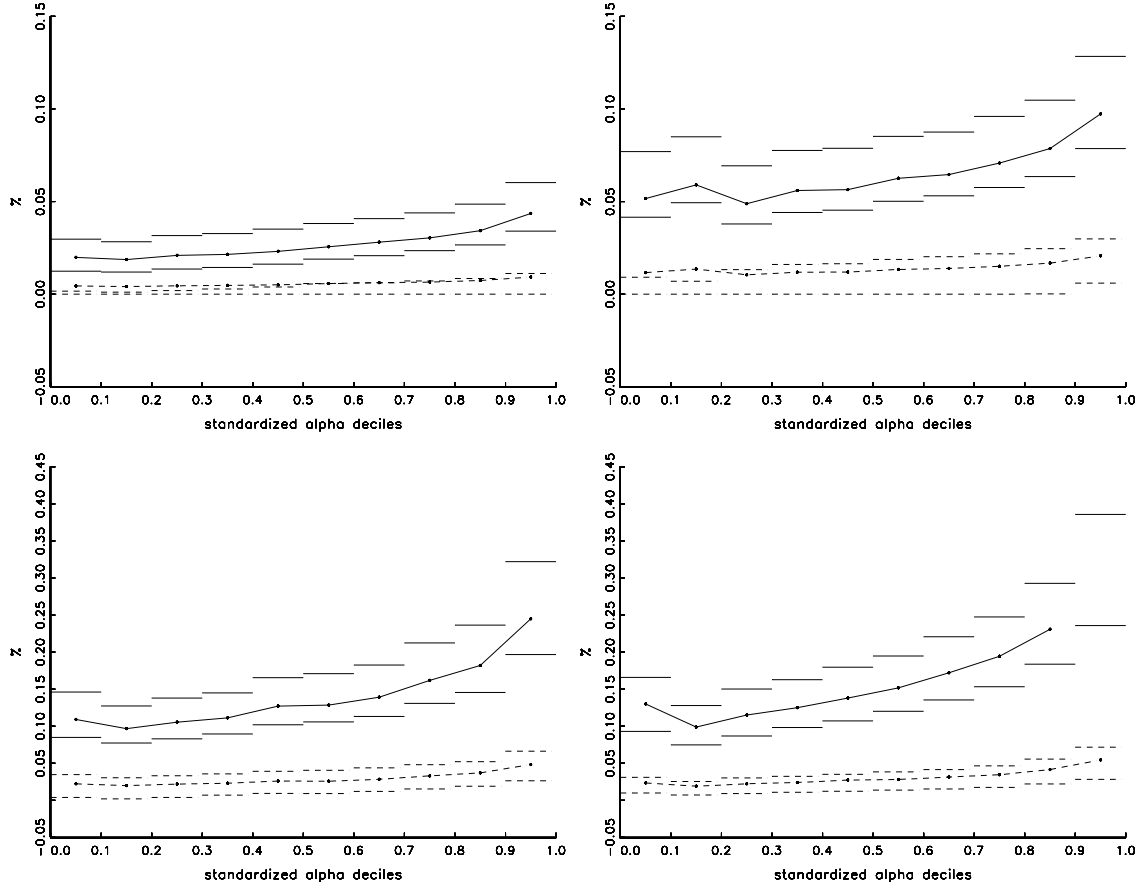


Figure 6: **Book liquidity beyond the best quotes (buy side) versus trade informativeness.** The figures depict means, medians, and 0.75-quantiles of bid price impacts $bp_i(v)$ versus deciles of the standardized adverse selection component α_j^H . The panels display the results for four groups of stocks which are ordered according to their daily trading frequency. The top left corner displays the results for the group of most frequently trades stocks, the top right panel shows the results for the second trade frequency group. The lower left panel depicts the results for the third group. The lower right panel presents the results for the least frequently traded stocks. We pool all observations of stocks belonging to the same group to compute the mean and median price impacts as well as the 0.75 quantiles for each standardized α^H -decile. The dashed lines correspond to the $v = 50,000$ price impact and the solid lines to the $v = 250,000$ euro price impact. Median and 0.75-quantile price impacts are displayed with horizontal lines. The decile means for each price impact are connected with corresponding line types.

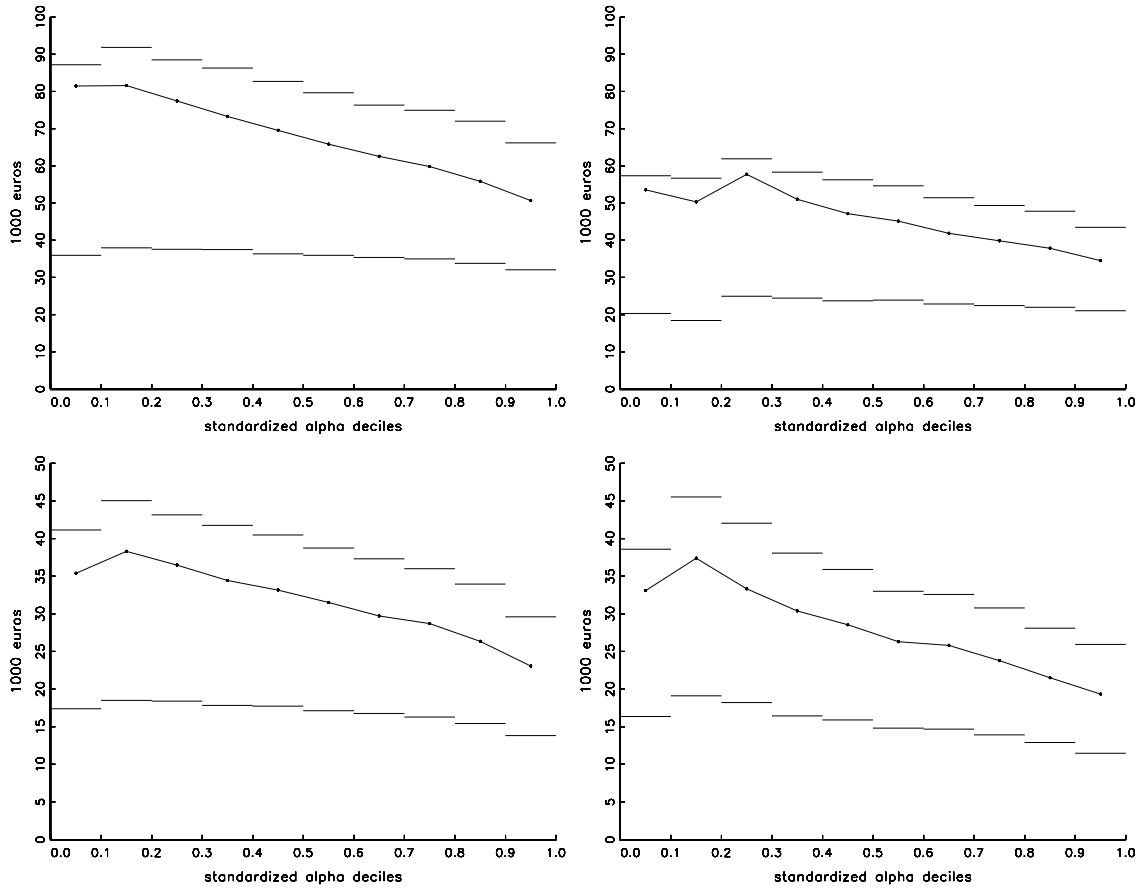


Figure 7: **Trade size versus trade informativeness.** The figures depict means, medians, and 0.75-quantiles of the trading volume (in euros) versus deciles of the standardized adverse selection component α_j^H . The panels display the results for four groups of stocks which are ordered according to their daily trading frequency. The top left corner displays the results for the group of most frequently trades stocks, the top right panel shows the results for the second trade frequency group. The lower left panel depicts the results for the third group. The lower right panel presents the results for the least frequently traded stocks. We pool all observations of stocks belonging to the same group to compute the mean and median volume as well as the 0.75 quantile for the respective standardized α^H -decile. Median volume and 0.75-quantile are displayed with horizontal lines. The decile means are connected with corresponding line types.

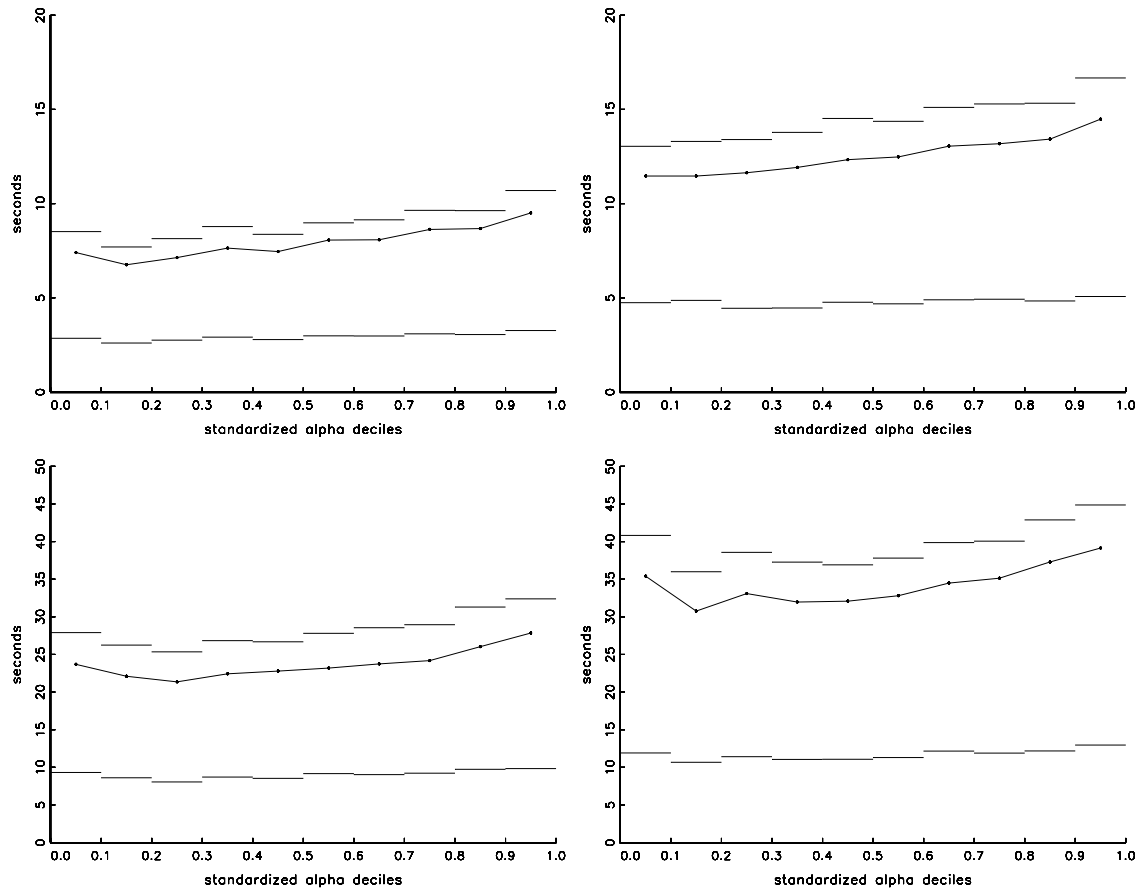


Figure 8: **Trade duration versus trade informativeness.** The figures depict means, medians, and 0.75-quantiles of the trade durations (in seconds) versus deciles of the standardized adverse selection component α_j^H . The panels display the results for four groups of stocks which are ordered according to their daily trading frequency. The top left corner displays the results for the group of most frequently trades stocks, the top right panel shows the results for the second trade frequency group. The lower left panel depicts the results for the third group. The lower right panel presents the results for the least frequently traded stocks. We pool all observations of stocks belonging to the same group to compute the trade duration mean, median and 0.75 quantile of the respective standardized α^H -decile. Median duration and 0.75-quantile are displayed with horizontal lines. The decile means are connected with corresponding line types.

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