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Price efficiency and trading behavior in limit order markets with competing insiders.*

Thomas Stöckl†

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Abstract

We study price efficiency and trading behavior in laboratory limit order markets with asymmetrically informed traders. Markets differ in the number of insiders present and in the subset of traders who receive information about the number of insiders present. We observe that price efficiency (i) is the higher the higher the number of insiders in the market but (ii) is unaffected by changes in the subset of traders who know about the number of insiders present. (iii) Independent of the number of insiders, price efficiency increases gradually over time. (iv) The insiders' information is reflected in prices via limit (market) orders if the asset's value is inside (outside) the bid-ask spread. (v) In situations where limit and market orders yield positive profits, insiders clearly prefer market orders, indicating a strong desire for immediate transactions.

JEL classification: C92, D82, G12, G14

Keywords: Insider, competition, asset market, price efficiency, trading behavior, experimental economics

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1 Introduction

Limit order markets (LOM) are the major trading protocol on financial markets nowadays.[1] Despite the common application of this trading mechanism, little is known about the process of information aggregation into prices. Two major problems complicate the use of theoretical and empirical methods. Theoretical studies have to deal with extremely large action spaces that originate from the possibility to trade in continuous time and the freedom to choose between limit orders (LO) and market orders (MO).[2] Empirical studies suffer from the availability of data that reliably identifies persons trading in the asset while in possession of new and relevant information. This problem is mainly driven by legal prosecution of traders holding that relevant information, commonly referred to as (corporate) insiders.

In this study we analyze laboratory LOMs that differ in the realizations of two treatment variables. We manipulate (i) the number of insiders in a market and (ii) we vary the subset of traders who receives information on the number of insiders present. With these treatment variations we elaborate on three research questions (RQ).

> **RQ 1)** How does competition among insiders affect price efficiency in limit order markets?

So far, no study systematically investigates this RQ. Consequently, predictions on competition effects can only be deduced from studies loosely related to LOMs. While these studies suggest a positive impact of competition on price efficiency, little can be said about the development of price efficiency over time. Kyle (1985), Holden and Subrahmanyam (1992), and Grossman and Stiglitz (1980) provide some insights but must be interpreted cautiously as these models implement pricing mechanisms other than LOMs. The same constraints apply to experimental studies as no study specifically focuses on competition issues (Plott and Sunder, 1982; Friedman et al., 1984; Bloomfield et al., 2005; Huber et al., 2011). Schnitzlein (2002) is an exemption but while he focuses on insider competition, his setup deviates in serval important aspects from LOMs.

[1] See Parlour and Seppi (2008) and Gould et al. (2013) for surveys on limit order markets. Examples for limit order markets are: Euronext (Brussels, Amsterdam, Paris), Stockholm Stock Exchange, Toronto Stock Exchange, and Archipelago Exchange. Examples for trading systems: INET, ArcaEx, Reuters D2000-2. NYSE, Nasdaq, London stock exchange are hybrid markets where designated market makers have to compete with other traders submitting quotes to the limit order book.

[2] Limit orders are offers to buy/sell at a predetermined price and are collected in the limit order book. Market orders accept outstanding offers. The two order types have distinct features and traders face the following trade-off: LOs feature better conditions in terms of prices, however execution is uncertain as it requires the order's acceptance by another trader. On the other hand, MOs offer immediate execution but at less favorable prices. Note that other commonly used market institutions only allow for one trading channel. Call markets allow traders to submit LOs, while market maker institutions allow for MOs only.

RQ 2 elaborates on a specific aspect of real world markets that cannot be addressed in theoretical models. These models assume that traders are informed about the underlying structure of the economy. Concealing information on the presence of insiders undermines this assumption causing models to break down. However, real markets are characterized by high uncertainty about the presence of insiders (potentially) limiting the predictive power of theoretical results. By varying the subset of traders who receives information about the number of insiders present we study potential consequences of dropping the assumption of common knowledge about the underlying structure of the economy in LOMs.

> **RQ 2)** How does the subset of traders who receives information about the number of insiders present affect price efficiency in limit order markets?

So far, the literature did not agree on likely consequences. In his market maker experiments, Schnitzlein (2002) is the first who deliberately challenges the common knowledge assumption and finds that price efficiency is significantly lower when the number of insiders must be inferred. However, Camerer and Weigelt (1991), Meulbroek (1992), and Bruguier et al. (2010) challenge the result and argue that human traders are able to infer the presence of insiders from the trading process. Still, we know little about the robustness of these results and how manipulations in the degree of competition affect them.

In RQ 3 we elaborate on a specific feature of LOMs: the freedom of choice between limit and market orders to make transactions. The insiders' choice is of particular interest as it determines the way in which information is reflected in prices.

> **RQ 3)** Which order types do insiders choose to make transactions?

While there is ample evidence that insiders show abnormally high trading activity (Easley and O'Hara, 1987; Meulbroek, 1992) the literature does not provide clear results on the insiders' preferred channel and no study explores the insiders' behavior conditional on competition. Several studies suggest the use of both, LOs and MOs, by insiders (Chakravarty and Holden, 1995; Harris, 1998; Kaniel and Liu, 2006; Bloomfield et al., 2005; Goettler et al., 2009). Barner et al. (2005) emphasize that insiders are the first to enter the market with early contracts initiated by limit orders.

To evaluate RQ 1 to 3 we conduct laboratory LOMs. Each market is populated by either 0, 1, 2 or 4 insiders, who learn the asset's value, and 6 uninformed traders, who do not receive that piece of information. Furthermore, we define three information sets that determine whether none of the traders, only insiders, or all traders learn the number of insiders present in the market. We observe that price efficiency (i) is the higher the higher the number of insiders in the market but (ii) is unaffected by changes in the subset of traders who know about the number of insiders present. (iii) Independent of the number of insiders, price efficiency increases gradually over time. (iv) The insiders' information is reflected in prices via limit (market) orders if the asset's value is inside (outside) the bid-ask spread. (v) In situations where limit and market orders yield positive profits, insiders clearly prefer market orders, indicating a strong desire for immediate transactions.

2 The experiment

In each experimental session, ten subjects form a cohort and interact in a sequence of sixteen independent periods. Subjects receive an endowment of 20 Euros as compensation for their participation in the experiment. Earnings (losses) generated during the experiment are added (subtracted) to (from) this amount. At the beginning of each period a subject is assigned to either participate in the market experiment or to perform a calculation task.[3] The subjects' assignment to one of the two tasks may change from period to period and does not follow any particular rule.

2.1 The market experiment - being a trader

Subjects assigned to participate in the market experiment in a given period, called traders, are endowed with 60 assets and 4800 Taler, the experimental currency. Assets have a lifespan of one period and are bought back by the experimenter at the end of the market (period) at their buy-back value (BBV).[4] Before trading starts a random draw from a uniform distribution $U(20, 80)$ determines the BBV (with one decimal place).

The trading mechanism is a continuous double auction with open order books. While the mechanism used in the experiment replicates all major features of existing LOMs, we nevertheless tried to keep the environment simple and easily understandable.[5] Figure 1 shows a screenshot of the trading screen used in the experiment. In the following explanation, references to numbered boxes indicate the area of the screen associated with the corresponding action or information.

Traders are free to choose any trading strategy, i.e. they are free to submit buy and sell offers (referred to as limit orders, Box 1) or accept outstanding

[3]The calculation task was created to keep all subjects busy in each period.
[4]Taler and asset holdings are reset at the beginning of each period.
[5]We conducted two trial periods to allow subjects to become familiar with the trading procedure.

offers placed by other traders (referred to as market orders, Box 2). There are no restrictions to the size of limit orders and the partial execution of limit orders is possible. Order books are empty at the beginning of trading and limit orders are executed according to price and then time priority. Posted limit orders can be canceled at any time without costs (Box 3). Shorting stocks and borrowing money is not allowed.[6] No interest is paid on Taler holdings and there are no transaction costs. The trading protocol and the experimental implementation guarantee traders' anonymity. Each period lasts 240 seconds.[7]

The left hand side of the trading screen (Box 4) provides traders with current information on their asset and Taler holdings and their current wealth (assets evaluated at the *most recent* transaction price). In a separate box the trader's information (BBV if an insider and/or information on the presence of insiders) is displayed. All transaction prices with the corresponding trading time are shown in a real time chart.

2.1.1 Treatments

Markets differ in two treatment variables. First, to study competition effects, we vary the number of insiders. Each market is populated by either 0, 1, 2 or 4 insiders (traders who learn the BBV of the asset before trading starts) and six uninformed traders who do not learn the BBV. Thus six to ten traders constitute a market. Second, we vary the subset of traders who receives information about the number of insiders present. This is done to study situations where the traders' information about the structure of the economy is incomplete. Three information sets exist. Either none of the traders (information set A), only insiders (information set B), or all traders (information set C) learn the number of insiders present in the market. The experiment has a 4x3 design and combining both variables in all reasonable ways, yields eleven treatments. Columns 2-4 in Table 1 provide details on the composition of the trader population and the information sets across treatments. We use the following notation to discriminate treatments: Treatments are labelled $\mathrm{T}^{\mathrm{X}}_{\mathrm{Y}}$ with the superscript X depicting the number of insiders (0, 1, 2, 4) and the subscript Y depicting information set (A, B, C). E.g. $\mathrm{T}^{2}_{\mathrm{A}}$ subsumes markets with two insiders and information set A (no trader is informed about the number of insiders present); $\mathrm{T}^{4}_{\mathrm{ABC}}$ subsume markets with four insiders irrespective of information set.

[6]See Section 3.1 for a detailed discussion on the implications of these restrictions.

[7]In general, the length of a trading period varies considerably between different market experiments. E.g. Friedman et al. (1984) have 300 sec. of double-oral auction, Barner et al. (2005) have 300 sec. trading time, whereas Palfrey and Wang (2012) only have 50 sec. of trading, and Kirchler et al. (2012) have 150 sec. With a trading time of 240 seconds we choose a value on the upper end of the scale to allow price convergence to be completed before trading time expires. See Section 3.1 for a discussion.

The experiment is designed to be best suited for addressing our research questions. This requirement made it impossible to build on existing designs without implementing substantial changes. Schnitzlein (2002) implements a market maker structure with computerized traders, whereas we are interested in LOMs with human traders. The design in Bloomfield et al. (2005) is similar to the one implemented here but the use of trading requirements for uninformed traders impedes adaptation to our RQs. Traders in Plott and Sunder (1982) feature different incentives and the possible state of nature was restricted to 2 or 3 states. Friedman et al. (1984) and Barner et al. (2005) study markets that span over several periods with asset values changing in each period.

Two design choices necessitate a more detailed discussion. Obviously, each manipulation of the number of insiders leads to simultaneous changes in two parameters: the number of insiders (our variable of interest) changes, but as we keep the number of uniformed traders constant the total number of traders, i.e. the market size, changes too. Strictly speaking, we violate the ceteris paribus condition and a joint hypothesis problem emerges. The issue might be solved by adding additional sessions featuring markets with a constant number of insiders and variations in the number of uninformed traders.

However, we do not expect these variations to impact our results as the number of uninformed traders is already large and variations imply only minor changes.[8] Thus, we abstain from conducting additional sessions.

A closely related issue concerns the number of outstanding assets and cash holdings. As each trader is endowed with assets and cash, the total number of shares and the cash holdings vary with the number of traders. Note, however, that the relation between cash and asset value (C/A-ratio) is unaffected by the number of traders, though it takes different values depending on the realization of the BBV. Consider the following three (extreme) examples. (i) BBV = 20. In this case the C/A-ratio equals 4 (4800/(20*60)). (ii) If BBV = 50 the C/A-ratio equals 1.6 (4800/(50*60)). (iii) If the BBV equals the highest possible realization (80), the C/A-ratio equals 1 (4800/(80*60)). Note that the parametrization ensures that there is enough cash in the market to allow all outstanding shares to be transacted at their BBV. With C/A-ratios between 1 and 4, the variation across markets is comparatively small and thus of minor importance. We do not expect a significant impact on our results.[9]

[8] Plott and Sunder (1982), Smith (1982), and Friedman et al. (1984) highlight the low number of traders needed in LOMs to achieve efficient outcomes. Huck et al. (2004) derive similar conclusions from varying the competitiveness in experimental Cournot markets.

[9] See Kirchler et al. (2012) for a discussion.

2.1.2 Traders' earnings

Each trader's final wealth is the sum of her asset holdings evaluated at the BBV plus her Taler holdings at the end of the market. The difference between the trader's final wealth and the average wealth in the market (sum of all traders' wealth divided by the number of traders) determines the payout in Euro. The exchange rate is 300 Taler = 1 Euro. If the trader's final wealth exceeds (falls short of) the average wealth, the trader's period earnings are positive (negative).[10]

2.2 The calculation task - being a bookkeeper

Each period those subjects who do not participate in the market experiment (ten minus the number of traders) participate in a calculation task and are called bookkeepers. They are asked to solve as many multiplications of a two digit number by a one digit number as possible within 240 sec. Bookkeepers earn five Eurocent for each correctly solved calculation.[11]

2.3 Implementation of the experiment

Within a session (16 periods) each treatment specification was implemented at least once. The remaining five periods were used for replications of treatments. The sequence of treatments within a session did not follow any particular rule.[12] We conducted 12 sessions yielding 15 observations from treatments with no insiders ($\mathrm{T}^0_{\mathrm{AC}}$) and 18 observations from each of the remaining treatments ($\mathrm{T}^1_{\mathrm{ABC}}$, $\mathrm{T}^2_{\mathrm{ABC}}$, $\mathrm{T}^4_{\mathrm{ABC}}$). In total we have 192 observations. Sessions were conducted in June 2011 at the University of Innsbruck with a total of 120 students (bachelor and master students from different fields). Most subjects already took part in other experiments in economics but each subject participated in only one session of this study. The software was programmed with z-Tree 3.3.6. by Fischbacher (2007) and subjects were recruited using ORSEE by Greiner (2004).

At the beginning of each session subjects had 15 minutes to study the written instructions on their own. This was done to eliminate any possible experimenter bias. Afterwards, the trading mechanism and screen were explained in detail, followed by two trial markets to allow subjects to become familiar with the trading procedure. All subjects received identical instructions and the same

[10] An inactive trader's final wealth equals the average wealth in the market. Thus, earnings for inactive traders are by definition 0. This is public knowledge (see the Instructions in Appendix B for details).

[11] The average number of solved calculations was 28 and the maximum number was 60.

[12] We generated four treatment sequences and each of these sequences was used in three sessions. See Appendix A for a summary of sequences A to D.

amount of training.[13]

At the beginning of a period subjects were informed about whether they participate in the market experiment or in the calculation task. If a trader was an insider in that period, he learned the BBV before trading started. At the same time, traders received information as defined by information sets A, B, and C.

Within a session, each subject participated in the market experiment in 12 or 13 periods (being an insider in three or four periods and an uninformed trader in nine or ten periods) and in the calculation task in three or four periods. Each session lasted approximately 1 hour 45 min. Average earnings in the experiment were 24.61 Euro, which consisted of the initial endowment (EUR 20) plus/minus earnings/losses from the market experiment (on average ± 0 with a s.d. of 5.74) and the calculation task (+4.61 with a s.d. of 1.78).

3 Results

3.1 Price efficiency

To quantify the degree of convergence between prices and the asset's buy-back value (BBV) we calculate AD, which is the absolute deviation between the (volume weighted) mean price ($\overline{P}$) and the BBV in a market. Lower values of AD indicate smaller deviations and thus a higher level of price efficiency.

$$AD = \left|\overline{P} - \mathrm{BBV}\right| \qquad (1)$$

The specific parameters of the experiment allow to calculate a benchmark level of AD, given that the asset is traded at random prices within the range of possible BBV realizations ($U(20, 80)$). The threshold level for AD depends on the number of transactions. In the limit, as the number of transactions converges to infinity, AD is uniformly distributed around a value of 15.[14] We refer to this benchmark as the "random trading benchmark" (RTB) and use it to distinguish price efficiency levels driven by random trading activity from levels where prices reliably reflect insider information. Average values of AD by treatment are plotted in Figure 2. Numbers on top of the bars are p-values derived from testing AD against the RTB using t-tests.

The figure reveals a strong relationship between the number of insiders and price efficiency with values of AD ranging between 24.13 (T^0_A) and 3.46 (T^4_C).

[13] In the trial periods all subjects took part in the market experiment once being an insider and once being an uninformed trader. This was done in order to familiarize subjects with the payment structure.

[14] For a single, randomly priced transaction AD is a random number drawn from a triangular distribution with mean=20.

It is no surprise that the highest value of AD is realized in markets without insider participation and no information on their absence. With increasing insider participation the level of mispricing decreases. However, values of AD in markets with a monopoly insider still lack statistically significant difference from the RTB. Only with competing insiders in treatments $\mathrm{T}^2_{\mathrm{ABC}}$ and $\mathrm{T}^4_{\mathrm{ABC}}$ prices are significantly more efficient than the RTB. The lowest values of AD are collectively found in $\mathrm{T}^4_{\mathrm{ABC}}$ where prices are a mere 4.07 ($\mathrm{T}^4_{\mathrm{A}}$), 4.20 ($\mathrm{T}^4_{\mathrm{B}}$), and 3.46 ($\mathrm{T}^4_{\mathrm{C}}$) Taler off the BBV, on average. Figure 2 reveals little difference in price efficiency between treatments with the same number of insiders. This observation points at a marginal influence of information sets on price efficiency.

To elaborate on RQ 1 and RQ 2, we estimate the following fixed effects regression using AD as dependent variable. Session, indexed s, is the panel variable taking values from 1 to 12 and market, indexed m, define the time dimension taking values from 1 to 16. The total number of observations is 192.

$$\begin{aligned} AD_{s,m} \quad = \quad & \alpha + IN_1 + IN_2 + IN_4 + IS_B + IS_C + \\ & DISTANCE + INACT_{in} + INACT_{uninf} + \epsilon_{s,m} \end{aligned} \qquad (2)$$

The following variables constitute the set of regressors: $IN_{1,2,4}$ are dummies specifying markets populated by 1, 2 or 4 insiders, respectively. $IS_{B,C}$ are dummies specifying markets with information set B or C, respectively. $DISTANCE$ is the absolute difference between the BBV realization and its expected value of 50. Larger values of $DISTANCE$ indicate more extreme BBV realizations in the sense that they are closer to the boundaries of the BBV's distribution (20 or 80). The extremeness of a realization may impede price efficiency as the mean of the distribution may serve as a natural focal point for traders. Traders who refrain from trading in order to avoid losses reduce the available liquidity in the market making full price discovery more difficult. To control for effects that originate from non-active traders we include two controls indicating the number of inactive insiders ($INACT_{in}$) and inactive uninformed traders ($INACT_{uninf}$).[15] Standard errors are adjusted for clusters in sessions, i.e. they allow for intra-session correlation as the observations are independent across sessions (clusters) but not necessarily within sessions (see Petersen, 2009, for a comparison of different standard error correction procedures in panel data sets). Results are given in Table 2 (column 2, labeled AD). We formulate Result 1 on the effects of competition among insiders on price efficiency in limit order markets (RQ 1).

Result 1. *Competition between insiders has a significantly positive effect*

[15]An inactive trader neither posts limit orders nor engages in trading activity via market orders.

on price efficiency.

The coefficient values for IN_1, IN_2, and IN_4 are negative and decreasing with competition level providing evidence that a higher number of insiders leads to higher levels of price efficiency. Values of AD in monopoly insider treatments are significantly higher compared to treatments with two (Wald test, $F(1,172)=8.12$, p-value=0.0049) or four insiders (Wald test, $F(1,172)=29.93$, p-value=0.0000). Efficiency is highest in markets with four insiders with significantly lower values of AD compared to $\mathrm{T}^1_{\mathrm{ABC}}$ and $\mathrm{T}^2_{\mathrm{ABC}}$ (Wald test, $F(1,172)=7.79$, p-value=0.0058). These results support evidence in Huber et al. (2011) and Bossaerts et al. (2013) on the positive marginal effect of additional insiders on price efficiency.

The distinct effects of competition on AD may provoke reasonable suspicion that the price discovery process is incomplete due to constraints in trading time. To challenge this argument we analyze market conditions in the last 30 sec. of a market to see whether there is still information being incorporated into prices. Therefore, we calculate the difference between AD of the first and AD of the last price that occurred during that interval. Although transactions take place in each of the 192 markets, trading activity is depressed toward the end of a period. Within the last 30 sec. we do not record a single transaction in 40 markets and only one transaction in 51 markets. The differences in AD of the remaining 101 markets almost splits equally with 59 (42) markets exhibiting an increase (decrease) in market efficiency. Split by competition level, we find that differences in AD are not significantly different from zero for three out of four tests.[16] We thus reject the argument that the price discovery process was not jet completed by the last 30 sec. and conclude that trading time constraints do not compromise the reported results.

A further design feature needs closer elaboration. We do not allow negative cash and stock holding, i.e. traders are not allowed to borrow additional cash or sell stocks short. Thus, insiders might be cash or asset constrained, making it impossible to further participate in the price discovery process. To tackle this point, we include additional variables in the regression measuring the share of insiders being constrained from active market participation ($BOUND$). We define an insider to be trading constrained if her end-of-period stock/money holdings are lower than 10% of initial endowments, i.e. stock holdings ≤ 6 and Taler holdings ≤ 480. We then rerun the regression specified in Equation 2 including three additional variables, where $BOUND$ is interacted with the IN_i dummies ($BOUND * IN_i$). Results are in Table 2 (column 3, labeled AD 2). Coefficient values for $BOUND * IN_i$ are positive suggesting a negative

[16] Results from the t-tests for $\mathrm{T}^0_{\mathrm{AC}}$: mean=-0.22, p=0.2067, N=19; $\mathrm{T}^1_{\mathrm{ABC}}$: mean=-0.65, p=0.2556, N=42; $\mathrm{T}^2_{\mathrm{ABC}}$: mean=-0.96, p=0.0204, N=45; $\mathrm{T}^4_{\mathrm{ABC}}$: mean=-.46, p=0.1516, N=46.

effect of the share of constrained insiders on price efficiency. However, none of the coefficients is statistically significant while significance on other coefficients does not change. Thus, prohibiting short sales and additional borrowing does not influence the reported results.

We now evaluate RQ 2 on the effects of manipulations in the subset of traders who receives information on the number of insiders present.

Result 2. *Manipulations in the subset of traders who receives information do not significantly impact price efficiency.*

Coefficient values for IS_B and IS_C, the dummies for information sets B and C in regression AD, indicates a positive effect on price efficiency, however they lack statistical significance.[17] The results support Camerer and Weigelt (1991), Meulbroek (1992), Nöth and Weber (1996) and Bruguier et al. (2010) who argue that traders are able to infer the presence of insiders from the trading process.

Unfortunately, we cannot directly evaluate this finding as we did not ask traders to estimate the number of insiders present after trading ended. However, Bruguier et al. (2010) suggest a method to provide indirect evidence on the argument. They observe that the only significant discrimination of markets populated by different numbers of insider is the persistence in the size of transaction price changes in calendar time measured in a variable called "GARCH intensity" ($GARCH^{int}$). We follow Bruguier et al. (2010) and calculate $GARCH^{int}$ for each market to test whether their conjecture also holds in our experimental setting. For the computation of GARCH intensity we first calculate the absolute transaction price changes over intervals of 2 seconds and then determine the first five autocorrelation coefficients of these transaction price changes. GARCH intensity in a market is the sum of the absolute values of the autocorrelation coefficients for lags 1 to 5.[18]

We rerun the regression outlined in equation 2 using $GARCH^{int}$ as the dependent variable. Results are given in Table 2 (column 4, labeled $GARCH^{int}$). We see that $GARCH^{int}$ increases monotonically with the number of insiders. The coefficient of IN_4 is significantly different from zero and also significantly larger than IN_1 (Wald test, F(1,172)=8.82, p-value 0.0034) but only marginally larger than IN_2 (Wald test, F(1,172)=3.47, p-value 0.0644). These results support the argument that uninformed traders are able to infer the presence of insiders from the trading process. However, they contradict results in Schnitzlein (2002) who reports lower price efficiency in treatments where the number of

[17] As robustness check we conduct Kruskal-Wallis rank tests, in which we compare treatment values of AD within each competition level. Again, we find no significant effect of information on the number of insiders. T^0_{AC}: N=30, χ^2=1.817, p-value=0.1776; T^1_{ABC}: N=54, χ^2=0.033, p-value=0.9838; T^2_{ABC}: N=54, χ^2=0.147, p-value=0.9292; T^4_{ABC}: N=54, χ^2=0.124, p-value=0.9397.

[18] For further details on GARCH intensity see Bruguier et al. (2010), p. 1718-1719.

insiders must be inferred. An explanation for the negative effect can be found in his experimental setup, where *computerized* noise traders provide liquidity to the market. These traders lack the capabilities of human traders to detect insider trading, which deteriorates the price discovery process.

So far we focused on average price efficiency in markets. The end of the section is devoted to analyzing the development of price efficiency over time. Therefore we divide each market into eight intervals of 30 sec. each and compute AD for each interval.[19] Average values of AD per competition level and interval are presented in Figure 3.[20] In the first interval markets in $\mathrm{T}^0_{\mathrm{AC}}$ (21.20) and $\mathrm{T}^1_{\mathrm{ABC}}$ (21.97) exhibit values of AD well above 20, while markets in $\mathrm{T}^2_{\mathrm{ABC}}$ (12.66) and $\mathrm{T}^4_{\mathrm{ABC}}$ (8.57) exhibit values of AD below 15. Only in $\mathrm{T}^4_{\mathrm{ABC}}$ are prices significantly more efficient than the random trading benchmark (T-test, N=42, t=-5.3412, p-value=0.0000). In general, the presence of insiders leads to increases in price efficiency over time and by the end of the market prices are significantly more efficient than the RTB.[21]

Figure 3 suggests that price efficiency evolves gradually over time irrespective of competition level. To evaluate these graphical results statistically we test three different regression models explaining the time development of AD against each other.

$$AD = \alpha + \beta_1 INTER + \epsilon \quad (3)$$
$$AD = \alpha + \beta_1 INTER + \beta_2 INTER^2 + \epsilon \quad (4)$$
$$AD = \alpha * \beta_1^{INTER} + \epsilon \quad (5)$$

Model 1 (equation 3) uses interval ($INTER$), ranging from 1 to 8, as regressor and assumes a linear development of AD over time. Model 2 (equation 4) and Model 3 (equation 5) are inspired by results of Holden and Subrahmanyam (1992) who predict that prices adjust more rapidly the more insiders are present suggesting a non-linear development of AD over time. In Model 2 this fact is reflected by including $INTER^2$ to the specification of Model 1, while in Model 3 we run an exponential regression with one asymptote.[22] In the latter, coefficient values of β_1 close to one are interpreted as a slow decay, while value close to zero indicate a rapid decay. The three regression models, run for each competition

[19] Results remain qualitatively unchanged if the length of the first interval is reduced to 10 seconds.

[20] We pool results by competition level as information sets do not insignificantly impact price efficiency.

[21] T-test, $\mathrm{T}^1_{\mathrm{ABC}}$: AD=11.92, N=43, t=-2.4403, p-value=0.0190; $\mathrm{T}^2_{\mathrm{ABC}}$: AD=6.37, N=46, t=-6.9956, p-value=0.0000; $\mathrm{T}^4_{\mathrm{ABC}}$: AD=1.92, N=47, t=-22.3216, p-value=0.0000.

[22] $INTER$ and $INTER^2$ are selected as regressors based on the results of a variable selection procedure additionally considering $INTER^3$ and $INTER^4$ as regressors. Details on the selection procedure are available from the author upon request.

level separately, are compared by the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The superior specification exhibits lower values in both measures. Standard errors are adjusted for clusters in sessions. Results are given in Table 3.

For T^0_{AC} we find no significant time trend in the development of AD. None of the coefficient values of $INTER$ and $INTER^2$ in Model 1 and 2 is significant and the coefficient of $INTER$ in Model 3 almost equals 1. Results for T^1_{ABC} reveal a significant time trend in the development of AD over time. Comparing models by AIC and BIC we find that Model 2 dominates in AIC while Model 3 dominates in BIC. However, coefficient values of $INTER^2$ in Model 2 and $INTER$ in Model 3 indicate a mild form of non-linearity in the development of AD. Similar results apply to T^2_{ABC} and T^4_{ABC}. While Model 3 dominates the other specifications, the speed of decay in price efficiency can be considered rather low.

Taken together, the evidence collected by the regression analyses support the notion that price efficiency evolves gradually over time.[23] We formulate

Result 3. *Prices reflect the insiders' information gradually over time independent of competition level.*

Result 3 contradicts predictions in Holden and Subrahmanyam (1992), however, they coincide with results in Bossaerts et al. (2013) who find strong evidence in favor of strategic information revelation, i.e., information is revealed slowly to the market.

3.2 Individual trading behavior

In this section we elaborate on RQ 3 about the traders' choice between order types. The analysis is organized along two lines. First, we examine the insiders' share in completed transactions (Section 3.2.1). By distinguish between trades originating from limit orders, referred to as limit trades (LT), and market orders (MO) we draw conclusions about how information finds its way into prices. Second, we analyze how the two trader types (insider/uninformed) solve the trade-off between limit and market orders (Section 3.2.2).

The analyses presented throughout these two sections are based on a novel approach that discriminates between two market situations. The discrimination centers on implications originating from the insiders' informational advantage. Knowing the asset's precise value, insiders are able to assess the profitability of transactions and to avoid unprofitable trades. This ability, however, limits

[23]The result is supported by an alternative approach, namely the Ramsey RESET test, which is a test of neglected nonlinearities in the choice of the functional form. The null posits that there are no neglected nonlinearities, i.e. E(y|X) is linear in the regressors. By running the test separately for each competition level we find that none of the tests is able to reject the null. Details on the tests are available from the author upon request.

the insiders' freedom to choose between limit and market orders. To see this, consider the following two market situations.

In market situation 1 (SIT_1) the asset's BBV lies *within* the bid-ask spread. This situation effectively restricts the insiders' trading options to posting LOs. Buy (sell) transactions based on MOs generate losses as they are executed at prices above (below) the BBV.

In market situation 2 (SIT_2) the asset's BBV lies *outside* the bid-ask spread, i.e. the BBV is either above or below the best bid and the best ask at the same time. In that situation LOs and MOs yield profits and insiders are free to choose. Recall, however, that the common trade-off between the order types in terms of execution risk and price improvement remains.[24] Thus, the prevailing market situation crucially influences the insiders' action space.

To provide an overview about the distribution of trades across situations we compute the percentage of assets transacted under SIT_1. In $\mathrm{T}^0_{\mathrm{AC}}$ only 8.2% of trades are executed under SIT_1, whereas 26.4%, 31.7%, and 44.6% of trades in $\mathrm{T}^1_{\mathrm{ABC}}$, $\mathrm{T}^2_{\mathrm{ABC}}$, and $\mathrm{T}^4_{\mathrm{ABC}}$, respectively, fall in this situation. Markets populated by different numbers of insiders thus differ in the volume executed under SIT_1.

3.2.1 The insiders' share in transactions

By analyzing the insiders' share in LTs and MOs we gain insights into the channels that convey the insiders' information. We define the insiders' market share as the volume in LT (MO) generated by all active insiders divided by the volume of LT (MO) generated by all active traders. The value falls in the interval [0,1] with higher values indicating increasing insider dominance.

In Figure 4 we plot the insiders' average market share in LTs and MOs by market situation (in columns), competition level (in rows), and minute trading time. Additionally, we include information on the insiders' expected market share to ease comparison across markets populated by different numbers of insiders. Assuming that all traders are equally active we expect the insiders' market share to equal the ratio of (active) insiders over all (active) traders.[25] We formulate

Result 4. *Insiders either dominate the trading process by successfully tendering limit orders (situation 1) or by triggering market orders (situation 2). Thus, conditional on the prevailing situation, either limit trades or market orders convey insider information.*

The graphs depicted in the left column of Figure 4 reveal that insiders are

[24] MO execute immediately at worse price conditions, whereas LO face execution risk but offer more favorable prices.

[25] Assuming all traders are active, insiders have an expected market share of 1/7, 1/4, and 2/5 in $\mathrm{T}^1_{\mathrm{ABC}}$, $\mathrm{T}^2_{\mathrm{ABC}}$, and $\mathrm{T}^4_{\mathrm{ABC}}$, respectively.

more (less) active than expected in the domain of LOs (MOs) across all competition levels when SIT_1 prevails. Thus, insiders are liquidity providers in SIT_1. In SIT_2 the picture reverses. Here, the insiders activity in LT is below expectations, whereas the activity in MO is clearly above expectations. Thus, if SIT_2 prevails, insiders act as liquidity consumers and their information is revealed to the market via market orders.

At first sight, these results partly contradict Barner et al. (2005) who postulate that the information dissemination process is initiated by insiders using LO more actively than uninformed traders. However, a closer examination reveals that the discrepancy is likely to be found in the experimental designs. In Barner et al. (2005) the information content that needs to be conveyed to the market is small. From its current level the asset's value either increase or decrease by a fixed amount. Therefore, the necessary information dissemination reduces to an up or down signal. Given this setting it is sensible to assume that Barner et al. (2005) are much more likely to observe markets dominated by SIT_1. In contrast, the traders' task in our experiment is much more complex as the BBV is one realization out of 600 possibilities and uninformed traders learn the precise BBV only after trading ended. In this setting SIT_2 is much more likely to occur. By distinguishing between market situations, we are able to better understand the results of Barner et al. (2005). The design choice of Barner et al. (2005) also accounts for the fact that the insiders' dominance in LO dissipates after the first minute whereas it remains constant in our experiment. The fast return to expected trading activity suggest that the signal transmission is completed by the first minute, wiping out the insiders' informational advantage.

3.2.2 The traders' order choice

The literature provides several theories on the insiders' choice between limit and market orders. By discriminating between SIT_1 and SIT_2 we are able to contribute valuable insights to the debate. We define a subject's trading strategy as the ratio of LTs over the total number of trades (LTs+MOs). Values fall in the the interval [0,1] with values above (below) 0.5 indicating a preference for LT (MO). In Figure 5 we plot the average trading strategy by trader type (in columns), competition level (in rows), and minute trading time. We formulate Result 5.

Result 5. *Insiders strongly prefer market over limit orders in market situations where both types are profitable.*

In the left column of Figure 5 we document marked differences in trading strategies for insiders conditional on market situation. As expected, average values of our trading strategy measure are high in SIT_1, indicating a clear preference for LT.[26] However, these values fall short of 1, the obvious benchmark as only LT are profitable in SIT_1. This discrepancy can be explained in several ways. E.g. insiders might try to manipulate prices in an attempt to generate higher future profit potentials; or traders might be confused being unable to exploit their favorable position.

More interesting, however, is SIT_2 where we observe how insiders' resolve the trade-off between LOs and MOs. Average values of our trading strategy measure are 0.23, 0.28, and 0.31 for T^1_{ABC}, T^2_{ABC}, and T^4_{ABC}, respectively. These values indicate that insiders strongly prefer MOs over LTs indicating that insiders favor immediate execution over more favorable prices. Again, preferences are independent of competition level and constant over time.

These results, based on the discrimination between SIT_1 and SIT_2, support findings in Anand et al. (2005). They show empirically that informed traders act as liquidity takers in the first half of a trading day and become liquidity suppliers in the second half of a day. Assuming that SIT_2 is more likely to occur at the beginning of a trading day and then evolves into SIT_1 our argument supports Anand et al. (2005).

The uninformed traders' strategies (right columns of Figure 5) basically represent the opposite picture. This observation reflects the fact that in most cases trades are between insiders and uninformed traders. Thus, in cases where insiders choose LO the trading partner takes the opposite position and vice versa.

4 Conclusion

We conducted experiments to study price efficiency and trading behavior in limit order markets populated by asymmetrically informed traders. Markets differed in the realization of two treatment variables. First, we varied the number of insiders to analyze competition effects. Each market was populated by either 0, 1, 2 or 4 insiders and 6 uninformed traders who did not learn the BBV. Second, markets were characterized by one of three information sets that defined the subset of traders who received information about the number of insiders present. Either none of the traders, only insiders, or all traders learned the number of insiders present in the market. With this manipulation we elaborated on the specific uncertainty about the presence of insiders that prevails in real world markets. The effects of this uncertainty could not be addressed in theoretical models.

We found that the degree of competition among insiders impacted limit order markets in a various ways and it influenced price efficiency and trading strate-

[26] Average values of our trading strategy measure are 0.91, 0.77, and 0.74 for T^1_{ABC}, T^2_{ABC}, and T^4_{ABC}, respectively.

gies available to insiders. Specifically, we documented that price efficiency (i) was the higher the higher the number of insiders supporting existing evidence in the literature. However, (ii) manipulations in the subset of traders who knew about the number of insiders present did not affect price efficiency. This result is in line with results reported in Camerer and Weigelt (1991), Meulbroek (1992), Nöth and Weber (1996), and Bruguier et al. (2010), indicating traders' ability to detect insider presence from market activity. Studying price efficiency over time revealed that (iii) prices reflected the insiders' information gradually. This result contradicts predictions from game theoretic models (Holden and Subrahmanyam, 1992) that suggest instantaneous reflection if two or more insiders compete for information rents.

To analyze trading behavior in the markets we developed a novel approach and defined two market situations based on the insiders' ability to assess the profitability of transactions. Market situation 1 prevailed if the asset's value lied *within* the bid-ask spread and it effectively restricted the insiders' trading options to limit orders. Market situation 2 described a situation in which the asset's value lied *outside* the bid-ask spread. In that situation limit and market orders yielded profits and insiders were free to choose. We found that (iv) the insiders' information was reflected in prices via limit (market) orders if the asset's value was inside (outside) the bid-ask spread. Thus, conditional on market situation either limit or market orders conveyed the insiders' information. (v) In situations where limit and market orders yielded positive profits, insiders clearly preferred market orders, indicating a strong desire for immediate transactions.

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Tables

Table 1: Treatment description.

Treatment	Info set	# insider (# inactive)	# uninf. (# inactive)
T^0_A	A	0 (–)	6 (1.00)
T^0_C	C	0 (–)	6 (0.60)
T^1_A	A	1 (0.00)	6 (1.22)
T^1_B	B	1 (0.00)	6 (0.83)
T^1_C	C	1 (0.00)	6 (1.22)
T^2_A	A	2 (0.06)	6 (1.22)
T^2_B	B	2 (0.00)	6 (1.72)
T^2_C	C	2 (0.06)	6 (1.06)
T^4_A	A	4 (0.22)	6 (1.83)
T^4_B	B	4 (0.11)	6 (1.50)
T^4_C	C	4 (0.17)	6 (1.56)

Notes: Treatments are labelled T^X_Y with the superscript X specifying the number of insiders [0,1,2,4] and the subscript Y specifying information set [A: no trader receives information about insiders present; B: only insider(s) know the number of insiders present; C: all traders know the number of insiders present]. Column 3 (4) shows the number of insiders (uninformed traders). Values in parenthesis (# inactive) specify the average number of inactive insider (uninformed traders) in a market, i.e., traders that neither post limit orders nor trade via market orders.

Table 2: Fixed effects panel regression estimating the effects of competition level and information sets on price efficiency and GARCH intensity.

	AD	AD 2	GARCH^{int}
α	14.865***	14.872***	0.289***
	(3.310)	(3.300)	(0.054)
IN_1	−7.517**	−7.603**	0.044
	(2.626)	(2.722)	(0.054)
IN_2	−11.846***	−12.250***	0.090
	(3.136)	(3.209)	(0.057)
IN_4	−16.172***	−17.042***	0.164**
	(2.222)	(2.079)	(0.063)
IS_B	−0.705	−0.623	−0.060
	(1.727)	(1.767)	(0.038)
IS_C	−1.754	−1.614	−0.023
	(1.130)	(1.076)	(0.039)
DISTANCE	0.448***	0.440***	0.001
	(0.092)	(0.086)	(0.001)
INACT_{in}	3.686	3.616*	−0.064
	(2.068)	(1.977)	(0.067)
INACT_{unin}	−0.695	−0.602	−0.029
	(0.511)	(0.497)	(0.019)
BOUND*IN_1		0.098	
		(3.010)	
BOUND*IN_2		5.554	
		(6.723)	
BOUND*IN_4		12.061	
		(6.736)	
N	192	192	192
R^2	0.46	0.47	0.08
F	94.74	3645.18	23.11
p	0.000	0.000	0.000

Notes: DEPENDENT VARIABLES: AD is the absolute difference between the (volume weighted) mean price in a market and the BBV. $GARCH^{int}$ is the GARCH intensity as outlined in Section 3.1 and in Bruguier et al. (2010). INDEPENDENT VARIABLES: $\text{IN}_{1,2,4}$ are dummies equaling 1 for markets populated by 1, 2 or 4 insiders, respectively, zero otherwise. $\text{IS}_{B,C}$ are dummies equaling 1 for markets with information set B or C, respectively, zero otherwise. $DISTANCE$ is the absolute difference between the expected value of BBV and its realization. $\text{INACT}_{in,uninf}$ is the number of inactive informed (uninformed) traders. $BOUND$ is the share of constrained insiders at the end of a market (stock holdings $\leq$6 and Taler holdings $\leq$480). Standard error (adjusted for clusters in sessions) are provided in parenthesis. *, ** and *** denote the 10%, 5% and the 1% significance levels.

Table 3: Regression analyses explaining the development of price efficiency (AD) over time.

	T^0_{AC}			T^1_{ABC}		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α	21.520***	22.763***	21.519***	19.558***	24.097***	20.906***
	(3.041)	(3.333)	(3.037)	(1.424)	(1.919)	(1.404)
INTER	0.018	−0.705	1.001***	−1.137***	−3.606**	0.918***
	(0.481)	(0.819)	(0.022)	(0.131)	(1.168)	(0.008)
INTER^2		0.080			0.264*	
		(0.075)			(0.127)	
N	170	170	170	308	308	308
AIC	1346.31	1348.18	1346.31	2274.09	2271.57	2272.56
BIC	1352.59	1357.59	1352.59	2281.55	2282.76	2280.02

	T^2_{ABC}			T^4_{ABC}		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
α	12.036***	12.937***	12.589***	8.579***	10.501***	10.722***
	(1.831)	(3.039)	(2.026)	(1.379)	(2.316)	(2.330)
INTER	−0.683***	−1.182	0.924***	−0.917***	−2.046**	0.800***
	(0.171)	(1.126)	(0.019)	(0.226)	(0.861)	(0.050)
INTER^2		0.054			0.124	
		(0.110)			(0.072)	
N	344	344	344	366	366	366
AIC	2506.74	2508.51	2506.55	2570.00	2570.19	2568.21
BIC	2514.42	2520.04	2514.23	2577.81	2581.90	2576.02

Notes: DEPENDENT VARIABLE: AD is the absolute difference between the (volume weighted) mean price and the BBV calculated for intervals of 30 sec. each. INDEPENDENT VARIABLES: INTER takes values from 1 to 8 conditional on time interval. INTER^2 is INTER to the power of 2. MODEL COMPARISON: AIC is the model's Akaike information criterion (lower values preferred). BIC is the model's Bayesian information criterion (lower values preferred). Standard error (adjusted for clusters in sessions) are provided in parenthesis. *, ** and *** denote the 10%, 5% and the 1% significance levels.

Figures

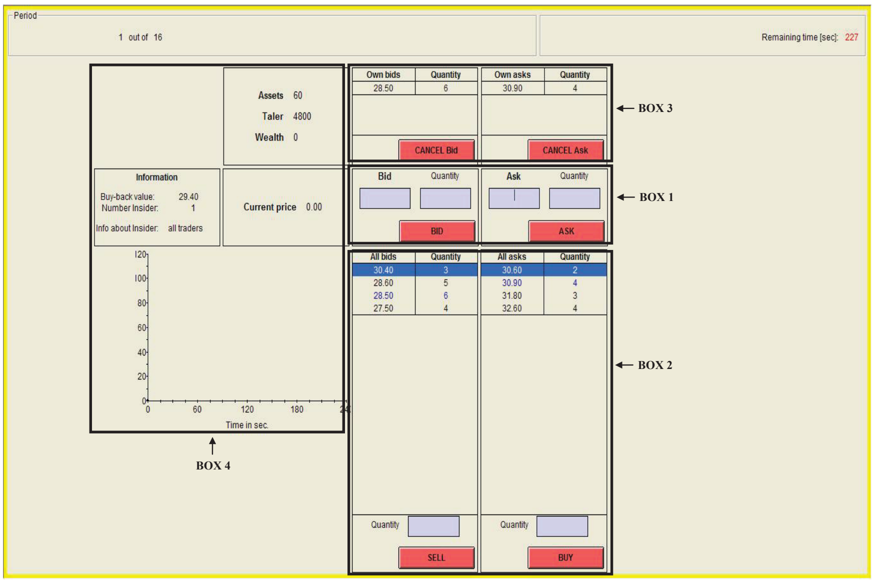


Figure 1: Trading screen.

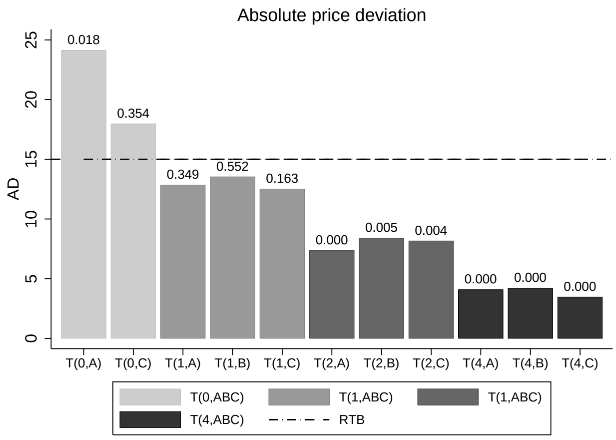


Figure 2: Average values of absolute price deviation (AD) across treatments and the random trading benchmark (RTB = 15). AD is the absolute difference between the (volume weighted) mean price in a market and the BBV. Treatments are labelled $\mathrm{T}_{\mathrm{Y}}^{\mathrm{X}}$ with the superscript X specifying the number of insiders [0,1,2,4] and the subscript Y specifying information set [A: no trader receives information about insiders present; B: only insider(s) know the number of insiders present; C: all traders know the number of insiders present]. Numbers above bars are p-values from t-tests of AD against the random trading trading benchmark (15).

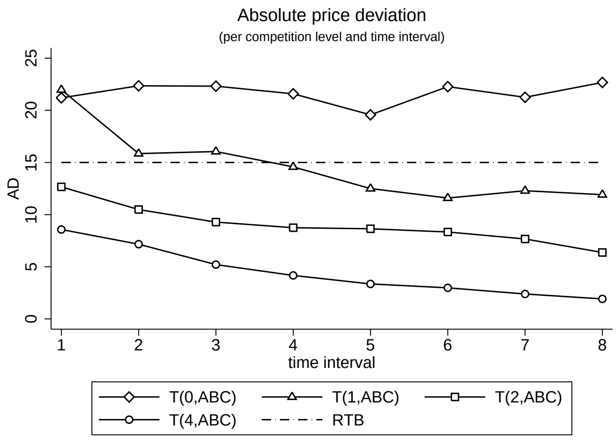


Figure 3: Development of absolute price deviation (AD; (volume weighted) mean price minus BBV) per time interval and competition level. A period of 240 sec. length is divided into eight intervals of 30 sec. length each. RTB is the random trading benchmark (15).

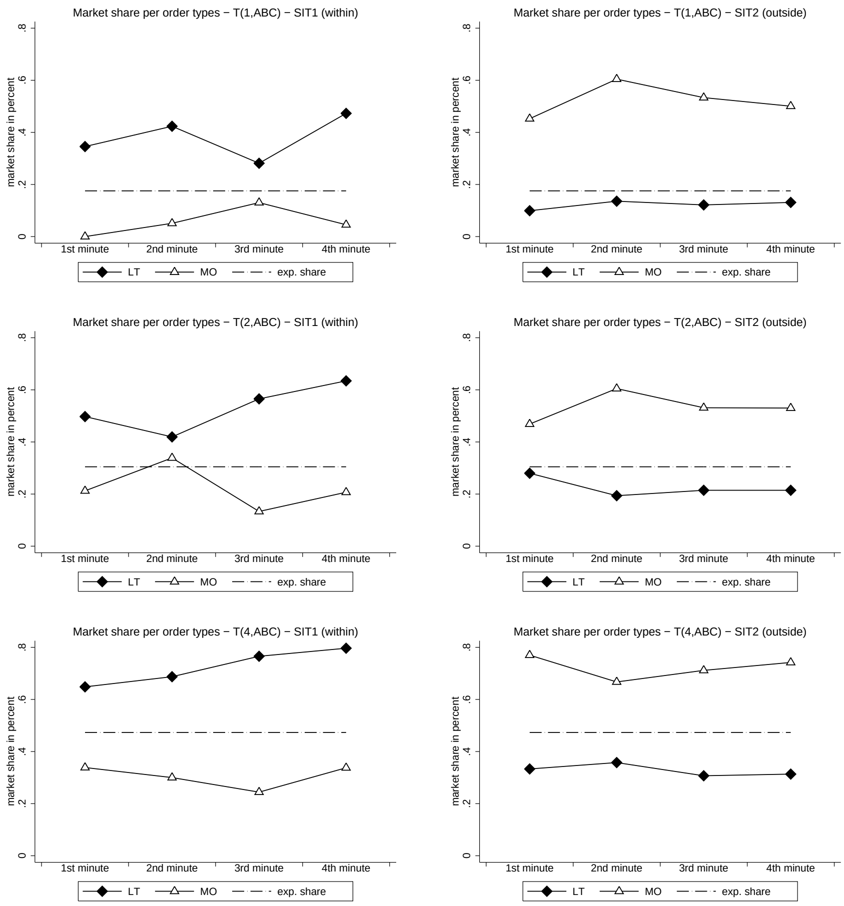


Figure 4: The insiders' market share in limit trades (LT, solid line with diamonds) and market orders (MO, solid line with triangles) by competition level (in rows) and market situation (columns) over time (1 minute trading intervals). Market share is defined as the volume of LT or MO by all insiders over the volume of LT and MO by all traders. The dashed line represents the insiders' expected market share based on the assumption that all traders are equally active, i.e. the ratio of active insiders over all active traders. In market situation 1 (SIT_1, left column) the asset's BBV lies *within* the bid-ask spread. In market situation 2 (SIT_2, right column) the asset's BBV lies *outside* the bid-ask spread. Market share is calculated on the market level; data points are averages of individual market values.

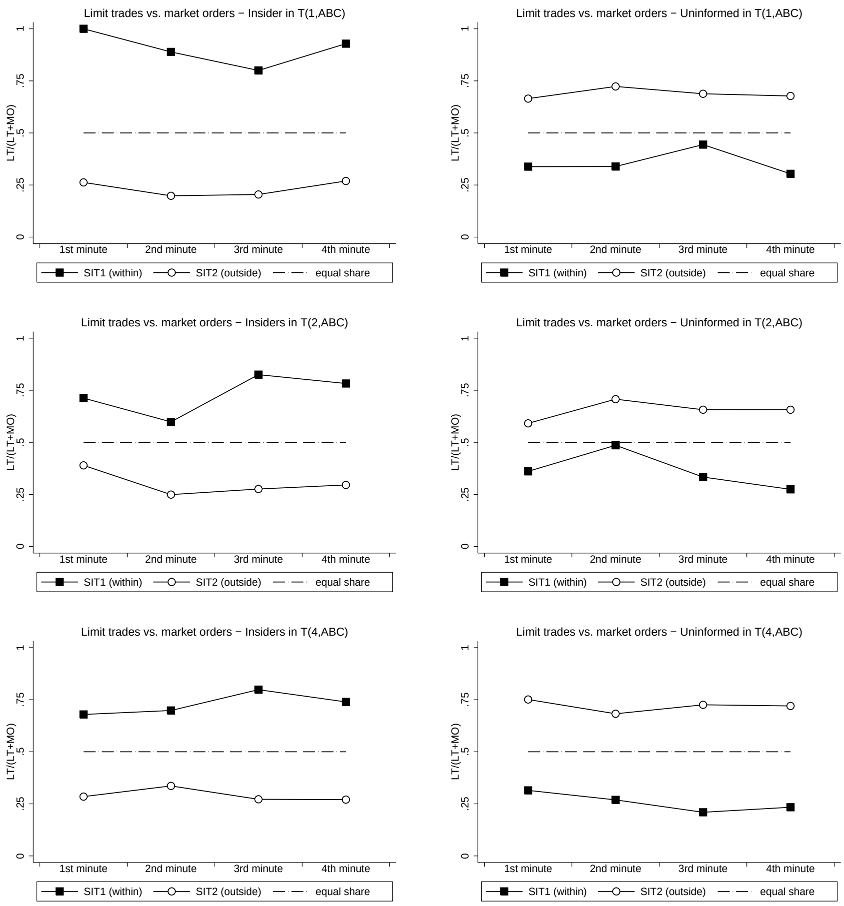


Figure 5: Ratio of limit trades (LT) over all trades, i.e. LT plus market orders (MO) per competition level (in rows) and trader role (insider/uninformed, in columns) over time (1 minute trading intervals). The ratio is calculated separately for market situation 1 (Solid lines with squares; in SIT_1 the asset's BBV lies *within* the bid-ask spread) and market situation 2 (Solid line with circles; in SIT_2 the asset's BBV lies *outside* the bid-ask spread). The dotted line presents the equal split between LT and MO, i.e. a ratio of 0.5. The ratio is calculated on the market level; data points are averages of individual market values.

Appendix

Appendix A: Information on the sequence of treatments

Table A1: Information on the treatment order for sequences A to D.

	Sequence A			Sequence B		
Period	treatment	# insider	info set	treatment	# insider	info set
1	T_A^1	1	A	T_B^2	2	B
2	T_B^1	1	B	T_C^0	0	C
3	T_C^0	0	C	T_A^0	0	A
4	T_A^1	1	A	T_C^1	1	C
5	T_B^1	1	B	T_A^4	4	A
6	T_C^1	1	C	T_A^1	1	A
7	T_C^2	2	C	T_C^1	1	C
8	T_A^0	0	A	T_C^4	4	C
9	T_C^4	4	C	T_A^4	4	A
10	T_A^4	4	A	T_A^2	2	A
11	T_B^2	2	B	T_B^4	4	B
12	T_A^2	2	A	T_C^2	2	C
13	T_C^4	4	C	T_B^2	2	B
14	T_B^4	4	B	T_A^4	4	A
15	T_A^2	2	A	T_B^1	1	B
16	T_C^2	2	C	T_B^2	2	B
	Sequence C			Sequence D		
Period	treatment	# insider	info set	treatment	# insider	info set
1	T_C^0	0	C	T_A^0	0	A
2	T_B^1	1	B	T_A^2	2	A
3	T_C^1	1	C	T_C^2	2	C
4	T_A^0	0	A	T_B^1	1	B
5	T_B^2	2	B	T_B^4	4	B
6	T_C^2	2	C	T_C^2	2	C
7	T_C^4	4	C	T_A^1	1	A
8	T_B^1	1	B	T_A^4	4	A
9	T_B^4	4	B	T_C^4	4	C
10	T_C^4	4	C	T_A^1	1	A
11	T_A^1	1	A	T_A^2	2	A
12	T_A^0	0	A	T_C^0	0	C
13	T_A^2	2	A	T_B^4	4	B
14	T_B^4	4	B	T_C^1	1	C
15	T_C^0	0	C	T_B^2	2	B
16	T_A^4	4	A	T_C^1	1	C

Appendix B: Experimental Instructions

Dear Participant!

We welcome you to this experimental session and kindly ask you to refrain from talking to each other for the duration of the experiment. If you have any questions regarding the procedure or the instructions of the experiments, contact one of the supervisors by raising your hand and your question will be answered privately.

Course of events during the session
This session consists of two experiments in which you can independently earn money. Before the experiment starts separate instructions will be handed out providing detailed information on the rules in the experiment.

Experiment 1 - Market experiment

- Instructions market experiment
- Explanation of the trading mechanism and trial periods (not relevant for your earnings)
- Experiment

Experiment 2[27]

- Instructions and experiment
- Questionnaire

Private payout

[27] Data from the second experiments are not used in the analysis. Instructions are available upon request.

Experiment 1 - Market experiment

General Information

This experiment replicates an asset market, which is populated by you and 9 other subjects. The composition of this cohort remains constant throughout the experiment, which consists of 16 independent periods.

Your payment from the experiment

You receive an amount of 20,- Euro for participating in the experiment. Profit and losses resulting from your activities during the 16 periods will be added to/subtratcted from the participation payment. Please note that your earning made in a specific period may be positive or negative (see below for details). Your payment from the experiment equals the participation payment plus the sum of your period earnings.

$$\text{Your payment} = 20 + \text{Sum of period earnings}$$

Your task within a period

At the beginning of each period you will learn your task within that period. You could either become a trader or a bookkeeper.

> **Trader:** As trader you are an active market participant and you can buy/sell assets (of a virtual company). In each period at least 6 but at most 10 subjects of your cohort are traders.
> **Bookkeeper:** You do not participate in the market. In each period at least 0 but at most 4 subjects of your cohort are bookkeepers.

In the following we inform you about the task of a trader and the task of a bookkeeper.

Trader

As a trader you are a market participant and you can buy and sell assets. The trading mechanism is a double auction, i.e., each trader can be a buyer and/or a seller.

At the beginning of each period, each trader receives an initial endowment of 60 assets and 4800 Taler (asset and Taler inventories are NOT transferred from on period to the next). Note that your asset and Taler inventories cannot fall below zero. Each trading period automatically terminates after 4 minutes (240 sec). Prices are solely determined by demand and supply of the traders within the market. If you buy assets, your Taler holdings decrease by the respective expenditures (price * volume). Inversely, if you sell assets, your Taler holding increase by the respective revenues (price * volume).

Buy-back value of the asset

At the end of each period the experimenter buys back the assets you are holding at their buy-back value. This value is determined by a random device at the beginning of the period, which draws a number (with one decimal place) from the interval [20,80]. Each number has the same probability to be drawn.

Information about the Buy-back value of the asset

Depending on the total number of traders, between 0 and 4 traders receive information on the precise buy-back value of the asset at the beginning of the period (these traders are called **insiders**). 6 traders do not receive this information about the buy-back value (these traders are called **uninformed traders**). They only know that the buy-back value is a random number between 20 and 80 with equal probability.

Information about the number of insiders

Additionally to receiving information on the buy-back value you may be informed about the number of insiders present. 3 information sets exist:

1. No trader receives information about the number of insiders. (You know for sure if you are an insider or not).
2. All insiders are informed about the total number of insiders in the market. Uninformed traders do not receive this information.
3. All traders (insiders and uninformed) receive information about the total number of insiders in the market.

Before trading starts you are informed whether you are an insider or an uninformed trader and you receive information corresponding to information set 1-3. This information is accessible on the trading screen as well.

Your period earnings as a trader

Your trading success in relation to the other traders' success determines your earnings. Your wealth at the end of a period is compared to the average wealth of all traders.

$$\text{Your wealth} = \text{Number of assets} * \text{Buy-back value} + \text{Taler holdings}$$

$$\text{Average wealth} = \frac{\text{Sum of all traders' wealth}}{\text{Number of traders}}$$

$$\text{Period earnings in Euro} = (\text{Your wealth} - \text{Average wealth})/300$$

Example 1: At the end of the period you own 65 assets and 4450 Taler. The buy-back value is 38.50. Your wealth equals 65 * 38.50 + 4450 = 6952.50. Average wealth in the market equals 6650. Your period earnings in Euro are (6952.50 - 6650)/300 = 1.01 Euro, which increases your final payment.
Example 2: At the end of the period you own 45 assets and 5450 Taler. The buy-back value is 62.50. Your wealth equals 45 * 62.50 + 5450 = 8271.50. Average wealth in the market equals 8600. Your period earnings in Euro are (8271.50 - 8650)/300 = -1.26 Euro, which reduces your final payment.
Example 3: If you refrain from trading during a period (i.e. you do not buy or sell assets), your wealth equals the average wealth. Thus, your period earnings will be 0.00 and your final payment remains unchanged.

Bookkeeper

As a bookkeeper you earn money by solving exercises. An exercise is a calculation in which you multiply a two digit number by a one digit number. If your calculation is correct, the exercise is solved. If your calculation is wrong an error message appears. You have 4 minutes time to solve as many exercises as possible.

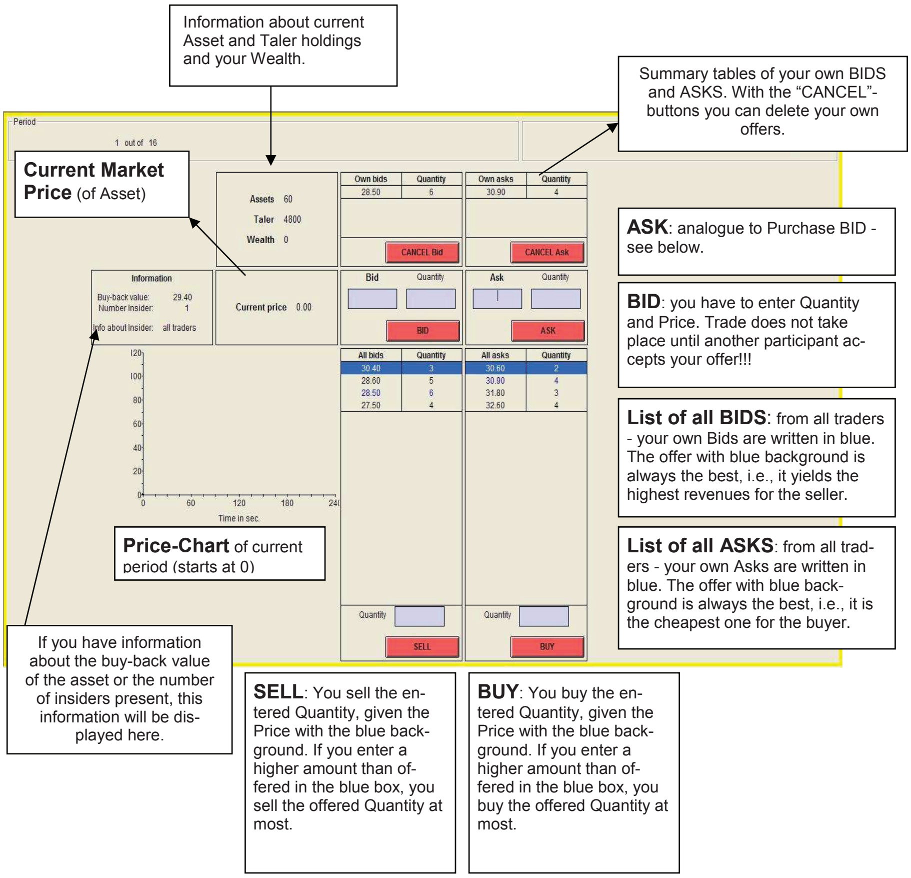
Your period earnings as a bookkeeper
For each correctly solved exercise you earn 0.05 Euro (5 Cent).

$$\text{Period earnings in Euro} = \text{Number of solved exercises} * 0.05$$

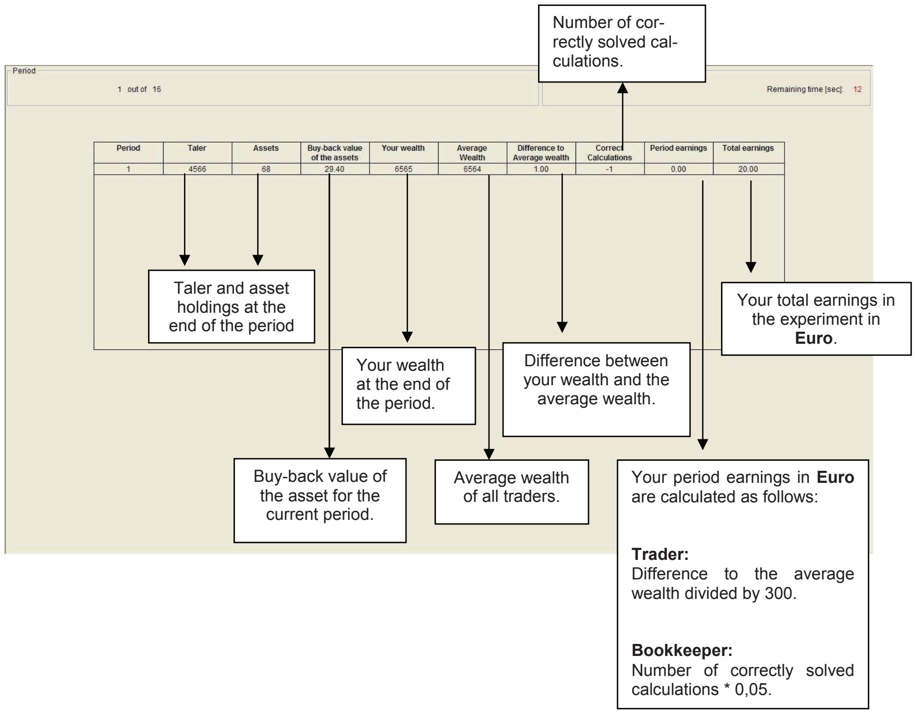
Important information

- No interest is paid for Taler holdings.
- Each trading period lasts for 240 seconds.
- The experiment ends after 16 periods.
- Offers to buy/sell the asset can be placed in the range from 0 to 999 (with at most two decimal places).
- The buy-back value is a random number with one decimal place.
- Use the full stop (.) as decimal place.

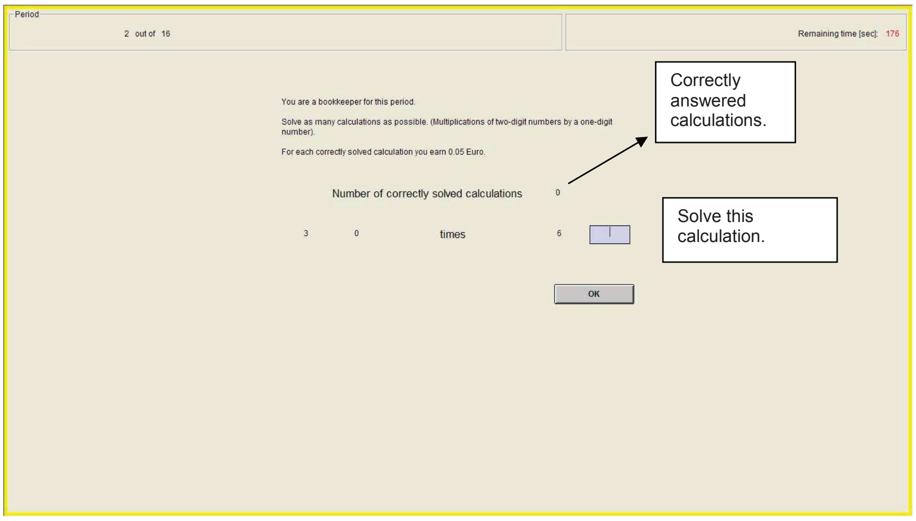
Trading screen: By means of the following figure, the procedure of trading (buying and selling) will be illustrated.


Information about current Asset and Taler holdings and your Wealth.
Summary tables of your own BIDS and ASKS. With the “CANCEL”-buttons you can delete your own offers.
Current Market Price (of Asset)
ASK: analogue to Purchase BID - see below.
BID: you have to enter Quantity and Price. Trade does not take place until another participant accepts your offer!!!
List of all BIDS: from all traders - your own Bids are written in blue. The offer with blue background is always the best, i.e., it yields the highest revenues for the seller.
List of all ASKS: from all traders - your own Asks are written in blue. The offer with blue background is always the best, i.e., it is the cheapest one for the buyer.
Price-Chart of current period (starts at 0)
If you have information about the buy-back value of the asset or the number of insiders present, this information will be displayed here.
SELL: You sell the entered Quantity, given the Price with the blue background. If you enter a higher amount than offered in the blue box, you sell the offered Quantity at most.
BUY: You buy the entered Quantity, given the Price with the blue background. If you enter a higher amount than offered in the blue box, you buy the offered Quantity at most.
Period
1 out of 16
Assets 60
Taler 4800
Wealth 0
Own bids
Quantity
Own asks
CANCEL Bid
CANCEL Ask
Information
Buy-back value: 29.40
Number Insider: 1
Info about Insider: all traders
Current price 0.00
Bid
Ask
BID
ASK
All bids
All asks
Time in sec.
SELL
BUY

History screen: appears after each trading period (for 15 seconds), providing you with information of past periods:



Screen seen by bookkeepers:



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Thomas Stöckl

Price efficiency and trading behavior in limit order markets with competing insiders

Abstract
We study price efficiency and trading behavior in laboratory limit order markets with asymmetrically informed traders. Markets differ in the number of insiders present and in the subset of traders who receive information about the number of insiders present. We observe that price efficiency (i) is the higher the higher the number of insiders in the market but (ii) is unaffected by changes in the subset of traders who know about the number of insiders present. (iii) Independent of the number of insiders, price efficiency increases gradually over time. (iv) The insiders' information is reflected in prices via limit (market) orders if the asset's value is inside (outside) the bid-ask spread. (v) In situations where limit and market orders yield positive profits, insiders clearly prefer market orders, indicating a strong desire for immediate transactions.

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