Gains from trade and prices
in an electronic call auction with insider trading
– An experimental analysis

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Abstract:
The present study contributes to the ongoing debate on possible costs and benefits of insider trading. In particular, we run three series of electronic call auctions in the laboratory where we change the probability of informed trading as a treatment variable. Over all treatments, subjects in our experiment realise about half of the possible gains from trade. Interestingly, markets are most liquid when there is a high probability of insider trading. Our hypothesis that the accuracy of prices as predictors of the true value of the asset increases with insider trading is not confirmed in our experiment.

JEL Classification: C92, G14, D82
Keywords: call auction, asymmetric information, experiment, insider trading
1. Introduction

This paper studies the impact of information asymmetries between traders on price discovery and liquidity. For regulators information asymmetries in securities markets and the ensuing insider trades are a growing concern. In 2000, the SEC adopted Regulation Fair Disclosure as an attempt to reduce information asymmetries. Regulation FD prohibits corporate issuers and corporate officials to leak information to selected market participants. The motivation for the introduction of regulation FD was that trading by better informed parties poses a “threat to market integrity and investor confidence” (Fisch, forthcoming). The effects of such a regulation on measures of market quality such as price discovery and liquidity, however, are not clear.

Understanding the effect of information asymmetries on price discovery and liquidity is important for two reasons. Firstly, increased competition over order flow and listings between stock exchanges around the world makes it vital for stock exchanges to tailor their trading institutions to generate the most accurate prices possible and at the same time keep liquidity high and trading costs low. Secondly, price discovery and liquidity are important determinants of transaction costs. Constantinides (1986) and Amihud and Mendelson (1986) show that an increase in transaction costs leads to fewer trades and a higher liquidity premium. Through this channel, information asymmetries in securities markets can have a substantial impact on firms’ financing decisions.

There is an ongoing debate about whether trading by better informed parties is beneficial for market quality or not. The most important argument in favour of insider trading is that it leads to more informative prices. One common objection against insider trading is that it discourages uninformed investors from trading and thereby leads to low trading volume (Leland, 1992). Thus, there appears to be a trade off: Insider trading improves the quality of prices as predictors of the true value of the asset and at the same time it decreases trading volume and the realised gains from trade.

More recently, Lambert, Leuz and Verrecchia (2012) study the impact of Regulation FD on the cost of capital. They show that whether information asymmetry affects the cost of capital depends crucially on the market structure. In a perfectly competitive market the degree of information asymmetry has no effect on the cost of capital. With imperfect competition, however, the degree of information asymmetry can affect the cost of capital.
The trading institution in which our analysis is set in is the electronic call auction. The electronic call auction is of particular interest for our purpose since many stock exchanges introduced electronic call auctions to obtain informative prices and facilitate trade in times when information is very asymmetrically distributed. Especially for infrequently traded stocks a high probability of insider trading causes huge transaction costs that can even lead to a drying-out of the market (Easley, Kiefer, O’Hara and Paperman, 1996).

In this study we analyse this trade off between liquidity and price discovery in a simple call auction framework. The model setup shares some features of Diamond and Verrecchia (1991). We consider large traders that are aware of the fact that their decisions have an effect on the price. Traders are motivated by liquidity needs, but one randomly determined trader may receive additional information about the true value of the asset. The equilibrium of our model also shares some properties with noisy rational expectation models, as e.g., Grossmann and Stiglitz (1980). Excess supply is random and in equilibrium the price partially reflects insider information. We find that increasing the probability that a trader receives superior information increases the accuracy of prices, i.e. moves prices closer to the true value of the asset. The gains from trade, however, fall as the probability that a trader receives additional information increases. The reason for this result is that the trader who receives the signal might buy (sell) the asset when she observes good (bad) news, although her liquidity needs require her to sell (buy) the asset.

We implement our asset market in the laboratory and vary the degree of information asymmetry. We find that in our electronic call auctions 50% of the gains from trade are realised when there is symmetric information. Comparing this share with Pouget (2007) who reports an efficiency of about 30% in an experiment similar to ours, we find our experimental markets to perform reasonably well. Contrary to Leland (1992), trading volume and the allocational efficiency relative to the Bayesian Nash equilibrium prediction increase when there is a high probability of informed trading. Thus, we find no evidence that investor confidence or market integrity suffers.

1At Euronext Paris the least liquid stocks (roughly one third of all stocks listed in 2005) trade only in call auctions. The London Stock Exchange introduced opening and closing auctions in 1997 and 2000, respectively. The Australian Stock Exchange (1997) and the Toronto Stock Exchange (2004) both introduced closing auctions. In 2004, NASDAQ created NASDAQ CROSS, an order facility to obtain single opening and closing prices.
Analysing the Bayesian Nash equilibria of the call auction we show that informational efficiency (which is inversely proportional to the average distance between the call auction price and the true value) increases in the probability of insider trading. This hypothesis is not confirmed in our experiment, the ability of call auction prices to reflect the true value does not improve with a high probability of insider trading. In general, the call auction prices are significantly higher than the true value of the asset.

There is a substantial literature on experimental call auctions that focuses on allocational and/or informational efficiency. Kagel and Vogt (1993) and Cason and Friedman (1997) investigate a call auction with privately known valuations. Davis and Williams (1997) also use a private value design together with cycling demand and/or supply curves. These studies find that the call auction performs well in terms of allocational efficiency even in a non-stationary environment as in Davis and Williams (1997).

Friedman (1993) compares the call auction with a continuous double auction by employing a private value design although in most of his treatments the private dividend payoffs were disclosed during the trading period. He finds informational efficiency to be similar between the two trading institutions but allocational efficiency to be slightly higher in the continuous market.

Theissen (2000) considers a common value environment with symmetrically dispersed signals and finds the call auction mechanism efficient in aggregating dispersed information, although it underreacts to new information.

Liu (1996) modifies Friedman’s (1993) design to allow for two kinds of information asymmetries: Symmetrically dispersed information, where every trader receives a signal with the same ex ante quality, and superior information, where only some traders receive a signal about the asset’s value and others remain uninformed. Liu (1996) finds that continuous trading is more efficient, both allocationally and informationally, for symmetrically dispersed information, while the call auction is better suited for asymmetrically distributed signals. The latter finding is surprising since it is often assumed that the gathering of orders in a call auction provides a good opportunity for insiders to place their orders without giving away their informational content. Reasons for Liu’s (1996) result might be the high number of insiders (half of the buyers and half of the sellers receive a signal) and the disclosure of the best standing quotes (the two highest limit buy prices and the two lowest limit sell prices) during the order
accumulation phase, making it difficult to hide the informational content of orders.

The study closest to ours is Pouget (2007). He compares a call market with a Walrasian Tatonnement in an environment that has features of both a common and a private value setting. As in Liu (1996), the proportion of informed traders is one half and equally distributed across different types of private valuations. In contrast to Liu (1996), however, traders do not observe any of the decisions of the other traders when they choose their orders. Pouget (2007) finds that the call market and the Walrasian Tatonnement yield efficient prices, but that the realised gains from trade are much lower in the call market than in the Walrasian Tatonnement. According to Pouget (2007), this is due to the fact that uninformed traders respond to strategic uncertainty in the call market by choosing conservative limit prices. In addition, part of the difference can be explained by bounded rationality. Despite these problems of the call market, however, Pouget’s (2007) study confirms the finding in Liu (1996) that call market prices efficiently reflect inside information.

Our study differs from these previous experiments by focusing on situations with very asymmetrically dispersed information: Only one of the traders receives an (imperfect) signal of the true value of the asset; all other traders remain uninformed. The fact that only one trader receives a signal creates the novel feature of our design that insider information affects the order imbalance, i.e., the signal determines whether there is excess demand for or excess supply of the stock.

2. The model

2.1. Symmetric information case. We formalise a typical call auction as follows. There is a single period lived asset with random terminal payoff $x$. The trading environment includes $n$ risk neutral traders, who can be buyers or sellers. Buyers have a higher valuation of the asset, $x + k$, while sellers have a lower valuation, $x - k$. In order to keep the model simple, we assume that all buyers have the same premium $k$ and all sellers have a discount of the same size. There are $n_B$ buyers and $n_S$ sellers in the model. To simplify the analysis we assume $n_B \neq n_S$, i.e., we have either more buyers than sellers or

\footnote{This difference in valuation $2k$ represents individual portfolio considerations or tax brackets.}
more sellers than buyers in our model. This assumption is well sustainable for any real market, where the probability that the number of buyers equals exactly the number of sellers is very small. Moreover, in all markets where the number of traders is odd, the probability above equals zero.

Each trader can enter one limit order for one unit of the asset into the call auction. Allowing only limit orders is not restrictive, because by choosing very high limit buy prices or very low limit sell prices, participants can mimic market buy or market sell orders, respectively.\(^3\) The order book is closed, i.e., traders cannot observe the orders placed by other traders.

The orders are collected in the order book, and after a specified time the market is cleared. The clearing price range corresponds to the interval of prices for which trading volume is maximised and no buy order with a higher limit price and no sell order with a lower limit price is left unexecuted. Given the clearing price range, the transaction price is determined by a pricing rule \(\kappa \in [0, 1]\). Let \(p_u\) and \(p_l\) denote the upper and lower bounds of the price range. The transaction price implied by pricing rule \(\kappa\) is then \((1 - \kappa)p_l + \kappa p_u\). Satterthwaite and Williams (1989) show that for \(\kappa = 1\) sellers have no incentive to act strategically. Demanding a price higher than their true valuation will just reduce the probability of having their order executed, but will not affect the price they receive. Buyers, however, might misrepresent their valuation to affect the price they have to pay. Conversely, for \(\kappa = 0\) buyers will have no incentive to misrepresent while sellers will demand more than their true valuations. Following many real world call auction algorithms\(^4\), we employ the following pricing rule: \(\kappa = 0\) when there are more sellers than buyers and \(\kappa = 1\), otherwise. As we will see, in equilibrium, this pricing rule discourages strategic misrepresentation of valuations for both buyers and sellers.

If there is excess demand or supply for a given transaction price, traders on the long market side with limit prices above the transaction price have their orders fulfilled, while traders whose limit prices equal the transaction price split the remaining shares equally between themselves. Other possible rationing methods are random execution or time priority. For risk neutral traders the proportionate allocation of assets and random execution is equivalent. In the

\(^3\)All the experiments discussed in the previous section, like Friedman (1993), Theissen (2000) and Pouget (2007), also restrict their attention to limit orders.

\(^4\)For example EURONEXT and Xetra, as the quotations in the introduction demonstrate.
experiment reported below, we use time priority, which is often employed in real asset markets, like NASDAQ CROSS, Euronext and Xetra, to encourage early order placement.

Before we describe the equilibrium of the model, we want to introduce the notion of allocational efficiency that will be important for evaluating the equilibrium and the experimental results. Our model exhibits strong incentives to trade due to the difference in valuation, $k$. Allocational efficiency requires that this difference in valuation is realised, i.e., that those traders who value the asset most buy and those who value the asset least sell. Since all the traders can only trade one asset at most, the maximum number of efficiency improving trades is $n = \min\{n_B, n_S\}$. Efficiency in our model corresponds to the utility surplus that is achieved through trade.

**Definition 1** (Allocational efficiency). We say that the outcome of a call auction is allocational efficient when the maximum amount of $n$ assets are traded from sellers to buyers; the maximal corresponding utility surplus is $2kn$.

In the analysis of the experimental data, we distinguish absolute allocational efficiency (AAE) as the realised gains from trade relative to the maximum gains from trade and relative allocational efficiency (RAE) as the realised gains from trade relative to the gains from trade realised in the most efficient Bayesian Nash equilibrium.

### 2.2. Equilibrium in the symmetric information case.

**Proposition 1.** For the symmetric information case there exists a symmetric Bayesian Nash equilibrium in which traders report their valuations truthfully. The corresponding equilibrium strategies for this call auction game are:

- Buyers set their limit prices to $b^* = E(x) + k$.
- Sellers set their limit prices to $s^* = E(x) - k$.

Consider the situation of the buyers and assume that all sellers choose the limit sell price $s^*$. There are two possible scenarios: either $n_B < n_S$ or $n_B > n_S$. In the first case, there is excess supply of the asset and buyer $j$’s order is executed with probability one as long as $b_j > s^*$. Buyer $j$’s limit price has no effect on the auction price and her expected profit is $2k$.

If $n_B > n_S$, there is excess demand and only those $n_S$ buyers with the highest limit prices have their orders executed. The call auction price is determined
by the $n_S$-th highest limit buy price. In this case, buyers want to bid high in order to increase their chance of having their order executed, but at the same time, they do not want to trade when the call auction price is greater than their valuation. Therefore, the $n_S$-th highest limit buy price must be equal to $E(x) + k$. Assuming symmetry across all buyers implies that all buyers choose $b^* = E(x) + k$. A similar argument shows that sellers choose a limit sell price of $s^* = E(x) - k$.

There are many other equilibria in this game. For example, there exists another symmetric Bayesian Nash equilibrium where buyers are only willing to pay 0 and sellers demand a price above $E(x) + k$. This is an equilibrium where no trade takes place.

The multiplicity of Nash equilibria is not surprising here at all. In contrast, it is a common property of games where the possible gains can only be realised by mutual actions of a group of players (here: by a buyer-seller pair). In a situation where only bilateral trade can possibly be profitable, the concept of Nash equilibrium that considers exclusively the profitability of unilateral deviations is too weak. However, there are several commonly used refinements as Pareto (weakly) undominated Nash equilibria, Strong Nash equilibria (Aumann, 1959) and coalition-proof Nash equilibria (Bernheim, Peleg and Whinston, 1987) that guarantee the unique outcome in the following sense:

**Corollary 1.** The equilibrium defined in Proposition 1 and all the (weakly) undominated Nash equilibria, Strong Nash equilibria and coalition-proof Nash equilibria have the following properties:

(i) The outcome of the call auction game is allocational efficient, i.e., $n$ assets are sold to the buyers by the sellers.

(ii) The equilibrium price is $b^*$ if there are more buyers than sellers, and $s^*$ if there are more sellers than buyers.

2.3. Asymmetric information case. In this part of the paper we would like to model a situation in which some of the agents, inherently still buyers or sellers, will receive an (imperfect) information. It is natural to assume that the information content of the insider’s signal is large enough to overturn the assignment to one of the two groups, i.e., a potential insider who values the asset at $x + k$ and observes a low signal would want to sell the asset in equilibrium.
The question how the market will react to insider information is interesting if there are enough (possibly) informed traders at the long side of the market that (in the case that these traders trade against their type), the long side becomes the short side of the market. (Otherwise the situation is identical to the model without insider.) To capture this we will take the simplest possible model, we will set $m + 1$ traders at the long side, $m$ traders at the short side of the market whereas one randomly determined trader on the long side of the market becomes an insider with probability $\lambda > 0$. The insider receives a binary signal indicating a high ($h$) or low ($l$) realisation of $x$. Ex ante, i.e., before the realisation of $x$, both signals are equally likely.

In the model with an insider, another notion of efficiency will be important for evaluating the equilibrium and the experimental results: informational efficiency. There are new incentives to trade in the model with an insider, namely superior information by the insider. Roughly speaking, informational efficiency requires that the auction reflects the distribution of valuations and information among traders. Thus, the auction price should now communicate two things: it should not only signal whether there is excess demand for the asset or excess supply; the auction price should also incorporate the information by the insider.

**Definition 2 (Informational efficiency).** We say that the outcome of a call auction is informational efficient when the auction price is as close as possible to the true value of the asset from the perspective of a trader on the long side of the market.

In order to measure informational efficiency in a series of experimental auctions indexed by $t = 1, ..., T$ we will use the following statistic:

$$(1) \quad IE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (p_t - x_t^*)^2},$$

where $p_t$ is the auction price in auction $t$ and $x_t^*$ equals the true value of the asset in period $t$, $x_t$, plus $k$ if the auction price is determined by a limit buy order, and $x_t^* = x_t - k$ if the auction price is determined by a limit sell order.

2.4. **Equilibrium in the model with an insider.**
Proposition 2. With a positive probability of insider information there is no symmetric Bayesian equilibrium in pure strategies. The equilibrium in mixed strategies for this call auction game is given by the following strategies: \({}^5\)

- The uninformed buyers choose their limit prices from the support \([\bar{b}, \overline{b}]\) according to the distribution \(F(b)\).
- The uninformed sellers choose their limit prices from the support \([\bar{s}, \overline{s}]\) according to the distribution \(G(s)\).
- If a trader receives a positive signal she chooses a limit buy order with limit price greater than \(\bar{b}\); if a trader observes a negative signal she chooses a limit sell order with limit price smaller than \(\bar{s}\).

The equilibrium in Proposition 2 shares some properties of the equilibrium in Proposition 1: When there is excess supply a buyer’s order is executed with probability 1 and buyers receive positive expected payoffs. When there is excess demand buyers are indifferent between having their order executed or not and they receive zero expected payoffs. The novel feature of the equilibrium in Proposition 2 is that the sign of the order imbalance is endogenous. If a trader receives a good signal about the true value of the asset she places a limit buy order, if she observes a bad signal she places a limit sell order. Whether there is excess demand or excess supply is then partly determined by the signal about the true value of the asset. As a consequence, the limit buy prices that make a buyer indifferent between having her order executed or not given that there is excess demand are higher than in the symmetric information case, i.e., \(\bar{b} > E(x) + k\). Similarly, the limit sell prices in the asymmetric information case are lower than the limit sell prices in the symmetric information case: \(\overline{s} < E(x) - k\).

Corollary 2. The equilibrium defined in Proposition 2 has the following properties:

(i) Since \(\bar{s} < \bar{b}\), \(m\) assets are traded.

(ii) The electronic call auction does not achieve full allocational efficiency.

(iii) If there are more buy orders than sell orders the equilibrium price \(p^+\) is the second-lowest limit buy price, and if there are more sell orders than

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\(^5\)The expressions for \(\bar{b}, \overline{b}, \bar{s}, \overline{s}\) and \(\bar{s}\) and the distributions \(F(b)\) and \(G(s)\) are derived in the appendix.
buy orders the equilibrium price $p^-$ is the second-highest limit sell price. Thus, $p^+ \in [b, \bar{b}]$ and $p^- \in [\underline{s}, \bar{s}]$.

(iv) The support of limit buy prices $[b, \bar{b}]$ shifts upwards as $\lambda$ increases and the support of limit sell prices $[\underline{s}, \bar{s}]$ shifts downwards as $\lambda$ increases.

The equilibrium requires that a trader who observes a signal has to follow that signal, i.e., she places a buy order when she observes a high signal and a sell order when she observes a low signal. Thus, whenever a buyer observes a low signal she sells her share to another buyer. Similarly, a seller who observes a high signal buys a share from another seller. Therefore, not all gains from trade are realised in the Bayesian Nash equilibrium. The last two points of Corollary 2 imply that the equilibrium prices are informational efficient, because they (imperfectly) reflect the signal that the insider receives. In the asymmetric information scenario there is a trade-off between allocational and informational efficiency: If the insider always follows her signal some gains from trade are lost but the information of the signal is passed on to other traders and the auction price; if the insider follows her type as buyer or seller all gains from trade are realised but the the information of the signal is not communicated to other market participants. Only the former situation is an equilibrium.

The general properties of the equilibrium of this game are not restricted to the situation with exactly $m$ buyers, $m$ sellers and one potential insider. What is important for the existence of this equilibrium is that the situation with more buy orders than sell orders and the situation with more sell orders than buy orders are equally likely and that this direction of the order imbalance contains some information about the true value of the asset.

3. Experimental design

There is a single asset traded in our experimental stock market that pays different dividends depending on the state of nature. In state D, which occurred with probability 50%, the asset paid 240 ECU. In the good state G, the asset paid 480 ECU, and in the bad state S, it paid 0 ECU. States G and S both occurred with probability 25%. The payoff to the traders also depends on their type. Type A traders have a premium of $k = 20$ ECU, type B traders a discount $k = 20$ ECU. In each auction, there are either 3 traders of type A and 4 of type B or 4 of type A and 3 of type B. Both situations are equally likely and types are newly assigned to the participants before each auction. The dividend payments
Table 1. Dividends that the asset pays to traders of type A and B conditional on the realised state: S, D or G. The probability of each state is given in parentheses.

<table>
<thead>
<tr>
<th>State</th>
<th>S (25%)</th>
<th>D (50%)</th>
<th>G (25%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type A</td>
<td>20</td>
<td>260</td>
<td>500</td>
</tr>
<tr>
<td>Type B</td>
<td>-20</td>
<td>220</td>
<td>460</td>
</tr>
</tbody>
</table>

of the asset conditional on the states of nature and trader types are displayed in Table 1.

3.1. Information structure. We consider three treatments reflecting different probabilities of the presence of the insider in the market. In the benchmark NO treatment (Sessions 1 and 2), the subjects knew only the dividend structure for the two types of traders as displayed in Table 1 and their own type. For the remaining two treatments, in each auction one of the seven traders received a binary signal with probability \( \lambda \), where \( \lambda = 1/3 \) in the LOW treatment (Sessions 3 and 4) and \( \lambda = 2/3 \) in the HIGH treatment (Sessions 5 and 6). The signal was determined in the following way: If the true state was G, the signal was “not S”; if the true state was S, the signal was “not G”; if the true state was D, the signal was either “not S” or “not G” with equal probabilities.

Since it is well known that people find it difficult to work out conditional probabilities\(^6\), the probabilities \( P(x = G| \text{“not } Z\text{”}) = P(x = D| \text{“not } Z\text{”}) = 1/2 \), and so on, are explained in the instructions, and the participants were asked to calculate the conditional expectations in the questionnaire at the beginning of each session.

To ensure that differences across treatments are not attributable to different realisations of the states of nature, the random draw was done just for the NO treatment and replicated for the other two treatments afterwards (as, e.g., in Dominitz and Hung (2009)). Therefore, the sequences of random variables were held constant across treatments, with identical random draws in Sessions 1, 3 and 5; and Sessions 2, 4 to 6.

3.2. The call auction mechanism. At the beginning of each auction, every trader is endowed with one asset and 500 ECU working capital. The subjects can, however, only generate profit from trading, i.e., by selling the asset at a

\(^6\)This situation is quite similar to the Monty Hall problem (Kluger and Wyatt, 2004).
price higher than the realised dividend or by buying the asset for a price lower
than the realised dividend since the working capital of 500 ECU has to be paid
back at the end of the auction. Each trader first decides whether to place a
limit buy or limit sell order and then specifies the limit price. A trader can
enter only one order per auction, and order size is standardised to one unit.
Limit prices are restricted to integers between 0 and 500. When entering their
orders, the traders are unaware of the other traders’ orders. Once all traders
have submitted their orders to the order book, the market is cleared. If there
are several identical orders and not all of them can be executed, those orders
that are entered earliest are given priority.

After each auction the state of nature is revealed and every trader sees all
orders, the auction price, the numbers of shares traded and her own period
profit and accumulated profits on her trading screens. The final payoff the
participants receive is the sum of all period profits converted into Euros at the
rate of 1 Euro = 500 ECU.

3.3. Experimental procedures. The call auction experiment was implemented
using the experimental software z-tree (Fischbacher, 2007). Subjects were stu-
dents of mathematics or economics at the University of Jena. Around 30 sub-
jects were invited to any of our six sessions. Having read the instructions, the
participants completed four test auctions against prespecified computer orders
to get familiar with the trading situation. After these test auctions the sub-
jects had to answer 12 questions to assess their understanding of the trading
environment. To guarantee that only subjects with intimate knowledge of the
market environment participate in the experiment, only the 21 subjects who
answered all questions with the fewest mistakes participated in the analysed
part of the experiment; the remaining subjects received a fixed fee of 5 Euros
and were asked to leave.\footnote{This introductory part of each session, where participants read the instructions, took part in four test auctions and answered the questions, lasted for about 40 minutes.}
The 21 participants in the particular Sessions 1-6 were grouped into 3 markets.
Each market lasted for 26 periods or auctions so that our sample consists of 468 auctions of altogether 18 markets of which
always 6 relied on each of our three treatments.\footnote{The participants were not informed in advance how many auctions were played.} Thus, we have six independent
observations for any treatment.
TABLE 2. Equilibrium limit prices: $b^*$ denotes the limit buy prices and $s^*$ the limit sell prices in the most efficient Bayesian Nash equilibrium. The treatments are the following. NO: all traders are uninformed, LOW: with probability 1/3, one trader becomes an insider, and HIGH: with probability 2/3, one trader becomes an insider.

<table>
<thead>
<tr>
<th></th>
<th>NO</th>
<th>LOW</th>
<th>HIGH</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b^*$</td>
<td>[284, 308]</td>
<td>[320, 343]</td>
<td></td>
</tr>
<tr>
<td>$s^*$</td>
<td>[172, 196]</td>
<td>[137, 160]</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Summary statistics of auction outcomes (Panel A) and the Bayesian Nash equilibrium predictions (Panel B). Absolute allocational efficiency (AAE) refers to the realised gains from trade relative to the maximum gains from trade, relative allocational efficiency (RAE) refers to the realised gains from trade relative to the gains from trade in the most efficient Bayesian Nash equilibrium. Informational efficiency (IE) is measured by the square root of the mean squared deviations between the auction price and the true value of the asset evaluated by a trader on the long side of the market.

Panel A: Experimental results

<table>
<thead>
<tr>
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<th></th>
<th></th>
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</thead>
<tbody>
<tr>
<td>NO</td>
<td>263.9</td>
<td>2.08</td>
<td>0.51</td>
<td>0.51</td>
<td>179.7</td>
</tr>
<tr>
<td>LOW</td>
<td>259.7</td>
<td>2.03</td>
<td>0.43</td>
<td>0.46</td>
<td>181.6</td>
</tr>
<tr>
<td>HIGH</td>
<td>251.2</td>
<td>2.35</td>
<td>0.55</td>
<td>0.64</td>
<td>176.5</td>
</tr>
<tr>
<td>All</td>
<td>258.3</td>
<td>2.15</td>
<td>0.50</td>
<td>0.54</td>
<td>179.3</td>
</tr>
</tbody>
</table>

Panel B: Bayesian Nash equilibrium predictions

<table>
<thead>
<tr>
<th>Avg. Price</th>
<th>Volume</th>
<th>Avg. AAE</th>
<th>Avg. IE</th>
</tr>
</thead>
<tbody>
<tr>
<td>NO</td>
<td>240</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>LOW</td>
<td>240</td>
<td>3</td>
<td>0.94</td>
</tr>
<tr>
<td>HIGH</td>
<td>240</td>
<td>3</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Including instructions and test auctions, the sessions lasted for almost two hours, and average earnings were around 13 Euros with a minimum of 7.80 and a maximum of 17.20 Euros.

4. Experimental results
4.1. **Allocational efficiency.** Average trading volume for the three different treatments and all treatments together are summarised in the third column of Table 3. In all three treatments average trading volumes are well below the predicted three units. But the auctions in the HIGH treatment traded, on average, 0.3 shares more than auctions in the other two treatments.\(^9\) Moreover, trading volume is more stable for positive probabilities of inside information in the sense that variation of volume decreases as the probability of an insider increases. Also, in the NO treatment four auctions failed to produce a price, i.e., the highest limit buy price was below the lowest limit sell price, and trade was not feasible. In the LOW treatment, only two auctions did not trade any shares, and in the HIGH treatment all auctions had strictly positive trading volumes. Thus, the HIGH treatment was the most stable treatment in terms of generating trade. However, trade as such is not welfare enhancing. In order to see whether the trades conducted increase welfare we have to turn to allocational efficiency.

An efficient allocation of assets arises if three type B traders sell their shares to three type A traders. Thus, each asset which is sold from a type B to a type A trader increases efficiency. A trade in which the asset is exchanged between traders of the same type does not affect efficiency. If a type A trader sells an asset to a type B trader this decreases efficiency. Figure 1 shows the classification of trades in the experimental auctions. The height of each bar represents the average number of trades per period for each treatment. The composition of these bars indicates how many of these trades were efficiency increasing (labelled POS), efficiency decreasing (labelled NEG) and efficiency neutral (labelled NEUT). In the NO treatment on average 1.65 trades per period are efficiency increasing while in the Bayesian Nash equilibrium all trades should increase efficiency. The remaining trades consist of some (0.31) efficiency neutral trades and a few efficiency decreasing trades (0.11). If there is a low probability of insider trading (LOW treatment) the number of efficiency increasing trades goes down to 1.45 on average. Efficiency neutral and decreasing trades increase slightly relative to the NO treatment. The most efficiency enhancing trades (1.83) are observed in the HIGH treatment.

\(^9\)The difference in average trading volume is weakly significant between the NO and HIGH treatment (one-sided Mann-Whitney \(p\)-value: 0.09) and significant between the LOW and HIGH treatment (one-sided Mann-Whitney \(p\)-value: 0.047).
Figure 1. Classification of trades: Average number of trades per treatment broken down into efficiency enhancing trades (POS), efficiency neutral trades (NEUT) and efficiency decreasing trades (NEG).

Note that in the most efficient Bayesian Nash equilibrium there are no efficiency decreasing trades, but for the asymmetric information case some trades are efficiency neutral. The absolute allocational efficiency measures the realised gains from trade relative to the maximum gains from trade. If all players played according to the equilibrium strategies the average absolute allocational efficiency (AAE) would be 94% in the LOW treatment and 87% in the HIGH treatment (see panel B of Table 3). Actual trading behaviour yields lower absolute allocational efficiency. Roughly 50% of all gains from trade are realised.

In contrast to the Bayesian Nash equilibrium, the absolute allocational efficiency does not deteriorate monotonically as the probability of insider trading increases. In fact, the relative allocational efficiency (RAE) is highest in the HIGH treatment (see Panel A of Table 3). On average, participants realise 2/3 of the gains from trade that would result in equilibrium.

The significant amount of deviation from our theoretical predictions and the participants’ failure to converge to the predictions over time are puzzling at first glance. We should stress, however, that the call auction in our experiment is a strategic situation and that traders do not have dominant strategies. Therefore, depending on beliefs of other traders’ strategies it might not be individually
Figure 2. Evolution of auction prices over periods: • indicates auction prices in the NO treatment, ◦ denotes auction prices in the LOW treatment and auction prices in the HIGH treatment are represented by *.

irrational to deviate from the predicted equilibrium behaviour. One can easily construct beliefs that rationalize the decision by a type A trader to place a limit sell order.

The experiment that is closest to ours is Pouget (2007) because he also models the call auction as a strategic game. He observes average gains from trade of around 30% of the full extraction level. In this perspective, despite of deviations from equilibrium strategies, our experimental call auction performs reasonably well.

Result 1. (Allocational efficiency) Overall the allocational efficiency of the call auction is about 50%. In contrast to the most efficient Bayesian Nash equilibrium, however, allocational efficiency does not decrease as the probability of insider information increases.

4.2. Informational efficiency. Figure 2 shows the auctions prices of our experimental markets for each period. Auction prices are indicated by dots for the NO treatment, by diamonds for the LOW treatment and by asterisks for
the HIGH treatment. Most auction prices are in the range of 200 and 350 ECU. There is no striking change in the dispersion of prices as subjects gained more experience over the periods. Therefore, no periods were discarded for the analysis of average auction prices.

In the Bayesian Nash equilibrium limit prices incorporate some of the information possibly held by an informed trader. Consequently, auction prices partly reflect insider information and, thus, auction prices are useful predictors for the true value of the asset. This is illustrated in Figure 3. The dashed line indicates the root mean square deviation between equilibrium auction prices and true values. As the probability of insider information increases the root mean square deviation decreases. The root mean squared deviations based on actual auction prices show a different picture. The dots indicate the informational efficiency of the six individual markets per treatment, the dotted line gives the cross-market mean efficiency per treatment. In the symmetric information case (NO treatment) actual informational efficiency is close to the equilibrium prediction (179.7 vs. 175.8, see Table 3). In the two asymmetric information treatments (LOW and HIGH) all, except one market in the LOW treatment, perform worse in terms of root mean square deviations from the asset’s true value than the equilibrium benchmark. Moreover, the cross-market average does not show an improvement in predicting the asset’s value as the probability that a trader receives a signal increases.

**Result 2. (Informational efficiency)** The call auction with asymmetric information is not informational efficient. An increase in the probability of insider information does not lead to more informative auction prices.

Analysing the limit prices we observe another behavioural pattern that is not related to any *a priori* hypothesis. Still we find it worthwhile to refer to it. Table 3 presents average auction prices for the 18 markets. The mean of these average auction prices is 258.3 ECU, i.e., well above the predicted 240 ECU. A *t*-test shows that this difference is significant (*t*-statistic: 4.4). While average auction prices are lower for the LOW and HIGH treatments than for the NO treatment, they are still well above 240. This suggests that the participants overvalue the asset, a tendency that decreases as the probability of informed traders increases.
Figure 3. Informational efficiency. Informational efficiency is measured by the square root of the mean squared deviations between the auction price and the true value of the asset evaluated by a trader on the long side of the market. The dots indicate the efficiency of the six individual markets per treatment, the dotted line gives the cross-market mean efficiency per treatment and the dashed line indicates the efficiency achieved in the Bayesian Nash equilibrium.

Analysing the data of the NO treatment in more detail we find that both limit sell orders and limit buy orders are in average roughly 20 ECU higher than the equilibrium prediction. One possible explanation of this phenomenon is that our subjects reveal risk-loving preferences.

Since traders in the call auction do not generally pay or receive the limit price they choose but often a more favourable price, there is a similarity to the second-price auction. Many experimental studies of the second-price auction find systematic overbidding (Kagel, Levin and Harstad, 1987; Kagel and Levin, 1993 and Cooper and Fang, 2008) which is consistent with the high limit buy prices in our study. Moreover, Bernard’s (2006) experimental study of the second-price procurement auction shows that sellers overreport their costs,
although by symmetry to the second-price auction one might expect underreporting of costs. This finding is in line with our result that sellers choose limit sell prices that are higher than their expected value of the asset.

In contrast to the “joy of winning” from the literature on overbidding in second-price auctions, we can interpret the overvaluation in our experiment as a “joy of holding the asset,” to reflect the fact that subjects were not only willing to pay a high price to buy the asset, but also seemed reluctant to sell their asset. This is demonstrated by both high limit sell prices as well as the large number of type B traders who chose to buy instead of sell.¹⁰

5. Discussion and conclusions

Low volume stocks traded in continuous trading institutions typically exhibit a large probability of insider trading (Easley, Kiefer, O’Hara and Paperman, 1996). These information asymmetries widen the spreads and make the market for these stocks even less liquid. As a result, many stocks fail to trade over a period of several days. Euronext Paris introduced electronic call auctions for infrequently traded stocks to tackle this problem. Based on our findings this measure is successful in facilitating trade. In our experimental call auction markets we observe the largest average volume in the HIGH treatment and none of the markets in the HIGH treatment failed to generate strictly positive trading volume. However, the increase in liquidity might come at the cost of lower informational efficiency. Informational efficiency requires that part of the information of the insider is reflected in the auction prices. But in our experiments, call auction prices have the same accuracy in predicting the true value of the asset no matter if there is high, low or zero probability of insider trading.

One reason why subjects fail to choose equilibrium limit buy and sell prices is that the call auction algorithm makes it difficult to learn the equilibrium. Only if all seven subjects of a market play equilibrium strategies for a couple of periods, do they begin to experience a noticeable increase in their earnings. Consequently, we do not observe significant changes in participants’ behaviour over time.

¹⁰Roughly 25% B traders choose the buy order in comparison to 15% of A traders who choose the sell order.
Another reason why uninformed traders’ limit prices do not reflect the potential presence of an insider is that the subjects do not seem to experience the competitive pressure that forces limit buy prices upwards and limit sell prices downwards as the probability of informed trading increases. A possible solution to this lack of competition is to increase transparency of the order book. This could be implemented by giving subjects a chance to revise their orders after looking at the order book. Another way to increase transparency is to provide an indicative auction price during the order accumulation phase. Comerton-Forde and Rydge (2006) show that the introduction of an indicative auction price significantly enhanced price efficiency in the opening and closing call auctions on the Australian Stock Exchange.

APPENDIX: DERIVATION OF THE MIXED STRATEGY EQUILIBRIUM

A buyer without a signal can face four different situations:

<table>
<thead>
<tr>
<th>situation</th>
<th>probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( (m+1)(1-\lambda) )</td>
</tr>
<tr>
<td>2</td>
<td>( m(1-\lambda) )</td>
</tr>
<tr>
<td>3</td>
<td>( m\lambda )</td>
</tr>
<tr>
<td>4</td>
<td>( m\lambda )</td>
</tr>
</tbody>
</table>

(B denotes a trader who values the asset with a premium \( k \) and S denotes a trader who discount the asset’s value with \( k \).) We assume that uninformed buyers play a mixed strategy \( f(b) \) on the interval \([b, \bar{b}]\) and uninformed sellers mix with density \( g(s) \) on \([s, \bar{s}]\). If a trader observes a positive signal she bids \( b_I > \bar{b} \) and receiving a negative signal a trader asks for \( s_I < s \). We further assume that \( \bar{b} > \bar{s} \). The expected utility of uninformed buyer \( j \) bidding \( b_j \in [b, \bar{b}] \) is (ignoring situations 2 and 4 which do not depend on \( j \)’s bid)

\[
Eu_j(b_j) = \frac{(m+1)(1-\lambda)}{2m+1-\lambda} \left\{ \int_b^{b_j} (E(x) + k - b)m(m-1)f(b)F(b)(1 - F(b))^{m-2} db \\
+ (E(x) + k - b_j)mF(b_j)(1 - F(b_j))^{m-1} \right\} \\
+ \frac{m\lambda}{2m+1-\lambda} \left\{ \int_b^{b_j} (E(x|h) + k - b)(m-1)(m-2)f(b)F(b)(1 - F(b))^{m-3} db \\
+ (E(x|h) + k - b_j)(m-1)F(b_j)(1 - F(b_j))^{m-2} \right\}
\]
In a mixed strategy equilibrium the first derivative of the expected utility with respect to \( b_j \) should be zero for all \( b_j \in [\bar{b}, \overline{b}] \). This yields the differential equation

\[
0 = (m + 1)(1 - \lambda)(1 - F(b_j)) \{ (E(x) + k - b_j)f(b_j) - F(b_j) \} \\
+ (m - 1)\lambda \{ (E(x|h) + k - b_j)f(b_j) - F(b_j) \}.
\]

with the following general solution

\[
b = \frac{\lambda(m - 1)(E(x|h) - E(x)) \log((\lambda - 1)F(b)(m + 1) + m + 1 - 2\lambda)}{F(b)(\lambda - 1)(m + 1)} \\
+ \frac{F(b)(m + 1)(\lambda - 1)(E(x) + k) - C(m + 1)(\lambda - 1)}{F(b)(\lambda - 1)(m + 1)}.
\]

The constant \( C \) is chosen such that \( \bar{b} \) exists:

\[
(2) \quad C = \frac{\lambda(m - 1)(E(x|h) - E(x)) \log(m + 1 - 2\lambda)}{(m + 1)(\lambda - 1)}
\]

Hence, the symmetric equilibrium mixed strategy is characterized by the following equation:

\[
b = \frac{\lambda(m - 1)(E(x|h) - E(x)) \log((\lambda - 1)F(b)(m + 1) + m + 1 - 2\lambda)}{F(b)(\lambda - 1)(m + 1)} \\
+ E(x) + k - \frac{\lambda(m - 1)(E(x|h) - E(x)) \log(m + 1 - 2\lambda)}{F(b)(\lambda - 1)(m + 1)}
\]

with upper and lower bound of the support given by

\[
\overline{b} = E(x) + k + \frac{\lambda(m - 1)(E(x|h) - E(x))}{(\lambda - 1)(m + 1)} \log\left(\frac{\lambda(m - 1)}{m + 1 - 2\lambda}\right)
\]

\[
\underline{b} = E(x) + k + \frac{m - 1}{m + 1 - 2\lambda} \lambda(E(x|h) - E(x)).
\]

The distribution functions \( F(b) \) for \( m = 3 \) and \( \lambda = 1/3 \) and \( 2/3 \) are given in the figures 4 and 5. The sellers’ equilibrium strategy \( G(s) \) can be derived similarly.
Figure 4. Distribution function $F(b)$ for $\lambda = 1/3$.

Figure 5. Distribution function $F(b)$ for $\lambda = 2/3$.

References


