

JENA ECONOMIC RESEARCH PAPERS



2008 – 090

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www.jenecon.de

ISSN 1864-7057

The JENA ECONOMIC RESEARCH PAPERS is a joint publication of the Friedrich Schiller University and the Max Planck Institute of Economics, Jena, Germany. For editorial correspondence please contact markus.pasche@uni-jena.de.

Impressum:

Friedrich Schiller University Jena
Carl-Zeiss-Str. 3
D-07743 Jena
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Jena Economic Research Papers 2008 - 090

Do prices in the unmediated call auction reflect insider information? – An experimental analysis

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Abstract:

The unmediated call auction is a useful trading mechanism to aggregate dispersed information. Its ability to incorporate information of a single informed insider, however, is less well understood. We analyse this question by presenting a simple call auction game where both auction prices and limit prices of uninformed traders reflect potential insider information. The predictions of the model are tested in the laboratory. While an insider improves the call auction outcomes in terms of increasing trading volume, uninformed traders fail to incorporate the (potential) insider information in their limit prices. We also derive an equilibrium relationship between auction returns and transaction costs similar to the relations that can be found in market microstructure models of continuous markets and which are commonly applied to estimate transaction costs. The experiment provides a good environment to assess the usefulness of this method to estimate transaction costs.

JEL Classification: C92, G14, D82

Keywords: call auction, asymmetric information, experiment, market microstructure

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1. Introduction

The last ten years have seen a sharp increase in the use of call auctions in stock markets all over the world. 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. On a practical level, this renaissance has been made possible by progress in information technology which enables the gathering of huge amounts of orders and processing them into a transaction price at great speed. On a theoretical level, the most prominent advantage of the call auction is the common belief that periodic call auctions are better suited to aggregate asymmetric information than continuous markets. As a result, call auctions are thought to be most useful in times of market stress, such as the beginning or end of a trading day, or the reopening of trade after a trading halt during a continuous trading session. Call auctions are also widely used for infrequently traded stocks for which continuous trading is not sustainable. At Euronext Paris, e.g., one third of the stocks listed in 2005 traded only in call auctions.

Abstracting from many minor differences in the implementation, there are two basic kinds of call auctions: A call auction can be run by a market maker who has control over the order book and the transaction price, or it can be automated. Historically, the former is more prevalent in the US, whereas the latter is found on many European stock exchanges. However, with the emergence of purely electronic trading platforms or networks the unmediated call auction has gained new attention. Although the algorithms used to determine auction prices in unmediated call auctions may differ in many details across exchanges, they all share the following properties: Given the orders in the order book, they maximise executable trading volume and minimise surplus. This implies that all limit orders with a more competitive limit price than the auction price must execute and all those limit orders with less competitive limit prices will not execute. If there is

an interval of prices that satisfy these conditions, the auction price equals the upper end of that interval when there is excess demand for the stock and the lower end when there is excess supply of the stock. This rule is adopted by the Xetra trading system and Euronext, as the following two quotes show.

> "Should this process determine more than one limit with the highest executable order volume and the lowest surplus for the determination of the auction price, the surplus is referred to for further price determination. The auction price is stipulated according to the highest limit if the surplus for all limits is on the buy side (surplus of demand) [...]. The auction price is stipulated according to the lowest limit if the surplus for all limits is on the sell side (surplus of offerings) [...]."

Xetra – Market Model Stock Trading

> "The auction price is the price with the maximum executable volume. Additionally the minimum surplus, the market surplus side and, if necessary, the reference price are taken into account when establishing the auction price."

EURONEXT CASH MARKETS TRADING MANUAL

While the performance of the unmediated call auction in the presence of symmetrically dispersed information is well established (see, e.g., Madhavan (1992)), the effect of insider information on the performance of the call auction is less clear. Kyle (1985) shows that competitive market makers incorporate asymmetric information in transaction prices to ensure non-negative expected profits. Exogenous noise traders, however, incur expected losses in Kyle's model. Brünner (2008) shows that in the absence of market makers, insider information is incorporated in the liquidity traders' limit prices and thus translates into transaction prices.

Schnitzlein (1996) tests the prediction of Kyle (1985) for the call auction in an experimental setting and finds that dealers earn expected profits while noise

traders lose. This suggests that market makers incorporate the information available only to an insider into their quotes. Experimental evidence on unmediated call auctions is relatively scarce.

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 an unstationary 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. The question we address here is whether this result still prevails when the number of insiders is low and they are not evenly distributed between buyers and sellers.

To shed light on this important issue, we construct an environment in which a single insider can hide her order while, at the same time, the uninformed traders can insure themselves against losses against the insider by adjusting their limit prices.

The remainder of the paper is organised as follows. In section 2, we present a model of a call auction market and derive the equilibrium predictions. Section 3 describes the experimental design and procedures. Section 4 presents the results and section 5 concludes.

2. The model

We formalise a typical call auction as follows. There is a single period lived asset with random terminal payoff x. The trading environment includes $2\,m+1$ risk neutral traders. The m buyers have a higher valuation of the asset, $x+k$, while m 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.[1] The remaining trader is a potential insider and belongs to the group of buyers or to the group of sellers with equal probabilities. In addition, with probability λ the potential insider receives a binary signal indicating a high (h) or low (l) realisation of x. It is natural to assume that the information content of the potential 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 $x + k$ ($x - k$) and observes a low (high) signal would want to sell (buy) the asset in equilibrium. This is ensured by the following condition:

Condition 1. The informational advantage of the insider exceeds the difference in valuation: $(1 - \lambda)[E(x|h) - E(x)] \geq 2\,k$ and $(1 - \lambda)[E(x) - E(x|l)] \geq 2\,k$.

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.[2]

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 κ 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

[1] This difference in valuation $2\,k$ represents individual portfolio considerations or tax brackets.

[2] All the experiments in the previous section, like Friedman (1993), Theissen (2000) and Pouget (2007), also restrict their attention to limit orders.

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[3], 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 behaviour 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 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.

Proposition 1. *Under Condition 1, the following strategies constitute a Bayesian equilibrium for this call auction game:*

- *The m buyers set their limit prices to $b^* = \lambda E(x|h) + (1-\lambda)E(x) + k$,*
- *sellers set their limit prices to $s^* = \lambda E(x|l) + (1-\lambda)E(x) - k$.*
- *As long as the potential insider does not receive a signal, she behaves like the group she is assigned to. If the insider observes a high (low) signal, she enters a buy (sell) order with a limit price above (below) that of uninformed traders.*

Proof. A typical buyer j's expected utility, given that all others players play the equilibrium strategies, is

$$\begin{aligned} Eu_j(b_j) &= \frac{1}{2}\big[(\lambda E(x|h) + (1-\lambda)E(x) + k - b^*)1_{\{b_j > b^*\}} \\ &+ \frac{m-1}{m}(\lambda E(x|h) + (1-\lambda)E(x) + k - b^*)1_{\{b_j = b^*\}}\big] \\ &+ \frac{1}{2}\big(\lambda E(x|l) + (1-\lambda)E(x) + k - s^*\big)1_{\{b_j \geq s^*\}}. \end{aligned}$$

[3]For example EURONEXT and Xetra, as the quotations in the introduction demonstrate.

Plugging in the equilibrium strategies, we get $Eu_j(b_j) = k \cdot 1_{\{b_j \geq s^*\}}$, where $1_{\{A\}}$ is an indicator function that equals one, when statement A is true and 0, otherwise. Since $b^* > s^*, b_j = b^*$ is in the set of best responses when all other traders play the Bayesian equilibrium.

A similar argument holds for all uninformed sellers. It is easy to check that, given these strategies, an insider will always buy when she observes a high signal, if $(1-\lambda)[E(x|h) - E(x)] \geq 2k$, and the insider will always sell when she observes a low signal, if $(1-\lambda)[E(x) - E(x|l)] \geq 2k$ holds. □

Note that in this game there are many equilibria. Consider, e.g., a situation where buyers are only willing to pay 0 and sellers demand a price above $E(x|h)$. This is an equilibrium where no trade takes places. We argue that the equilibrium limit prices b^* and s^* given in Proposition 1 are useful benchmarks in that there are no equilibria where m units are traded and one or more sellers ask for more than s^* or one or more buyers bid less than b^*.

Corollary 1. *The equilibrium defined in Proposition 1 has the following properties:*

(i) *m assets are sold to the buyers by the sellers at a price of b^* if there are more buyers than sellers, and at a price of s^* if there are more sellers than buyers.*

(ii) *The limit prices of buyers increase and the limit prices of sellers decrease as the probability of inside information λ increases.*

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

TABLE 1. Dividends

State:	S (25%)	D (50%)	G (25%)
Type A	20	260	500
Type B	-20	220	460

$k = 20$ 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 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 λ, 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 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[4], the probabilities $P(x = G|\text{"not Z"}) = P(x = D|\text{"not Z"}) = 1/2$, 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. Therefore,

[4]This situation is quite similar to the Monty Hall problem (see Kluger and Wyatt (2004)).

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.

Note that the information structure differs from the theoretical model above in that a participant knows for sure that she is an insider only when she receives a signal. Trader i's conditional probability that inside information is in the market, given that trader i did not receive a signal, is $\lambda' = \frac{6\lambda}{7-\lambda}$. Altogether, these chosen parameter values satisfy Condition 1, where λ is replaced by λ'.

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 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 students of mathematics or economics at the University of Jena. Around 30 subjects

TABLE 2. Equilibrium limit prices

	NO	LOW	HIGH
b^*	260	296	336
s^*	220	184	144

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 subjects 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.[5] 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.[6] Thus, we have six independent observations for any treatment.

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

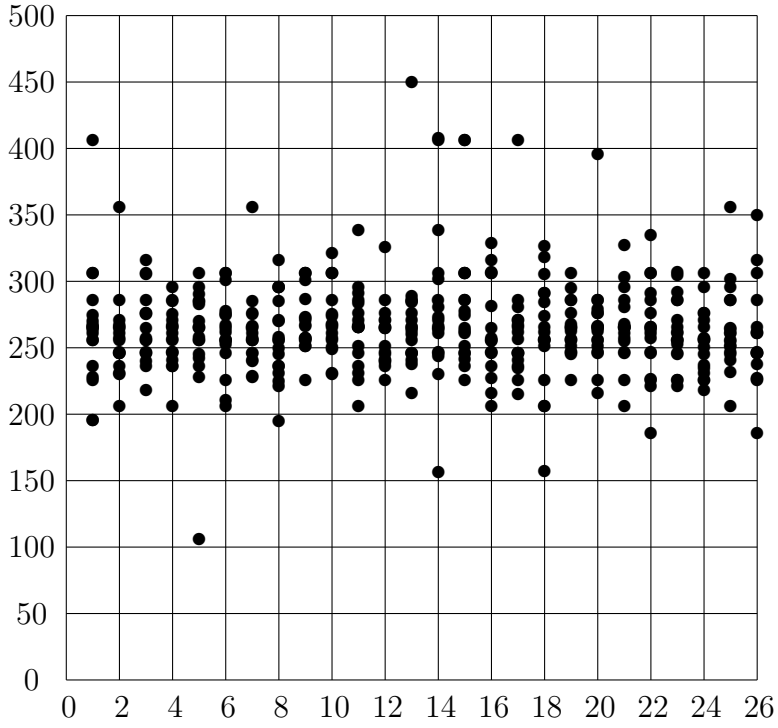
From the equilibrium derived in section 2, together with the parameter values chosen for the experiment, we obtain that, under risk neutrality, buyers bid at least $b^* = 260 + \lambda' 120$ and sellers ask for at least $s^* = 220 - \lambda' 120$. For the three treatments this results in the equilibrium prices given in Table 2.

Based on these equilibrium predictions, we form the following hypotheses:

[5]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.

[6]The participants were not informed in advance how many auctions were played.

FIGURE 1. Evolution of auction prices over periods



Hypothesis 1. Irrespective of λ, the average price is 240.

Hypothesis 2. Due to noise in participants' behaviour, we do not expect three assets to be traded in every single auction. An increase in the spread between b^* and s^*, however, makes the auction algorithm more robust against individual deviations from equilibrium predictions. Thus, the quantity traded in an auction increases with λ.

Hypothesis 3. Transaction costs, which contain both a difference in valuation and an asymmetric information component, can be inferred by regressing transaction returns on trade indicators.

The results of the experiment are discussed in three parts. First, we describe the summary statistics of call auction prices. Second, we analyse trading volume. To gain a better understanding of the results on the auction level we also analyse the individual bidding behaviour. In the third and last part, we show how transaction costs can be estimated using the call auction data.

TABLE 3. Summary statistics of average auction prices

	All	NO	LOW	HIGH
Mean	258.28	263.92	259.72	251.18
Median	254.63	266.33	252.67	251.09
Maximum	312.77	272.46	312.77	263.46
Minimum	232.38	252.02	232.38	237.62
Std. dev.	17.62	8.94	27.7	10.34
Observations	18	6	6	6

4.1. **Call auction prices.** From our experimental sessions we obtain data for 468 auctions: 18 markets × 26 periods. Figure 1 shows the resulting auction prices by periods.

Most auction prices are in the range of 200 and 320 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.

Table 3 presents average auction prices for the 18 markets. The mean of these average auction prices is 258.28 ECU, i.e. well above the predicted 240 ECU. A t-test shows that this difference is significant (t-statistic: 4.4). Thus, Hypothesis 1 has to be rejected.

While both the means and the medians of 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.

Result 1. (Average prices) Subjects overvalue the asset. Average auction prices are significantly above 240.

4.2. **Trading volume.** Trading volume data for the three different treatments and all treatments together are summarised in Table 4. In all three treatments average trading volumes are below the predicted three units. But the auctions

TABLE 4. Summary statistics of trading volumes

	All	NO	LOW	HIGH
Mean	2.1496	2.077	2.0256	2.3462
Median	2	2	2	2
Maximum	3	3	3	3
Minimum	0	0	0	1
Std. dev.	0.7264	0.7832	0.7177	0.6783
Observations	468	156	156	156

in the HIGH treatment traded, on average, 0.3 shares more than auctions in the other two treatments. 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. These results are in accordance with Hypothesis 2. However, it remains to be seen whether this increase in volume is in fact the result of a widening of the spread between limit buy and limit sell prices.

Before we turn to analysing whether limit prices are in accordance with our predictions, it is important to note that the participants' decisions were twofold. First, participants had to determine the type of their limit order, limit buy or limit sell order, then they had to choose the corresponding limit price. We therefore start by analysing the type of order chosen by the participants.

In equilibrium uninformed type A traders, whose valuation of the asset is above the average true value, place a limit buy order, and uninformed type B traders, who value the asset below the average true value, choose a limit sell order. Insiders should follow the signal they receive irrespective of their type, i.e., they should

TABLE 5. Order types in accordance with predictions (in %)

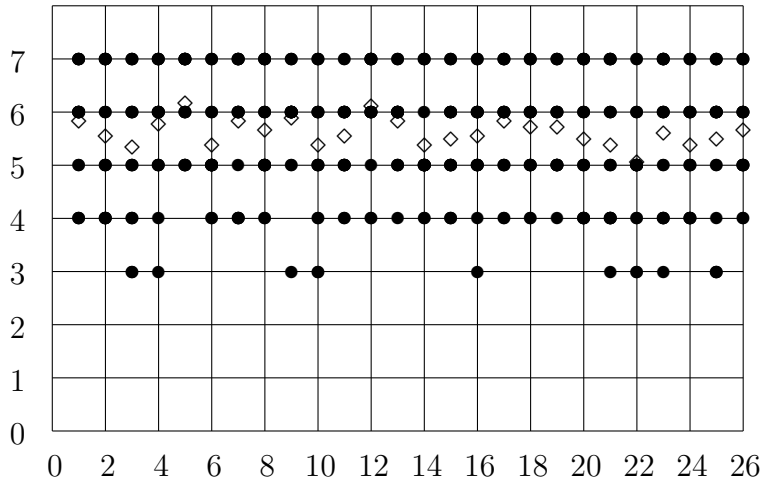
	NO	LOW	HIGH
Total	79.49	76.92	84.52
Uninformed	79.49	76.24	83.62
type A	84.6	82.43	87.86
type B	74.39	70.04	79.39
Insider	-	88.74	93.41

place a limit buy order if they receive a good signal and a limit sell order if they observe a bad one. We see, however, that roughly one fifth of the orders in our experiment are not of the predicted order type (Table 5). Especially uninformed type B traders who were supposed to place limit sell orders chose limit buy orders with probability 20 to 30%. The group of traders that acted closest to the predictions were the insiders; they followed their signal in around 90% of the auctions.

Figure 2 shows the number of traders per auction that chose the predicted type of order. Period averages are indicated by white diamonds. In all periods at least one of the 18 markets had all seven subjects choosing the predicted order type. The lowest number of predicted order decisions was 3. Looking at the period averages, there is no indication that subjects learned to choose the predicted type of orders over the trading periods.

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 irrational to deviate from the predicted equilibrium behaviour. There exist beliefs that rationalize the decision by a type A trader to place a limit sell order. Here is an example for the NO treatment:

FIGURE 2. Number of traders per auction choosing the predicted type of order by periods. (Period averages are denoted by ⋄.)



Suppose the trader believes that the other two or three type A traders choose limit buy orders, one type B trader places a limit buy order and the remaining two or three type B traders choose a limit sell order. Further she believes that limit buy prices are all 280 and all limit sell prices are 245. Since her own valuation is 260 her maximum limit buy price if she submits a limit buy order is 260 and she will not trade and receive payoff zero. If she submits a limit sell order with limit price 244 she will sell the asset and receive the price 244 or 280 with equal probabilities. Her payoff is then $(244+280)/2-260 > 0$. Thus, given these beliefs it is optimal for her to choose the limit sell order.

Note that these beliefs are not unreasonable: For the NO treatment we find across all auctions that 25% of type B traders choose a limit buy order, average limit buy prices are 277 and average limit sell prices are 241. Similarly, we can construct beliefs that rationalize the decision of an insider observing a high signal 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 our NO treatment the realized gains from trade are on average 51% of the full extraction level. Thus, despite deviations from equilibrium strategies the call auction performs reasonably well.

TABLE 6. Average limit prices of non-insiders. Standard deviations in parentheses.

	NO	LOW	HIGH
Limit buy price	276.67	267.62	262.30
	(47.77)	(49.21)	(33.84)
Limit sell price	240.75	229.30	226.92
	(35.39)	(52.10)	(38.63)
Difference	35.92	38.32	35.39

For the analysis of limit prices we consider only limit orders of the predicted order type. Those order placement decisions that already deviated in the type of order were based on a different kind of reasoning as the one we employed when deriving our equilibrium predictions, and consequently we can say nothing about the limit prices of these orders. Table 6 presents summary statistics of limit buy and limit sell prices of uninformed traders. Comparing Table 6 with Table 2, we observe an average overvaluation of roughly 20 ECU in the NO treatment. Both limit buy and limit sell orders decrease as the probability of an informed trade increases.

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 (2006)) 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.

The overvaluation of the asset vanishes as the probability that one trader receives a signal increases. The spread between limit buy and limit sell prices,

however, remains constant. This is in contrast to Hypothesis 2. The increase in trading volume in the HIGH treatment is not the result of a larger spread between limit buy and limit sell prices. It rather seems to be attributable to both a reduction in noise of the type of order chosen and lower dispersion of limit buy prices.

Result 2. (Insider increases volume) A high probability of insider participation leads to a higher trading volume. This increase in trading volume is not due to a wider spread between limit buy and limit sell prices as in Hypothesis 2; it results from a reduction in noise in subjects' behaviour.

4.3. **Measuring transaction costs.** Following the literature, we define transaction costs in a call market as the price impact of variations in order flow (see, e.g., Madhavan (1996) and Kehr, Krahnen, and Theissen (2001)). In our theoretical model, this means that transaction costs can be calculated as the difference between the auction price when there are more buy orders than sell orders, and the auction price when there are more sell orders than buy orders, or $b^* - s^* = 2\,k + \lambda(E(x|h) - E(x|l))$. So just as in continuous markets (see, e.g., Handa, Schwartz, and Tiwari (2003)), transaction costs arise due to differences in valuation ($2\,k$) and asymmetric information ($\lambda(E(x|h) - E(x|l))$).

In order to estimate transaction costs, we define the indicator variable q_{it} to be 1 if there are more buy orders than sell orders in the t-th auction of market i, and 0, otherwise. Noting that for the parameter values chosen for the experiment $E(x|h) - E(x) = E(x) - E(x|l) = 120$, we get the following predicted relationship

$$p_{it} - p_{it-1} = (20 + \lambda' 120)(q_{it} - q_{it-1}). \tag{1}$$

This equation is interesting because it stresses the connection to the transaction costs literature for continuous markets. It shows, e.g., that transaction costs can be inferred from the serial covariance of returns, as proposed by Roll (1984). But the equation also lends itself to direct estimation using our experimental data since by using first differences of auction prices, it automatically controls

TABLE 7. Estimated transaction costs

Expl. variable	Coefficient	Std. error	t-statistic	p-value
Constant	0.0270	0.9768	0.0276	0.9780
$q_{it} - q_{it-1}$	18.4598	2.6241	7.0346	0.0000
$LOW_i(q_{it} - q_{it-1})$	3.7926	3.4006	1.1153	0.2654
$HIGH_i(q_{it} - q_{it-1})$	-3.8342	2.9776	-11.2877	0.1986
AR(1)	-0.4318	0.0662	-6.5255	0.0000
$R^2 = 0.5072$				

for different average valuations of the asset across markets. We estimate this relation using the following regression model:

$$\begin{aligned} p_{it} - p_{it-1} = \beta_0 + \beta_1(q_{it} - q_{it-1}) \quad &+ \quad \beta_2\, LOW_i(q_{it} - q_{it-1}) \\ &+ \beta_3\, HIGH_i(q_{it} - q_{it-1}) + \varepsilon_{it}, \\ \varepsilon_{it} = \rho\, \varepsilon_{it-1} + u_{it}, \quad \text{where} \quad u_{it} \;\text{ is i.i.d.} \quad &\text{and} \quad t = 2, ..., 26\,,\ i = 1, ..., 18\,. \end{aligned}$$

LOW_i and $HIGH_i$ are dummy variables that are equal to one if market i belongs to the NO or HIGH treatment, respectively. The coefficients predicted by the equilibrium relationship in equation (1) are $\beta_0 = 0, \beta_1 = 20, \beta_2 = 36$ and $\beta_3 = 76$. The results of this regression are presented in Table 7. We see that the estimate of the difference in valuation component, k, is very precise with $\hat{\beta}_1 = 18.5$ ECU. The asymmetric information component of transaction costs, however, is not reflected in returns at all. As on the individual level, we observe a small increase in the spread for a low probability of inside information, but this tendency is not significant and vanishes completely for a high probability of inside information. The significantly negative AR(1) term suggests that participants overcorrected mistakes from the previous auction. Overall, these regression results mirror the findings of the previous two parts, namely that (i) the differences in valuations work reasonably well to induce trading, (ii) the possibility of inside information is not reflected in limit prices and hence auction prices, and (iii) with almost 50%

of the variation in auction returns that cannot be explained by the theoretical model, there is considerable noise in the auction outcomes.

Result 3. (Inferring transaction costs from auction prices) The theoretical model can be used to estimate transaction costs using only auction prices and information on the long side of the market. Differences in valuation are estimated very accurately. Estimated asymmetric information costs are zero, reflecting the fact that subjects fail to incorporate potential inside information in their limit prices.

5. Discussion and conclusions

The unmediated call auction is a highly decentralised trading institution that is successful in aggregating dispersed information. But whether a call auction also performs well in terms of incorporating information by a single informed trader, is an open question. We address this question by presenting a model of a simple call auction game. In equilibrium uninformed traders' limit prices efficiently reflect potential information of the insider. Our experimental tests of the model predictions show that uninformed traders do not efficiently adjust their limit prices when the possibility of an inside trade is introduced. Yet, introducing an insider to the market improves the market performance by increasing trading volume. This increase in the number of trades can be attributed to reduced noise in decision making. In fact, the experimental results that fit the theoretical predictions in the absence of an insider most closely, are the results for the treatment with a high probability of an insider.

One reason why subjects fail to choose equilibrium limit buy prices is that the call auction algorithm makes it very 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.

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. 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.

An interesting feature of our model is that it implies a relationship between returns and transaction costs that is similar to the relationship market microstructure models found for continuous markets, and which is widely used to estimate transaction costs.[7] In this light, our experiment can be understood as a test of the common procedure to estimate transaction costs by regressing returns on trade indicators. In the controlled environment of an experimental laboratory, we can compare our estimates with the chosen parameter values. We find that the regression yields a fairly good fit. Especially the difference in valuation component can be estimated very precisely.

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[7] See, e.g., Glosten and Harris (1988), Huang and Stoll (1997) and Madhavan, Richardson, and Roomans (1997).

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