

Brünner, Tobias; Levinsky, Rene

Conference Paper

Price discovery and gains from trade in asset markets with insider trading

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020: Gender Economics

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Brünner, Tobias; Levinsky, Rene (2020) : Price discovery and gains from trade in asset markets with insider trading, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2020: Gender Economics, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/224618>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Price discovery and gains from trade in asset markets with insider trading

Tobias Brüner¹

*Lincoln International Business School,
Brayford Pool, Lincoln, LN6 7TS, UK*

René Levínský²

*Center for Economic Research and Graduate Education – Economics Institute,
Politických vězňů 936/7, 110 00 Praha, Czech Republic*

Abstract: The present study contributes to the ongoing debate on possible costs and benefits of insider trading. We present a novel call auction model with insider information. Our model predicts that more insider information improves informational efficiency of prices, but this comes at the expense of reduced gains from trade. The model further implies that in the presence of insider information the call auction performs worse than continuous double auction. Testing these hypotheses in the lab we find that insider information increases informational efficiency of call auction prices but does not decrease the realized gains from trade. Contrary to the theoretical prediction, the call auction does not perform worse than the continuous double auction. In fact, when the probability of insider information is high, the call auction has the most informative prices and highest realized gains from trade. Our experiment provides new evidence, from markets with very asymmetrically dispersed information, that lends support to the decision by many stock exchanges to use call auctions when information asymmetries are severe and the need for accurate prices is large, e.g., at the open or close of the trading day.

JEL Classification: C92, G14, D82

Keywords: call market, call auction, double auction, asymmetric information, experiment, informational efficiency

¹Corr. author: tbruenner@lincoln.ac.uk, phone: +44-1522835645.

²Research supported by the grant GAČR 17-19672S.

1. INTRODUCTION

There is an ongoing debate whether trading by better informed parties is beneficial for market quality or not. The most important argument in favor 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 realized gains from trade.

This paper studies the impact of insider information on price discovery and realized gains from trade in call auctions and continuous double auctions. The call auction is of particular interest since many stock exchanges introduced call auctions to obtain informative prices and facilitate trade in times when information is very asymmetrically distributed, such as at the opening of the trading day, or when the accuracy of prices is especially important, such as at the market close.¹ More recently, the call auction has attracted additional attention as a possible remedy against some of the problems of high-frequency trading (see, e.g., Budish et al., 2015). To put our findings on the impact of insider information on price discovery and realized gains from trade in call auctions into perspective, we will also study continuous double auctions.

Understanding the effect of information asymmetries on price discovery and liquidity is important for two reasons. Firstly, any stock exchange has to tailor trading institutions to generate the most accurate prices possible and to keep liquidity high and trading costs low at the same time, and this interest is pronounced by the increased competition over order flow and listings between stock exchanges around the world. 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.

We begin our analysis by introducing a call auction model with insider information. Our 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

¹The 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.

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 next compare the theoretical results from our call auction model with the results of the continuous double auction, for which we employ the efficient market hypothesis as solution concept. The theoretical analysis predicts that the informational and allocational efficiency are lower in the call auction than in the continuous double auction.

Finally, we implement the call auction and continuous double auction in the laboratory and vary the degree of information asymmetry. We find that in call auctions 50% of the gains from trade are realized 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. Moreover, insider information increases informational efficiency of call auction prices but does not decrease the realized gains from trade. Contrary to the theoretical prediction, the call auction does not perform worse than the continuous double auction. In fact, when the probability of insider information is high, the call auction has the most informative prices and highest realized gains from trade. Our experiment provides new evidence, from markets with very asymmetrically dispersed information, that lends support to the decision by many stock exchanges to use call auctions when information asymmetries are severe and the need for accurate prices is large, e.g., at the open or close of the trading day.

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) use a private value design together with cycling demand and/or supply curves and Plott and Pogorelskiy (2017) add structural shifts in the market parameters. These studies find that the call auction performs well in terms of allocational efficiency even in non-stationary environments. Comparing the call auction with a continuous double auction in a private value design, Friedman (1993) 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 as efficient in aggregating dispersed information as the continuous double auction. In Palan et al. (2019), the continuous double auction aggregates symmetrically dispersed information better than the call auction.

To capture insider trading, 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 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 realized 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. CALL AUCTION

2.1. Symmetric information case. We formalize 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, $x - k$.² 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 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, traders 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 maximized 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 to pay. Conversely, for $\kappa = 0$ buyers will have no incentive to misrepresent while sellers will demand more

²This difference in valuation $2k$ represents individual portfolio considerations or tax brackets.

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

than their true valuations. Following many real world call auction algorithms⁴, 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, buyers (sellers) with limit prices above (below) 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.

Before we describe the equilibrium of the model, we want to introduce the notion of allocational efficiency which 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 realized, 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 $\underline{n} = \min\{n_B, n_S\}$. 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 \underline{n} assets are traded from sellers to buyers; the maximum gains from trade are $2k\underline{n}$.

To measure allocational efficiency in our experimental asset markets, we will use $AE = (\text{realized gains from trade}) / (\text{maximum gains from trade})$.

Proposition 1 describes the equilibrium for the symmetric information case:

Proposition 1. *For the symmetric information case there exists a symmetric BNE 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 $s^* = E(x) - k$.*

⁴For example EURONEXT and Xetra.

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 to increase the 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 BNE 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 places.

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 realized 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 which considers exclusively the profitability of unilateral deviations is too weak. However, there are several commonly used refinements such as Pareto (weakly) undominated Nash equilibria, Strong Nash equilibria (Aumann, 1959) and coalition-proof Nash equilibria (Bernheim et al., 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., \underline{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.*

2.2. Asymmetric information case. In this part of the paper we extend the model to include situations in which some of the agents, inherently still buyers or sellers, will receive (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 particularly interesting when there are enough informed traders (acting against their type) that could possibly overturn excess demand to excess supply or the other way around. (Otherwise the situation is identical to the model without insider.) To capture this we will take the simplest possible model: m traders will assume the buyer role, m traders will assume the seller role and the last trader (inherently buyer or seller) becomes an insider with probability $\lambda > 0$. The insider receives a binary signal indicating a high (h) or low (l) realization of x . Ex ante, i.e., before the realization 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 valuation of the asset.

To measure informational efficiency in a series of experimental auctions indexed by $t = 1, \dots, T$ we will use the root mean squared error (RMSE) of prices:

$$(1) \quad RMSE = \sqrt{\sum_{t=1}^T (p_t - x_t)^2 / T},$$

where p_t is the auction price in auction t and x_t equals the true value of the asset in period t .

Proposition 1 describes the equilibrium for the model with an insider:

Proposition 2. *With a positive probability of insider information there is no symmetric BNE in pure strategies. The equilibrium in mixed strategies for this call auction game is given by the following strategies:⁵*

⁵The expressions for \underline{b} , \bar{b} , \underline{s} and \bar{s} and the distributions $F(b)$ and $G(s)$ are derived in the appendix.

- *The m uninformed buyers choose their limit prices from the support $[\underline{b}, \bar{b}]$ according to the distribution $F(b)$.*
- *The m uninformed sellers choose their limit prices from the support $[\underline{s}, \bar{s}]$ 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 \underline{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., $\underline{b} > E(x) + k$. Similarly, the limit sell prices in the asymmetric information case are lower than the limit sell prices in the symmetric information case: $\bar{s} < E(x) - k$.

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

- (i) *Since $\bar{s} < \underline{b}$, m assets are traded.*
- (ii) *The 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 buy orders the equilibrium price p^- is the second-highest limit sell price. Thus, $p^+ \in [\underline{b}, \bar{b}]$ and $p^- \in [\underline{s}, \bar{s}]$.*
- (iv) *The support of limit buy prices $[\underline{b}, \bar{b}]$ shifts upwards as λ increases and the support of limit sell prices $[\underline{s}, \bar{s}]$ shifts downwards as λ 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 good signal and a sell order when she observes a bad signal.

Thus, whenever a buyer observes a bad signal she sells her share to another buyer. Similarly, a seller who observes a good signal buys a share from another seller. Therefore, not all gains from trade are realized in the BNE.

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 realized 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

Subjects in our experimental asset markets traded a risky asset that paid different dividends depending on the state of nature. In state S_A , which occurred with probability 50%, the asset paid 240 experimental currency units (ECU). In the good state S_G , the asset paid 480 ECU, and in the bad state S_B , it paid 0 ECU. States S_G and S_B both occurred with probability 25%. Traders' payoffs also depended on their type. Type A traders had a premium of $k = 20$ ECU, type B traders a discount $k = 20$ ECU. In each market, there were either 3 traders of type A and 4 of type B, or 4 of type A and 3 of type B. Both situations were equally likely and types were newly assigned to the subjects before each market. 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 NO treatment, subjects knew only the dividend structure for the two types of traders as displayed in Table 1 and their own type. This treatment corresponds to the symmetric information case. The other two treatments implemented the asymmetric information scenario. In each period one of the seven traders received a binary signal with

TABLE 1. Dividend payments to traders of type A and B conditional on the realized state: S_B , S_A or S_G . The probability of each state is given in parentheses.

State:	S_B (25%)	S_A (50%)	S_G (25%)
Type A	20	260	500
Type B	-20	220	460

probability λ , where $\lambda = 1/3$ in the LOW treatment and $\lambda = 2/3$ in the HIGH treatment. The signal was determined in the following way: If the true state was S_G , the signal was “not S_B ”; if the true state was S_B , the signal was “not S_G ”; if the true state was S_A , the signal was either “not S_B ” or “not S_G ” with equal probabilities.

Since it is well known that people find it difficult to work out conditional probabilities⁶, the probabilities $P(S_G|\text{“not } S_B\text{”}) = P(S_A|\text{“not } S_B\text{”}) = 50\%$, and so on, were explained in the instructions, and the subjects 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 realizations of the states of nature, the random draw was done just for the six call auction markets in the NO treatment and replicated for the markets in the other treatments (as, e.g., in Cason and Friedman, 1997). This allows for pairwise comparisons across markets with different probability of insider information.

3.2. The trading mechanisms. At the beginning of each market, every trader was endowed with one unit of the asset and 500 ECU working capital. The subjects could, however, only generate profit from trading, i.e., by selling the asset at a price higher than the realized dividend or by buying the asset for a price lower than the realized dividend, since the working capital of 500 ECU had to be paid back at the end of each market.

We consider two different trading mechanisms. In the first six sessions, markets were organized as call auctions. In sessions 7–12 markets were organized as continuous double auctions. For both trading mechanisms we ran 2 sessions under the NO treatment, 2 sessions under the LOW treatment and 2 sessions under the HIGH treatment.

3.2.1. The call auction. At the beginning of each call auction each trader first chose whether to place a limit buy or limit sell order and then specified the limit price. Each trader could enter only

⁶This situation is quite similar to the Monty Hall problem (Kluger and Wyatt, 2004).

one order per auction, and order size was standardized to one unit. Limit prices were restricted to integers between 0 and 500. When entering their orders, traders were unaware of other traders' orders. Once all traders had submitted their orders to the order book, the market was cleared. If there were several identical orders and not all of them could be executed, those orders that were entered earliest were given priority. After each auction the state of nature was revealed and traders saw all orders, the auction price, the numbers of shares traded and their own period profit and accumulated profits on their trading screens.

3.2.2. The continuous double auction. In the continuous double auction a period lasted for 90 seconds during which subjects could enter limit buy orders and limit sell orders or accept a limit order entered by another subject. All open limit orders and the last transaction price were displayed to all subjects on their trading screens. A trader could only buy a unit of the asset if she had sufficient ECU. Similarly, a trader could only sell a unit of the asset if she owned at least one unit, i.e., short-selling is not possible. At the end of the 90 second period, the state of nature was revealed and traders saw their own period profits and accumulated profits on their trading screens.

3.3. Experimental procedures. The 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 were invited to each of our 12 sessions. Having read the instructions, subjects 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 a good understanding of the market environment participate in the experiment, only those 21 subjects who answered all questions with the fewest mistakes participated in the analyzed part of the experiment; the remaining subjects received a fixed fee of 5 Euro and were asked to leave.⁷ The 21 subjects in a particular session were grouped into 3 markets. Each market lasted for 26 periods, so that our sample consists of $12 \times 3 \times 26 = 936$ auctions of altogether 36 markets.⁸ Thus, we have six independent observations for each treatment.

A subject's final payoff was the sum of all her period profits converted into Euro at the rate of 1 Euro = 300 ECU. Including instructions and test auctions, the sessions lasted for about 100

⁷This introductory part of each session, where subjects read the instructions, took part in four test auctions and answered the questions, lasted for about 40 minutes.

⁸Subjects were not informed in advance how many auctions were played.

TABLE 2. Predictions of the BNE and the strong-form Efficient Market Hypothesis.

	Avg Price	Volume	Avg AE	Avg RMSE
Call auction (BNE):				
NO	240	3	1	176.2
LOW	240	3	0.94	168.6
HIGH	240	3	0.87	141.8
Continuous double auction (EMH):				
NO	240	≥ 3	1	176.2
LOW	240	≥ 3	1	156.7
HIGH	240	≥ 3	1	137.0

minutes, and average earnings were around 13 Euro with a minimum of 7.80 and a maximum of 17.20 Euro.

3.4. Hypotheses. To formulate hypotheses for the experimental call auction markets, we use the BNE described in the preceding section. For the continuous double auction we use the strong-form Efficient Market Hypothesis (EMH) as the theoretical benchmark. The EMH states that a “capital market is said to be efficient if it fully and correctly reflects all relevant information in determining security prices” (Malkiel, 1992). In the strong-form EMH the relevant information set includes all information known to any market participant, including insider information.

The theoretical benchmarks for our key performance measures (average price, average volume, allocational efficiency and informational efficiency) for the two trading institutions are summarized in Table 2. From these theoretical predictions we derive the following hypotheses:

Hypothesis 1. In the call auction allocational efficiency is decreasing in the probability of insider information.

Hypothesis 2. In the call auction informational efficiency is increasing in the probability of insider information.

Hypothesis 3. Allocational and informational efficiency are lower in the call auction than in the continuous double auction.

TABLE 3. Summary statistics of auction outcomes. Allocational efficiency (AE) refers to the realized gains from trade relative to the maximum gains from trade. Informational efficiency is measured by the square root of the mean squared deviations between the auction price and the true value of the asset (RMSE).

	Markets	Avg Price	Avg Volume	Avg AE	Avg RMSE
Call auction:					
NO	6	263.9	2.08	0.51	180.6
LOW	6	259.7	2.03	0.43	182.3
HIGH	6	251.2	2.35	0.55	173.6
All	18	258.3	2.15	0.50	178.8
Continuous double auction:					
NO	6	257.3	3.94	0.44	177.0
LOW	6	262.7	2.97	0.48	178.7
HIGH	6	257.7	4.2	0.45	177.4
All	18	259.2	3.70	0.45	177.7

4. RESULTS

The summary statistics for the experimental asset markets are presented in Table 3. We will first discuss the results for the call auction markets and, in particular, how allocational and informational efficiency change across the NO, LOW and HIGH treatments. Next, we will contrast these findings with the results for the continuous double auction markets.

4.1. Call auction. The results for the call auction markets are summarized in the first four rows of Table 3. Average prices are above the predicted average of 240. The average price decreases from 263.9 in the NO treatment to 259.7 in the LOW treatment and 251.2 in the HIGH treatment. 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 In the NO treatment four auctions failed to facilitate trade, 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

⁹The difference in average trading volume is not significant between the NO and HIGH treatment and significant between the LOW and HIGH treatment (p -value of one-sided Wilcoxon signed rank test: 0.02953).

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. To see whether the trades conducted increase welfare we have to turn to allocational efficiency.

4.1.1. *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. Note that in the efficient BNE there are no efficiency decreasing trades, but for the asymmetric information case some trades are efficiency neutral. Allocational efficiency measures the realized gains from trade relative to the maximum gains from trade. If all players played according to the equilibrium strategies, the average allocational efficiency (AE) would be 94% in the LOW treatment and 87% in the HIGH treatment (see panel B of Table 3).

Actual trading behavior yields lower allocational efficiency. Over all information treatments, 50% of the maximum gains from trade are realized in the call auction markets. The finding that only half of the maximum gains from trade are realized can be regarded as coordination failure due to multiple equilibria. In a very stylized call auction experiment that focuses on precisely this coordination problem, Biais et al. (2014) find that in 60% of auctions subjects fail to coordinate on the equilibrium that maximizes the gains from trade. The experiment that is closest to ours is Pouget (2007) which also models the call auction as a strategic game. He observes average gains from trade of around 30% of the full extraction level. Compared to these studies, our experimental call auction markets perform reasonably well, despite deviations from the efficient BNE.

Comparing the different information treatments, we find that, in contrast to the BNE, allocational efficiency does not deteriorate monotonically as the probability of insider information increases. In fact, we observe the highest allocational efficiency of 55% in the HIGH treatment, which is significantly better than in LOW treatment (p -value of one-sided Wilcoxon signed rank test: 0.01776). We, therefore, reject Hypothesis 1.

Result 1. Allocational efficiency does not decrease as the probability of insider information increases.

4.1.2. *Informational efficiency.* In the efficient BNE, limit prices incorporate some of the information 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. In the symmetric information case (NO treatment) actual informational efficiency, measured by the average RMSE, is close to the theoretical prediction (180.6 vs. 176.2, see Table 3). In contrast to the prediction, informational efficiency does not improve when going from the NO to the LOW treatment; the average RMSE increases slightly to 182.3. However, informational efficiency improves significantly in the HIGH treatment; the average RMSE of 173.6 is significantly below the corresponding number for NO treatment (p -value of one-sided Wilcoxon signed rank test: 0.01563) and LOW treatment (p -value of one-sided Wilcoxon signed rank test: 0.03125).

Result 2. An increase in the probability of insider information leads to more informative call auction prices.

4.2. Comparing the call auction with the continuous double auction. Rows 5–8 of Table 3 show the results for the continuous double auction markets, which serve as a benchmark. With an overall average of 259.2, average prices are higher than the average value of the asset, 240. In contrast to the call auction, however, average prices do not move closer to the average value as the probability of insider information increases. Although average trading volume is above 3 (except for the LOW treatment where it is slightly below), allocational efficiency is at only 45%. This implies that many trades do not improve allocational efficiency. The average RMSE for the continuous double auction markets in the NO treatment is quite close to predicted average RMSE. But contrary to the EMH the average RMSE does not decrease as the probability of insider information increases.

Comparing these results with those of the call auction, we find no significant differences across all information treatments. But focusing on the HIGH treatment, we find that the call auction is better, not worse, than the continuous double auction in terms allocational and informational efficiency. The difference is weakly significantly for allocational efficiency (p -value:0.0781) and highly significant for informational efficiency (p -value:0). We, therefore, reject Hypothesis 3.

Result 3. Allocational and informational efficiency are not lower in the call auction than in the continuous double auction.

5. INDIVIDUAL BEHAVIOR

The analysis of our experimental results rejects Hypotheses 1 and 3 and confirmed Hypothesis 2, although the improvement in informational efficiency is less than predicted. To better understand

the discrepancy between the theoretical predictions and actual behavior, this section will look at some possible explanations.

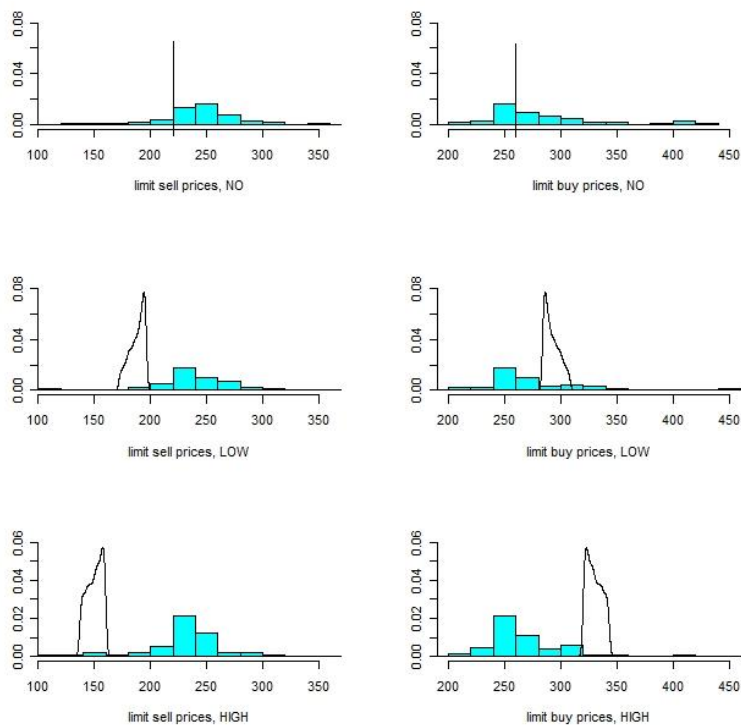
5.1. Bidding behavior in the call auction. The BNE requires that the insider buys the asset when she receives a good signal and sells when she receives a bad signal, irrespective of her type. If the insider fails to trade according to her signal, uninformed traders cannot infer anything about the asset's true value from the fact that the price is determined by a limit buy order (positive order imbalance) or a limit sell order (negative order imbalance). We, therefore, check if insiders followed the signals they received. Out of 162 auctions in which a trader received a signal the informed trader followed the signal in 149 cases. Thus, in 92% of the cases the informed traders played according to the BNE.

The analysis in subsection 4.1 implies that uninformed traders did not always trade according to their type; sometimes type A traders decided to place limit sell orders and type B traders placed limit buy orders. As a result, even if the insider always followed the signal she receives, the order imbalance might not reflect the signal, if the insider's decision is superimposed by noise in the decisions of the uninformed. To check whether the sign of the order imbalance is informative about the asset's true value, we calculate the expected value of the asset given a positive and negative order imbalance, respectively. In the LOW treatment the average value of the asset is 247.3 across all auctions with excess demand and 227.4 for all auctions with excess supply. A positive order imbalance is associated with a greater expected value of the asset, but this difference is not significant. In the HIGH treatment the average value of the asset is 268.1 across all auctions with a positive order imbalance and 197.4 for all auctions with a negative order imbalance and this difference of more than 70 ECU is highly significant (The p -value of a one-sided Mann-Whitney test is 0.0073).

Result 4. (Informativeness of the order imbalance) The sign of the order imbalance is informative about the asset's true value.

We then turn to the uninformed traders and analyze if they incorporate the information contained in the order imbalance in their limit prices. Figure 1 depicts the histograms of the uninformed

FIGURE 1. Histograms of limit prices



traders' limit sell prices (left column) and limit buy prices (right column).¹⁰ The two histograms in the first row correspond to the NO treatment. Here the BNE predicts all limit sell prices to equal 220 and all limit buy prices should be 260. A majority of actual limit prices, however, is well above these predictions for both, sell and buy, order types. The second and third row show limit prices for the LOW and HIGH treatment, respectively. Limit prices should shift outwards as the probability of insider information increases, i.e., limit sell prices should decrease and limit buy prices should increase. For the actual limit prices we do not observe such a shift in location. It rather seems that the location of the distribution stays the same but the dispersion of limit prices goes down.

¹⁰The histograms only include limit prices of traders who trade according to the type they are assigned to, i.e., all limit buy prices are from type A traders and all limit sell prices are from type B traders. But the picture looks almost identical if we include all limit prices.

To summarize, the reason for the low informational efficiency of call auction markets is not that insider information is not reflected in the order imbalance but the failure of uninformed traders to condition on the event of the insider being on the same market side as them. This is reminiscent of the winner's curse in common value auctions. In a common value auction, a bidder who wins the auction has the highest estimate of the true value of the object. Therefore this bidder's estimate is likely to be an overestimate of the object's value and the winning bidder overpays. To avoid the winner's curse, in BNE bidders make their bids conditional on the event of having the highest estimate of the object's value. Thus, common value auctions have an adverse selection component and the failure to realize this leads to too aggressive bidding and the winner's curse.

The call auction markets that we study here have an advantageous selection component, because the limit price of an uninformed trader can only be effective, i.e. determine the auction price, when the potential insider trades on the same market side. The failure to account for this advantageous selection component leads to too conservative limit prices. This is exactly what we observe in Figure 1.

5.2. Overvaluation of the asset. Analyzing the limit prices we observe another behavioral 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 experimental asset markets. The mean of these average auction prices is 258.3 for the call auction markets and 259.2 for the continuous double auction markets, i.e., well above the predicted 240. For both market institutions these differences are highly significant. (The p -value of a one-sided Wilcoxon signed rank test is 0.00003 for the call auction and 0.00013 for the continuous double auction.) While average call auction prices are lower for the LOW and HIGH treatments than for the NO treatment, they are still well above 240. This suggests that in call auctions, subjects' tendency to overvalue the asset decreases as the probability of informed traders increases. Analyzing the data of call auction markets in the NO treatment in more detail we find that both limit sell orders and limit buy orders are on 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 favorable price, there is a similarity to the second-price auction. Many experimental studies of the second-price auction find systematic overbidding (Kagel et al., 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.

5.3. Failure of EMH. The key reason why the data rejects Hypothesis 3 is that the EMH fails to predict behavior in the continuous double auction. Recall that, whereas prices in the efficient BNE only partly reveal insider information, the EMH states that the prices fully reflect all insider information. In our experiment, however, prices in the continuous double auction markets reveal no insider information at all. To highlight this, it is useful to split the continuous double auction markets into those where the insider received information and those where the insider did not receive information. When there is no insider information in the market, the EMH predicts a RMSE similar to the NO treatment (176.2), with insider information the RMSE is predicted to be much lower (120). In the experimental continuous double auction markets, there is no significant difference in the RMSEs of markets with and without insider information.

6. CONCLUSIONS

The present study contributes to the ongoing debate on possible costs and benefits of insider trading. We present a novel call auction model with insider information. Our model predicts that more insider information improves informational efficiency of prices, but this comes at the expense of reduced gains from trade. The model further implies that in the presence of insider information the call auction performs worse than continuous double auction. Testing these hypotheses in the lab we find that insider information increases informational efficiency of call auction prices but does not decrease the realized gains from trade. Contrary to the theoretical prediction, the call auction does not perform worse than the continuous double auction. In fact, when the probability of insider information is high, the call auction has the most informative prices and highest realized gains from trade. This result is consistent with Pagano and Schwartz (2003) and Pagano et al. (2013) who study the effect of the introduction of opening and closing call auctions on Euronext Paris and Nasdaq, respectively, and find that the introduction of call auctions helped to improve price efficiency.

Using a controlled laboratory experiment, we show that the call auction's good performance in terms of informational efficiency is not restricted to situations where information is symmetrically

dispersed, but also extends to situations with a single insider. Moreover, the finding that call auctions are more informationally efficient than continuous double auctions, despite the low trading volume, is also consistent with recent empirical evidence that call auctions auction prices incorporate insider information in markets that are deemed too illiquid to be organized as continuous double auctions (Brüner, 2019).

Although our experiments show that call auctions perform well under high information asymmetries, our theoretical highlights that they could do even better. One reason why uninformed traders' limit prices do not fully reflect the potential presence of an insider is that 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 for 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. However, these market design changes can lead to manipulation and other unintended consequences (see, e.g., Biais et al., 2014).

APPENDIX: DERIVATION OF THE MIXED STRATEGY EQUILIBRIUM

A buyer without a signal can face four different situations:

	situation	probability
1	$m + 1$ buyers and m sellers	$\frac{(m+1)(1-\lambda)}{2m+1-\lambda}$
2	m buyers and $m + 1$ sellers	$\frac{m(1-\lambda)}{2m+1-\lambda}$
3	m buyers, m sellers and insider buys	$\frac{m\lambda}{2m+1-\lambda}$
4	m buyers, m sellers and insider sells	$\frac{m\lambda}{2m+1-\lambda}$

(Buyers are traders who value the asset with a premium k and sellers discount the asset's value by k .) We assume that uninformed buyers play a mixed strategy $f(b)$ on the interval $[\underline{b}, \bar{b}]$ and uninformed sellers mix with density $g(s)$ on $[\underline{s}, \bar{s}]$. If a trader observes a positive signal she bids $b_I > \bar{b}$ and receiving a negative signal a trader asks for $s_I < \underline{s}$. We further assume that $\underline{b} > \bar{s}$. The expected utility of uninformed buyer j bidding $b_j \in [\underline{b}, \bar{b}]$ is (ignoring situations 2 and 4 which do

not depend on j 's bid)

$$\begin{aligned}
Eu_j(b_j) &= \frac{(m+1)(1-\lambda)}{2m+1-\lambda} \left\{ \int_{\underline{b}}^{b_j} (E(x) + k - b)m(m-1)f(b)F(b)(1-F(b))^{m-2} db \right. \\
&\quad \left. + (E(x) + k - b_j)mF(b_j)(1-F(b_j))^{m-1} \right\} \\
&+ \frac{m\lambda}{2m+1-\lambda} \left\{ \int_{\underline{b}}^{b_j} (E(x|h) + k - b)(m-1)(m-2)f(b)F(b)(1-F(b))^{m-3} db \right. \\
&\quad \left. + (E(x|h) + k - b_j)(m-1)F(b_j)(1-F(b_j))^{m-2} \right\}
\end{aligned}$$

In a mixed strategy equilibrium the first derivative of the expected utility with respect to b_j should be zero for all $b_j \in [\underline{b}, \bar{b}]$. This yields the differential equation

$$\begin{aligned}
0 &= (m+1)(1-\lambda)(1-F(b_j)) \{ (E(x) + k - b_j)f(b_j) - F(b_j) \} \\
&\quad + (m-1)\lambda \{ (E(x|h) + k - b_j)f(b_j) - F(b_j) \}.
\end{aligned}$$

with the following general solution

$$\begin{aligned}
b &= \frac{\lambda(m-1)(E(x|h) - E(x)) \log((\lambda-1)F(b)(m+1) + m+1 - 2\lambda)}{F(b)(\lambda-1)(m+1)} \\
&\quad + \frac{F(b)(m+1)(\lambda-1)(E(x) + k) - C(m+1)(\lambda-1)}{F(b)(\lambda-1)(m+1)}.
\end{aligned}$$

The constant C is chosen such that \underline{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:

$$\begin{aligned}
b &= \frac{\lambda(m-1)(E(x|h) - E(x)) \log((\lambda-1)F(b)(m+1) + m+1 - 2\lambda)}{F(b)(\lambda-1)(m+1)} \\
&\quad + E(x) + k - \frac{\lambda(m-1)(E(x|h) - E(x)) \log(m+1 - 2\lambda)}{F(b)(\lambda-1)(m+1)} \\
&= E(x) + k + \frac{\lambda(m-1)(E(x|h) - E(x))}{F(b)(\lambda-1)(m+1)} \log\left(\frac{(\lambda-1)F(b)(m+1) + m+1 - 2\lambda}{m+1 - 2\lambda}\right)
\end{aligned}$$

with upper and lower bound of the support given by

$$\begin{aligned}
\bar{b} &= E(x) + k + \frac{\lambda(m-1)(E(x|h) - E(x))}{(\lambda-1)(m+1)} \log\left(\frac{\lambda(m-1)}{m+1 - 2\lambda}\right) \\
\underline{b} &= E(x) + k + \frac{m-1}{m+1 - 2\lambda} \lambda(E(x|h) - E(x)).
\end{aligned}$$

The distribution functions $F(b)$ for $m = 3$ and $\lambda = 1/3$ and $2/3$ are given in the figures 2 and 3.

The sellers' equilibrium strategy $G(s)$ can be derived similarly.

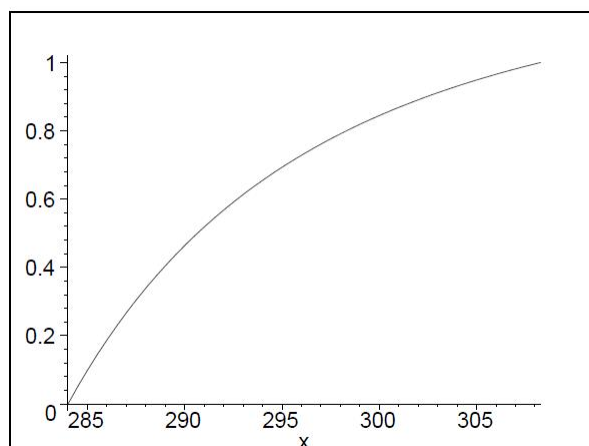


FIGURE 2. Distribution function $F(b)$ for $\lambda = 1/3$.

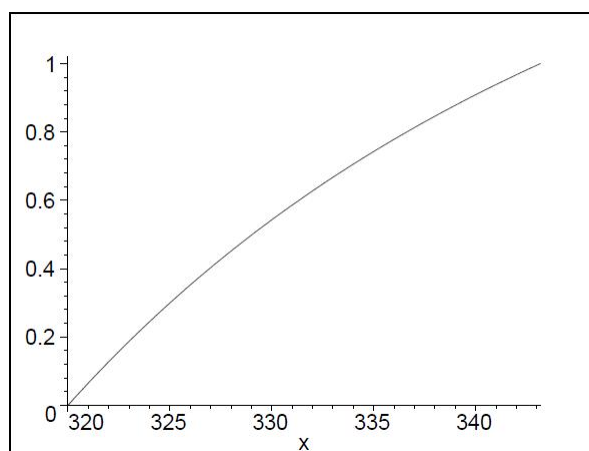


FIGURE 3. Distribution function $F(b)$ for $\lambda = 2/3$.

REFERENCES

- Amihud, Yakov and Haim Mendelson**, “Asset pricing and the bid-ask spread,” *Journal of Financial Economics*, 1986, 17, 223–249.
- Aumann, R.**, “Acceptable points in general cooperative n -person games,” in A. W. Tucker and R. D. Luce, eds., *Contributions to the Theory of Games IV*, Princeton, N.J.: Princeton University Press, 1959, pp. 287–324.
- Bernard, John C.**, “Finding and retaining the dominant strategy: The second-price, English and ‘sealed offer’ English auctions,” *Journal of Economic Behavior & Organization*, 2006, 60,

553–561.

- Bernheim, B. Douglas, Bezalel Peleg, and Michael D. Whinston**, “Coalition-Proof Nash Equilibria,” *Journal of Economic Theory*, 1987, *42*, 1–12.
- Biais, Bruno, Christophe Bisière, and Sébastien Pouget**, “Equilibrium discovery and pre-opening mechanisms in an experimental market,” *Management Science*, 2014, *60* (3), 753–769.
- Brünner, Tobias**, “Price formation in call auctions with insider information,” *Studies in Economics and Finance*, 2019, *36* (3), 408–426.
- Budish, Eric, Peter Cramton, and John Shim**, “The high-frequency trading arms race: Frequent batch auctions as a market design response,” *Quarterly Journal of Economics*, 2015, *130* (4), 1547–1621.
- Cason, Timothy N. and Daniel Friedman**, “Price formation in single call markets,” *Econometrica*, 1997, *65*, 311–345.
- Comerton-Forde, Carole and James Rydge**, “The influence of call auction algorithm rules on market efficiency,” *Journal of Financial Markets*, 2006, *9*, 199–222.
- Constantinides, George M.**, “Capital market equilibrium with transaction costs,” *Journal of Political Economy*, 1986, *94* (4), 842–862.
- Cooper, David J. and Hanming Fang**, “Understanding overbidding in second price auctions: An experimental study,” *The Economic Journal*, 2008, *118* (532), 1572–1595.
- Davis, Douglas D. and Arlington W. Williams**, “The effects of nonstationarities on performance in call markets,” *Journal of Economic Behavior & Organization*, 1997, *32* (1), 39–54.
- Diamond, Douglas W. and Robert E. Verrecchia**, “Disclosure, liquidity, and the cost of capital,” *Journal of Finance*, 1991, *46* (4), 1325–1359.
- Fischbacher, Urs**, “z-Tree: Zurich Toolbox for Ready-made Economic experiments,” *Experimental Economics*, 2007, *10* (2), 171–178.
- Friedman, Daniel**, “How trading institutions affect financial market performance: Some laboratory evidence,” *Economic Inquiry*, 1993, *31*, 410–435.
- Grossmann, Sanford and Joseph Stiglitz**, “On the impossibility of informationally efficient markets,” *American Economic Review*, 1980, *70*, 393–408.
- Kagel, John and Dan Levin**, “Independent private value auctions: Bidder behavior in first-, second-, and third price auctions with varying number of bidders,” *Economic Journal*, 1993, *103*, 868–879.

- _____, _____, and **Ronald Harstad**, “Information impact and allocation rules in auctions with affiliated private values: A laboratory study,” *Econometrica*, 1987, *55* (6), 1275–1304.
- Kagel, John H. and William Vogt**, “Buyer’s bid double auctions: Preliminary experimental results,” in Daniel Friedman and John Rust, eds., *The Double Auction Market. Institutions, Theories, and Evidence*, Addison-Wesley Reading, Massachusetts 1993, pp. 285–305.
- Kluger, Brian D. and Steve B. Wyatt**, “Are judgement errors reflected in market prices and allocations? Experimental evidence based on the Monty Hall problem,” *Journal of Finance*, 2004, *59* (3), 969–997.
- Leland, Hayne E.**, “Insider trading: Should it be prohibited?,” *Journal of Political Economy*, 1992, *100* (4), 859–887.
- Liu, Yu-Jane**, “Auction mechanisms and information structure: An experimental study of information aggregation in securities markets,” *Research in Experimental Economics*, 1996, *6*, 165–211.
- Pagano, Michael S. and Robert A. Schwartz**, “A closing call’s impact on market quality at Euronext Paris,” *Journal of Financial Economics*, 2003, *68*, 439–484.
- _____, **Lin Peng, and Robert A. Schwartz**, “A call auction’s impact on price formation and order routing: Evidence from the NASDAQ stock market,” *Journal of Financial Markets*, 2013, *16*, 331–361.
- Palan, Stefan, Jürgen Huber, and Larissa Senninger**, “Aggregation mechanisms for crowd predictions,” *Experimental Economics*, 2019.
- Plott, Charles R. and Kirill Pogorelskiy**, “Call market experiments: Efficiency and price discovery through multiple calls and emergent Newton adjustments,” *American Economic Journal: Microeconomics*, 2017, *9* (4), 1–41.
- Pouget, Sébastien**, “Financial market design and bounded rationality: An experiment,” *Journal of Financial Markets*, 2007, *10*, 287–317.
- Satterthwaite, Mark A. and Steven R. Williams**, “The rate of convergence to efficiency in the buyer’s bid double auction as the market becomes large,” *Review of Economic Studies*, 1989, *56*, 477–498.
- Theissen, Erik**, “Market structure, informational efficiency and liquidity: An experimental comparison of auction and dealer markets,” *Journal of Financial Markets*, 2000, *3*, 333–363.