THE JOURNAL OF FINANCE • VOL. LI, NO. 2 • JUNE 1996

Call and Continuous Trading Mechanisms Under Asymmetric Information: An Experimental Investigation

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ABSTRACT

I examine the relative performance of call and continuous auctions under asymmetric information by manipulating trading rules and information sets in laboratory asset markets. I find significant differences in an environment that extends the Kyle (1985) framework to permit the exogenous liquidity trading motive to have a natural economic interpretation. The adverse selection costs incurred by noise traders are significantly lower under the call auction, despite no significant reduction in average price efficiency. This result suggests that discussions of the costs and benefits of insider trading should take place within the context of a specific trading mechanism.

UNDERSTANDING THE INFLUENCE of the trading process on the price formation process is a fundamental goal of the large microstructure literature. An important feature of much of this work has been the replacement of the "Walrasian auctioneer" of general equilibrium theory with market makers who stand ready to provide liquidity and immediacy when buy and sell orders are imperfectly synchronized. In this framework, the presence of agents with "inside information" has an important influence on market liquidity and the price formation process. Seminal theoretical works here include Glosten and Milgrom (1985) and Kyle (1985). A primary purpose of this study is to extend this work by examining the behavior of competitive market makers under alternative trading arrangements that differ on the fundamental dimension of whether orders are temporally consolidated prior to execution. The method of inquiry is experimental economics.

The two mechanisms I investigate are a call auction, in which all buy and sell orders arriving during a specified interval are batched and executed at a single price, and a continuous auction, in which each buy and sell order is executed upon arrival. Both mechanisms are widely employed. While a call auction is the primary trading mechanism on many continental European stock exchanges, the growing Nasdaq over the counter (OTC) market relies exclusively on a continuous mechanism. In addition, hybrid systems that

* University of Miami. I thank Kerry Back, Don Coursey, Phil Dybvig, Ron King, Chris Lamoureux, Hal Pedersen, Charles Plott, an anonymous referee, René Stulz (the editor), and numerous seminar participants for helpful comments and discussions. Susan Fields provided programming assistance. Financial support was provided by the Business, Law, and Economics Center, and the Ph.D. program, both of the Olin School of Business, Washington University in St. Louis.

combine call and continuous mechanisms are employed in some of the most important markets worldwide, including the New York Stock Exchange and the Tokyo Stock Exchange. The participation of market makers who provide a dealership function in addition to a brokerage function is an important feature of this study and is motivated by their presence in all major stock markets in the United States.

This study is designed to address questions pertaining to differences in relative performance arising from insider trading. For example, do insiders and noise traders fare differently under different forms of market organization? On average, are there differences in the informational efficiency of transaction prices? Are there systematic differences in market liquidity?

A further goal of this study is to examine whether optimal policies with respect to insider trading may be trading mechanism specific. In the debate on the regulation of insider trading, serious arguments have been made both for and against insider trading restrictions. An influential argument frequently made is that insider trading is beneficial since it promotes efficient prices, and therefore, the efficient allocation of capital. In contrast, the microstructure literature has focused on the cost in terms of reduced market liquidity.[1] I examine whether the relative costs and benefits of insider trading are trading mechanism dependent. In addition to the diversity of trading mechanisms employed worldwide, the degree to which insider trading is proscribed varies widely. Is there an economic explanation for this phenomenon?

One motivation for this study is theoretical research that suggests noise traders incur lower levels of adverse selection costs under a call auction. Kyle (1985) models a continuous market as an infinite sequence of call auctions, and finds that noise traders' losses double in the continuous market relative to the case of a single call auction. In a similar framework, Pagano and Röell (1996) find that the greater transparency of the call auction leads to lower expected trading costs for noise traders than in a continuous auction characterized by sequential trade. Utilizing a very different modeling approach, Madhavan (1992) shows that a trading system based on periodic auctions is less likely to close down than a continuous trading system when informational asymmetries are severe. It is perhaps noteworthy that despite very different approaches to modeling the formidably complicated interactions in sequential trade under asymmetric information, the theoretical evidence is qualitatively consistent.

Recent empirical work (Amihud and Mendelson (1987, 1991), Amihud, Mendelson, and Murgia (1990), and Stoll and Whaley (1990)) has also uncovered differences in the performance of continuous and call mechanisms, and the conclusions of these studies have, in some cases, been inconsistent with the theoretical results. Unfortunately, these studies employ research designs that are not ideally suited for comparing the two mechanisms. Since they examine markets in which both call and continuous mechanisms are employed during the trading session, controlling for strategic considerations that dictate the

[1] An example of the former is Manne (1966). Glosten (1989) analyzes liquidity costs due to asymmetric information.

choice of trading mechanism, the effects of nontrading prior to the opening of the market, and the effect of the juxtaposition of the call and continuous mechanisms is problematic. In addition, these studies do not address the extent to which reported performance differences are explicitly due to the presence of traders with superior information.

Laboratory asset markets are a useful tool for understanding relative performance because they permit the controlled manipulation of the rules and procedures that constitute a trading mechanism. This control is an essential feature of the experimental markets I discuss below. I also exploit the laboratory setting in order to introduce controlled informational asymmetries, and to introduce the noise trading motive in a way that has a natural economic interpretation, but which has not proven tractable in equilibrium models. The experimental markets therefore afford a direct comparison of performance differentials associated with insider trading in a setting that better captures the essential features of sequential trade than do formal models, and without the data limitations inherent in empirical studies based on data from field markets.

This research adds to the large experimental literature that considers the performance of alternative trading institutions. The most closely related work is by Van Boening, Williams, and LaMaster (1993). They compare the performance of a call auction to that of a continuous double auction in an environment of symmetric information without competitive market makers. In this study, I focus on performance differentials due to asymmetric information in a common value setting, with liquidity provided by competing market makers.

I find significant performance differences between the call and continuous mechanisms. From the perspective of noise traders, the call auction is far more robust to asymmetric information; these markets are more liquid, and noise traders suffer lower losses than in the continuous markets. In addition, despite the larger net positions taken by insiders in the continuous markets, average prices are no more efficient than in the markets employing the call auction.

This article is organized as follows. In Section I, I explain the experimental design and procedures. In Section II, I develop a set of testable predictions that motivate the data analysis. Section III contains the data and statistical tests, and Section IV concludes the article.

I. Experimental Design and Procedures

The experimental markets are organized into two treatments (call auction and continuous auction), with each treatment distinguished by the trading rules which govern the trading of a single risky asset.[2] All interactions between subjects were conducted via networked personal computers with custom

[2] Under each treatment, I conducted six experimental sessions. Each experimental session involved the same group of subjects on the same day, and consists of ten trading periods. As explained in the next section, each trading period is distinct in the sense that it contains an independent set of random draws for all random variables, and positions in the risky asset are closed out prior to the start of a new trading period.

software. Since I am interested in studying the effect of trading mechanism design on market outcomes, the agent types, information structures and the distributions of all random variables (and their realizations) are held constant across treatments.

There are three types of agents; a single insider who knows the end-of-period liquidation value of a single risky asset, three competing dealers, and (computerized) noise traders. The framework is similar to Kyle (1985). Under each form of market organization, the insider trades to exploit an informational advantage, and the dealers compete to take the order flow resulting from trades initiated by the insider and the noise traders without learning the trader type. The trades of the noise traders are independent of the end-of-period asset value, and are typically assumed in the literature to be liquidity motivated. The key feature of the design is that in the call auction, all orders are batched and executed simultaneously at a single price, while in the continuous auction, each individual order is executed upon arrival.

Call Auction: Trading proceeds as follows in the call auction. At the start of each trading period, the insider observes the end-of-period asset value, and then chooses the aggregate order to be sent to the dealers for execution. The aggregate order of the insider is composed of individual market orders for one, two, or three units of the asset, with the sign $(+, -)$ indicating a buy or sell order. There is no constraint on the number of market orders that can be submitted.

After the insider has entered each market order individually, the orders are mixed with a random number of computer generated "noise trader" orders before appearing on the trading screens of the three dealers. The dealers observe each individual order in addition to the net order imbalance, and then compete in a first-price sealed-bid auction to take the other side of the net order imbalance. The "winning" dealer (lowest offer if the net order is to buy, highest bid if the net order is to sell) clears the market, with all orders executed at a price equal to the high (low) bid (offer). Profits or losses are then calculated for the insider, the successful dealer, and the noise traders in aggregate on the basis of net positions relative to the difference between the end-of-period asset value and the transaction price.[3] Prior to the start of a new trading period, all dealers learn the transaction price and the end-of-period asset value.

Continuous Auction: Prior to the start of each continuous trading period the insider observes the end-of-period asset value. At the start of the trading period, a two-minute trading interval clock begins to count down. The insider is allowed to submit a market buy or sell order of one, two, or three units of the asset at anytime during the trading period. There is no constraint on the total number of market orders that may be submitted. Computer generated orders of random number, size, and arrival times also arrive to the dealers. Upon each order arrival, the trading interval clock is paused while the dealers compete in

[3] For example, the insider's trading period profits equal $(\Sigma Q_{\text{insider}})(V - P)$, where Q is the signed order size, V is the end-of-period asset value, and P is the transaction price established in the first-price sealed-bid auction.

a first-price sealed-bid auction to take the other side of the trade. The highest bid or lowest offer establishes the transaction price. Upon completion of the auction, the dealers and the insider learn the transaction price, and then the trading interval clock resumes its countdown. At time zero the trading period ends. Profits or losses on each transaction are then calculated on the basis of the order size, and the end-of-period asset value relative to the transaction price.[4]

The fundamental differences between the call and continuous sessions and a sequence of steps for an individual trading period are summarized in Table I. Below is information pertaining to parameter values, variable distributions, information sets, the experimental procedures, and a discussion of the experimental design.

A. Variable Distributions, Parameter Values, Agents, and Information Sets

Risky Asset Value: The asset value each trading period is drawn from an approximate normal distribution with mean of 100 cents, standard deviation of 6.5 cents, and support on the whole cents between 78 and 122. There is a riskless asset (cash) with an interest rate of zero.

Noise Traders' Orders: The noise traders' (computer generated) buy orders are determined for each trading period as follows. The number of buy order arrivals is determined by a draw from an approximate Poisson distribution with intensity equal to four.[5] The size of *each* buy order is determined independently. Possible order sizes are for one, two, or three units of the risky asset, with the probability of each order size 0.25, 0.50, and 0.25, respectively. Noise traders' sell orders are determined in an identical fashion.

In the call sessions, the noise traders' orders are combined with the insiders' orders and then submitted to the dealers. The dealers observe each individual order in addition to the net order imbalance, but never learn with certainty which orders are submitted by the insider, and which are exogenous noise traders' orders. The *net* noise traders' order has an expected value equal to zero, and variance equal to 33.5, and is closely approximated by a normal distribution with these parameters and support on the integers.

In the continuous sessions, the timing of each individual noise trader order is determined by an independent draw from a uniform distribution with endpoints 1 and 120. For example, a draw of 50 indicates the order will arrive after 50 seconds of the 120 second trading interval have elapsed. The random arrival of noise traders' orders in clock time in conjunction with the assumption that the number of orders is drawn from a Poisson distribution is consistent with liquidity buy and sell orders governed by independent compound Poisson processes. The only difference between the noise trader order process

[4] Trading profits on trade $t(\Pi_t)$ are defined as $\Pi_t = Q_t(V - P_t)$, where P_t is the transaction price, and Q_t is the signed trade size.

[5] A Poisson distribution with intensity equal to 4 is truncated so that the maximum number of arrivals is equal to 10. The probability mass is redistributed to maintain 4 as the expected number of arrivals.

Table I

Sequence of Events for a Single Trading Period in the Experimental Markets

Parameters and random variable distributions are held constant across trading mechanisms and are reported in the first column. All parameters, distributions, and trading rules are known by the subjects prior to the beginning of trade.

Call Sessions	Continuous Sessions
1. The insider learns the end-of-period liquidation value of the asset. It is common information that only the insider learns the end-of-period value and that it is a draw from an approximately normal distribution (100, 42.5) with support on the whole cents.	1. The insider learns the end-of-period liquidation value of the asset.
2. The insider submits orders to the dealers. Before arriving to the dealers, the insider's orders are combined with random noise traders' (computer generated) orders. The number of computer buy orders is determined by a draw from an approximate Poisson distribution with intensity equal to four. The size of *each* buy order is determined independently. Possible order sizes are for one, two, or three units of the risky asset, with the probability of each order size .25, .50, and .25, respectively. Noise traders' sell orders are determined in an identical fashion. The net order imbalance due to noise trader activity is approximately normal (0, 33.5).	2. The 2 minute trading period begins. The insider is permitted to submit an unlimited number of orders to the dealers. The dealers also receive noise trader (computer generated) orders that arrive randomly over the trading interval. The timing of each individual noise trader order is determined by an independent draw from a uniform distribution with endpoints 1 and 120. The dealers do not learn which orders are submitted by the insider, and which are submitted by the noise traders.
3. The dealers compete to trade the quantity necessary to satisfy the net order imbalance, without learning the source of each order. The price at which the trade takes place is determined by a first-price sealed-bid auction. If the net order is to buy (sell), the dealer with the lowest offer (highest bid) clears the market.	3. Upon each order arrival, the trading interval clock pauses, and a first-price sealed-bid auction is conducted among the dealers to determine the execution price. If the order is to buy (sell), the dealer with the lowest offer (highest bid) takes the other side of the trade.
4. The value of the asset is revealed, and trading profits are calculated by comparing the direction and size of each trade with the difference between the market clearing price, and the end-of-period asset value.	4. At the completion of the 2 minute trading period, the value of the asset is revealed, and trading profits are calculated. Trading profits on trade t are $Q_t(V - P_t)$, where V is the end-of-period value of the asset, P_t is the transaction price, and Q_t is the signed volume of the trade.

in the call and continuous trading periods is that under the call, the orders are presented to the dealers (along with the insider's orders) simultaneously, while in the continuous trading periods each noise order is realized at a randomly determined time on the trading interval, as explained above.

Insider: Under both trading mechanisms, the insider learns the end-of-period asset value prior to the start of trade. There are no constraints on the aggregate order of the insider, including no short sales constraints. The only constraint on the composition of the aggregate order is the previously mentioned restriction to market orders for one, two, and three assets.

In the call auction, the insider is permitted to place both buy and sell orders in a single trading period. In the continuous auction, the insider is permitted an unlimited number of temporally separated buy or sell market orders. In both the call and continuous sessions, at the end of each trading period the insider's position in the risky asset is reset to zero by closing it out at a price equal to the end-of-period asset value. Trading profits (or losses) are added to initial cash balances and carried forward to subsequent periods.

Dealers and Auction Rules: The first-price sealed-bid auction used to establish trading prices is conducted as follows. If a market order (continuous auction) or the net order (call auction) is positive (a buy order), the dealer who submits the lowest offer sells the quantity necessary to clear the market. If the order is negative (a sell order), the dealer who submits the highest bid buys the outstanding order. The only dealer who participates in each trade is the dealer who offers to sell at the lowest price, or bids to buy at the highest price; ties are broken randomly. After the auction is completed, all dealers learn the transaction price, but do not learn the bids submitted by the other dealers.

Dealers are not permitted to initiate trades. In the continuous trading periods, there are no constraints on the number of trades in which an individual dealer may participate. As is the case with the insider, in both the call and continuous sessions, trading profits (losses) are carried forward, but risky asset positions are not. They are closed out at a price equal to the end-of-period asset value. There are no explicit trading costs, fees, or cash inducements for dealers to trade.

Initial Cash Endowments and Payments: In the call sessions, dealers receive an initial cash endowment of \$5.00, and the insider receives an initial endowment of \$4.00.[6] At the end of the ten periods of trade, cash balances (endowments plus accumulated trading profits) are tripled, and subjects are paid that amount. In the continuous sessions, dealers receive an initial en-

[6] Granting initial endowments reduces the probability of bankrupt agents, a troubling possibility in asset market experiments. To the extent that it is not credible that a negative end-of-experiment cash balance will be extracted from the subject in the form of a cash payment from the subject to the experimenter, putatively negative expected value gambles may in fact appear profitable to subjects with negative (or low) cash balances. Endowments therefore provide a buffer in the event of decisions or random draws that result in losses. No bankruptcies (or near bankruptcies) occurred in this experiment. If they had, the data from such sessions would have been discarded.

dowment of \$7.00, and the insider receives an initial endowment of \$1.50.[7] Payments are again based on the tripled ending cash balance.

Information: All of the above information pertaining to distributions, parameters, payments, and the rules governing trade is contained in detailed experimental instructions that subjects received during the training phase of the experiment, and is common information.[8] Important features of the experimental design are that only the insider observes the end-of-period asset value prior to the end of the trading period, the insider does not observe each noise trader order prior to its realization, and during each trading period, insider and noise trades are presented to the dealers in an identical fashion. At the end of each trading period, although the dealers learn the asset value, they never learn with certainty which trades were submitted by the insider.

B. Subjects and Procedures

Subjects were full-time MBA students in the Olin School of Business, Washington University in St. Louis. A total of 32 subjects participated in the 12 experimental sessions, which were conducted in March of 1993. Four initial sessions were conducted under each of the two trading mechanisms with inexperienced subjects. These were then followed by two additional sessions in each setting with experienced subjects.

At the commencement of each experimental session, subjects received written instructions that were read aloud by the experimenter. After clarifying questions were answered, subjects were given a three-question quiz that reviewed the information in the written instructions. For each question answered entirely correctly, subjects received a payment of \$1.00 (each question consisted of four true/false questions). Upon completion of the quiz, all quiz questions were reviewed, and additional questions were answered. (The quiz was sufficiently general so that an identical quiz could be employed for both treatments). Subjects were then randomly assigned to roles, seated at computer terminals, and given instructions that familiarized them with the operation of the computer and the display of information on the computer screens. After final questions were answered, ten periods of trading were conducted. After the completion of the tenth trading period, each subject completed a questionnaire, was privately paid his earnings for the session in cash, and was then dismissed.

Call sessions lasted approximately 1.75 hours with inexperienced subjects and 1.25 hours with experienced subjects, and cash earnings averaged about

[7] Differences in endowments equalized expected hourly earnings across trading mechanisms and trader types. Endowment payments are not salient and not expected to influence experimental outcomes (see Smith (1982)), but to the extent possible, it is desirable to hold such "nuisance" variables at a constant level. Given the impossibility of equalizing both nominal initial endowments and average session earnings, in my judgment it is preferable to equalize the latter.

[8] Smith (1982) argues that experimental control is enhanced when subjects do not know the influence of an action on the rewards of others (privacy). Although trades between the insider and a dealer are zero-sum, the trading game is not because of the random noise trades.

\$18.00. Continuous sessions lasted approximately 2.75 hours with inexperienced subjects and 2.25 hours with experienced subjects, and cash earnings averaged about \$29.00. Sessions with experienced subjects were of shorter duration because they did not retake the quiz, and they asked fewer questions while the instructions were being read. Subjects indicated in the questionnaire that they fully understood the instructions, felt adequately compensated in cash for the effort expended in participating in the experiment, and understood how their decisions affected their cash payments.

C. Computer Displays

The trading rules composing each trading mechanism were enforced by computer programs that coordinated all communications between subjects, and reported outcomes to each participant's screen. All data collection was computerized.

In the call trading periods, each dealer's screen displays the cumulative number of buy and sell orders of each size, the net order, a history of trading prices, asset values and net orders from prior trading periods, and the current and previous cash balances. The insider's screen displays similar information, but does not report information pertaining to the noise traders' orders (computer generated orders) until after the insider's aggregate order has been submitted.

In the continuous trading periods, the screens of the dealers and the insider contain continuously updated market information, including the cumulative number of buy and sell orders of each size, the time of each order, the net order flow, a history of trading prices, and cash balances. The cash balance of the insider is updated at the completion of each trade, while the cash balances of the dealers are updated at the end of each trading period.

D. Discussion of the Experimental Design

The single call auction of these experimental markets is the benchmark on the dimension of temporal consolidation and market transparency because the entire order flow is consolidated and observed by dealers prior to the market clearing auction. The continuous mechanism establishes the opposing benchmark for auction markets on both dimensions. This design therefore allows an investigation of the primary issue of interest. I discuss below some of the important features of the experimental design.

First, there are no constraints on insider strategies, so that strategies which involve initial attempts to destabilize the market are permitted. This is an important design feature because of the possibility of trading mechanism specific differences in susceptibility to insider manipulation.[9]

Second, I maintain the separation of trading for liquidity purposes and information based trading. This avoids constraining the insider to satisfy

[9] Strategies admitting manipulation are precluded in models of continuous auctions that constrain the insider to a single trading opportunity.

liquidity motives through unprofitable trades in a market where an informational advantage is enjoyed.

Third, the realization of the exogenous liquidity trading motive has a natural economic interpretation. The Poisson arrival process is consistent with a large population of shareholders, each of whom will trade to satisfy an exogenous liquidity motive with very low probability, at random times. The multiple order sizes permit an examination of the relation between order size and market depth, an issue that has received considerable attention in the microstructure literature.

Fourth, asymmetric information has been introduced in perhaps the simplest way possible within the noise trader framework that I have adopted. Schnitzlein (1994) shows that market outcomes are sensitive to the number of insiders, and specifically, to whether the presence and number of insiders is common information. How the differences in trading mechanism performance reported in this research would extend to a more complex environment in which the number of insiders is an unobserved random variable is a question beyond the scope of this article.[10]

Fifth, the approximate normality of both the asset value and the net noise trader order allows comparisons of the experimental outcomes with theories of the call auction that assume normality.[11] In addition, the large state space that this affords is a characteristic feature of the field markets in which I seek to understand the importance of trading mechanism design.

Finally, there are numerous variants of both call and continuous markets that have been considered in both the experimental and theoretical literature. While the assumptions of theoretical models have to some extent been dictated by the formidably difficult modeling challenge, a large body of experimental literature (including this research) demonstrates clearly that varying the rules and regulations that compose a trading institution matter. I chose the present design because it affords a controlled investigation of the importance of temporal consolidation (and transparency) in an auction market.[12]

II. Relative Performance: Hypotheses

Two models of insider trading provide strong intuitions that the temporal consolidation of market orders will affect market outcomes. I summarize these

[10] O'Brien and Srivastava (1991, pp. 1812–1813) provide a brief review of the literature pertaining to information aggregation in experimental asset markets. Successful aggregation has been shown to depend on the information structure and the homogeneity of trader types.

[11] Multiple order sizes play a role here by permitting the approximate normality of the net noise trader order with a relatively small number of noise trader arrivals. This in turn allows a relatively large number of trading periods per experimental session. This is desirable because it gives subjects more rapid exposure to the trading strategies of opponents.

[12] For example, permitting the dealers to observe only the net order flow in the call auction would have been consistent with the Kyle (1985) framework, which I have for the most part maintained, but since dealers observe individual orders in the continuous auction, the present design maintains experimental control.

results below, and formulate testable hypotheses that are primarily intended to motivate the data analysis in the following section.

In a seminal model that focuses on the dynamic strategy of a monopoly insider, Kyle (1985) derives a sequential equilibrium. At prespecified times on the trading interval, the insider's order and a random liquidity order are mixed, the net order imbalance is displayed to risk neutral dealers, and then executed at a price equal to the expected value conditional on the trading history. Kyle finds that increasing the number of auctions on the interval while holding constant the total variance of random liquidity trades increases the expected losses of the liquidity traders. In the limit when the market is continuously open, the expected losses of the liquidity traders double relative to the case of a single call auction.

In this framework, reducing temporal consolidation is important for two reasons. First, at each auction a portion of the aggregate noise trader order is realized, permitting an optimal insider response, with the dynamic insider's strategy accounting for the noise trader order at the previous auction. Second, a greater number of trading opportunities permits the insider to reduce trading costs (which are due to the responsiveness of price to order flow) by trading smaller quantities at each auction. Since the pricing function is linear, trading smaller quantities a greater number of times increases insider profits in the same way that price discrimination is profitable for a monopolist in a product market. Larger insider profits imply larger noise trader losses since the dealers earn expected profits of zero.

In a model based on the Kyle framework (a single monopoly insider, and noise traders with inelastic demands) Pagano and Röell (1996) show that market transparency is a trading mechanism characteristic that influences market liquidity. Defining transparency to be the extent to which market makers can observe the size and direction of the trading interval order flow when they price and satisfy an order, they rank market structures on the dimension of market transparency, and derive the influence of market transparency on the profits of noise traders. The trading mechanism is important because it determines how hard it is for the dealers to infer the insider's trading strategy.

In their comparison of a single call auction and a continuous auction market, the monopoly insider is constrained to submit a single order, and employ a trading strategy that depends only on the asset value. The call auction is the benchmark on the dimension of transparency because the entire interval order flow is observable prior to the establishment of a trading price. In their model of a continuous auction, each noise trader and the insider draw lots to determine the sequence in which their trades will be executed. Each trading price is the expected asset value conditional on the order flow history. In this setting, they show the expected trading costs of a noise trader are higher in the continuous auction.

Both models provide strong intuition for anticipating greater depth and lower liquidity trader losses in the call auction. Pagano and Röell demonstrate that the piecewise realization of order flow is not equivalent to its instantaneous revelation even in the absence of insider dynamic strategies. Kyle shows that reducing temporal consolidation in the presence of a dynamically optimizing insider increases insider profits, and reduces market liquidity with a corresponding increase in noise trader losses. The following hypotheses are based on these results.[13] First, noise trader losses will be higher in the continuous auction (H1). Second, the continuous auction will be less liquid (deep) in the sense that the average change in price per unit order flow will be lower in the call auction (H2). Third, the net insider order will be higher in the continuous auction (H3). Finally, insider profits will be higher in the continuous auction (H4).

III. Results

A. *The Relative Performance of Call and Continuous Auctions*

I analyze below the last five trading periods of each session, yielding thirty observations under each trading mechanism. Earlier trading periods are ignored because of the complexity of the markets. All per period figures are reported net of initial endowments.

Statistical significance is assessed by regressing each variable of interest on a constant and a dummy variable that distinguishes between trading mechanisms (ANOVA). In order to account for possible interdependencies in intrasession results, the reported p-values are based on GMM t-statistics. In the construction of the GMM variance-covariance matrix, I experiment with different lag lengths since the Andrews (1991) approach to determining the optimal lag length is inappropriate for this dummy-variable setup. None of the following inferences are sensitive to the choice of lag length.[14] Other regressions use the optimal lag length determined by Andrews' method. Hypotheses are also tested with the nonparametric approximate randomization test.[15] Under this approach, results are unchanged relative to a 5% significance threshold.

H1 (Noise Trader Losses): Noise trader profits are reported in Table II (Column 1). Noise traders incur losses in each experimental session, with the average per period loss across call sessions equal to \$0.69, and the average per

[13] Despite the large number of microstructure models developed in recent years, modeling markets which are open on an interval has proven to be a difficult challenge, and no generally accepted theory exists. Model builders have in general taken one of two approaches; either precluding by assumption dynamic insider strategies, or forcing the insider and the noise traders to trade simultaneously. Neither restriction has been imposed on the (continuous) experimental markets. This "model" of insider trading implicit in the experimental design has not been solved analytically.

[14] Autocorrelation in the usual sense is not present, but this specification allows for intrasession dependencies in the residuals. The data are stacked so that every other observation is from the same session. Since five trading periods per session are analyzed, the maximum lag length necessary to account for possible intrasession dependencies in the residuals is ten. This lag length is employed in the dummy-variable regressions.

[15] Edgington (1980) discusses this test, including issues related to power.

Table II

Summary Statistics for the Last 5 Trading Periods of Each Experimental Session

There are four call sessions (CALL-1-4) and four continuous sessions (CONT-1-4) with inexperienced subjects, and two additional sessions with experienced subjects (CALL-EXP1,2 and CONT-EXP1,2). Two sets of asset value and noise trader draws were made. One set was employed in sessions with inexperienced subjects, and the second set was employed in sessions with experienced subjects. Figures are session averages, weighting each trading period equally. The measure of market depth and liquidity found in column (4) is the mean price change per unit order flow ($\Delta P/\Delta Q$). Mean insider net volume (5) is the average per period net order submitted by the insider. Since noise trader volume is held constant across sessions, this is the measure of comparative market volume. The mean price error in absolute value (MPE) is computed both for all trades and for trades by trader type. The MPE of the last transaction in the continuous sessions (9) indicates the convergence of price to the asset liquidation value. The last column (10) shows the PE that would have resulted if trades had occurred at the asset's unconditional expected value. Comparing columns (6) and (10) gives an indication of the gain in informational efficiency due to the presence of the insider.

Session	Noise Traders' Profits (Avg. $ per Period) (1)	Insider Profits (Avg. $ per Period) (2)	Dealers' Profits (Avg. $ per Period) (3)	Mean Price Change per Unit Order Flow ($) (4)	Mean per Period Insider Net Volume (5)	MPE per Period (cents) (6)	MPE by Trader Type: Noise (7)	MPE by Trader Type: Insider (8)	MPE of Last Trade per Period (Continuous Sessions) (9)	MPE if P = 100 (10)
CALL-1	−0.81	0.48	0.32	0.0050	2.4	5.64	5.64	5.64		6.6
CALL-2	−0.89	0.76	0.12	0.0071	5.4	4.60	4.60	4.60		6.6
CALL-3	−0.34	0.31	0.03	0.0034	9.0	5.60	5.60	5.60		6.6
CALL-4	−0.96	0.44	0.52	0.0050	3.0	6.00	6.00	6.00		6.6
CALL-EXP1	−0.48	0.54	−0.07	0.0083	4.2	4.98	4.98	4.98		7.2
CALL-EXP2	−0.67	0.50	0.17	0.0083	3.4	5.62	5.62	5.62		7.2
AVG CALL	−0.69	0.51	0.18	0.0062	4.6	5.41	5.41	5.41		6.8
CONT-1	−3.29	0.12	3.16	0.0390	5.0	5.68	7.24	2.74	7.44	6.6
CONT-2	−0.91	2.14	−1.23	0.0090	18.2	4.62	4.75	4.61	0.86	6.6
CONT-3	−2.71	0.18	2.53	0.0336	7.2	6.06	7.21	5.32	2.22	6.6
CONT-4	−1.45	1.84	−0.39	0.0150	12.8	5.23	6.22	3.58	2.10	6.6
CONT-EXP1	−1.48	0.55	0.93	0.0159	6.0	3.49	4.06	2.63	1.98	7.2
CONT-EXP2	−2.10	0.33	1.77	0.0220	6.6	3.45	4.48	1.68	3.48	7.2
AVG CONT	−1.99	0.86	1.13	0.0224	9.3	4.76	5.66	3.43	3.01	6.8

period loss across continuous sessions equal to \$1.99. This difference is highly significant ($p < 0.01$), and supports the hypothesis of higher noise trader losses in the continuous auction.

H2 (Market Liquidity): The measure of market liquidity I employ is the average price change per unit of order flow, with per period averages across sessions reported in Table II (Column 4). This is a more comprehensive measure than the bid-ask spread in a quote-driven market since it incorporates the influence of large orders, and is therefore related to market depth.

The results support the hypothesis of greater market depth in the call sessions. The average price change per unit of order flow is \$0.0062 in the call trading periods and \$0.0224 in the continuous trading periods. Although the difference narrows in the markets with experienced subjects, the call trading periods remain more than twice as deep. The reported difference is highly significant ($p < 0.01$).

H3 (Net Insider Volume): The average per period net insider order for each session is reported in Table II (Column 5). This measure characterizes the insider's net demand for the dealers' liquidity services, and is predicted to be higher in the continuous sessions. The net order placed on the market by insiders is twice as high in the continuous trading periods ($p < 0.01$).[16] Table III provides detailed volume data for each trading period, aggregating across sessions.

H4 (Insider's Profits): The average per period insider's profit in each session is reported in Table II (Column 2). Insiders earned profits in every session, with the average per period profit across call sessions equal to \$0.51, and the average per period profit in the continuous sessions equal to \$0.86. This difference is in the predicted direction, but is not statistically significant ($p < 0.11$). Besides being higher on average, profits are also far more variable across experimental sessions in the continuous auction, with both the lowest and highest insider profits recorded in these sessions. I discuss the weak support for H4 below in the context of a discussion of dealer profits.

Dealer Profits: The average per period profits by session are reported in Table II (Column 3). Average per period profits in the call sessions equal \$0.18 per period. Profits increase to \$1.13 in the continuous sessions. Dealer profits in the continuous trading periods are significantly greater than zero ($p < 0.02$), while dealer profits in the call auction trading periods are not.

Although average dealer profits are six times higher in the continuous trading periods, both the highest and lowest per session profits occur here. The difference in dealer profits is close to significant at conventional significance levels ($p < 0.07$). Comparing the call and continuous trading periods with experienced subjects, the difference is highly significant ($p < 0.01$).

[16] In call trading periods, the insider is permitted to submit offers simultaneously on both sides of the market, with the profit calculation based on the net order. In the continuous trading periods, the insider submits orders sequentially. If the price overshoots the asset value, the insider is permitted to reverse the direction of trade. This measure therefore underestimates the difference in the effective activity of the insider under the two mechanisms since in the continuous auction the insider may make profitable trades on both the buy and sell sides of the market.

Table III

Volume Data for the Last 5 Periods of Each of the Experimental Sessions

Under the call auction (call) and the continuous auction (cont), data for each trading period is aggregated across sessions with inexperienced subjects (CALL-1-4, CONT-1-4), and experienced subjects (CALL-EXP1,2, CONT-EXP1,2). Sessions with inexperienced and experienced subjects are given equal weights. The average mean insider net volume in absolute value (5) is not equal to (5) in Table II because, on net within a trading period, insiders in different sessions may be on different sides of the market.

Sessions and Trading Period	Asset Value (1)	Net Noise Trader Order (2)	Noise Trader Buy Volume (3)	Noise Trader Sell Volume (4)	Mean Insider Net Volume (5)	Mean Insider Buy Volume (6)	Mean Insider Sell Volume (9)
CALL-1-4							
Period 6	90	−3	10	13	−0.5	11.0	11.5
Period 7	106	7	12	5	3.5	8.3	4.8
Period 8	108	−11	1	12	6.5	10.5	4.0
Period 9	98	−6	5	11	−1.3	6.8	8.0
Period 10	93	5	8	3	−7.5	7.8	15.3
CALL-EXP1,2							
Period 6	90	3	12	9	−5.5	2.5	8.0
Period 7	109	0	13	13	5.0	5.0	0.0
Period 8	107	13	15	2	4.0	5.0	1.0
Period 9	102	−5	1	6	1.5	7.0	5.5
Period 10	92	3	8	5	−3.0	0.0	3.0
AVG CALL	**99.5**	**0.6**	**8.5**	**7.9**	**3.8 (absolute value)**	**6.4**	**6.1**
CONT-1-4							
Period 6	90	−3	10	13	−13.0	5.0	18.0
Period 7	106	7	12	5	0.3	4.5	4.3
Period 8	108	−11	1	12	24.8	26.8	2.0
Period 9	98	−6	5	11	−2.5	3.3	5.8
Period 10	93	5	8	3	−9.0	1.5	10.5
CONT-EXP1,2							
Period 6	90	3	12	9	−9.5	1.0	10.5
Period 7	109	0	13	13	8.5	8.5	0.0
Period 8	107	13	15	2	1.0	2.0	1.0
Period 9	102	−5	1	6	5.0	5.5	0.5
Period 10	92	3	8	5	−9.0	0.0	9.0
AVG CONT	**99.5**	**0.6**	**8.5**	**7.9**	**8.25 (absolute value)**	**5.8**	**6.15**

Two potential explanations for the importance of dealer profits in the continuous trading periods are tacit collusion among dealers and risk averse dealers who command risk premia. The more frequent dealer interactions, and the greater demand for dealer liquidity services (due to the larger net positions of the insiders) in the continuous trading periods suggest potentially important dimensions of temporal consolidation in a dealership market not considered in formal models of insider trading. A large game theory literature recognizes that repeated games are complicated because of the possibility of cooperative behavior.[17] Also, if dealers are risk averse, the larger positions required in continuous markets will imply larger risk premia.[18] To the extent that these engender less competitive prices, there may be economically significant behavioral differences that are a function of temporal consolidation.[19]

In each of the continuous sessions, the level of dealer profits explains the level of insider profits, with the link being the average level of market depth (price change per unit order flow). An illiquid market reduces the frequency and magnitude of profitable trading opportunities for the insider, and increases the profitability of dealers' trades with noise traders. With all trades a zero sum game, the relationships between market depth and the profits of both insiders and dealers follow directly.

These relationships are strong. Comparing sessions, the correlation between insider profits and the average price change per unit order flow is equal to -0.81. The correlation between dealer profits and the average price change per unit order flow is equal to 0.94. Finally, the correlation between dealer profits and insider profits is -0.96.

The level of dealer profits (and hence, market depth) also explains the level of noise trader profits. The correlation between noise trader profits and dealer profits is -0.95, and the correlation between noise trader profits and the average price change per unit order flow is -0.99.

Decomposing the Determinants of Noise Trader Losses: Are noise trader losses higher in the continuous sessions because of the higher level of dealer profits and the inverse relation between dealer and noise trader profits detailed above, or is there also a fundamental trading mechanism specific difference? The evidence indicates a difference that does not depend on the role of dealer profits. Isolating the two continuous sessions in which dealers incurred losses, the average level of noise trader losses in each of these sessions is greater than the overall average for the call sessions. This is despite positive

[17] Both the call and continuous sessions are repeated games with ten distinct trading periods in each experimental session. In each call session, dealers engage in a single competitive interaction each trading period. In the continuous sessions, the average number of trades (and hence competitive interactions) per session is 157.

[18] Although the aggregate demand for liquidity is greater in the continuous sessions, the average (per dealer) required positions are smaller because in the call sessions one dealer takes the entire order imbalance, while in the continuous sessions each dealer has the opportunity to compete for each individual trade. Risk aversion may also have differential effects under the two trading mechanisms. In the continuous sessions, uncertainty surrounding the asset value is higher for initial trades. Dealers may also be able to offset positions with subsequent trades. In the call sessions there is a single trading opportunity for both the insider and the dealer. Ho and Stoll (1983) examine the dynamics of competition between risk averse dealers when the order flow is not informative.

[19] Christie and Schultz (1994) detail apparent tacit collusion among Nasdaq dealers despite a large number of "competing" dealers.

Table IV

Determinants of Noise Trader Losses

In order to better understand the role of dealer profits in the determination of noise trader profits, I estimate the following model with Ordinary Least Squares (OLS):

$$\prod_N = b_0 + b_1\text{CONT} + b_2\prod_D + b_3\prod_D{*}\text{CONT} + b_4\text{COV} + b_5\text{COV}{*}\text{CONT} + \varepsilon;$$

Variable definitions are as follows. Π_N is per period noise trader profits, CONT is an indicator variable that takes on the value of one for continuous trading periods and zero for call trading periods, Π_D is per period dealer profits, and COV is the product of the trading period net noise trader order and the difference between the end-of-period asset value and its expected value. M^* is the optimal lag length determined by Andrews' (1991) rule for constructing t-statistics that are consistent in the presence of heteroskedasticity and autocorrelation.

$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	$\hat{b}_4$	$\hat{b}_5$	M^*	Trading Periods	adj. R^2
−18.20	−33.56	−0.49	−0.35	0.53	0.54	2	60	0.75
(−7.01)	(−7.40)	(−2.56)	(−4.76)	(4.08)	(4.41)			

average dealer profits in the call sessions. Furthermore, the average level of noise trader losses from the two continuous sessions in which the dealers earned losses is 20 percent higher than the noise trader losses in the call session with the highest dealer profits.

In order to better understand the role of dealer profits, I estimate with ordinary least squares (OLS) the following model of noise trader profits (Table IV):

$$\prod_N = b_0 + b_1\text{CONT} + b_2\prod_D + b_3\prod_D{*}\text{CONT} + b_4\text{COV} + b_5\text{COV}{*}\text{CONT} + \varepsilon \quad (1)$$

Variable definitions are as follows: Π_N is per period noise trader profits, CONT is an indicator variable that takes on the value of one for continuous trading periods and zero for call trading periods, Π_D is per period dealer profits, and COV is the product of the net noise trader order and the difference between the asset value and its expected value. These variables capture the mechanism specific effects of market liquidity (dealer profits) and the direction of the noise traders' net order relative to the asset value on noise trader profits. This model describes noise trader profits well with an adjusted R^2 of 0.75.

The highly significant and negative coefficient estimate of b_1 indicates a mechanism specific difference that does not depend on the role of dealer profits. With dealer profits set to zero and COV equal to its theoretical mean (zero), noise trader losses are predicted to be 2.8 times higher in the continuous auction. This is further evidence that the difference in noise trader losses is not due solely to differences in the profitability of the dealer industry under the two mechanisms.

Relative Price Efficiency: Did the larger net order placed on the market by the insider in the continuous trading periods result in greater informational efficiency in an average sense? The measure of price efficiency I employ is the mean price error in cents (MPE), which is the mean difference in absolute value between each transaction price and the end-of-period asset value. MPEs are reported in Table II (Column 6), and equal 5.41 in the call sessions and 4.76 in the continuous sessions. This difference is not statistically significant with more variability in the continuous sessions.

Although there is not a significant difference between the level of average price efficiency in the call and continuous sessions, more of the insider's information is revealed by the end of the continuous trading periods. The MPE associated with the last transaction in the continuous sessions is 44 percent lower than the MPE from the call sessions ($p < 0.01$).

A measure of price efficiency gains due to the presence of the insider is the extent to which pricing errors are smaller in the experimental markets than they would have been if all transactions had occurred at the unconditional expected value of the asset. The MPE consistent with all transactions equal to the unconditional expectation is 26 percent higher than the MPE in the call trading periods, and 43 percent higher than the MPE in the continuous trading periods. These differences are significant, with ($p < 0.02$) and ($p < 0.01$) in the call and continuous trading periods, respectively.

A final distinction between the call and continuous auctions is that MPEs may differ by trader type in the continuous trading periods, while in the call trading periods, the orders of insiders and noise traders are executed at identical prices. MPEs by trader type are reported in Table II (Columns 7, 8). In the continuous trading periods, the average MPE for noise trades is 5.66, while the average for trades initiated by the insider is 3.43. In addition, the ratio $\mathrm{MPE_{NOISE}}/\mathrm{MPE_{INSIDER}}$ is highest in the markets with experienced subjects. The reported difference is significant ($p < 0.01$).

B. Results Pertaining to the Call Auction

In models of the call auction such as Kyle (1985) and Subrahmanyam (1991), dealers observe only the net order flow, and trading strategies are linear by assumption. In the experimental markets, dealers observe the aggregate order flow, there are no restrictions on trading strategies, and prices are the culmination of a competition among dealers. Specifically, the insider is permitted to submit multiple orders, including orders on both sides of the market, with profits based on the net order.

In 18 of the 30 call trading periods the insider submitted orders on both sides of the market. In the two sessions with experienced subjects, both insiders followed mixed strategies in the sense that each submitted orders on both sides of the market in some of the trading periods.

The strategies of the insiders with respect to the net order placed on the market (X) are highly linear in the difference between the asset value (V) and its unconditional expectation. Combining the two sessions with experienced subjects, the OLS regression $X = \alpha + \beta[V - \mathrm{E}[V]]$ yields an intercept insignificantly different from zero, an estimate of β equal to 0.52 ($t = 14.08$), and R^2 of 0.96.[20]

The dealers' strategies with respect to the establishment of trading prices as a function of the net order flow are also roughly linear. The OLS regression $P = \alpha + \lambda Q$ for the two experimental sessions combined yields an intercept insignificantly different from the asset's unconditional expectation, an estimate of λ equal to 0.57 ($t = 8.88$), and R^2 of 0.91. When a trading volume variable is added to this regression, its coefficient is insignificant.

The evidence is, therefore, that insiders may attempt to camouflage their orders with high volume, but that dealers focus on the net order imbalance when competing for order flow. In addition, the insiders net order submission strategy and the dealers price setting strategy are both approximately linear. This is consistent with the modeling strategy employed in theoretical models of the single call auction.

C. Results Pertaining to the Continuous Auction

In this section, I characterize the informational efficiency and liquidity characteristics of the continuous trading periods. An example of a trading period from a continuous trading period is portrayed in Figure 1.

The first question I consider is whether the trading activity of the insider leads to the convergence of price to intrinsic asset value. Figure 2 plots mean price errors by time quartile. MPEs decline monotonically as the trading interval proceeds. In each of the continuous sessions with experienced subjects (CONT-EXP1, CONT-EXP2), regressing the price error of each transaction on a constant and the time of the transaction yields a negative coefficient estimate for the time of trade variable of -0.03 ($t = -2.56$) and -0.02 ($t = -1.37$), respectively. Adding an indicator variable which equals one for trades initiated by the insider and zero otherwise (controlling for the insiders' tendency to trade early in the trading interval), in both regressions the coefficient estimates for the time of trade and insider indicator variables are negative and significant. This analysis indicates that the insider's information is gradually incorporated in the market price.[21]

In order to examine the liquidity characteristics of the continuous trading periods, I estimate the following model:

$$|\Delta P| = b_0 + b_1\text{TIME} + b_2|Q| + b_3\text{REVERSAL} + \varepsilon \tag{2}$$

Variable definitions are as follows: $|\Delta P|$ is the absolute value of the price change, TIME is the elapsed clock time of the transaction, $|Q|$ is the absolute value of the trade size, and REVERSAL is an indicator variable that takes on

[20] Markets with experienced subjects are examined here because of the evidence that experimental markets with experienced subjects converge more rapidly to equilibrium. See for example Smith, Suchanek, and Williams (1988).

[21] Schnitzlein (1994) shows that temporal patterns in price efficiency are affected by the number of insiders present, and whether this number is common information.

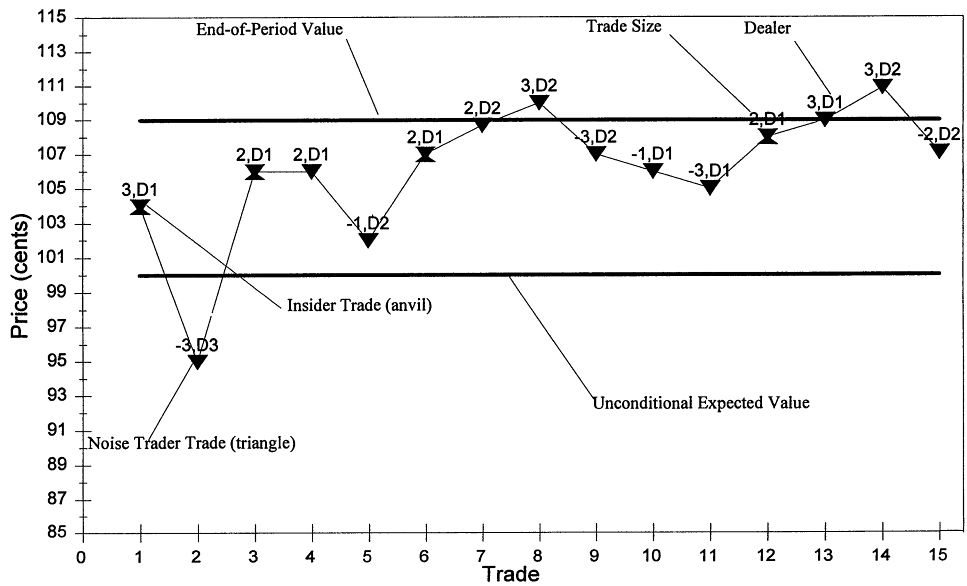

Figure 1. An Example of a Continuous Trading Period. The figure depicts the seventh trading period in the first session with experienced subjects. The unconditional expected asset value is \$1.00, and the end-of-period asset value is \$1.09. Trades initiated by the insider are marked with anvils, and noise traders' (exogenous) computer generated orders are marked with triangles. Above each trade market is the signed order size, and the dealer (D1, D2, D3) that took the other side of the trade. Features of this trading period which are characteristics of the continuous auction sessions include larger price changes on price reversals than on price continuations, and increasing depth and declining price errors as the trading interval proceeds.

the value of +1 for a transaction in the opposite direction of the previous transaction (a reversal), and zero for a transaction which is a continuation. The results of the OLS regressions are reported in Table V.

With $\hat{b}_1 < 0$ and highly significant in both CONT-EXP1, and CONT-EXP2, market liquidity increases over the trading interval. This finding is consistent with a reduction in the adverse selection problem faced by dealers as the insider's information becomes impounded in the price. To test for the same relationship in economic time, I estimate the same model, but replace the time of trade variable with a variable that numbers each trade (the first trade of each period is trade 1, the second is trade 2, and so on). Results are unchanged.

The positive and significant estimates for the trade size variable indicate a positive relation between trade size and price changes. This is consistent with the theoretical model of Easley and O'Hara (1987) in which trade size affects security prices because of an information-quantity link. The order size strategies of the insiders are relevant here. In both sessions with experienced subjects, insiders chose trade sizes which mimicked those of the noise traders.

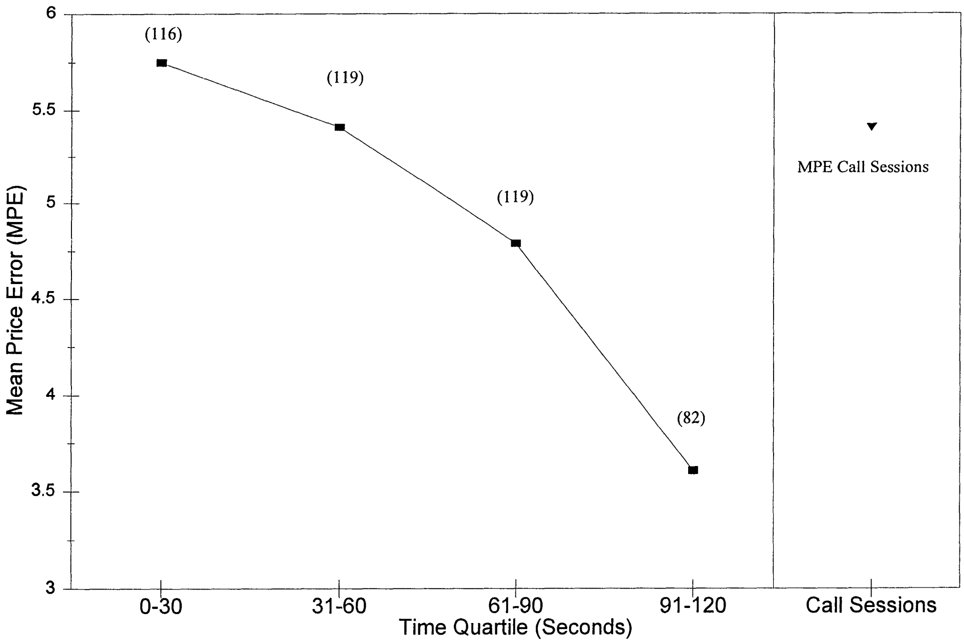

Figure 2. Price Efficiency and Time in the Continuous Sessions. Price efficiency is inversely related to the mean price error (MPE), the average deviation (in absolute value) of the transaction price from the asset value. MPEs are aggregated by time quartile for the six continuous auction sessions, and compared with the MPE for the six call auction sessions.

Insiders did, however, tend to concentrate their trades early in the trading interval.[22]

A feature of the data generated from the continuous auction trading periods is the significant impact of reversals on market liquidity. (This result can be inferred from the coefficient estimates for β_3 reported in Table V.) A potential explanation for this characteristic of the continuous auction is that dealers earn premia over the informationally efficient price. This can be illustrated in a simple example. Assume the dealers revise their conditional expectations of the asset value according to the simple rule, $\Delta E[V|\Delta Q] = \lambda \Delta Q$. A single unit buy order would therefore imply an upward revision in the conditional expectation by λ. Assume the dealer who takes the trade earns a premium of δ on the transaction, with δ equal to the difference (in absolute value) between the conditional expectation of the asset value and the price. A second single unit buy order following the initial buy order (continuation) therefore implies a price change of λ, while a single unit sell order following the buy order

[22] The average insider trade sizes (in absolute value) are 2.05 and 1.95 in the two continuous sessions with experienced subjects. The expected noise trader order size is two. The average insider trade size did not differ systematically over the trading interval. The average (per session) insider order times are 48.7 and 42.6 seconds. The average arrival time of noise trades is 61.4 seconds.

Table V

Market Liquidity in the Continuous Sessions with Experienced Subjects

The following model is estimated (OLS) in order to examine the determinants of market liquidity:

$$|\Delta P| = b_0 + b_1\text{TIME} + b_2|Q| + b_3\text{REVERSAL} + \varepsilon;$$

Variable definitions are as follows. $|\Delta P|$ is the absolute value of the price change, TIME is the clock time of the transaction, $|Q|$ is the absolute value of trade size, and REVERSAL is an indicator variable that takes on the value of +1 for a transaction in the opposite direction of the previous transaction (reversal), and 0 for a transaction that is a continuation. M^* is the optimal lag length determined by Andrews' (1991) rule for constructing t-statistics that are consistent in the presence of heteroskedasticity and autocorrelation.

Session	$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_2$	$\hat{b}_3$	M^*	Trades	adj. R^2
CONT-EXP1	2.06	−0.036	1.04	2.24	0	60	0.35
	(2.11)	(−3.57)	(3.06)	(4.50)			
CONT-EXP2	1.12	−0.025	0.57	6.30	4	60	0.84
	(2.23)	(−4.79)	(2.97)	(10.82)			

(reversal) would imply a price change of $-(\lambda + 2\delta)$. The result is larger price changes (in absolute value) on reversals than on continuations, with a symmetric argument holding for an initial sell order.

An alternative explanation is that the reversals phenomenon is related to the way in which the conditional expectation is updated. For example, Easley and O'Hara (1992) develop a model in which a single risky asset has two possible liquidation values and prices equal the expected asset value conditional on the order flow. Here the price change is higher for a reversal than a continuation as an implication of the dealers' zero-profit condition.

Outside the context of an equilibrium model with the features of the continuous auction of the experimental markets, a definitive explanation of the reversal's effect is not possible. The importance of dealer profits in the continuous trading periods, however, suggests an explanation that incorporates dealers earning premia over informationally efficient prices. Dealer premia, in turn, may plausibly be due to either a failure to achieve the competitive outcome or dealer risk aversion.

IV. Summary and Conclusion

The analysis of the experimental markets suggests important differences in the performance of the call and continuous trading mechanisms in the presence of insider trading. A significant result is the greater liquidity of the call markets in the sense that the markets are deeper, and noise traders incur lower losses. This result is consistent with theoretical models that examine the influence of temporal consolidation and market transparency on market performance.

In both the call and continuous trading periods, insider trading results in gains in price efficiency. There are no significant differences in average price efficiency, although more of the insider's information becomes impounded in the price by the end of the continuous sessions. There are also significant differences in the characteristics of prices by trader type in the continuous markets. While the insider trades at prices that are significantly more efficient than the asset's unconditional expectation, noise traders do not.

The evidence I have presented demonstrates that there are significant mechanism-specific performance differences due to asymmetric information. Since an important feature of any trading system will be regulations pertaining to insider trading, I have shown that optimally balancing the tradeoffs between informational efficiency, liquidity, and enforcement costs is an exercise that must be trading mechanism-specific.

There are other important aspects of trading mechanism performance not examined here. For example, despite the advantages considered above, a call mechanism does not provide immediate execution, and it may place a greater informational burden on traders in the sense that recent prices are not continually available. Nevertheless, there has been recent interest in employing periodic mechanisms more widely in U.S. financial markets. This is counter to the trend in Europe, where there has recently been an increased reliance on continuous mechanisms, with an increase in the regulation and enforcement of insider trading prohibitions.

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