Price Formation and Market Quality When the Number and Presence of Insiders Is Unknown

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In most models of market microstructure tractability requires that all market participants know the number (and presence) of competing insiders. I drop this assumption in experimental asset markets. Outcomes are qualitatively consistent with theoretical models when the number of insiders is disclosed prior to trade. When it is not, insiders use the timing and size of trades interactively to hide from the dealers and each other, dealers have difficulty identifying insider trades, and liquidity patterns do not differ as a function of the number of insiders. In general, insider behavior has strategic dimensions not admitted in Kyle (1985) and extensions.

Much recent research in market microstructure examines the implications of informational asymmetries for the time-series properties of asset prices. A characteristic of most of this literature is that an information event is assumed to have occurred and the presence of insiders is certain. For example, in the Kyle strategic trader framework, an insider's trading strategy depends on the number of competing insiders, and the market-maker's price-setting rule depends on how aggressively insiders compete in equilibrium. In Glosten and Milgrom (1985) and related sequential trade models, although the number of insiders is not specified, the probabilistic structure governing insider arrivals is known, with dynamic insider strategies precluded by assumption.

The inference problem faced by both dealers and informed traders in actual asset markets is more difficult since events that give rise to informational asymmetries, such as mergers, acquisitions, lawsuits, mineral finds, etc., occur randomly. Dealers must therefore infer the informational content of the order flow from trading activity. Also, since insiders do not announce their presence, traders must use trading activity to gauge their competitive positions.

In this article I investigate the importance of embedding more plausible background assumptions than are common in the microstructure literature,

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including the random occurrence of information events and a random number of competing insiders. I accomplish this by comparing the outcomes from experimental asset markets in which I manipulate the information structure. In the first set of markets I maintain the information structure of the Kyle model framework, with the number of insiders (2, 1, or 0) disclosed prior to the start of trade, and insiders (if present) free to choose the timing of trades. In the second set of markets the number of insiders is not disclosed and market participants must infer both the presence and number of insiders from market activity. Thus I study the marginal effect of uncertainty with respect to the number of insiders on the (interdependent) price setting behavior of dealers and trading behavior of insiders.

Results include the following. When there are two insiders and the number of insiders is disclosed to all participants, aggressive competition between the insiders and the initially high responsiveness of price to order flow cause rapid convergence of price to fundamental value. When the presence of a single insider is disclosed to market participants, the monopoly insider exploits her information gradually over time. When the absence of insiders is disclosed to the market, prices remain anchored to the unconditional expectation of the asset value, but respond to order flow in a way consistent with dealer inventory management. These results are qualitatively consistent with theoretical models that assume the number and presence of insiders is known [Kyle (1985), Subrahmanyam (1991), Holden and Subrahmanyam (1992), and Foster and Viswanathan (1996)].

When the presence of insiders must be inferred, insiders do not compete aggressively. Here they delay their trades both at the beginning of the trading interval and in response to profitable trading opportunities that arise from noise trader activity. There is also evidence that insiders use trade size and the timing of trades interactively: a positive relationship exists between trade size and the time until an insider responds to a profitable trading opportunity. This leads to insider trading patterns that do not significantly differ as a function of the number of insiders. The insiders' strategic use of time in turn makes it difficult for the dealers to discern the number and presence of insiders from order flow patterns, thus liquidity patterns established by dealers also do not differ significantly as a function of the number of insiders. This implies much slower convergence to intrinsic value when there are two insiders, and large sustained price movements away from intrinsic value when insiders are absent and imbalances in noise trader demands cause dealers to falsely infer the presence of insiders. Overall, price efficiency is significantly reduced relative to the benchmark case where the number of insiders is disclosed.[1]

[1] Camerer and Weigelt (1991) construct a laboratory asset market experiment to test whether traders who are sometimes informed overreact to uninformative trades. In their setting, traders are endowed with two assets, and belong to one of three dividend types, with the trader type determining the dividend payment in each state (good or bad). In most sessions there is a 50% chance that half of the traders learn the state and a 50% chance that no traders learn the state. "Information mirages" occur in 28% of the periods without insiders.

An implication of this work is that the intuitions from strategic trader models [Kyle (1985) and extensions] may not generalize to realistic market settings where the number and presence of insiders is not disclosed prior to trade. Easley and O'Hara (1992) model the random presence of insiders in a sequential trade framework that precludes strategic insider behavior.[2] They derive the stochastic process of prices and explicitly characterize the relation between the time between trades and market liquidity, showing the time between trades is informative with respect to whether an information event (which engenders the presence of insiders) has occurred. I do not find support for this prediction. This appears due to the strategic timing of trades (including the interactive use of timing and trade size) by insiders. This type of strategic behavior also provides a potential explanation for recent empirical results that find the time between trades is of minor importance in explaining price changes after controlling for volume and other microstructure variables [see Hausman, Lo, and MacKinlay (1992) and Dufour and Engle (2000)].

I also estimate an empirical spread decomposition model proposed by Glosten and Harris (1988). Exploiting the observation of dealer inventories, I find evidence suggesting dealer inventory management effects are nonlinear, and stronger in the environment where the number of insiders must be inferred. The latter result is consistent with another experimental study [Bloomfield (1996)] and suggests that factors contributing to uncertainty with respect to the informational content of the order flow (e.g., the proximity of an earnings announcement) will affect the accuracy of a spread decomposition if the inventory management motive is present.

This article is organized as follows. In Section 1, I explain the experimental design and procedures. In Section 2, I review relevant theoretical models. Section 3 presents the results. In Section 4, I summarize and conclude.

1. Experimental Design and Procedures

Trading in the experimental markets is conducted under two different information structures. Since my intention is to study the effect of manipulating the information structure on market outcomes, trading mechanisms and the distributions of random variables are held constant across information structures.

The markets are organized as order-driven (auction) dealer markets in which noise trades of random size arrive at random times and insiders are free to submit orders (which may vary in size) at anytime the market is open. The design includes three key features. First, the realization of the liquidity trading motive differs in economically important ways from that typically assumed in the literature. The Poisson probability model incorporated in the

[2] O'Hara (1995, Section 3.5) reviews the relative strengths and weaknesses of sequential trade and strategic trader models.

experimental design is consistent with a large number of potential "liquidity" traders, each of whom will trade with very low probability. Furthermore, liquidity trades occur at random times when the market is open.[3] An economic interpretation of the Brownian motion assumption employed in Kyle (1985) and subsequent work is that there are many liquidity traders, each of whom trades a very small quantity with certainty at a prespecified time on the trading interval. Second, there are no constraints on insider strategies: dynamic strategies are permitted, including strategies that involve attempts to destabilize the market. Third, there is a separation of trading for liquidity purposes and trading to exploit superior information. This avoids constraining an insider to satisfy liquidity trading motives through negative expected profit trades in a market where she enjoys an informational advantage. Despite the relative simplicity of the design, this environment has not been successfully modeled.

The experimental markets include three types of agents: two potential insiders who may learn the end-of-period value of a single risky asset, three competing dealers, and (computerized) uninformed "noise" traders. The basic framework is similar to Kyle (1985). The insider(s) trades to exploit an informational advantage and market makers compete to take the orders submitted by the insider(s) and noise traders. The trades of the noise traders are independent of the end-of-period asset value, and are typically interpreted in the literature as liquidity motivated.

The experimental markets are organized into two treatments. The key difference is whether or not the number of insiders who learn the asset liquidation value prior to the start of a market is public information. In the first, prior to the start of each trading period, the probability that each potential insider learns the liquidation value of the asset is 1/2 and independent of the other draw. If a potential insider learns the liquidation value, she is free to trade during the market period. If not, she is precluded from trading,[4] and instead plays a forecasting game that has no influence on market outcomes. Of importance is that dealers and insiders do not learn the number of insiders present during the market period, but they do know the above probabilistic structure. Since the actual number (or presence) of insiders is not announced, but must be inferred from the market activity, this treatment is referred to as NI (number inferred). In the second set of trading periods, prior to the beginning of each trading period, the number of insiders is disclosed to all dealers and insiders. This treatment is referred to as ND (number disclosed).

Trading proceeds as follows under both information structures. During the two-minute trading period (economic time), the insider(s) is permitted to submit an unlimited number of orders to the dealers. The dealers also

[3] Easley, Kiefer, and O'Hara (1996), and Easley et al. (1996) are two recent articles that incorporate the Poisson probability model as the governing process for liquidity trades.

[4] This is in order to avoid creating a fourth class of agents who would not be present in every period.

receive computer-generated "noise" orders that arrive randomly over the trading interval. The dealers do not learn which orders are submitted by the insider and which are noise traders' orders. Upon each order arrival, the trading interval clock stops, and a first-price sealed-bid auction is conducted among the dealers to determine the execution price. Upon execution of an order, all participants learn the transaction price and order size, and then after a brief pause, the trading interval clock resumes. At the expiration of time, the value of the asset is revealed, and cash balances are updated.

Each experimental session consists of 12 trading periods. The asset value, and timing and size of each liquidity trade are determined independently for each trading period. In order to enhance experimental control, I create two sets of random draws. The first is applied to all sessions with inexperienced subjects, and the second to sessions with experienced subjects. The sequence of steps for an individual period is summarized in detail in Table 1. I provide more details on the trading protocol and experimental design below.

Table 1
Sequence of events for a single period in the experimental markets

Number of insiders inferred (NI) sessions	Number of insiders disclosed (ND) sessions
1. Prior to the start of each trading period, each of the two potential insiders learns the asset liquidation value with probability = 0.5 (independent probabilities). If a potential insider learns the liquidation value, he/she will be free to trade during the trading period. If not, he/she is precluded from trading, but plays a forecasting game that has no influence on market outcomes. Prior to the beginning of each trading period, dealers and insiders do not learn the number of insiders that will be present, but they do know the above probabilistic structure. The asset value distribution and the process governing the arrival of noise traders' (computer) orders are included in the experimental instructions.	1. Same as in the NI sessions ***except*** prior to the start of each trading period, all potential insiders and dealers learn the number of insiders that will be active during that trading period.
2. The two-minute (economic time) trading period begins. Over the course of the trading interval, the insider(s) is permitted to submit an unlimited number of buy and/or sell orders to the dealers. The only constraint is that each order be for one, two, or three units of the risky asset. The dealers also receive noise traders' (computer-generated) orders that arrive randomly over the trading interval. The noise trader buy volume each trading period is determined by a draw from a Poisson distribution with intensity equal to four. Buy orders are distributed randomly over the trading interval, with the size (probability) of each buy order as follows: 1 (0.25), 2 (0.5), 3 (0.25). An identical process determines noise trader sell volume. The initiator of a trade (noise trader or insider) is not disclosed to the dealers, or in the event of multiple insiders, the insider.	2. Same as NI sessions.
3. Upon each order arrival, the trading interval clock is paused, and a first-price sealed-bid auction is conducted among the dealers to determine the execution price. If the market order is to buy (sell), the dealer with the lowest offer (highest bid) takes the other side of the trade. Upon execution of an order involving an insider, the insider's cash balance is updated to reflect trading profits (losses).	3. Same as NI sessions.
4. At the end of the trading period the value of the asset is revealed. Trading profits of the dealers 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. Same as NI sessions.

1.1 Price rules

All orders are market orders, with prices established by competing dealers. The sealed-bid first-price auction used to establish trading prices is conducted as follows. Upon the arrival of an order, the dealers are notified of the order size. If the order is a buy order, the dealer who submits the lowest price sells the quantity necessary to clear the market, while if the order is to sell, the dealer who submits the highest price buys the order. Ties are broken randomly. Profits on each trade are $(V-P)Q$, where V is the end-of-period value of the asset, P is the transaction price, and Q is the signed quantity.

1.2 Trading rules

If a potential insider becomes informed, she may, at any time, submit buy or sell orders. There are no constraints on the number or timing of insider(s) orders. Permissible trade sizes are for one, two, or three units of the asset, and there are no constraints on short sales.[5] Dealers are not permitted to submit orders. As explained above, the insider(s) and the dealers receive initial cash endowments, with cash balances brought forward to subsequent periods; they do not receive an endowment of the risky asset. Asset positions are reset to zero at the start of each new trading period.

1.3 Parameter values and variable distributions

Monetary units: The monetary unit employed in the experiment is the laboratory dollar (henceforth L$). L$s are U.S. dollars (the currency in which payments are made to subjects) multiplied by 33.33.
Asset value: The asset value of each market period is drawn from an approximate normal distribution with mean of L$100, standard deviation of L$8.7, and support on the whole L$. There is zero probability that the asset value is less than L$70 or more than L$130. There is a riskless asset (cash) with an interest rate of zero.
Noise traders' (computer-generated) orders: The noise traders' buy orders are determined for each period as follows. First, the number of buy orders is determined by a draw from an approximate Poisson distribution with intensity equal to four.[6] The size of each arrival is then determined by an independent draw from a trinomial distribution with possible order sizes of $(1, 2, 3)$ and probabilities of $(0.25, 0.5, 0.25)$, respectively. 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 has elapsed. The number, size, and timing of noise trader sell orders are

[5] Multiple trade sizes are allowed in order to permit insiders dynamic strategies that incorporate both the size and timing of trades. Computer-generated "noise trader" orders are also for one, two, or three assets, with more information on their frequency and timing below.

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

determined in an identical fashion, with the only exception that sell order sizes are submitted and reported as negative quantities $(-1, -2, -3)$.

The random arrival of noise trader orders is consistent with liquidity buy and sell orders governed by independent compound Poisson processes. The distribution of the net noise trader order (the sum of noise trader buy and sell orders) each trading period is approximately Gaussian. An economic interpretation of this assumption is that there is a large population of shareholders, each of whom trades with very low probability to satisfy an exogenous liquidity motive.

1.4 Communications and computer displays

All interactions between subjects were conducted on networked personal computers with custom-designed software. The computer screen in front of each dealer and trader contains continuously updated market information indicating 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 balance. The cash balances of the insiders are updated at the completion of each trade, while the cash balances of the dealers are updated at the end of each trading period.

1.5 Subjects and procedures

Subjects were recruited from a senior-level undergraduate finance class and an elective MBA finance class in the Olin School of Business, Washington University in St. Louis. A total of 30 subjects participated in 10 experimental sessions. Three initial sessions were conducted under each of the two experimental treatments with inexperienced subjects. These were then followed by two additional sessions in each setting with subjects from the initial sessions in the same setting (experienced subjects).

At the commencement of each experimental session, subjects received written instructions that were read aloud by the experimenter.[7] After clarifying questions were answered, subjects were given instructions to familiarize them with the operation of the computer and the display of information on the computer screens. They were then randomly assigned to roles that they retained for the entire session and were seated at computer terminals. The experimental laboratory had physical barriers that prevented participants from making visual contact and verbal communication was prohibited. Each potential insider was located in a separate side room so that it was impossible for dealers to associate incoming orders with insiders through the sound of keystrokes. After final questions were answered, the 12 periods of trading commenced. At the completion of trading, each subject completed a questionnaire, was privately paid his/her earnings in cash, and was dismissed. Subjects indicated in the questionnaire that they had fully understood the

[7] A copy of the instructions is available from the author upon request.

instructions, felt adequately compensated in cash for the effort expended in participating in the experiment, and understood how their decisions affected their cash payments.

Dealers received an initial cash endowment of L$750 and potential insiders received initial cash endowments of L$450.[8] At the end of the 12 trading periods, cash balances (endowments plus accumulated trading profits) were multiplied by 0.03 and subjects were paid that amount. Sessions lasted approximately 2.5 hours with inexperienced subjects and 2 hours with experienced subjects, and cash earnings per subject averaged $25.05.

2. Theoretical Results and Hypotheses

Theoretical models of insider trading provide strong intuitions for insider strategies in the experimental markets when the number of insiders is disclosed. However, modeling has proved intractable when the number (or presence) of insiders must be inferred and insiders are permitted dynamic strategies. I use the existing theoretical results to characterize the trade-offs faced by insiders and dealers where theoretical results are not available, and formulate a set of testable hypotheses that I detail below.

Kyle (1985) derives a sequential equilibrium in a model of the dynamic strategy of a monopoly insider. At prespecified times on the trading interval, the insider's order and a random liquidity order are combined, 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. Important features of the equilibrium are that the insider maximizes profit by exploiting her information gradually over time, and when the number of auctions on the trading interval is large, price pressure (the change in price per unit order flow) is roughly constant over the trading interval.

Holden and Subrahmanyam (1992) extend the Kyle model to allow multiple insiders with identical information. The primary result is that insiders compete aggressively, reducing insiders' profits in the aggregate. Even with two insiders, a large number of auctions on the trading interval imply that the insiders' information is incorporated into the price almost immediately. Foster and Viswanathan (1996) confirm this result when there are multiple insiders who receive highly correlated signals.

When the number of insiders is unknown, there is no linear equilibrium in the Kyle framework due to the loss of conditional normality of the updated asset value distribution given the order flow. Nevertheless, the equilibria in the models assuming certainty with respect to the number of insiders establish the nature of the trade-offs faced by the insider in this complex problem.

[8] Differences in initial cash endowments equalized earnings per session by agent type. The average hourly compensation was above the average level for other experiments at the same site at the time the experiment was conducted.

Aggressive trading at the start of the trading interval may avoid the loss of profitable trades to a potential competitor, but reveal the insider's presence when she is a monopolist. Patient trading may reduce the insider's trading costs by causing the dealers to revise their beliefs with respect to the probability of an insider being present downward (reducing implicit spreads and increasing market depth), but increase the probability that profitable trades are lost to a potential competitor. The problem is by its nature dynamic. The insider updates her beliefs with respect to her competitive position as order flow is realized over the trading interval, again confronting the trade-off between aggressiveness and patience, recognizing that the dealers also update their beliefs.

These trade-offs faced by insiders and the dealers' inference problem imply that when there are two insiders and the number of insiders must be inferred, insiders will trade less aggressively than when their presence is disclosed. This is due to a benefit to delayed trade in the NI setting that is not present in the ND setting: delayed trade may lead the dealers to falsely infer the absence of insiders. Moreover, with two insiders, there are no incentives for aggressive trading in the NI setting that are not also present in the ND setting. When there is a single insider, in the NI setting there is an incentive to be aggressive not present in the ND setting (trading in front of a potential competitor) and an incentive to be less aggressive (inducing the dealers to falsely infer the absence of insiders). It is not clear a priori which effect should dominate. The theoretical results summarized above and their application to the NI setting lead to a set of testable hypotheses pertaining to insider behavior.

Hypothesis 1. *Two insiders will compete more aggressively under the ND information structure than the NI counterparts.*

Hypothesis 2. *Insider behavior will be similar across information structures when there is a monopoly insider.*

Hypothesis 3. *Within information structures, insider behavior will differ significantly as a function of the number of insiders, although differences will be more significant in the ND setting.*

Support for Hypothesis 3 will depend on how rapidly insider behavior allows insiders to learn their competitive position: an issue on which the theoretical models are silent.

The second set of hypotheses pertains to dealer behavior. Theory predicts implicit spreads and depth correspond to the probability a trade was initiated by an insider. For example, in Holden and Subrahmanyam (1992) the initial competition between multiple insiders makes the informational content of early trades high, and thus the responsiveness of price to order flow is also initially high, falling rapidly and monotonically over the trading interval as the market approaches strong-form efficiency. The monopoly insider in

Kyle (1985) exploits her informational advantage gradually, and thus when the number of auctions on the trading interval is large, price pressure (the change in price per unit order flow) is roughly constant over the trading interval. These results, as well as the intuition that the responsiveness of price to order flow should depend on the probability a trade is initiated by an insider, lead to two hypotheses concerning dealer behavior.

Hypothesis 4. *The initial responsiveness of price to order flow will be* (1) *higher under the ND information structure when there are two insiders,* (2) *similar across information structures when there is a monopolist insider,* (3) *higher under the NI information structure when insiders are absent.*

Hypothesis 5. *Over the trading interval, the responsiveness of price to order flow will* (1) *decline more rapidly under the ND information structure with two insiders,* (2) *be roughly constant across information structures with a monopolist insider,* (3) *be higher when insiders are absent under the NI information structure.*

In Holden and Subrahmanyam (1992) and Kyle (1985) the derivations of the Bayesian–Nash equilibrium patterns in strategic insider trading and price pressure require that the presence and number of insiders is known. In a sequential trade framework with nonstrategic insiders, Easley and O'Hara (EO) (1992) model a market in which the presence of insiders is uncertain. They argue that this specification is realistic because traders who do not receive insider information may also not know whether material new information exists. In the model an exogenous process brings potential traders to the trading post. If an information event has occurred, then each arriving trader becomes informed with an exogenously determined probability. If the trader becomes informed, she makes a trade of one unit and leaves. If the trader is not informed, he may transact in order to satisfy a liquidity motive, with the probability of a liquidity-motivated buy or sell also exogenous. In equilibrium, the time between trades is informative with respect to the presence of insiders, and market liquidity is increasing in the time between trades because of the downward revision in the probability that an information event has occurred. This result leads to the following prediction.

Hypothesis 6. *Under the NI information structure, the responsiveness of price to order flow will be inversely related to the time between trades.*

I note that insiders in the experimental markets are afforded a large strategy space, while in the EO model they are nonstrategic. This result from a sequential trade model is therefore used to provide a benchmark in a setting where theoretical results in a strategic trader setting are not available.

The final hypothesis concerns relative informational efficiency across information structures. Aggressive competition between two insiders under the ND information structure suggests more rapid convergence to intrinsic value than in the corresponding NI trading periods. Also, if statistically likely imbalances in the net noise trader order lead to the false inference of insider trading in some NI trading periods when insiders are absent, price errors on average will exceed those in the corresponding ND trading periods where the absence of insiders is disclosed.

Hypothesis 7. *Informational efficiency will be higher in the ND sessions.*

Uncertainty with respect to the number of insiders per se is predicted to lead to differences in informational efficiency despite identical uncertainty in all other dimensions.

3. Results

There are five sessions under each information structure. Each session consists of 12 trading periods with the same group of subjects. I discard the first five trading periods in the sessions with inexperienced subjects and the first two trading periods in the sessions with experienced subjects because of the complexity of the markets.[9] This leaves a total of 82 trading periods, which are evenly split between information structures. I report parameter values and summary statistics by trading period in Table 2, and summary statistics for each information structure grouping trading periods by the number of insiders present and the experimental session in Table 3.

All analysis on the level of the trading period or individual transaction reports p-values that are based on GMM t-statistics that are consistent in the presence of heteroscedasticity and autocorrelation.[10] As a robustness check, I also analyze session-level data (a single mean from each session under each information structure) with the nonparametric Wilcoxon rank-sum (Mann–Whitney) test. All reported p-values are for two-tailed tests.

I organize the results around the hypotheses developed in the previous section, considering first hypotheses pertaining to insider behavior, and then hypotheses relating to dealer behavior and market efficiency. This ordering is for expositional convenience only, since I show below that dealers correctly anticipate patterns in insider behavior (which themselves depend on information structure and the number of insiders). I conclude this section by examining the effect of information structure on dealer inventory management.

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[9] I exclude trading periods from the analysis due to the complexity of the markets and my interest in studying equilibrium behavior. The number of periods is based on results from a pilot study for a similar experiment [Schnitzlein (1996)]. The two sessions with experienced subjects under each information structure use subjects that gained experience under the same information structure. Each session with experienced subjects had at least one randomly selected subject from each of the three sessions with inexperienced subjects and subjects maintained the same roles (dealer or insider).

[10] In the construction of the GMM variance-covariance matrix I use the optimal lag length determined by Andrews' (1991) rule for constructing t-statistics that are consistent in the presence of heteroscedasticity and autocorrelation.

Table 2
Parameter values and summary statistics by trading period

Session and trading period	Asset value (L$) (1)	Noise trader buy volume (2)	Noise trader sell volume (3)	Number of insiders (4)	Mean insider buy volume (5)	Mean insider sell volume (6)	Mean dealer profits (7)	Mean noise trader profits (8)	Mean insider profits (9)	Mean $\|\Delta P\|$ (L$) (10)	MPE (L$) (11)
NI 1–3											
Period 6	95	10	7	2	1.67	9.33	18.63	−28.77	10.13	1.88	2.81
Period 7	105	5	4	0	0	0	5.37	5.37	0.00	1.84	5.94
Period 8	98	6	6	1	1	1.67	10.50	−10.00	−0.50	1.20	1.28
Period 9	86	2	4	2	2	14	−86.70	3.93	82.77	2.41	5.51
Period 10	112	17	7	1	13.67	1	−85.00	24.27	60.73	2.18	6.60
Period 11	88	9	10	0	0	0	13.20	−13.20	0.00	2.09	12.52
Period 12	103	5	10	1	8.33	0	24.93	−34.10	9.17	2.61	2.96
NI exp 1–2											
Period 3	92	13	7	2	0	10	33.75	−80.25	46.50	3.16	4.44
Period 4	101	4	11	2	12.5	1	20.65	−57.85	37.20	2.17	3.84
Period 5	105	10	6	0	0	0	8.25	−8.25	0.00	2.58	6.97
Period 6	93	11	8	1	0.5	2.5	51.70	−55.80	4.10	4.38	3.58
Period 7	116	5	3	2	13.5	0	−97.30	1.65	95.65	3.42	7.08
Period 8	89	0	7	1	0	3.5	−33.25	25.55	7.70	1.40	3.28
Period 9	87	8	2	0	0	0	123.90	−123.90	0.00	5.51	18.89
Period 10	97	7	16	1	9	0	45.50	−73.00	27.50	3.09	4.09
Period 11	92	4	12	2	3.5	8.5	9.70	−64.70	55.00	4.51	5.57
Period 12	101	13	6	0	0	0	82.3	−82.35	0.00	3.07	9.46
ND 1–3											
Period 6	95	10	7	2	1.67	9	26.90	−32.60	5.70	2.97	2.17
Period 7	105	5	4	0	0	0	14.83	−14.83	0.00	2.87	5.43
Period 8	98	6	6	1	0	0.67	19.77	−19.00	−0.77	2.52	1.78
Period 9	86	2	4	2	2	16.33	−56.67	−15.80	72.47	2.36	3.81
Period 10	112	17	7	1	8.67	2.33	−29.20	−12.17	41.37	3.34	5.64
Period 11	88	9	10	0	0	0	14.10	−14.10	0.00	1.76	13.14
Period 12	103	5	10	1	10.67	0.67	27.60	−61.53	33.93	3.18	4.14
ND exp 1–2											
Period 3	92	13	7	2	0.5	10	24.60	−36.05	11.45	2.05	1.76
Period 4	101	4	11	2	13	1.5	17.10	−38.75	21.65	1.52	2.23
Period 5	105	10	6	0	0	0	−2.55	2.55	0.00	1.13	4.93
Period 6	93	11	8	1	2	3	2.95	−9.40	6.45	1.46	1.37
Period 7	116	5	3	2	12	5	−59.10	−10.75	69.85	2.11	3.07
Period 8	89	0	7	1	1.5	3.5	−24.80	19.30	5.50	2.45	2.97
Period 9	87	8	2	0	0	0	110.00	−110.00	0.00	2.06	17.65
Period 10	97	7	16	1	17.5	2.5	33.45	−95.30	61.85	3.01	4.71
Period 11	92	4	12	2	7.5	6.5	44.40	−66.25	21.85	3.74	2.94
Period 12	101	13	6	0	0	0	38.15	−38.15	0.00	3.62	2.84

There are three sessions with inexperienced subjects and two sessions with experienced subjects under each information structure. 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. For example, the random draws in trading period 6 in sessions 1–3 are the same in each sixth trading period with inexperienced subjects across both information structures. Reported figures average outcomes across trading periods within each information structure. The asset value [column (1)] is the realized draw from the distribution governing asset value (approximately Gaussian, with unconditional expectation of 100, and standard deviation of 8.7). The noise trader buy volume each trading period [column (2)] is determined by a draw from a Poisson distribution with intensity equal to four. Buy orders are distributed randomly over the trading interval, with the size (probability) of each buy order as follows: 1 (0.25), 2 (0.5), 3 (0.25). An identical process determines noise trader sell volume [column (3)]. Mean insider buy volume [column (5)] is the average of insider buy volume across trading periods. Mean insider sell volume [column (6)] is the average of insider sell volume. Profits are averages by trading period in L$. Mean $|\Delta P|$ [column (10)] is the mean price change in absolute value. MPE [column (11)] is the mean price error, in absolute value.

Table 3
Summary statistics by number of insiders and experimental session

	Asset value extremeness (L$) (1)	Mean insider volume (2)	Mean dealer profits (3)	Mean noise trader profits (4)	Mean insider profits (5)	Mean $\|\Delta P\|$ (L$) (6)	MPE (L$) (7)
Panel A: Number of insiders by information structure							
NI							
0 insiders	7.4	0	40.4	−40.4	0	2.84	10.50
1 insider	6.2	7.2	−1.40	−17.4	18.8	2.38	3.63
2 insiders	8.8	13.5	−19.3	−34.1	53.4	2.81	4.77
ND							
0 insiders	7.4	0	31.5	−31.5	0	2.29	8.88
1 insider	6.2	8.6	5.2	−29.9	24.7	2.73	3.52
2 insiders	8.8	14.2	−2.5	−32.1	34.6	2.49	2.71
Panel B: Results by experimental session							
NI1	7.57	9.43	−26.5	−5.71	32.21	1.79	4.76
NI2	7.57	5.43	−9.13	−11.27	20.40	2.48	5.63
NI3	7.57	7.71	−6.83	−10.11	16.94	2.05	5.74
Niexp1	7.30	8.10	−0.92	−36.58	37.50	2.10	6.76
Niexp2	7.30	4.80	49.97	−67.2	17.21	4.77	6.68
NI-Avg	**7.44**	**7.24**	**4.71**	**−29.82**	**25.10**	**2.66**	**6.03**
ND1	7.57	4.57	13.86	−33.07	19.21	4.05	6.04
ND2	7.57	10.86	−5.43	−21.43	26.86	2.60	5.40
ND3	7.57	6.86	−1.00	−18.37	19.37	2.02	4.03
Ndexp1	7.30	8.70	5.26	−22.16	16.90	1.52	4.04
Ndexp2	7.30	8.50	31.58	−54.40	22.82	3.29	4.85
ND-Avg	**7.44**	**8.00**	**10.25**	**−31.11**	**20.87**	**2.52**	**4.81**

I report summary statistics under each information structure, aggregating trading periods by the number of insiders in panel A, and by experimental sessions in panel B. The asset value extremeness [column (1)] is the average difference between the realized draws from the distribution governing asset value (approximately Gaussian, with unconditional expectation of 100, and standard deviation of 8.7) and the unconditional expectation. Insider profits are increasing and dealer profits are decreasing in extremeness. Mean insider volume [column (2)] is the average level of insider volume, mean profits by trader type are in laboratory dollars (L$), mean $|\Delta P|$ [column (6)] is the mean price change in absolute value, and MPE [column (7)] is the mean price error. All averages (including averages across sessions) are computed weighting each trading period equally. There are 7 trading periods in each session with inexperienced subjects and 10 trading periods in sessions with experienced subjects.

3.1 Hypotheses pertaining to insider behavior

Hypothesis 1 (insider behavior across information structures: two-insiders). When there are two insiders and their presence is disclosed to the market (ND), the insiders compete aggressively. In this case 48% of total insider trading volume is realized in the first 10 seconds (8.33%) of the trading interval and the average time until the first insider trade is 1.86 seconds.[11] In contrast, when the number of insiders must be inferred (NI), only 10% of insider volume is realized in the first 10 seconds, and the average time until the first insider trade is 14.29 seconds (Figure 1, panel A).[12] An important benchmark for the significance of insider volume patterns is insider volume relative to expected noise trader volume. Over the

[11] Since the trading period clock is paused while each auction is conducted, trading periods take an average of eight minutes. With heavy volume, the first 10 seconds of "economic" time requires two to four minutes of "clock" time.

[12] I show in Section 3.2 that dealers anticipate the realized insider trading patterns: differences in insider trading patterns reported in this section are not explained by differences in liquidity patterns.

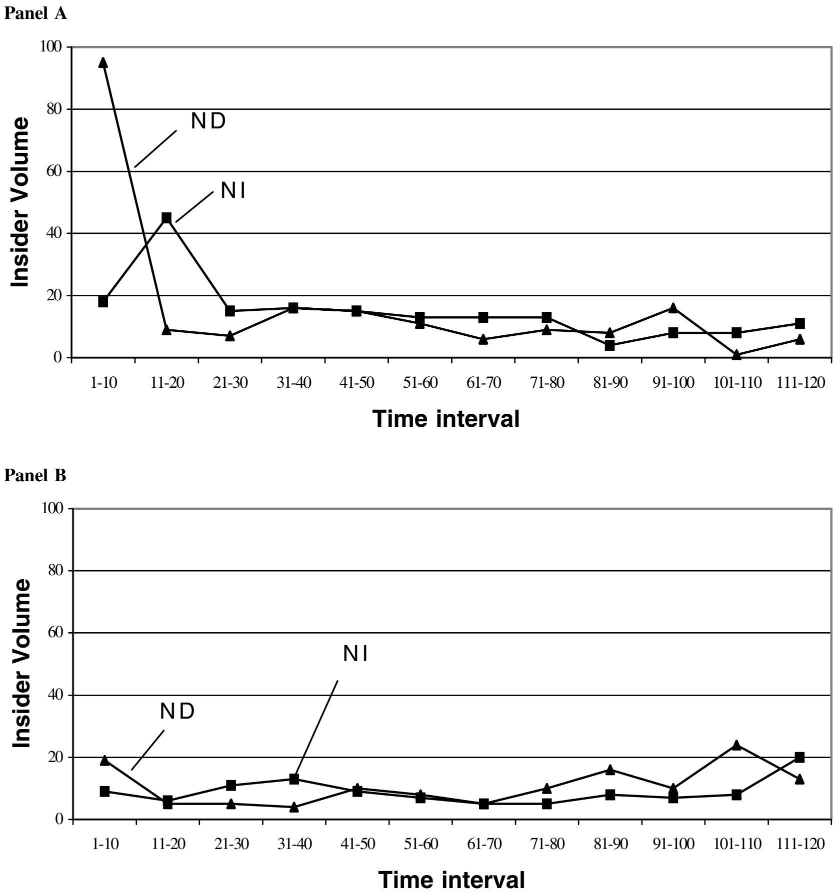
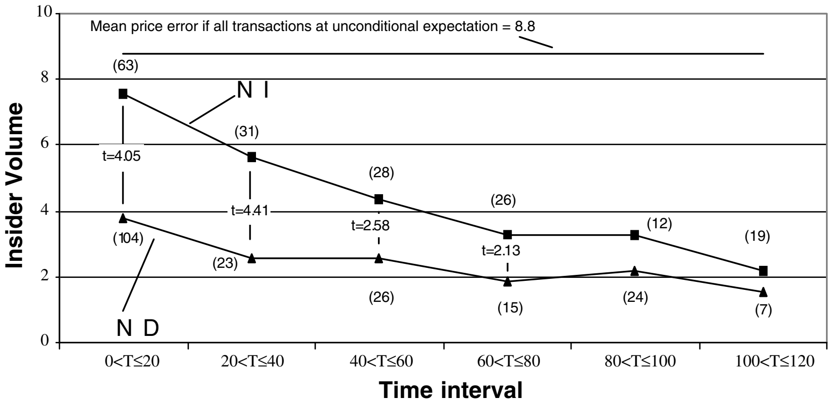


Figure 1
Insider trading volume and time
Trading periods in which the number of insiders is disclosed prior to the start of trade are indicated "ND" and trading periods where the number of insiders must be inferred from trading activity are labeled "NI." Panel A shows insider trading volume for each 10-second time interval in trading periods with two insiders. Panel B shows the same for trading periods with a single insider. Patterns in the number of trades by time interval are virtually identical, and not reported. There are 14 trading periods under each information structure with two insiders and 15 with a single insider. Trading periods with the same number of insiders are directly comparable across information structures because other random draws (asset value and the timing and size of noise trades) are held constant.

first 10 seconds, ND insider volume exceeds expected noise trader volume by more than a factor of five, while NI insider volume is 96% of expected noise trader volume. I assess the significance of the difference in insider volume in the first 10 seconds of the trading interval when two insiders are present by regressing the percentage of total insider trading that occurs in each trading period in the first 10 seconds on a constant, the difference in absolute value between the asset's value and its unconditional expectation

Panel A



Panel B

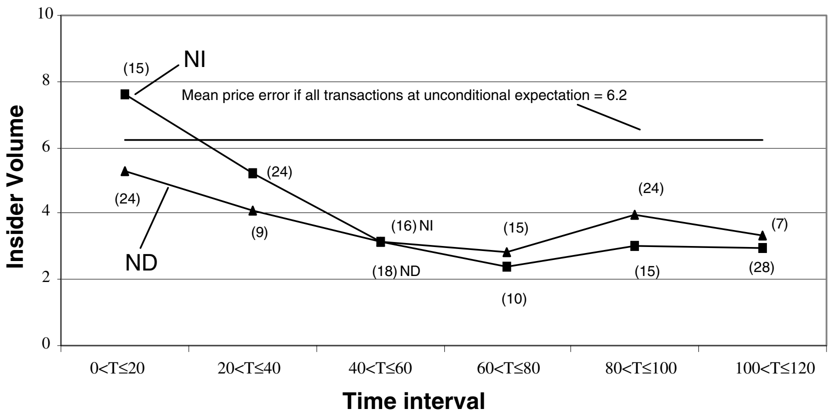


Figure 2
Price errors and time
Panel A shows average price errors for each 20-second time interval in trading periods with two insiders. Panel B shows the same for trading periods with a single insider. Insider trading volume for each time interval is indicated in parentheses adjacent to each marker that indicates the price error. Panel A indicates the rapid convergence to fundamental value when the presence of two insiders is disclosed to all market participants. Here more than two-thirds of the price efficiency gained by the end of the trading interval occurs in the first 20 seconds of trading. When the presence of two insiders must be inferred, convergence to fundamental value is gradual. Significant differences in price errors across information structures (by time interval) are indicated by reporting significant t-statistics. When there is a monopolist insider (panel B), convergence patterns are not significantly different across information structures.

(Extremeness), and an information structure indicator variable (Info) that takes on the value of one in the NI sessions and zero in the ND sessions. The results are reported below with GMM t-statistics in parentheses. The adjusted R^2 is 0.48 and $N = 28$.[13]

$$\begin{array}{l} \text{Percentage of trades in first 10 seconds} \\ \text{(two insiders)} \\ \qquad = \underset{(-1.18)}{-0.10} \; \underset{(2.45)}{+0.021} \text{ Extremeness } \underset{(-5.14)}{-0.41} \text{ Info} \end{array} \tag{1}$$

The extremeness of the asset value matters because when the asset value is within the implicit spread of the unconditional expectation, no profitable trading opportunities are immediately available. The more extreme the asset value, the greater the foregone profits if a competing insider trades first.

Insight into why the information structure matters is gained by running the above regression with interactions between the information structure and Extremeness. Here Extremeness is positive and highly significant when it is interacted with an ND indicator variable ($p < 0.01$), but positive and insignificant when interacted with an NI indicator ($p = 0.46$). The certainty of insider competition in the ND setting leads to aggressive competition between insiders if there is a profitable trading opportunity. In the NI setting, an insider does not know if she has competition, and thus trades more cautiously.

A similar pattern emerges when analyzing insider trades subsequent to liquidity trades. I verify this by regressing the time until an insider exploits a profitable trading opportunity (either on the first trade or created by a liquidity trade) on the magnitude of the profitable trading opportunity (the difference between the price and intrinsic value on the previous transaction (PE_{t-1})), and the information structure indicator. The adjusted R^2 is 0.24, $N = 106$.

$$\begin{array}{l} \text{Time until insider response} \\ \text{(two insiders)} \end{array} = \underset{(4.49)}{3.07} \; \underset{(-1.33)}{-0.18\, PE_{t-1}} \; \underset{(5.58)}{+5.59 \text{ Info}} \tag{2}$$

Again, the information structure indicator is highly significant ($p < 0.01$).[14] Thus the aggressive competition between insiders derived in Holden and Subrahmanyam (1992), and described as a "rat race" by Foster and Viswanathan (1996), is realized in the sessions in which insiders are certain to have competition. Much less aggressive insider behavior is the rule when the presence of a competitor is not disclosed: an insider risks losing profitable trades to a possible competitor in order to conceal her presence from the dealers. These results confirm Hypothesis 1.

[13] As a robustness check I calculate the average percentage for each session and then compare the session means under each information structure with the Wilcoxon rank-sum test ($p = 0.02$).

[14] The difference is significant using session level data ($p = 0.02$).

Although overall insider profitability does not vary as a function of information structure, less aggressive trading proves to be profitable in the case where there are two insiders. Weighting each trading period with two insiders equally, insider profits are higher in the NI sessions with two insiders by 54%, although using session level data, this difference is not significant ($p = 0.21$).

Hypothesis 2 (insider behavior across information structures: monopoly insider). When there is a single insider present, there is no significant difference in the distribution of insider trades over the trading interval (Figure 1, panel B), however, monopoly insiders in the NI setting take longer to exploit profitable trading opportunities. I verify this by repeating the regression from Equation (2) using the trading periods with a single insider. The adjusted R^2 is 0.13, and $N = 90$.

$$\begin{array}{lcccc} \text{Time until insider response} = & 7.95 & -0.64\ PE_{t-1} & +4.33\ \text{Info} \\ \text{(one insider)} & (5.99) & (-3.49) & (2.58) \end{array} \quad (3)$$

Again, the information structure indicator is significant ($p = 0.01$). As a robustness check I calculate the mean time until an insider response under each information structure and compare these session-level means ($p = 0.06$). A possible explanation for the relative cautiousness of the NI monopoly insider is that she may benefit if patient trading causes dealers to falsely infer the absence of an insider. Evidence on this score is gained by repeating the regression on segments of the trading interval. Over the first time quartile the effect of information structure is insignificant ($p < 0.31$). Over the second time quartile, the coefficient on the information indicator is positive and highly significant ($p < 0.01$). This is consistent with the NI monopoly insider becoming less aggressive relative to her ND counterpart as she updates her beliefs relative to the probability of a competitor. There is, however, no significant difference in insider profitability ($p = 0.30$). These results partially confirm Hypothesis 2, however, there is evidence for a strategic dimension in the use of time that depends on the uncertain presence of insiders. I consider this effect further in the discussion of Hypothesis 6 below.

Hypothesis 3 (insider behavior as a function of the number of insiders within information structures). When the number of insiders is disclosed, insider behavior differs significantly as a function of the number of insiders. This can be seen in Figure 1 by comparing the ND time series in panels A and B. Analysis that controls for differences in asset value and liquidity trader draws confirms what is apparent from Figure 1. I show this by regressing the average time of insider volume in each trading period on the extremeness of the asset value draw, the average time of liquidity trader volume, and the number of insiders.

Avg. time insider	=	b_0	$+b_1$ Extremeness	$+b_2$ Avg. time of liquidity	$+b_3$ Number of insiders
NI: coefficient		56.85	−3.07	0.50	−13.23
GMM t-statistic		(2.64)	(−4.95)	(1.70)	(−1.62)
$N=29$, adjusted $R^2=0.39$					
ND: coefficient		31.51	−2.53	0.79	−24.55
GMM t-statistic		(2.05)	(−5.60)	(3.30)	(−3.28)
$N=29$, adjusted $R^2=0.63$					

(4)

Under the ND information structure, the average time of insider activity declines significantly with two insiders ($p<0.01$), however, the difference is not significant under the NI information structure ($p=0.12$). I analyze session level results by comparing the mean time of insider activity under each information structure as a function of the number of insiders. Two insiders trade significantly earlier in the ND sessions ($p=0.03$), but the difference is not significant in the NI sessions ($p=0.11$).[15, 16] These results confirm Hypothesis 3, in the sense that the number of insiders has a more significant effect on the timing of insider trades in the ND setting.

3.2 Hypotheses pertaining to dealer behavior

In this section I examine the influence of information structure on the dealer's information extraction problem. Under the auction protocol of the experimental markets, the dealers compete to take market orders submitted by the insiders and the noise traders. Over the course of the trading interval, the terms of trade therefore depend on the probability that each dealer assigns to a trade having been initiated by an insider, and the magnitude of the insider's remaining informational advantage. These in turn depend on dealers' beliefs with respect to strategies employed by insiders.

[15] The session level test is biased in favor of finding a difference, since it does not control for the more extreme asset value draws when there are two insiders.

[16] Insider profits are higher in the NI trading periods with two insiders than in the NI trading periods with a single insider ($p=0.02$). This difference is explained by the more extreme asset value draws in the trading periods with two insiders. In the Kyle model, a monopoly insider earns higher profits than two competing insiders, while in the ND trading periods, two insiders earn higher profits, although the difference is not statistically significant. The higher insider profits with two insiders are due to the more extreme asset value draws and fewer liquidity trades that diminish the value of the insiders' information in these trading periods. Controlling for these factors in a model of insider profits by regressing profits on a constant, extremeness, extremeness interacted with the number of insiders, the product of the net liquidity trade, and the difference between the asset value and its unconditional expectation (the extent to which noise traders compete with the insider(s)), and the number of insiders predicts lower insider profits with two insiders, although the coefficient on the number of insiders is not significant ($p=0.16$).

Hypothesis 4 (the initial responsiveness of price to order flow as a function of the number of insiders and information structure). I examine dealers' ex ante beliefs with respect to insiders' strategies as a function of the number of insiders and information structure by examining the magnitude of price changes on the first trade of each period, controlling for order size and information structure. Variable definitions are as follows: $|\Delta P|$ is the absolute value of the initial price movement away from the unconditional expectation, $|Q|$ is the size of the order in absolute value, and Info is the information structure indicator variable that takes on the value of one in the NI sessions and zero in the ND.

	$\|\Delta P\| =$ b_0	$+\ b_1\|Q\|$	$+\ b_2$ Info $+\ e$	
Insiders = 2	5.86	−0.49	−2.34	Adjusted $R^2 = 0.35, N = 28$
	(7.00)	(−1.46)	(−4.34)	
Insiders = 1	1.60	0.87	−0.86	Adjusted $R^2 = 0.21, N = 30$
	(2.82)	(2.50)	(−1.73)	
Insiders = 0	1.76	0.24	0.48	Adjusted $R^2 = -0.07, N = 24$
	(1.51)	(0.44)	(0.55)	

(5)

When there are two insiders, the coefficient on the information structure indicator is negative and significant ($p < 0.01$). The relatively large price change when the number of insiders is disclosed to be two is consistent with the dealers anticipating the aggressive competition between insiders: since the first trade is likely due to an insider, the price change is relatively large. With a single insider, this effect is much weaker ($p = 0.10$), and when there are no insiders, information structure is insignificant.[17] These results strongly confirm Hypothesis 4(1), marginally support Hypothesis 4(2), and do not support Hypothesis 4(3): initial price changes are larger in the NI trading periods when insiders are absent, but not significantly.

The marginal contribution of information structure after accounting for its influence on the time of the first trade is difficult to determine when there are two insiders because the time of the first trade and information structure are highly correlated ($\rho = 0.81\%$), with the time of the first trade clustered around one second when the presence of two insiders is disclosed. Replacing Info with the time of the first insider trade when there are two insiders, the coefficient remains highly significant, although the adjusted R^2 drops by 1%. In order to investigate the role of time when there are two insiders, I estimate the following regression: $|\Delta P| = b_0 + b_1|Q| + b_2\text{ND}^*\text{TIME} + b_3\text{NI}^*\text{TIME} + e$;

[17] As a robustness check I perform the Wilcoxon rank-sum test on session-level mean price changes on the first trade (five observations under each information structure). p-values for two, one, or zero insiders are 0.04, 0.21, and 0.83, respectively.

interacting the time of the first trade with the information structure. The time variable is insignificant when the number of insiders is disclosed to be two ($p = 0.79$), but negative and highly significant when the presence of two insiders must be inferred ($p < 0.01$).

Repeating the analysis from Equation (5), but holding constant the information structure and now using an indicator variable to control for the number of insiders, the results are consistent with dealers correctly anticipating realized patterns in insider trading. In the ND sessions, the magnitude of the initial price change is greater when there are two insiders than when there is a single insider ($p < 0.03$), and greater when there is a single insider than when there is no insider present ($p = 0.19$). In the NI sessions, there are no differences that approach even marginal significance.

Hypothesis 5 (responsiveness of price to order flow over the trading interval). I examine liquidity patterns over the trading interval by estimating the following model, with the results reported in Table 4:[18]

$$|\Delta P| = b_1\text{S1} + b_2\text{S2} + b_3\text{S3} + b_4\text{S4} + b_5\text{S5} + b_6\text{Time} + b_7\Delta\text{Time} + b_8|Q| + b_9\text{Reversal} + e. \qquad (6)$$

The variables are as follows: $|\Delta P|$ is the absolute value of the price change, S1, .., S5 are session indicator dummy variables, Time is the clock time of the transaction counting up from zero, ΔTime is the clock time since the previous transaction, $|Q|$ is the absolute value of the 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 zero for a buy order following a buy order, or a sell order following a sell order (continuation). Under the NI information structure I estimate the model for all trading periods grouped together, and for trading periods grouped by the number of insiders present. Under the ND information structure, the global regression is misspecified since dealer and insider behavior clearly depend on the number of insiders, so I only report the results where the trading periods are grouped by the number of insiders.

In the ND trading periods, the coefficient estimate on the time variable is positive and insignificant in the trading periods without insiders, negative and insignificant in the trading periods with a single insider, and negative and highly significant when the presence of two insiders is known. These liquidity patterns over time are consistent with Kyle model theoretical predictions.

[18] I experimented with various specifications, including price change per unit order flow on the left-hand side with and without the order size variable on the right-hand side. Qualitative results are unchanged. The inclusion of session dummy variables does not change statistical significance for any variable, but increases the adjusted R^2 by an average of 92%.

Table 4
The determinants of market liquidity

Session/no. of insiders	$\hat{b}_1$ S1	$\hat{b}_2$ S2	$\hat{b}_3$ S3	$\hat{b}_4$ S4	$\hat{b}_5$ S5	$\hat{b}_6$ Time	$\hat{b}_7$ ΔT	$\hat{b}_8$ $\|Q\|$	$\hat{b}_9$ Rev	Adjusted R^2	M^*	Trades/ periods
NI	0.63	1.23	0.80	1.16	3.54	−0.010	0.003	0.352	2.16	0.50	7	444/41
All trades	(1.60)	(2.84)	(2.23)	(3.45)	(8.66)	(−3.33)	(0.40)	(2.88)	(9.19)			
NI	1.12	1.42	1.32	1.80	3.45	−0.009	0.021	0.087	1.86	0.43	2	87/12
0 insiders	(1.75)	(2.45)	(2.10)	(2.31)	(4.67)	(−1.62)	(1.22)	(0.26)	(5.33)			
NI	0.38	1.30	0.63	0.60	4.02	−0.009	0.009	0.303	2.15	0.51	5	180/15
1 insider	(0.58)	(1.77)	(1.02)	(0.99)	(5.20)	(−1.99)	(0.74)	(1.84)	(5.86)			
NI	0.65	0.96	0.68	1.10	3.13	−0.008	−0.015	0.484	2.29	0.50	4	177/14
2 insiders	(1.52)	(1.40)	(1.35)	(2.11)	(5.44)	(−1.66)	(−0.90)	(2.98)	(6.87)			
ND	1.10	3.48	−0.53	−0.10	3.44	0.007	−0.014	−0.223	2.02	0.44	3	87/12
0 insiders	(1.71)	(4.93)	(−0.90)	(−0.15)	(3.10)	(0.81)	(−0.82)	(−0.75)	(3.60)			
ND	3.13	0.28	0.61	0.02	1.21	−0.004	−0.019	0.662	1.75	0.41	3	191/15
1 insider	(6.21)	(0.55)	(1.17)	(0.04)	(1.98)	(−0.89)	(−1.58)	(4.74)	(5.28)			
ND	2.97	1.61	1.02	0.59	2.38	−0.020	0.003	0.450	2.11	0.37	3	200/14
2 insiders	(4.55)	(2.73)	(1.79)	(1.23)	(4.89)	(−4.50)	(0.21)	(2.21)	(6.02)			

I estimate the following model (OLS) in order to examine the determinants of market liquidity:

$$|\Delta P| = b_1\text{S1} + b_2\text{S2} + b_3\text{S3} + b_4\text{S4} + b_5\text{S5} + b_6\text{Time} + b_7\Delta\text{Time} + b_8|Q| + b_9\text{Reversal} + e.$$

The variables are as follows. S1, S2, S3, S4, and S5 are session indicator variables. $|\Delta P|$ is the price change in absolute value. $|Q|$ is the absolute value of the trade size. Time is the clock time of the transaction, with each trading period starting at 0 and ending at 120. ΔTime is the clock time since the previous transaction. 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 heteroscedasticity and autocorrelation. In order to verify that individual sessions had results consistent with the results aggregated across sessions, I also estimate (but do not report) the model using disaggregated data. This is a test for cohort effects, since the same group of subjects participates together during an entire session. First I use data from each of the five sessions under the NI setting. In four of the five sessions, all of the significant coefficients from the global regression have the same sign as in the session-level regressions. In the fifth, two of the three have the same sign. In addition, 60% of these coefficients are statistically significant, and there are no other significant coefficient estimates. As a further check I also estimate the model in the ND setting using disaggregated data on the level of the session, running three regressions (holding the number of insiders constant) for each of the five sessions. Here the significant coefficients from the global regression have the same sign in 29 of 30 cases in the 15 regressions. Of these, 12 are significant despite much smaller sample sizes. In addition, there are only two new significant coefficient estimates, and these occur in different sessions with a different number of insiders present. The evidence for cohort effects is therefore minimal.

In the NI trading periods, time has a significant impact on liquidity, but there are no patterns specific to the number of insiders. In the global regression, the coefficient is negative and significant, suggesting that the implicit spread tightens as dealers gain more confidence in their estimates of intrinsic value. Disaggregating by the number of insiders, coefficient estimates are similar, suggesting that dealers fail to detect the absence of insiders. Insider trading patterns are far subtler in the NI trading periods, and there is no evidence that dealers accurately detect them.

Examining in more detail the trading periods with two insiders highlights the magnitude of the difference in liquidity patterns across information structures. In the ND sessions, the coefficient on the time of trade variable is 2.5 times higher than in the NI sessions. Figure 3 provides further evidence on liquidity patterns with two insiders. Here the measure of liquidity is price pressure (price change per unit order flow) on price continuations. I choose continuations because if there is a fixed component of the implicit spread (due, for example, to uncompetitive dealer behavior), then continuations will more closely reflect the informational content of an order. In the first 10 seconds of trading in the ND trading periods with two insiders there are 3.7 times more price continuations, and price pressure is 41% higher than during the first 10 seconds of trading in the corresponding NI trading periods. This is due to the aggressive competition between insiders in the ND setting: unidirectional trades drive price directly to intrinsic value. By the second time decile, price pressure falls to a level lower than in the NI trading periods, as the insiders' information is exhausted.[19] This evidence strongly supports Hypothesis 5(1).

There are no significant differences in liquidity patterns across information structures when there is a single insider confirming Hypothesis 5(2). When insiders are absent, the coefficient on the time of trade variable is negative and marginally significant in the NI trading periods ($p = 0.11$), and positive and insignificant in the ND trading periods ($p = 0.42$). Mean price changes by session are 15% higher under the NI information structure, but the difference is insignificant ($p = 0.68$), and fails to support Hypothesis 5(3). I discuss price changes in the absence of insiders in Sections 3.3 and 3.4.

The ability of the dealers to identify insiders' trades has implications for dealer profitability. In the ND trading periods with two insiders, the early detection of insiders leads to higher dealer profits than in the corresponding NI trading periods ($p = 0.11$). When there are no insiders present, NI dealers move price more aggressively in response to order flow, with the mean difference between the transaction price and the unconditional expectation of the asset value 70% higher than in the ND trading periods. This leads to dealer profits that are higher by 22% higher in the NI sessions, although this difference is not significant ($p = 0.58$).[20]

[19] There are liquidity features common to both information structures. The coefficient estimates on the trade size variable ($|Q|$) are positive in all of the NI regressions, and in both of the ND regressions when insiders are present. The positive relationship between trade size and price change is consistent with the theoretical model of Easley and O'Hara (1987): trade size affects security prices because of an information-quantity link.

A second feature of market liquidity common to both information structures is the significant impact of price reversals on the magnitude of price changes (Rev). A potential explanation for this phenomenon is that dealers earn (or believe they earn) premia over the informationally efficient price. This is illustrated in the following example. Assume that dealers revise their expectations of the asset value conditional on an order (Q) according to a simple rule: the change in the expected asset value equals λQ. A single unit buy order therefore implies an upward revision in the conditional expectation by λ. Assume the dealer who takes the trade earns a premium of δ, with δ equal to the difference in absolute value between the conditional expectation and the price. A single-unit buy order, which is a continuation, therefore implies a price change of λ, while a single-unit sell following a buy order (a reversal) implies a price change of $-(\lambda + 2\delta)$. If dealers earn fixed premia on all trades then larger price changes (in absolute value) on reversals will result. A symmetric argument holds for an initial sell order. An alternative explanation is that the reversal effect is related to the way in which dealers update their conditional expectations.

[20] Overall, in the ND sessions, dealer profits are positive and marginally significant ($p = 0.29$). In the NI sessions, dealer profits are positive but insignificantly different from zero ($p = 0.96$).

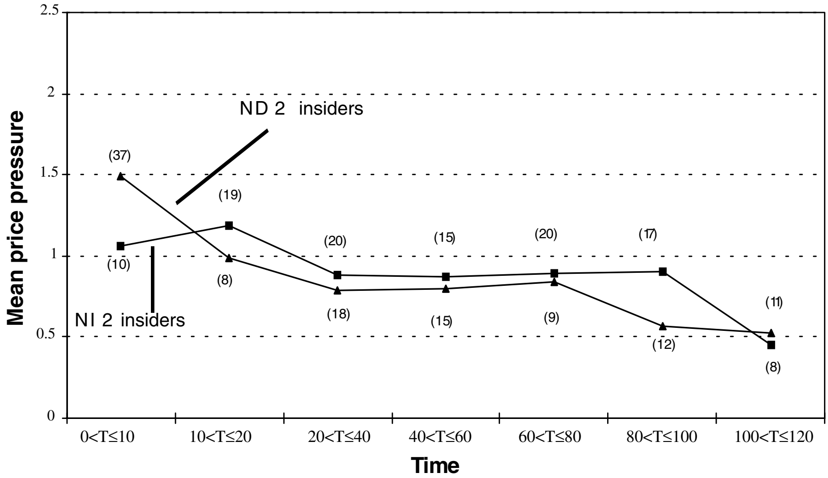


Figure 3
Mean price change per unit order flow and time on price continuations in trading periods with two insiders
The number of transactions per time period is given in parentheses for each information structure. When the presence of two insiders is disclosed, liquidity increases rapidly. When the presence of insiders must be inferred, the increase is gradual, with the largest gain in the last time sextile.

Hypothesis 6 (responsiveness of price to order flow and the time between trades). In the Easley and O'Hara (EO) (1992) model, market liquidity increases in the time between trades because of the downward revision in the probability that an information event has occurred. I examine the relationship between the time between trades and market liquidity in the regressions reported in Table 4, and do not find evidence in support of the predicted relationship in the NI trading periods. The coefficient on the time between trades variable is *positive* and insignificant in the estimation using all trading periods, and when trading periods are grouped by the number of insiders.

There are important differences between the experimental design and the assumptions in EO. Perhaps most important are the multiple trade sizes in the experimental markets and the ability of an insider to optimize by selecting a dynamic trading strategy that explicitly accounts for the timing of recent trading activity. I examine next the extent to which the larger strategy space contributes to this result.

Insiders in the NI sessions use the timing and size of trades interactively to avoid detection by the dealers. Since a profitable trade size is constrained by the magnitude of the profitable trading opportunity, I verify this by analyzing insider trades when the price error on the previous transaction is at least L$12: the smallest error that allows a profitable order on the largest trade size (three units) on all transactions in every session. I then divide this sample into two groups around the median time until the profitable trading opportunity is exploited and compare the mean trade size for the two groups with the

Wilcoxon rank-sum test. When an insider responds rapidly, the mean trade size is significantly lower (2.22 versus 3.00, $p < 0.02$).[21] This is consistent with insiders behaving as if they believe there is a trade-off between timing and order size in the optimal exploitation of inside information. The strategic interactive use of time and order size is not a feature of extant models, which either assume agents are strategic but time plays no role (Kyle model) or time plays a role but informed traders are not strategic (EO).

Insiders do not use the timing of trades and order size interactively in the ND sessions. Two insiders compete to immediately and fully exploit a profitable trading opportunity, while a single insider consistently responds more rapidly than her NI counterpart when a profitable trading opportunity arises. For example, when a liquidity trade moves the price away from intrinsic value, the ND monopoly insider responds more rapidly than an NI insider. This effect is strong. Even when there are two active NI insiders, the mean time until either insider trades is twice as long as a monopoly insider under the ND information structure ($p = 0.05$ using session-level data, $p = 0.02$ using transaction data in a regression that controls for the magnitude of the profitable trading opportunity [Equation (2)]). Evidently in this case the ND insider finds the direction of the previous trade relatively more important than its timing in hiding her information from the dealers, while the NI insider uses timing to camouflage both her presence and information. The interaction between time and order size and the strategic use of time in general thus seem to be related to whether there is uncertainty over the existence of information, in addition to its value.

The relationship between the time between trades and price changes has been studied empirically, although the importance of the time between trades after accounting for order size has not been settled. Dufour and Engle (DE) (2000) is a recent study of 18 large NYSE stocks that extends the Hasbrouck (1991) bivariate VAR model of trades and quote revisions to examine the role played by the time between transactions in the price formation process. They find that as the time between trades decreases, the price impact of a trade increases. They attribute this effect to the increased presence of informed traders.[22] However, when they test whether time offers any new information besides that conveyed by other variables, such as volume (trade size) and bid-ask spreads, they find that "The evidence suggests that dynamics of volume and spread predominantly characterize the price impact of trades and,

[21] The positive relation between the time an insider delays before exploiting a profitable trading opportunity and the order size is statistically significant, varying the price error threshold between L$9 and L$14. At a price error of L$11, the choice of order size becomes constrained in one session and at a price error of L$8, 2.2% of trades result in a price change greater than L$8. Beyond a price error of L$14 there are too few observations to make inferences. This effect holds at a comparable significance level when the test compares the significance of the correlation between trade size and the delay until the insider's trade.

[22] In DE, the importance of the time between trades effect (which is attributed to informed trading) is stronger for the higher volume stocks in the sample. Easley et al. (1996) estimate a continuous-time microstructure model using a broader sample of NYSE stocks and find the risk of information-based trading is lower for more actively traded securities.

especially for some stocks, the net effect of time duration is only marginal" (p. 2493).[23] They do not model the complex interactions between the specialist, the limit order book, and how they are affected by the frequency of trade and the common practice of "breaking up" large trades: they maintain the assumption that the trade arrival process is exogenous to past prices and trades.

Hausman, Lo, and MacKinlay (1992) estimate the conditional distribution of trade-to-trade price changes using an ordered probit model that explicitly accounts for price discreteness and the variable time intervals between trades. They find that both the sequence of trades and trade size are important factors in the conditional distribution of price changes (with larger trades creating more price pressure), but they find only a marginal role for the time between transactions.

Ultimately the relationship between the time between trades and price changes depends critically on the order submission strategies of informed traders [evidence suggests that cumulative stock-price movements are due largely to private information revealed through trading activity; see, e.g., Barclay and Warner (1993)]. Whether informed traders use time strategically (as in the experiment) or nonstrategically (as assumed in EO) depends on factors such as an informed trader's wealth constraints, risk aversion, and the precision of the trader's information. There is no a priori reason to expect these factors to be constant across time and securities. In assessing the role that time plays in the price formation process, I show the potential importance of accounting for the strategic use of time. This will be particularly relevant in those settings and securities where the specialist (or a small number of NASDAQ dealers) participates in a high percentage of trades and unusual order flow conditions are easily detected. These would most likely be the low-volume stocks that Easley et al. (1996) identify as having the greatest risk of informed trading, or even derivatives.

3.3 Patterns in relative price efficiency across information structures

In this section I analyze how the information structure-induced differences in insiders' strategies generate differences in informational efficiency across information structures. The first measure of price efficiency I employ is the price error, defined as the absolute value of the difference between the transaction price and the end-of-period liquidation value of the asset. Mean price

[23] The results in DE on the importance of volume differ from those of Jones, Kaul, and Lipson (1994). They use daily data of NASDAQ-NMS stocks to find at the aggregate daily level the well-documented positive volatility-volume relation is due to the positive relation between volume and the number of transactions: the occurrence of trades per se, and not their size, best explain volatility. They conclude that theoretical research needs to entertain scenarios in which both the frequency and size of trades are endogenously determined, yet the size of trades has no information content beyond that contained in the number of transactions. In contrast, I find that frequency and size are endogenously determined, but trade size continues to convey information (see Table 4).

errors (MPEs) by trading period (aggregating outcomes from sessions in which subjects have the same experience level) are reported in Table 2. MPEs by the number of insiders and experimental session are reported in Table 3.

Hypothesis 7 (informational efficiency across information structures). Price efficiency is higher when the number of insiders is disclosed prior to the start of trade. Weighting each session equally, MPEs are 21% higher in the sessions in which dealers must infer the presence of insiders. I assess statistical significance using both trading period and session level data and find p-values of 0.01 and 0.14, respectively.[24] As a robustness check I regress the mean price error from each session on a constant, an information structure indicator, and the absolute value of the mean price change on each transaction from each session. The last variable accounts for the significant session-specific differences in market depth (documented in Table 4) that may be related to dealer risk aversion or competitiveness. Both the information structure and price change variable are significant ($p = 0.02$ and $p = 0.01$, respectively) with $N = 10$ and an adjusted R^2 of 0.56.

Insight into the source of this difference is gained by decomposing relative price efficiency by the number of insiders present (Table 3, column 7). In the trading periods without insiders, price efficiency is higher in the ND trading periods ($p = 0.14$). This result appears due to dealers falsely inferring the presence of insiders in some NI trading periods without insiders. When this occurs, on average the variance of the price error will exceed the variance of the asset value because price changes and order flow are correlated, while order flow is independent of the asset liquidation value. This phenomenon is depicted in Figure 4, where average prices under each information structure are displayed for trading period 12 with experienced subjects. In this trading period the first three noise trader orders are buys. Although prices respond to order flow in the ND trading periods, prices remain centered on the unconditional expectation. In the NI trading periods, prices move away from the unconditional expectation of intrinsic value.

In the trading periods with a single insider, price efficiency is similar across information structures (Figure 2, panel B). With two insiders, differences are large and significant. Price efficiency is highest in the ND trading periods with two insiders, despite the most extreme asset value draws in trading periods with two insiders (Figure 2). Efficiency gains due to the presence of insiders also occur in the NI trading periods with two insiders, however, the difference in price efficiency across information structures is large and significant ($p = 0.04$ using session-level data). Figure 2 (panel A) depicts

[24] The test on trading period data most likely overstates significance because observations from the same session are not independent in the sense that they are produced by the same group of subjects. The test on session level data most likely understates significance because it underweights the trading periods with experienced subjects (where efficiency differences are more pronounced): there are 43% more trading periods in each session with experienced subjects.

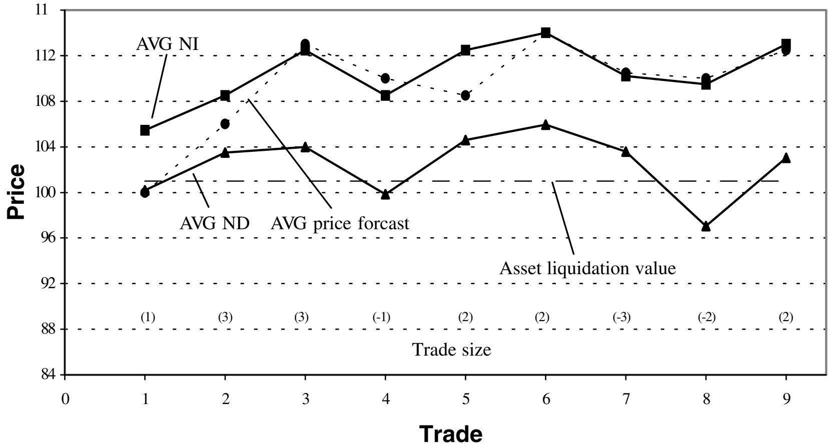


Figure 4
Average prices in NIexp1 and NIexp2, and NDexp1 and NDexp2
This figure compares mean prices (aggregating outcomes under each information structure) in trading period 12 with experienced subjects. In addition, average price forecasts are reported from NIexp1 and NIexp2. When the number of insiders is disclosed to be zero (ND), prices respond to order flow, but remain centered on the unconditional expectation of the asset value (100). When the number of insiders must be inferred (NI), it appears that dealers falsely infer the presence of insiders.

the relative convergence of price to intrinsic value with two insiders. Here, MPEs are reported by time sextile. Most of the efficiency gains due to insider trading occur in the first time sextile, when the presence of the insiders is disclosed. By contrast, in the NI trading periods, efficiency gains are much more gradual, and continue over the entire trading interval. This difference is explained by the greater intensity of insider trading in the first time sextile, when the number of insiders is disclosed (Figure 1, panel A).

Table 5 reports the results from estimating a regression model of the determinants of price efficiency, grouping the trading periods by the number of insiders present. Here the dependent variable is the absolute value of the price error. ND and NI are information structure indicators: both are interacted with Time (the time of the transaction, with each trading period starting at 0 and ending at 120), and Extremeness. Info is the information structure indicator. These regressions indicate the significant impact of information structure on price efficiency when there are zero or two insiders present. When there are two insiders present, Extremeness matters when the number of insiders must be inferred, but not when the number of insiders is disclosed. This is because in the ND trading periods price is driven to intrinsic value very rapidly (see Figure 2, panel A). The ND*Time interaction is also of much smaller magnitude than the NI*Time interaction for this reason: the relationship between price errors and time in the ND sessions with two insiders is highly nonlinear.

Table 5
Price efficiency

	$\hat{b}_1$ b_1	$\hat{b}_2$ ND*Time	$\hat{b}_3$ NI*Time	$\hat{b}_4$ ND*Extremeness	$\hat{b}_5$ NI*Extremeness	$\hat{b}_6$ Info	Adjusted R^2	M^*	Trades/ periods
0 insiders	1.31	−0.01	−0.09	1.09	0.62	5.18	0.59	7	174/24
	(1.19)	(−1.21)	(−0.67)	(9.27)	(3.20)	(2.45)			
1 insider	3.92	−0.01	−0.03	0.09	0.26	0.25	0.13	9	371/30
	(3.65)	(−0.90)	(−2.42)	(0.75)	(2.62)	(0.17)			
2 insiders	3.13	−0.02	−0.47	0.06	0.18	2.63	0.27	6	377/28
	(6.22)	(−3.18)	(−5.23)	(1.29)	(2.30)	(2.71)			

I estimate the following model (OLS) in order to examine the influence of information structure on price efficiency:

$$|PE| = b_1 + b_2\text{ND*Time} + b_3\text{NI*Time} + b_4\text{ND*Extremeness} + b_5\text{NI*Extremeness} + b_6\text{Info} + e.$$

Variable definitions are as follows. $|PE|$ is the absolute value of the difference between the transaction price and the asset value in laboratory dollars (L\$). ND is an indicator that takes on the value of one in the trading period where the number of insiders is disclosed and zero for the number inferred trading periods. NI is an indicator that takes on the value of one in the trading periods where the number of insiders must be inferred and zero in the ND trading periods. Both information structure indicators are interacted with Time (the clock time of the transaction, with each trading period starting at 0 and ending at 120) and Extremeness (the absolute value of the difference between the asset value and the unconditional expectation of the asset value in L\$). Info is an indicator variable that takes on the value of one in the NI trading periods and zero in the ND trading periods. M^* is the optimal lag length determined by Andrews' (1991) rule for constructing t-statistics that are consistent in the presence of heteroscedasticity and autocorrelation.

3.4 Dealer inventory management and the decomposition of the implicit spread

In a recent article, Neal and Wheatley (1998) show that in a setting where inventory management effects are expected to be absent, a commonly used econometric approach overestimates the portion of the bid-ask spread due to adverse selection. In this section I show that in the dealer market setting of the experimental markets, the spread decomposition problem is further compounded by complex inventory management effects that are nonlinear in the aggregate dealer industry position, and stronger in the setting (NI) where the information content of the order flow is less certain.

Following Neal and Wheatley (1998), I use the bid-ask spread decomposition model of Glosten and Harris (GH) (1988). The basic model is

$$\Delta P_t = b_0(I_t - I_{t-1}) + b_1 Q_t + e_t, \tag{7}$$

where ΔP_t is the change in the transaction price, I_t is an indicator variable which takes on the value of +1 if transaction t is initiated by a buyer and −1 if initiated by a seller, Q_t is signed volume, and e_t is the innovation in the true price due to the arrival of public information. Under their assumption that there are two components of the spread, the fixed component is b_0 and the adverse selection component is b_1.[25]

[25] Studies of NYSE specialists have, in general, concluded that the inventory control motive is weak and economically unimportant relative to the influence of asymmetric information [see, e.g., Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993)]. Recent evidence from the London Stock Exchange indicates inventories play an important role in dealer markets. Hansch, Naik, and Viswanathan (1998) find a significant

I estimate this model using the data from the experimental markets and report the results in Table 6, panel A.[26] In the NI trading periods, the estimate of the adverse selection component of the implicit spread is 55% for a trade of two assets. This estimate does not differ significantly when the model is estimated using data from trading periods grouped by the number of insiders present.

Under the ND information structure, the estimates of the adverse selection component of the spread are higher when the presence of insiders is certain than in the NI trading periods. Although the estimate of the adverse selection component is lowest when the *absence* of insiders is disclosed, it is a significant 42% of the implicit spread. This is due to the response of price to order flow after controlling for movements across the implicit spread. This in turn may be due in part to dealers requiring compensation for taking on a position which is long or short in the aggregate.

Since this specification of the model confounds dealer inventory management with adverse selection, I add two ad hoc inventory variables to the GH model that are motivated by the analysis of Ho and Stoll (1983). The first takes on the value of 1 when a buy order increases the aggregate dealer industry short position to four or more units of the risky asset, -1 when a sell order increases the dealer industry long position to four or more units of the risky asset, and 0 otherwise [column (3)]. A positive coefficient estimate here (b_2) indicates a larger price change when a trade increases a large dealer industry inventory imbalance. The second indicator takes on the value of 1 when a sell order reduces an aggregate dealer industry short position of four or more units, -1 when a buy order reduces a dealer industry long position of four or more units, and 0 otherwise [column (4)]. A negative coefficient estimate here (b_3) indicates a smaller price change when a trade reduces an already large dealer industry inventory imbalance.[27] These results are reported in Table 6, panel B. In the global regression including all of the NI trading periods, the inventory variables are highly significant in the predicted direction, their inclusion reduces the magnitude of the coefficient on the signed volume variable by 42%, and the adjusted R^2 increases by 2%. In the ND trading periods when the number of insiders is disclosed to be zero, the coefficient on the volume variable is reduced by 45% and it

relationship between quote changes and inventory changes consistent with Ho and Stoll (1983). Also, Reiss and Werner (1998) uncover strong evidence of dealer inventory management as a motive for interdealer trade. Experimental studies that find dealer inventory management are Bloomfield (1996), Schnitzlein (1996), and Lamoureux and Schnitzlein (1997).

[26] Econometric problems in the estimation of the model with data from field markets are not present when estimating the model with data from the experimental markets because of the absence of intramarket period information events, knowledge of whether a trade was buyer or seller initiated, and the clear evidence that the minimum "tick" size in the experimental markets was not binding. [For example, in ND3 (the most liquid session), the average price change on a trade of a single asset was more than 10 times the minimum tick size.] Therefore OLS provides efficient estimation.

[27] The results are not sensitive to varying this threshold between three and six. Beyond six, the number of nonzero realizations of this indicator declines dramatically.

Table 6
Estimates of the components of the implicit spread

Panel A

Session/no. of insiders	$\hat{b}_0$ (1)	$\hat{b}_1$ (2)	Trades/ periods (3)	Adjusted R^2 (4)	M^* (5)	Adverse selection (%) (6)	Mean $\Delta P/Q$ (continuations) (7)	Mean $\Delta P/Q$ (reversals) (8)
NI-all trades	1.18	0.71	444/41	0.70	8	55	0.84	2.20
	(8.48)	(13.63)						
NI-0 insiders	1.09	0.76	87/12	0.73	3	58	0.84	2.32
	(5.24)	(6.89)						
NI-1 insider	1.16	0.59	180/15	0.64	7	50	0.80	1.98
	(5.22)	(6.84)						
NI-2 insiders	1.30	0.80	177/14	0.74	4	55	0.87	2.41
	(6.71)	(11.57)						
ND-0 insiders	1.24	0.44	87/12	0.43	4	42	0.59	2.25
	(4.17)	(2.99)						
ND-1 insider	0.91	0.86	191/15	0.72	4	65	0.91	2.04
	(5.21)	(9.28)						
ND-2 insiders	1.06	0.75	200/14	0.63	5	59	0.84	2.26
	(5.43)	(7.06)						

Panel B

	$\hat{b}_0$ (1)	$\hat{b}_1$ (2)	$\hat{b}_2$ (3)	$\hat{b}_3$ (4)	Trades/ periods (5)	Adjusted R^2 (6)	M^* (7)
NI-all trades	1.26	0.41	0.94	−1.10	444/41	0.72	8
	(8.14)	(6.13)	(2.90)	(−5.55)			
NI-0 insiders	1.23	0.37	1.16	−1.74	87/12	0.78	4
	(5.48)	(2.17)	(1.61)	(−2.87)			
NI-1 insider	1.20	0.30	1.25	−1.09	180/15	0.66	7
	(4.94)	(3.96)	(2.00)	(−4.18)			
NI-2 insiders	1.40	0.56	0.41	−0.80	177/14	0.75	5
	(5.10)	(4.83)	(0.83)	(−2.97)			
ND-0 insiders	1.25	0.24	1.48	−0.82	87/12	0.44	5
	(3.77)	(1.35)	(0.71)	(−0.91)			
ND-1 insider	0.90	0.77	0.36	−0.39	191/15	0.71	4
	(4.31)	(5.38)	(0.61)	(−1.06)			
ND-2 insiders	1.05	0.55	0.40	−0.67	200/14	0.64	5
	(5.36)	(3.64)	(0.90)	(−2.00)			

I estimate the components of the implicit spread with the following variant of the spread decomposition model due to Glosten and Harris (1988) and report the results in panel A:

$$\Delta P_t = b_0(I_t - I_{t-1}) + b_1 Q_t + e_t.$$

Variable definitions are as follows. ΔP_t is the transaction price change. I_t is an indicator $(+1, -1)$ of a buy or sell order for trade t. Q is signed volume (t-values in parentheses). In this model, dealers earn a premium on each trade relative to the informationally efficient price (which depends upon the informational content of the order flow). Column (6) gives the estimate of the proportion of the implicit spread due to adverse selection for a trade of two assets. Column (7) reports the average price change per unit order flow on continuations (consecutive buy or consecutive sell orders). Column (8) is the same for reversals (a buy order that follows a sell order, or vice versa). M^* is the optimal lag length determined by Andrews' (1991) rule for constructing t-statistics that are consistent in the presence of heteroscedasticity and autocorrelation. In panel B I add two indicator variables. The first takes on the value of 1 when a buy order increases the aggregate dealer industry short position to four or more units of the risky asset, -1 when a sell order increases the dealer industry long position to four or more units of the risky asset, and 0 otherwise [column (3)]. A positive coefficient estimate here (b_2) indicates a larger price change when a trade increases a large dealer industry inventory imbalance. The second indicator takes on the value of 1 when a sell order reduces an aggregate dealer industry short position of four or more units, -1 when a buy order reduces a dealer industry long position of four or more units, and 0 otherwise [column (4)]. A negative coefficient estimate here (b_3) indicates a smaller price change when a trade reduces an already large dealer industry inventory imbalance.

becomes insignificant. This evidence that dealers earn risk premia for bearing inventory risk helps explain the false inference of adverse selection costs: the volume dependency of the spread is due to both adverse selection and inventory effects. Since the inventory positions of the suppliers of liquidity are typically not observable, controlling for inventory effects is problematic.

The evidence suggests stronger inventory management effects in the NI trading periods. Breaking out the trading periods by the number of insiders present, all six coefficient estimates for the two inventory management indicators have the signs consistent with inventory management effects and five are significant. In the ND trading periods, all six coefficient estimates also have signs consistent with inventory management, although they are of smaller magnitude in five of the six cases and only one of the six is significant. Bloomfield (1996) is a dealer market experiment employing a very different experimental design that also finds stronger evidence of dealer inventory management when there is greater uncertainty regarding the informativeness of order flow.

4. Summary and Discussion

Models of insider trading in the Kyle strategic trader framework require certainty with respect to the number of insiders for tractability. In this study I embed more realistic background assumptions in experimental markets to determine whether the intuitions garnered from these models extend to a setting where the number or presence of insiders is not disclosed prior to the start of trade.

When the certainty assumption is operationalized by disclosing the number of insiders prior to the start of trade, outcomes are qualitatively consistent with theoretical results. Multiple insiders compete aggressively, and liquidity patterns established by dealers anticipate this competition. A monopolist insider exploits her informational advantage gradually. When insiders are absent, prices stay anchored to the unconditional expectation of the asset value.

When the number of insiders is not disclosed to the market, insiders delay their trades and dealers have difficulty identifying them. In general, liquidity patterns do not differ as a function of the number of insiders, and dealers even have difficulty detecting the absence of insiders: here an imbalance in the noise trader demand causes the false inference of insider trading. Efficiency is significantly lower in this setting due to both slow convergence when two insiders are present and the large pricing errors when insiders are absent. The significant change in insider behavior, the dramatic increase in the difficulty of the dealers' inference problem, and the large reduction in informational efficiency suggest caution seems warranted before applying the intuitions from models that assume the number of insiders is known to realistic market settings: especially if they are intended to assess the costs and benefits of insider trading.

Models of sequential trade in the spirit of Glosten and Milgrom (1985) are also of limited usefulness in interpreting the results of this experiment. For example, Easley and O'Hara (1992) find the time between trades informative with respect to the presence of insiders, and hence a determinant of the terms of trade. I do not find this effect in these markets: furtive insiders use the time between trades and the size of trades interactively and incorporate the history of trading activity in order to minimize the price impact of trades. In general, insiders utilize the large strategy space in the experimental markets to effectively hide from the dealers and each other. This suggests that sequential trade models are most useful in interpreting settings where informationally advantaged agents do not behave strategically, and calls for the development of models where time plays a role *and* insiders are strategic. It also helps explain why, after controlling for volume, empirical studies find a minor role for the time between trades as a determinant of price changes: strategic traders will determine trade size and the timing of trades simultaneously.

An advantage of experiments is that they permit the observation of all market variables. I use the observation of dealer inventories to show that the effect of inventory risk management on dealer price-setting behavior is nonlinear in the aggregate dealer industry position, and the importance of inventory management depends on the information structure: the greater uncertainty in the setting where the number and presence of insiders is not disclosed implies stronger price effects associated with inventory management.

A potential disadvantage of experiments is that experimental tractability dictates that a limited number of parameterizations be considered: results may depend on the particular combinations that are selected. For this reason I included the treatment in which the information structure of the theoretical models is maintained as a robustness check. The consistency of the results in this setting with the predictions of the theoretical models is evidence that the experimental design captures the essential features of this microstructure setting.

References

Andrews, D. W. K., 1991, "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation," *Econometrica*, 59, 817–858.

Barclay, M. J., and J. B. Warner, 1993, "Stealth Trading and Volatility: Which Trades Move Prices?" *Journal of Financial Economics*, 34, 281–305.

Bloomfield, R., 1996, "Quotes, Prices, and Estimates in a Laboratory Market," *Journal of Finance*, 51, 1791–1808.

Camerer, C., and K. Weigelt, 1991, "Information Mirages in Experimental Asset Markets," *Journal of Business*, 64, 463–493.

Dufour, A., and R. F. Engle, 2000, "Time and the Price Impact of a Trade," *Journal of Finance*, 55, 2467–2498.

Easley, D., N. M. Kiefer, and M. O'Hara, 1996, "Cream Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow," *Journal of Finance*, 51, 811–834.

Easley, D., N. M. Kiefer, M. O'Hara, and J. B. Paperman, 1996, "Liquidity, Information, and Infrequently Traded Stocks," *Journal of Finance*, 51, 1405–1436.

Easley, D., and M. O'Hara, 1987, "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics*, 19, 69–90.

Easley, D., and M. O'Hara, 1992, "Time and the Process of Security Price Adjustment," *Journal of Finance*, 47, 577–606.

Foster, F. D., and S. Viswanathan, 1996, "Strategic Trading When Agents Forecast the Forecasts of Others," *Journal of Finance*, 51, 1437–1478.

Glosten, L. R., and L. E. Harris, 1988, "Estimating the Components of the Bid/Ask Spread," *Journal of Financial Economics*, 21, 123–142.

Glosten, L. R., and P. R. Milgrom, 1985, "Bid, Ask, and Transaction Prices in a Speculative Market with Heterogeneously Informed Traders," *Journal of Financial Economics*, 14, 71–100.

Hansch, O., N. Y. Naik, and S. Viswanathan, 1998, "Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange," *Journal of Finance*, 53, 1623–1656.

Hasbrouck, J., 1991, "Measuring the Information Content of Stock Trades," *Journal of Finance*, 46, 179–208.

Hasbrouck, J., and G. Sofianos, 1993, "The Trades of Market Makers: An Empirical Analysis of NYSE Specialists," *Journal of Finance*, 48, 1565–1593.

Hausman, J. A., A. W. Lo, and A. C. MacKinlay, 1992, "An Ordered Probit Analysis of Transaction Stock Prices," *Journal of Financial Economics*, 31, 319–380.

Huang, R. D., and H. R. Stoll, 1997, "The Components of the Bid-Ask Spread: A General Approach," *Review of Financial Studies*, 10, 995–1034.

Ho, T., and H. R. Stoll, 1983, "The Dynamics of Dealer Markets Under Competition," *Journal of Finance*, 38, 1053–1074.

Holden, C. W., and A. Subrahmanyam, 1992, "Long-Lived Private Information and Imperfect Competition," *Journal of Finance*, 47, 247–270.

Jones, C. M., G. Kaul, and M. L. Lipson, 1994, "Transactions, Volume, and Volatility," *Review of Financial Studies*, 7, 631–651.

Kyle, A. S., 1985, "Continuous Auctions and Insider Trading," *Econometrica*, 53, 1315–1335.

Lamoureux, C. G., and C. R. Schnitzlein, 1997, "When It's Not the Only Game in Town: The Effect of Bilateral Search on the Quality of a Dealer Market," *Journal of Finance*, 52, 683–712.

Madhavan, A., and S. Smidt, 1993, "An Analysis of Changes in Specialist Inventories and Quotations," *Journal of Finance*, 48, 1595–1628.

Neal, R., and S. M. Wheatley, 1998, "Adverse Selection and Bid-Ask Spreads: Evidence from Closed-End Funds," *Journal of Financial Markets*, 1, 121–149.

O'Hara, M., 1995, *Market Microstructure Theory*, Blackwell Publishers, Cambridge, MA.

Reiss, P. C., and I. M. Werner, 1998, "Does Risk Sharing Motivate Interdealer Trading?" *Journal of Finance*, 53, 1657–1703.

Schnitzlein, C. R., 1996, "Call and Continuous Trading Mechanisms Under Asymmetric Information: An Experimental Investigation," *Journal of Finance*, 51, 613–636.

Subrahmanyam, A., 1991, "Risk Aversion, Market Liquidity, and Price Efficiency," *Review of Financial Studies*, 4, 417–441.