THE JOURNAL OF FINANCE • VOL. LI, NO. 5 • DECEMBER 1996

Quotes, Prices, and Estimates in a Laboratory Market

ROBERT BLOOMFIELD*

ABSTRACT

This study examines the behavior of laboratory markets in which two uninformed market makers compete to trade with heterogeneously informed investors. The data provide three main results. First, market makers set quotes to protect against adverse selection and to control inventory. Second, when investors are less well-informed, their trades are less reliable measures of their information, and market makers respond to those trades with greater skepticism. Third, errors in market makers' reactions to trades cause the time-series behavior of quotes and prices to depend on the information environment in ways beyond those captured in extant theory.

THEORETICAL MODELS PREDICT THE behavior of quotes and prices by imposing strict assumptions about agents' knowledge and beliefs. This study uses data from laboratory financial markets to show that these models can predict quotes and prices quite well in a setting in which these assumptions are not satisfied, and to demonstrate specific ways in which violations of these assumptions affect behavior. The study complements empirical research in market microstructure by observing dependent variables that cannot be observed in naturally occurring markets, as well as by controlling an independent variable—the information asymmetry between investors and market makers—which cannot be controlled in naturally occurring markets. The study complements previous experimental work by focusing on the ability of market microstructure theory to predict the *process* by which market-clearing prices arise. In contrast, most previous market experiments have focused primarily on the ability of rational expectations theories to predict the information content of the market-clearing prices ultimately attained (Plott and Sunder (1982, 1988), Copeland and Friedman (1987, 1991), Forsythe and Lundholm (1990), Lundholm (1991), O'Brien and Srivastava (1991), Bloomfield and Libby (1996), Bloomfield (1996)).

The markets combine features of both "quote driven" and "order driven" markets (as defined in Madhavan (1992)). Data from the markets show that

* Johnson Graduate School of Management, Cornell University. Thanks to Robert Forsythe, Larry Glosten, Bob Jarrow, Ananth Madhavan, John O'Brien, Maureen O'Hara, Joe Paperman, Thomas Reitz, and seminar participants at the 1994 Conference for Financial Economics and Accounting at the University of Michigan, the 1994 Economic Science Association meetings, and the 1995 Journal of Financial Intermediation Symposium on Market Microstructure. The Johnson Graduate School of Management provided financial support.

spreads are wider when market makers face greater adverse selection pressures, and that spreads decline over the course of trading, much as spreads decline early in a trading day for New York Stock Exchange (NYSE) stocks (Brock and Kleidon (1992), McInish and Wood (1992)) and toward the end of a trading day for Nasdaq stocks (Chan, Christie, and Schultz (1995)). The evidence regarding adverse selection is more direct than in empirical studies (Glosten and Harris (1988), Hasbrouck (1988, 1991), Madhavan and Smidt (1991, 1993), Stoll (1989)), that must infer both the existence of and the reaction to adverse selection from variables that may be influenced by noninformational factors. The data also show that market makers set quotes to control their inventories. This evidence on inventory control is also more direct than in empirical studies, because it compares market makers' quotes to their estimates of value (which cannot be observed in empirical studies). As hypothesized by Garman (1976), Amihud and Mendelson (1980), and Ho and Stoll (1983), market makers' quotes tend to be lower (higher) relative to their value estimates when they have accumulated a positive (negative) inventory.

The data also show that when investors are less well-informed, their trades are less reliable measures of their information, and market makers respond to those trades with greater skepticism. Moreover, closing price is often a weighted average of the true value and the prior expected security value, as if market makers never become certain of the information they extract from trades. These results are consistent with conjectures of how the markets might behave if risk preferences and beliefs were not common knowledge.

Finally, the data show that market makers' reactions to trades of low information content tend to be noisy but relatively unbiased, while their reactions to trades of high information content tend to be less noisy but more systematically biased toward underreactions. As a result, the time-series behavior of quotes and prices depends on the information environment in ways beyond those captured in extant theory. Studies attempting to draw inferences about the information environment from the time series of price and quote variables (such as Glosten and Harris (1988) and Hasbrouck (1988, 1991)) may therefore lead to biased estimates of information asymmetry.

Section I describes the design of the markets, Section II presents the results, and Section III discusses their implications.

I. The Markets

A. Overview

In order to examine the behavior of quotes, prices, and estimates of value, I construct simple financial markets and manipulate the degree of information asymmetry between market makers and investors. Six groups of 10 subjects trade securities in successive independent markets. At the beginning of each market, 8 "informed investors" learn some information about the value of the security, while 2 "market makers" learn no such information. Investors and market makers are referred to collectively as "traders." The use of two market

	1-SIGNAL SETTING				2-SIGNAL SETTING			
	X_1	X_2	X_3	X_4	X_1	X_2	X_3	X_4
I_1	x				x	x		
I_2	x				x	x		
I_3		x			x	x		
I_4		x			x	x		
I_5			x				x	x
I_6			x				x	x
I_7				x			x	x
I_8				x			x	x

Figure 1. Distribution of information among investors. Each security has a value equal to 50 plus the sum of four random numbers, denoted X_1, X_2, X_3, and X_4, where each X_i is equally likely to have a value of +10 or −10. The figure shows the distribution of information among the 8 investors I_i, $i = 1, 2, \ldots, 8$. For each of the two settings, an "x" indicates that investor I_i holds signal X_i.

makers enforces the competitive quote setting that is assumed in most microstructure models (such as Glosten and Milgrom (1985)). The investors and market makers trade for up to 10 periods, or until market prices converge to a steady value. At that point, the value of the security is revealed, and a market for a new security begins.

The value of each security traded in the markets is equal to 50 plus the sum of four random numbers, each taking on a realization of either +10 or −10 with equal probability. Thus, each security has a value of either 90, 70, 50, 30, or 10. Information is distributed in two different ways, as shown in Figure 1. In a "1-signal setting," each investor knows one of the four random numbers, with each signal known by two investors. In a "2-signal" setting, each investor knows two signals, and each signal is known by four investors. The market makers never hold any of the signals. All participants always know whether they are in the 1-signal or 2-signal setting. In both settings, the market as a whole has perfect information on the value of the security; however, the information asymmetry between investors and the market makers is greater in the 2-signal setting.

B. Subjects' Actions

In each trading period, each trader takes three actions. First, the trader enters his or her best estimate of the expected value of the security given all of the information available to him or her. Second, the trader enters his or her degree of confidence that the estimate is correct, with a confidence level of 100 (0) indicating that the trader believes that the true value is likely to be very close to (far from) the estimate. Third, the trader enters the prices at which he or she is willing to buy and sell the security. If the trader is a market maker, these prices represent bid and ask quotes. If the trader is an investor, these prices represent limit orders submitted to a fictitious broker. If the lowest (market) ask is below an investor's buy limit, the investor's broker enters an order on his or her behalf; otherwise, the broker enters no order. Rules governing sales are analogous. There are no restrictions on short-selling. The use of binding quotes by market makers and limit orders by investors makes the market a hybrid of "quote driven" and "order driven" markets (Madhavan (1992)). Unlike in most markets, investors do not observe the market makers' quotes before entering orders.

C. Incentives

Each investor can buy or sell only $1/(n + m)$ shares in each round, where n and m represent the total number of buy and sell orders entered in that round of trading by all investors. Thus, in each round, an investor's change in wealth upon entering a buy order is equal to (VALUE − ASK)/$(n + m)$; an investor's change in wealth upon entering a sell order is equal to (BID − VALUE)/$(n + m)$. Allowing partial execution of orders makes the setting similar to one (such as Glosten and Milgrom (1985)) in which one order is executed at random: instead of receiving a gain of (VALUE − ASK) with probability $1/(n + m)$, the investor receives the expected gain (VALUE − ASK)/$(n + m)$. The chosen method reduces the effect of chance on players' actual payoffs.

A market maker who enters the lowest ask sells $n/(n + m)$ shares at a gain or loss of (ASK − VALUE) per share, and also earns a flat commission of 3 francs for engaging in trade. Thus the market maker who enters the lowest ask experiences a total change in wealth (in francs) of (ASK − VALUE) $[n/(n + m)] + 3$ if there are buy limits above that ask, and 0 otherwise. Similarly, the market maker who enters the highest bid experiences a total change in wealth of (VALUE − BID)/$[m/(n + m)] + 3$ if there are sell limits below that bid, and 0 otherwise. The commission serves a role similar to that of noise traders in typical models: it permits the market makers to sell for less and buy for more, without altering the expected gains of the investors. As a result, investors can gain money through trade without forcing market maker losses. A commission is employed (instead of introducing noise traders) in order to keep the market simple.

A trader's estimate and confidence level have no direct effect on payoffs. However, investors cannot sell for less than their estimate or buy for more than their estimate. For market makers, these restrictions are relaxed by a few francs, to account for commissions. These restrictions encourage traders to think carefully about estimates, because an unreasonable estimate might rule out a profitable trade.

Traders are given an initial endowment of 200 francs. Francs are converted into cash according to the equation

$$\text{Cash Payment} = \text{Max}\{0, \text{ francs} \times 15 \text{ cents} - \$15\}. \tag{1}$$

D. Information on Market Activity

After each round of trading, market makers are told whether they (or a competitor) set the highest bid or the lowest ask, and investors are told whether their brokers entered orders to buy at the ask or sell at the bid (or both). Investors and market makers learn the market bid, the market ask, the number of buy orders entered (i.e., the number of investors who were willing to buy at or above the market ask), and the number of sell orders entered (i.e., the number of investors who were willing to sell at or below the market bid). At the end of each market, subjects learn the true value of the security, and receive summary information on the number of trades in which they gained and lost money, as well as the number of periods in which they could have traded profitably but failed to capitalize on that opportunity.

E. Administration

Almost all of the participants are MBA students in the Johnson Graduate School of Management at Cornell University. These subjects participated in a "qualifying" session to gain experience in the market; three subjects who lost very large amounts of money in the qualifying markets were not invited back to participate in the markets reported in this article. This qualifying market and screening rule ensures that subjects possess at least a minimal understanding of and familiarity with the rules of the market. The qualifying markets were nearly identical to the markets reported in this paper.

Each 2.5 hour market session begins with a 45 minute training session, in which subjects read written instructions and a proctor reviews the instructions aloud. All aspects of distributions and rules of trading are disclosed publicly, in an attempt to make them common knowledge. Subjects then answer a series of questions about the market, and participate in three "practice markets" that are identical to later markets, except that there are no cash incentives.

II. Results

A. General

A total of 6 market sessions are conducted, with three sessions each in the 1-signal and 2-signal settings. Each session consists of three practice markets and three or four markets with incentives, yielding a total of 12 1-signal and 16 2-signal markets (after deleting practice markets).[1] Throughout the analysis, bids are reduced by 3 francs and asks are increased by 3 francs to eliminate the effect of the commission provided to market makers. The results are almost identical without this adjustment.

Panel A of Figure 2 depicts the absolute deviation of price from value, plotted over trading rounds. The price in round 0 is defined as the prior expected value of 50 francs. In subsequent rounds in which there was trade, the price is defined as

$$\mathrm{P}_t = \frac{\mathrm{BUYS}_t}{\mathrm{BUYS}_t + \mathrm{SELLS}_t}\,\mathrm{ASK}_t + \frac{\mathrm{SELLS}_t}{\mathrm{BUYS}_t + \mathrm{SELLS}_t}\,\mathrm{BID}_t, \tag{2}$$

[1] In the first market of one session, a specialist showed considerable confusion regarding his task, and had to be removed from that role. This market is eliminated from the analysis.

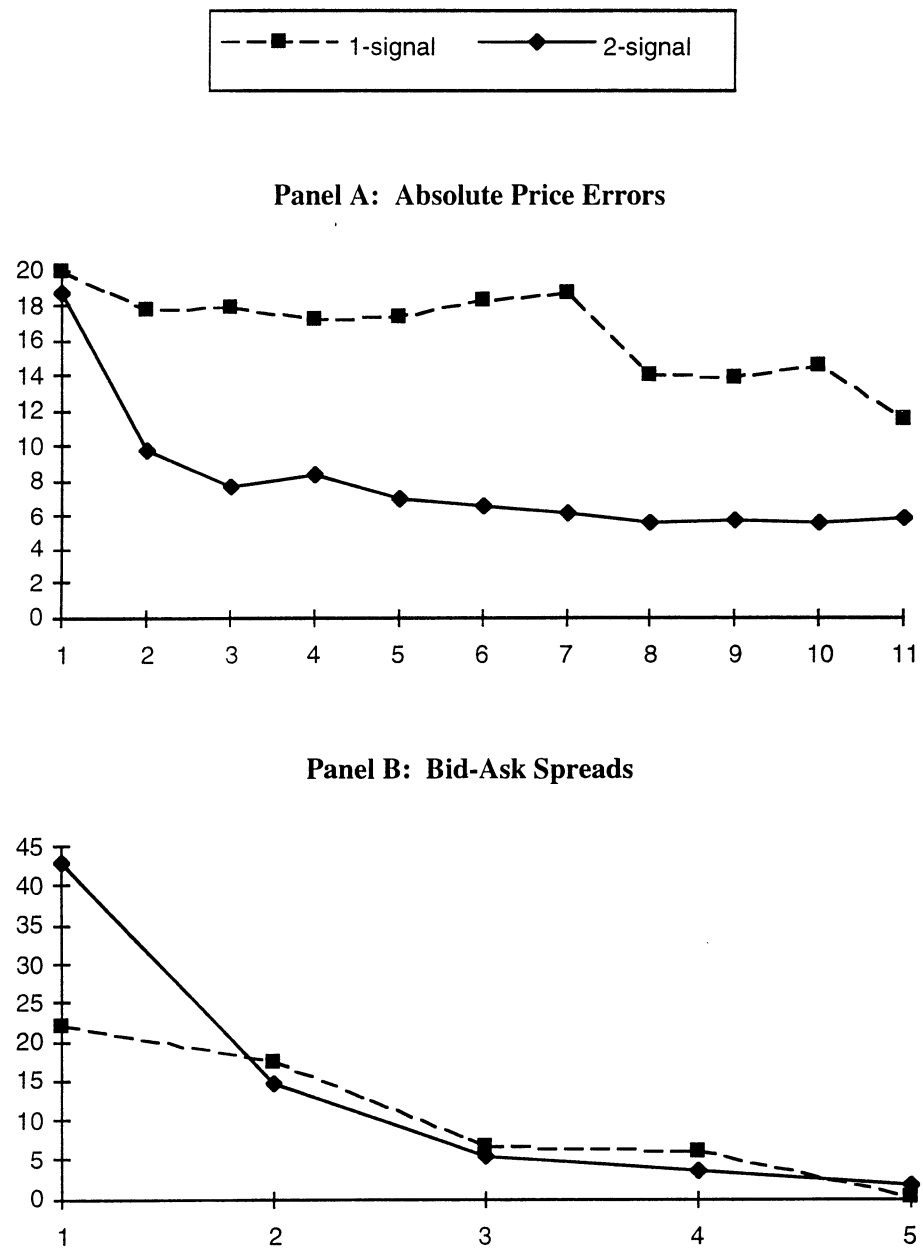

Figure 2. Absolute price errors and bid-ask spreads. This figure depicts the absolute deviation of market price from true value (Panel A) and the bid-ask spread (Panel B) in each round for 12 1-signal markets and 16 2-signal markets. In Panel A, Round 0 price is always taken to be 50 francs; prices in other rounds are a weighted average of the high bid and the low ask, with weights determined by the proportion of trades at each quote. The market spread in Panel B is the difference between the low ask and the high bid; bids are reduced by 3 francs and the asks are increased by 3 francs to eliminate the effect of the market makers' commissions.

where BID_t and ASK_t are the highest market maker bid and the lowest market maker ask in round t. In rounds with no trade, price is defined as $P_t = 0.5\ ASK_t + 0.5\ BID_t$. Due to time constraints, markets are closed once it appears that no further price changes are likely. If a market is closed before 10 rounds (many of the 2-signal markets close by round 6), the closing price is used as the price in subsequent rounds.

The figure shows that trading does impound information into prices. In the 1-signal setting, absolute price errors decrease from 20 francs at the opening to 12.7 francs at the close, a decrease of 36.5 percent ($p < 0.01$). Information aggregation is both faster and more complete in the 2-signal setting. In that setting, absolute price errors decrease from 18.75 francs to only 6 francs, a decrease of 68 percent ($p < 0.01$). Possible reasons for the difference in closing price errors are discussed in Section II.E below.

B. Bid-Ask Spreads

Whenever investors have information the market maker does not have, the market makers must set their bids lower than their asks to avoid losing money due to "adverse selection" (Glosten and Milgrom (1985), Easley and O'Hara (1987), Madhavan (1992)). It is difficult to test the relation of adverse selection and bid-ask spreads using empirical data, because such a study needs to infer the extent of adverse selection as well as the market's reaction to it. Empirical studies, such as Easley, Kiefer, O'Hara, and Paperman (1996), Glosten and Harris (1988), Hasbrouck (1988, 1991), Madhavan and Smidt (1991, 1993), and Stoll (1989), might therefore be viewed as estimations of models which are assumed to be true, rather than as direct tests of models relating spreads and adverse selection. In contrast, this study directly manipulates the degree of adverse selection across two settings. Because the experimental design controls for other differences across the settings, differences in bid-ask spreads can be unambiguously attributed to the manipulation of adverse selection.

The experimental design also differs considerably from previous laboratory studies which have examined bid-ask spreads in a double auction market. For example, Copeland and Friedman (1987) find that "bid-ask spreads increase with greater uncertainty." However, because the equilibrium behavior of spreads in their double-auction market is not well understood, it is difficult to know whether they are reflecting adverse selection or a more general uncertainty as to the functioning of the market. The latter possibility is suggested by the observation that their spreads decline as traders gain experience in the market. There is no such association in the present study.

Average market spreads in the first five rounds of trading are plotted in Panel B of Figure 2. The opening market spread is wider in the 2-signal setting than in the 1-signal setting, confirming that greater information asymmetry between investors and market makers leads to wider opening spreads. Spreads decline rapidly toward zero in both settings; after the fifth round of trading, changes in spreads are statistically insignificant in both settings. Spreads appear to decline faster when they are larger (they decline roughly exponentially), consistent with the notion that the size of the spread serves as a measure of the information content that would be conveyed by a trade (Madhavan (1992)), which in turn determines the extent to which the trade reduces information asymmetry. The decline in spreads over time may also be related to the decline in spreads early in a trading day for NYSE stocks (Brock and Kleidon (1992), McInish and Wood (1992)) and toward the end of a trading day for Nasdaq stocks (Chan, Christie, and Schultz (1995)); this possibility is discussed further in Section III.

For statistical tests, I delete one 1-signal market for which the opening spread was 0, which makes it a rather severe outlier. (Including this observation would reduce opening spreads and the rate of decline in the 1-signal setting, biasing in favor of finding the hypothesized effects.) A standard t-test establishes the statistical significance of the difference in opening spreads across settings (18.66 francs, $p < 0.01$, t-stat = 3.01); the reduction in spreads resulting from the first round of trading in the 1-signal setting ($\Delta = -8.36$ francs, $p < 0.01$, t-stat = -4.782) and in the 2-signal setting ($\Delta = -28.15$, $p < 0.01$, t-stat = -6.685); and the greater reduction in spreads in the 2-signal setting ($p < 0.01$, t-stat = -6.685).

Analysis of the market makers' subjective confidence indices also support the relation of the bid-ask spread to the precision of the information they hold. I regress market makers' expression of confidence onto market spreads and the number of trading rounds elapsed in the market. The coefficient on the spread is -0.118 in the 1-signal setting ($p = 0.349$) and -0.470 in the 2-signal setting ($p < 0.001$). The R^2 values of the regressions are 46.4 percent in the 1-signal setting ($n = 72$) and 56.8 percent in the 2-signal setting ($n = 96$). Thus, spreads and confidence levels are negatively related, particularly in the 2-signal setting.

C. Inventory Control

Risk averse market makers should alter the levels of their quotes to control their inventory position, setting higher bids and asks when they have a negative inventory, and setting lower bids and asks when they have a positive inventory (Garman (1976), Amihud and Mendelson (1980), Ho and Stoll (1983)). Because observers of naturally occurring markets cannot determine the market makers' true expectations of value, they can provide only indirect support for this hypothesis. For example, Hasbrouck (1991) shows that quote increases tend to induce investor selling and quote decreases tend to induce investor buying, indicating that specialists are trying to reverse their positions, but this result might be driven by errors in the recording of quotes. Madhavan and Smidt (1991, 1993) and Hasbrouck and Sofianos (1993) show that inventory levels tend to show mean reversion, but the rates of mean reversion are surprisingly slow, even after allowing for changes in market makers' desired inventory levels.

This study allows a direct analysis of market makers' quotes, value estimates, and inventories. In round t of trading, the average midpoint of both market makers' bids and asks is denoted Q_t. The market makers' average value estimate is denoted EST_t.[2] The number of shares bought by the market makers from period 1 through $t-1$ is denoted $INVENT_{t-1}$. Panel A of Table I shows that in the 1-signal setting, the difference $Q_t - EST_t$ decreases as $INVENT_{t-1}$ increases ($\beta = -0.346$, $p = 0.015$), indicating that quotes fall relative to estimates as inventory rises. There is no such relationship in the 2-signal setting ($\beta = 0.053$, $p = 0.479$).

Inventory control should be more apparent in the 1-signal setting, because the slower and less complete revelation of information (as seen in Panel A of Figure 2) increases the risk of inventory buildup before the value of the security is known. I test for the differences in associations across settings by estimating the coefficient β_3 in the regression

$$Y = \alpha + \beta X + \beta_2 D + \beta_3 X * D + \varepsilon. \tag{3}$$

where Y is the dependent variable, X is the independent variable, and D is a dummy variable with value 1 for the 2-signal market and value 0 in the 1-signal setting. Substituting $INVENT_{t-1}$ and $Q_t - EST_t$ for Y and X, the coefficient on β_3 is negative and significant at the $p = 0.025$ level (1-tailed), confirming that inventory management is more important in the 1-signal setting.

Panel A of Table I also replicates the analysis of Hasbrouck (1991) on the influence of quote changes on future order imbalances. Imbalances are measured as the proportion of orders which are buy orders, less 0.5; if no orders are entered, the imbalance is defined as 0. The 1-signal setting shows a negative association of quote changes and future order imbalances ($\beta = -0.016$, $p = 0.024$), indicating that (as in Hasbrouck (1991)) market makers are managing their inventories: upward quote changes, which arise after market makers sell to investors, are followed by rounds in which market makers buy from investors. In contrast, quote changes lead to marginally significant *positive* imbalances in the 2-signal setting ($\beta = 0.007$, $p = 0.095$). The difference between the settings is highly significant ($\beta_3 = 0.022$, $p = 0.004$), again confirming the greater importance of inventory control in the 1-signal setting.

D. Trades and Information

Rational investors choose their trading actions as a function of their information, risk preferences, and beliefs about how past and present trades are interpreted. Market makers infer an investor's information by inverting this function, determining the information that is likely to have led to the investor's

[2] The estimates are entirely private, and do not affect the market makers' wealth. While this lack of incentive may increase the noisiness of this measure, it ensures that the reported estimate does not expose the market maker to risk or adverse selection; therefore, reported estimates should be unbiased representations of market makers' value estimates. The correlation of EST_t with Q_t is 0.739 in the 1-signal setting and 0.632 in the 2-signal setting, indicating that both measures are largely capturing the same underlying construct.

Table I

Lag-Lead Relationships

For each setting, this table estimates simple univariate linear regressions of various dependent variables Y onto independent variables X over the first four rounds for which all necessary data is available. Q_t denotes the average of both market makers' bids and asks in round t. EST_t denotes the average of the market makers' estimates. $INVENT_{t-1}$ denotes the average cumulative holding of the market makers through round $t-1$. $IMBAL_t$ denotes the proportion of orders which are buy orders, less 0.5; if no orders are entered, $IMBAL_t$ is defined as 0. P_t denotes a weighted average of the high bid and the low ask, with weights determined by the proportion of trades at each quote; if no orders are entered, the weights are equal.

Statistical tests for the differences between associations in the 1-signal and 2-signal settings are computed by the t-statistic on the parameter β_3 in the regression

$$Y = \alpha + \beta_1 X + \beta_2 D + \beta_3 X * D + \varepsilon$$

where D is a dummy variable with value 1 for the 2-signal market and value 0 in the 1-signal setting. All p-values are 1-tailed.

Y	X	1-signal (t-stat) p-value $n = 48$	2-signal (t-stat) p-value $n = 64$	Difference (t-stat) p-value $n = 112$
		Panel A: Inventory Control		
$Q_t - EST_t$	$INVENT_{t-1}$	−0.346	0.053	−0.398
		(−2.507)	(0.712)	(−2.269)
		$p = 0.015$	—	$p = 0.025$
$IMBAL_t$	$Q_{t-1} - Q_{t-2}$	−0.016	0.007	0.022
		(−2.310)	(1.690)	(2.901)
		$p = 0.024$	—	$p = 0.004$
		Panel B: Autocorrelations in Prices and Estimates		
$P_t - P_{t-1}$	$P_{t-1} - P_{t-2}$	−0.368	−0.146	0.223
		(−3.02)	(−1.830)	(1.454)
		$p < 0.01$	$p = 0.036$	$p = 0.075$
$EST_t - EST_{t-1}$	$EST_{t-1} - EST_{t-2}$	−0.393	−0.107	0.286
		(−2.381)	(0.849)	(1.332)
		$p = 0.021$	$p = 0.40$	$p = 0.093$
		Panel C: Underreactions and Delayed Reactions to Trades		
$Q_t - Q_{t-1}$	$Q_{t-1} - Q_{t-2}$	0.132	0.570	0.438
		(1.109)	(9.534)	(3.523)
		$p = 0.272$	$p < 0.01$	$p < 0.01$
$Q_t - Q_{t-1}$	$IMBAL_{t-2}$	2.364	6.523	4.159
		(1.054)	(5.117)	(1.710)
		$p = 0.297$	$p < 0.01$	$p = 0.045$

trading decisions. Bayesian reasoning suggests that the role of information in the trading function should become greater as the investor's information becomes more precise. An investor with perfect information can ignore risk preferences and beliefs, and simply choose a trading action entirely on the

Table II

Information Content of Trading Decisions

This table measures the information content of investors' trades in two ways. Panel A estimates the association of investors' value estimates and their choice of buy and sell limits over the first three periods of each market, using both the averages of investors' buy and sell limits, denoted CENTER_t, and the spreads between those limits, denoted SPREAD_t. The regression model is

$$\text{EST}_t = \alpha + \beta_1\text{CENTER}_t + \beta_2\text{SPREAD}_t + \beta_3\text{CENTER}_t * \text{SPREAD}_t + \varepsilon$$

Panel B estimates the market makers' responses to investors' trades, by regressing the change in the market makers' value estimates ($\text{EST}_{t+1} - \text{EST}_t$) onto the difference between the market price P_t and the market makers previous estimate EST_t, as well as the market makers' previous estimate change ($\text{EST}_t - \text{EST}_{t-1}$). The regression model for Panel B is

$$(\text{EST}_{t+1} - \text{EST}_t) = \alpha + \beta_1(\text{P}_t - \text{EST}_t) + \beta_2(\text{EST}_t - \text{EST}_{t-1}) + \varepsilon,$$

Setting	α (t-stat)	β_1 (t-stat)	β_2 (t-stat)	β_3 (t-stat)	R^2
Panel A: Association of Investors' Limit Orders and Estimates					
1-signal	−3.996	1.123	0.602	−0.014	58.9%
(n = 288)	(−1.176)	(16.701)	(5.122)	(−6.210)	135.75
2-signal	−2.289	1.049	0.334	−0.007	88.2%
(n = 384)	(−1.881)	(43.046)	(5.813)	(−6.991)	950.43
Panel B: Market Makers' Responses to Trades					
1-signal	−0.001	0.293	−0.269	14.6%	
(n = 72)	(−0.001)	(1.369)	(−1.443)	(3.844)	
2-signal	0.208	0.595	−0.072	58.4%	
(n = 96)	(0.336)	(9.157)	(−0.871)	(42.764)	

basis of that information; an investor with very imprecise information must be highly sensitive to risk preferences and beliefs.

To test whether investor's actions are less precise signals of their information when they have only one signal, Panel A of Table II reports the results of the regression

$$\text{EST}_t = \alpha + \beta_1\text{CENTER}_t + \beta_2\text{SPREAD}_t + \beta_3\text{CENTER}_t * \text{SPREAD}_t + \varepsilon \quad (4)$$

which infers the investors' information from the average of the investors' buy and sell limits (CENTER_t), the spread between those limits (SPREAD_t), and the interaction between CENTER_t and SPREAD_t.

As predicted, the explanatory power of the model is much higher in the 2-signal setting (R^2 = 88.2 percent, F = 950.43) than in the 1-signal setting (R^2 = 58.9 percent, F = 135.75). In both the 1-signal and 2-signal settings, the correlation between CENTER_t and EST_t is very close to 1, indicating that after controlling for the spread and the interaction of CENTER_t and SPREAD_t, investors' bids and asks are centered on their estimates. The strong negative interaction between CENTER_t and SPREAD_t further supports the hypothesis that buy and sell limits provide less information about estimates when investors have less information (and therefore choose wider spreads to shield themselves from risk).

If investors' trading actions are less reliable indicators of their information in the 1-signal setting, then market makers should respond less strongly to those actions. I test this hypothesis by estimating the regression

$$(\mathrm{EST}_{t+1} - \mathrm{EST}_t) = \alpha + \beta_1(\mathrm{P}_t - \mathrm{EST}_t) + \beta_2(\mathrm{EST}_t - \mathrm{EST}_{t-1}) + \varepsilon, \quad (5)$$

where $\mathrm{P}_{t-1} - \mathrm{EST}_{t-1}$ captures the information content of investors' trades. In the traditional analysis of the trading equilibrium (assuming common knowledge of preferences and beliefs), the martingale property of prices implies that EST_t is exactly equal to P_{t-1}, so that β_1 is equal to 1. However, to the extent that common knowledge assumptions are violated, the coefficient will tend to be lower.[3] (Because estimate changes may include a component for correction of previous estimate errors, it is necessary to include a term $(\mathrm{EST}_t - \mathrm{EST}_{t-1})$ to control for autocorrelations in estimate changes.)

The results in Panel B of Table II show that the weighting on the information conveyed by the current trading round is only 0.293 in the 1-signal setting, compared to 0.595 in the 2-signal setting. Both coefficients are significantly less than 1 ($p < 0.01$). A pooled correlation including a dummy variable for setting and all interactions between that variable and the other independent variables shows that the difference between these coefficients is significant (t-stat $= 1.510$, $p = 0.067$), confirming that market makers place less confidence in the information conveyed by the trades of less well-informed investors. Note that this result does not simply reflect the fact that a buy (sell) by a better-informed investor indicates a higher (lower) value. That relation is controlled for by the independent variable $(\mathrm{P}_t - \mathrm{EST}_t)$.

As an additional test, I include the variable IMBAL_t to capture market makers' reactions to imbalances. In the 2-signal setting, the imbalance appears to convey no information beyond that conveyed by price, as would be predicted in a traditional equilibrium analysis. However, in the 1-signal market, the imbalance conveys considerable incremental information. This suggests that deviations from traditional common knowledge assumptions may allow imbalances to convey information beyond that contained in prices.

The effects which I argue arise from a lack of common knowledge may in fact arise from the use of the multiperiod strategies described in Leach and Madhavan (1992), Foster and Viswanathan (1996), or Holden and Subrahmanyan (1994)). However, reestimating regressions (3) and (4) with additional variables to reflect the main effect of passage of trading rounds and its interaction with the original independent variables shows that the passage of trading rounds actually *reduces* the correlation of investors' trading actions with their estimates, as well as the correlation of market makers' quotes to their esti-

[3] In a traditional analysis, the feedback permits an equilibrium in which the true value of the security is fully revealed by the first round of trading. However, Figure 1 shows that this does not happen, suggesting that these assumptions are not satisfied.

Table III

Deviation of Closing Prices from Values

This table presents data on the differences from closing prices and value in each market. Each closing price is defined as a weighted average of the high closing bid and the low closing ask, with weights determined by the proportion of trades at each quote; if no orders are entered, the weights are equal. Deviations are reported as positive when closing price lies between 50 and the true value; otherwise they are reported as negative. Numbers in parentheses indicate the individual observations from the markets. All deviations are rounded to the nearest franc.

Setting	V = 50	V = 30 or 70	V = 10 or 90
1-Signal			
Observations	(0, 0, 0, −5)	(21, 0, 0, 10)	(20, 29, 25, 42)
Mean	−1.25	7.75	29.00
2-Signal			
Observations	(0, 0, 0, −8, 0)	(0, 5, 0, 0, 20, 0, −1)	(21, 20, 21, 0)
Mean	−1.6	3.428	15.5

mates. This is more consistent with the effect of common knowledge problems (which would be exacerbated as the history of trading increases) than with the effect of multiperiod strategies (which would be diminished as the final trading round approaches).

E. Closing Prices

In 24 of the 26 markets, the bid-ask spread (adjusted for commissions) converges to approximately 0, and the price does not vary significantly over the last few rounds of trading. Thus, further trading seems unlikely to have changed prices significantly. If by the completion of the trading process market makers are able to extract investors' information perfectly, then the closing price of each security should exactly equal its value. To the extent that market makers extract information imperfectly, closing prices should represent a weighted average of the true value and the prior expected value of 50 francs. The weight on the prior expected value should be greater in the 1-signal market, because information extraction is expected to be less complete.

Table III supports these hypotheses by showing that pricing errors almost uniformly lie between the true value and 50 francs. The average signed deviation of closing price from value (with a positive sign indicating a price between true value and 50 francs) is 11.833 francs in the 1-signal setting (p = 0.01) compared to 4.875 francs in the 2-signal setting (p = 0.031); the difference in signed deviations across settings is 6.958 francs (p = 0.075). Errors become larger as the true value of the security deviates more from the ex ante expected value of 50 francs. This pattern of errors suggests that the ex ante expectation influences prices more as the value deviates further from that expectation. However, controlling for this variation does not account for the difference between the 1-signal and 2-signal markets: for each class of securities, prices are more accurate in the 2-signal setting. Thus, overall the evidence indicates that closing prices incorporate information less completely in the 1-signal setting than in the 2-signal setting.

Interestingly, the 12 markets in which closing prices do not converge to the true value appear essentially the same as the other markets at the end of trading. In all but 2 of these markets, the bid-ask spread converges to approximately 0, and the price does not vary significantly over the last few rounds of trading. The variance of traders' estimates and traders' expressions of confidence in their valuation are not significantly different from markets in which prices converge close to the true value. This "false convergence" might arise because specialist commissions allow the bid to be higher than the ask, so that investors can engage in riskless arbitrage by simultaneously buying low and selling high. However, this conjecture cannot explain why subjects are as confident about their beliefs as they are when prices converge to the correct price.

F. Autocorrelations in Prices and Estimates

Many empirical studies use autocorrelations in price changes and quote changes to draw inferences about adverse selection or inventory control. Table I reports that price changes show autocorrelations of -0.368 in the 1-signal setting ($p < 0.01$) and -0.146 in the 2-signal setting ($p = 0.036$). Such results, consistent with the empirical findings of French and Roll (1986) and Hausman, Lo and MacKinlay (1992), would typically be interpreted as showing that bid-ask spreads include a noninformational component in both settings. This component causes price reversals as trades "bounce" from the bid to the ask (Niederhoffer and Osborne (1966), Roll (1984), Glosten and Milgrom (1985), Glosten (1987)). The difference in autocorrelation in price changes is 0.223 across the two settings ($p = 0.075$), suggesting that the noninformational component is larger in the 1-signal setting.

The inference that negative autocorrelations imply a noninformational component in the spread relies on the assumption that market makers' estimates follow a martingale (and therefore exhibit no autocorrelations in estimate changes). However, autocorrelations in price changes might also be driven by errors in market makers' interpretations of trades. Market makers whose estimates are noisy but unbiased versions of the best (martingale) estimate will tend to exhibit negative autocorrelations in their estimate changes. In this case, an upward movement in estimates will indicate that prices moved upward too far, on average, so that estimates must fall as the errors are corrected (French and Roll (1986)). For the same reason, market makers who overreact to the information contained in trades will also generate negative autocorrelations in estimate changes. On the other hand, market makers who underreact to the information contained in trades will generate positive autocorrelations in price changes. In this case, an upward movement in prices will indicate that prices did not move upward enough, and the upward movement will be followed by more upward movements.

There are at least two reasons to believe that market makers' errors will depend on the distribution of information among investors. First, the discussion in Section II.D suggests that market makers will be less able to extract information from the trades of poorly-informed investors. As a result, ex post noise in market makers' estimates should be greater, increasing the forces toward negative autocorrelation in estimate changes. Second, experiments by Griffin and Tversky (1992) demonstrate that individuals tend to place too much reliance on signals of low precision, while placing too little reliance on signals of high precision. As a result, ex post underreactions to investors' trades are likely to be more prevalent when investors are better informed, increasing the forces toward positive autocorrelation in estimate changes. Both of these arguments indicate that autocorrelations in market makers' estimate changes should be more negative (or less positive) when investors hold less information.

Panel B of Table I confirms these hypotheses. Estimate changes are negatively associated with previous changes in both settings, but significantly so only in the 1-signal setting ($\beta = -0.393$, $p = 0.021$). The difference in coefficients is 0.286, which is in the predicted direction, and significant at $p = 0.093$. This indicates that, as hypothesized, market makers' estimates may be subject to greater random error and/or less underreaction in the 1-signal setting.

Discerning differences in estimate autocorrelations may be hindered by the noisiness of the estimates. Panel C of Table I presents evidence that quote changes are positively associated with previous changes, with the association insignificant in the 1-signal setting ($\beta = 0.132$, $p = 0.272$), and high significant in the 2-signal setting ($\beta = 0.570$, $p < 0.01$). The positive association suggests that quote revisions are indeed less noisy than estimate revisions; moreover, the difference of 0.438 across the settings is highly significant ($p < 0.01$) and in the predicted direction. Hasbrouck (1991) also notes lagged effects in quote changes, but ascribes their existence to mechanical imperfections in the market, such as restrictions prohibiting large quote revisions. That such an effect appears in this market as well suggests that the result may be more general.

The last regression in Panel C of Table I shows underreactions more clearly, by demonstrating that imbalances in round $t-2$ affect the market makers' quote changes from round $t-1$ to round t, with a positive and highly significant association in the 2-signal setting ($\beta = 6.523$, $p < 0.01$), but an insignificant association in the 1-signal setting ($\beta = 2.364$, $p = 0.297$). The difference in the associations is also significant ($\Delta = 4.159$, $p = 0.045$), suggesting that underreactions are more severe in the 2-signal setting.

The relation of information distribution and market makers' revision errors has important implications for empirical studies which attempt to draw inferences from the time-series behavior of prices. For example, Glosten and Harris (1988), Hasbrouck (1988, 1991), Madhavan and Smidt (1991, 1993) and Hasbrouck and Sofianos (1993) use the negative autocorrelation in price changes as an inverse measure of the adverse-selection component of the bid-ask spread. In the present setting, a decrease in adverse selection increases negative autocorrelations in price changes more than predicted by traditional theory, because it also causes market makers to underreact to trades. As a result, tests relying on price changes would overstate information asymmetry when it is high, and understate it when it is low.

III. Discussion

This study examines the dynamic behavior of dealer markets under two conditions of information distribution. The data support general predictions of market behavior, consistent with empirical findings: bid-ask spreads rise with increases in adverse selection and decline over time, market makers set quotes to control their inventories, and trading impounds information into prices. The study also presents some results that lie outside the traditional bounds of microstructure research. When investors are better-informed, so that each round of trading conveys more information to market makers, market makers are better able to extract the information contained in those trades, but underreact to trades more consistently. This affects the autocorrelations in market makers' estimate changes, which in turn affect autocorrelations in price changes. Because many empirical studies rely on the time-series characteristics of prices to draw inferences about the information environment, a better understanding of these relations between information and errors would be valuable.

The particular trading mechanism used in the experiment combines characteristics of order-driven and quote-driven markets, as well as batch and sequential markets. For example, investors are required to enter limit orders without observing market makers' quotes, and although there are multiple rounds of trading, orders are batched for execution and may be only partially filled. Most of these details of the markets were chosen to simplify the task of the subjects; it is unclear whether changes in these details would cause qualitative changes in the results reported here.

The markets also differ from real-world markets in that competitive quote-setting is enforced by the existence of two market markets. On Nasdaq stocks, competition is enforced by many market makers. On the NYSE, a single market maker is forced to compete against limit orders. Allowing a single market maker to set quotes without competition might affect the results in important ways. Leach and Madhavan (1993) and others suggest that monopolistic market makers may engage in "active learning," deviating from competitive pricing in any given round in order to extract additional information from the order flow (and increase profits in future rounds). Markets with a single market maker might therefore exhibit different time-series characteristics, and may also be less susceptible to the "false convergence" to incorrect closing prices observed in this study.

Enforcing competitive quote-setting in different ways (making market makers compete against many other market makers or only against limit orders) might also affect results, altering the speed of information revelation, the accuracy of market makers' interpretations of trades, and the magnitude of errors in closing prices. Altering the degree of competition in this fashion might also alter the behavior of spreads over time, and might shed light on the differences in intraday spread behavior across Nasdaq and NYSE stocks (Brock and Kleidon (1992), Chan, Christie, and Schultz (1995), McInish and Wood (1992)), which may be driven at least partly by variations in the degree of competitiveness in quote-setting across exchanges.

REFERENCES

Amihud, Yakov, and Haim Mendelson, 1980, Dealership markets: Market making with inventory, *Journal of Financial Economics,* 8, 31–53.

Bloomfield, Robert, and Robert Libby, 1996, Market reactions to differentially available information in the laboratory, *Journal of Accounting Research*, Forthcoming.

Bloomfield, Robert, 1996, The interdependence of reporting discretion and informational efficiency in laboratory markets, *The Accounting Review*, Forthcoming.

Brock, William A., and Allan Kleidon, 1992, Periodic market closure and trading volume: A model of intraday bids and asks, *Journal of Economic Dynamics and Control* 16, 451–489.

Chan, K.C., William G. Christie, and Paul H. Schultz, 1995, Market structure and the intraday pattern of bid-ask spreads for Nasdaq securities, *Journal of Business* 68, 35–60.

Copeland, Thomas E., and Daniel Friedman, 1987, The Effect of sequential information arrival on asset prices: An experimental study, *Journal of Finance* 42, 763–797.

Copeland, Thomas E., and Daniel Friedman, 1991, Partial revelation of information in experimental asset markets, *Journal of Finance* 46, 265–295.

Easley, David, and Maureen O'Hara, 1987, Price, quantity, and information in securities markets, *Journal of Financial Economics* 19, 69–90.

Easley, David, Nicholas Kiefer, Maureen O'Hara, and Joseph Paperman, 1996, Liquidity, information, and infrequently traded stocks, *Journal of Finance,* 51, 1405–1436.

Forsythe, Robert, and Russell J. Lundholm, 1990. Information aggregation in an experimental market, *Econometrica* 58, 309–348.

Foster, F. Douglas, and S. Viswanathan, 1996, Strategic trading when agents forecast the forecasts of others, *Journal of Finance* 51, 1437–1478.

French, Kenneth, and Richard Roll, 1986, Stock return variances: The arrival of information and the reaction of traders, *Journal of Financial Economics* 17, 5–26.

Garman, Mark, 1976, Market microstructure, *Journal of Financial Economic* 3, 257–275.

Glosten, Lawrence, and Lawrence Harris, 1988, Estimating the components of the bid-ask spread, *Journal of Financial Economics* 21, 123–142.

Glosten, Lawrence, and Paul Milgrom, 1985, Bid, ask, and transaction prices in a market maker market with heterogeneously informed traders, *Journal of Financial Economics* 13, 71–100.

Glosten, Lawrence R., 1987, Components of the bid-ask spread and the statistical properties of transaction prices, *Journal of Finance* 42, 1293–1307.

Griffin, Dale, and Amos Tversky, 1992. The weighting of evidence and the determinants of confidence. Cognitive Psychology 24, 411–435.

Hasbrouck, Joel, 1988, Trades, quotes, inventories, and information, *Journal of Financial Economics* 22, 229–252.

Hasbrouck, Joel, 1991, Measuring the information content of stock trades, *Journal of Finance* 46, 179–208.

Hasbrouck, Joel, and George Sofianos, 1993, The trades of market makers: An empirical analysis of NYSE market makers, *Journal of Finance* 48, 1565–1593.

Hausman, Jerry A., Andrew Lo, and A. Craig MacKinlay, 1992, An ordered probit analysis of transaction stock prices, *Journal of Financial Economics* 31, 319–379.

Ho, Thomas, and Hans Stoll, 1983, The dynamics of dealer markets under competition, *Journal of Finance* 38, 1053–1074.

Holden, Craig W., and Avanidhar Subrahmanyan, 1992, Long-lived private information and imperfect competition, *Journal of Finance* 47, 247–270.

Leach, J. Christopher, and Ananth Madhavan, 1992, Intertemporal price discovery by market makers: Active versus passive learning, *Journal of Financial Intermediation* 2, 207–235.

Lundholm, Russell, 1991, What affects the efficiency of a market? Some answers from the laboratory, *The Accounting Review* 66, 486–515.

Madhavan, Ananth, 1992, Trading mechanisms in securities markets, *Journal of Finance* 47, 607–641.

Madhavan, Ananth, and Seymour Smidt, 1991, A Bayesian model of intraday market maker pricing, *Journal of Financial Economics* 30, 99–134.

Madhavan, Ananth, and Seymour Smidt, 1993, An analysis of changes in market maker inventories and quotations, *Journal of Finance* 48, 1595–1628.

McInish, Thomas H., and Robert A. Wood, 1992, An analysis of intraday patterns in bid/ask spreads for NYSE stocks, *Journal of Finance* 47, 763–764.

Niederhoffer, V., and M.F.M. Osborne, 1966, Market making and reversal on the stock exchange, *Journal of the American Statistical Association* 61, 897–916.

O'Brien, John, and Sanjay Srivastava, 1991, Dynamic stock markets with multiple assets: An experimental analysis, *Journal of Finance* 46, 1811–1838.

Plott, Charles R., and Shyam Sunder, 1982, Efficiency of experimental security markets with insider information: An application of rational expectations models, *Journal of Political Economy*, 663–698.

Plott, Charles R., and Shyam Sunder, 1988, Rational expectations and the aggregation of diverse information in laboratory security markets, *Econometrica* 56, 1085–1118.

Roll, Richard, 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *Journal of Finance* 39, 1127–1139.

Stoll, Hans, 1989, Inferring the components of the bid-ask spread: Theory and empirical tests, *Journal of Finance* 44, 115–134.