Market Microstructure and Stock Return Predictions

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To what extent are the empirical regularities implied by market microstructure theories useful in predicting the short-run behavior of stock returns? A two-equation econometric model of quote revisions and transaction returns is developed and used to identify the relative importance of different microstructure theories and to make predictions. Microstructure variables and lagged stock index futures returns have in-sample and out-of-sample predictive power based on data observed at five-minute intervals. The most striking microstructure implication of the model, confirmed by the empirical results, specifies that the expected quote return is positively related to the deviation between the transaction price and the quote midpoint while the expected transaction return is negatively related to the same variable.

The burgeoning literature on the microstructure of securities markets contains substantial evidence of systematic behavior in the short-run pattern of stock prices. Prices exhibit reversals as they bounce between

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bid and ask quotes [Roll (1984), Stoll (1989)]. Specialists, motivated by inventory costs and fears of adverse information, adjust quotes in a complex response to the evolution of observed transactions [Hasbrouck (1988, 1991), Hasbrouck and Ho (1987), Madhavan and Smidt (1991), Petersen and Umlauf (1991)]. Prices of individual stocks appear to adjust with a lag to price changes in the index futures contract and in certain stock segments, even after controlling for the infrequent trading problem [Stoll and Whaley (1990), Lo and MacKinlay (1990)]. Tests of scientific theories lie in their predictive power. Yet, surprisingly few attempts have been made to determine the ability of microstructure theories to predict the very short-run behavior of stock prices. We construct an econometric model of quote revisions and stock-price changes that incorporates the various theories of the market microstructure and use the model to make predictions.

The model and our empirical tests distinguish this article in several ways from other microstructure research. First, the model integrates the determinants of quotes and transaction prices in a two-equation framework that we use to identify the relative importance of different microstructure theories. We also test cross-equation restrictions that are implied by microstructure theory. The empirical results support both the adverse selection theory of the bid–ask spread and the inventory theory. The results show that price quotations adjust as predicted to reflect the adverse information conveyed by the last trade. Prices of stocks also exhibit reversals that compensate providers of immediacy for inventory and order-processing costs.

Second, the model is used to predict five-minute quote revisions and transaction returns on the basis of microstructure variables and lagged stock index futures returns. We make out-of-sample predictions and compare the mean-squared error of our forecasts to naive forecasts. Our results indicate that short-run quote and price changes are predictable on the basis of information available when the predictions are made, including the lagged stock index futures return. However, profitable arbitrage opportunities are not necessarily implied since transaction costs probably overwhelm the potential profits for most investors. Nevertheless, the evidence of predictability can be useful to investors interested in minimizing trading costs and to market makers interested in setting optimal quotes.

Third, a useful feature of the model and the empirical specification is that it is straightforward to implement. The model is linear and the use of data observed at five-minute intervals is sufficient to capture past return behavior without an elaborate lag structure.

In Section 1 we develop an empirical model of quotations and transaction prices. The data are described in Section 2. In Section 3, we examine bivariate relations between the variables used in the model and returns for quotes and transaction prices. Section 4 contains the principal empirical results of the article. In Section 5, we analyze the model's out-of-sample predictive power. The article ends with conclusions in Section 6.

1. An Empirical Model of Quotations and Transaction Prices

Let q_t be the logarithm of the average of bid and ask prices quoted just prior to a trade and let p_t be the logarithm of the transaction price. Define

$$p_t = q_t + z_t. \tag{1}$$

where z_t is the deviation of the log of the observed transaction price from the log midpoint of the quotes and can be thought of as one-half the effective bid–ask spread expressed as a proportion of the quotes' midpoint. The effective spread is less than the quoted spread because transactions may take place inside the quoted spread. Public purchases (dealer sales) results in $z_t > 0$. Public sales (dealer purchases) results in $z_t < 0$. In our empirical work, the minimum sampling interval is five minutes. First differencing Equation (1) yields

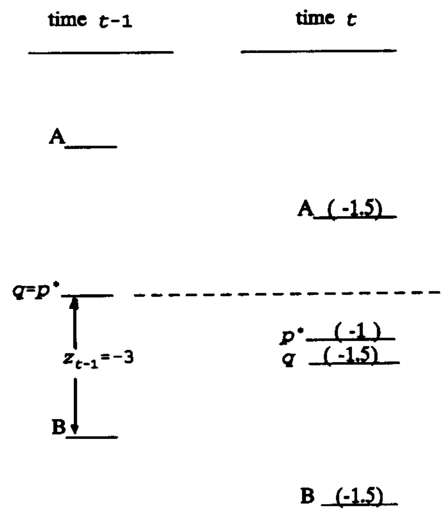
$$r_t^p = r_t^q + z_t - z_{t-1}, \tag{2}$$

where $r_t^p = p_t - p_{t-1}$ and $r_t^q = q_t - q_{t-1}$. As stated, definition (1) or (2) lacks empirical content. We develop a testable model by specifying the quote setting behavior for r_t^q and the process generating z_{t-1}.

1.1 Illustration of microstructure effects

Before detailing the empirical model, we illustrate in Figure 1 the four market microstructure effects we seek to capture. At time $t - 1$, the bid price, B, and the ask price, A, are assumed to bracket the unobservable consensus price, p^*, so that $q_{t-1} = p^*_{t-1}$. The consensus price of the stock is the price that reflects all public information (including the price and quantity of the last trade) and that would arise in the absence of trading costs.[1] For concreteness, assume that the half-spread has a value of 3 (eighths) composed of an adverse information component of 1, an inventory holding cost component of 0.5, and an order processing component of 1.5. The adverse information component, modeled in Glosten and Milgrom (1985) and Copeland and Galai (1983), reflects the expected value of the private information conveyed by a public seller or public buyer. The inven-

[1] The concept of a consensus value that is unobservable and at which no transactions may occur is also used by Glosten and Milgrom (1985, p. 77) and others.



Assumed components of half-spread:

adverse information	= 1.0
inventory holding cost	= 0.5
order processing cost	= 1.5
	3.0

Figure 1
Illustration of quote adjustment at time t subsequent to a transaction at the bid at time $t-1$
Spread is held constant at 6. A = ask price, B = bid price, q = quote midpoint, p^* = unobservable consensus price, and z = difference between trade price and quote midpoint. Numbers in parentheses denote price changes between $t-1$ and t.

tory holding cost component, modeled in Stoll (1978) and Ho and Stoll (1981), reflects the return required to compensate dealers for accumulating unwanted inventory. The order processing component compensates dealers for the costs of processing trades, such as the costs of communicating, clearing, and record keeping.

Assume that a public sale takes place at the bid price at time $t-1$, so that $z_{t-1} = -3$. Microstructure theory provides predictions for subsequent changes in bid and ask prices. Also assume that the spread remains constant, a result that is implied by some theories, but is not necessary in our empirical work. The first microstructure effect we model is the adverse information effect. Under this effect, A and B will be lowered to reflect the expected value of the private information conveyed by the public sale, or -1 under our assumption. The consensus price changes by one-third the value of z_{t-1} or by -1.

The second microstructure effect we model is the inventory effect.

Under this effect, A and B are lowered by an additional amount that provides compensation for the risk of holding inventory, changing the quote midpoint, q, relative to p^* by -0.5. The half-spread remains at 3.

The third microstructure effect we capture is the order processing cost. Providers of immediacy recover their costs of trading and processing orders by buying at the bid and selling at the ask, thus profiting from the bid–ask spread. If the only source of the spread were the order processing cost, the spread would be 3. Given equal probabilities of purchases and sales, the expected revenue of the dealer would be 1.5, which is one half the spread and just sufficient to cover order-processing costs.

In the figure, the spread of 6 reflects the presence of adverse information and inventory costs as well as order-processing costs. Given the downward adjustment of A and B after a public sale at time $t-1$, market-maker revenues are 4.5 if the trade at time t occurs at A and -1.5 if the trade at time t occurs at B. Assuming a one-period horizon, dealers must, in equilibrium, earn expected revenues of 2 to cover order-processing costs of 1.5 and inventory-holding cost of 0.5. The expected revenue is therefore

$$E(\text{Rev}) = 4.5\pi + (1 - \pi)(-1.5) = 2,$$

where π is the probability of a public purchase and $1 - \pi$ is the probability of a public sale at time t. The value of π that is consistent with equilibrium is therefore $\pi = 0.583$.

Note that in this illustration the expected revenue on a trade is one-third the spread. If the only source of the spread were adverse information, the spread would be 2, bids and asks would change to reflect the information conveyed by trades, but the expected revenue on a trade would be zero. If the only source of the spread were the inventory-holding cost of 0.5, the spread would be 1, bids and asks would change to induce changes in order arrivals, and the expected revenue on a trade would be 0.5.[2]

The fact that the probability of a public purchase differs from 0.5 illustrates the fourth market microstructure effect we seek to capture, namely, an induced order arrival effect. The probability of a public purchase changes through time as dealer price adjustments change q with respect to p^*. More formally, the induced order arrival effect states that

$$\text{Prob}[z_t > 0 \mid (p_t^* - q_t) > 0] > 0.5.$$

[2] Articles that seek to separate the influence of inventory effects, order processing effects and information effects include Glosten and Harris (1988), Stoll (1989), Hasbrouck (1991), George, Kaul, and Nimalendran (1991), and Sirri (1990).

Since p^* is unobservable, we specify a proxy to measure the induced order arrival effect. The divergence of q from p^* depends on the inventory holdings of suppliers of immediacy. The levels of inventory in turn depend on the observed sequence of buys and sells as proxied by past values of z. In the two-period setting depicted in Figure 1, the value of past z is -3, and the price adjustment, motivated by the past accumulation of public sales, increases the probability of future public purchases from 0.5 (when $q_{t-1} = p^*_{t-1}$) to 0.583 (when $q_t = p^*_t - .5$); that is[3]

$$\text{Prob}(z_t = 3 \mid z_{t-1} = -3) = 0.583.$$

Thus, dealer pricing to equilibrate inventory induces negative serial correlation in transaction arrivals. However, other factors, such as investors' trading demands and trading mechanics, may induce positive serial dependence in order arrivals. For example, Easley and O'Hara (1987) argue that adverse information can induce positive serial dependence in orders. Limitations on transaction size at posted quotes may also cause trades to be split up into a sequence of buy or sell orders.

1.2 Quote revisions

We now return to a detailed specification of inventory, information and other effects in our empirical model. The quote return, r^q_t, in Equation (2) can be decomposed into an expected consensus return, an inventory effect and an unexpected component as follows:

$$r^q_t = E[r^*_t \mid \Omega_{t-1}] + g(\Delta I_{t-1}) + \epsilon_t. \tag{3}$$

$E[\cdot \mid \cdot]$ is the conditional expectations operator, r^*_t is the consensus return, Ω_{t-1} is the public information set available just after the transaction at $t - 1$, and ϵ_t represents the change in the quote midpoint due to the arrival of new information after the quote at $t - 1$. The function $g(\Delta I_{t-1})$ captures the effect of inventory change on the quoted return.

To incorporate the information effects, the expected component in Equation (3) can be conditioned on a subset of the available information by the law of iterated expectations. Specifically, we focus on the variable z_{t-1} and the change in the logarithm of the S&P 500 index futures price, r^f_{t-1}:

$$E[r^*_t \mid \Omega_{t-1}] = f(z_{t-1}, r^f_{t-1}). \tag{4}$$

[3] In practice, this probability directly affects the inventory holding cost set by the market maker.

We restrict the specification to a single lag because experimentation indicates that more distant lags provide little additional explanatory power.[4]

The z_{t-1} term is included to determine if market makers adjust quotes on the basis of private information revealed through trading. Glosten and Milgrom (1985) show that, when the only source of the bid–ask spread is private information, the quote's midpoint is adjusted by z_{t-1} because the preceding price deviation is the expected value of the private information conveyed by the trade. In our empirical model, we permit the quote to be adjusted by some fraction of z_{t-1} in accordance with the presence of additional microstructure effects as illustrated in Figure 1.

The lagged change in futures prices is included to account for possible lags in the response of quotes to public information. Since trading in stock index futures is less costly than trading in stocks, general economic news may induce trading in index futures before inducing trading in individual stocks. If limit orders and specialist quotes are not adjusted instantaneously due to structural impediments as noted by Miller (1990), lagged index futures returns may have predictive power. Stoll and Whaley (1990) provide evidence that stock index futures lead stock indexes and IBM stock prices.

As seen in Figure 1, inventory changes may cause the market maker to adjust the quotes relative to the consensus price implied by public information.[5] In practice, the representation of inventory effects is complicated by the fact that the inventory of the specialist and other traders that act like market makers is not public information.[6] It is reasonable to assume, however, that the inventory change at time $t - 1$ is given by the cumulative signed share volume of the trades since the last observed trade at $t - 2$, a variable we denote as Q_{t-1}.[7] Public sales (dealer purchases) are given a negative sign and public purchases (dealer sales) are given a positive sign. We identify a public sale as a trade with a price below the quote midpoint and a public

[4] Instead of focusing on economic determinants in a structural setting as we do, an alternative approach is to rely on the information in the autoregressive lag structure of quotes or prices [see, for example, Hasbrouck (1991)].

[5] We use the terms "market maker," "dealer," and "supplier of immediacy" more or less interchangeably. While we identify each of these terms with the specialist, other traders often perform the same function. Traders other than the specialist can act like market makers by placing limit orders or by standing ready to trade in "the crowd." Thus, our single market maker really represents a group of traders that provide immediacy (among which the specialist is most central).

[6] However, see Madhavan and Smidt (1991), who examine inventory data made available by a specialist.

[7] Under the inventory theory, the bid and ask prices (relative to the market maker's opinion of the "true" price) are related to inventory levels; but changes in bid and ask prices are related to changes in inventory, that is, volume. Since our interest here is in price changes, volume is appropriate.

purchase as a trade with a price above the quote midpoint.[8] Under the convention that public sales (dealer purchases) produce negative Q_{t-1} and public purchases (dealer sales) produce positive Q_{t-1}, cumulative signed volume should have a positive influence on quote revisions.

We also account for the inventory effects of large orders by large-block indicator variables.[9] Let V_{t-1} be share volume of the trade at time $t - 1$ and define the indicator variables

$$
\begin{aligned}
L^A_{t-1} &= 1 \qquad \text{if } z_{t-1} > 0 \text{ and } V_{t-1} > 10{,}000, \\
&= 0 \qquad \text{otherwise}, \\
L^B_{t-1} &= 1 \qquad \text{if } z_{t-1} < 0 \text{ and } V_{t-1} > 10{,}000, \\
&= 0 \qquad \text{otherwise}.
\end{aligned}
$$

The impact on quote revisions is expected to be positive for L^A_{t-1} and negative for L^B_{t-1}.

Our empirical specification illustrates the practical difficulties of isolating inventory effects and information effects on the quotes. Specifically, the variable z_{t-1} is included to convey information about the direction of last period's trade, but it is also used in signing the cumulative volume, Q_{t-1}. In addition, the large-trade indicator variables might represent an information effect as well as an inventory effect.

We also include two additional variables motivated by the joint presence of information and inventory effects. The first variable is the difference between the logarithm of the quoted volume at the ask (depth at the ask) and the logarithm of the quoted volume at the bid (depth at the bid), D_{t-1}.[10] An inventory effect would predict a positive impact on quote changes, but the impact would be negative if a signaling effect dominates. The inventory effect is predicated on the assumption that a dealer adjusts both quotes and depth to encourage transactions that equilibrate inventory. Under the inventory effect, a dealer who has a large inventory at time $t - 1$ simultaneously lowers quotes and raises depth at the ask at time $t - 1$ to attract buyers.[11]

[8] The signing procedure we follow has been used by Hasbrouck (1991) and others.

[9] An alternative to a separate large block indicator variable is to capture the effect of large trades in Q_{t-1}. However, for our data sets, a log transformation of Q_{t-1} did not increase the statistical significance of the variable and, in addition, introduced multicollinearity that had not existed before. For a detailed examination of the reaction of quotes to large orders see Sirri (1990).

[10] The specialist has discretion over the depth levels that he reports. The depth may reflect the depth on the book rounded up, or may also include trading interests by the specialist and the crowd.

[11] The discrete nature of price changes may also cause the market maker to adjust the depth variable as a substitute for a quote change smaller than the standard eighth of a dollar. For evidence that quotes and depth move together, see Lee, Mucklow, and Ready (1993).

Since prices are low at time $t - 1$, there is a higher probability of a positive than of a negative return from $t - 1$ to t; therefore, positive association between r_t^q and D_{t-1} results under the inventory effect.[12] Under the signaling effect, large depth at the ask at time $t - 1$ indicates the presence of sellers on the limit order book, which induces market participants to revise quotes downward at time t; therefore, negative association between r_t^q and D_{t-1} results under the signaling effect. Another effect is the barrier effect that yields the same prediction as the signaling effect. Large depth at the ask relative to the bid creates a barrier to price increases relative to price decreases, which will tend to induce price decreases. If orders arrive more or less randomly, the buying power at the bid is more likely to be exhausted (thereby causing a decline in the bid) than the selling power at the ask (thereby causing the ask price to remain unchanged).

The second variable is the lagged quote revision, r_{t-1}^q. This variable may provide useful information in an imperfect world of noninstantaneous quote revisions due to limit orders, stabilization rules, and transaction costs. If quotes are slow to adjust, the lagged quote return would have a positive effect on the subsequent quote return. Alternatively, the past quote return could capture inventory effects that induce negative serial correlation in quote returns. Negative serial correlation would arise from the quote adjustments made by market makers in order induce inventory equilibrating trades.

Specification (3) is now expressed as a linear function of the information and inventory variables to produce a quote revision rule:

$$\begin{aligned} r_t^q = {} & a_0 + a_1 r_{t-1}^q + a_2 r_{t-1}^f + a_3^q z_{t-1} \\ & + a_4 Q_{t-1} + a_5 L_{t-1}^A + a_6 L_{t-1}^B + a_7 D_{t-1} + \epsilon_t. \end{aligned} \tag{5}$$

1.3 Price prediction

Equation (2) shows that the price prediction rule can be obtained by combining the quote revision rule with the generating process for z_t. We allow z_t to depend on the past observed value of z_t to capture characteristics of the order arrival process induced by inventory effects and other effects. Specifically, we posit

$$z_t = \rho z_{t-1} + u_t, \tag{6}$$

where ρ is a parameter and u_t is the order arrival shock. If the probability of a purchase or a sale is independent of the past sequence of trades, $\rho = 0$. In the Easley and O'Hara (1987) model with asymmetric information or in a world with institutional rigidities that cause trades

[12] The depth variable potentially reflects an inventory *level* effect, whereas Q_t reflects an inventory *change* effect associated with the last trade.

to bunch, positive correlation between the present and past z_t is predicted, that is $\rho > 0$. If dealer pricing induces inventory equilibrating trades, we expect $\rho < 0$.

Combining Equations (2) and (6) leads to

$$r_t^p = r_t^q + (\rho - 1)z_{t-1} + u_t. \tag{7}$$

Substitution of Equation (5) into Equation (7) then results in

$$\begin{aligned} r_t^p = a_0 &+ a_1 r_{t-1}^q + a_2 r_{t-1}^f + a_3^p z_{t-1} \\ &+ a_4 Q_{t-1} + a_5 L_{t-1}^A + a_6 L_{t-1}^B + a_7 D_{t-1} + e_t, \end{aligned} \tag{8}$$

where $a_3^p = a_3^q + \rho - 1$ and $e_t = \epsilon_t + u_t$. The generating process for z_t as specified in Equation (6) permits a decomposition of the coefficient, a_3^p, into three microstructure effects. The first component, a_3^q, represents the asymmetric information effect. We expect this component to be positive and to represent the information conveyed by the last trade. The second component, ρ, represents the induced order arrival effect modeled by Equation (6). The third component, -1, represents the bid–ask bounce effect. In the absence of information or order arrival effects, the coefficient of z_{t-1} in Equation (8) would be -1, reflecting the tendency of price returns to be negatively serially correlated. For example, a coefficient of -1 is implied by Roll's (1984) model. In Roll's model, bid and ask quotes are not adjusted to manage inventory or to incorporate information conveyed by a trade. The bid–ask bounce simply compensates the dealer for the cost of processing the order. The bid–ask bounce effect is also evident in Equation (2). If r_t^q is independent of z_{t-1}, and if the z's are serially independent, a coefficient of -1 is implied for z_{t-1}. Quote revisions attenuate this negative serial correlation in price returns but are unlikely to eliminate it.

Equations (5) and (8) can be viewed primarily as equations for predicting stock returns in the short run on the basis of microstructure theory and other variables. Equation (5) predicts the quote's midpoint return, which can be thought of as the inventory-adjusted equilibrium return. Equation (8) predicts the transaction price on the basis of an adjustment for the bid–ask bounce around the quoted return and for induced order arrival.

1.4 Hypotheses

Our model incorporates various market microstructure theories that are not necessarily mutually exclusive. Following is a summary of the restrictions imposed on our model by each of the theories.

Order processing theory: $a_3^q = 0$, $a_3^p = -1$. In this, the simplest of the spread models, quotes are not adjusted and prices bounce between the bid and the ask.

Adverse information theory: $a_3^q = 1$, $a_3^p = 0$. In the pure adverse information theory of Glosten and Milgrom (1985) and Copeland and Galai (1983), quotes are adjusted to reflect the information contained in the last trade, z_{t-1}, but the expected transaction price change does not depend on z_{t-1}.

Inventory holding cost theory: $1 > a_3^q > 0$, $0 > a_3^p > -1$, $a_4 > 0$. In the pure inventory holding theory of Stoll (1978) and Ho and Stoll (1983), quotes are adjusted in the same direction as the prior trade, and prices tend to bounce back. Additionally, quote returns are adjusted by an amount that depends on the inventory change, Q_{t-1}.

Induced order arrival effect: $\rho < 0$, $a_1 < 0$, $a_7 > 0$. An implication of inventory theories is that order arrivals are influenced by changes in the quote midpoint, leading to negative serial correlation in z, that is $\rho < 0$. The same effect is also captured in the coefficient of r_{t-1}^q since one expects successive quote returns to be negatively correlated if quotes are adjusted to equilibrate inventory. If depth is used to encourage order arrivals that equilibrate inventory, one expects $a_7 > 0$. Alternatively depth may provide a signal or act as a barrier, in which case $a_7 < 0$.

Large trades: $a_5 > 0$, $a_6 < 0$. Both the adverse information theory and the inventory theory imply a positive value for a_5 and a negative value for a_6.

Our sole nonmicrostructure variable, lagged stock index futures return, has implications for market efficiency.

Efficiency of futures and stock market: $a_2 = 0$. In an efficient stock market, one expects stock quotes to reflect the information contained in stock index futures prices. This implies that the futures return has no predictive power in both the quote and price equations; that is, $a_2 = 0$.

Finally, the two-equation model imposes testable cross-equation constraints. It implies that all the microstructure coefficients in the quote equation are equal to their counterparts in the price equation with one exception. The exception is that the coefficients of z_{t-1} in the quote and price equations be of opposite sign.

Cross-equation restrictions: a_1, a_4, a_5, a_6, a_7 coefficients are the same for both quote and price equations.

2. Data

Data for this study are taken from the transactions data files compiled by the Institute for the Study of Security Markets (ISSM). The analysis covers 20 actively traded stocks constituting the Major Market Index over all trading days in calendar year 1988. We take two measures to correct for the possibility that trades and quotes are not reported in the sequence in which they occurred. First, because quotes are reported more quickly than trades, we adjust the time of quotes relative to trades.[13] If the time of quote is five seconds or less prior to the time of trade, we place the time of quote immediately after the time of trade. Second, we divide the trading day into 78 five-minute intervals and take an observation from each interval. We expect data taken at five-minute intervals to be in the correct time sequence. From the perspective of predicting returns, the five-minute criterion is conservative since market participants have access to more data than we use.

We report the results based on two data sets for each of the 20 stocks. The first contains current quotes and current trades and the second contains standing quotes and current trades. For each data set, we begin by retaining the last transaction price in the five-minute interval. If a transaction price is not available in the interval, the interval is excluded. We next determine the bid–ask quote preceding the transaction price (after having made the five-second adjustment). In the data set we call "current quotes and current trades," we retain only those intervals in which a quote appeared in the same interval as a transaction price. Quotes are recorded if a bid or ask price changes or if the quantity bid (depth at the bid) or offered (depth at the ask) changes. This data set has the advantage of maximizing variability in the variables of interest—quote and price returns. It has the disadvantage that intervals in which quotes are not revised are ignored. Since no news may still be news, we also test our model on a broader data set we call "standing quotes and current trades." In this data set, all intervals containing a trade price are retained for which a prior quote is available in the same day.

We also retrieve the stock transaction size in shares (which is recorded at the same time as the price) and the number of shares offered at the ask and sought at the bid (depth at the ask and at the bid, which are recorded at the same time as the quotes) from the ISSM data. If these data were missing, the five-minute interval is excluded. In addition, we collect the last stock index futures price in period $t - 1$ that precedes the transaction price in period $t - 1$

[13] See Lee and Ready (1991).

by at least five seconds.[14] The stock index futures price is the price of the nearby S&P 500 futures contract. We switch from the nearby contract to the next maturity on the second Friday of the expiration month. Tick by tick data were kindly provided by the Chicago Mercantile Exchange. S&P 500 stock index futures are actively traded with the result that data for this variable are always available for the five-minute sampling intervals.

For each data set, returns are calculated from the price observation in one five-minute interval to the price observation in the next five-minute interval. If a five-minute period is excluded, the return spans more than five minutes. On the basis of past returns and other past data, predictions of quote returns and price returns are made to the following interval. Overnight returns are excluded from the analysis, and no attempt is made to predict overnight returns.[15]

Our sample includes a few very large transactions that can be traced to dividend capture trading strategies (for example, a trade of 7,500,000 shares in Sears on May 26, 1988). Dividend capture trading results in the offsetting purchase and sale trades executed at the same time but with different settlement dates spanning the dividend ex date. These are wash trades that are not influenced by the factors we are investigating. As a result, we exclude intervals in which we could identify the presence of a large dividend capture trade.[16]

Table 1 contains summary statistics for the stocks in the sample. A list of the company names and their ticker symbols is provided in the Appendix. The total number of possible five-minute intervals in 1988 was 19,734. In the case of current quotes and current trades, which we will refer to as data set *A*, the number of observations per stock ranges from a high of 15,736 to a low of 5471, with an average of 8926 per stock. In the case of standing quotes and current trades, which we will refer to as data set *B*, the number of observations ranges from a high of 16,355 to a low of 12,561, with an average of 14,464 per stock.

[14] This procedure ensures that information contained in the futures price at time $t-1$ has time to be reflected in the stock price at time $t-1$ (if the two markets react to information at the same time).

[15] To check on the robustness of our results, we also use two analogous data sets for current and standing quotes that are confined to five-minute returns and revisions. These extensions produce comparable conclusions to those reported in the article.

[16] Dividend capture trading is examined by Choe and Masulis (1991). They kindly provided us with a list of large trades that specified nonstandard delivery. Dividend capture trading involves two sets of trades at about the same time, one for standard five-day delivery and one for nonstandard delivery. We deleted any nonstandard trade or a trade for the same volume observed in the same interval or in one of the two adjacent five-minute intervals. This rule caused us to delete a total of 18 large trades. The number of deleted trades are indicated in parentheses next to each ticker symbol: AXP (1), CHV (1), DOW (1), EK (1), GM (6), S (1), T (3), X (2), XON (2). We were unable to remove all dividend capture trades since we were not always able to identify an offsetting trade to a nonstandard trade.

Table 1
Summary statistics of 20 MMI stocks

Statistic	N	r^q	r^p	r^f	$\|z\|$	V	DA	DB	L^A	L^B
				A: Current quotes and current trades						
Ave (μ)	8,926	−0.001	−0.001	−0.001	0.118	22.4	107.3	95.2	0.020	0.016
Ave (σ)		0.207	0.250	0.151	0.091	82.3	105.0	92.0	0.133	0.124
Min	5,471	−0.003	−0.004	−0.002	0.049	13.2	35.6	31.7	0.007	0.006
Max	15,736	0.002	0.002	−0.001	0.206	36.3	447.2	395.4	0.047	0.031
				B: Standing quotes and current trades						
Ave (μ)	14,464	−0.001	−0.001	−0.001	0.116	21.6	117.9	104.7	0.019	0.016
Ave (σ)		0.161	0.216	0.118	0.090	109.0	110.2	96.4	0.132	0.124
Min	12,561	−0.002	−0.002	−0.001	0.049	13.0	37.9	33.7	0.008	0.006
Max	16,355	0.001	0.001	−0.001	0.207	31.4	507.8	452.1	0.042	0.030

The four rows contain the average of the means, the average of the standard deviations, the minimum, and the maximum values. N denotes number of observations, r^q denotes quote return, r^p denotes price return, r^f denotes return on S&P 500 index futures, $|z|$ denotes absolute difference between logarithm of transaction price and logarithm of quote's midpoint, V denotes trade volume, DA denotes depth at ask, DB denotes depth at bid, L^A_{t-1} is the indicator variable for public buys that exceed 10,000 shares, and L^B_{t-1} is the indicator variable for public sales that exceed 10,000 shares. The means and standard deviations of r^q, r^p, r^f, and z are multiplied by 100.

As expected, the standard deviation of returns based on quote midpoints is less than the standard deviation of returns based on transaction prices (0.207 percent versus 0.250 percent for data set A and 0.161 percent versus 0.216 percent for data set B). The standard deviation of the return of the index futures contract (0.151 percent in data set A and 0.118 in data set B) is always less than the standard deviation of quote returns or price returns of any stock. This is expected since the index futures contract represents a portfolio. The ranking of the standard deviation of quote returns, price returns, and futures returns holds for each stock as well as for the averages shown in Table 1. Also observable in Table 1 is the higher variability of returns in data set A than in data set B. This reflects the fact that data set A includes those intervals in which quotes were revised. A quote revision is more likely if prices are changing.

The absolute value of z, which is the deviation between log of the transaction price and the log of the quote midpoint, is one-half the proportional effective spread. The proportional effective spread is less than the proportional quoted spread because transactions can occur inside the quotes. For data set A, the mean of $|z|$ ranges from a low of 0.049 percent (for IBM) to a high of 0.206 percent (for American Express), with an overall average of 0.091 percent. The means are virtually identical for data set B. The effective spreads of 0.098 percent for IBM and 0.412 percent for American Express compare to quoted spreads of 0.146 percent and 0.664 percent respectively for these same stocks. Given the average prices for IBM and American Express of \$116.5 and \$26 respectively, the average effective spreads are 11.4

cents and 10.7 cents per share while the average quoted spreads are 17.01 cents and 17.26 cents per share.[17]

The average transaction size of the sampled trades, V, averages 22.4 round lots in data set A and 21.6 round lots in data set B. The average number of round lots ranges from 13.2 to 36.3 in data set A and from 13 to 31.4 in data set B. In data set A (B), Johnson and Johnson (Johnson and Johnson) is the stock with the lowest average trade size and AT&T (American Express) is the stock with the largest average trade size.

The average depth at the ask, DA, ranges from a low of 35.6 round lots (Johnson and Johnson) to a high of 447.2 round lots (AT&T) in data set A.[18] Comparison of the DA and DB columns shows that the grand average depth at the ask exceeds the grand average depth at the bid, something that holds for almost every stock in our sample. A comparison of depths for data set A and data set B indicates that depths are smaller in the more volatile data set A periods.

The last two columns represent the proportion of a stock's sampled transactions exceeding 10,000 shares. Block trades in excess of 10,000 shares at the ask or the bid are quite rare. In data set A, the stock with the maximum proportion of purchase (sale) blocks has a block purchase (sale) in 4.7 percent (3.1 percent) of the sampled trades. The stock with the minimum number of blocks experiences block purchases in 0.7 percent of the trades and block sales in 0.6 percent of the trades.

3. Univariate predictions

In this section, we perform nonparametric tests of the ability of single variables to predict the direction of changes in quote midpoints and transaction prices. These tests are not contingent on distributional assumptions and provide evidence on the ability of single variables to predict quote returns and price returns. They also serve to further characterize our data. Parametric tests of our multivariate model are provided in the next section.

The variables used as predictors are the past quote return, r^q_{t-1}, the past futures return, r^f_{t-1}, the past difference between the transaction price and the quote midpoint, z_{t-1}, and the past difference between

[17] As this example illustrates, there seems to be more constancy across stocks if the spread is stated in cents per share than when it is stated as a percent of value. This also holds for the NASDAQ market as shown in Stoll (1989). The fact that the effective spread is approximately the same fraction of the quoted spread for IBM and American Express (at 0.67 and 0.63 respectively) is accidental in the data set for the MMI 20 stocks. It turns out that IBM has the largest ratio of effective to quoted spread. The ratio declines to a low of 0.41 for Eastman Kodak.

[18] Depths in excess of 999 round lots are reported as 999. This fact may bias downward the average depth for a stock like AT&T with large depth.

Table 2
Contingency tables for pooled sample

A: Current quotes and current trades

r^q_t/r^q_{t-1}	<0	=0	>0		r^p_t/r^q_{t-1}	<0	=0	>0	
<0	20,664	17,748	21,583	59,995	<0	18,045	15,601	16,557	50,203
=0	18,144	24,330	17,434	59,908	=0	25,440	28,394	24,886	78,680
>0	21,268	17,656	19,685	58,609	>0	16,631	15,739	17,259	49,629
	60,076	59,734	58,702	178,512		60,076	59,734	58,702	178,512

r^q_t/r^f_{t-1}	<0	=0	>0		r^p_t/r^f_{t-1}	<0	=0	>0	
<0	34,982	4,455	20,558	59,995	<0	26,816	3,772	19,615	50,203
=0	27,386	5,171	27,351	59,908	=0	35,966	6,423	36,291	78,680
>0	19,559	4,338	34,712	58,609	>0	19,145	3,769	26,715	49,629
	81,927	13,964	82,621	178,512		81,927	13,964	82,621	178,512

r^q_t/z_{t-1}	<0	=0	>0		r^p_t/z_{t-1}	<0	=0	>0	
<0	30,228	18,150	11,617	59,995	<0	10,527	13,389	26,287	50,203
=0	24,599	12,093	23,216	59,908	=0	29,876	21,248	27,556	78,680
>0	11,567	17,178	29,864	58,609	>0	25,991	12,784	10,854	49,629
	66,394	47,421	64,697	178,512		66,394	47,421	64,697	178,512

r^q_t/D_{t-1}	<0	=0	>0		r^p_t/D_{t-1}	<0	=0	>0	
<0	14,924	12,522	32,549	59,995	<0	16,714	10,205	23,284	50,203
=0	22,706	10,225	26,977	59,908	=0	28,926	14,951	34,803	78,680
>0	27,980	12,625	18,004	58,609	>0	19,970	10,216	19,443	49,629
	65,610	35,372	77,530	178,512		65,610	35,372	77,530	178,512

B: Standing quotes and current trades

r^q_t/r^q_{t-1}	<0	=0	>0		r^p_t/r^q_{t-1}	<0	=0	>0	
<0	19,659	30,028	20,784	70,471	<0	18,885	32,991	17,364	69,240
=0	30,876	90,806	28,755	150,437	=0	34,466	83,995	33,013	151,474
>0	20,166	29,215	18,997	68,378	>0	17,350	33,063	18,159	68,572
	70,701	150,049	68,536	289,286		70,701	150,049	68,536	289,286

r^q_t/r^f_{t-1}	<0	=0	>0		r^p_t/r^f_{t-1}	<0	=0	>0	
<0	41,538	6,118	22,815	70,471	<0	35,819	6,288	27,133	69,240
=0	66,833	16,368	67,236	150,437	=0	67,675	15,744	68,055	151,474
>0	21,320	5,975	41,083	68,378	>0	26,197	6,429	35,946	68,572
	129,691	28,461	131,134	289,286		129,691	28,461	131,134	289,286

r^q_t/z_{t-1}	<0	=0	>0		r^p_t/z_{t-1}	<0	=0	>0	
<0	39,254	20,103	11,114	70,471	<0	11,486	17,667	40,087	69,240
=0	57,932	42,060	50,445	150,437	=0	56,958	46,748	47,768	151,474
>0	11,046	19,164	38,168	68,378	>0	39,788	16,912	11,872	68,572
	108,232	81,327	99,727	289,286		108,232	81,327	99,727	289,286

r^q_t/D_{t-1}	<0	=0	>0		r^p_t/D_{t-1}	<0	=0	>0	
<0	16,972	15,247	38,252	70,471	<0	23,039	15,205	30,996	69,240
=0	52,096	36,064	62,277	150,437	=0	52,342	36,184	62,948	151,474
>0	32,991	15,150	20,237	68,378	>0	26,678	15,072	26,822	68,572
	102,059	66,461	120,766	289,286		102,059	66,461	120,766	289,286

The variables are quote return (r^q), price return (r^p), change in S&P 500 index future prices (r^f), deviation of the transaction price from the quote's midpoint (z), and the difference between the quoted volumes at ask and bid quotes (D).

the depth at the ask and depth at the bid, D_{t-1}. Descriptive information for pooled data set A and for pooled data set B are contained in panels A and B of Table 2 in the form of three-by-three contingency tables.[19] Results of a formal test of forecasting ability are contained in Table 3.[20]

3.1. Descriptive information

The contingency tables categorize the observations into negative, zero, and positive values, and provide additional insight into the nature of the transactions process. In panel A, which tabulates the 178,512 pooled observations in data set A, quote returns are about equally divided into negative, zero, and positive values, but price returns are zero with greater frequency (78,680) than they are negative (50,203) or positive (49,629). This difference is understandable since data set A contains intervals in which a new quote was posted. It is interesting to note that one-third of the new quotes do not involve a change in the quote midpoint, but reflect a change in the depth at the ask or bid.

In panel B, which tabulates the 289,286 observations in data set B, the distributions of quote returns and price returns are the same, with more than twice as many zeros as either negative or positive observations. Most interesting is the finding that quote changes are as frequent as price changes. This finding is not consistent with a world in which randomly arriving orders trade at the maintained quotes. Rather, quotes are adjusted as limit orders are placed and executed, and as the specialist changes quotes in response to observed trades and new information.

The frequency distribution for z_{t-1} indicates that 26.6 percent of the trades in data set A (47,421) and 28.1 percent in data set B (81,327) occurred at the quote midpoint. This may reflect the result of a successful negotiation to trade within the quotes or the fact that quotes from the floor or the book are not reported.

Stock index futures returns are zero 8.9 percent of the time in data set A and 9.8 percent of the time in data set B. The remaining variable, D_{t-1}, is zero about 20 percent of the time and is positive with the greatest frequency.

3.2 Prediction

This section tests the ability of the lagged predictors to forecast correctly positive and nonpositive returns in quotes and transaction prices. The first prediction rule is that $r^q_{t-1} > 0$ predicts $r^q_t > 0$ and $r^p_t > 0$.

[19] Results for individual companies are available from the authors.

[20] Jang and Venkatesh (1991) provide similar cross-tabulations for some of the variables we provide in this section, but they do not use the information as a basis for any statistical tests.

Table 3
Univariate nonparametric forecasts of returns on quotes (r^q_t) and prices (r^p_t) for the pooled 20 MMI stocks

	Lagged predictors									
	$r^q_{t-1} > 0$		$r^f_{t-1} > 0$		$z_{t-1} > 0$		$z_{t-1} < 0$		$D_{t-1} < 0$	
Forecast	P_1	P_2	P_1	P_2	P_1	P_2	P_1	P_2	P_1	P_2
A: Current quotes and current trades										
$r^q_t > 0$	0.336*	0.675*	0.592*	0.600*	0.510*	0.709*	0.197	0.543	0.477*	0.686*
$r^p_t > 0$	0.348*	0.678*	0.538*	0.566*	0.219	0.582	0.524*	0.687*	0.402*	0.646*
B: Standing quotes and current trades										
$r^q_t > 0$	0.278*	0.776*	0.601*	0.592*	0.558*	0.721*	0.162	0.560	0.482*	0.687*
$r^p_t > 0$	0.265*	0.772*	0.524*	0.569*	0.173	0.602	0.580*	0.690*	0.389*	0.658*

The predictors are lagged quote return (r^q_{t-1}), lagged change in S&P 500 index futures prices (r^f_{t-1}), lagged deviation of the transaction price from the quote's midpoint (z_{t-1}), and the lagged difference between the quoted volumes at ask and bid quotes (D_{t-1}). P_1 and P_2 are conditional probabilities of a correct forecast made at time $t-1$ given that $r^i_t > 0$ and $r^i_t \leq 0$ for $i = q, p$ respectively. The null hypothesis of no forecasting ability is $P_1 + P_2 = 1$. An asterisk indicates rejection of the null hypothesis at the 5 percent significance level using Henriksson and Merton's (1981) hypergeometric test.

This rule is based on the assumption that quotes and prices do not adjust instantaneously due to structural features such as stabilization rules and limit orders. The second prediction rule is that $r^f_{t-1} > 0$ predicts $r^q_t > 0$ and $r^p_t > 0$. This rule is based on the assumption that stock quotes and transaction prices do not instantaneously reflect S&P 500 future prices. The third prediction rule is that, for quote returns, $z_{t-1} > 0$ predicts $r^q_t > 0$; for price returns, that $z_{t-1} < 0$ predicts $r^p_t > 0$. The third rule, under which opposite predictions are made for quote returns and price returns, reflects microstructure theory. Under the adverse information theory of spreads, quotes are updated to incorporate the information contained in z_{t-1}. Inventory theories of the spread would also predict a positive quote return following a positive z because the specialist raises quotes to discourage public purchases and encourage public sales. On the other hand, reversals in transaction returns are necessary if the specialists and others providing immediacy are to earn revenues to cover the costs they incur in supplying immediacy. Therefore, the price return prediction rule is that positive values of z (trade at the ask) are most likely to be followed by negative values of z (trade at the bid). The fourth prediction rule is that $D_{t-1} < 0$ predicts $r^q_t > 0$ and $r^p_t > 0$. This rule is based on the assumption that greater depth at the ask than at the bid leads to a drop in quotes and trade prices because the excess of sell orders over buy orders signals bad news and/or sets a barrier to price increases relative to price decreases.

Table 3 presents the proportion of outcomes that are correctly predicted for each of the pooled data sets. For each prediction rule, the table reports two probabilities, P_1 and P_2, that are the conditional probabilities of a correct forecast made at time $t - 1$ given that $r^i_t > 0$ and $r^i_t \leq 0$ for $i = q, p$, respectively. For example, for the first rule, $P_1 = \text{Prob}[r^q_{t-1} > 0 \mid r^q_t > 0]$ is the probability that a positive return was correctly forecast, given that the outcome was a positive return, and $P_2 = \text{Prob}[r^q_{t-1} \leq 0 \mid r^q_t \leq 0]$ is the probability that a nonpositive return was correctly forecast given that the outcome was a nonpositive return. Merton (1981) shows that the prediction rule has no value if and only if $P_1 + P_2 = 1$. In particular, a rule has forecasting power when $P_1 + P_2 > 1$. Henriksson and Merton (1981) propose a nonparametric hypergeometric test of the null hypothesis, H_0: $P_1 + P_2 = 1$. A one-tailed test at the 5 percent significance level for the above example involves finding the value of x^* that solves

$$\sum_{x=x^*}^{\bar{n}_1} \frac{\binom{N_1}{x}\binom{N_2}{n-x}}{\binom{N}{n}} = .05,$$

where $\bar{n}_1 = \min(N_1, n)$, n_1 is the number of correct forecasts given that $r_t^q > 0$, N_1 is the number of $r_t^q > 0$, n is the number of times $r_t^q > 0$ is predicted, N_2 is the number of $r_t^q \leq 0$, and $N = N_1 + N_2$.[21] The null hypothesis is then rejected if $n_1 \geq x^*$. An asterisk in the table on the P_1, P_2 pair indicates that the null hypothesis, H_0: $P_1 + P_2 = 1$, is rejected in favor of the alternative hypothesis, H_A: $P_1 + P_2 > 1$.

The proportions in Table 3 are calculated from the data reported in Table 2. To illustrate, consider the prediction rule, $z_{t-1} > 0$, and refer to the third contingency table in the left-hand column of Table 2, panel A. Of the total sample, $N = 178{,}512$, $N_1 = 58{,}609$ quoted returns are positive; and of these, $n_1 = 29{,}864$, or 51.0 percent, are correctly predicted. Nonpositive quote returns amounted to $N_2 = 119{,}903$; and of these, 85,070, or 70.9 percent, are correctly predicted. The total number of times a positive quote return is predicted is $n = 64{,}697$.

The number of asterisks in Table 3 indicates that each predictor, taken alone, has forecasting power. The lagged quote return, although statistically significant, is the weakest of the predictors. While positive lagged quote returns predict positive quote and price returns, $P_1 + P_2 = 1.011$ in the case of quote return predictions and $P_1 + P_2 = 1.026$ in the case of price return predictions in panel A, the values barely exceed one. The corresponding values in panel B are 1.054 and 1.037, respectively.

The futures return is a statistically significant predictor for both quote returns and price returns. In data set *A*, 59.2 percent of the positive quote returns are correctly predicted by prior positive futures returns, and 60 percent of the nonpositive quote returns are correctly predicted by prior nonpositive futures returns. The sum of these proportions significantly exceeds one under the hypergeometric test. The prediction of price returns is also statistically significant. The results are virtually identical for data set *B*.

The third column of Table 3 show that positive z values predict positive quote returns as implied by the adverse information and inventory theories of the spread. Positive z values do not predict positive price returns. The fourth column of the table shows that negative z values do not predict positive quote returns, but they do predict positive price returns. The prediction of positive price returns by negative z reflects the well-known tendency of prices to reverse as they bounce between the bid and ask.

The final column shows that negative values of the depth variable, D, predict positive quote and price returns, which supports the sig-

[21] As the numbers in the contingency tables indicate, a much simpler normal approximation also suggested by Henriksson and Merton (1981) is not applicable here.

naling and barrier effects of depth. In other words, when depth at the bid exceeds depth at the ask, subsequent quote and price returns tend to be positive.

4. Model estimation and inference

In this section, we report the results of estimating the quote equation (5) and the price equation (8). The quote return at time t is the predicted return in the stock based on the available information at time $t-1$ after adjusting for inventory effects as specified in Equation (5). The price return in Equation (8) is the predicted quote return adjusted for the bid–ask bounce and the order arrival effect as described in Equation (7). The predictors are the same in both equations, and theory predicts the coefficients of the microstructure predictors to be the same, except for z_{t-1}.

The two equations are estimated simultaneously by Hansen's (1982) generalized method of moments (GMM) procedure. The GMM approach has several advantages. First, the residuals from the regressions may be conditionally heteroskedastic. Since, the predictors are predetermined and not exogenous, this is a likely scenario. Second, GMM permits a simple procedure to account for the presence of serially correlated errors.

Third, GMM makes it unnecessary to impose a specific distributional assumption for the residuals. This is a relevant consideration in light of the discreteness in quotes and prices, which are measured in eighths of a dollar. Discreteness has the effect of inducing rounding errors in observed price returns and quote revisions relative to their continuous values.[22] The observational model is identical to Equations (5) and (8) except that the residuals now include the first difference in rounding errors. Glosten and Harris (1988) use maximum likelihood estimation procedures to estimate a model with rounding errors in the residuals by making specific distributional assumptions for the residuals and the rounding errors. A more direct approach to account for discreteness is to use an ordered probit model as proposed by Hausman, Lo, and Mackinlay (1992). This approach requires a nonlinear maximum likelihood estimation procedure and specific distributional assumptions.

To illustrate the estimation procedure, let $Y' = (r^q, r^p)$ where r^i is an $n \times 1$ vector with typical element r^i_t, Z be an $n \times 8$ matrix with typical row element $Z_{t-1} = (1, r^q_{t-1}, r^f_{t-1}, z_{t-1}, Q_{t-1}, L^A_{t-1}, L^B_{t-1}, D_{t-1})$, $b' = (b^1, b^2)$, where b^i is an 8×1 vector of coefficients, and $U' = (\epsilon,$

[22] Although we use five-minute returns, which mitigate the discreteness problem, discreteness is still observed. For example, if price returns at t are plotted against lagged price returns at $t-1$, one observes clusters of points that radiate from the zero return point at the center of the graph.

e), where ϵ and e are $n \times 1$ vectors of residuals with typical elements denoted as U_t. Stack the two-equation system as

$$Y = Xb + U,$$

where

$$X = \begin{bmatrix} Z & 0 \\ 0 & Z \end{bmatrix}.$$

Next consider the 16×1 vector function $f(r_t^i, Z_{t-1}, b^i) = U_t \otimes Z_{t-1}'$, where $\otimes$ represents the Kronecker product. The GMM procedure involves choosing the parameters that minimize the quadratic function $g_n(b)' W_n g_n(b)$, where $g_n(b)$ is the sample mean of the 16 orthogonality conditions $E[f(Y_t, X_{t-1}, b)]$, $E[\cdot]$ is the unconditional expectation operator, and W_n is the 16×16 symmetric weighting matrix designed to make $g_n(b)$ as close to zero as possible. We use the weighting matrix shown by Hansen (1982) to yield the smallest asymptotic covariance matrix among the class of estimators that employ the orthogonality conditions. The weighting matrix is appropriately adjusted for the presence of serial correlation and conditional heteroskedasticity in the error terms. The results we present account for first-order serial correlation in the residuals since a few companies were found to exhibit weak first-order serial correlation. All the standard errors are also adjusted for conditional heteroskedasticity.[23]

Since the parameter estimates are consistent and asymptotically normal, straightforward inference procedures are applicable for testing cross-equation and within-equation restrictions. For example, to conduct a Wald test of equal coefficients across equations, we compute the following χ^2 statistic with one degree of freedom:

$$\theta(b_n)' \left[\left(\frac{\partial \theta}{\partial b'} \right) V(b_n) \left(\frac{\partial \theta}{\partial b'} \right)' \right]^{-1} \theta(b_n),$$

where the cross-equation constraint is expressed as $\theta(b_n) = Rb_n - r = 0$, where R is a 16×16 matrix and r is a 16×1 vector.

Regression results for each company are presented in Tables 4 and 5. The averages across companies of the coefficients and their t-ratios are presented in the last rows of the tables. Since no cross-equation restrictions are imposed in Tables 4 and 5, simultaneous estimation of Equations (5) and (8) produce estimated coefficients that are equiv-

[23] We also conduct two additional set of estimations to check the robustness of our results. First, we apply GMM without any adjustment for serial correlation. Second, we apply maximum likelihood estimation assuming the error terms to be normally distributed, serially uncorrelated, and conditionally homoskedastic. These additional estimations, which yield similar inferences, are not presented in the article.

Table 4
Quote revision rule for 20 MMI stocks arranged alphabetically by ticker symbol

Co.	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2
				A: Current quotes and current trades					
AXP	0.06	−74.57*	449.47*	249.69*	0.13	0.93*	−0.93*	−0.49*	0.21
CHV	0.05	−64.20*	343.45*	307.70*	0.05	0.73*	−0.87*	−0.30*	0.23
DD	−0.02	−74.68*	343.89*	479.55*	0.04	0.27	−0.45*	−0.20*	0.24
DOW	−0.01	−63.78*	336.90*	397.04*	0.47*	0.39*	−0.38*	−0.22*	0.21
EK	−0.05	−64.16*	328.01*	303.62*	0.06	0.99*	−0.58*	−0.41*	0.14
GE	0.04	−153.84*	525.89*	197.84*	0.01	0.64*	−0.59*	−0.23*	0.20
GM	0.02	−36.18	351.63*	371.43*	0.00	0.24	−0.21	−0.22*	0.17
IBM	0.02	−204.91*	389.99*	281.49*	0.27*	0.18	0.01	−0.12*	0.18
IP	−0.06	−79.73*	330.30*	311.68*	0.28	0.98*	−0.64*	−0.34*	0.19
JNJ	0.00	−66.06*	329.98*	378.12*	0.02	0.39	−0.37	−0.23*	0.19
KO	0.03	−70.40*	340.12*	325.43*	0.17	0.33	−0.24*	−0.35*	0.17
MMM	−0.03	−112.71*	439.33*	451.26*	0.08	0.29	−0.71*	−0.22*	0.22
MO	0.02	−71.19*	257.80*	397.43*	0.02	0.37	−0.25	−0.18*	0.18
MOB	0.06	−68.04	303.84*	347.26*	0.22	0.65	−0.79*	−0.45*	0.20
MRK	−0.04	−119.62*	346.76*	403.57*	0.01	0.62*	−0.45	−0.20*	0.22
PG	−0.02	−112.91*	292.40*	372.25*	0.00	0.34	−0.60*	−0.25*	0.19
S	0.06	−13.61	320.60*	311.03*	0.35	0.75*	−0.84*	−0.42*	0.22
T	0.11*	−19.95	302.51*	122.11*	0.07*	1.10*	−1.01*	−0.43*	0.18
X	0.02	−38.82	334.91*	255.26*	0.10	1.43*	−0.97*	−0.44*	0.22
XON	0.14*	−93.95*	439.34*	325.01*	0.03	0.30	−0.54	−0.29*	0.17
μ(coeff)	0.02	−80.16	355.36	329.44	0.12	0.60	−0.57	−0.30	
μ(t)	0.83	−5.46	16.58	16.65	1.61	3.64	−3.19	−17.01	
				B: Standing quotes and current trades					
AXP	0.05*	−49.56*	429.66*	216.71*	0.09	1.19*	−1.03*	−0.32*	0.21
CHV	0.04	−55.33*	341.65*	254.63*	0.01	0.84*	−0.83*	−0.23*	0.23
DD	−0.01	−53.96*	337.97*	464.13*	0.08	0.24	−0.42	−0.16*	0.27
DOW	0.00	−50.97*	320.59*	392.21*	0.57*	0.38*	−0.37*	−0.18*	0.22
EK	−0.02	−33.58	348.01*	259.90*	0.09	1.15*	−0.80*	−0.28*	0.18
GE	0.04*	−150.27*	536.92*	174.21*	0.02	0.66*	−0.60*	−0.21*	0.21
GM	0.01	−26.73	374.01*	340.95*	0.01	0.25	−0.33*	−0.13*	0.20
IBM	0.02	−203.68*	388.55*	275.05*	0.27	0.20	0.00	−0.12*	0.18
IP	−0.04	−91.38*	333.93*	300.14*	0.71*	0.86*	−0.68*	−0.26*	0.22
JNJ	0.00	−41.90	314.68*	346.93*	0.03	0.52*	−0.67*	−0.17*	0.20
KO	0.03*	−50.54*	323.89*	275.45*	0.26	0.72*	−0.62*	−0.22*	0.19
MMM	−0.03	−83.27*	404.03*	439.58*	0.12	0.44*	−0.57*	−0.18*	0.23
MO	0.01	−54.92*	258.38*	384.59*	0.02	0.41*	−0.27*	−0.13*	0.21
MOB	0.03	−43.78	280.55*	234.15*	0.63*	0.77*	−0.82*	−0.24*	0.21
MRK	−0.03	−104.97*	344.24*	357.34*	0.02*	0.58*	−0.51*	−0.15*	0.23
PG	−0.02	−82.46*	303.12*	325.81*	0.00	0.34	−0.62*	−0.20*	0.22
S	0.05*	4.28	317.10*	222.17*	0.76*	0.83*	−0.87*	−0.24*	0.23
T	0.07*	−12.72	355.29*	78.03*	0.07	1.17*	−1.28*	−0.24*	0.19
X	0.02	−24.35	328.33*	199.97*	0.17	1.39*	−1.09*	−0.30*	0.22
XON	0.12*	−54.13*	412.38*	247.59*	0.13	0.45*	−0.74*	−0.16*	0.19
μ(coeff)	0.02	−63.21	352.66	289.48	0.20	0.67	−0.66	−0.20	
μ(t)	1.50	−4.78	19.06	21.35	2.36	6.14	−5.86	−18.65	

The model is

$$r^q_t = a_0 + a_1 r^q_{t-1} + a_2 r^f_{t-1} + a_3 z_{t-1} + a_4 Q_{t-1} + a_5 L^A_{t-1} + a_6 L^B_{t-1} + a_7 D_{t-1} + \eta_t,$$

where r^q_t is the change in quotes, r^f_{t-1} is the change in S&P 500 index futures prices, z_{t-1} is the deviation of the transaction price from the quote's midpoint, Q_{t-1} is the cumulative signed volume, L^A_{t-1} is the indicator variable for public buys that exceed 10,000 shares, L^B_{t-1} is the indicator variable for public sales that exceed 10,000 shares, and D_{t-1} is the difference between the quoted volumes at ask and bid quotes. The table presents the coefficient estimates and the R^2 of each stock. The last two rows contain the average of the coefficients (μ(coeff)) and the average of the heteroskedasticity-consistent t-statistics ($\mu(t)$). All the coefficient estimates except for Q_{t-1} are multiplied by 1000. The coefficients estimates for Q_{t-1} are multiplied by 1,000,000. An asterisk indicates a t-statistic that exceeds the value implied by a posterior odds ratio of 1.

Table 5
Price prediction rule for 20 MMI stocks arranged alphabetically by ticker symbol

Co.	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2
				A: Current quotes and current trades					
AXP	−0.25*	−89.79*	569.71*	−711.29*	0.19	0.98*	−0.81*	−0.45*	0.21
CHV	0.04	−78.66*	406.56*	−629.95*	0.01	0.60	−0.55	−0.29*	0.17
DD	0.04	−93.16*	401.27*	−484.32*	0.05	0.32	−0.37	−0.20*	0.10
DOW	0.02	−92.63*	373.97*	−574.80*	0.43*	0.35	−0.26	−0.19*	0.13
EK	0.01	−68.09*	401.32*	−646.78*	0.04	1.01*	−0.57	−0.39*	0.15
GE	0.00	−165.13*	558.70*	−748.91*	0.05	0.63*	−0.38	−0.24*	0.22
GM	0.01	−36.01	384.29*	−606.55*	0.00	0.33	−0.28	−0.28*	0.14
IBM	−0.02	−213.98*	386.80*	−682.39*	0.38*	0.11	0.09	−0.12*	0.15
IP	0.10*	−88.88*	442.10*	−631.55*	0.31	0.76*	−0.74	−0.29*	0.15
JNJ	0.05	−93.43*	367.07*	−600.63*	0.02	0.22	−0.32	−0.21*	0.13
KO	−0.05	−87.21*	398.18*	−603.88*	0.21	0.26	−0.01	−0.33*	0.13
MMM	0.07	−137.24*	520.79*	−489.35*	0.26	0.24	−0.74*	−0.20*	0.11
MO	0.03	−70.54*	292.62*	−565.79*	0.05	0.42	−0.25	−0.16*	0.11
MOB	0.05	−90.45*	328.22*	−627.02*	0.30	0.40	−0.72	−0.36*	0.20
MRK	0.07*	−122.10*	401.93*	−564.90*	0.00	0.48	−0.52	−0.20*	0.14
PG	0.03	−146.72*	344.06*	−595.16*	0.01	0.41	−0.35	−0.23*	0.13
S	0.04	−7.23	376.87*	−621.02*	0.55*	0.54	−0.63	−0.42*	0.15
T	−0.28*	−66.78*	348.33*	−805.29*	0.08	0.77*	−0.92*	−0.40*	0.27
X	0.01	−57.11	460.97*	−658.30*	0.06	1.26*	−1.20*	−0.42*	0.19
XON	−0.13*	−110.65*	488.49*	−660.12*	0.13	0.28	−0.53	−0.28*	0.14
μ(coeff)	−0.01	−95.79	412.61	−625.40	0.16	0.52	−0.50	−0.28	
μ(t)	0.05	−5.63	16.82	−27.27	1.70	2.64	−2.26	−13.17	
				B: Standing quotes and current trades					
AXP	−0.27*	−82.45*	602.27*	−708.95*	0.11	1.07*	−0.89*	−0.36*	0.25
CHV	0.01	−91.05*	447.86*	−632.58*	0.03	0.59*	−0.50*	−0.22*	0.21
DD	0.04	−85.78*	416.59*	−488.29*	0.08	0.37	−0.37	−0.16*	0.12
DOW	0.02	−81.25*	363.82*	−569.93*	0.54*	0.27	−0.25	−0.15*	0.14
EK	0.00	−50.35*	431.20*	−622.29*	0.12	1.00*	−0.60*	−0.32*	0.19
GE	0.00	−154.20*	551.98*	−723.90*	0.05	0.58*	−0.39*	−0.24*	0.23
GM	0.00	−35.14	423.92*	−545.50*	0.01	0.22	−0.34*	−0.21*	0.16
IBM	−0.02	−213.67*	384.87*	−684.39*	0.39*	0.11	0.09	−0.12*	0.15
IP	0.09*	−101.54*	480.49*	−619.30*	0.84*	0.63*	−0.52	−0.22*	0.18
JNJ	0.04	−77.86*	356.81*	−607.78*	0.02	0.34	−0.45	−0.17*	0.15
KO	−0.09*	−66.34*	402.80*	−574.79*	0.28	0.54*	−0.34	−0.26*	0.15
MMM	0.06*	−109.85*	505.82*	−482.95*	0.33	0.18	−0.52	−0.17*	0.12
MO	0.02	−73.21*	312.13*	−537.43*	0.05	0.44*	−0.15	−0.13*	0.13
MOB	0.02	−83.81*	360.18*	−603.44*	0.43	0.40	−0.59*	−0.21*	0.20
MRK	0.07*	−106.11*	407.07*	−576.71*	0.00	0.53*	−0.63*	−0.15*	0.16
PG	0.04	−129.72*	395.77*	−630.39*	0.01	0.37	−0.42	−0.20*	0.17
S	0.00	16.54	407.29*	−631.42*	1.00*	0.74*	−0.46*	−0.30*	0.21
T	−0.35*	−71.25*	427.84*	−792.89*	0.08	0.81*	−0.99*	−0.32*	0.32
X	0.01	−46.27	468.66*	−668.02*	0.13	1.19*	−1.00*	−0.34*	0.23
XON	−0.21*	−71.83*	488.57*	−649.28*	0.17	0.46*	−0.52*	−0.22*	0.18
μ(coeff)	−0.03	−85.76	431.80	−617.51	0.23	0.54	−0.49	−0.22	
μ(t)	−1.16	−5.58	20.06	−38.68	2.34	4.04	−3.45	−15.34	

The model is

$$r_t^p = a_0 + a_1 r_{t-1}^q + a_2 r_{t-1}^f + a_3 z_{t-1} + a_4 Q_{t-1} + a_5 L_{t-1}^A + a_6 L_{t-1}^B + a_7 D_{t-1} + \eta_t,$$

where r_t^p is the change in transaction prices, r_t^q is the change in quotes, r_{t-1}^f is the change in S&P 500 index futures prices, z_{t-1} is the deviation of the transaction price from the quote's midpoint, Q_{t-1} is the cumulative signed volume, L_{t-1}^A is the indicator variable for public buys that exceed 10,000 shares, L_{t-1}^B is the indicator variable for public sales that exceed 10,000 shares, and D_{t-1} is the difference between the quoted volumes at ask and bid quotes. The table presents the coefficient estimates and the R^2 of each stock. The last two rows contain the average of the coefficients (μ(coeff)) and the average of the heteroskedasticity-consistent t-statistics ($\mu(t)$). All the coefficient estimates except for Q_{t-1} are multiplied by 1000. The coefficient estimates for Q_{t-1} are multiplied by 1,000,000. An asterisk indicates a t-statistic that exceeds the value implied by a posterior odds ratio of 1.

alent to single-equation OLS estimates, but the standard errors differ from OLS estimates. The results of Wald tests are presented in Table 6.

Since the sample size in each regression often exceeds 10,000 observations, it is easy to reject a specific null hypothesis against a diffuse alternative using the usual values of the t-ratio.[24] Therefore, we consider a coefficient to be statistically significant only if its t-ratio exceeds a break-even value, t^*, at which the ratio of the posterior probability of the null hypothesis ($a_i = 0$) equals the posterior probability of the alternative hypothesis ($a_i \neq 0$). We follow the procedure of Rossi (1988) in calculating the posterior odds ratio $K \equiv \Pr(H_0)/\Pr(H_A)$.[25] Strictly speaking, the posterior odds ratios are defined only for maximum likelihood procedures. Since maximum likelihood estimation also yields similar results, we use the ratios to provide a more conservative criterion.

Rossi (1988, p. 363) computes the approximate posterior odds ratio as

$$K = \exp\left\{\frac{1}{2}[q \ln \nu - \chi_q^2]\right\},$$

where χ_q^2 is the likelihood ratio statistic, q is the number of restrictions, $\nu = n - q$, and n is the number of observations. When the significance of a particular coefficient is tested as in Tables 4 and 5, the posterior odds ratio is calculated as[26]

$$K = \exp\left\{\frac{1}{2}[\ln(n - 1) - t_{n-1}^2]\right\}.$$

For example, at $n = 10{,}000$, the odds ratio, K, is 1 at a t-ratio of $t^* = 3.03$. For t-ratios above 3.03, the probability of the alternative exceeds the probability of the null, and vice versa. In Tables 4 and 5, an asterisk is assigned to a coefficient if its t-ratio exceeds its break-even t-value. In Table 6, we use the break-even value of χ^2 that yields a posterior odds ratio of unity (a) for tests of exclusion on all the coefficients in each regression except the constant, and (b) for tests on the individual cross-equation restrictions.

The results indicate that the predictive power of the equations is surprisingly strong and uniform across the companies for both data sets. For the quote equations, the R^2's range from 14 percent (EK) to 24 percent (DD) based on data set A and from 18 percent (EK) to

[24] This problem with standard statistical tests is sometimes referred to as Lindley's paradox after Lindley (1957). With type I error constant, type II error can be reduced to zero with a sufficiently large sample.

[25] See also Connor and Korajczyk (1988, p. 283).

[26] To obtain this equation, we use the fact that $q = 1$ and that $\chi_q^2 = \chi_1^2 \approx F_{1,n-1} = t_{n-1}^2$ for large n.

Table 6
Wald tests of the cross-equation restrictions between quote and price equations

Co.	$a_{i>0} = 0$	$b_{i>0} = 0$	$a_1 = b_1$	$a_2 = b_2$	$a_3 - 1 = b_3$	$a_4 = b_4$	$a_5 = b_5$	$a_6 = b_6$	$a_7 = b_7$
				A: Current quotes and current trades					
AXP	1862.77*	1368.06*	2.16	34.69*	10.36*	10.14*	0.08	0.49	2.70
CHV	1452.53*	1316.61*	1.72	13.72*	18.79*	14.26*	0.69	3.75	0.45
DD	1945.40*	724.60*	5.20	29.86*	8.84	0.09	0.18	0.48	0.05
DOW	2031.42*	1079.61*	14.54*	21.23*	6.39	0.35	0.34	2.49	15.57*
EK	748.65*	888.24*	0.17	38.46*	12.14*	0.75	0.02	0.00	0.75
GE	2457.15*	3045.46*	2.19	6.99	26.90*	6.96	0.03	7.11	1.17
GM	895.63*	677.84*	0.00	13.35*	3.01	0.81	1.07	0.62	26.71*
IBM	2015.08*	1196.43*	2.59	0.35	14.85*	8.50	2.60	1.66	0.38
IP	1648.89*	1254.70*	0.78	44.10*	18.33*	0.07	1.72	0.31	12.82*
JNJ	1514.77*	696.43*	13.59*	14.98*	3.17	0.12	1.72	0.15	3.29
KO	1160.48*	729.03*	2.13	17.47*	18.40*	0.34	0.29	2.05	0.73
MMM	1634.59*	808.09*	8.20	37.40*	19.97*	2.73	0.11	0.03	4.65
MO	1444.29*	842.05*	0.01	19.77*	9.17	32.97*	0.43	0.00	5.78
MOB	773.10*	305.32*	2.32	2.22	2.21	0.68	2.72	0.17	9.98*
MRK	969.44*	665.92*	0.10	19.91*	7.26	3.41	1.33	0.27	0.00
PG	1068.19*	1036.39*	13.05*	20.19*	6.19	27.72*	0.33	3.41	1.25
S	1356.48*	992.35*	0.33	13.96*	18.26*	5.54	2.44	1.35	0.08
T	1291.14*	2647.84*	12.87*	8.12	34.60*	0.09	7.02	0.42	2.01
X	1591.10*	1439.49*	2.07	42.66*	39.67*	3.51	1.02	1.96	0.92
XON	845.29*	884.61*	2.39	13.09*	1.07	3.87	0.07	0.01	0.13
				B: Standing quotes and current trades					
AXP	2565.05*	3903.18*	10.93*	77.36*	57.75*	0.87	0.81	1.19	4.26
CHV	2238.53*	2681.60*	11.01*	45.67*	111.32*	1.45	4.80	7.79	0.99
DD	2828.79*	1102.10*	16.57*	60.69*	20.80*	0.10	1.68	0.31	0.02
DOW	2626.91*	1501.11*	17.00*	30.40*	14.96*	0.17	3.16	3.49	9.59
EK	1437.38*	2171.73*	3.61	58.64*	125.21*	3.10	2.83	5.08	6.06
GE	2648.29*	3764.71*	0.28	1.57	113.00*	7.54	1.24	7.99	11.91*
GM	1370.29*	1193.69*	1.28	36.29*	31.33*	0.79	0.23	0.01	76.84*
IBM	2027.08*	1218.05*	3.14	0.47	18.75*	8.59	3.30	2.73	0.02
IP	2557.17*	2303.00*	1.00	83.89*	56.18*	0.67	3.09	1.39	13.16*
JNJ	2149.90*	1146.01*	24.27*	19.67*	19.77*	0.15	3.22	4.24	0.42
KO	1865.03*	1545.95*	2.11	37.93*	157.88*	0.06	3.02	6.02	5.26
MMM	2047.88*	1162.91*	9.66*	62.07*	47.57*	3.13	4.78	0.18	0.46
MO	2248.39*	1464.27*	6.25	52.45*	62.37*	91.46*	0.24	3.89	0.14
MOB	1391.33*	1397.71*	5.87	31.77*	146.97*	2.53	13.12*	4.95	2.37
MRK	1417.94*	1412.14*	0.02	29.25*	40.20*	5.73	0.33	1.19	0.53
PG	1530.12*	483.19*	27.96*	67.95*	17.07*	28.94*	0.07	3.64	0.08
S	2198.52*	2792.44*	1.47	44.70*	182.62*	7.76	1.07	19.52*	21.37*
T	1913.21*	5974.90*	24.09*	20.01*	196.28*	0.36	12.87*	6.55	33.10*
X	2293.29*	3445.39*	3.21	53.69*	171.63*	3.10	2.33	0.54	5.20
XON	1432.95*	2275.31*	3.53	42.41*	101.27*	0.38	0.04	12.26*	27.37*

The model is

$$r^q_t = a_0 + a_1 r^q_{t-1} + a_2 r^f_{t-1} + a_3 z_{t-1} + a_4 Q_{t-1} + a_5 L^A_{t-1} + a_6 L^B_{t-1} + a_7 D_{t-1} + \eta^q_t,$$
$$r^p_t = b_0 + b_1 r^q_{t-1} + b_2 r^f_{t-1} + b_3 z_{t-1} + b_4 Q_{t-1} + b_5 L^A_{t-1} + b_6 L^B_{t-1} + b_7 D_{t-1} + \eta^p_t,$$

where r^p_t is the change in transaction prices, r^q_t is the change in quotes, r^f_{t-1} is the change in S&P 500 index futures prices, z_{t-1} is the deviation of the transaction price from the quote's midpoint, Q_{t-1} is the signed cumulative volume variable, L^A_{t-1} is the indicator variable for public buys that exceed 10,000 shares, L^B_{t-1} is the indicator variable for public sales that exceed 10,000 shares, and D_{t-1} is the difference between the quoted volumes at ask and bid quotes. The table presents χ^2-statistics for 20 MMI stocks arranged alphabetically by ticker symbol. An asterisk in the first two columns indicates a χ^2-value that exceeds the value implied by a posterior odds ratio of 1 for the restriction that all coefficients except the constant are zero. An asterisk in the remaining columns indicates a χ^2-value that exceeds the value implied by a posterior odds ratio of 1 for the restriction $a_i = b_i$.

27 percent (DD) based on data set B. For the price equations, the R^2's range from 10 percent (DD) to 27 percent (T) in data set A and from 12 percent (DD, MMM) to 32 percent (T) in data set B. The first two columns of statistics in Table 6 also show that the null hypothesis of zero coefficients for all the variables in each regression is soundly rejected by the Wald tests since the χ^2-values are far in excess of their break-even values. Three variables—r^f_{t-1}, z_{t-1}, D_{t-1}—are statistically significant in every regression in Tables 4 and 5 in the sense that they always exceed their break-even t-values. In most cases, the t-values exceed 15. The other variables are not statistically significant in every regression. Since a comparison of panels A and B in each table indicates that the results for the two data sets are qualitatively the same, we focus most of our discussion on data set A.

The key variable from the perspective of microstructure theory is z_{t-1}. On the basis of the estimated coefficient of z_{t-1} in Tables 4 and 5, we can reject the pure order-processing theory, which requires $a^q_3 = 0$, $a^p_3 = 1$, and the pure adverse-information theory, which requires $a^q_3 = 1$, $a^p_3 = 0$. In data set A, the coefficient of z_{t-1} for the quote equation averages 0.32944, which is significantly different from 0 and 1. The coefficient of z_{t-1} for the price equation in the same data set averages -0.6254, which is significantly different from 0 and -1. The results are consistent with a mixture of order-processing and adverse-information effects. As implied by the adverse-information theory, quotes are changed to incorporate the information conveyed by trades. On average 32.94 percent of the deviation of a transaction price from the quote midpoint is reflected in a change in the quote midpoint in the next interval. It is interesting to note that the smallest value of a^q_3 is for AT&T (at 0.12211), a widely held stock for which it is not unreasonable that adverse-information effects are small. The largest coefficients are for DuPont (DD) and 3M (MMM) (at 0.47955 and 0.45126, respectively).

The coefficient of z_{t-1} in the price equation is negative, albeit not equal to -1 as implied by the order-processing theory. The average coefficient of -0.6254 indicates that 62.5 percent of the price deviation in an interval is reversed the next interval. This negative coefficient reflects an attenuated bid–ask bounce in price returns. The coefficient reflects three components as shown in the cross-equation restriction, $a^p_3 = a^q_3 + \rho - 1$. If past trades convey no information (so that $a^q_3 = 0$) and if the order arrival process is immaterial (so that $\rho = 0$), the coefficient would reflect a bid–ask bounce effect of $a^p_3 = -1$. That the coefficient is greater than -1 implies that adverse-information and/or order arrival effects (induced by dealer pricing) are present. The most negative coefficient is for AT&T (at -0.77349), implying that a large fraction of this stock's spread compensates market makers for order-processing and inventory costs. The least negative values are for DuPont and 3M.

The fact that the coefficient of z_{t-1} has a positive effect on quote returns and a negative effect on price returns is initially surprising. One might expect quote returns and price returns for the same stock, defined over the same time period, to be highly correlated and to respond in the same way to a given stimulus. However, the opposite effects, which are observable in the short run, are fully consistent with microstructure theory that includes both order-processing effects and adverse-information effects.

The estimated coefficients on z_{t-1} are also consistent with the inventory-holding cost theory. Support for the inventory theory is also provided by the change in inventory variable, Q_{t-1}, although the support is not strong. The variable has a positive sign in every regression in Tables 4 and 5, as predicted by the inventory theory, but the coefficients' t-values only infrequently exceed their break-even value.[27]

An implication of inventory theories of the spread is that quotes are adjusted to induce orders that equilibrate inventory. Consider first the induced order arrival effect as measured by ρ. The sixth column of Table 6 tests whether ρ is zero in the cross-equation restriction $a_3^p = a_3^q + \rho - 1$ by testing whether $a_3 - 1 = b_3$. This null hypothesis is rejected for 11 of 20 stocks in data set A and for all stocks in data set B. Assuming that the cross-equation restriction holds also provides an estimate of ρ. Based on the average coefficients in data set A, $\rho = 1 - 0.329 - 0.625 = 0.046$, and based on the average coefficients in data set B, $\rho = 1 - 0.289 - 0.616 = 0.095$. The fact that $\rho > 0$ is inconsistent with the inventory-induced order arrival effect since it implies that order arrivals are positively correlated. Positive serial correlation can arise from the breakup of a large order or from the process by which private information is incorporated into the price.

Other evidence of quote setting behavior reflecting inventory effects is provided by the coefficient r_{t-1}^q. This coefficient is negative for all stocks except Sears in data set B. Its average t-ratio is -5.46 in data set A and -4.78 in data set B. The negative coefficient indicates negative serial correlation in quote returns. Under an inventory theory of the spread, quotes exhibit negative serial dependence because market makers shift quotes away from the true price to induce inventory equilibrating trades. As inventory returns to normal, quotes also reverse.[28] Price returns are also negatively correlated with prior quote

[27] One of the difficulties is that the procedure for signing and cumulating volume is inaccurate. In addition, cumulative volume may not reflect the change in inventory of the participants who establish the quotes. We also used the volume of the sampled trade rather than cumulative volume, but similar results are obtained.

[28] A recent article by Jegadeesh and Titman (1990) shows that the reversal in quotes is more important over the long run (10 days) rather than the short run (1 day).

returns, indicating that quote changes are successful in inducing offsetting trades. Quote returns are positively correlated in the univariate results reported in Tables 2 and 3, but, in the multivariate setting, a negative correlation is observed after accounting for the effect of other variables.

The coefficient of the depth variable, D_t, is uniformly negative and significant in both the quote regression and the price regression and in both data sets. The coefficient's negative sign indicates that signaling and barrier effects rather than an inventory effect are operating. When depth at the ask exceeds depth at the bid at $t-1$, declared sellers exceed declared buyers, and this causes quote returns and price returns to be negative over the next interval.

The large-trade indicator variables, L^A_{t-1}, L^B_{t-1}, have the correct sign in all but one case, and their effect may be capturing volume effects that had been expected for Q_{t-1}. When a transaction at $t-1$ is a large purchase, both the quote return and the price return tend to be positive in the next period. When a transaction at $t-1$ is a large sale, both the quote return and the price return tend to be negative in the next period. The results are consistent with both the inventory and the adverse-information theories of the spread. The large trade variables are, however, not always statistically significant. Their significance is greater in the quote equations than in the price equations.

In addition to the microstructure variables, the lagged stock index futures return, r^f_{t-1}, is included to improve the predictive power of the model. This variable is significantly different from zero in all the regressions, which rejects the hypothesis of efficiency of quote and price formation. In short, stock quotes and prices do not immediately reflect information contained in the latest futures return. Based on the average coefficient in data set *A*, the quote midpoint changes by 35.54 percent of the index futures return in the preceding period. The average coefficient for the price equation implies a higher impact (0.41261). Every individual coefficient for r^f_{t-1} is smaller in the quote equation than in the price equation except for IBM. This is also true for data set *B*. Table 6 provides formal tests for the equality of r^f_{t-1} coefficients across equations. The equality constraint is rejected for 16 of 20 companies in data set *A* and for 18 of 20 companies in data set *B*.

The predictive power of the index futures return is not due to infrequent trading of the stocks, since the sample only consists of those intervals in which stock transactions occurred. Furthermore, the index futures price precedes the stock price in each five-minute interval. The stock transaction in the lagged period could, in principle, have incorporated the information from the futures market, but did not do so fully since some of the effect is observed in the next period.

A final implication of our two-equation model is that the coefficients of the microstructure variables in the two equations are equal except for the coefficient of z_{t-1}. Table 6 provides Wald tests of the equality constraints on the coefficients of r^q_{t-1}, Q_{t-1}, L^A_{t-1}, L^B_{t-1}, D_{t-1}. The results are broadly consistent with our specification since the chi-square values of these microstructure variables rarely exceed the break-even value.

5. Out-of-Sample Predictions

In this section, we analyze out-of-sample forecasts of the model. The model is estimated for the first 90 days of 1988, and the estimated parameters are used to predict quote and price returns for each interval the following day. Each day, the model is then reestimated for the most recent 90 days and used to forecast returns on the following day, and this process continues for the remainder of 1988.

The mean-squared error of the model forecasts is reported in Table 7 for each data set. The mean-squared error is defined as

$$\mathrm{MSE} = \frac{1}{n} \sum_{t=1}^{n} (F_t - A_t)^2,$$

where F is the forecast and A is the actual outcome. For comparison, we also report the mean-squared error for two naive forecasts. Naive1 predicts a quote or price return of zero; that is, $F = 0$. This is a highly demanding criterion since a large fraction of the quote and price returns in our data are zero. Naive2 predicts a quote (price) return equal to the most recent quote (price) return.

Of the two standards of comparison, Naive2 has a larger MSE than Naive1 in every stock in each data set. In part this reflects the fact that a large fraction of the returns is zero. Moreover, prices and to some extent quotes tend to reverse, which implies that a forecast of last period's return is likely to be incorrect. The MSE is always larger for price returns than for quote returns in each data set, an understandable feature since prices are more volatile than quotes. The forecasting power of the model is reflected in the fact that the model MSE is less than the MSE of Naive1 or Naive2 in every stock for both quote and price returns.

As one would expect, the mean-squared errors are larger in data set A than in data set B. This reflects the fact that periods in which quotes are updated are likely to be more volatile, resulting in larger errors. Data set B includes all periods irrespective of whether quotes

Table 7
Mean-squared errors of out-of-sample forecasts for 20 MMI stocks arranged alphabetically by ticker symbol

Co.	Quote Returns Model	Quote Returns Naive1	Quote Returns Naive2	Price Returns Model	Price Returns Naive1	Price Returns Naive2
			A: Current quotes and current trades			
AXP	0.5723	0.7101	1.4920	0.9984	1.2600	3.1360
CHV	0.2758	0.3562	0.7238	0.5131	0.6179	1.4860
DD	0.1719	0.2260	0.4458	0.2869	0.3242	0.7334
DOW	0.1216	0.1515	0.2878	0.1753	0.2079	0.4632
EK	0.3336	0.3916	0.8212	0.4465	0.5392	1.2510
GE	0.2312	0.2831	0.6226	0.3219	0.4227	1.0330
GM	0.1947	0.2181	0.4075	0.2557	0.2854	0.6062
IBM	0.0817	0.1008	0.2092	0.1021	0.1200	0.2600
IP	0.3236	0.3983	0.8172	0.6001	0.7240	1.7580
JNJ	0.1517	0.1890	0.3733	0.2387	0.2813	0.6475
KO	0.3690	0.4445	0.8881	0.5397	0.6357	1.4300
MMM	0.2779	0.3447	0.7090	0.4177	0.4692	1.0640
MO	0.1397	0.1695	0.3349	0.2060	0.2346	0.5177
MOB	0.4462	0.5385	1.1720	0.5877	0.6819	1.5940
MRK	0.2254	0.2803	0.5740	0.3849	0.4672	1.1210
PG	0.2031	0.2515	0.5042	0.3522	0.4096	0.9660
S	0.3645	0.4468	0.8630	0.5381	0.6427	1.4270
T	0.3061	0.3713	0.7737	0.6019	0.8785	2.3000
X	0.4530	0.5665	1.2440	0.8581	1.0980	2.8120
XON	0.3128	0.3674	0.7136	0.4333	0.5069	1.1110
Avg	0.2778	0.3403	0.6988	0.4429	0.5403	1.2859
			B: Standing quotes and current trades			
AXP	0.3225	0.4068	0.8440	0.7720	1.0320	2.7290
CHV	0.1530	0.1938	0.3936	0.3819	0.4894	1.2760
DD	0.1179	0.1585	0.3127	0.2196	0.2538	0.5938
DOW	0.0867	0.1109	0.2103	0.1402	0.1689	0.3891
EK	0.1626	0.1992	0.4125	0.2905	0.3714	0.9222
GE	0.1906	0.2328	0.5102	0.2868	0.3803	0.9435
GM	0.1002	0.1171	0.2220	0.1536	0.1809	0.4038
IBM	0.0778	0.0960	0.1992	0.0991	0.1170	0.2554
IP	0.2030	0.2575	0.5374	0.4576	0.5743	1.4530
JNJ	0.0963	0.1207	0.2359	0.1788	0.2160	0.5229
KO	0.1801	0.2203	0.4421	0.3245	0.3909	0.9342
MMM	0.1878	0.2405	0.4885	0.3167	0.3635	0.8483
MO	0.0849	0.1069	0.2116	0.1417	0.1661	0.3822
MOB	0.1522	0.1851	0.3964	0.3240	0.4165	1.0790
MRK	0.1390	0.1743	0.3571	0.2834	0.3533	0.8805
PG	0.1307	0.1616	0.3196	0.3056	0.3900	0.9915
S	0.1684	0.2078	0.3989	0.3351	0.4262	1.0370
T	0.1406	0.1659	0.3333	0.4800	0.7396	2.0660
X	0.2306	0.2873	0.6251	0.6619	0.9138	2.4930
XON	0.1361	0.1614	0.3139	0.2443	0.3049	0.7324
Avg	0.1531	0.1902	0.3882	0.3199	0.4124	1.0466

The last row provides the averages for the MMI stocks. Forecasts for five-minute returns within each day are obtained from regression coefficients estimated with data covering the preceding 90 days. The models for quote return and price return forecasts are stated in the text as Equations (5) and (8), respectively. Naive1 predicts a zero return, and Naive2 predicts a return realized over the preceding interval. All MSEs are multiplied by 100,000.

are updated, resulting in less average volatility and lower mean-square errors than for data set A.[29]

6. Conclusions

The two-equation econometric model of short-run quote returns and price returns developed and tested in this article provides new evidence on microstructure theories. Transaction returns based on prices sampled every five minutes react negatively to the deviation of the trade price from the quote midpoint in the prior period, z_{t-1}. The coefficient, which averages -0.625 in the data set containing current quotes and current trades, reflects an attenuated bid–ask bounce necessary to compensate market makers for the cost of processing orders. In contrast, quote revisions react positively to the deviation of the trade price from the quote midpoint in the prior period, z_{t-1}. The coefficient, which averages 0.329, reflects the adjustment of quotes to private information contained in the prior trade. Information is also conveyed by the prior depth. When depth at the ask exceeds depth at the bid, that is $D_{t-1} > 0$, quote returns and price returns tend to be negative over the next interval.

Evidence of inventory effects emerges in several forms. Quote midpoints and transaction prices increase in response to inventory change as measured by public volume, Q_{t-1}, although this variable is not very reliable. The reaction of returns to the large trade indicator variables is consistent with an inventory model of quotes, but it is also consistent with an adverse-information model if the amount of private information conveyed by trades depends on the size of the trade. Evidence from the time-series behavior of z_{t-1} indicates the presence of first-order serial dependence in z_t, which is inconsistent with the negative serial dependence implied by inventory-induced order arrival. Holding constant other effects, we find negative serial dependence in quote returns, which is consistent with dealer pricing to stabilize inventory.

In addition to the data on past prices, quotes, and volumes, we use a nonmicrostructure variable to predict stock returns. Specifically, past returns on the S&P 500 futures contract (r^f_{t-1}) are always significant in predicting quote returns and price returns.

The two-equation model of quote and price returns is estimated with generalized method of moments using data for 20 Major Market Index stocks in 1988. Since the regressions often contain in excess of 10,000 observations, standard t-tests make it easy to reject a specific null hypothesis against a diffuse alternative. Therefore, we calculate

[29] We have also decomposed the mean-squared error into bias, variance, and covariance components, but we do not present these lengthy results here. The basic finding is that the forecasts are not biased.

a break-even t-ratio that equates the posterior odds of the null to the posterior odds of the alternative to aid in the interpretation of the results. With the break-even t-ratios, the variables z_{t-1}, D_{t-1}, and r^f_{t-1} are always significant in both the quote and price equations. For the data set containing currently revised quotes, we are able to explain between 14 and 24 percent of the variation in returns and between 10 and 27 percent of the variation in price returns strictly on the basis of lagged variables. For the larger data set containing standing quotes and current trades, we explain between 18 and 27 percent of the variation in quote returns and between 12 and 32 percent of the variation in price returns. The model is also successful in making out-of-sample predictions in comparison to naive alternatives.

The ability to predict stock returns on the basis of microstructure variables is not necessarily inconsistent with an efficient market. Microstructure theory states that prices adjust to past prices and trades to incorporate private information, to manage inventory, and to cover operating costs. That prices behave according to this theory does not imply the existence of positive expected trading profits. Inconsistent with an efficient market is the fact that past stock index futures returns predict subsequent stock returns. In a perfectly efficient market, one would expect the quotes of the specialist and limit orders to adjust to price changes in the futures market, but this does not appear to be so. Institutional constraints, such as the specialist's stabilization requirements and the difficulty of continuously adjusting limit orders to information contained in futures price, may explain the predictive power of stock index futures. Transaction costs are likely to make it difficult for most investors to take advantage of this predictive power.

Appendix. Major Market Index Securities

Company name	Symbol
American Express	AXP
Chevron	CHV
Du Pont	DD
Dow Chemical	DOW
Eastman Kodak	EK
General Electric	GE
General Motors	GM
IBM	IBM
International Paper	IP
Johnson & Johnson	JNJ
Coca Cola	KO
3M	MMM
Philip Morris	MO
Mobil	MOB
Merck	MRK
Procter & Gamble	PG
Sears Roebuck	S
AT&T	T
USX	X
Exxon	XON

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