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TRADES, QUOTES, INVENTORIES, AND INFORMATION

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This empirical examination of the relation between trades and quote revisions for New York Stock Exchange-listed stocks is designed to ascertain asymmetric-information and inventory-control effects. This study finds that negative autocorrelation in trades consistent with inventory-control behavior characterizes low-volume stocks, but not high-volume stocks. The evidence of inventory control in the impact of trades on quote revisions is inconclusive. The information content of trades, on the other hand, is found to be substantial. There is also strong evidence that large trades convey more information than small trades.

1. Introduction

This paper examines empirically the relation between trades and quote changes for stocks traded on the New York Stock Exchange (NYSE), a continuous auction market with public limit orders and a designated market-maker (dealer or specialist). Interest in the precise process by which agents interact in such a setting has led to much recent microstructure research. In broad terms, most of the theoretical models in this area have focused on either the inventory-control or the asymmetric-information problem faced by the dealer. Although these two themes have generally evolved along separate lines, they can in no sense be considered competing paradigms. Rather, the separate evolution seems to be a consequence of the analytical difficulties of jointly solving two problems, each of which is highly complex in its own right. It is widely accepted, however, that both effects arise in practice, and the primary goal of this paper is a partial empirical resolution.

The key features of the inventory-control and asymmetric-information models arise as natural extensions of a simpler framework. In this view, a dealer provides liquidity by offering to buy and sell at quoted bid and ask prices. In

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the simple efficient market described by Roll (1984), henceforth termed the simple bid–ask model, all participants have the same information. The dealer sets the quotes symmetrically around the 'true' ('efficient') price, and his profit is a consequence of the random and equally probable arrival of buy and sell orders.

The inventory-control models focus on the problem that, in the simple bid–ask model, the dealer's inventories of stock and cash follow a random walk leading to large positive or negative positions. [See Garman (1976), Stoll (1976), Amihud and Mendelson (1980, 1982), Ho and Stoll (1980, 1981, 1983), and O'Hara and Oldfield (1986).] These models follow from the imposition of nonnegativity constraints and carrying costs, and predict that the dealer will set quotes as an inventory-control mechanism, to elicit an imbalance of buy and sell orders, so as to maintain the inventory level in some optimal neighborhood.

The asymmetric-information models drop the assumption of uniform information, and address the problem of an uninformed dealer who by offering to buy and sell at the quoted prices suffers exposure to informed traders. [See Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1984), and Easley and O'Hara (1987). For a model of the strategic problem faced by the informed investor, see Kyle (1985).] In these models, the dealer views orders as originating with some positive probability from an informed trader. As such, orders convey information and motivate quote changes. These models usually ignore inventory considerations.[1]

The relevant empirical work has been limited and has for the most part evolved along the same distinct lines as the theory. Smidt (1971) finds for a sample of NYSE-listed stocks that daily closing specialist inventory positions have a contemporaneous and subsequent price impact. In an analysis of intraday transaction and inventory data for a small number of American Stock Exchange (AMEX) options, Ho and Macris (1984) confirm that dealer inventory position affects price determination. Both of these studies, however, assume that the impact of trades on price is a consequence of inventory considerations, and not of information revealed by the trades. With respect to the asymmetric-information model, Glosten and Harris (1988) and Harris (1987) analyze transaction data for NYSE stocks, and discern a component of the bid–ask spread due to asymmetric information. Their estimation procedure, though, assumes an absence of inventory affects.

[1]Although it is useful and essentially accurate to characterize the inventory-control and asymmetric-information approaches as dichotomous schools of thought, there is some overlap. At least two of the cited inventory-control studies refer to asymmetric-information effects. Amihud and Mendelson (1982) treat private information as another factor causing incoming order imbalance. Stoll (1976) treats the loss to informed traders as an average cost per transaction. In neither study, however, are dealer expectations rational in the sense of optimally extracting private information from the realized trades.

The present empirical framework admits the simultaneous existence of inventory-control and asymmetric-information effects. The analysis does not encompass the full implications of either effect; it seeks only to discern empirical evidence for some of the salient and differentiating characteristics of these effects. In particular, the study examines the trades and movements in the average of the bid and ask quotes. Spread size, although clearly of interest, is not studied.[2]

The data set underlying this study is a two-month record of quotes and trades for NYSE issues. This information is publicly available through subscription to the market 'feed'. From these observations, it is possible to construct one series of quote revisions and another of trade sized signed to indicate whether the trade is buyer- or seller-initiated. The empirical analysis focuses on these two series.

The paper is organized as follows. Section 2 discusses the implications of inventory-control and asymmetric-information effects for trades and quote revisions, and develops empirical specifications. Section 3 describes the data and algorithms used to construct the trade series. Section 4 presents estimation results and tentative conclusions. Section 5 examines the information content of trade size, and the paper concludes with a brief summary.

2. The model for trades and quote revisions

The simple models of trade and quote behavior presented here clarify the distinctive features induced by asymmetric-information and inventory-control considerations. For the asymmetric-information model, the key results are that quote revisions are serially uncorrelated and that the impact of trades on quotes is persistent. In the inventory-control model, quote revisions are serially correlated and the impact of trades on quotes is transient. These models are not estimated directly, but instead are used to motivate a general empirical specification in which asymmetric-information and inventory-control effects can plausibly coexist.

Initially the market is assumed to consist of a single monopolistic dealer (specialist) who sets the quoted bid and ask prices, informed traders, and uninformed (liquidity) traders. The bid and ask quotes are denoted by q_t^{b} and q_t^{a}, and the quote midpoint price is defined as $q_t = (q_t^{\mathrm{a}} + q_t^{\mathrm{b}})/2$. The bid–ask spread $q_t^{\mathrm{a}} - q_t^{\mathrm{b}}$ is assumed to be constant and q_t is therefore sufficient to determine q_t^{a} and q_t^{b}. The operation of the market consists of trades followed

[2]Stoll (1987) has recently proposed a resolution of both effects based on first-order autocorrelation of quote changes. Aside from the similarity of purpose, however, Stoll's analysis is quite different from the present time. This study is directed at quote-setting behavior and is somewhat more general in the sense that it examines the joint time-series behavior of quotes and trades at all lags. Marsh and Rock (1986b) report some estimations similar to those presented here for quote revisions.

by quote revisions. The quote set at time $t-1$, q_{t-1}, remains effective until time t. At time t, a single trader arrives and buys z_t units of the security from the dealer at price q^{a}_{t-1}. (If $z_t < 0$, the trade is a sale to the dealer at price q^{b}_{t-1}.) On the basis of the z_t, the dealer sets the new quote q_t. The public information set, Φ_t, consists of the trading history $\{z_t, z_{t-1}, \dots\}$, current and lagged quotes $\{q_t, q_{t-1}, \dots\}$, and additional information (such as publicly released accounting data) assumed to be updated immediately after the tth trade, but before the quote is revised. Informed traders possess additional private information.

2.1. *A simple asymmetric-information model*

The essential feature of an asymmetric-information model is the (partial) revelation of private information in the trades. When a trade occurs, the dealer revises the quote in light of the possibility that the trade originated from an informed trader. We may describe the resulting series of quote revisions as

$$r_t = q_t - q_{t-1} = \alpha\left[z_t - \mathrm{E}[z_t|\Phi_{t-1}]\right] + u_t, \tag{1}$$

where the term within brackets is the unexpected component of the trade and α is a coefficient reflecting the dealer's assessment of the trade's information content. Only the unanticipated component reveals new information. Easley and O'Hara (1987) and Glosten (1988) have presented models in which the revealed information is a positive function of trade size. Here, the quote revisions are assumed to be linear in trade size; alternative specifications will be introduced later. The stochastic disturbances $\{u_t\}$ derive from updates in the public nontrade information and are assumed to be independent of the trade process. The demand z_t is permitted to depend on the current quote, past trade history, other public nontrade information, and (implicitly) the private information. The zero-expected-profit condition generally imposed in the asymmetric-information models ensures that the prevailing quotes are set so that $\mathrm{E}[r_t|\Phi_{t-1}] = 0$, which implies that the $\{r_t\}$ process is serially uncorrelated.

2.2. *A simple inventory-control model*

Inventory control enters the quote setting process to induce an imbalance in incoming orders that will restore inventory to some desired level. I maintain the notation and structure of the asymmetric-information model, but drop the possibility of private information. It is provisionally assumed that the control is linear in inventory:

$$q_t = v_t - \beta\left(I_t - \bar{I}\right), \tag{2}$$

where I_t is the level of inventory (after the tth trade) and $\bar{I}$ is the desired level. Here v_t is a market-clearing price in the sense that, if $q_t = v_t$, the expected incoming demand is zero, $E[z_{t+1}|\Phi_t] = 0$. If the current inventory is above the desired level, for example, then, with $\beta > 0$, the quotes will be set low to elicit a surplus of buy orders over sell orders.[3]

The quote revisions are obtained as

$$r_t = q_t - q_{t-1} = v_t - v_{t-1} - \beta(I_t - I_{t-1}) = u_t + \beta z_t, \tag{3}$$

where u_t is the change in the quote resulting from newly revealed information (as in the asymmetric-information model). This form is quite similar to the quote revision associated with the asymmetric-information model in (1). When $E[z_t|\Phi_{t-1}] = 0$, the two specifications are indistinguishable. The following demonstrates, however, that the inventory-control model implies distinctive behavior for the $\{z_t\}$ process and, by implication, for the quote-revision process.

2.3. The structure on trades imposed by inventory control

The key assumption underlying the following analysis is that the control policy causes the inventory level to be a stationary stochastic process. To motivate this assumption, note that in a simple bid–ask model the trades are serially uncorrelated, which implies that the dealer's inventory is nonstationary and with the passage of time unbounded. The primary purpose of an inventory-control policy is the prevention of large positive or negative inventory positions, i.e., an imposition of bounds. Inventory stationarity is not necessarily a consequence of boundedness, but is nevertheless a reasonable feature if the control policy is consistent and stable. The consequences of this assumption are developed below and are considerably more general than the specific inventory-control model in (2).[4]

Since all trades are presumed to clear against the dealer's inventory, $z_t = -(I_t - I_{t-1})$. Assume that inventory is initially at the long-run mean (the desired level). If a buy order arrives, the inventory-control policy must be such that the associated drop in inventory is eventually offset, i.e., that amount z_t is eventually sold to the dealer. As a simple example, suppose that the dealer can set quotes so that the inventory level is white noise: $I_t = -\varepsilon_t$, where the $\{\varepsilon_t\}$

[3] This structure permits demand to depend on dealer inventory. Amihud and Mendelson (1980) show, however, that the bid–ask spread will be large enough to preclude any profitable exploitation of this information.

[4] Most of the inventory-control models cited here are consistent with inventory stationarity. (The O'Hara and Oldfield model, however, is not: due to end-of-day effects the stochastic properties of the inventory vary over time.)

are i.i.d. random variables. The resulting trade series is given by

$$z_t = -(I_t - I_{t-1}) = \varepsilon_t - \varepsilon_{t-1}.$$

This is a first-order moving-average process in which the innovation at time t is completely offset in the subsequent period. That is, if the inventory level is one share higher than desired, the dealer will set the quotes so that in expectation the next trade is a one-share buy (from the dealer). The control policy is such that the current trade (in expectation) offsets the previous trade. This causes the demand, z_t, to be negatively autocorrelated and also causes the sum of the coefficients of the $\{\varepsilon_t\}$ to be zero.

The last point concerning the coefficient sum is a special case of a more general result. The differencing operation used here to relate trades to inventory levels is customarily applied in time-series analysis to achieve stationarity. If the operation is applied to a series that is already stationary, the moving-average representation is noninvertible and the coefficients in the representation will sum to zero. [See Harvey (1981, p. 181).] In the present application, this implies that, if inventory is stationary, the trades (which are the first differences of the inventory level) will be characterized by a moving-average representation in which the coefficients sum to zero.

As an empirical matter, this point motivates estimation of a moving-average model for demand,

$$z_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3} + \cdots, \tag{4}$$

where the $\{\varepsilon_t\}$ are i.i.d. disturbance terms. The extent of trade reversal and the significance of inventory control can be assessed from the sum of the estimated coefficients, $1 + \sum\theta_i$. For this sum to equal zero, at least one of the θ_i coefficients must be negative.[5] The assumption of inventory stationarity does not preclude the existence of asymmetric-information effects.

If the trade representation (4) is used in the quote revision expression (3), then

$$r_t = u_t + \beta[\varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3} + \cdots]. \tag{5}$$

The moving-average coefficient sum result carries over to the quote revisions: when quote revisions are regressed against current and prior trade innovations, the leading coefficient should be positive and the sum of the coefficients should

[5]Alternatively, the development to this point suggests that inventory stationarity could be examined directly by means of a unit root test applied to the integrated (summed) trade series. Other considerations, however, particularly public limit orders and observational noise, will introduce a nonstationary component into the integrated trade series. Accordingly, stationarity (or the moving-average coefficient sum constraint) must be viewed as a polar case that is not likely to characterize all stocks.

be zero. This result implies that trades have no persistent impact on quotes. If an unexpected buy order causes dealer inventory to drop, the dealer raises the quote to elicit an offsetting sell order and then lowers it once the inventory position has been restored.

In the simple asymmetric-information model, by way of contrast, the unexpected component of the trade conveys information, which leads to a permanent change in the quote. To see this, note that the unexpected component may be expressed as $z_t - \mathrm{E}[z_t|\Phi_{t-1}] = \varepsilon_t - \mathrm{E}[\varepsilon_t|\Phi_{t-1}]$.[6] Eq. (1) therefore becomes

$$r_t = q_t - q_{t-1} = \alpha\varepsilon_t - \alpha\,\mathrm{E}[\varepsilon_t|\Phi_{t-1}] + u_t. \tag{6}$$

Since $\alpha > 0$, the impact of the trade innovations on quotes in the asymmetric-information model is persistent.

2.4. General empirical considerations

The preceding analysis has described the distinctive features of the asymmetric-information and inventory-control models. The following discusses the empirical implications of these effects in a framework where both are present.

One key difference between the models lies on the behavior of the trade series, motivating an estimation of the moving-average model for z_t, (4). The sum of the estimated coefficients $\sum\theta_i$ indicates the extent to which the unexpected component of a trade is reversed over time. The above analysis suggests that with stationary inventories, $\sum\theta_i = -1$, implying that the reversal is eventually total. This restriction holds whether or not asymmetric-information effects are present.

The analysis of the quote revisions is more involved. The inventory-control model in (5) suggests regressing quote revisions against the ε_t, the univariate trade innovations. With this simplification, both (5) and (1) are special cases of the specification

$$r_t = b_0\varepsilon_t + b_1\varepsilon_{t-1} + b_2\varepsilon_{t-2} + \cdots + v_t, \tag{7}$$

where the u_t are assumed to be i.i.d. and uncorrelated with the ε_t. The meaningful quantities to be assessed here are the $\{b_i\}$ coefficients themselves, which reveal the path of the quotes following a trade innovation, and the sum $\sum b_i$, which reflects the persistent impact of the innovation of the quote.

[6] This follows from:

$$\begin{aligned} z_t - \mathrm{E}[z_t|\Phi_{t-1}] &= z_t - [\theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3} + \cdots] \\ &\quad + [\theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \theta_3\varepsilon_{t-3} + \cdots] - \mathrm{E}[z_t|\Phi_{t-1}] \\ &= \varepsilon_t - \mathrm{E}[z_t - \hat\theta_1\varepsilon_{t-1} + \hat\theta_2\varepsilon_{t-2} + \hat\theta_3\varepsilon_{t-3} + \cdots|\Phi_{t-1}] = \varepsilon_t - \mathrm{E}[\varepsilon_t|\Phi_{t-1}] \end{aligned}$$

The interpretation of these quantities is straightforward if it is assumed that the asymmetric-information and inventory-control effects operate in a simple additive fashion. Both models suggest that the contemporaneous impact of a trade innovation is positive, $b_0 > 0$. If, in an asymmetric-information model, the information conveyed by a trade is fully reflected in quotes only with a lag, then b_i may be positive for $i > 0$. Inventory-control effects predict, on the other hand, that b_i will be negative at some lags [cf. (5)]. If both effects are present, the lagged coefficients are of indeterminate sign.

In the simple asymmetric-information model [(1) or (6)] the impact of trades on quote revisions is permanent, whereas in the simple inventory-control model it is transient. This suggests interpreting the coefficient sum $\sum b_i$ as a measure of the information effect. A sum of zero would imply the absence of any information content in the trades. A positive sum would be consistent with information content, but would not rule out the presence of transient inventory effects.

It must be emphasized that this discussion of the impact of trades on quote revisions assumes that asymmetric-information and inventory-control effects are additive. Since no formal solution has been posed for the dealer control problem when both inventory-control and asymmetric-information features are present, the possibility of interactions that belie the simple additive solution must be considered. In the discussion, for example, positive adjustment coefficients for lagged trades ($b_i > 0$ for $i > 0$) are held to be suggestive of a delayed information impact, whereas negative values ($b_i < 0$ for $i > 0$) are viewed as deriving from inventory control. Interactions between inventory-control and asymmetric-information problems may upset this resolution of transient effects.

There is nevertheless a strong case for continuing to interpret the persistent effect of trade innovations (as measured by the sum $\sum b_i$) as the information effect, even in the presence of unspecified interactions with inventory-control effects. Under the assumption that the inventory level is stationary, inventory control is inherently a transient concern and trades in the remote past should have vanishing influence on the current quotes.

2.5. Public limit orders

The preceding is based on the assumption that all trades are cleared through a monopolistic dealer. This section considers the impact of public limit orders, i.e., orders placed by traders in which price and quantity are specified and execution is uncertain. Cohen, Maier, Schwartz and Whitcomb (1981) analyze the placement of such orders in the absence of inventory-control or asymmetric-information considerations. In their model, limit orders are placed by traders who are willing to risk execution to obtain a better expected price than would be achieved with a market order. Their key finding is that with costly order placement, equilibrium in a market permitting both limit and market orders is characterized by a positive bid–ask spread. This result provides a rationale for an observed spread even in the absence of the costs borne by the dealer in the inventory-control or asymmetric-information models. For the most part, existing models of asymmetric information and inventory control do not consider public limit orders. [An exception is the sequential-call-market model proposed by O'Hara and Oldfield (1986).]

To maintain tractability, I assume that public limit orders originate from uninformed (liquidity) traders. This will be the case, for example, if the informed traders place such a high premium on execution certainty that they trade solely by means of market order. I further assume that the public limit orders are placed at the current dealer quotes.[7] As long as some nontrivial portion of uninformed traders continues to trade by means of market orders, the trading mechanism will remain feasible.[8] A market order will originate (with some positive probability) from an informed trader, and therefore will convey a private information signal.

Public limit orders cause a problem for the empirical analysis because it is no longer possible to determine which trades clear against dealer inventory and which clear against limit orders. This indeterminacy weakens the zero-sum condition on the moving-average representation of trades. Under certain assumptions about the stochastic nature of the limit orders, however, some structure persists. To see this, it is first necessary to expand the notation somewhat. As before, z_t denotes the observed trade, but now this is considered as the sum of two components:

$$z_t = x_t + e_t, \tag{8}$$

where x_t is the component of the tth trade that clears against dealer inventory and e_t is the part that clears against a public limit order.

Even though the zero-sum constraint characterizes the moving-average representation of the trades that clear the dealer (x_t), this constraint does not apply to the observed trade series (z_t). With the current system, a trade that clears in part against the specialist and in part against a public limit order is reported as two trades. Thus e_t and x_t cannot both be nonzero and $\mathrm{E}e_t x_t = 0$. Under the somewhat stronger assumptions that $\mathrm{E}e_t = 0$ and $\mathrm{E}e_t x_{t+k} = 0$ for all k, the $\{e_t\}$ may be viewed from an econometric perspective as observa-

[7] This view is slightly different from the position taken by O'Hara and Oldfield. In their model, the existing limit orders can affect the dealer quotes. The limit-order traders in the model presented here, in contrast, are passive: they wait to observe the quotes and then submit limit orders.

[8] If it is known that all uninformed traders will trade by means of limit orders, then all market orders will originate from informed traders. Since the dealer loses to informed traders, no one will be willing to be a dealer.

tional errors. The autocorrelations of $\{z_t\}$ and those of $\{x_t\}$ are then related by a simple proportionality constant.[9]

If inventory-control effects are present, at least one of the moving-average coefficients in the dealer trade (x_t) representation must be negative and at least one of the autocorrelations must be negative. Since the autocorrelations for the observed trade series (z_t) are proportional to those for the dealer trades, at least one of the autocorrelations for the observed trades must be negative. More realistically, if the dealer's inventory control is a gradual adjustment over time, there will be lags for which the autocorrelations in dealer trades are negative. By the proportionality argument, there should be a similar (though attenuated) pattern in the autocorrelations for the observed trades. Similarly, the extent of observed trade innovation reversal, as measured by the $\sum\theta_i$ in (4), should be reduced.

This analysis is contingent, however, on an assumed absence of correlation between x_t and e_t at all leads and lags. Serial dependence might plausibly arise from a specialist's affirmative obligation. For example, a market buy order that absorbs the entire amount offered by existing public limit orders at a given price may lead the specialist to enter a bid at that price. This increases the likelihood that the next buy order will trade against the specialist. The extent of the correlation introduced by such a mechanism and the effect on the present analysis are unknown.

Since public limit orders are viewed as originating from uniformed traders, the quote revision specification (7) and the interpretation of the coefficients are unaffected. Any private information will be revealed in the trade innovations, and the b_i coefficients will reflect the impact of these innovations on quote revisions. In accordance with the above discussion, however, innovations based on observed trades will be correlated imperfectly with those based on dealer-cleared trades. The existence of public limit orders is therefore likely to reduce the apparent role of inventory control.

3. The data

The data set is a transcription of the NYSE tape for March and April of 1985 and consists of ordered, time-stamped quote and transaction records.[10]

[9]Denote by σ_x^2 the variance of the $\{x_t\}$ process; the autocovariance at lag k is defined as $\gamma_x(k) = \mathrm{E}x_t x_{t-k}$ and the autocorrelation at lag k is defined as $\rho_x(k) = \gamma_x(k)/\sigma_x^2$. σ_e^2, σ_z^2, $\gamma_z(k)$, and $\rho_z(k)$ are defined similarly. It is apparent from (8) that $\sigma_z^2 = \sigma_x^2 + \sigma_e^2$ and $\gamma_z(k) = \gamma_x(k)$ for $k > 0$. Therefore $\rho_z(k) = \lambda\rho_x(k)$, where the proportionality factor λ is $\sigma_x^2/(\sigma_x^2 + \sigma_e^2) \leq 1$. That is, the autocorrelation function for the observed trades is proportional to that of the trades that clear against dealer inventory. The relative importance of market-maker activity is captured in λ.

[10]The data were collected by a firm under contract to the American Stock Exchange and comprise NYSE, AMEX, and NASDAQ/NMS securities, although only NYSE issues are used in this study. These are the same data used in Hasbrouck and Schwartz (1988), Marsh and Rock (1986a, b), and Hasbrouck and Ho (1987).

After issues that split during the sample period are deleted, the sample consists of 1,497 issues. Prices are adjusted for dividends: on the ex dividend day and all subsequent days, the amount of the dividend is added to the reported trade price. Trade and quote revision series ($\{z_t, q_t\}$ in the notation of the last section) are computed for each issue as described below. To assess the impact of liquidity, I further divide the total sample into deciles ranked on the basis of trade volume (measured by the number of $\{z_t, q_t\}$ observations). In addition, this study draws on my observations of trading activity and conversations with exchange personnel.

The technique by which these data are collected is as follows. The posts near which trading occurs are circular desks with large interior areas. On the exchange floor, a trade or quote revision is called out to a floor reporter, who checks off the relevant boxes on a computer card and feeds it into a device that reads the card optically. Henceforth the process of display (on the tape) and dissemination to outside vendors (such as the one collecting these data) is totally automated. Up to this point, however, there is a large component of human involvement and an attendant possibility for error. Trades resulting from orders routed to the specialist post via the designated order turnaround (DOT) system enter the reporting system without manual intervention.

My observations of the reporting process suggest that, while there are several points that have ramifications for the data, the overall performance is quite good. The reporting system is one of the facets of a market that is visible to the trading public, and the importance of this is apparently appreciated by the exchanges. In the first place, an event (trade or quote revision) is usually recorded on a card with essentially no delay. The volume of information (issue, price, volume, transactor identity) is such that to be retained at all, it must be recorded immediately as it is called out. Also, when the card is placed on the desk of the post, it is usually picked up within five to ten seconds and placed in the hopper of the optical reader immediately.

It is not uncommon, however, for an event to require several cards. For example, the specialist may satisfy a 1,000-share order by taking 300 himself at one price and 700 off the limit order book at another price, and immediately calling out the new quotes. In reporting such an event, the three cards summarizing the two trades and the quote revision will be held by the floor reporter until the last one is filled in and then handed to the interior clerk in a group. When this occurs, the event may not be reported in the correct sequence. The present data set exhibits instances of a quote revision followed by a trade with the same time stamp. Taking the view that these are reporting anomalies, I sort events occurring with the same time stamp to place the transactions before the quote revisions. I also have some concern about the accuracy of the quotes. The specialists and clerks give priority to making and reporting trades. In heavy trading, the quotes are not always updated in a timely fashion.

Table 1

Classification of transactions as buys and sells for NYSE-listed stocks in March and April of 1985.

The reported values are the proportion of transactions and proportion of trade volume classified as buy or sell using the indicated rule. Classifications made by the preceding quote are those in which the transaction price is at or outside the prevailing bid or ask. The remaining rules deal with cases in which the reported transaction price is between the prevailing quotes. Using the contemporaneous transaction rule, when a midpoint transaction is found to be contemporaneous with a transaction at a quote, the buy/sell classification of the latter is applied to the former. Using the subsequent transaction rule, when a transaction at a posted quote occurs subsequent to a midpoint transaction, but prior to a quote revision, the midpoint is taken as the *de facto* quote. Using the subsequent quote revision rule, when quote revision immediately follows a midpoint transaction, the order type is inferred from the direction of the quote revision.

Buy or sell	Classification rule	Proportion of transactions	Proportion of volume
Buy	Preceding quote	0.392	0.402
Sell	Preceding quote	0.442	0.457
Buy	Contemporaneous transaction	0.001	0.001
Sell	Contemporaneous transaction	0.001	0.001
Buy	Subsequent transaction	0.042	0.031
Sell	Subsequent transaction	0.038	0.029
Buy	Subsequent quote revision	0.032	0.030
Sell	Subsequent quote revision	0.034	0.036
Unclassified		0.017	0.013

3.1. Determination of buys and sells

The model described here is one of a market-maker who sets take-it-or-leave-it quotes and traders who trade against these quotes. In this framework, a trade can easily be classified as a buy or sell order by reference to the current quotes. The proportion of trades and trading volumes that can be classified in this fashion for the current data set is reported in table 1. Roughly 85% of the transactions can be so classified.

The substantial remainder consists of transactions occurring at the midpoint of the current quotes. (The most common situation involves a bid–ask spread of $\frac{1}{4}$ and a transaction on the middle $\frac{1}{8}$th.) Although the present model does not allow for midpoint transactions, they are clearly an important consideration.

Midpoint transactions can arise in several situations. The most benign occurs when market buy and sell orders exist simultaneously. Market orders may not be executed instantly. A floor broker acting as agent for a public customer may have some leeway in presenting the order to the specialist and other floor brokers. This leads to the possibility that market buy and sell orders will exist at the same time. Under exchange rules, the buy order must be presented at one minimum fraction (generally $\frac{1}{8}$) below the current ask and the sell order must be presented at one minimum fraction above the current bid. When these prices coincide, the orders are crossed at the quote midpoint. For the present purposes, the crossing of public orders is essentially immaterial: there is no effect on market-maker inventory and no information can be inferred from two offsetting orders. Unfortunately, at no time did I observe such simultaneous existence of orders and discussions with a specialist confirmed that such events are relatively rare.

More often, the midpoint transaction arises when the specialist or floor trader responds to a broker's inquiry by bettering the current quote. Suppose, for example, that the quotes currently stand at (20, $20\frac{1}{4}$), but when a trader presents a buy order at $20\frac{1}{8}$, the market-maker accepts it. Microstructure models typically assume that the posted quotes accurately reflect the market-maker's demand function, and do not permit this behavior. In these situations, it appears that the market-maker benefits from concealing his actual propensity to trade.

Although no clear-cut rules help the researchers classify midpoint transactions in these cases some considerations offer partial relief. These admittedly crude rules are described below, and the proportions of transactions classified are reported in table 1.

1. Contemporaneous Transaction. I occasionally observed that when a midpoint transaction occurs it represents only a portion of the total order size, with the remainder being filled at the quoted price. Within this data set, therefore, when a midpoint transaction is found to be contemporaneous with a transaction at a quote price, the buy/sell classification of the latter is applied to the former.

2. Subsequent Transaction. When a transaction at a posted quote occurs after a midpoint transaction, but before a quote revision, the midpoint is taken as the *de facto* quote. For example, if the current quotes are (bid, ask) (20, $20\frac{1}{4}$) and a midpoint transaction occurs (at $20\frac{1}{8}$), and if a later transaction occurs at $20\frac{1}{4}$ (a buy), then $20\frac{1}{8}$ is taken as the *de facto* bid quote and the midpoint transaction is considered a sale.

3. Subsequent Quote Revision. When quote revision immediately follows a midpoint transaction the order type is inferred from the direction of the revision. In this view, a midpoint transaction indicates the *de facto* quote by marking the side of the market opposite the direction of the movement. Take, for example, current quotes at (20, $20\frac{1}{4}$), a midpoint transaction at $20\frac{1}{8}$, followed by new quotes at ($20\frac{1}{8}$, $20\frac{3}{8}$). The midpoint transaction is classed as a sell, with the interpretation that the seller is unwilling to meet the currently posted bid quote, necessitating an upward revision.

Since this classification scheme uses subsequent quotes to determine trade sign, it causes a spurious relation between trades and subsequent quote revisions, which will be confounded with the actual effect. Accordingly, z_t based on the above classification scheme were used only in the univariate time-series analysis of trade behavior. In the bivariate trade/quote revision analyses, trades were classified solely on the basis of preceding quotes.

4. Empirical analysis

4.1. Analysis of the trade series

The preceding analysis has motivated the use of trade autocorrelations as an important tool in assessing the extent of inventory-control behavior. Accordingly, the autocorrelation functions for the $\{z_t\}$ are estimated for each stock in the sample. The first-order autocorrelations are generally strongly positive, a feature more fully discussed in Hasbrouck and Ho (1987), and in part due to fragmentation of orders by the reporting process. The autocorrelations of higher order, however, are highly variable and evince no striking negative autocorrelation of the sort predicted by inventory-control considerations. To obtain a clearer picture of any dependencies, I compute average autocorrelation functions across all stocks in the sample, weighted by the number of observations for each stock. These too fail to exhibit any negative autocorrelation.

When the analysis is repeated for the volume-decile subsamples, however, evidence more supportive of inventory-control effects emerges. Fig. 1 depicts plots of the average autocorrelation function for the trades for the lowest and highest volume-decile subsamples. The autocorrelation function for the high-volume subsample is essentially flat, but that of the low-volume subsample is negative at medium to long lags. The presence of negative autocorrelation is consistent with inventory-control effects. Its absence for the high-volume sample is consistent with the lesser importance of specialist activity for these stocks.

Further analysis of the trade series involves the use of a moving-average model to assess (by means of the coefficient sum) the strength of inventory-control effects. Unfortunately, estimation of a moving-average model invariably involves a nonlinear computation and can become quite unwieldy when the order is large (up to 200 in the present case). To render the computation tractable, two approaches are taken.

First, preliminary estimates of the moving-average model parameters for the total sample and for each volume-decile subsample are formed by computing

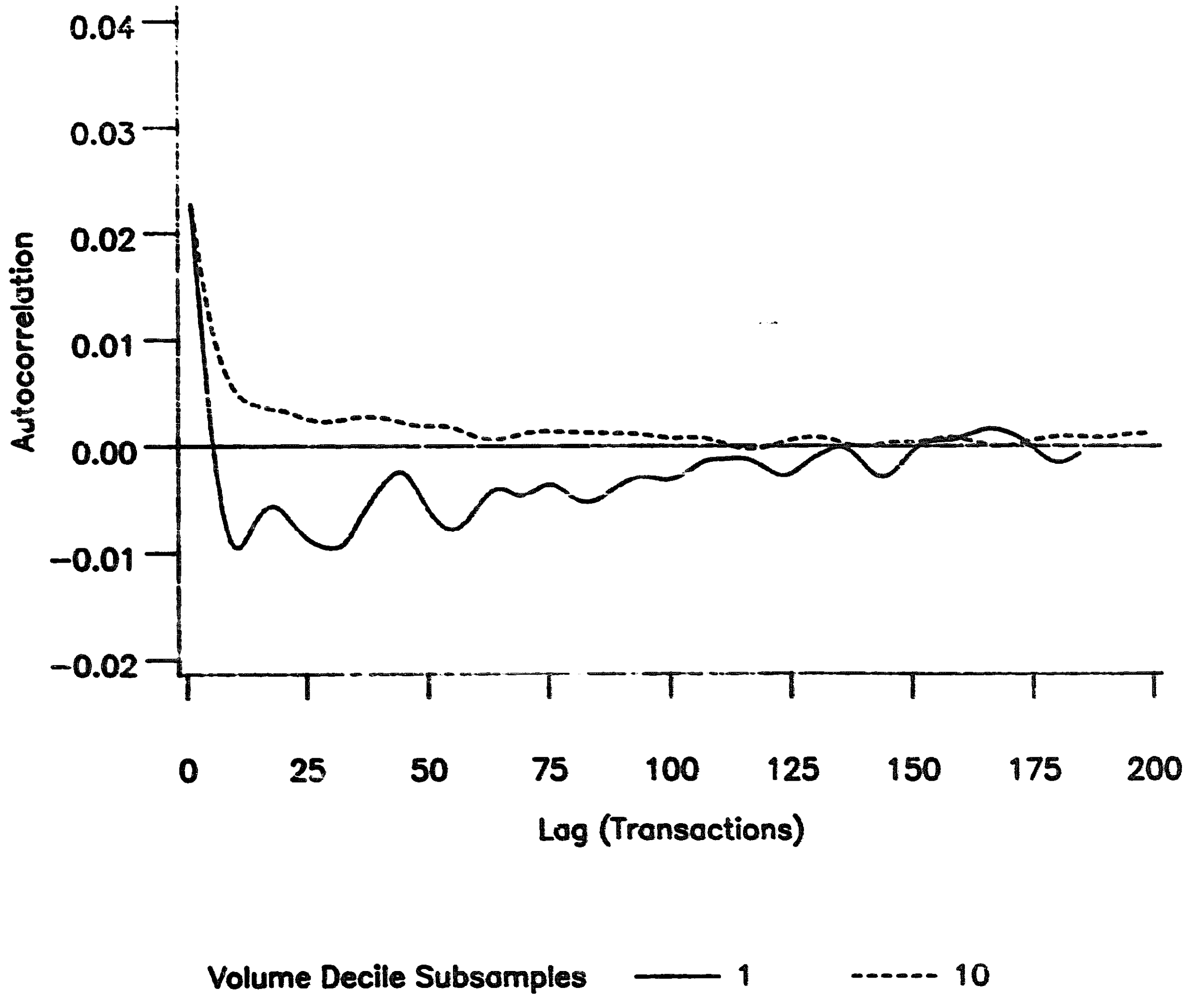

Fig. 1. Trade autocorrelations for volume deciles 1 and 10 for NYSE-listed stocks in March and April of 1985.

The figure depicts the average autocorrelation coefficients for z_t (signed transaction volume, positive if the transaction is a buy, negative if a sell) for the lowest (decile 1) and highest (decile 10) volume deciles. The autocorrelations are computed with the mean removed and with Fuller's (1976, p. 242) approximate correction for small-sample bias. The plots are spline-smoothed.

the $\{\theta_i\}$ coefficients of a moving-average model similar to (4) from the nonlinear system of equations relating them to the autocorrelations. Box and Jenkins (1976) suggest estimating the coefficients by solving the system with the estimated autocorrelations. This procedure is relatively easy to implement, but does not yield confidence intervals for the coefficients. To implement this technique, I first compute the average autocorrelations for each sample. The nonlinear solution technique locates values for the $\{\theta_i\}$ that generate the observed autocorrelations. The order of the equation system is the order of the moving average, up to 200 in the present case, which is too large for convenient computation. To reduce the dimensions of the nonlinear optimization, the $\{\theta_i\}$ are constrained using a polynomial distributed lag scheme. Point estimates are obtained for θ_1, θ_2, θ_3, θ_4, θ_5. The remaining θ_i are con-

Table 2

Moving-average models of observed trades for NYSE-listed stocks in March and April of 1985.

This table summarizes estimations of the moving-average model:

$$z_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_N\varepsilon_{t-N},$$

where z_t is the observed trade at transaction t and N is 200 for all samples except the lowest volume decile (for which $N = 180$). The coefficient sums and square sums reported in the table are computed using the method of moments based on autocorrelation estimates pooled over the subsample. Subsamples are deciles based on trade volume as measured by the number of transactions.

Sample	Sum of coefficients $(1 + \Sigma\theta_i)$	Sum of squared coefficients $(1 + \Sigma\theta_i^2)$
All stocks	1.12	1.002
Volume decile 1	0.19	1.009
Volume decile 2	−0.25	1.013
Volume decile 3	0.53	1.004
Volume decile 4	0.72	1.003
Volume decile 5	0.85	1.002
Volume decile 6	0.93	1.002
Volume decile 7	1.03	1.002
Volume decile 8	1.09	1.002
Volume decile 9	1.18	1.002
Volume decile 10	1.30	1.004

strained to lie on joined segments quadratic in i on the intervals [6,10], [11,20], [21,40], [41,60], [61,80], [81,100], [101,120], [121,140], [141,160], [161,180], [181,200].

The analysis of section 2 suggests that the sum of the moving-average coefficients for the trade process is a good indicator of the presence of inventory control. These sums are reported in table 2 for the total sample and volume-decile subsamples. [For brevity, the individual $\{\theta_i\}$ coefficients are not reported.] In interpreting the sums, it is important to note that by construction the coefficient of the contemporaneous disturbance is one. The sum of 0.19 for the first volume-decile subsample, for example, indicates that the sum of the lagged coefficients, $\Sigma\theta_i$, is -0.81, implying that 81% of a given trade innovation is reversed within 180 transactions. The sum is below unity for volume deciles one through six, indicating that at least some reversal takes place. Further, the sums are nearly monotonic across the subsamples, indicating a more pronounced inventory-control effect in low-volume issues. Since public limit orders are likely to be relatively less important for such stocks, it is not surprising (following the analysis of section 2) that the observed inventory effects are stronger.

Since the estimation technique used to this point does not yield standard errors, a pooled maximum-likelihood estimation is attempted. In view of the large computational costs, the procedure is applied to the second volume-

Table 3

Moving-average coefficient estimates for the trades in the second volume decile of NYSE-listed stocks in March and April of 1985.

The estimated specification is

$$z_{jt} = \mu_j + \varepsilon_{jt} + \theta_1 \varepsilon_{j,t-1} + \theta_2 \varepsilon_{j,t-2} + \cdots + \theta_{200} \varepsilon_{j,t-200} \quad \text{for } t = 1,\dots, M_j, \quad j = 1,\dots,150,$$

where z_{jt} is the trade for stock j at transaction t, μ_j is the mean value of z_{jt} for stock j, and M_j is the number of trade/quote pairs for stock j. The θ_i coefficients are constrained to be constant over the indicated ranges. The estimation method is maximum-likelihood. S.E. are the asymptotic standard errors.

Variables	Estimated value	S.E.
θ_1	0.0350	0.0050
θ_2	0.0126	0.0050
θ_3	−0.0015	0.0050
θ_4	0.0022	0.0050
θ_{5-10}	−0.0029	0.0021
θ_{11-25}	−0.0863	0.0014
θ_{26-50}	−0.0076	0.0010
θ_{51-100}	−0.0061	0.0008
$\theta_{101-150}$	−0.0043	0.0009
$\theta_{151-200}$	−0.0036	0.0010
$1 + \Sigma\theta_i$	0.0116	0.0435

decile subsample only, and the $\{\theta_i\}$ coefficients are constrained to be fixed over certain lags. The second volume-decile subsample is used in preference to the first volume-decile subsample because the latter have substantially fewer observations. The model estimated is

$$z_{jt} = \mu_j + \varepsilon_{jt} + \theta_1 \varepsilon_{j,t-1} + \theta_2 \varepsilon_{j,t-2} + \cdots + \theta_{200} \varepsilon_{j,t-200} \qquad (9)$$

$$\text{for} \quad t = 1,\dots, M_j, \quad j = 1,\dots,150,$$

where j indexes the stocks in the sample, μ_j is the mean value of z_{jt} for stock j, and t runs up to M_j, the number of trade/quote pairs for stock j. To keep the order of the nonlinear optimization tractable, the $\{\theta_i\}$ values are assumed to be fixed over certain intervals. In all, ten values are estimated: θ_1, θ_2, θ_3, θ_4, θ_{5-10}, θ_{11-25}, θ_{26-50}, θ_{51-100}, $\theta_{101-150}$, and $\theta_{151-200}$. These parameter estimates and their standard errors are reported in table 3. The standard errors suggest that even at long lags the coefficients are statistically significant.

The details of the maximum-likelihood estimation are as follows. For each stock in the subsample, the trade series is standardized (by subtracting the mean and dividing by the standard deviation). For a given parameter choice $\{\theta_i,\ i = 1,\dots,200\}$, the log-likelihood of a particular stock is computed under the assumption that the model is Gaussian using the Kalman filter algorithm of Gardner, Phillips, and Phillips (1980). The log-likelihood function for the entire subsample is computed as the sum of the individual log-likelihoods. The sample log-likelihood function is then maximized over the $\{\theta_i\}$ parameter space using the GQOPT program, and standard errors are computed from the Hessian in the usual fashion. These can only be viewed as approximate. Besides the usual caveat regarding small samples, the computation assumes normality and independence of observations across stocks.

The sum of the coefficients was estimated as 0.0116 with an asymptotic standard error of 0.0435, a value close to zero. Although it is tempting to regard this as conclusive evidence of inventory-control effects fully accounted for, more caution is in order. It is well known that when the true parameters of moving-average models are in the general vicinity of the noninvertible (unit circle) region, maximum-likelihood estimates tend to land precisely on the unit circle. [See Harvey (1981, pp. 136–139).] Nevertheless, the preliminary and maximum-likelihood estimations suggest that, to a substantial degree, buys and sells are reversed over long lags.

For this subsample, trade reversal seems essentially complete over roughly 200 lags. Since stocks in the second volume decile average 249 transactions in the 42 trading days, the time horizon of the inventory adjustment appears to be about 34 trading days. This duration is of the same magnitude but longer than the 11–20 day duration for the price impact of an inventory position found by Smidt (1971, p. 1909).

The autocorrelation properties of trades suggest a partial explanation for a phenomenon found by French and Roll (1986). They report that daily returns exhibit statistically significant negative autocorrelations through roughly 13 days and that the negative autocorrelation is more pronounced for issues with low market value. This encompasses a lag over which fig. 1 depicts negative autocorrelation in the observed trade series. Since buys occur at the bid price and sells at the ask, this suggests that the negative correlation in trades partly accounts for the negative autocorrelation in returns.

One purpose of the trade analysis is to construct an innovations representation such as (4) for trades. The results obtained so far indicate that even though the coefficients in the moving-average representation are statistically significant, the explanatory power of the model is small. For a moving-average process, the ratio of the innovation (unexplained) variance to total variance is given by the inverse of the sum of the squared moving-average coefficients. For process (4), for example,

$$\sigma_\varepsilon^2/\sigma_z^2=\left[1+\theta_1^2+\theta_2^2+\theta_3^2+\cdots\right]^{-1}.$$

The sum of the squared estimated moving-average coefficients for the second volume decile is 1.008, based on the maximum-likelihood estimates. This suggests that $1.008^{-1}=98.2\%$ of the variance in observed trades is left unexplained by past trades. (Sums of squared coefficients based on the preliminary estimation method for all subsamples are reported in table 2.)

4.2. The impact of trades on quote revisions

To assess the impact of trades on quote revisions, regressions of the form (7) are estimated, with the following modifications. First, a departure is made from the trade series $\{z_t\}$ discussed in section 3. There, certain midpoint transactions are classified as buys or sells by reference to a subsequent quote revision, a practice clearly prejudicial to the present analysis. In constructing the $\{z_t\}$ series used in this and the following sections these trades are considered unclassifiable (and assigned a numerical value of zero). Also, the trade series is replaced with an indicator variable:

$$T_t = \begin{cases} +1 & \text{if} \quad z_t > 0 \\ 0 & \text{if} \quad z_t = 0, \\ -1 & \text{if} \quad z_t < 0. \end{cases}$$

An indicator variable is used because trades vary considerably in size, and the relationship between trade size and quote revision is presumably highly nonlinear. Second, because of the different trade behavior for high- and low-volume stocks, separate estimation approaches are taken. The analysis for the low-volume stocks is described here. Section 5 discusses the analysis of the high-volume stocks, which includes a specification allowing for differential trade-size effects.

A pooled estimation is performed for the stocks in the second volume decile. First, a moving-average model is estimated for the indicator series. This model has the same form as the trade model estimated above and is estimated using the same maximum-likelihood procedure. The standardized prediction errors from the Kalman filter used in estimation, denoted $\tilde{T}_t$, are used in lieu of the actual (unobservable) innovations in the series. Both these prediction errors and the quote revisions are normalized (for each issue) by subtracting off the mean and dividing by the standard deviation. The specification estimated for the quote revisions is then [cf. (7)]:

$$r_{jt} = b_0 \tilde{T}_{jt} + b_1 \tilde{T}_{j,t-1} + b_2 \tilde{T}_{j,t-2} + \cdots + b_{200} \tilde{T}_{j,t-200} + u_{jt} \tag{10}$$

$$\text{for} \quad t = 1, \ldots, M_j, \quad j = 1, \ldots, 150.$$

In this specification, the $\{b_i\}$ coefficients specify the impulse response function, i.e., the response over time to a shock in the driving variable (the trade indicator innovation). As with the moving-average estimations, to reduce the

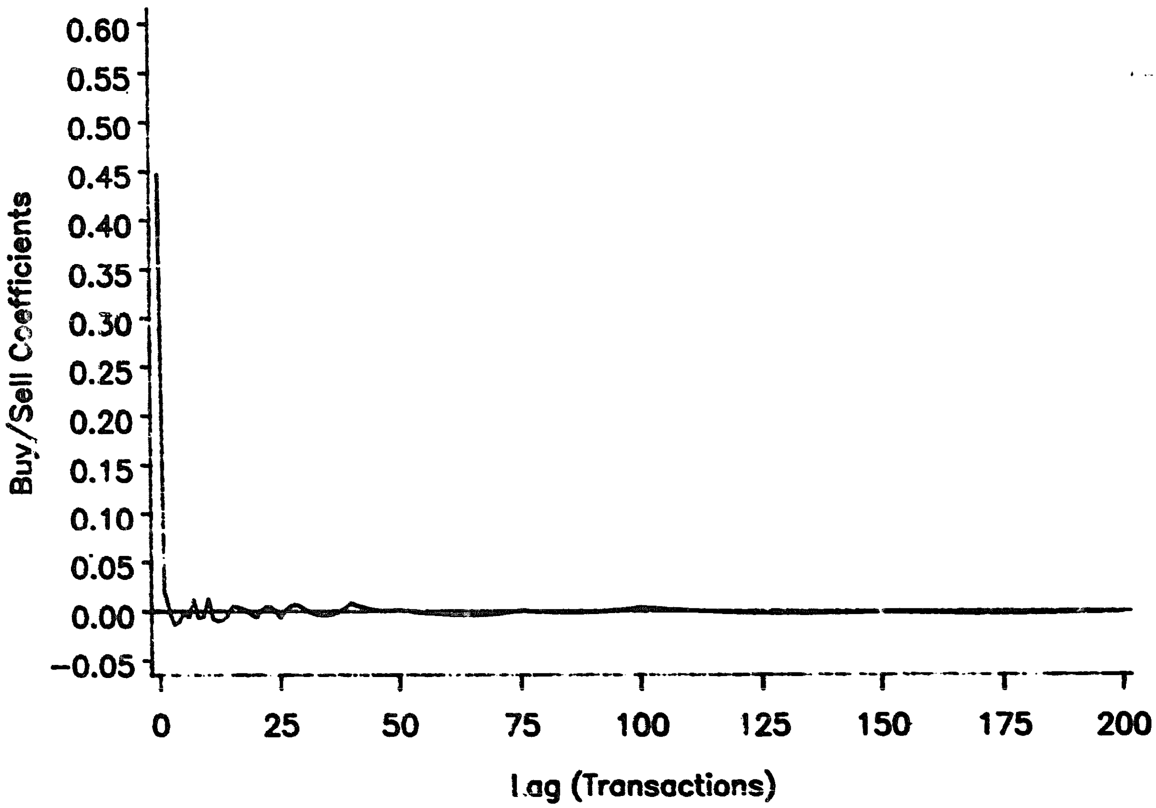

Fig. 2. Trade indicator innovation coefficients for the second volume decile for NYSE-listed stocks in March and April of 1985.

The figure plots the b_i coefficients from the OLS estimation of

$$r_{jt} = b_0\tilde{T}_{jt} + b_1\tilde{T}_{j,t-1} + b_2\tilde{T}_{j,t-2} + \cdots + b_{200}\tilde{T}_{j,t-200} + u_{jt} \quad \text{for} \quad t = 1,\ldots,M_j, \quad j = 1,\ldots,150,$$

where r_{jt} is the quote revision for stock j at transaction t and M_j is the number of transactions for stock j. The $\tilde{T}_{jt}$ are the Kalman filter innovations in the trade indicator series. Both r_{jt} and $\tilde{T}_{jt}$ are standardized; they are divided by their respective standard deviations estimated for stock j. The b_i are constrained over fixed ranges to lie on second-order polynomials.

dimensions of the problem, polynomial distributed lags are used: the $\{b_i\}$ coefficients are constrained to lie on functions quadratic in i.[11]

The coefficients are plotted in fig. 2. The impact of trades at low lags is strongly positive, a finding consistent with both information and inventory effects. Beyond low lags the trade coefficients are close to zero. Inventory-control effects would predict some reversal in these coefficients [cf. (5)]. The lagged coefficients are in fact predominately negative. This pattern is not statistically significant, however, and so this finding carries little weight. This analysis suggests therefore that the impact of trades on quotes is due primarily to information.

[11]More precisely, point estimates are made for b_i, $i = 0,\ldots,10$. The b_i are constrained to lie on joined quadratic segments on the intervals (in i) [11,15], [16,20], [21,25], [26,30], [31,40], [41,50], [51,75], [76,100], [101,150], [151,200].

The statistical power of the analysis to detect significant inventory-control effects on quote revisions is low. This low power is partly a consequence of measurement error: the trade series includes orders that cleared against other traders as well as those which cleared against the dealer. In addition, the trade autocorrelations suggest that inventory control takes place over long intervals. Over such periods, quote changes are almost entirely driven by new information. Inventory-control effects are presumably much weaker and thus are much more difficult to detect.

5. High-volume stocks and trade size effects

Previous empirical work has generally investigated the impact of block trades on transaction prices. Kraus and Stoll (1972) find a persistent impact of block sales (consistent with an information effect), as well as some reversal of the initial impact, suggesting transient liquidity effects. On the theoretical side, Easley and O'Hara (1987) present an asymmetric-information model in which the private information revealed by an order and the consequent quote revision are positive functions of the size of the order.

The general character of these effects can be assessed within the present framework by including an order-size variable. Because order size is presumed to affect quote revisions in a nonlinear fashion, a size variable is computed as

$$S_t = \begin{cases} +\log(z_t) & \text{if} \quad z_t > 0, \\ 0 & \text{if} \quad z_t = 0, \\ -\log(-z_t) & \text{if} \quad z_t < 0. \end{cases}$$

(Alternate specifications included quadractic size variables. The coefficients of these terms were generally negative, suggesting concavity in the relation.) To assist in the interpretation of the coefficients, S_t is transformed by regressing it against current and lagged values of the trade indicator variable T_t. The residuals from this regression, denoted $\tilde{S}_t$, are by construction uncorrelated with the T_t indicator variable. Because the analysis of order autocorrelations in this sample found no evidence of inventory-control effects, no effort was made to use the trade innovations in the regressions of this section.

The specification estimated is

$$r_t = a_0 + \sum_{i=0}^{9} b_i T_{t-i} + \sum_{i=0}^{9} c_i \tilde{S}_{t-i} + \eta_t. \tag{11}$$

Because the constructed size variables are orthogonal to the indicator variables, the b_i coefficients are identical to those that would be found in an

Table 4

Quote revision estimation for American Information Technology in March and April of 1985. The estimated specification is

$$r_t = a_0 + \sum_{i=0}^{9} b_i T_{t-i} + \sum_{i=0}^{9} c_i \tilde{S}_{t-i} + \eta_t,$$

where r_t is the quote revision at transaction t, T_t is an indicator variable (+1 if a buy order, −1, if a sell), $\tilde{S}_t$ is the signed logarithm of the order size, orthogonalized to T_t. S.E. are the asymptotic standard errors.

	Coefficient	S.E.
a_0	0.0048	0.0012
b_0	−0.0204	0.0012
b_1	−0.0024	0.0012
b_2	−0.0023	0.0012
b_3	0.0002	0.0012
b_4	0.0007	0.0012
b_5	0.0008	0.0012
b_6	−0.0022	0.0012
b_7	0.0011	0.0012
b_8	−0.0011	0.0012
b_9	0.0003	0.0012
c_0	0.0108	0.0009
c_1	−0.0006	0.0009
c_2	0.0008	0.0008
c_3	0.0009	0.0008
c_4	−0.0014	0.0008
c_5	−0.0017	0.0008
c_6	0.0002	0.0008
c_7	0.0008	0.0008
c_8	−0.0000	0.0008
c_9	−0.0000	0.0008
Σb_i	0.0155	0.0031
Σc_i	0.0098	0.0022

estimation in which the $\tilde{S}_t$ variables were not present. Estimations are performed on the first thirty stocks in the ninth volume decile.

Table 4 contains the coefficient estimates for a representative stock, American Information Technology. The coefficients of the contemporaneous trade indicator and the trade size indicator (b_0 and c_0) are strongly positive. The lagged coefficients of both the indicator and size are on average negative, indicating some reversal of the initial impact, but the net effect is not statistically significant. The persistent effects of the trade indicator and size variables as measured by the sums of the b_i and c_i coefficients through the tenth lag are positive. This suggests that order size, in addition to direction of trade, conveys information.

The coefficients for American Information Technology are quite typical. For the thirty issues analyzed, the contemporaneous and persistent effects of both trade and size are almost invariably positive. (The $\sum b_i$ sum is always significantly positive at the 0.05 level; the $\sum c_i$ sum is significantly positive in all but three instances.) This is consistent with the hypothesis that larger trades convey more information. A pattern of reversal (negative lagged indicator and size coefficients) usually is observed, but is rarely statistically significant.

6. Conclusion

This paper has examined the interaction of trades and quote changes in an attempt to ascertain the nature of inventory-control and asymmetric-information effects. The key findings are:

(i) Trades for low-volume stocks exhibit the negative autocorrelation consistent with inventory-control effects. No such pattern, however, characterizes high-volume stocks. This is perhaps a consequence of the relatively greater importance for these stocks of public limit orders and relatively lesser importance of specialist transactions.
(ii) For all stocks, the persistent impact of trades on quote revisions is strongly positive. This is consistent with an information effect of trades.
(iii) Effects of dealer inventory-control behavior on quotes, as ascertained from the transient impact of trades on quote revisions, are insignificant.
(iv) For high-volume stocks, a persistent order-size effect on quote revisions is found. This is consistent with the view that large orders convey more information.

Findings (ii) and (iv) confirm the existence of effects consistent with current asymmetric-information models. Findings (i) and (iii) provide mixed evidence on inventory-control effects. Such effects appear to be present in the observed trade sequence, but the effects on price (quote) determination are relatively weak at best. The apparent inconsistency can be reconciled by noting that the statistical power of the analysis to detect inventory effects on quote revisions is weak. This weakness stems from measurement error, and long lag over which inventory effects operate, and the large variation in quote changes due to information.

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