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Modeling Market Microstructure and Time Series in Nigerian Exchange Limited

OMEHE Raphael
Department of Accounting and Finance
Faculty of Management Sciences,
University of Delta, Agbor, Delta State,
Phone Number: 08063310477
e-mail address: omeheralph@yahoo.com
omehe.raphael@unidel.edu.ng

Dr. EYIDE Michael Ugeoritsete
Department of Accounting and Finance,
Faculty of Management Science,
University of Delta, Agbor
email: michael.eyide@unidel.edu.ng

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Abstract
Microstructure data typically consist of trades and bid and offer quotes for financial securities that are collected at fine sampling intervals (often within the day). This paper reviews approaches taken to modeling these data. The emphasis is on techniques of stationary multivariate time series analysis: autoregressive and moving average representations of standard microstructure models, vector autoregressive estimation, random-walk decompositions and cointegration. The paper also discusses the challenges posed by irregular observation frequencies, discreteness and nonlinearity.

KEY WORDS: *Microstructure, Bivariate models, Inventory models, Univariate, Time-Series.*

Introduction

Market microstructure is the area of financial economics that focuses on the trading process. Factors both practical and academic are motivating research here. On the practical side, innovation in financial markets has resulted in increased trading volume in standard securities (stocks, bonds, etc.), creation of new types of securities, and greater experimentation with alternative trading mechanisms. From the academic perspective comes a fuller understanding of the role played by trading in the incorporation of new information into security prices. Empirical work in the area has also benefited from the increasing availability of detailed transaction data.

Microstructure research seeks to address two sorts of questions. The first belong to the study of markets narrowly defined: how should transaction costs be estimated; what are the optimal trading strategies; and, how should markets be organized? The second and broader set of questions arises from the role that the market plays in price discovery (the incorporation of new information into the security price): how can we characterize the determinants of security value that we loosely refer to as public and private information?

Ultimately these two types of questions are related. The organization of a market may affect the transactions costs, and therefore the net return to an investor, the valuation of the asset and the allocation of real resources (Amihud & Mendelson (1986).

Conversely, the characteristics of an asset (risk, return, homogeneity, divisibility) may favor certain holding patterns among investors and certain market structures (Grossman & Miller (1988).

Empirical microstructure analyses draw on three areas of knowledge. The first is comprised by the formal economic models of individual behaviour that offer substantive predictions about how observable variables should behave. The second area is statistical time series analysis. The third area concerns the "institutional realities: the actual procedures by which individuals and automated systems work to accomplish trades in a particular market.

The theoretical work in market microstructure has centered around several reasonably well-defined paradigms that serve as a common basis for variations. The evolution of thought on security transaction price behaviour has passed from basic martingale models, to non-informational cost models (order processing and inventory control paradigms), and finally to models that incorporate the distinctly informational and strategic aspects of trading. Although this paper will describe the intuitions behind these models, it does not present a rigorous discussion. O'Hara (1994) provides a comprehensive textbook discussion that establishes much of the economic background for this paper.

Present empirical work in microstructure is characterized by a wide diversity of techniques. Market data exhibit a panoply of features that are hostile to statistical modeling: complex dynamics, nonlinearities, nonstationarities, and irregular timing to name a few. The impracticality of modeling all of these features jointly, in a specification that can also potentially resolve alternative economic hypotheses, leads to a multitude of more modest models that simply try to capture one or two phenomena relevant to the problem at hand.

To establish a common footing, however, the models considered in this paper are cast in the framework of linear multivariate time series analysis. Most of the statistical techniques discussed here were originally developed and applied to macroeconomic time series. (Lutkepohl (1993) & Hamilton (1994) are excellent textbook presentations. The reader approaching the present paper from a macro perspective will find most of the time series results familiar. But time series analysis is not a mechanical procedure, and the application of any technique to a new problem involves some reflection on the economics of the situation and the nature of the data.

Some issues that cause great difficulty in macro applications are conveniently absent in microstructure data: microstructure observations are exceedingly numerous and the fine time intervals over which the data are collected greatly mitigate the simultaneity induced by time aggregation. On the other hand, microstructure data often exhibit troublesome properties such as discreteness that rarely arise in macro analyses.

Literature Review

Simple Bivariate Models of Prices and Trades

The univariate price models described above are capable of exhibiting dynamics that reflect microstructure phenomena and can also capture the first dichotomy mentioned in the introduction, that between permanent (informational) and transient (market) effects. The models described in this section encompass trades as well, with a view toward establishing the second important distinction, that between trade-related and -unrelated sources of price variation.

Inventory Model

Buyers and sellers in the simple bid-ask spread model are assumed to arrive independently and with equal probability. Let *Xr* denote the signed trade quantity, positive if the arriving trader buys from the dealer and negative if the trader sells. The cumulative quantity from time zero through time *t* is ***L:*** $=X;$. In the paper that introduced the term "microstructure", Garman (1976) pointed out that as *t* increased, this sum would diverge, implying that the dealer bought or sold (net) an infinite amount. Real-world dealers face capital constraints, however, and would in any event avoid large positions due to risk- aversion. This motivates the need for some sort of inventory control or position management.

The inventory control problem in classical microeconomics is one of specifying a restocking strategy subject to order and stock-out costs. The security market dealer, on the other hand has traditionally been supposed to achieve inventory control by shifting the quotes to elicit an imbalance of buy and sell orders. Formal models of this effect include Amihud and Mendelson (1980), Ho and Stoll (1981), O'Hara and Oldfield (1986) and Stoll (1978).

As an illustration, consider a generalization of the simple bid-ask spread model in which quote-setting is depends on the dealer's inventory position and incoming order flow depends on the quotes:

$m, = m,- 1 + w, q, = m, - b/1 - 1 I, = 11 - 1 - x,$

$x, = -a(q, -m,)+ v, p,$

The first equation describes the random-walk evolution of the efficient price. The quotes are summarized by the quote midpoint (the average of the bid and ask quotes), *q*. This is equal to the efficient price plus an inventory control component, where *I,* is the dealer's inventory at the close of period *t*. Without loss of generality, the dealer's target inventory is assumed to be zero. The quote-midpoint equation specifies that with *b>O,* the dealer lowers his price if he has a long position. The net demand, *x,* is driven by a price sensitive component *(a>O)* and a random component. The usefulness of the quote position as an inventory-management tool is based on the demand price elasticity.

Since the dealer is assumed to be the counter party to all trades, the change in inventory is equal to the negative of the net demand. The transaction price is equal to the quote midpoint, plus a cost component *ex,*. This cost is proportional to trade size: rather than quoting a bid and offer price, the dealer quotes a linear bid and offer schedule. A trader wanting to buy an amount Jx,I will be quoted an ask price of $q; = qt + cl x,$I, and a trader wanting to sell will be quoted a bid price of $q: = qt - cl\ x,$1- The trade innovation *v,* is assumed to be serially correlated, and uncorrelated at all leads and lags with w.

The essential features of this model can be illustrated by examining the impulse response function for a particular set of parameter values. Let a = 0.8, $b = 0.04$ and $e = 0.5$, and consider the paths of price and inventory subsequent to a trade shock at time zero of $v_0 = 1$, i.e., a purchase of one unit from the dealer. These paths are graphed in Figure 2. The buy is associated with an immediate price jump due to the cost component. Reversion is not immediate, however, subsequent to the trade, the dealer has an inventory shortfall and must raise his quotes to elicit an incoming sell order. As the sell orders arrive (in expectation), the dealer resets the quotes to the initial level. The inventory path reflects the initial depletion caused by the purchase *(from* the dealer) and the subsequent sales *(to* the dealer). At the end of the adjustment process, both price and inventory have completely reverted. There is no permanent price impact of a trade in this model because trades are independent of information.

The permanent component of the price change is Wr, which is due entirely to public information. The pricing error is:

$$s_t = p_t - m_t = cx_t - bI_{t-1} \quad (2.2)$$

This is entirely trade-driven. As in the simple bid-ask model, the buyer pays the half-spread *cxr*. The second term depends on the dealer's previous inventory position. If the dealer happened to have an inventory surplus, the buyer's cost would be reduced.

If both *pr* and *Ir* are observable, the model may written as:

¾Jr = -*cit* + (2c-b) Ir_1 +*(b-c)It-z* + w_1 and!,= (l-ab)/1_1 -*v1*.

Formally, this is a bivariate vector autoregressive (VAR) model, with a contemporaneous recursive structure, which may be estimated directly by least squares. There is sufficient structure here to recover both *w,* and *Sr* from current and past observations.

Among the various sorts of microstructure data available, however, dealer inventory data are about the rarest. Implicit in these data are the dealer's trading strategies and trading profits, both of which are usually kept private. If *Ir* is not known, then inference must proceed solely from prices. On the basis of the univariate time-series representation of the price changes, the structural model is under-identified. Two important structural parameters are identified, however: the variances of the random-walk and pricing error components.

Due to the paucity of inventory data, there are few analyses of pure inventory control models. In a U.S. S.E.C. (1971) study, Smidt presents some results for NYSE stock specialists based on daily positions and price changes. Ho and Macris (1984) estimate a transaction level model for an American Stock Exchange options specialist. Most recent studies allow for the possibility of asymmetric information in addition to inventory control, and these are discussed below.

Asymmetric Information

The models considered to this point have assumed that all market participants possess the same information. This sort of public information may be thought of as instantaneous news releases, in response to which bid and offer quotes would adjust with no necessity of trading. The most important recent developments in theoretical microstructure, however, have been models that allow for heterogeneously informed traders. If a trade might be motivated by superior information, the occurrence of a trade (a public event in most models) will communicate to the market something about this private information. Some studies that initially addressed this phenomenon in microstructure settings are Bagehot (1971), Copeland and Galai (1983), Glosten and Milgrom (1985), Kyle (1985) and Easley and O'Hara (1987). O'Hara (1994, Ch. 3) provides an overview.

A simple model of private information with fixed transaction costs can be given as:

m1 = *m1-1* + w1

w1 = *u,* + *gx1*

$q_t = m_{t-1} + u_t$
$P_t = q_t + cx_t$ (2.3)

Relative to the earlier models, the novelty here is in the random-walk innovation, W_t. It is now composed of two components. The first, u_t, is assumed to reflect updates to the public information set. The second, gx_t, with $g>0$, reflects the market's estimate of the information $\sigma_w^2 = \sigma_u^2 + g^2\sigma_x^2$,e trade. For this component to be serially uncorrelated, it must be the case that x_t is serially uncorrelated, i.e., we are back to assuming that buy and sell orders arrive randomly. This model is a variant of one suggested by Glosten (1987).

Actual transaction prices are subject to a bid-ask spread related to the direction of the trade. There are two ways of interpreting the ext term in the price specification. First, if the magnitude of the trade is fixed, say $x_t \in \{-1, +1\}$, then c is one-half the bid-ask spread (S/2), with transactions occurring at the bid and offer prices ($q_t = q_t$ -S/2 and $q_t = q_t$ + S/2). Alternatively, if trade size is continuous, then c gives the slope of the dealer's linear bid and offer schedule. The dynamic behaviour of prices and trades may be illustrated by the impulse response function based on parameter values $c = 0.5$ and g = 0.2, subsequent to an initial buy order of one unit $(x_0 = 1)$. These are graphed in Figure 3. The initial price jump simply reflects the bid-ask bounce, but in contrast with the inventory control model, the reversion is not total. Of the initial 0.5 price jump, 0.2 is the $s_t = p_t - m_t = (c-g)x_t$ content, which remains permanently impounded in the stock price. By assumption there are no serial dependencies in trades: the initial purchase engenders no subsequent order flow effects.

The evolution in the efficient price now reflects both public and private information components, so (2.4)
which isolates the non-trade and trade-related components of the efficient price change. A useful summary measure of the relative importance of trades in explaining movements in the efficient price is the proportion

$$R_{w,x}^2 = g^2\sigma_x^2/\sigma_w^2 \quad (2.5)$$

The R^2 notation denotes the usual "proportion of total variance explained." This measure generalizes beyond the present model, and is a useful proxy for the extent of asymmetric information.

The private information effects in this model reflect the market's beliefs about the probabilistic structure of the private information, not the actual level of private information. That is, the price impact of a particular trade depends only on the market's general beliefs about extent and nature of private information, and not directly on the actual information possessed by the trader. A model of this sort cannot be used to identify, for example, illegal insider trades in a sample of data.

The pricing error is

The pricing error is entirely trade driven. Relative to the simple bid-ask model with no private information, however, S_t is reduced by the information content of the trade, gx_t. It is generally assumed that $c>g$ because the dealer is setting the half-spread to recover both information costs g and additional order processing costs.

The return series is given by:

$$\Delta p_t = p_t - p_{t-1} = u_t + cx_t - (c-g)x_{t-1} \quad (2.6)$$

If trades and prices are observable, this may be estimated directly. Early transaction- based estimations of trade impacts on price are Marsh and Rock (1986), Glosten and Harris (1988), and Hasbrouck (1988).

When trades are not observed, however, the inference must proceed solely on the basis of transaction prices. This model superficially resembles the simple bid-ask model considered in section 2.3. Like the earlier model, it possesses an MA(l) representation of the form (2.6). Here, however, the two parameters of the MA model {o-;,0} are insufficient to identify the four parameters of the structural model{c,g,o-! ,o-;}. The random walk variance is identified as before: a:, = (1+ 0)^2 a; = a:+ g^2a;. In contrast with the earlier model, however, we cannot assume that the pricing error is uncorrelated with the increment to the efficient price.

In summary, based on knowing the parameters of the return process for this model (autocovariances or, equivalently, the moving average parameters), we can compute the random-walk (implicit efficient price) variance. Neither the pricing error variance nor derived measures such as the spread, however, are identified in the absence of further restrictions. Unfortunately, neither of the two identification restrictions considered above is particularly attractive, as they involve a choice between suppressing all public information or alternatively all private information.

Methodology

Vector Auto regressions (VARs)

A vector auto regression is a linear regression specification in which current values of all variables are regressed against lagged values of all variables. The inventory and asymmetric information models discussed in the last section, for example, can be specified as bivariate vector autoregressions. More general and flexible models can be obtained by extending the number of lags in estimation. VARs are relatively easy to estimate (least squares usually suffices) and interpret (via the impulse response functions or other transformations considered below). Their value in microstructure studies also rests, however, on their ability to characterize very general time series models. It is useful at this point to outline the assumptions underlying this generality, and also the ways in which they might be violated in microstructure applications.

The broad applicability of VARs ultimately rests on the World theorem. A zero- mean vector time series *Yt* is said to be weakly stationary (covariance stationary) if the autocovariances do not depend on *t,* E *y*]*y*;$_{-1}$ = r_1. The World theorem states that a zero-mean weakly stationary nondeterministic process can be written as a convergent vector moving average (VMA) process (possibly of infinite order):

$$y_t = e_t + B_1 e_{t-1} + B_2 e_{t-2} + \cdots = B(L) e_t, \qquad (3.1)$$

Where the *et* are serially uncorrelated homoskedastic increments with covariance[1] matrix n and *L is* the backshift operator, *L(J* = (}_ (Hamilton (1994) and Sargent (1987). This is nothing more than the innovations representation of the process. This section assumes that the conditions of the World theorem are satisfied. The stationarity assumption will be examined in greater detail in section 5.

Suppose that we are working with price changes and trades (as in the model of 2.4), so that the state vector is

$$y_t = \begin{bmatrix} \Delta p_t \\ x_t \end{bmatrix} \text{ and } e_t = \begin{bmatrix} u_t \\ v_t \end{bmatrix};\ Var(e_t) = \Omega = \begin{bmatrix} \sigma_u^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix} \quad (3.2)$$

The orthogonality of the residuals is based on the economic assumption that contemporaneous causality flows from trade to the transaction price. This characterized all of the simple structural models discussed in the last section. It is easy to contemplate market structures in which this assumption might be violated, but in many settings it is a reasonable approximation.

If all of the roots of the polynomial equation det($B(z)$) = 0 lie outside of the unit circle, then the VMA representation is said to be invertible, that is, it may be reworked to give a (possibly infinite) convergent VAR representation:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + e_t = A(L)y_t + e_t. \quad (3.3)$$

In microstructure applications, the invertibility assumption is commonly violated by over differencing or cointegration. As noted in section 3.4, over differencing is a real possibility when the model involves inventories, but the data contain only trades (the first difference of the inventory). Cointegration arises when the state vector includes two or more price variables for the same security (like the bid and ask quotes, or the transaction price and either quote), and is discussed further in section 8. All of the simple models discussed in the preceding sections may be represented in the form (4.3).

A minor inconvenience arises because all of the bivariate VAR models in the last section include a contemporaneous term on the right hand side:

Yt = A;yt + A;Yt-i + A;yt_2 +··+e;.

It is easy to rework this into the form (4.3) by noting

Yt = (I-A;)$^{-1}$ A;y1^{-1} + (I-A;)$^{-1}$ A;yt_ +·+(I-A;)$^{-1}$e;

2

Estimating the model in the form that includes the contemporaneous term is a convenient way of forcing orthogonality on the estimated residuals. Most econometric texts, however, employ the form (4.3), and this will be used here as well. There are several ways of computing the VMA (4.1) from the VAR. Conceptually, the simplest procedure involves simulating the behaviour of the system subsequent to one-unit initial shocks (Hamilton (1974).

Analysis
Time

The microstructure models studied in the earlier sections were implicitly cast in real time, sometimes referred to as "calendar time" by macro econometricians or "wall-clock time" by microstructure students. In the interest of simplicity we implicitly took the time subscript t in the usual sense, as an index of equally-spaced points in real time.

The stationarity assumptions necessary to support inference were assumed to hold with respect to this time index.

Timing considerations in actual markets, however, are considerably more involved. Markets do not usually operate continuously. The few that are in principle open twenty- four hours per day exhibit strong concentration of activity. Furthermore, trades usually take place at random times throughout the market session. This section discusses ways in which more realistic notions of time can be incorporated into statistical models.

Deterministic Time Considerations

Some of the time properties of markets appear to be deterministic, like the regular or predictable seasonalities encountered in macro time series. Two related examples in microstructure data are market closures and intraday patterns. In most markets, trading takes place continuously during organized trading sessions.

In between are periods of nontrading, typically over a lunch break, overnight, or over a weekend or holiday. If we are interested only in the behaviour of the market during a trading session, we may drop from the sample all observations that span trading sessions, e.g., we might ignore an overnight return. If the aim of the analysis is a comprehensive model of the market evolution during periods of trading and non-trading, however, the econometrician must first take a position on whether or not the market evolution is time homogeneous, i.e., whether prices (security values) behave in the same way during trading and nontrading periods. If homogeneity is assumed, then we are taking the view that the timing of the observations in our sample is merely an artifact of some sampling process that is not related to the behaviour of the system. Obviously for models in which trading plays a central role (such as those involving asymmetric information), time homogeneity is not an attractive assumption.

In testing less refined hypotheses, however, the conjecture might be a workable approximation. This motivates consideration of how time homogeneity is empirically examined.

Most of what we know about the role of time in microstructure data derives from the analysis of price-change variances (rather than means). This reliance on second moment properties characterizes not only the analysis of trading vs. nontrading periods, but also most of the work done on intra-trading session evolution. The reasons for this emphasis are the ones raised in Section 2.1: if the price follows a random walk, the precision of variance estimates is improved by more: frequent sampling, the precision of mean estimates is not.

In U.S. equity markets, at least, the hypothesis that the return variance per unit time is constant over trading and nontrading periods is easily rejected (Fama (1965), Granger and Morgenstern (1970), Oldfield and Rogalski (1980) and Christie (1981)). Based on an analysis of returns computed using daily closing prices, French and Roll (1986) estimate that the return variance per unit time is at least an order of magnitude higher when the market is open than when it is closed. This is due in part to the fact that production of public information (such as news releases) is more likely to occur during normal business hours, but it is also due to the role of trading itself in the price discovery process.

As a general rule, microstructure data exhibit distinctive behaviour at the beginning and end of trading sessions. Most notably, return variances per unit time exhibit "U"-shapes, i.e., elevations at the session endpoints. Marked intraday patterns are also found in measures of trading activity such as transaction frequency, trading volume rates and bid-ask spreads (Jain and Joh (1988), Mclnish and Wood (1990), Mclnish and Wood (1992) and Wood, Mcinish and Ord (1985)).

Stochastic Time Effects

Although trading processes unfold in continuous time, they are marked by discrete events (e.g., trades or quote revisions). The determination of these occurrence times is at least in part random. Ideally, then, how should these processes be modeled from a purely statistical perspective? Furthermore, what is the economic significance of the occurrence times? Specification of continuous-time models that allow for random intervals between events is difficult. There is a well-established literature on the analysis of irregularly spaced time series. (See Parzen (1984), Jones (1985), and the references therein.) It is commonly assumed in these models that the irregularity is a property of the observational process per se, i.e., that the underlying process evolves homogeneously in real time, and that the irregular observation times are either fixed or are at least exogenous to the evolution of the process. In microstructure applications both of these assumptions are problematic, the former on account of intraday volatility patterns and the latter for reasons yet to be discussed. Nevertheless, this approach does achieve an appealing unity in capturing the discrete and continuous time aspects of a simple model. Furthermore, the techniques used to specify and estimate these models may yet be generalized to more complicated and realistic situations. From an economic perspective, time deformation in market data is usually assumed to result from variation in the "information intensity" of the market, the rate at which the informational primitives (public and private signals) evolve. This is difficult to operationalize because these primitives, with the exception of sharply defined events like press conferences, are rarely observed. Also, in most theoretical models, the informational primitives are exogenous, implying that the resulting time deformation would also be exogen. Other economic considerations, however, strongly suggest endogenous time effects. A market-maker, for example, might diminish the frequency of incoming order arrival simply by widening the bid-ask spread. This sometimes occurs in response to a particularly significant informational announcement. In this instance, the econometrician relying on trade frequency as a proxy for informational intensity will draw exactly the wrong inference. Easley and O'Hara (1992), Easley, Kiefer and O'Hara (1993, 1994) and Easley, O'Hara and Paperman (1995) discuss these effects and suggest empirical tests. Strategic quote-setting behaviour that can also lead to trade frequency effects is discussed by Leach and Madhavan (1992, 1993).

5. Conclusion And Recommendations

From a statistical perspective, the current state of the art falls considerably short of a plausible comprehensive model of transactions data. But statistical models in this area must be ultimately judged by their implications for the economic questions. From an economic perspective, the standing questions are those of how information enters market prices, how traders should behave (private welfare) and how markets should be organized (social welfare). Studies of trade-price behaviour have yielded a modest understanding of the first issue. It is an empirical fact that trades seem to explain part but not all of price changes. This confirms the existence of private information and establishes the importance of trading for the revelation or incorporation of this information. Answers to the other two fundamental questions, however, remain elusive. Trading strategy in most markets remains the province of human judgment, guided by experience and intuition, beyond the limits of existing normative models, even outside the realm of most ex post performance measurement excepting that of the roughest sort ("Did our investment strategy make money, net of trading costs?"). Nor have academic efforts to define economically efficient trading arrangements been particularly successful. While we have garnered greater insights into the workings of existing markets, we have yet to create yardsticks capable of ranking potential alternative arrangements. No consensus on these questions among academics, practitioners and regulators has yet emerged. It is certainly to be hoped that improved econometric models will provide useful in sign.

Recommendations

Incorporating realistic time effects into microstructure models is a difficult task that is likely to call forth more and better research efforts. But if time *per se* is not the focus of a particular analysis, the econometrician needs to match the method to the immediate problem and the data. For investigating broad hypotheses about intraday patterns in market data and associations in these patterns, it appears sufficient to rely on data aggregated over fixed time intervals (e.g., hours). For investigating causal relations (such as trade price impacts) that would be obscured by aggregation, the econometrician should lean toward modeling the data purely in event time, intuition of the formal time deformation approach: the "clock" of the process is assumed to be events.

Summary and Directions for Further Study

This paper has attempted to provide an overview of the various approaches to modeling microstructure time series. Rather than recapitulate these developments, it is perhaps more useful to return to the questions that motivated them. It was claimed in the introduction that microstructure models can potentially examine both narrow questions of trading behaviour and market organization and also broader issues of valuation and the nature of information. The present paper has focused, however, almost exclusively on the former. This emphasis can be justified on the grounds that any study using market transaction data must employ methods that reflect the market realities. But as a practical matter the economic importance of security valuation and the implications for the allocation of real assets almost certainly outweighs the welfare improvements that might result from modest changes in the trading mechanisms for most securities. It is therefore appropriate to briefly indicate the some of the ways in which microstructure studies can illuminate aspects of corporate finance.

The classic event study measures the impact of a public information event by the associated change in the security price. The insight of the asymmetric information models is that when the "event" is a trade, the price reaction summarizes the market's estimation of the private information behind the trade. Studies of the price impact of trades, the spread (under certain assumptions), or the summary *R;.,,x* measure introduced in section 3.2 thereby broadly characterize the market's beliefs about the magnitude of information asymmetries. Since these beliefs cannot usually be measured directly, the window offered by microstructure data may well be the only vantage point. Recent studies that explore asymmetric information in the vicinity of corporate announcements include Foster and Viswanathan (1995) (takeover announcements) and Lee, Mucklow and Ready (1993) (earnings announcements). Neal and Wheatley (1994) discuss the asymmetric information characteristics of closed-end mutual funds.

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