Do Bid-Ask Spreads Or Bid and Ask Depths Convey New Information *First*?

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Abstract

This paper investigates the *order* in which new information is first reflected in the market – through changes in spreads or through updated depths. We develop an error correction model of spreads and depths and estimate Gonzalo-Granger common factor components using two years of tick-by-tick quote data on all stocks in the Dow Jones Industrial Average. We show that indeed depths rather than spreads are first to impound new information that leads to new quote trends. Specifically, (bid and ask) depths convey information first in virtually every stock in both years, while spreads almost never convey information in 1998, and do so in only 8 out of 30 cases in 1995. Even in those 8 cases, the percentage of new information revealed by spreads ranges from 50 – 59% with the depths accounting for the rest. Our results have important implications for academic research on asymmetric information trading, for security market design, and for public policy.

JEL Classification: G12

1. Introduction

An important role of financial exchanges is to facilitate price discovery. In several related studies, Hasbrouck (1991, 1993, 1995, 2001), Harris et al. (1995, 2000, 2001), Liberman et al. (1999) and Frino et al. (2001) use time series techniques to answer questions about which market first discovers the innovations in security prices that prove to be new permanent trends.[2] While knowing which exchange or execution channel first captures price discovery is critical for effective execution of trading strategy and for security market public policy, none of these studies address the more fundamental question as to whether these information events are first reflected in price quotes or in the depths quoted at the bid and the ask.

Beginning with the seminal work of Demsetz (1968), the role of bid-ask spreads as a cost of immediacy and, by extension, market liquidity, has been studied extensively.[3] More recently, however, it has been recognized that a complete characterization of market liquidity should include both the bid-ask spread and the associated bid and ask size quotes (see, for example, Harris (1990)).[4] Intuitively, any information event like an earnings announcement or corporate restructuring that leads to an unambiguous decline in market liquidity would be reflected in a widening of the bid-ask spread and a declining size or depth (see, for example, Lee, Mucklow and Ready (1993)). Although a sizeable and growing literature examines the role of spreads and depths as a way to characterize the changing market liquidity around such events (see, for example, Lee et al. (1993), Chakravarty and McConnell (1997), Chung and Zhao (1999), and Chakravarty et al. (2001)), the extant theory is incapable of telling us the *order* in which new information should be reflected in the market—i.e., through changes in spreads first or through updated

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[2] Frino, Harris, McInish and Tomas (2001) apply a VECM to the electronic and floor execution channels in the Sydney Futures Exchange and the CBOT. Liberman, Ben-Zion, and Hauser (1999) and Ding, Harris, Lau and McInish (1999) showed multi-lateral error correction of dual-listed international stocks.

[3] The theoretical research is represented by Garman (1976), Stoll (1978), Ho and Stoll (1981), Copeland and Galai (1983), Glosten and Milgrom (1985), Easley and O'Hara (1987), among others.

[4] Bid and ask size quotes represent the number of shares for which the corresponding bid or ask price quotes are guaranteed.

depths first. This determination of the relative importance of depths versus spreads in revealing new information that leads to permanent price changes is ultimately an empirical issue and is the focus of the current paper.

To investigate this question, we develop a vector error correction model (VECM) that incorporates both spreads and depths. We estimate the model with a long time series of high frequency quote data on each of the thirty stocks in the DJIA over the calendar years 1995 and 1998. This time period was chosen to additionally investigate the changing role (if any) of spreads and depths in the wake of significant market reforms, like the decrease in the minimum quoted spreads from eighths to sixteenths.

VECMs allow us to study both the long-term equilibrium properties and the short-term adjustment dynamics of time-series variables that are cointegrated. Failure to detect and analyze the cointegration between microstructure-theoretic variables like price quotes, spreads and depths has often led to the serious misinterpretation of spurious regressions as long-run economic relationships rather than evidence of the common trends contained in non-stationary cointegrated time series. For example, Huberman and Halka (1999), Pastor and Stambaugh (2001) and Chordia, Roll and Subermanyam (2001) have all attempted to extract the liquidity premium in asset pricing models of the expected return without addressing the common stochastic trends in prices and order flows. Our work is perhaps closest in motivation to Hasbrouck and Seppi (2001) who use principal components and canonical correlation analysis to examine common factors in prices, order flow and liquidity. However, these authors do not model the dynamic adjustment process between spreads and depths and find their covariation to be small. In contrast, in this paper, we first conduct a unit root, system lag length, and cointegration analysis that establishes the appropriate specification of the prices, spreads and depths empirical model as a VECM. That is, the equilibrium dynamic adjustment process is shown to be an error correction mechanism.[5] We

[5] Engle and Patton (2001) have also employed a VECM to analyze price quotes and the spread as an error correction process. Our purpose is broader and our focus is different in that we feature the additional role of the size quotes in a prices, spreads and depths model.

then employ Gonzalo and Granger's (1995) common factor procedure to estimate the contribution of the spread and each depth to the common trend(s) underlying these three cointegrated variables.

We show that indeed depths rather than spreads are first to impound new information that leads to new quote trends. Specifically, (bid and ask) depths convey new information in virtually every stock in both years, while spreads almost never convey new information in 1998, and do so in only 8 out of 30 cases in 1995. Even in those 8 cases, the percentage of new information reflected in spreads ranges from 51% to 59% with the depths accounting for the rest. Our VECM parameter estimates over the two years 1995 and 1998 also suggest that while a tightening of the spreads in 1998, due to increased competition and a decrease in the minimum tick size to sixteenths from eighths, leads to an increased role of spreads in the error correction process, our basic conclusion of depths first revealing changes in the common stochastic trend remains intact.

Our results highlight the active role played by the limit order book in the price discovery process. This finding has important implications for academic research as well as for exchange regulators concerned with market liquidity -- especially due to the fact that that most of the depth changes in the limit order book represent the inflow of limit orders to the specialist rather than the specialist's personal interest. Specifically, theoretical modeling and empirical measures of adverse selection will need to provide at least as much weight to depths as to spreads. The limit order book, with its order sizes at the various pricing grids (the depths), needs to be monitored for continuity at least as closely as spreads are monitored. There is indication that such scrutiny has already begun. In March 2001, the NYSE started disseminating "depth indications" on eight of its stocks (WSJ, March 15, 2001, C1) – and has since been expanded to include all NYSE stocks. Its purpose is to show investors the existence of a meaningful number of shares of a given stock available beyond the best price being bid and offered for the stock..
The rest of the paper is structured as follows. Section 2 motivates the current research in light of recent literature. Section 3 develops an error correction model of spreads and depths. Section 4 provides an overview of the data used for the analyses. Section 5 addresses the appropriate specification of an error

correction model involving various pairs of price and depth quotes.[6] Section 6 reports tests of cointegration involving the spread and two depths and estimates the proportion of new information reflected in depths versus spreads. Section 7 provides a conclusion and directions for further research. The appendix provides estimates and tests of cointegrating vectors involving bid and ask quotes and bid and ask depths for all thirty stocks in our sample over 1995 and 1998.

2. Related Literature

The classical models of specialist pricing under asymmetric information effectively ignore depth by assuming unit size for all trades (Copeland and Galai (1983), Glosten and Milgrom (1985) and Easley and O'Hara (1992)). Other models capture depth implicitly by having the specialist quote complete pricing functions rather than individual bid and ask prices (Kyle (1985) and Rock (1999)). Even in these latter models, there is no discussion of how the spread and depths interact, especially in response to a changing information signal.

But a complete characterization of market liquidity should encompass both the bid-ask spreads and the market depth, i.e., the number of shares available at each bid and ask price (Harris (1990)). When liquidity is defined in these two dimensions, it is conceivable that a reduction in liquidity could occur through a reduction in bid or ask depth even though the quoted or effective spread is unchanged. Consistent with this intuition, Lee, Mucklow and Ready (1993) report the empirical result that spreads widen and depths fall in response to an increase in the amount of adverse selection present before earnings announcements. Harris, McInish, and Chakravarty (1995) show that a comparison of volume within a price regime to announced depth is a statistically significant determinant of subsequent quote revision for NYSE stocks. Chung and Zhao (1999) provide empirical evidence that Nasdaq dealers use both spreads and depths to manage market liquidity. Recently, Chakravarty, Harris and Wood (2001) find

[6] Appendix A provides results of cointegration tests involving four variables--the two price quotes and two depth quotes--for the representative stocks in the DJIA.

that while NYSE spreads have reduced considerably following decimalization, the corresponding bid and ask depths have also fallen. Thus, the empirical evidence appears to provide powerful evidence to support the notion that spreads and depths are actively managed by specialists and limit order traders.

The relationship between the limit order book and the order strategies of the traders has been theoretically examined by Cohen, Maier, Schwartz and Whitcomb (1981), O'Hara and Oldfield (1986), Rock (1999), Easley and O'Hara (1992), and Glosten (1994). Unfortunately, these early models either did not consider adverse selection issues or did not allow informed traders to submit limit orders. The limit order book, therefore, plays an insignificant role in the price discovery process.

Chakravarty and Holden (1995) were among the first to theoretically investigate the interaction between spreads and depths by explicitly allowing an informed trader to choose both market and limit orders to maximize his expected profit. Under fairly general conditions, the authors obtain a closed-form equilibrium where the informed trader chooses both market and limit orders, and, more importantly, uses the limit orders as a "safety net" for his market orders. Since both uninformed and the informed traders use limit orders in this framework, we can think of the resultant supply and demand schedule, the limit order book, to be (partially) informative. The Chakravarty and Holden model is, however, a single period model that precludes examining the spread-depth relationship in an intertemporal context.

Recently, Kavajecz (1998) formalizes the Lee, Mucklow and Ready (1993) empirical result by modeling a specialist choosing prices and depths jointly to maximize profits. In a similar vein, Dupont (2000) provides an asymmetric information model of spread and depth where the equilibrium depth is proportionally more sensitive than the spread, to changes in the degree of information asymmetry.

Two institutional features of asset markets also attest to the fact that the depth is an important empirical proxy for market liquidity. First, the NYSE specialist has an affirmative obligation to keep a fair and orderly market, which includes quoting tight spreads with reasonably indicative depths. The average spreads and depths are part of the monthly statistics reported on each specialist, and affect his performance evaluation. Excessive spreads or inadequate depths are regarded as indicators of poor performance, since they suggest relatively thin liquidity. Second, although there is some discreteness in both prices and depths, stock prices were quoted in large discrete intervals of quarters, 1/8ths and 1/16ths during 1995 and 1998 while depths were disaggregated into small 100 share lots. Accordingly, Lee, Mucklow and Ready (1993) argue that changes in market liquidity should be more easily detected in depths than in spreads.

In summary, the prevailing intuition in the microstructure theory literature is that both spreads and depths matter. The available empirical evidence, related to specific corporate/market events, also provides circumstantial evidence supporting this view. The extent and nature of the relationship between spreads and depths, however, especially in the context of how new information is reflected in subsequent updating of the spreads and depths, is an important empirical issue that has never been rigorously examined.

3. An Error Correction Model of Spreads and Depths

To investigate the comparative importance of depths and spreads in revealing new information, we employ an econometric dual of error correction--i.e., common trends estimation--first proposed by Stock and Watson (1988), refined by Hall, Anderson and Granger (1992), fully developed and applied to interest rate markets by Gonzalo and Granger (1995), and adapted to the Eurodollar futures market by Tse, Lee and Booth (1996). Recently, several papers have employed common trends estimation as a way to measure and test the comparative importance in stock price discovery of international exchanges involved in dual listings (Ding, Harris, Lau, and McInish, 1999; Liberman, Ben-Zion and Hauser, 1999)), of different execution channels within an exchange (Frino, Harris, McInish, and Tomas, 2001), and of the NYSE versus the regional exchanges (Harris, McInish and Wood, 2000).

3.1 The model

Suppose that a stock's unobservable implicit efficient price is a continuous series that can be represented as a random walk given by

$$\textbf{(1)} \qquad \mathbf{P_t = P_{t-1} + w_t} \quad \textbf{where } \mathbf{w} \overset{iid}{\sim} \mathbf{N(0, \sigma_w^2)}$$

where w_t is the random information arrival over the interval between (t-1) and t. Further, assume that the *observed* ask and bid price quotes at time t span,

$$\textbf{(2)} \qquad \mathbf{Ask}_t = \mathbf{P}_t + \varepsilon_{a,t}$$

and

$$\textbf{(2')} \qquad \mathbf{Bid}_t = \mathbf{P}_t + \varepsilon_{b,t}$$

where $\varepsilon_{a,t}$ and $\varepsilon_{b,t}$ are identically distributed zero mean covariance stationary random variables that may be autocorrelated. In addition, $E(w_t \varepsilon_{j,t-s}) \neq 0$ but w_t cannot be forecasted from $\varepsilon_{j,t-s}$ in the sense that $\varepsilon_{j,t-s}$ does not Granger cause w_t. Since these observed (bid and ask) price quotes do not mean revert, information arrivals lead to permanent shocks cumulating over the time between quote adjustments into a stochastic trend. Thus, at any realization, such as at t= T, both price quote sequences impound a common factor that is the stochastic trend in the unobserved implicit efficient price,

$$\textbf{(3)} \qquad \mathbf{Ask}_T = \mathbf{Ask}_0 + \sum_{t=1}^{T} w_t + \varepsilon_{a,T} \quad \textbf{and} \quad \mathbf{Bid}_T = \mathbf{Bid}_0 + \sum_{t=1}^{T} w_t + \varepsilon_{b,T},$$

and between any interval (t-1, t), we can write

$$\textbf{(4)} \qquad \mathbf{Ask}_t = \mathbf{Ask}_{t-1} + \mathbf{w}_t + \Delta\varepsilon_{a,t} \quad \textbf{and} \quad \mathbf{Bid}_t = \mathbf{Bid}_{t-1} + \mathbf{w}_t + \Delta\varepsilon_{b,t.}$$

Since Ask_t and Bid_t in equation (4) are both I(1) by maintained hypothesis, a linear combination representing the observed spread given by

$$\textbf{(5)} \qquad (\mathbf{Ask}_t - \mathbf{Bid}_t) = \varepsilon_{a,t} - \varepsilon_{b,t},$$

is stationary and we can write by the Granger Representation Theorem, a vector error correction model (VECM), as

$$\textbf{(6)} \quad \Delta\mathbf{Ask}_t = \alpha_{ask} + \sum_{t=1}^{S} \beta_{ask,\,ask,\,t-s}\, \Delta\mathbf{P}_{ask,\,t-s} + \sum_{t=1}^{S} \beta_{ask,\,bid,\,t-s}\, \Delta\mathbf{P}_{bid,\,t-s} + \gamma_{ask}\,(\mathbf{z}_{t-1}) + \mathbf{u}_{ask,\,t}\,.$$

where a natural definition for the error correction term (z_{t-1}) is the arbitrage-free condition that the equilibrium spread equal a constant that reflects the execution and inventory costs of market-making plus an I(0) white noise error term.

As an error correction term in this formulation of the model, the spread is assumed to be I(0). In later formulations, however, we specify a spread that is an I(1) variable in the cointegrating relations themselves. Which model is the appropriate specification depends on order of integration tests for the spread series, which we report below. Substituting from (5) into (6), we obtain

$$\textbf{(7)}\quad \Delta Ask_t = \alpha_{ask} + \beta_{ask}\, w_{t-s} + \beta_{ask, ask, t-s}\, \Delta\varepsilon_{a, t-s} + \beta_{ask, bid, t-s}\, \Delta\varepsilon_{b, t-s} + \gamma_{ask}\, (\varepsilon_{a, t-1} - \varepsilon_{b, t-1}) + u_{ask, t}.$$

We can similarly express the bid side VECM as

$$\textbf{(7')}\quad \Delta Bid_t = \alpha_{bid} + \beta_{bid}\, w_{t-s} + \beta_{bid, ask, t-s}\, \Delta\varepsilon_{a, t-s} + \beta_{bid, bid, t-s}\, \Delta\varepsilon_{b, t-s} + \gamma_{bid}\, (\varepsilon_{a, t-1} - \varepsilon_{b, t-1}) + u_{bid, t}.$$

Notice that in either (7) or (7'), $\mathbf{w}_{t-s}$ is the common factor capturing the permanent effects of new information on subsequent ask or bid price adjustments, $\Delta\varepsilon_{a, t-s}$ and $\Delta\varepsilon_{b, t-s}$ are idiosyncratic factors capturing the temporary effects and $(\varepsilon_{a, t-1} - \varepsilon_{b, t-1})$ is the error correction term that captures equilibrium adjustment to disparities in the level of the idiosyncratic disturbances.

Motivating our study is the idea that, rather than having the (updated) price quotes convey new information about informed trades, the depths at the pre-existing ask and bid could convey the arrival of information in the market. An analogous empirical model can therefore be developed for the size quotes, and the VECM for this information structure would then be written:

$$\textbf{(8)}\quad \Delta Asksz\ t = \alpha_{asz} + \beta_{asz}\, w_{t-s} + \beta_{asz, asz, t-s}\, \Delta\varepsilon_{asz, t-s} + \beta_{asz, bidsz, t-s}\, \Delta\varepsilon_{bsz, t-s} + \gamma_{asz}\, (\varepsilon_{asz, t-1} - \varepsilon_{bsz, t-1}) + u_{asz, t}$$

$$\textbf{(8')}\quad \Delta Bidsz\ t = \alpha_{bsz} + \beta_{bsz}\, w_{t-s} + \beta_{bsz, asz, t-s}\, \Delta\varepsilon_{asz, t-s} + \beta_{bisz, bsz, t-s}\, \Delta\varepsilon_{bsz, t-s} + \gamma_{bsz}\, (\varepsilon_{asz, t-1} - \varepsilon_{bsz, t-1}) + u_{bsz, t}$$

This second empirical framework highlights the role of strategic traders who time their trades to execute when the depths on one or both sides of the market are large and/or the net depth is at a minimum, so as to minimize the price impact of their trades. By assumption, the error correction term $(\varepsilon_{asz,\,t\text{-}1} - \varepsilon_{bsz,\,t\text{-}1})$ is the non-information-based source of different depths in the order flow at the ask and at the bid --i.e., simply that portion of the order imbalance at the pre-existing price quotes that results from market frictions. Comparing and assessing the origins of order flow on the opposite sides of the market is a function of the specialist and the crowd in floor trading environments but is increasingly performed by limit order and other traders in screen-based electronic trading environments.

Finally, it is also possible to formulate a composite information structure that combines the above hypothesized roles of price quotes and size quotes. As we suggested earlier, the time-series properties of the bid-ask spread may provide an error correction mechanism that conveys information to limit order traders who thereby adjust the size of their orders at the pre-existing price quotes. The specialist may similarly adjust depth quotes in response to his observation of the spread on incoming limit orders. For this information structure, the VECM looks as follows:

$$\text{(9)}\quad \Delta Asksz_t = \alpha_{asz} + \beta_{asz}\, w_{t\text{-}s} + \beta_{asz,\,asksz,\,t\text{-}s}\, \Delta\varepsilon_{asz,\,t\text{-}s} + \beta_{asksz,\,bidsz,\,t\text{-}s}\, \Delta\varepsilon_{bsz,\,t\text{-}s} + \gamma_{asz}\,(Spread_{t\text{-}1}) + u_{asz,\,t}.$$

$$\text{(9')}\quad \Delta Bidsz_t = \alpha_{bsz} + \beta_{bsz}\, w_{t\text{-}s} + \beta_{bsz,\,asz,\,t\text{-}s}\, \Delta\varepsilon_{asz,\,t\text{-}s} + \beta_{bisz,\,bsz,\,t\text{-}s}\, \Delta\varepsilon_{bsz,\,t\text{-}s} + \gamma_{bsz}\,(Spread_{t\text{-}1}) + u_{bsz,\,t}.$$

Other more hybrid information structures are clearly possible. In section 4, we test empirically whether price quotes themselves, depth quotes themselves, or prices and depths are cointegrated and if so, whether depths or spreads first convey the permanent innovations in an error correction/common factor components model.

3.2 Gonzalo and Granger decomposition

Although $\mathbf{w}_{t\text{-}s}$ in eqns. (7)-(9') is the first difference of the unobservable implicit efficient price, we can derive the β_{ask}, $\beta_{bid,}$ β_{asz}, and β_{bsz} parameters from estimates of γ_{ask}, γ_{bid}, γ_{asz}, and γ_{bsz} using the Gonzalo-Granger (1995) (GG) procedures. The GG decomposition involves expressing p cointegrated series as an additively separable function of k common factor(s), $\mathbf{f}_t$, and r stationary error correction terms, $\mathbf{z}_t = \alpha' \mathbf{P}_t$, where α' is an r x p matrix of the cointegrating vectors and $\mathbf{z}_t$ is I(0),

$$\text{(10)} \qquad \mathbf{P}_t = \mathbf{A_1} \mathbf{f}_t + \mathbf{A_2} \mathbf{z}_t$$

$$\text{(10')} \qquad \mathbf{P}_t = \mathbf{A_1} \gamma_\perp' \mathbf{P}_t + \mathbf{A_2} \alpha' \mathbf{P}_{t-1}.$$

$\mathbf{P}_t$ is a p x 1 vector of cointegrated prices or depths, $\mathbf{A_1}$ and $\mathbf{A_2}$ are loading matrices, and $\gamma_\perp'$ is a k x p matrix of common factor weights on the contemporaneous prices or depths in the k common factor vector(s) $\mathbf{f}_t$ where k = (p - r). Gonzalo and Granger (1995) show that under the above restrictions, the p x k matrix $\mathbf{A_1} = \alpha_\perp(\gamma_\perp' \alpha_\perp)^{-1}$ and the p x r matrix $\mathbf{A_2} = \gamma(\alpha'\gamma)^{-1}$, where, by definition, $\gamma_\perp'\gamma = 0$. Since the vector of common factor weights $\gamma_\perp$ is orthogonal to the coefficient vector γ on the error correction terms in a fully-specified VECM, the γ estimates in eqns. (7) -(9') provide a way to identify the permanent components $\gamma_\perp'\mathbf{P}_t$.

For example, consider an information structure that incorporates three I(1) variables—i.e., the price quote midpoint (MPQ), ½ of the summed size quote (SSZ), and the spread (SP)[7]--for the special case in which the spread is totally (100%) responsible for revelation of the permanent innovations in the common stochastic trend. Further, suppose that cointegration tests reveal two cointegrating vectors (r = 2) implying one common factor (k = 3 - 2) corresponding to $\Sigma\, \mathbf{w}_t$ in the foregoing model structure. With $k = 1$, the rank of the 3 x k loading matrix $\mathbf{A_1}$ in equation (10') would be 1 (i.e., each row of $\mathbf{A_1}$ is identical), and the elements of $\gamma_\perp$ would therefore cumulate the response of each series to an innovation in the composite common factor. The error correction terms of the VECM in equation (10') would then be estimated as

$$\text{(11)} \qquad \gamma \ \alpha' \ \mathbf{P}_{t-1} = \begin{bmatrix} \gamma_{SP} & \gamma_{SP} \\ \gamma_{MPQ} & \gamma_{MPQ} \\ \gamma_{SSZ} & \gamma_{SSZ} \end{bmatrix} \begin{bmatrix} \Pi_{1SP} & \Pi_{1MPQ} & \Pi_{1SSZ} \\ \Pi_{2SP} & \Pi_{2MPQ} & \Pi_{2SSZ} \end{bmatrix} \begin{bmatrix} P_{SP,\ t-1} \\ P_{MPQ,\ t-1} \\ P_{SSZ,\ t-1} \end{bmatrix}$$

[7] Our order of integration tests show that the spread is generally not I(0) but I(1) for most DJIA stocks during 1995 and 1998 when many institutional features of the security market design were changing rapidly.

where $\Pi_{1,i}$ and $\Pi_{2,i}$ are the elements of the cointegrating vectors. By hypothesis, $\gamma_{SP} = 0$ so that

(12) $$\gamma \ \alpha' \ \mathbf{P}_{t-1} =$$

$$\begin{bmatrix} 0 & 0 & 0 \\ \gamma_{MPQ}(\Pi_{1SP}+\Pi_{2SP}) & \gamma_{MPQ}(\Pi_{1MPQ}+\Pi_{2MPQ}) & \gamma_{MPQ}(\Pi_{1SSZ}+\Pi_{2SSZ}) \\ \gamma_{SSZ}(\Pi_{1SP}+\Pi_{2SP}) & \gamma_{SSZ}(\Pi_{1MPQ}+\Pi_{2MPQ}) & \gamma_{SSZ}(\Pi_{1SSZ}+\Pi_{2SSZ}) \end{bmatrix} \begin{bmatrix} P_{SP,\ t-1} \\ P_{MPQ,\ t-1} \\ P_{SSZ,\ t-1} \end{bmatrix}$$

Under this unilateral information discovery hypothesis, spreads do not error correct to changes in quote midpoints or summed depths whereas both the quote midpoint and summed depth do error correct to changes in spreads in order to maintain their equilibrium (cointegration) relationship to the permanent stochastic trend. To identify the GG common factor vector $\gamma_{\perp}$ for this case, one simply applies the orthogonality condition $\gamma_{\perp}' \gamma = 0$ which here implies $\gamma_{\perp}' = [\ 1 \quad 0 \quad 0\ ]$. That is, the factor weight $\gamma_{\perp,SP}$ corresponding to the first series in equations (11) and (12) is 1.0. One could therefore conclude spreads are 100% responsible for revealing the common stochastic trend.

3.3 Testing common factor weights

Gonzalo and Granger (1995) show how to take an equation of the form given by (7) - (9') and decompose it into permanent and temporary components and estimate $\gamma_{\perp}$ in (10') with reduced rank regression and eigenvector computations similar to those used by Johansen (1991) for estimating the cointegrating vectors $\alpha' \mathbf{P}_t$.[8] Most importantly, Gonzalo and Granger also develop a χ^2 distributed test statistic (Q_{GG}) for the elements of the common factor vector $\gamma_{\perp j}$. Because of the linear combination restriction on the $\gamma_{\perp j}$, these coefficients can be normalized and interpreted as a vector of factor weights on the underlying time series that together are responsible for the multivariate cointegration.

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[8] For detailed accounts of the estimation procedures to obtain common factor results, see Johansen (1995, chapter 8) and Gonzalo and Granger (1995). Hamilton (1994, chapters 19, 20) and Enders (1995, chapter 6), Booth, So and Tse (1999), and Huang (2000) provide useful treatments of cointegration econometrics.

These common factor weights provide a direct test of the revelation by price quotes, size quotes, or spreads of permanent innovations associated with the common stochastic trend. Under the null hypothesis of multi-lateral information discovery, each of the common factor weights can be tested seperately or in subgroups as significantly greater than zero --i.e., $H_0 : \gamma_{\perp j} > 0$ and $H_a : \gamma_{\perp j} = 0$. Consequently, one can test whether spreads are in fact responsible for revealing 100% of the common factor. As execution strategy becomes a focus of microstructure research, the kinds of comparisons allowed by these Q_{GG} statistical tests take on potentially pivotal meanings. In this paper, we use the common factor weights attributable to prices, spreads and depths to uncover the information structure of quote adjustment in DJIA stocks.

4. Data Overview

To estimate the cointegration-error correction relationship between the spread and the bid and ask depths, we use quote data for all 30 stocks comprising the DJIA in 1995 and then repeat the analysis for 1998. The tick-by-tick quote data are extracted from TAQ, available from the NYSE. Table 1 provides a breakdown of the thirty stocks in our sample in terms of the number of new quotes and average interval of time (SPAN, in seconds) between new quotes. For a new quote to be recorded in our dataset, at least one of the four parameters (bid, bid depth, ask or ask depth) has to be different. The average interval between new quotes declines sharply over the four years under study from 91 seconds in 1995 to 26 seconds in 1998.

The growth of market activity from 1995 to 1998 is also clear from the explosion in the number of quotes. For example, a typical increase ranges from 61,737 quotes at 95-second mean intervals for Chevron in 1995 to 229,866 quotes at 32-second mean intervals in 1998. In the current study, we consider only quotes originating from the NYSE. Having avoided the measurement bias issues introduced by ECN and regional autoquotes, our data set still comprises an average of 74,058 quotes per stock in 1995 and 260,927quotes per stock in 1998.

Table 1 also provides average spreads as well as the average bid depth and the average ask depth for each stock in 1995 and 1998. Across all DJIA stocks, the quoted spread declined by 27% from 16.5 to 12.1 cents. Depth measured by ½ of the summed size quotes plummeted by 61% from 150 to 59 round lots. Whether or not this massive decline in market liquidity that accompanied the tighter spreads over 1995-98 had an impact on the relative role of spreads and depths in revealing new information is one of the questions we seek to address.

5. Cointegration tests involving price quotes and depths

If multiple times-series contain common stochastic trends, they will error correct to temporary idiosyncratic disparities and their difference (or some other linear combination) will be a stationary stochastic process. In such an event, the underlying series are cointegrated. Thus, the notion of cointegration mimics the existence of a stable long-run equilibrium in economic systems that are not always in equilibrium. Kroner and Ng (1998) use this property to distinguish cointegration equilirium from arbitrage equilibrium. In cointegrated financial variables and markets, noise as well as news is generated continuously, and there is a lag with which the news can be incorporated. This gives rise to temporary disparities (or disequilibrium) that weave in and out of any underlying long-run relationships between the variables. A simple but effective way to capture both short and long-run effects of a system of economic variables, hypothesized to have such a relationship, is provided by a cointegration-error correction model.

In Table 2, we present Johansen's (1991) cointegration tests and Gonzalo and Granger's (1995) common factor weights for various combinations of price quotes and size quotes using all the TAQ data on IBM and AT&T in both 1995 and 1998. These Johansen tests were preceded by augmented Dickey-Fuller tests on the order of integration of the series. All were I(1). The Akaike Information Criterion was minimized for the set of VAR equations at six lags. We repeated all analyses with the other stocks in our DJIA sample (not reported for brevity). In all cases, our statistical inferences were the same.

In Panel A, testing for no cointegrating vector (r = 0) versus the alternative of one cointegrating vector (r = 1) in the bid and ask price series, the trace and Hmax (maximum eigenvalue) statistics indicate that the null is rejected at the 0.01 level. The implication is that the two series represented by the bid and ask prices are themselves cointegrated.[9]

Similarly, panel B provides cointegration test results of the bid depth and ask depth series for the same two stocks over 1995 and 1998. The conclusion, again, is that bid and the ask depths are cointegrated C(1); trace and Hmax test statistics reject H_0: r=0 at the 0.01 level. We then examine the obvious next question as to whether all four price and depth quotes are cointegrated. In the Appendix, we report results of Johansen's (1991) test for all 30 Dow stocks. In every case we are unable to reject the null hypothesis of zero as opposed to one or more cointegrating vectors. No linear combination of all four series is a mean reverting stationary long-term equilibrium process. The raw price quotes and depth quotes do not appear to error correct to discrepancies in one another's separate equilibrating relationships.[10]

Consistent with our earlier modeling discussion and with much of the direction of microstructure theoretical research, in panel C, we test for cointegration between the bid-ask spread (ask price – bid price) and the ask depth, while in panel D we test for cointegration between the spread series and the bid depth series. Motivating these specifications was a finding that spreads and depths were both 1(1) while an error correction term that combines the spread and net depth was I(0). Here, there is strong evidence suggesting that both spread and bid depth or spread and ask depth are, in fact, cointegrated. Finally, in Panel E, we relate spreads to ½ the summed size quotes from both sides of the market. Here, again, we see that spreads and depths are cointegrated C(1) with 99% confidence.

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[9] The $\gamma_{\perp\ ask}$ or $\gamma_{\perp\ bid}$ results, in the last two columns, are the common factor components which we discuss below.

[10] We looked for possible cointegration among the ask price and ask depth series. Using again the trace and Hmax test, we are unable to reject the null of no cointegration for all stocks in 1995 and 1998. The same is true for the bid price and bid depth series and for the bid price and ask depth series. These results are available from the authors.

In summary, from our VECM specification analysis, with the intra-day quote data for DJIA stocks over calendar years 1995 and 1998, we conclude that the bid and ask quotes appear to be cointegrated as do the bid and ask sizes. Importantly, however, individual price quote and depth quote series are not cointegrated while the quoted spread is significantly cointegrated with both the bid depth and the ask depth. This result concerning the appropriate specification of the VECM is robust to several definitions of depths as individual size quotes or ½ the summed size quotes.

6. Information Discovery Role of Depths over Spreads

6.1 Cointegration tests involving spreads and synchronous, paired bid and ask depths

Having found that the quoted spread and depths are cointegrated, we determine, in this section, the order of integration, optimal lag length, and cointegrating vectors for the system of <u>three</u> equations formed by the spread and the two depth series. Table 3 provides tests of the cointegrating vectors for the quoted spread and the corresponding bid and ask depths. These cointegrating vectors define the equilibrium errors that we subsequently employ in the systems estimation of the three-equation error correction model.

For each of the 30 stocks in our sample, and in each of the years 1995 and 1998, we provide results of the trace test to determine the rank of the cointegrating vector matrix using Johansen's (1991) analysis. Examining the null hypothesis of r cointegrating vectors against r+1, we run two tests of r = 0 against r = 1 and of r = 1 against r = 2. Table 3 indicates that in all 30 cases in 1995, the null of 0 cointegrating vectors is rejected in favor of the alternative of one cointegrating vector at the 99% level, and the null of one cointegrating vector is rejected in favor of the alternative of two cointegrating vectors at the 95% level in 10 of the 30 stocks. We also find that for 1998, we reject the null hypothesis of zero cointegrating vectors (in favor of the alternative of r = 1) in 27 out of the thirty stocks at the 95% level. Three of the sixty cases (GT98, MO98 and XON98) have no cointegrating vectors. The implication of these results is that in 47 of 60 stocks (20 in 1995 and 27 in 1998) the three-equation system of spread and depths is characterized by one cointegrating vector and two common stochastic trends.[11] For the ten cases in 1995 with two cointegrating vectors we infer one common trend.

6.2 Proportion of information discovery by spreads versus depths

The cointegration results of the previous section allow us to apply the Gonzalo-Granger common factor estimation and testing procedure to the three-variable model formed by the spread and the two depths. Table 4 displays our estimates of the common factor weights that reflect the contribution to the common trend attributable to the spread versus the bid and ask depths. For the 10 cases with two cointegrating vectors and one common trend (in boldface in Table 4), the common factor weights are derived from the third eigenvector of the common factor matrix orthogonal to the adjustment vector matrix (Gonzalo and Granger (1995)). For the 47 of 50 remaining cases with r =1, the weights for the first common trend are also reported in Table 4, and the weights for the second common trend (available from the authors) derive from the second eigenvector of this same matrix. We interpret the three elements of each of these eigenvectors as a factor weight—i.e., all reported weights are normalized to sum to 1.

We test each of the separate elements of the vector of common factor weights for statistical significance. In each case, the null hypothesis is that the individual factor weight of the indicated series is zero. This Gonzalo-Granger Qgg test statistic is distributed chi-squared with one degree of freedom. From Table 4, we reject the null hypothesis for the two depth series in all fifty-seven cases at the one percent level. In contrast, for the quoted spread series, we reject the null of zero common factor weight (at the 1% level) in only one case out of 27 in 1998 and in only 8 cases out of 30 in 1995. Our interpretation is that the (bid and ask) depths convey new information in literally every stock in the DJIA in 1995 and 1998 while the quoted spreads almost never convey information in 1998, and do so in only 8 of the 30 cases in 1995.

Interestingly, in those eight cases in 1995 and one in 1998 where the common factor weight on spreads is significant, the percentage of information discovery attributable to the spread varies between

[11] In addition to the $\Sigma\ w_t$ information arrivals for the first common trend, an illustration of a second common trend affecting these primarily multinational DJIA stocks might be the trade-weighted U.S. dollar exchange rate.

only 50 and 59%, with the depths revealing the remaining 41-50% of the information. Since seven of these nine total cases indicate just one cointegrating vector among the three series and therefore two common trends, we can examine the factor weight on spreads in the second common trend as a further indication of the role of spreads versus depths in information discovery. In each instance, the proportion of information discovery is decidedly smaller in spreads (the first number listed) than in depths (the last two numbers listed): (BA95: 0.255, 0.409, 0.336); (EK95: 0.023, 0.481, 0.495); (GE95: 0.042, 0.463, 0.495); (IP95: 0.066, 0.484, 0.450); (MO95: 0.245, 0.408, 0.346); (XON95: 0.005, 0.466, 0.529); (WMT98: 0.076, 0.446, 0.478). All depth numbers are statistically significant at the 1% level. At the mean, in these seven cases, the second common factor weight on spreads is just 10.8% with depths accounting for 89.2%, and in no cases is $\gamma_{\perp \text{ SPREADS}}$ ever significant.

To examine further the inference that depths rather than spreads predominantly convey new information, we present in Table 5 the Gonzalo and Granger (1995) Q_{gg} statistic for the null hypothesis that the common factor weight for the quoted spreads is 1 and that the common factor weights of the two depths are both 0. The test statistic is distributed chi-squared with two degrees of freedom. The table indicates that we reject the null hypothesis at a 1% level of significance in 55 of the 57 cases and at 2% in the other two cases.[12]

The implication from Tables 4 and 5 is that, relative to the quoted bid-ask spreads, the depths appear to convey significantly more information. The fact that our results are also consistent across the years 1995 and 1998 entailing dynamic institutional change in the NYSE attests to the robustness of our conclusions.

6.3 Error Correction Model for A DJIA Stock

In this section, we provide details of the VECM parameter estimates for IBM. The purpose is to characterize the nature of the underlying equilibrium relationship between spreads and depths for a typical stock in our DJIA sample. We detail exactly how information inherent in current changes in depth gets

[12] Recall that in three stocks listed as n.a., Johansen's test indicated no cointegrating vectors.

incorporated in future adjustments of the spread more so than the reverse case of current changes in the spread getting incorporated in future adjustments of the depth(s).

The Johansen procedure for IBM yields the following two equilibrium error relationships implied by the cointegrating vectors (in parenteses) for IBM95,

$$\textbf{(11)} \quad -\gamma_1 Z1_{t-1} = -\gamma_1 (0.0180\, \textbf{\textit{SPREAD}}_{t-1} + 0.000922\, \textbf{\textit{ASKSIZE}}_{t-1} + 0.000876\, \textbf{\textit{BIDSIZE}}_{t-1})$$

$$\textbf{(12)} \quad -\gamma_2 Z2_{t-1} = -\gamma_2 (0.000264\, \textbf{\textit{SPREAD}}_{t-1} - 0.00337\, \textbf{\textit{ASKSIZE}}_{t-1} + 0.00334\, \textbf{\textit{BIDSIZE}}_{t-1}),$$

and for IBM98 the corresponding error correction terms are

$$\textbf{(13)} \quad -\gamma_2 Z1_{t-1} = -\gamma_2 (0.0115\, \textbf{\textit{SPREAD}}_{t-1} + 0.00176\, \textbf{\textit{ASKSIZE}}_{t-1} + 0.00191\, \textbf{\textit{BIDSIZE}}_{t-1})$$

$$\textbf{(14)} \quad -\gamma_2 Z2_{t-1} = -\gamma_2 (0.00076\, \textbf{\textit{SPREAD}}_{t-1} - 0.00395\, \textbf{\textit{ASKSIZE}}_{t-1} + 0.00365\textbf{\textit{BIDSIZE}}_{t-1}).$$

In either year, an increase in *BIDSIZE* relative to *ASKSIZE* (an increased buy-side order imbalance) with no change in spread will increase both Z1 and Z2. Remembering that error correction terms are specified by convention as $-\gamma Z_{t-1}$ in the VECM, an increased Z1 and Z2 result in lower *SPREAD*, lower *BIDSIZE* and lower *ASKSIZE* if the estimated $\gamma_i > 0$. With increased spreads (and no change in the order balance/imbalance), again both Z1 and Z2 increase with the same results for *SPREAD*, *BIDSIZE* and *ASKSIZE*. *ASKSIZE*, on the other hand, raises Z1 but lowers Z2. We should, therefore, expect opposite signs on the γ_1 and γ_2 parameters for the *ASKSIZE* equation in the VECM estimates. For example, if increased *ASKSIZE* leads to sell order imbalance, we should expect changes in the *SPREAD*, *ASKSIZE*, and *BIDSIZE* error correction system that results in reduced size order imbalance. With Z1 increased, $\gamma > 0$ on Z1 leads to *ASKSIZE* reduction whereas with Z2 diminished, $\gamma < 0$ on Z2 leads to *ASKSIZE* reduction. We now examine Table 6 to look for this pattern of hypothesized results.

Recall the vector error correction model is specified as,

$$(15)\ \Delta SPREAD_t = \alpha_{SP} + \beta_{SP, SP, t-1} \Delta SPREAD_{t-1} + \beta_{SP,SP\ t-2} \Delta SPREAD_{t-2} + \ldots + \beta_{SP, SP, t-p} \Delta SPREAD_{t-p}$$

$$+ \beta_{SP, ASZ, t-1}\ \Delta ASKSIZE_{t-1} + \beta_{SP, ASZ, t-2}\ \Delta ASKSIZE_{t-2} + \ldots + \beta_{SP, ASZ, t-p}\ \Delta ASKSIZE_{t-p}$$

$$+ \beta_{SP, BSZ, t-1}\ \Delta BIDSIZE_{t-1} + \beta_{SP, BSZ, t-2}\ \Delta BIDSIZE_{t-2} + \ldots + \beta_{SP, BSZ, t-p}\ \Delta BIDSIZE_{t-p} - \gamma_{11}\ Z1_{t-1} - \gamma_{12}\ Z2_{t-1} + u_{1t}$$

$$(16)\ \Delta ASKSIZE_t = c2 + b_{11} \Delta SPREAD_{t-1} + b_{12} \Delta SPREAD_{t-2} + \ldots. + b_{1p} \Delta SPREAD_{t-p}$$

$$+ b_{21} \Delta ASKSIZE_{t-1} + b_{22} \Delta ASKSIZE_{t-2} + \ldots\ldots\ldots + b_{2p} \Delta ASKSIZE_{t-p}$$

$$+ b_{31} \Delta BIDSIZE_{t-1} + b_{32} \Delta BIDSIZE_{t-2} + \ldots\ldots\ldots + b_{3p} \Delta BIDSIZE_{t-p} - \gamma_{21}\ Z1_{t-1} - \gamma_{22}\ Z2_{t-1} + u_{2t}$$

$$(17)\ \Delta BIDSIZE_t = c3 + c_{11} \Delta SPREAD_{t-1} + c_{12} \Delta SPREAD_{t-2} + \ldots. + c_{1p} \Delta SPREAD_{t-p}$$

$$+ c_{21} \Delta ASKSIZE_{t-1} + c_{22} \Delta ASKSIZE_{t-2} + \ldots\ldots\ldots + c_{2p} \Delta ASKSIZE_{t-p}$$

$$+ c_{31} \Delta BIDSIZE_{t-1} + c_{32} \Delta BIDSIZE_{t-2} + \ldots\ldots\ldots + c_{3p} \Delta BIDSIZE_{t-p} - \gamma_{31}\ Z1_{t-1} - \gamma_{32}\ Z2_{t-1} + u_{3t}$$

where p is the lag length. If γ_{11} and γ_{12} are insignificantly different from zero, then spreads do not respond to changes in depths, and spreads are considered the source of permanent stochastic trends. Similarly, if γ_{21} and γ_{22} (γ_{31} and γ_{32}) are insignificantly different from zero, then ask depth (bid depth) does not respond to changes in spreads or bid depth (ask depth), and ask depth (bid depth) is considered the source of the permanent stochastic trend. The cointegrating vectors define the long-run equilibrium relationship while the error correction dynamics characterize the information discovery process. The possibility that one or two variables in a system of n cointegrated series might play this information discovery role motivates our use of error correction models.

Table 6 Panel A provides the Seemingly Unrelated Regression (SUR) estimates for IBM95 of the three error correction equations with six estimated as the optimal lag length in the unrestricted system of VAR equations. All starred coefficient estimates are significant at the 1% level. The coefficient magnitudes of lagged *SPREAD*, lagged *ASKSIZE*, and lagged *BIDSIZE* all decline throughout the optimal lag structure, as expected. The sets of variables are tested with an F test at the bottom of the table. All three sets of lagged variables are statistically significant at the 1% level with the six lagged spreads most influential in the spreads equation, and the six lagged depths most influential in each of the respective depth equations. Each of the compound error correction terms Z1 and Z2 is statistically significant at 1% in all three equations.

Moreover, the Z terms have exactly the expected pattern of signs discussed above. An increased Z1 results in lower spreads, asksizes and bidsizes (remembering again that the error correction terms are specified as $-\gamma_1 Z1_{t-1}$ and noting that we find $\gamma_1>0$). For example, an idiosyncratic (i.e., noise-related) increase in spreads results in a positive Z1 equilibrium error which is self-correcting in that SPREAD adjusts downwards in response. Similarly, an idiosyncratic increase in either depth results in a positive Z1 equilibrium error that sets off self-correcting retrenchment in the corresponding depth. The Z2 term is more complicated. Because increased ASKSIZE in equations (11) through (14) raises Z1 but lowers Z2, we find that increased ASKSIZE reduces the sell order imbalance not only (as just explained) through higher Z1 but also, as expected, through the inverse effect of Z2. That is, because of our finding throughout Table 6 of a negative $\gamma_{2, ASZ}$ parameter on Z2 in the ASKSIZE equation, a lower Z2 also results in continuing downward adjustment of idiosyncratically high ASKSIZE. On the other hand, the Z2 equilibrium error in the SPREAD and BIDSIZE equation operates through direct effects. Higher idiosynchratic SPREAD or BIDSIZE increases Z2 which with $\gamma_{2, S}$ or $\gamma_{2, BSZ} > 0$ and a $-\gamma_2$ Z2 error correction term implies lower SPREAD or BIDSIZE, respectively.

To confirm our VECM specification, we also provide in Table 7 the corresponding unrestricted vector autoregession (VAR) estimates for IBM95. The only difference between the VAR and the VECM is the two error correction terms. Comparing the R-square and regression F-statistics between the VAR and VECM models shows that the equilibrium errors ($Z1_{t-1}$ and $Z2_{t-1}$) are responsible for a significant proportion of the variation explained in *ΔSPREAD*, *ΔBIDSIZE*, and *ΔASKSIZE*. Thus, for example, with the addition of the error correction terms, R-square increases from 0.33 to 0.39 in the *ΔSPREAD* equation, from 0.19 to 0.24 in the *ΔASKSIZE* equation and from 0.18 to 0.22 in the *ΔBIDSIZE* equation. The F-statistics for the Z1 and Z2 variable set are 4,231 and 2,488 and 2,174, respectively. Clearly, the VECM specification of this model is preferred over an unrestricted VAR in levels, providing confirmation of our error correction-common factor empirical methodology.

Table 6 Panel B provides the VECM estimates for IBM 1998. While in sign and significance of parameter estimates, IBM 1995 and IBM 1998 are almost identical, the magnitude of the parameter estimates themselves are significantly different, and this finding has some important implications discussed in the next section.

6.4 Discussion of Results

Our consistent finding in essentially all the DJIA stocks in 1995 and 1998 is that depths convey new information first. This finding is robust across several specifications of depth in the spreads-depth VECM. Between the years 1995 and 1998, three differences in the results stand out. All three relate to the role of spreads in information discovery. First, the error correction parameters on lagged spreads in the *ASKSIZE* and *BIDSIZE* equations in Table 6 Panel A are approximately twice as large as the same parameters in Panel B that reports the same VECM for IBM in 1998. Apparently the wider spreads in the earlier period (1995 in Table 6 Panel A) conveyed less accurate information and necessitated wider fluctuations of the depths to adjust to the possible multiple interpretations of the spread changes. In contrast, with tighter spreads in 1998 (see Table 1 for a comparison stock by stock), specialists and limit order traders felt confident in making smaller depth adjustments in response to the order flow that warranted changing the spread. This, of course, is an indirect role for spreads in the information discovery process since depth adjustment is where information-based, permanent innovations in the stochastic process first show up.

Second, however, we detect some evidence suggesting an enhanced direct role for spreads in 1998 information discovery. When the spreads tightened in 1998, the bottom three rows of Table 3 convey that in 27 out of 30 DJIA stocks only one, not two, cointegrating vectors were statistically significant in the error correction process. This cointegrating vector test result is mirrored in the error correction results in Table 6 Panel B for IBM 1998 where the second "equilibrium error" is not significant in the spreads equation. This finding (which differs from the significance of the same term in Table 6

Panel A for IBM 1995) relates to our conjecture in section 6.1 that finding only one equilibrium error process in 1998 opens a role for a second stochastic common trend involving spreads. Recall that in the pure case of two cointegrated variables and an error correction term expressed as their difference, the source of the common stochastic trend does not error correct to the equilibrium error (the Z term) whereas the subsidiary variable does. Here, of course, we have a compound error correction term involving a linear function of all three variables. Nevertheless, the insignificance result on Z2(t-1) in the *SPREAD* equation of Table 6 Panel B is suggestive of an enhanced information discovery role for the tighter 1998 spreads that is not present in the 1995 data.

Third, this enhanced role for tighter spreads in information discovery is further suggested by the magnitude of the common factor weights in Panel E of Table 2. There we were investigating the appropriate specification of a spreads and depths VECM model. Recall that in Table 2 Panel E, the spreads were found to be cointegrated with ½ the summed depths for IBM in 1995 and 1998. In addition, the last two columns report common factor weights for spreads and depths. As in other specifications of the spreads-depth model reported throughout the paper, depths predominate and are statistically significant in setting the common trend. Notice, however, that an overwhelming common factor weight on summed depths in 1995 (0.768) becomes a more nearly equal weight in 1998 (0.490). The remainder of the common trend in 1998 -- namely, 51%-- is associated with innovations in the spread. Although there is still too much noise in spread changes to allow the 0.510 factor weight to test out as statistically significantly different from zero, some increased role of these tighter 1998 spreads in information discovery is suggested.

Contrary to the intuition in the early theoretical microstructure models, our results also underscore the important role played by the limit order book in the price discovery process. It appears that informed traders actively use the limit order book to effect all or part of their trades. This execution strategy is consistent with the intuition modeled in Chakravarty and Holden (1995). Optimal execution strategy would also lead the informed traders to choose their trade sizes (and, by extension, their aggressiveness) as a function of uninformed trading properties (Admati and Pfleiderer (1988, 1989)), and this could also predominantly involve the limit order book.

It is likely that the wider spreads in 1995 reflected in part a barrier to effective price competition perpetuated by the 1/8th minimum tick size. Following the reduction in the minimum tick size from eighths to sixteenths in 1997, the resulting narrower spreads were significantly more informative than their earlier counterparts in 1995. Nevertheless, our conclusion remains in place for 1998: Depths overwhelmingly account for the common stochastic trend(s).

7. Concluding Summary

We use a vector error correction framework and a long time-series of high frequency data to analyze the relative importance of bid-ask spreads and the associated bid and ask depths in revealing new information that affects quote revision. The importance of the current work lies in the fact that the microstructure theory literature has traditionally recognized (changes in) the bid-ask spread as the primary measure of adverse selection and information-based trading in security markets (McInish and Wood (1992), Peterson and Fialkowski (1994), Huang and Stoll (1996), Bessembinder (1997)). To our knowledge, our research is the first to investigate, within a cointegration/error correction framework, whether depths play an even more important role (than spreads) in this information revelation process.

Our results indicate that new information is reflected overwhelmingly in (bid and ask) depth updates rather than in spread updates. At first glance, our central result may appear to violate many researchers' priors that prices should, in general, lead rather than follow. But perhaps it is not surprising to find that size leads and prices follow, especially when one remembers that size offers strategic limit order traders a variety of options including raising the aggregate depth statistic at the prevailing BBO simply by improving the best bid or offer prices one tick.

An implication of our finding is that the emphasis on bid-ask spreads as a determinant of execution strategy and as a signal of information arrivals in financial market microstructure may have been somewhat misplaced. Our finding provides support for recent theoretical models that attempt to formalize the intuition that depths are at least as important as spreads in permanently incorporating new information arrival in the market.

References

Admati, A., and P. Pfleiderer, 1988, A theory of intraday patterns: volume and price variability, Review of Financial Studies, 1, 3-40.

Admati, A., and P. Pfleiderer, 1989, Divide and conquer: a theory of intraday and day-of-the-week mean effects, Review of Financial Studies, 2, 189-224.

Bessembinder, H., 1997, The degree of price resolution and equity trading costs, *Journal of Financial Economics*, 45, 9-34.

Booth, G.G., R. So, and Y. Tse, 1996, Price discovery in the German equity index derivatives markets, *Journal of Futures Markets*, 19, 619-643.

Chakravarty, S. and C. Holden, 1995, An integrated model of market and limit orders, *Journal of Financial Intermediation*, 4, 213-241.

Chakravarty, S., and J.J. McConnell, 1997, An analysis of prices, bid/ask spreads and bid and ask depths surrounding Ivan Boesky's illegal trading in Carnation stock, *Financial Management,* 26, 18-34.

Chakravarty, S., S. Harris, and R.A. Wood, 2001, Decimal trading and market impact, Working paper, Purdue University.

Chakravarty, S., 2001, Stealth Trading: Which Trader's Trades Move Stock Prices, *Journal of Financial Economics*, 61, 289-307.

Chordia, T., R. Roll, and A. Subrahmanyam (2001), Order imbalance, liquidity, and market returns, *Journal of Financial Economics,* forthcoming.

Chung, K. H. and X. Zhao, 1999, Making a market with spreads and depths, Working paper, University of Memphis, TN.

Cohen, K., S. Maier, R. Schwartz, and D. Whitcomb, 1981, Transaction costs, order placement strategy, and existence of the bid-ask spread, *Journal of Political Economy*, 89, 287-305.

Copeland, T., and D. Galai, 1983, Information effects and the bid-ask spread, *Journal of Finance*, 38, 1457-1469.

Demsetz, H., 1968, The cost of transacting, *Quarterly Journal of Economics*, 82, 33-53.

Ding, D., F. H. deB. Harris, S. T. Lau, and T. H. McInish, 1999, An investigation of price discovery in informationally-linked markets: Equity trading in Malaysia and Singapore, *Journal of Multinational Financial Management*, 9, 317-29.

Dupont, D., 2000, Market making, prices and quantity limits, *Review of Financial Studies*, 13, 1129-51.

Easley, D. and M. O'Hara, 1987, Price, trade size and information in securities markets, *Journal of Financial Economics*, 19, 69-90.

Easley, D. and M. O'Hara, 1992, Time and the process of security price adjustment, *Journal of Finance*, 47, 577-605.

Engle, R. and A. Patton, 2001, Impacts of trades in an error correction model of quote prices, Working paper, University of California, San Diego.

Enders, W., 1995, *Applied Econometric Time Series*, Wiley-Interscience: New York, NY.

Frino, A., F. Harris, T. McInish, and M. Tomas, 2000, Price discovery in the pits: The role of floor brokers on the Sydney Futures Exchange and the CBOT, Working Paper, Wake Forest University.

Frino, A., Harris, F. H. deB., and T.H. McInish, 1999, Evidence of price discovery on the CBOT and Sydney futures exchange, Working paper, Wake Forest University, Winston-Salem, NC.

Garman, M., 1976, Market microstructure, *Journal of Financial Economics*, 3, 257-275.

Glosten, L.R., and P.R. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, *Journal of Financial Economics*, 14, 71-100.

Glosten, L.R., 1994, Is the electronic open limit order book inevitable? *Journal of Finance*, 49, 1127-1161.

Gonzalo, J. and C. Granger, 1995, Estimation of common long-memory components in cointegrated systems, *Journal of Business and Economic Statistics*, 13, 1-19.

Hall, A.D., H.M. Anderson, C.W. J. Granger, 1992, A cointegration analysis of Treasury bill yields, *Review of Economics and Statistics*, 74, 116-126.

Hamilton, J.D., 1994, *Time series analysis*, Princeton University Press, Princeton, New Jersey.

Harris, F. H. deB., McInish, T.H., Shoesmith, G. L., and R.A. Wood, 1995, Cointegration, error correction, and price discovery on informationally linked security markets, *Journal of Financial and Quantitative Analysis*, 30, 563-579.

Harris, F. H.deB., McInish, T.H., and R. Chakravarty, 1995, Bids and asks in disequilibrium market microstructure, *Journal of Banking and Finance*, 19, 323-345.

Harris, F. H. deB., McInish, T.H., and R.A. Wood, 2000, Security price adjustment across exchanges: an investigation of common factor components for Dow stocks, *Journal of Financial Markets, forthcoming*.

Harris, F. H. deB., McInish, T.H., and R.A. Wood, 2001, Common factor components versus information shares, *Journal of Financial Markets,* forthcoming.

Harris, L.E., 1990, Liquidity, trading rules and electronic trading systems, *New York University Monograph Series in Finance and Economics*, Monograph No. 1990-4.

Hasbrouck, J., 1991, The summary informativeness of stock trades: an econometric analysis, *Review of Financial Studies*, 4, 571-595.

Hasbrouck, J., 1993, Assessing the quality of a security market: A new approach to transaction cost measurement, *Review of Financial Studies*, 6, 191-212.

Hasbrouck, J., 1995, One security, many markets: Determining the contributions to price discovery, *Journal of Finance*, 50, 1175-1201.

Hasbrouck, J. and D. Seppi, 2001, Common factors in prices, order flows and liquidity, *Journal of Financial Economcis,*59, 383-411.

Hasbrouck, J., 2001, Stalking the efficient price, *Journal of Financial Markets,* forthcoming.

Ho, T., and H.R. Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, Journal of Financial Economics, 9, 47-73.

Huang, R.D., and H.R. Stoll, 1996, Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE, *Journal of Financial Economics*, 41, 313-357.

Huang, R.D., 2000, Price discovery by ECNs and Nasdaq market makers, working paper, University of Notre Dame, Indiana.

Hubermann, G. and D. Halka, 1999, Systematic liquidity, Paine Weber Working Paper Series in Money, Economics and Finance, Columbia Business School.

Johansen, S., 1991, A statistical analysis of cointegration for I(2) variables, working paper, University of Copenhagen.

Johansen, S., 1995, *Liklihood-Based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press, New York, NY.

Kavajecz, K.A., 1998, A specialist's quoted depth as a strategic choice variable, Working paper, University of Pennsylvania, PA.

Kroner, K. E., and V.K. Ng, 1998, Modeling asymmetric comovements of asset returns, Review of Financial Studies, 11, 817-844.

Kumar, P., and D. Seppi, 1993, Limit and market orders with optimizing traders, Working paper, Carnegie-Mellon University.

Kyle, A.S., 1985, Continuous auctions and insider trading, *Econometrica*, 53, 1315-1336.

Lee, C. M. C., Mucklow, B., and M. Ready, 1993, Spreads, depths and the impact of earnings information: an intraday analysis, *Review of Financial Studies*, 6, 345-374.

Liberman, O., U. Ben-Zion, and S. Hauser, 1999, A characterization of the price behavior of international dual-listed stocks: An error-correction approach *Journal of International Money and Finance*, 18(2), 289.

McInish, T.H., Wood, R.A., 1992, An analysis of intraday patterns in bid-ask spreads for NYSE stocks, *Journal of Finance*, 47, 753-764.

O' Hara, M., and G. Oldfield, 1986, The microeconomics of market making, *Journal of Financial and Quantitative Analysis*, 21, 361-376.

Pastor, L. and R. Stambaugh, 2001, Liquidity risk and expected stock returns, Working paper, Graduate School of Business, University of Chaicago.

Peterson, M. and D. Fialkowski, 1994, Posted versus effective spreads, *Journal of Financial Economics*, 35, 269-292.

Rock, K., 1999, The specialist's limit order book, *Review of Financial Studies, forthcoming*.

Stock, J. and M.W.Watson, 1988, Testing for common trends, *Journal of the American Statistical Association,* 83, 1097-1107.

Tse, Y., Lee, T.H. and G.G. Booth, 1996, The international transmission of information in Eurodollar futures markets: A continuous markets hypothesis, *Journal of International Money and Finance*, 15, 447-465.

Table 1. Descriptive Statistics

DJIA 30 stocks showing the number of quote observations in 1995 and 1998, the average time interval between observations, the average ask price minus bid price, and the average depths (expressed in round lots of 100 shares).

	1995					1998				
Stock	**No. Obs.**	**Span (secs)**	**Spread (cents)**	**Depth at Ask**	**Depth at Bid**	**No. Obs.**	**Span (secs)**	**Spread (cents)**	**Depth at Ask**	**Depth at Bid**
AA	74,459	79	18.8	80.6	60.6	165,322	35	13.6	42.4	32.1
ALD	42,900	136	17.5	110.3	98.4	183,307	33	14.6	57.0	52.1
AXP	50,759	115	15.5	261.5	240.4	290,043	32	14.7	33.7	26.2
BA	54,028	108	17.8	100.6	109.8	341,570	20	9.4	103.6	106.3
CAT	58,210	100	17.8	75.0	66.3	184,673	17	11.1	67.3	38.4
CHV	61,737	95	16.1	163.9	118.4	229,866	32	12.5	47.3	35.5
DD	114,203	51	15.9	135.3	104.6	425,811	25	12.4	55.3	42.2
DIS	104,717	56	15.4	181.9	138.7	312,174	14	10.7	108.9	76.7
EK	90,668	65	15.8	105.7	88.6	224,131	26	12.3	45.9	38.1
GE	97,823	60	15.7	205.3	182.4	121,832	48	9.8	76.9	56.7
GM	53,163	110	16.3	198.2	210.9	260,588	22	9.9	63.9	56.6
GT	56,868	103	17.0	109.9	94.7	137,116	43	16.5	40.3	32.3
HWP	174,666	33	19.0	61.3	47.6	391,003	15	11.0	64.9	52.8
IBM	122,705	48	17.2	131.6	108.6	336,014	17	13.7	52.2	42.1
IP	92,799	63	17.6	91.3	71.9	199,380	29	12.0	59.1	42.9
JNJ	101,870	57	15.4	120.3	96.3	279,775	21	10.0	67.2	49.1
JPM	63,923	92	17.5	57.2	43.6	232,834	25	19.3	25.8	19.6
KO	98,629	59	14.7	178.5	157.9	346,350	17	9.1	83.6	61.3
MMM	58,096	101	17.2	95.3	80.6	197,681	30	14.6	38.3	30.2
MO	79,982	73	15.6	157.2	152.1	436,053	13	9.4	153.4	137.4
MRK	51,238	114	15.5	324.0	292.3	173,082	34	12.2	41.5	33.3
MCD	53,251	110	14.8	254.4	205.4	247,650	24	10.6	68.6	56.7
PG	96,940	60	17.0	81.9	70.2	392,998	15	13.9	47.1	35.6
S	51,507	114	16.3	184.9	147.8	225,368	26	11.8	50.8	45.6
T	58,610	100	15.6	316.9	259.0	236,918	25	10.2	127.2	89.0
TRV	43,659	134	17.8	106.9	98.1	327,322	18	10.0	115.1	81.9
UK	45,482	129	16.4	92.6	82.9	133,489	44	12.2	50.0	36.6
UTX	50,958	115	19.8	60.4	57.6	188,633	31	16.4	39.2	25.6
WMT	31,485	186	15.0	522.4	504.2	294,922	20	9.4	77.1	59.1
XON	86,392	68	15.1	214.7	176.1	311,905	19	10.7	80.1	72.1
Mean	**74,058**	**91.1**	**16.5**	**159.8**	**139.5**	**260,927**	**25.7**	**12.1**	**66.1**	**52.3**

Table 2. Specification Analysis for Quote Data.

The various panels of the table indicate the stock ticker and the year for which the cointegration tests are carried out; Hypothesis indicates the specific nature of the null and the alternative; Trace and Hmax are Johansen's (1991) cointegration test statistics, and Conclusion summarizes whether the variables are cointegrated. Σ_γ is the sum of the magnitudes of the cointegrating vector (suggesting the magnitude of possible arbitrage profit opportunities) while $\gamma_{\perp\,ask}$ and $\gamma_{\perp\,bid}$ are common factor weights for the ask and the bid (or the ask size and the bid size), respectively. Note that $\gamma_{\perp\,ask} + \gamma_{\perp\,bid} = 1$. The results are provided for IBM and AT&T, estimated over calendar years 1995 and 1998. Similar results were obtained for other DJIA stocks.
** (*) denotes significance at the 0.01 (0.05) level.

Panel A: Price Quotes

	Hypothesis	Trace	Hmax	Conclusion	$\Sigma\gamma$	$\gamma_{\perp\,ask}$	$\gamma_{\perp\,bid}$
IBM95	H_0:r = 0, H_a:r =1	26.75**	26.74**	C (1)	0.00003	0.496**	0.504**
IBM98	H_0:r = 0, H_a:r =1	19.64*	16.63*	C (1)	0.0001	0.554**	0.446**
T95	H_0:r = 0, H_a:r =1	28.03**	28.02**	C (1)	0.000006	0.237**	0.763**
T98	H_0:r = 0, H_a:r =1	17.78*	17.75*	C (1)	0.00023	0.553**	0.447*

The estimated equations:

$$\Delta Ask_t = \alpha_a + \sum_{i=1}^{6} \beta_{aa,t-i}\, Ask_{t-i} + \sum_{i=1}^{6} \beta_{ab,t-i}\, Bid_{t-i} + \gamma_a (Ask - Bid)_{t-1}$$

$$\Delta Bid_t = \alpha_b + \sum_{i=1}^{6} \beta_{ba_1\, t-i}\, Ask_{t-i} + \sum_{i=1}^{6} \beta_{bb,t-i}\, Bid_{t-i} + \gamma_b (Ask - Bid)_{t-1}$$

Panel B: Depth Quotes

	Hypothesis	Trace	Hmax	Conclusion	$\Sigma\gamma$	$\gamma_{\perp\,asz}$	$\gamma_{\perp\,bsz}$
IBM95	H_o:r = 0, H_a:r = 1	25.84**	16.75*	C(1)	0.00008	0.414*	0.586*
IBM98	H_o:r = 0, H_a:r = 1	29.75**	17.30*	C(1)	0.00002	0.491*	0.509
T95	H_o:r = 0, H_a:r = 1	24.62**	16.81*	C(1)	0.000002	0.421*	0.579*
T98	H_o:r = 0, H_a:r = 1	22.93**	14.64*	C(1)	0.000002	0.352	0.648*

The estimated equations:

$$\Delta Asksz_t = \alpha_{asz} + \sum_{i=1}^{6} \beta_{asza,t-i}\, Asksz_{t-i} + \sum_{i=1}^{6} \beta_{aszb,t-i}\, Bid_{t-i} + \gamma_{asz}(Asksz - Bidsz)_{t-1}$$

$$\Delta Bidsz_t = \alpha_{bsz} + \sum_{i=1}^{6} \beta_{bsza,t-i}\, Asksz_{t-i} + \sum_{i=1}^{6} \beta_{bszb,t-1}\, Bid_{t-i} + \gamma_{bsz}(Asksz - Bidsz)_{t-1}$$

Panel C: Spreads (Ask – Bid) and Ask Depth

	Hypothesis	Trace	Hmax	Conclusion	Σγ	f_s	f_{asz}
IBM95	H_0:r = 0, H_a:r =1	42.31**	28.35**	C(1)	n.a.	0.509	0.491**
IBM98	H_0:r = 0, H_a:r =1	32.49**	19.21**	C(1)	n.a.	0.572	0.428*
T95	H_0:r = 0, H_a:r =1	42.08**	27.53**	C(1)	n.a.	0.573	0.427**
T98	H_0:r = 0, H_a:r =1	32.73**	21.30**	C(1)	n.a.	0.632	0.368**

The estimated equations:

$$\Delta Spread_t = \alpha_a + \sum_{i=1}^{6} \beta_{SS,t-i}\, Spread_{t-i} + \sum_{i=1}^{6} \beta_{Saszt-i}\, Asksz_{t-i} + \gamma_S(Spread - Asksz)_{t-1}$$

$$\Delta Asksz_t = \alpha_{asz} + \sum_{i=1}^{6} \beta_{aszS,t-i}\, Spread_{t-i} + \sum_{i=1}^{6} \beta_{aszasz,t-1}\, Asksz_{t-i} + \gamma_{asz}(Spread - Asksz)_{t-1}$$

Panel D: Spreads (Ask – Bid) and Bid Depth

	Hypothesis	Trace	Hmax	Conclusion	Σγ	$\gamma_{\perp S}$	$\gamma_{\perp bsz}$
IBM95	H_0:r = 0, H_a:r =1	41.98**	28.56**	C(1)	n.a.	0.460	0.540**
IBM98	H_0:r = 0, H_a:r =1	32.03**	18.97**	C(1)	n.a	0.580	0.420*
T95	H_0:r = 0, H_a:r =1	41.15**	27.40**	C(1)	n.a.	0.533	0.467**
T98	H_0:r = 0, H_a:r =1	32.14**	20.77**	C(1)	n.a	0.521	0.479**

The estimated equations:

$$\Delta Spread_t = \alpha_a + \sum_{i=1}^{6} \beta_{SS,t-i}\, Spread_{t-i} + \sum_{i=1}^{6} \beta_{Sbszt-i}\, Bidsz_{t-i} + \gamma_S(Spread - Bidsz)_{t-1}$$

$$\Delta Bidsz_t = \alpha_{bsz} + \sum_{i=1}^{6} \beta_{bszS,t-i}\, Spread_{t-i} + \sum_{i=1}^{6} \beta_{bszbsz,t-1}\, Bidsz_{t-i} + \gamma_{bsz}(Spread - Bidsz)_{t-1}$$

Panel E: Spreads (Ask – Bid) and ½ Summed Depths (Asksz + Bidsz)

	Hypothesis	Trace	Hmax	Conclusion	$\Sigma\gamma$	$\gamma_{\perp S}$	$\gamma_{\perp ½ (asz + bsz)}$
IBM95	H_0:r = 0, H_a:r =1	31.65**	22.72**	C(1)	n.a.	0.232	0.768**
IBM98	H_0:r = 0, H_a:r =1	28.12**	16.32**	C(1)	n.a	0.510	0.490*
T95	H_0:r = 0, H_a:r =1	35.54**	28.09**	C(1)	n.a.	0.211	0.789**
T98	H_0:r = 0, H_a:r =1	26.70**	18.90**	C(1)	n.a	0.428	0.572**

The estimated equations:

$$\Delta Spread_t = \alpha_a + \sum_{i=1}^{6} \beta_{SS,t-i}\, Spread_{t-i} + \sum_{i=1}^{6} \beta_{S,asz+bsz,t-i}\, 1/2\, (Asz+Bsz)_{t-i} + \gamma_S (Spread - ½\, (Asz+Bsz))_{t-1}$$

$$\Delta\, 1/2\, (Asksz_t + \text{Bidsz t}) = \alpha_{asz+bsk} + \sum_{i=1}^{6} \beta_{asz+bsz,S,t-i}\, Spread_{t-i} + \sum_{i=1}^{6} \beta_{asz+bsz,t-1}\, 1/2\, (Asz+Bsz)_{t-i} + \gamma_{asz+bsk} (Spread - ½\, (Asz+Bsz))_{t-1}$$

Table 3. Estimates and tests of cointegrating vectors.

For each Dow 30 stock, we estimate the cointegrating vectors for the quoted spread and the two depths at the quotes. These cointegrating vectors define the equilibrium errors that we employ subsequently in the estimation of the error correction version of the model. For each firm, we present results of the trace test of r = 0 against r ≥ 1 and of r = 1 against r ≥ 2. The 99% critical values for rejecting the null hypotheses are 37.29 and 21.96 and for 95% 31.26 and 17.84, respectively (Enders, 1995). Twenty of the thirty cases in 1995 and all thrity in 1998 fail to reject the null hypothesis of one cointegrating vector. In all sixty cases we can reject the null hypothesis of two cointegrating vectors and only one common factor.

Firm symbol	**AA95**	**ALD95**	**AXP95**	**BA95**	**CAT95**	**CHV95**	**DD95**	**DIS95**	**EK95**	**GE95**
Test of r = 0 against r = 1	40.84**	40.97**	**48.30****	40.67**	41.64**	44.73**	40.76**	40.64**	42.44**	43.55**
Test of r = 1 against r = 2	17.65	15.80	**21.02***	15.77	17.97*	18.92*	17.37	16.19	17.67	17.25
Firm symbol	**GM95**	**GT95**	**HWP95**	**IBM95**	**IP95**	**JNJ95**	**JPM95**	**KO95**	**MMM95**	**MO95**
Test of r = 0 against r = 1	45.82**	39.07**	36.91**	45.29**	38.72**	42.54**	41.80**	41.60**	42.40**	42.16**
Test of r = 1 against r = 2	17.20	16.23	15.60	18.13*	15.94	16.45	17.55	15.15	18.23*	17.82
Firm Symbol	**MRK95**	**MCD95**	**PG95**	**S95**	**T95**	**TRV95**	**UK95**	**UTX95**	**WMT95**	**XON95**
Test of r = 0 against r = 1	48.87**	46.97**	38.98**	44.76**	48.62**	40.65**	41.26**	34.91*	48.92**	44.27**
Test of r = 1 against r = 2	20.76*	19.95*	16.62	18.64*	21.23*	16.06	17.24	14.11	20.64*	17.68
Firm symbol	**AA98**	**ALD98**	**AXP98**	**BA98**	**CAT98**	**CHV98**	**DD98**	**DIS98**	**EK98**	**GE98**
Test of r = 0 against r = 1	30.84*	34.21*	31.32*	33.01*	37.20*	35.50*	35.65*	33.98*	34.59*	31.36*
Test of r = 1 against r = 2	17.65	15.80	13.77	13.84	15.97	15.51	16.24	16.21	15.67	13.36
Firm symbol	**GM98**	**GT98**	**HWP98**	**IBM98**	**IP98**	**JNJ98**	**JPM98**	**KO98**	**MMM98**	**MO98**
Test of r = 0 against r = 1	34.67*	30.41	33.21*	35.37*	32.63*	35.58*	31.36*	31.32*	34.42*	26.16
Test of r = 1 against r = 2	13.94	13.36	14.31	16.89	14.30	14.78	16.01	12.83	14.35	11.58
Firm Symbol	**MRK98**	**MCD98**	**PG98**	**S98**	**T98**	**TRV98**	**UK98**	**UTX98**	**WMT98**	**XON98**
Test of r = 0 against r = 1	34.28*	37.31**	32.29*	32.36*	35.33*	34.37*	31.86*	32.26**	38.06**	29.37
Test of r = 1 against r = 2	16.74	16.93	14.02	13.70	14.62	15.92	13.11	14.21	16.14	10.66

****Significant at 0.01, *Significant at 0.05**

Table 4. Proportion of information discovery by spreads versus depths at the quote. For each of the three series (spreads, asksizes, bidsizes), we present the common factor weights (in percent), which are normalized so that for a given stock for a given year, the weights sum to 100%, except for rounding errors. With two cointegrating vectors (r = 2) there is only one common factor--i.e., one relevant vector of the common factor matrix orthogonal to the adjustment vectors. We test each of the elements of this last eigenvector of the common factor matrix for significance using the methodology developed by Gonzalo and Granger (1995). In each case the null hypothesis is that the factor weight for the indicated series is 0. The test statistic is distributed chi-squared with one degree of freedom. In all sixty cases, we reject the null hypothesis for depths. The boldface stocks are those for which the Johansen test statistics in Table 3 indicate two cointegrating vectors and therefore one common trend. The factor weights and tests for the second common trend for the non-boldface stocks are available from the authors.

	1995			**1998**		
Stock Symbol	Spread	Ask size	Bid size	Spread	Ask size	Bid size
AA	0.523	0.234**	0.242**	0.520	0.252**	0.228**
ALD	0.475	0.274**	0.251**	0.490	0.284**	0.226**
AXP	**0.568****	**0.213****	**0.219****	0.522	0.252**	0.226**
BA	0.522**	0.200**	0.278**	0.535	0.226**	0.229**
CAT	**0.532**	**0.220****	**0.246****	0.520	0.221**	0.229**
CHV	**0.530**	**0.234****	**0.236****	0.517	0.259**	0.224**
DD	0.565	0.211**	0.229**	0.550	0.236**	0.214**
DIS	0.514	0.230**	0.236**	0.484	0.242**	0.274**
EK	0.548**	0.218**	0.234**	0.550	0.206**	0.244**
GE	0.503**	0.238**	0.259**	0.547	0.208**	0.245**
GM	0.461	0.261**	0.278**	0.446	0.239**	0.315**
GT	0.552	0.220**	0.228**	n.a.	n.a.	n.a.
HWP	0.482	0.265**	0.263**	0.541	0.212**	0.247**
IBM	**0.419**	**0.268****	**0.313****	0.486	0.252**	0.272**
IP	0.532**	0.222**	0.246**	0.515	0.262**	0.223**
JNJ	0.496	0.248**	0.246**	0.511	0.259**	0.230**
JPM	0.513	0.246**	0.244**	0.509	0.255**	0.236**
KO	0.542	0.208**	0.250**	0.524	0.224**	0.252**
MMM	**0.516**	**0.252****	**0.232****	0.512	0.231**	0.257**
MO	0.587**	0.186**	0.227**	n.a.	n.a.	n.a.
MRK	**0.505****	**0.232****	**0.263****	0.469	0.261**	0.270**
MCD	**0.537**	**0.228****	**0.235****	0.532	0.220**	0.258**
PG	0.518	0.234**	0.248**	0.538	0.230**	0.232**
S	0.477	0.253**	0.270**	0.556	0.206**	0.248**
T	0.491	0.240**	0.268**	0.500	0.233**	0.267**
TRV	0.498	0.264**	0.238**	0.479	0.224**	0.227**
UK	0.499	0.247**	0.254**	0.429	0.294**	0.277**
UTX	0.482	0.250**	0.268**	0.483	0.271**	0.246**
WMT	**0.557**	**0.220****	**0.223****	0.589**	0.201**	0.210**
XON	0.518**	0.238**	0.244**	n.a.	n.a.	n.a.
Mean	0.5154	0.2351	0.2489	0.5131	0.2393	0.2447

****Significant at the 0.01 level.**

Table 5. Test of the null hypothesis that no information discovery occurs in depths.
Using the Gonzalo and Granger (1995) Q_{GG} statistic, we test the null hypothesis that the common factor weight for spreads is 1.0 and that the common factor weights for the two depths are both 0.0. The test statistic is distributed chi-squared with two degrees of freedom. We reject the null hypothesis at 99% in 58 of the 60 sixty cases.

	1995		1998	
Stock	χ^2	p-value	χ^2	p-value
AA	12.61	0.01	7.29	0.01
ALD	15.71	0.01	8.93	0.01
AXP	18.96	0.01	9.27	0.01
BA	14.97	0.01	9.95	0.01
CAT	13.85	0.01	8.73	0.01
CHV	15.80	0.01	10.59	0.01
DD	15.03	0.01	9.41	0.01
DIS	15.71	0.01	6.60	0.01
EK	15.11	0.01	9.77	0.01
GE	17.56	0.01	9.61	0.01
GM	18.99	0.01	11.33	0.01
GT	13.74	0.01	n.a.	n.a.
HWP	12.71	0.01	9.38	0.01
IBM	15.87	0.01	5.48	0.02
IP	16.40	0.01	8.77	0.01
JNJ	17.89	0.01	11.61	0.01
JPM	14.94	0.01	5.39	0.02
KO	17.50	0.01	10.73	0.01
MMM	15.70	0.01	6.78	0.01
MO	15.75	0.01	n.a.	n.a.
MRK	18.84	0.01	8.18	0.01
MCD	16.97	0.01	11.98	0.01
PG	13.71	0.01	8.05	0.01
S	17.71	0.01	9.61	0.01
T	17.97	0.01	10.51	0.01
TRV	15.15	0.01	8.58	0.01
UK	14.05	0.01	10.21	0.01
UTX	12.62	0.01	7.11	0.01
WMT	14.29	0.01	12.67	0.01
XON	18.04	0.01	n.a.	n.a.

Table 6. Error-correction models. For each series in the three-variable information structure, we present Seemingly Unrelated Regression (SUR) estimates of the error correction model for log changes. In each case, the error-correction term z specified as - (Spread + AskSize - BidSize) has the expected sign and is statistically significant at the 0.05 level (signified by a single-asterisk)

PANEL A					
IBM 1995					
VECTOR ERROR CORRECTION MODEL					
ΔSPREADS		ΔASKSIZE		ΔBIDSIZE	
Constant	-0.699 (-90.85)*	Constant	-0.645 (-36.35)*	Constant	-0.664 (-40.31)*
ΔSPREADS (t-1)	-0.103 (-14.96)*	ΔSPREADS (t-1)	0.226 (14.24)*	ΔSPREADS (t-1)	0.248 (16.86)*
ΔSPREADS (t-2)	-0.115 (-17.95)*	ΔSPREADS (t-2)	0.138 (-9.3)*	ΔSPREADS (t-2)	0.165 (12.01)*
ΔSPREADS (t-3)	-0.105 (-17.84)*	ΔSPREADS (t-3)	0.111 (-8.12)*	ΔSPREADS (t-3)	0.122 (9.64)*
ΔSPREADS (t-4)	-0.087 (-16.36)*	ΔSPREADS (t-4)	0.087 (-7.16)*	ΔSPREADS (t-4)	0.096 (8.46)*
ΔSPREADS (t-5)	-0.062 (-13.65)*	ΔSPREADS (t-5)	0.061 (-5.78)*	ΔSPREADS (t-5)	0.069 (7.03)*
ΔSPREADS (t-6)	-0.035 (-9.47)*	ΔSPREADS (t-6)	0.047 (5.47)*	ΔSPREADS (t-6)	0.048 ((6.02)*
ΔASKSIZE (t-1)	0.015 (8.27)*	ΔASKSIZE (t-1)	-0.207 (-46.96)*	ΔASKSIZE (t-1)	-0.104 (-25.60)*
ΔASKSIZE (t-2)	0.018 (-1.31)	ΔASKSIZE (t-2)	-0.138 (9.3)*	ΔASKSIZE (t-2)	-0.072 (-17.95)*
ΔASKSIZE (t-3)	0.015 (8.35)*	ΔASKSIZE (t-3)	-0.116 (-27.29)	ΔASKSIZE (t-3)	-0.057 (-14.57)*
ΔASKSIZE (t-4)	0.016 (9.49)*	ΔASKSIZE (t-4)	-0.086 (-21.27)*	ΔASKSIZE (t-4)	-0.042 (-11.18)*
ΔASKSIZE (t-5)	0.011 (6.74)*	ΔASKSIZE (t-5)	-0.063 (16.25)*	ΔASKSIZE (t-5)	-0.033 (-9.21)*
ΔASKSIZE (t-6)	0.006 (4.36)*	ΔASKSIZE (t-6)	-0.038 (-10.75)*	ΔASKSIZE (t-6)	-0.023 (-7.15)*
ΔBIDSIZE (t-1)	0.021 (10.52)*	ΔBIDSIZE (t-1)	-0.115 (24.72)*	ΔBIDSIZE (t-1)	-0.234 (54.13)*
ΔBIDSIZE (t-2)	0.023 (11.64)*	ΔBIDSIZE (t-2)	-0.075 (-16.15)*	ΔBIDSIZE (t-2)	-0.165 (-38.4)*
ΔBIDSIZE (t-3)	0.022 (11.37)*	ΔBIDSIZE (t-3)	-0.054 (-11.94)*	ΔBIDSIZE (t-3)	-0.123 (-29.25)*
ΔBIDSIZE (t-4)	0.019 (10.15)*	ΔBIDSIZE (t-4)	-0.040 (-9.09)*	ΔBIDSIZE (t-4)	-0.097 (-23.83)*
ΔBIDSIZE (t-5)	0.016 (8.97)*	ΔBIDSIZE (t-5)	-0.033 (-8.07)*	ΔBIDSIZE (t-5)	-0.069 (-17.89)*
ΔBIDSIZE (t-6)	0.010 (6.13)*	ΔBIDSIZE (t-6)	-0.027 (-7.00)*	ΔBIDSIZE (t-6)	-0.041 (-11.65)*
Z1(t-1)	61.2 (91.97)*	Z1(t-1)	62.0 (40.35)*	Z1(t-1)	53.59 (37.58)*
Z2(T-1)	1.38 (3.38)*	Z2(T-1)	-54.1 (-57.22)*	Z2(T-1)	48.07 (54.76)*
R^2	0.393	R^2	0.235	R^2	0.223
F Statistics	2592*	F Statistics	1231*	F Statistics	1150*
ΔSpreads	61.6*	ΔSpreads	37.9*	ΔSpreads	50.92*
ΔAsksize	23.2*	ΔAsksize	380*	ΔAsksize	113.75*
ΔBidsize	35.1*	ΔBidsize	104*	ΔBidsize	510.30*
Z1,Z2	4231*	Z1,Z2	2488*	Z1,Z2	2174*

Table 6 PANEL B

IBM 1998					
VECTOR ERROR CORRECTION MODEL					
ΔSPREADS		ΔASKSIZE		ΔBIDSIZE	
Constant	-0.363 (-68.10)*	Constant	-0.309 (-29.49)*	Constant	-0.372 (-36.56)*
ΔSPREADS (t-1)	-0.272 (-52.60)*	ΔSPREADS (t-1)	0.099 (9.82)*	ΔSPREADS (t-1)	0.107 (10.91)*
ΔSPREADS (t-2)	-0.174 (-34.61)*	ΔSPREADS (t-2)	0.061 (-6.15)*	ΔSPREADS (t-2)	0.078 (8.13)*
ΔSPREADS (t-3)	-0.134 (-27.71)*	ΔSPREADS (t-3)	0.052 (-5.48)*	ΔSPREADS (t-3)	0.055 (6.05)*
ΔSPREADS (t-4)	-0.098 (-21.60)*	ΔSPREADS (t-4)	0.046 (-5.18)*	ΔSPREADS (t-4)	0.055 (6.37)*
ΔSPREADS (t-5)	-0.071 (-17.07)*	ΔSPREADS (t-5)	0.046 (-5.65)*	ΔSPREADS (t-5)	0.047 (5.93)*
ΔSPREADS (t-6)	-0.045 (-12.74)*	ΔSPREADS (t-6)	0.030 (4.36)*	ΔSPREADS (t-6)	0.035 (5.24)*
ΔASKSIZE (t-1)	0.017 (7.80)*	ΔASKSIZE (t-1)	-0.213 (-48.85)*	ΔASKSIZE (t-1)	-0.062 (-14.73)*
ΔASKSIZE (t-2)	0.016 (-7.44)*	ΔASKSIZE (t-2)	-0.153 (-35.57)*	ΔASKSIZE (t-2)	-0.049 (-11.87)*
ΔASKSIZE (t-3)	0.014 (6.87)*	ΔASKSIZE (t-3)	-0.110 (-26.25)*	ΔASKSIZE (t-3)	-0.043 (-10.69)*
ΔASKSIZE (t-4)	0.007 (3.72)	ΔASKSIZE (t-4)	-0.086 (-21.27)*	ΔASKSIZE (t-4)	-0.033 (-8.43)*
ΔASKSIZE (t-5)	0.010 (5.18)*	ΔASKSIZE (t-5)	-0.061 (16.04)*	ΔASKSIZE (t-5)	-0.064 (-17.07)*
ΔASKSIZE (t-6)	0.005 (3.07)	ΔASKSIZE (t-6)	-0.040 (-11.55)*	ΔASKSIZE (t-6)	-0.042 (-11.87)*
ΔBIDSIZE (t-1)	0.022 (10.15)*	ΔBIDSIZE (t-1)	-0.079 (-18.17)*	ΔBIDSIZE (t-1)	-0.172 (40.70)*
ΔBIDSIZE (t-2)	0.017 (7.84)*	ΔBIDSIZE (t-2)	-0.060 (-14.04)*	ΔBIDSIZE (t-2)	-0.135 (-32.44)*
ΔBIDSIZE (t-3)	0.014 (6.56)*	ΔBIDSIZE (t-3)	-0.053 (-12.68)*	ΔBIDSIZE (t-3)	-0.108 (-26.52)*
ΔBIDSIZE (t-4)	0.010 (5.17)*	ΔBIDSIZE (t-4)	-0.048 (-11.95)*	ΔBIDSIZE (t-4)	-0.085 (-21.54)*
ΔBIDSIZE (t-5)	0.009 (4.81)*	ΔBIDSIZE (t-5)	-0.043 (-11.25)*	ΔBIDSIZE (t-5)	-0.064 (-17.07)*
ΔBIDSIZE (t-6)	0.009 (5.17)*	ΔBIDSIZE (t-6)	-0.026 (-7.19)*	ΔBIDSIZE (t-6)	-0.042 (-11.87)*
Z1(t-1)	28.7 (70.68)*	Z1(t-1)	23.9 (29.96)*	Z1(t-1)	29.9 (38.59)*
Z2(T-1)	-1.20 (-2.95)	Z2(T-1)	-43.2 (-54.04)*	Z2(T-1)	39.0 (50.31)*
R^2	0.2924	R^2	0.1953	R^2	0.1768
F Statistics	1652*	F Statistics	970*	F Statistics	858.5*
ΔSpreads	465*	ΔSpreads	17.5*	ΔSpreads	21.4*
ΔAsksize	14.5*	ΔAsksize	415*	ΔAsksize	41.4*
ΔBidsize	20.4*	ΔBidsize	68.1*	ΔBidsize	317*
Z1,Z2	2502*	Z1,Z2	1908*	Z1,Z2	2009*

Table 7. Unrestricted VAR. For each series in the three-variable information structure, we present SUR estimates of the vector autoregressions (VAR) for log changes. In each equation, this misspecification results in sign switches on several lagged variables and a substantially reduced R^2 relative to the correct specification of this model as a VECM (Table 6).

IBM 1995					
VECTOR AUTOREGRESSIONS					
ΔSPREADS		**ΔASKSIZE**		**ΔBIDSIZE**	
Constant	6.16E–7 (0.00)	Constant	2.47E–5 (0.01)	Constant	6.06E–6 (0.00)
ΔSPREADS (t-1)	-0.647 (-174.77)*	ΔSPREADS (t-1)	-0.317 (-37.86)*	ΔSPREADS (t-1)	-0.234 (-30.23)*
ΔSPREADS (t-2)	-0.576 (-134.97)*	ΔSPREADS (t-2)	-0.321 (-33.26)*	ΔSPREADS (t-2)	-0.242 (-27.21)*
ΔSPREADS (t-3)	-0.477 (-104.76)*	ΔSPREADS (t-3)	-0.259 (-25.22)*	ΔSPREADS (t-3)	-0.207 (-21.76)*
ΔSPREADS (t-4)	-0.368 (-80.69)*	ΔSPREADS (t-4)	-0.193 (-18.70)*	ΔSPREADS (t-4)	-0.153 (-16.09)*
ΔSPREADS (t-5)	-0.255 (-59.30)*	ΔSPREADS (t-5)	-0.130 (-13.40)*	ΔSPREADS (t-5)	-0.101 (-11.32)*
ΔSPREADS (t-6)	-0.141 (-37.80)*	ΔSPREADS (t-6)	-0.057 (-6.84)*	ΔSPREADS (t-6)	-0.046 (-5.93)*
ΔASKSIZE (t-1)	-0.022 (-13.94)*	ΔASKSIZE (t-1)	-0.389 (-107.09)*	ΔASKSIZE (t-1)	-0.017 (-5.07)*
ΔASKSIZE (t-2)	-0.012 (-7.12)*	ΔASKSIZE (t-2)	-0.292 (-75.76)*	ΔASKSIZE (t-2)	0.004 (1.29)
ΔASKSIZE (t-3)	-0.008 (-4.89)*	ΔASKSIZE (t-3)	-0.243 (-61.85)*	ΔASKSIZE (t-3)	0.008 (-2.39)
ΔASKSIZE (t-4)	-5.03E–4 (-0.29)	ΔASKSIZE (t-4)	-0.187 (-47.65)*	ΔASKSIZE (t-4)	0.012 (3.43)
ΔASKSIZE (t-5)	1.61E–4 (0.09)	ΔASKSIZE (t-5)	-0.138 (-35.90)*	ΔASKSIZE (t-5)	0.010 (2.92)
ΔASKSIZE (t-6)	0.002 (1.20)	ΔASKSIZE (t-6)	-0.086 (-23.88)*	ΔASKSIZE (t-6)	0.008 (2.44)
ΔBIDSIZE (t-1)	-0.027 (1-15.83)*	ΔBIDSIZE (t-1)	-0.021 (-5.47)*	ΔBIDSIZE (t-1)	-0.397 (-109.84)*
ΔBIDSIZE (t-2)	-0.016 (-8.59)*	ΔBIDSIZE (t-2)	0.007 (1.86)	ΔBIDSIZE (t-2)	-0.303 (-78.75)*
ΔBIDSIZE (t-3)	-0.009 (-4.72)*	ΔBIDSIZE (t-3)	0.016 (3.88)*	ΔBIDSIZE (t-3)	-0.237 (-60.28)*
ΔBIDSIZE (t-4)	-0.004 (-2.33)*	ΔBIDSIZE (t-4)	0.019 (4.46)*	ΔBIDSIZE (t-4)	-0.188 (-47.83)*
ΔBIDSIZE (t-5)	-6.58E–5 (0.04)	ΔBIDSIZE (t-5)	0.012 (3.06)	ΔBIDSIZE (t-5)	-0.137 (-35.64)*
ΔBIDSIZE (t-6)	0.001 (0.90)	ΔBIDSIZE (t-6)	0.006 (1.70)	ΔBIDSIZE (t-6)	-0.085 (-23.61)*
R^2	0.329	R^2	0.187	R^2	0.181
F Statistics	2180*	F Statistics	1027*	F Statistics	983*
ΔSpreads	5649*	ΔSpreads	289.3*	ΔSpreads	189.9*
ΔAsksize	37.1*	ΔAsksize	2309*	ΔAsksize	9.8*
ΔBidsize	45.7*	ΔBidsize	13.2*	ΔBidsize	2402*

*Significant at 0.05

APPENDIX

Estimates and tests of cointegrating vectors involving bid and ask quotes and bid and ask depths. For each Dow 30 stock, we estimate the cointegrating vectors for the four-variable model of the two price quotes and the two depths at the quotes and present results of the trace test of r = 0 against r ≥ 1, r = 1 against r ≥ 2, and r = 2 against r ≥ 3. The 90% critical values for rejecting the null hypothesis of no cointegration are 45.24, 28.44, and 15.58, respectively (Enders, 1995).

Firm symbol	**AA95**	**ALD95**	**AXP95**	**BA95**	**CAT95**	**CHV95**	**DD95**	**DIS95**	**EK95**	**GE95**
Test of r = 0 against r = 1	36.05	38.46	43.14	37.84	36.73	38.45	36.06	36.06	35.84	40.28
Test of r = 1 against r = 2	14.36	14.51	16.53	13.73	14.78	14.55	14.18	14.18	12.96	14.10
Test of r = 2 against r = 3	8.42	8.63	8.48	8.95	7.72	7.11	5.54	5.54	6.89	7.57
Firm symbol	**GM95**	**GT95**	**HWP95**	**IBM95**	**IP95**	**JNJ95**	**JPM95**	**KO95**	**MMM95**	**MO95**
Test of r = 0 against r = 1	42.82	34.50	31.73	39.30	32.27	38.82	37.02	38.72	38.09	36.74
Test of r = 1 against r = 2	14.03	12.72	11.96	16.46	11.61	13.59	13.54	12.39	14.39	13.85
Test of r = 2 against r = 3	8.51	7.19	8.33	9.39	7.08	7.21	8.12	7.46	7.15	7.13
Firm Symbol	**MRK95**	**MCD95**	**PG95**	**S95**	**T95**	**TRV95**	**UK95**	**UTX95**	**WMT95**	**XON95**
Test of r = 0 against r = 1	45.62*	43.77	35.43	42.30	45.35*	40.53	35.17	31.65	45.11	39.77
Test of r = 1 against r = 2	17.05	16.38	13.48	15.46	16.90	13.99	13.21	12.23	17.32	13.18
Test of r = 2 against r = 3	9.78	9.47	7.31	6.80	8.13	9.14	8.95	6.22	11.02	6.03
Firm symbol	**AA98**	**ALD98**	**AXP98**	**BA98**	**CAT98**	**CHV98**	**DD98**	**DIS98**	**EK98**	**GE98**
Test of r = 0 against r = 1	25.58	25.99	28.41	28.19	28.10	29.52	29.80	30.21	27.67	24.95
Test of r = 1 against r = 2	10.24	10.79	12.17	10.95	11.24	12.29	13.10	13.7	11.24	8.75
Test of r = 2 against r = 3	7.43	8.63	7.99	7.11	6.40	8.56	7.80	9.29	6.78	5.54
Firm symbol	**GM98**	**GT98**	**HWP98**	**IBM98**	**IP98**	**JNJ98**	**JPM98**	**KO98**	**MMM98**	**MO98**
Test of r = 0 against r = 1	28.98	24.19	28.29	33.66	28.25	30.79	30.37	27.09	26.16	20.93
Test of r = 1 against r = 2	10.34	10.23	11.81	16.59	11.87	11.53	12.80	9.66	10.08	8.45
Test of r = 2 against r = 3	7.23	7.51	7.81	11.94	7.62	7.13	9.38	5.73	8.59	5.25
Firm Symbol	**MRK98**	**MCD98**	**PG98**	**S98**	**T98**	**TRV98**	**UK98**	**UTX98**	**WMT98**	**XON98**
Test of r = 0 against r = 1	29.08	27.33	25.85	27.33	31.12	29.22	26.67	28.27	29.11	29.46
Test of r = 1 against r = 2	12.84	10.75	9.91	10.75	12.12	12.93	9.71	11.50	10.34	9.04
Test of r = 2 against r = 3	8.04	7.11	6.37	7.11	7.65	8.74	5.43	8.33	5.89	7.23