Information Revelation in Financial Markets: Impulse Response Functions for Cointegrated Spreads and Depths

Sugato Chakravarty
Purdue University
West Lafayette, IN 47906
E-mail: sugato@purdue.edu

Frederick H. deB. Harris
Babcock Graduate School of Management
Wake Forest University
Winston-Salem, NC 27109
E-mail: rick.harris@mba.wfu.edu

Robert A. Wood
Institute for the Study of Security Markets
University of Memphis
Memphis, TN 38152.
E-mail: rawood@pobox.com

For Presentation at
National Bureau of Economic Research
Market Microstructure Meeting
December 11, 2003

Current Version: November 11, 2003

Acknowledgements: Please direct all comments to Harris. This research was supported in part by the research grants program of the Babcock Graduate School of Management, Wake Forest University, and by the Purdue Research Foundation. Comments by Amber Anand, Robert Battalio, Rob Engle, Joel Hasbrouck, Robert Jennings, Uday Rajan and Avanidhar Subrahmanyam and seminar participants at Virginia, Babcock GSM, and University of New South Wales on earlier versions are gratefully acknowledged. Ernest Lang and Amy Cecil provided exceptional research assistance. The usual disclaimer applies.

.

Abstract

We investigate the path through which an information or liquidity shock reveals itself in subsequent adjustments of the bid-ask spreads and corresponding depths. Our simple three-equation error correction model incorporates both the short term and long term effects of the spread and depths on the dynamics of adjustment. In particular, we study both the stochastic properties of spreads and depths as well as their permanent impounding of stochastic common trends. Using two years of tick-by-tick quote data on all the DJIA stocks, we show that indeed depths rather than spreads are first to impound new information. Specifically, (bid and ask) depths adjust first in virtually every stock in both years, while spreads almost never adjust first in 1998, and do so in only 8 out of 30 cases in 1995. Analysis of the orthoganalized impulse response functions shows that spreads widen initially in response to positive depth shocks but that subsequent tightening occurs within 2 minutes and is a permanent effect. Depths decline in response to positive shocks to the spread but this effect is not permanent. In addition, bid depths and ask depths respond to one another in asymmetrical ways. Our results have important implications for testing competing theories of asymmetric information trading, for security market design, and for public policy.

JEL Classification: G12

1. Introduction

We examine the exact path through which new information is assimilated into the subsequent price and depth dimensions of a specialist's quote in the NYSE. Beginning with the seminal work of Demsetz (1968), a fundamental thrust of the classical market microstructure literature has been to show how the specialist may use quoted prices (and, by extension, the bid ask spreads) to manage inventory, mitigate adverse selection problems and promote price discovery. While the role of spreads in the price discovery process has been well documented (see O'Hara (1995) and Madhavan (2000) for comprehensive summaries of the relevant literature), the quantity dimension –i.e., the bid and ask depths--of the specialists' quotes have been significantly less investigated.[1] However, two institutional features of asset markets 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 have historically been quoted in large discrete intervals of quarters, 1/8ths and 1/16ths while depths have always been 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.

Moreover, by virtue of his strategic location on the trading floor, a specialist has knowledge of liquidity over and beyond that displayed to other market participants -- information that he is free to use in determining the direction and magnitude of his posted price and quantity quotes. For example, the specialist has "not held" orders wherein he is given discretion regarding when to execute the order. In particular, the specialist will seek an opportune time for execution to provide the customer with the least price impact. The specialist can also "stop" an order whereby he seeks price improvement while providing the buyer/seller a BBO guarantee at the time of the order. In addition, the specialist has orders to execute that are not displayed. He is aware of limit orders

[1] In particular, a specialist posts a bid and an ask depth, along with the corresponding bid and ask price quotes, signaling the maximum shares the market is willing to buy or sell at those prices and a complete characterization of market liquidity should include both the spread and the associated depths (see Harris (1990)). In recent years, a growing body of empirical research has examined the role of spreads and depths as a way to characterize the changing market liquidity around specific corporate events (see, for example, Lee, Mucklow, and Ready (1993), Chakravarty and McConnell (1997), Chung and Zhao (1999), and Chakravarty, Van Ness and Wood (2003)).

being worked by the crowd of two-dollar brokers acting as agents for buyers/sellers. And specialists are often aware of trading patterns of large market participants – money funds or brokers – that reveal forthcoming order flow.[2] Finally, communication between block trading desks and specialists is common, wherein specialists have advance knowledge of forthcoming order flow. All this would also argue in favor of the specialists' best price and depth quotes as being informative of the ebb and flow of information in the market.

To underscore the importance of depth quotes, Kavajecz (1999) reports that specialists in the NYSE change their quoted depths in 90% of all quote changes while only 50% of all quote changes are accompanied by changes in quoted prices. It appears, therefore, as though specialists actively manage their quoted depths even when prices are not changing. In general, bid and ask prices, as well as the corresponding bid and ask depths, should be optimally adjusted by the market maker until all incoming information is incorporated in prices. Using TORQ data Kavajecz (1999) finds that the specialist decreases his component of the depth at times of high adverse selection while Harris and Panchapagesan (2002), investigating limit orders from the same data source, find that the limit order book is informative about future price movements.

Kavajecz and Odders-White (hereafter KOW, 2001) build on Kavajecz (1999) by estimating a simulatenous equation system of the bid and ask prices and the associated bid and ask depths, using the TORQ data, and report that the changes in the best prices and depths in the limit order book have a significant impact on the posted price schedule, thereby underscoring the important role of the limit order book in the price discovery process. Thus, for example, KOW opine that (p. 683): "The prominence of the limit order book's impact on the price schedule suggests that the book is an important channel of information to the market." However, while the role of the limit order book in the price discovery process is beyond question, what is not clear and cannot be extrapolated from exisiting studies is: What is the exact path through which an information/liquidity shock reveals itself in the subsequent adjustment of the bid and ask prices and the corresponding bid and ask depths? What is the resiliency of the market to various magnitudes of liquidity/information shocks

[2] For example, VWAP trading is widely employed whereby let's say Merrill Lynch is buying a 50,000 shares of IBM for a customer during a trading day. In order to obtain approximately the value-weighted average price for the day (or better), the order will be "sliced and diced" into 78 five-minute trading intervals throughout the day wherein 640 shares will be traded in each interval. (In practice the volume submitted in each five-minute interval is altered to mimic the u-shaped volume pattern observed for each stock.) Initially in each interval a limit buy order will be submitted by Merrill. If the order is not executed within five minutes it is cancelled and a 640-share market order entered. Then the pattern is repeated for the next five-minute interval. The IBM specialist readily observes this process and can anticipate volume throughout the day with a high degree of reliability.

on the limit order book? Investigating such questions is the goal of the current paper. [3]

To do so, we develop an empirical model to capture the dynamics of how relevant information in quotes is incorporated into the subsequent adjustments in both the bid and ask prices and the bid and ask depths. [4] In particular, our model allows us to study both the long-term and short term equilibrium properties of time-series variables that move together (or, are cointegrated). Failure to detect and analyze cointegration between microstructure-theoretic variables like price quotes, spreads and depths can led to the serious misinterpretation of spurious regression coefficients as evidence of long-run economic relationships when all they might truly provide is mere evidence of contemporaneous correlations with unidentified causal variables. In that regard, our work builds on an important body of research spearheaded by Huberman and Halka (1999), Pastor and Stambaugh (2001) and Chordia, Roll and Subrahmanyam (2001), all of whom extract the liquidity premium from asset pricing models of expected returns but do not allow for the possible presence of common stochastic trends inherent in prices and order flows. [5]

We estimate our model of spreads and depths 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 in June of 1997. To confirm the stationarity of all underlying series of interest, either in first differences or in levels, we first conduct detailed tests (including unit root, system lag length, and cointegration tests) to establish the appropriate specification of the system of prices, spreads and depths as a cointegrated system. We then employ a common factor procedure by Gonzalo and

---

[3] Although a growing body of empirical research has examined the role of spreads and depths as a way to characterize the changing market liquidity around particular events (see, for example, Lee, Mucklow, and Ready (1993), Chakravarty and McConnell (1997), Chung and Zhao (1999), and Chakravarty, Van Ness and Wood (2003)), the extant literature is incapable of providing an answer to the general question of the resiliency of the markets to information and liquidity shocks.

[4] The impact of trades on both the price and size components of the spread is another key measure of the amount of friction present in the market and is therefore important to academics, practitioners and regulators alike, but is beyond the scope of the present paper.

[5] 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. Their main result is that the informed trader can use limit orders as a "safety net" for his market orders. 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.

Granger (1995), discussed in detail later, to estimate the contribution of the spread and the bid and ask depth to the common underlying trend(s) among these three cointegrated variables.[6]

We show that indeed depths, rather than spreads, are the 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 first in spreads ranges from 51% to 59% with the depths accounting for the rest. Our parameter estimates over the two years 1995 and 1998 also suggest that 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 the now tighter depths in the error correction process.

We also focus on the short-run dynamics of the price-quantity adjustment process through a close inspection of the orthoganalized impulse response functions of our VECM model. We find that spreads widen temporarily in response to positive depth shocks but that subsequent tightening occurs within 2 minutes and is a permanent effect. Depths decline in response to positive shocks to the spread but this effect is not permanent. However, bid depths and ask depths respond to one another differently. While both eventually increase in response to positive shocks, the ask depth declines initially in response to positive sell-side shocks at the bid while the bid depth increases continuously in response to positive buy-side shocks.

Our results highlight the active role played by the specialist at the NYSE and by the limit order book in the price discovery process and thereby enrich the fabric of intuition provided by Kavajecz and Odders-White (2001). Our results also underscore the exponential growth over the last few years of marketable and near-the-quote limit orders, a large percentage of which are canceled if a fill is not obtained soon. To the extent that these orders originate from big institutional traders with private information about the direction of stock prices in the short run, depths would be expected to convey new information first. Our finding on the role of depth has important implications for academic research as well as for exchange regulators concerned with market

---

[6] Currently there are two popular common factor models that are used to investigate the mechanics of price discovery: The Hasbrouck (1995) information share approach and the Gonzalo and Granger (1995) approach of decomposing co-integrated series into their permanent and transitory components. Both models use the VECM as their basis and, as Hasbrouck (1996) argues, the VECM approach is consistent with several market microstructure models in the extant literature. Thus, even though we use the Gonzalo and Granger approach in this paper (discussed in section 3.1 and in appendix B), both approaches are considered (see, for example, Tse (2000)) to lead to virtually identical results with tick-by-tick high frequency intraday data on the thirty stocks comprising the Dow Jones Industrial Average (DJIA) used here.

liquidity -- especially due to the fact that that the depth changes in the limit order book represent a combination of the specialists' personal trading interests as well as the inflow of public limit orders. Overall, our results suggest that depths are orchestrated by the specialists' beliefs about the changing rubric of the adverse selection pressure that they face over the course of the trading day, consistent with Kavajecz (1999).

The US equity markets have also undergone significant structural changes in recent years through the reduction in minimum tick sizes first from eighths to sixteenths (in 1997) and then from sixteenths to a penny three years later. The consensus result emerging from this stream of research is that spreads – both quoted and effective – have decreased following a reduction in tick size but so has market depth.[7] This result coupled with our finding of the increasing importance of depths before and after the changeover to sixteenths implies an even greater role of depth in a post decimal world. The recent regulatory changes in NASDAQ of decreasing the minimum depth requirement from 1,000 shares to 100 shares for dealers posting quotes also reflects the increasing importance and scrutiny of this long overlooked parameter of market liquidity and is consistent with our finding of the increasingly important role played by depths.

In the policy realm, our findings suggest that depth indicators need to be publicly disseminated by the exchanges to provide traders and other market participants with an accurate estimation of prevailing liquidity. Furthermore, theoretical modeling and empirical measures of adverse selection should provide at least as much weight to depths as is done 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 this program 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 remainder of the paper is structured as follows. Section 2 motivates the current research in light of recent literature and develops an error correction model of spreads and depths. Section 3 provides an overview of the data used for the analyses, discusses the stochastic properties of spreads,

[7] See, for example, Bacidore (1997), Bollen and Whaley (1998), Ricker (1998), Ronen and Weaver (1998), Goldstein and Kavajecz (2000), and Jones and Lipson (2001). Bacidore, Battalio and Jennings (2001), Chakravarty, Van Ness and Wood (2002), and Chung, Van Ness and Van Ness (2001) present similar results following the introduction of decimal pricing for a select group of pilot NYSE stocks before the market-wide switchover in January 2001.

and addresses the appropriate specification of an error correction model involving various pairs of price and depth quotes. [8] Section 4 reports tests of cointegration involving the spread and two depths and estimates the proportion of new information reflected in depths versus spreads. Section 5 investigates the adjustment dynamics of spreads and depths using impulse response functions. Section 6 concludes. Appendix A 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, while Appendix B provides details about the Gonzalo and Granger decomposition of co-integrated series into permanent and transitory components.

2. A model of endogenous spreads and depths

2.1 Background

Although our work is parallel to a fast growing literature on liquidity (e.g., Hasbrouck and Seppi 2001, or Chordia, Roll and Subrahmanyam 2001), it is most closely related to vector auto regression (VAR) and vector error correction models (VECM) examining questions like: How is new information incorporated into prices? In particular, this branch of research is spearheaded by Hasbrouck (1991) who finds that infrequently traded stocks have greater price impacts than frequently traded stocks. Hasbrouck, however, assumes that price impacts are constant over time -- an assumption relaxed by Dufour and Engle (2000) who show that the price impact is especially large when trades are frequent, presumably because the cumulative order size has exceeded the depth at the previous BBO.

Kavajecz and Odders-White (2001) estimate the bid and ask price and depth changes in a system of four simultaneous equations that incorporates trading activity, the specialist's inventory position, and the derived limit order book using a proprietary algoritm. The authors assume that full reaction to new information occurs instantaneously. That is, their empirical model does not include serial dependence, lagged effects, and the possibility of cointegration and error correction among their variables. While providing important insights, their model also includes the unfortunate possibility that if price and or depth levels are cointegrated, their model of the changes in these variables would be seriously misspecified since it omits an error correction term.

Engle and Patton (2001) test exactly this error correction specification and show that the way in which information inherent in trades is incorporated into quoted prices is indeed via an error

[8] 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.

correction model for the log difference of the bid and ask prices with the spread acting as the error-correction term. Controlling for several trade-related characteristics, Engle and Patton include the difference in the log depths at the ask and at the bid as a non-stochastic explanatory variable and interpret the negative sign on this excess depth regressor as evidence of asymmetric information in the depth quotes, consistent with Huang and Stoll (1994). However, Engle and Patton do not incorporate the possible error correction of bid and ask depths in their analysis – an important innovation of the current paper.[9]

To investigate the comparative importance of the bid and ask depths and the bid-ask spread in the error correction adjustment dynamics and in revealing new information leading to permanent trends, we develop a simple model from fundamental intuition that is related to a common trends estimation model first proposed by Stock and Watson (1988), refined by Hall, Anderson and Granger (1992), and fully developed as common factor components estimation by Gonzalo and Granger (1995). Common factor components estimation allows us to summarize with a single metric the adjustment dynamics when there are more than two cointegrated series. [10]

In order to address our central question of the relative importance of spreads versus depths in reflecting new information that results in permanent quote or spread trends, our focus and testing framework differ from Engle and Patton in several important and distinct ways. First, and most importantly, we allow for depths to convey new information (see our discussion in the introduction) and explicitly model the stochastic process imbedded in the depth quotes. In particular, we initially test for the appropriate specification of our cointegrated model of prices and depths. We find that depth quotes are cointegrated and adjust to excess depth, analogous to Engle and Patton's (2001) error correction of price quotes to the spread, but that the full system of bid and ask prices and the bid and ask depths are not cointegrated.

---

[9] Hasbrouck and Seppi (2001) use principal components and canonical correlation analysis to examine common factors in prices, order flow and liquidity. They, too, do not model the dynamic adjustment process between spreads and depths.

[10] Recently, several papers have employed common factor components estimation as a way to measure and test the comparative importance in price discovery of competing exchanges involved in international dual listings (see, for example, Ding, Harris, Lau, and McInish, 1999; Liberman, Ben-Zion and Hauser, 1999; and Harris, McInish, and Wood, 2002a); examination of distinct trade execution channels within an exchange (Frino, Harris, McInish, and Tomas, 2001); and price informativeness of the NYSE versus the regional exchanges (Harris, McInish and Wood, 2002b; Hasbrouck, 2002). Similarly, Huang (2002) and Chakravarty, Gulen and Mayhew (2002) have used the information share approach of Hasbrouck to investigate how much price discovery occurs in the ECNs relative to the NASDAQ quotes and in the option market relative to the stock market.

Second, we find that intraday spreads are <u>non</u>-stationary I(1) processes in the DJIA stocks, contrary to the widely-reported stationary stochastic process for spreads in closing DJIA prices.[11] Non-stationarity is consistent with the well-established U-shaped pattern of intraday spreads (see McInish and Wood, 1992). Moreover, non-stationary spreads are consistent with the underlying motivation of our paper that information effects are seldom impounded continuously into prices alone and, instead, trigger multi-period and multi-dimensional adjustments spanning both spreads and depths.[12]

Consequently (and third), we investigate whether spreads and depths are themselves cointegrated and result in a (newly discovered) linear combination of price and depth quotes in equilibrium. Our results confirm this hypothesis and show the existence of one cointegrating vector of spreads and excess depth, leading to two distinct common stochastic trends.

2.2 *A model of endogenous time-varying spreads and depths*

Assume that price and depth quotes reflect two unobservable continuous random walks – i.e., an implicit efficient price random walk underlying the price quotes and, analogously, an immediacy random walk underlying the depth quotes. These random walks cumulate into long-term stochastic trends of prices and liquidity variables. This 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, so as to minimize the price impact of their trades (see, for example, Admati and Pfleiderer (1988)). Comparing and assessing the level and 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.

To decipher the economic content of this model it is instructive to analyze the explicit dynamics of price and depth quote adjustment. We begin with a conceptual framework used by Hasbrouck (2002) to characterize half-spreads (S/2), implicit efficient prices $\mathscr{P}$ and stale quotes in microstructure models. Thus, at time t, the observed price p_t can be expressed as:

$$p_t = \mathscr{P}_t + c\, q_t, \tag{1}$$

[11] In contrast, Engle and Patton (2001) examine a random sample of *continuous* quotes for 100 TAQ stocks and proceed with an assumption that spreads are I(0). We investigate at length this question of trend and difference stationarity of spreads in the empirical results reported below.

[12] We should caution readers that our finding that spreads are I(1) series does not necessarily imply that the variance of the innovation in spreads could grow very large over time. Roll (2002), for example, argues that the non-stationarity is to be expected in rational expectations models and that the variance of the error term may well be constant as in the random walk i.i.d. innovation.

where c is a time-invariant half-spread, q_t is an equi-probable random indicator variable for the direction of the last trade (+1 for trades at the ask, -1 for trades at the bid) , $\mathcal{P}_t$ evolves as an I(1) random walk of pure information arrivals (w_t) and contemporaneous trading pressure (λq_t),

$$\mathcal{P}_t = \mathcal{P}_{t-1} + w_t + \lambda q_t, \qquad (2)$$

with w_t and q_t being i.i.d. $N(0, \sigma_w^2)$ and i.i.d. bivariate normal random variables, respectively. In addition, w_t and q_t are assumed independent of one another.

At this point, we wish to adapt and amend Hasbrouck's framework in three ways to capture 1) the a priori endogeneity of time-varying spreads (see Glosten and Milgrom (1985) and Campbell, Lo and MacKinlay (1997, pp. 103-107)), 2) the observable *lagged* trade direction indicator variable q_{t-1}, rather than q_t (see Huang and Stoll, 1997),

$$\mathcal{P}_t = \mathcal{P}_{t-1} + w_t + \lambda q_{t-1}, \qquad (2')$$

and 3) an empirically-estimated I(1) order of integration of the stochastic process for the spread (see our results in Table 2 discussed below). First, we introduce a time-varying component of the half-spread by inserting an asymmetric information risk premium that is a function of the pure information arrivals:

$$(S/2)_t = (c + \theta w_t), \qquad (3)$$

where c can be reinterpreted to represent the order processing and inventory-carrying cost components of market-making, and θw_t represents a market-makers's spread premium for picking off risk—i.e., the prospect of being picked off when offering to trade at stale prices against an asymmetrically informed trader already updated about w_t. Consistent with prior literature (e.g., Hasbrouck (1996)), note that the half-spread in (3) is a covariance-stationary I(0) series varying $N(0, \sigma_w^2)$ around c.

The price quote sequence

$$p_t = \mathcal{P}_t + (c + \theta w_{t-1})q_{t-1}, \qquad (4)$$

would then be written as,

$$p_t = [p_{t-1} + w_t + \lambda q_{t-1}] + c\Delta q_{t-1} + \theta\Delta(w_{t-1}\, q_{t-1}), \qquad (4')$$

or, as two stochastic trends $\sum w_T$ and $\sum q_{T-1}$ (that cumulate information arrivals to time period T and trade directions to time period T-1) plus the product of two zero-mean covariance stationary r.v.s,

$$P_T = P_0 + \sum w_T + \lambda \sum q_{T-1} + (c + \theta\, w_{T-1})\, q_{T-1}. \qquad (4'')$$

Examining the time-varying spreads in (3) and the price quotes in (4′′), one notes that spreads and quotes share a common stochastic disturbance structure – i.e., ($c + \theta w_T$) and ($c + \theta w_{T-1}$), respectively. Any serial correlation of the w_t could therefore lead to correlation between spreads and price quotes. However, even time-varying spreads and quotes that are correlated may well *not* be cointegrated. In particular, the I(0) spreads in (3) and the I(1) price quotes in (4′) and (4″) do not share a Stock-Watson common stochastic trend. Consequently, these spreads and quotes can not be cointegrated.

Our empirical results reported below suggest just the opposite, however. Spreads and some quotes *are,* in fact, cointegrated. Specifically, we find that spreads and *depth* quotes share a common stochastic trend. Again, our empirical work confirming the maintained hypotheses for this study suggests why. In pretesting the order of integration of spreads, price quotes, and depth quotes for all Dow 30 stocks, we found not only that the spread is time-varying but also that the spread is a *non-stationary* series (again, see Table 2 below). To illustrate this empirical fact in our modeling framework, consider a case in which spreads are themselves representable as an I(1) simple random walk,

$$(S/2)_t = [(S/2)_{t-1} + \varepsilon_t], \tag{5}$$

where the random disturbance epsilon is interpreted as an i.i.d. N(0, σ^2_ε) order imbalance, again (like w_t) provisionally assumed to be independent of q. [13] Michaely and Vila (1995), Michaely, Vila and Wang (1996), and Fernando (2003) also model common shocks to liquidity fundamentals separate from information shocks to valuation fundamentals. Hence, systematic liquidity becomes a priced factor in asset pricing equilibrium even in the absence of trading. Moreover, discretionary liquidity-driven trading (reflected in the idiosyncratic shocks q_t) is endogenously-determined as heterogeneous investors with lower exposure to systematic shocks supply liquidity to investors with higher exposure.

Equation (5) implies spreads can be written as a cumulative stochastic trend of liquidity fundamentals,

$$(S/2)_T = (S/2)_0 + \sum \varepsilon_T. \tag{5′}$$

Drawing a parallel between implicit efficient price fundamentals, $\mathcal{P}_t$, and liquidity fundamentals, $\mathcal{D}_t$, by mirroring (2′) and (4′), the depth (size) quote sequence could then be written

[13] These are assumptions of convenience to allow us to demonstrate as simply as possible a cointegration relationship between spreads and depths. Later, in specifying regression relations for empirical modeling, we require a more complex approach addressing the possible non-independence of ε_t, q_t, and w_t. See Campbell, Lo, and MacKinlay (1997).

$$D_t \quad = \quad \mathcal{D}_t \;+\; (S/2)_{t-1}\, q_{t-1} \tag{6}$$

$$\quad = \quad [D_{t-1} \;+\; \varepsilon_t \;+\; \lambda q_{t-1}] \;+\; \Delta[(S/2)_{t-1}\, q_{t-1}], \tag{6′}$$

$$D_T \quad = \quad D_0 \;+\; \sum \varepsilon_T \;+\; \lambda \sum q_{T-1} \;+\; [(S/2)_{T-1}\, q_{T-1} \;-\; (S/2)_{T-2}\; q_{T-2}], \tag{6″}$$

Comparing (5′) and (6″), both time-varying spreads and depths then contain the common stochastic trend $\sum \varepsilon_T$. Said another way, these spreads and depths are I(1) variables whose linear combination can be a stationary I(0) error correction term. Consequently, time-varying spreads and depth quotes can indeed be cointegrated C(1).

To estimate this C(1) relationship between spreads and depths, we therefore hypothesize a three-variable system of the Spread (S) , the Ask depth (Asz) and the Bid depth (Bsz) based on an error correction mechanism involving both spreads and excess depth -- specifically, the spread plus ask depth minus the bid depth (the net supply of stocks available to investors at the best quotes):

$$\Delta\, Spread_t = \alpha_S + \sum_{i=1}^{6} \beta_{S,\,t-i}\, \Delta Spread_{t-i} + \sum_{i=1}^{6} \beta_{S,\,asz,\,t-i} \Delta\, Asksz_{t-i} + \sum_{i=1}^{6} \beta_{S,\,bsz,\,t-i} \Delta Bidsz_{t-i}$$
$$- \;\gamma_S\, (Spread + Asksz - Bidsz)_{t-1} + u_t \tag{7}$$

$$\Delta\, Asksz_t = \alpha_{asz} + \sum_{i=1}^{6} \beta_{asz,\,S,\,t-i}\, \Delta Spread_{t-i} + \sum_{i=1}^{6} \beta_{asz,\,asz,\,t-i} \Delta\, Asksz_{t-i} + \sum_{i=1}^{6} \beta_{asz,\,bsz,\,t-i}$$
$$\Delta Bidsz_{t-i} - \;\gamma_{asz}\, (Spread + Asksz - Bidsz)_{t-1} + v_t \tag{8}$$

$$\Delta\, Bidsz_t = \alpha_{bsz} + \sum_{i=1}^{6} \beta_{bsz,\,S,\,t-i}\, \Delta Spread_{t-i} + \sum_{i=1}^{6} \beta_{bsz,\,asz,\,t-i}\, \Delta\, Asksz_{t-i} + \sum_{i=1}^{6} \beta_{bsz,\,bsz,\,t-i}$$
$$\Delta Bidsz_{t-i} - \;\gamma_{bsz}\, (Spread + Asksz - Bidsz)_{t-1} + w_t \tag{9}$$

The system of equations given by (7), (8) and (9) form the basis of our empirical investigation with the appropriate high frequency trading data. Observe that our model has a simple but intuitive interpretation. The change in spread at any given point in time, $\Delta Spread_t$, is a function of the actual past spread changes and the past bid and ask depth changes (the relatively long term effect) and on the spread and the net depth (i.e., ask depth minus the bid depth) associated with the last quote revision (the short term, or error correction, effect). Note that the error correction term simply measures the speed of adjustment back to the long-run equilibrium whenever the system is perturbed from its equilibrium path. Hence, our model accommodates both a long term and a short term effect of past spreads and depths on the current spread adjustment. The same logic holds individually for the ask and bid depths, as well. By putting minimal structure on our empirical model, we let the data tell us the actual path by which new information gets impounded in successive adjustments of the spreads and depths.

3. Data and Time-series Properties

There are multiple ways of solving the above system of equations (7) - (9). Among them, the information shares of Hasbrouck (1995, 2002) and the Gonzalo and Granger (1995) common factor components provide competing approaches to estimating parameters of cointegrated time series. The July 2002 Special Issue on Price Discovery in the *Journal of Financial Markets* debates the pros and cons of the two approaches. Lehrmann (2002), the editor of the Special Issue, concludes, "In summary, the Hasbrouck information shares correctly measure price discovery only when the price [and depth] change innovations are uncorrelated while the Gonzalo-Granger [common factor] weights generically do so only when price [and depth] change innovations have the same variance…"[p. 273, brackets added].[14]

Since price and depth innovations are likely to be highly correlated, we use the Gonzalo-Granger (1995) (GG) procedure to decompose the permanent and temporary components in the jointly cointegrated spread and two depth series. In so doing, we derive from the error correction terms, γ_S, γ_{asz}, and γ_{bsz}, in equations (7) – (9), a set of common factor component estimates of the long-run impact on quotes and spreads from innovations in quotes and spreads. Further details on the operationalization of the GG decomposition for our purposes are provided in a Technical Appendix for the interested reader.

3.1 Data Methodology

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 and then filtered to detect 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. 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, measured in

[14] With the very high frequency (continuous) data analyzed below, Harris, McInish and Wood (2002b) and Tse (2002) show that the information share and common factor approaches are virtually identical.

seconds) between new quotes. The average SPAN 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 the average of the ask and bid depths plummeted by 61% from 159 and 139 round lots at the best ask and bid in 1995 to 66 and 52 round lots, respectively, in 1998. The last line of Table 1 shows that the standard deviation of spreads declined slightly over the period as well, and that the volatility of ask and bid depth declined by 37% and 41% over their respective prior levels. Whether or not the massive decline in market liquidity and the volatility of 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 in this study.

3.2 Stochastic Properties of Spreads

In Table 2, we investigate the time-series and stochastic properties of the spreads that arise from our series on new price or depth quotes. To provide a familiar reference point from analysis of CRSP data, we contrast the stochastic properties of spreads in daily closing prices with those from high frequency intraday data. One of the series is clearly I(0), and the other is just as clearly I(1). In particular, the change in the closing ask price minus the closing bid price over 252 days in 1995 and 1998 is related to a set of lagged spread changes but not to the level of spreads. However, the augmented Dickey-Fuller tests documented on the right of Table 2 show that changes in intraday spreads follow a random walk. Note that drift parameters and occasional deterministic time trends arise in many daily spread series but never do so in the high frequency intraday data. That is, intraday spreads are related with a unit root coefficient to immediately past spreads plus an error term, just as in equation (5) above. Although the estimates are shown for 10,000 intraday observations on new quotes (approximately one month for DJIA stocks), very similar results hold for one week, one quarter or one year of data. [15]

In sum, we find that the conventional wisdom that spreads are I(0) stationary holds only for closing trades--that is, for data that has been aggregated to the daily level (or higher) . By contrast, intra-day spreads unquestionably display an I(1) difference stationary pattern. This has not been widely discussed in the literature and is a contribution of the current research.

3.3 Cointegration tests involving price quotes, spreads and depths

Before estimating our empirical model, it is important to check for the cointegration properties of the price and depth series on either side of the market for the stocks in our data over the time period investigated. Accordingly, in Table 3, we present Johansen's (1991) cointegration tests 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 to determine the order of integration of the series. All were found to be I(1) series. The Akaike Information Criterion was minimized for the set of VAR equations at six lags. We repeated all analyses with the other DJIA stocks (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, and error correct (or, adjust back) to the spread at a rate to be determined by the estimated coefficient of the error correction term.[16] 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 I(1) and error correct to excess depth; trace and Hmax test statistics reject H_0: r=0 at the 0.01 level.

To discern whether the common stochastic trends in price and depth quotes were one and the same, we then examine whether the ask price and ask depth series are cointegrated (and similarly whether the bid price and bid depth series are cointegrated. Using again the trace and Hmax test, we are unable to reject the null of no cointegration. Therefore, we next investigated the order of

---

[15] These results are available from the authors.

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

integration and cointegration relationships between spreads and depths suggested by the analysis of microstructure dynamics in Section 2.2 above. Thus, in Panels C and D of Table 3, we report evidence at the 0.01 level that I(1) spreads are cointegrated with each separate depth size quote series. Similarly, in Panel E of Table 2, I(1) spreads are shown to be cointegrated with ½ the summed depth (bid depth plus the ask depth). In the next section, we estimate and analyze at length our preferred specification of I(1) spreads, ask depth, and bid depth in a three-equation VECM model with a linear combination of spreads and excess depth forming the error correction (or the speed of adjustment) term.

Finally, we round out the specification pretesting part of the estimation of our empirical model, associated with the order of integration and cointegration, by examining whether all four price and depth quotes are cointegrated. In Appendix A, 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. Put differently, no linear combination of all four series appears to be a mean-reverting stationary long-term equilibrium process. Excess depth does not appear to display a pattern of declining when the spread rises and vice versa. Rather than reflecting a simple asymmetric information story about depth drying up when spreads increase in periods of informed trading (see, for example, Kavajecz, 1998), price quotes and depth quotes appear instead to reflect distinct equilibrium processes. This is an important finding not reflected in the extant literature. We now trace the effect of these two separate adjustment processes on spreads.

4 Information Discovery Role of Depths

4.1 Modeling Spreads and Depths

In our initial investigation (see Section 3), we discovered that our intra day spreads were I(1) in 1995 and 1998 for Dow stocks and that an error correction term (comprised of the spread and excess depth), reflecting the adjustment back to a long term equilibrium, was I(0). The finding that spreads themselves are not I(0), as would be hypothesized in a full information batch market environment, is pivotal to our modeling approach.[17] Specifically, quoted spreads do not appear to represent white noise market frictions alone. Instead, as argued by Huang and Stoll (1994), a component of the spread is a systematic reflection of information content in recent trades or orders

[17]When prices are fully informative and when there's continuous market-clearing, any spread fluctuations should be white noise. For further details, see Hasbrouck (1996). Section 2.2 above suggests why this will not hold when time-varying spreads reflect order imbalances.

(the information effect) while another component of the spread is a systematic reflection of the variation in execution reliability at a price and therefore should be related to market depth (the inventory effect).[18]

To investigate the possible cointegration relationship between spreads and depths, we therefore determined an optimal lag length and the cointegrating vectors for the system of three equations (7) – (9). Using the SAS subroutine TSULMAR, the optimal system lag length proved to be less than ten for all DJIA stocks, e.g., six (new) quotes for IBM. Table 4 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 can be employed in a simultaneous estimation of our three-equation model.

For each of the 30 stocks in our sample, and in each of the years 1995 and 1998, we provide results of the Johansen's (1991) trace test to determine the rank of the cointegrating vector matrix. 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 4 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 95% level. This implies that spreads and depths display a long-term equilibrium relationship with each other. 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. In addition, subsequent testing of r=1 against the alternative r=2 indicates that ten cases in 1995 have two cointegrating vectors and one common trend. The implication of these results is that for all 27 cointegrated DJIA stocks in 1998 and for 20 of 30 cointegrated DJIA stocks in 1995, the three-equation system of the spread and two depths is characterized by one cointegrating vector and therefore two common stochastic trends. That is, depths and spreads may represent two distinct stochastic trends – and are not consistently inversely related to each other as has been postulated by other empirical studies (see, for example, Lee, Mucklow and Ready (1993)).

4.2 Proportion of long-run impact attributable to spreads versus depths

The cointegration results of the previous section allow us to apply the Gonzalo-Granger common factor estimation and testing. Table 5 displays our estimates of the common factor weights attributable to the spread versus the bid and ask depths that reflect their respective contributions to

[18] Brock and Kleidon (1992) and Harris, McInish and Chakravarty (1995) have characterized the inventory effects in continuous (or, non-Walrasian) trading environments.

the first common trend.[19] These common factor weights are proportional to the impact multipliers associated with the information discovery processes. That is, the common factor weights associated with each depth quote and the spread indicate the proportion of long-run impact on the Stock-Watson common stochastic trend attributable to each respective series. 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. The Gonzalo-Granger Qgg test statistic is distributed chi-squared with one degree of freedom.

From Table 5, we reject the null hypothesis for the quoted spread series (at the 1% level) in 8 cases out of 30 in 1995 and in only 1 case out of 27 in 1998. In contrast, we reject the null hypothesis of zero effect for each of the depth series in all 57 cases. Our interpretation of these findings 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 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 depths 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]. Note that a Gonzalo-Granger chi-squared test finds the depth numbers (i.e., the last two numbers for each stock) to be statistically significant at the 1% level in each of the seven cases while in no case is $\gamma_{\perp\ \mathrm{SPREADS}}$ (i.e., the first number in each set) ever significant. Also, at the mean in these seven cases, the factor weight on spreads is just 10.8% with depths accounting for 89.2%.

---

[19] Note that these weights derive from the third eigenvector of the common factor matrix orthogonal to the adjustment vector matrix (for further details, see Gonzalo and Granger (1995)). The weights for the second common trend derived from the second eigenvector of this same matrix are available from the authors. We report the three elements of each of these eigenvectors as a factor weight—i.e., all reported weights are normalized to sum to 1.

To examine further the inference that depths rather than spreads predominantly convey new information, we present, in Table 6, 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. Table 6 indicates that we can reject the null hypothesis of no information discovery by depths at a 1% level of significance in all 30 cases in 1995 and in 25 of 27 cases in 1998. The null hypothesis is rejected at just 2% in the other two cases.[20]

4.3 *Discussion of Results*

Our finding from Tables 5 and 6 is that, relative to the quoted bid-ask spreads, the depths appear to convey significantly more information. The fact that these results are consistent across the years 1995 and 1998 entailing dynamic institutional change at the NYSE attests to the temporal generalizability of our conclusion. The results are also robust across several specifications of the spreads-depth VECM that we have tried including average depth (or, ½ the summed depth), and the two separate depths as reported above.

These results underscore the important role played by the limit order book in the price discovery process. Optimal execution strategy rationally clusters informed traders to where the uninformed traders execute their trades, which may be predominantly in the limit order book. It appears that informed traders also actively use the limit order book to affect all or part of their trades through attention to the value of immediacy revealed by the depth at various prices on the book. Thus, for example, informed traders could submit marketable (or even near-the-quote) limit orders and then quickly cancel if they did not obtain a quick fill and/or the price moved away from them. The significantly high percentage of such orders that are canceled bear testament to their possible strategic use by informed traders.[21]

Even though our findings pertain to the specialist market of the NYSE, we should emphasize that our results apply even to quote driven markets without specialists like the burgeoning ECNs and other order matching systems. It is easy to see that in such markets, outstanding orders (the depths) at each discrete price points have to be exhausted before a nice price point is established which in and of itself guarantees that depths will change more frequently than spreads. Our findings

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

[21] Such strategic uses of limit orders differs from the early theoretical models of market and limit orders which allowed informed (or, strategic) traders to submit only market orders and uninformed traders to submit only limit orders (see, for example, Angel (1992) and Rock (1999)).

also provide a compelling reason why depth information from options markets needs to be made available to off-floor participants in much the same way as equity markets disseminate both spread and depth information in real time. Currently, only intra day spread information in options is widely available to off-floor participants.

From a regulatory perspective, 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. Nevertheless, our conclusion remains in place; even with the tighter spreads of 1998, information first revealed in the depths overwhelmingly accounts for the common stochastic trends in price and depth quotes.

5. Adjustment Dynamics with Impulse Response Functions

To investigate further the adjustment of depths to an innovation shock in spreads and vice versa, we next examine the equilibrium error term Z ≡ (Spread + Asksz – Bidsz) in the estimated VECM. In 20 of 30 cases in 1995 and in all 30 in 1998, the cointegration estimates in Table 4 imply one cointegrating vector (Z1) defining the equilibrium of spreads and depths. From the VECM results in Tables 7A and 7B, the sign of the equilibrium responses to Z1 are straight-forward analytically. An increase in spreads raises the error correction term which is defined in the VECM specifications (see Eqns. (7) – (9)) as a negative adjustment to the left-hand side variables. Consequently, the positive sign on the Z1 term in the fourth and sixth columns of Tables 7A and 7B indicates that a higher spread results in a decrease in depths, ceteris paribus. Turning the question around and examining the Z1 term in the second column of Tables 7A and 7B, a positive innovation shock to net depths (i.e., Asksize - Bidsize) reduces spreads. Other specifications (not reported) show the same result for summed depths; an increase in summed depth decreases the spread. In short, greater depth, however measured, implies tighter spreads. These permanent effects can be interpreted as the traditional effect of increased liquidity in reducing costs for both specialists and limit order traders making markets in competition with off-exchange dealers.

However, in ten cases in 1995 the cointegration evidence in Table 4 suggests not one but two cointegrating vectors—i.e., a more complex equilibrating condition between spreads and depths than would be represented by Z1 alone. IBM in Table 7 illustrates one such case. Examining then the Z2 term in the fourth column of Table 7A, an increase in spreads raises Z2 and increases asksize while a decrease in spreads, lowers Z2, and lowers asksize. In short, here in the second equilibrating condition, an exogenous shock resulting in tighter spreads lowers depths. This result is familiar to those who have studied the effect of tick-size reduction. At smaller tick sizes 1995-2000, the picking off risk associated with writing limit orders at the BBO increased for any given underlying volatility in the true efficient price. Consequently, essentially all traders backed off from their regular trading intensity by posting smaller limit orders at any given price. Just as pricing one's uninformed limit orders less aggressively (at wider spreads) makes sense in the face of increased volatility (Foucault 1999), so too smaller tick sizes increases the probability of being picking off at stale quotes. Tighter quotes therefore reduce the optimal order size for uninformed traders.

Thus, cointegrating vectors Z1 and Z2 have opposite signs in Table 7 and do not carry distinct implications for a given shock, holding all else constant. Our careful specification analysis in section 4 shows that the identifying restrictions that could reduce this complexity are rejected by tests of restrictions on the cointegrating vectors. In just such circumstances, Lutkepohl and Reimers (1992) recommend investigating the dynamics of adjustment with regard to magnitudes and speed by examining the orthoganalized impulse response functions of the VAR processes.

Impulse response functions (IRFs) track the multi-period response paths of time-series variables as they return to long-run equilibrium relationships after experiencing a one-time single-variable shock to a system of VARs like

$$S_t = \acute{\alpha}_{st} + \Delta_{ss} S_{t-1} + \Delta_{sa} Asz_{t-1} + \Delta_{sb} Bsz_{t-1} + \ldots + v_{st} \qquad (10)$$

$$Asz_t = \acute{\alpha}_{at} + \Delta_{as} S_{t-1} + \Delta_{aa} Asz_{t-1} + \Delta_{ab} Bsz_{t-1} + \ldots + v_{at} \qquad (11)$$

$$Bsz_t = \acute{\alpha}_{bt} + \Delta_{bs} S_{t-1} + \Delta_{ba} Asz_{t-1} + \Delta_{bb} Bsz_{t-1} + \ldots + v_{bt} \qquad (12)$$

where S is spreads, Asz is asksize, and Bsz is bidsize. Even with C(1) series in (10)-(12), since the derivatives of the normalized cointegrating vector(s) do not capture all the possible feedback loops in (10)-(12), impulse response function analysis can prove quite useful. Coopejans, Domowitz and Madhavan (2001), for example, employ IRFs for forecasting liquidity dynamics in an electronic limit order book.

Often in finance and economics, however, IRFs that are fine for forecasting are of little interest for testing implications of competing theories. In particular, if $Cov(v_{it}, v_{jt}) \neq 0$ in (10)-(12), IRFs will capture global, system-wide shocks in multiple series at once (because of contemporaneous cross-equation correlation of the error terms). In our case, innovations to the price of immediacy, to discretionary liquidity trading, and to information shocks themselves may well co-vary causing $Cov(v_{it}, v_{jt}) \neq 0$. Therefore, following Lutkepohl (1993), we propose to isolate impulse responses from individual series by orthoganalizing with a Cholesky factorization procedure for which the results will be dependent on the order of the variables in the model.[22]

In particular, we define an orthogonal innovation in spreads as $dv_{st} = [S_t - S_{eq}]$ where dv_{st} is a one-time-only unit standardized innovation in spreads. Since the variance of standardized orthogonal components is 1.0, a unit innovation can be thought of as just an innovation of size one standard deviation (Lutkepohl, 1993). The orthoganalized impulse response function (OIRF) for spreads on spreads Φss is then

$$\Phi ss_t \quad = \quad dv_{st} \quad = \quad +1\sigma_v \ > \ 0$$

$$\Phi ss_{t+1} \quad = \quad \Delta_{ss}\, dv_{st} \Rightarrow \quad \text{sign } \Phi ss_{t+1} > 0 \text{ since } 0 < \Delta_{ss} \leq 1 \qquad (13)$$

$$\Phi ss_{t+2} \quad = \quad (\Delta_{ss})^2\, dv_{st} \quad \Rightarrow \quad \text{sign } \Phi ss_{t+2} > 0 \text{ and } \Phi ss_{t+2} < \Phi ss_{t+1}$$

….

An own-impulse response function should therefore be monotonically decreasing like the four OIRFs in Figure 1. These are average ORIFs across all DJIA stocks for the spreads and depths in 1995 and 1998. The horizontal axis is time which from Table 1 averages 91.1 seconds (1.5 mins.) between quotes in 1995 and 25.7 seconds (0.4 mins.) between quotes in 1998. The vertical axis is a percentage change where the units are standard deviations of the series. Spreads in 1998, for example, are 36% of a standard deviation higher 0.4 minutes after a unit standard deviation positive shock – i.e., 36% of a $0.072 standard deviation or 2.6 cents. This 2.6 cents can be related to the 12.1 cents average spread of DJIA stocks throughout 1998 shown in Table 1. By comparison, ask depths in 1998 are 81% higher 0.4 minutes after a positive shock – i.e., 81% of a 87.7 standard deviation or 71 rounds lots relative to an average depth of DJIA stocks in 1998 of 60.7 round lots.[23] This is our first indication that depths are more sensitive than spreads to shocks.

In response to a unit innovation to each series, subsequent values of that series erode asymptotically back to the initial zero coordinates position. For example, 91 seconds (one quote) after the initial positive shock of one unit standard deviation, 1995 ask depths in DJIA stocks are 81% of the size of the innovation. Approximately 6 minutes (4 quotes) after the initial shock, ask depth is

[22] We report below the average impulse responses associated with all possible orderings of variables in the Cholesky factorization model, consistent with the recommendations of Lutkepohl (1993, p. 297). Ballie, Booth, Tse and Zabotina (2002) also recommend this procedure in using Cholesky factorization to calculate Hasbrouck's information shares.

[23] The Bidsize OIRF was very similar to the Asksize OIRFs displayed in the bottom panels of Figure 1. For example, 0.4 minutes after a positive shock, 1998 bid depths are 76% higher. After three minutes, 1998 ask depths are 12% higher, and 1998 bid depths are 11% higher.

only 21% increased, and by 23 minutes (15 quotes later) ask depth is back to its initial level. The OIRF for bid depths is very similar. 1995 spreads, on the other hand, decline to 29% of the innovation within one quote, 2% within four quotes (6 minutes), and essentially back to their previous level within 11 minutes (seven quotes) in DJIA stocks.

In addition, note from Figure 1 that more frequent 1998 quotes only 25.7 seconds apart lead to a faster adjustment process for depths but not for spreads. Although it still takes four quotes for the effect of a positive shock on ask depths to decline to 20% above its initial level, those four quotes take less than 2 minutes in 1998 versus six minutes in 1995. In addition, depths in DJIA stocks returned to their pre-shock level in about six minutes in 1998 versus 23 minutes in 1995. DJIA spreads, on the other hand, took 11 minutes to return to their initial level following a positive shock in 1995 and took 6 minutes to do so in 1998. Depths were about twice as slow to adjust as spreads in 1995 but by 1998 both depths and spreads adjust equally quickly, in just six minutes.

As opposed to these very regularized own-impulse response functions, orthoganalized cross-impulse response functions can display any pattern. Figure 2 shows the effect of ask depth innovations on spreads in 1995 and 1998. Initially, in response to greater buy-side depth at the ask, spreads widen by 18% in 1995 and 12% in 1998. That is, traders appear to respond to the informational uncertainty signaled by the depth innovation by less aggressively pricing their limit orders, consistent with Foucault (1999). However, within three minutes in 1995 and within 50 seconds in 1998, spreads actually fall precipitously to a lower level than that at which they started. That is, as the informational uncertainty is resolved and perceived picking off risk declines, spreads tighten and stay below normal for 20 minutes in 1995 and for 6 minutes in 1998. Hence the permanent effect on spreads is in the opposite (negative) direction from the positive transitory effect of the increased information uncertainty triggered by such a sharp increase in depth.

The maximum decline in 1995 spreads is 4% (of a \$0.067 standard deviation, so \$0.0027 relative to a mean DJIA spread of \$0.17) at about 5 minutes after the depth innovation, and the maximum decline in 1998 spreads is 4% (of a \$0.07 standard deviation, so \$0.0028 relative to a mean DJIA spread of \$0.126) at about 2 minutes after the depth innovation. The permanent effect on 1998 spreads of a one standard deviation positive shock to ask depths (87 round lots in 1998) is negative 1%, or about 1/10th cent.

Turning the question around, do depths error correct to spreads and if so, in which direction? In the bottom two panels of Figure 2, 1995 depths are seen to decline 10% in response to a sharp (one standard deviation, 8.2 cent) increase in the spread. And 1998 ask depth declines 6.5% in response to a shock to spreads. At wider (bid and ask) quotes, the picking off risk associated with writing limit orders at the BBO increases for any given underlying volatility in the true efficient price. At the same time, the execution risk increases for any given deviation from the midpoint of the quote (see, for example, Foucault 1999). Consequently, for both reasons one might expect uninformed traders to decrease their order sizes. Wider quotes therefore reduce the optimal order size for uninformed traders.

Depths error correct to one another as well. Figure 3 shows the OIRF of bid depths to an innovation in ask depths in 1995 and 1998. Within 8 minutes (5 quotes) in 1995 and within 2 minutes (5 quotes) in 1998, bid depth steadily increases to 4.5% above its starting value. The magnitude of this positive effect of depth on the sell side of the market to depth on the buy side varies across securities by almost a 100%. The top right panel of Figure 3, for example, shows the 5% to 9% increases in 1995 bid depth across individual securities. The second row of Figure 2 shows that a similar variation in the magnitude of these transitory effects is observed across securities in 1998. In both years, the transitory positive effects gradually decline to a statistically significant permanent positive effect. Specifically, a 131 round lots (a unit standard deviation) positive shock to 1995 ask depth generates a permanent 9/10ths of 1% x 124 round lots (1 round lots) increase in 1995 bid depth. Similarly, a 88 round lots positive shock to 1998 ask depth generates a permanent 1.3% x 76 round lots (1 round lot) increase in 1998 bid depth.

Figure 4, displaying the ORIF for ask depths in response to an innovation in bid depths, shows an asymmetry. The first effect of increased selling pressure at the bid is that the ask depth falls 9% (in 1995) as buyers back off their order sizes. One security was even observed to have a 22% decline in initial ask depth. Within 5 minutes, however, in these thickly-traded DJIA stocks, ask depth on the third post-innovation quote has increased. At 9 minutes, the ask depth is up 3% and then gradually erodes back to a permanent slight increase. In 1998 data, the same initial backing off of buy-side depth occurs, though the variation across individual stocks is a much smaller -3% to -8% (-2% on average). Faster quotes also again imply speeder adjustment, with ask depths going positive about one minute after the positive bid depth shock, reaching the maximum 4% increase in 1998 (4% of 88 = 3.5 round lots) within 2 ½ minutes as opposed to the 9 minute delay of peak buy-side liquidity in 1995. Again, the permanent effect is a 95% statistically significant increase in 1998 ask depth of 1.2% -- i.e., 1 round lot.

We also investigated variation across days of the week, morning versus afternoon, and times of the day. The impulse responses security by security do exhibit such variation but not these OIRF averages across the DJIA stocks, with one exception. The less aggressive limit pricing that results in initially wider spreads in response to depth shocks exhibited in Figure 2 is less apparent at the open on Mondays. Figure 5 shows that between 9:30 -10:00 a.m. Mondays, spreads increase by only 15% in 1995 in response to ask depth shocks of +131 rounds lots. The rest of the day and rest of the week, the increased spread in response to the information conveyed by such a depth shock is almost twice as large -- i.e., 27% in 1995. Three minutes later on the Monday openings in 1995, spreads have plummeted to 10% *below* their initial value, and this process takes longer (5 minutes) and tightens less (-7% rather than -10%) the rest of the day and the rest of the week.

In 1998, the permanent effect tightening the spread in response to additional buy-side liquidity required the same 2 minutes on Monday openings as at other times, but the initial, transitory effects are different. On Monday openings, the spread rises only 10% in response to an 88 round lot shock to ask depth, whereas the typical widening of the spread is 17% at other times and days of the week. Both facts suggest an enhanced information processing role of those market makers especially prevalent in the Monday openings.

6. Concluding Summary

We develop and estimate a simple, but intuitive, three-equation system of the bid-ask spread and the bid and ask depths with 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 first that, in turn, affects subsequent quote revisions. 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)). Furthermore, the existing studies of spreads and depths, such as Kavajecz (1998), make important stylized assumptions for tractability that may, or may not, be accurate. An example of such an assumption is the inverse relationship between spreads and depths. In contrast, our general model derived from fundamentals is able to tease out the nature of the relationship between spreads and depths when confronted with the data. To our knowledge, our research is the first to investigate, within a cointegration/error correction framework, whether depths play a significant role -- and if so, by how much -- in the information revelation process.

Our results indicate that new information is reflected overwhelmingly in (bid and ask) depth updates rather than in spread updates. Our findings are intuitive from the point of view 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. This is especially relevant in the current post-decimal trading environment of penny ticks. The increasingly important role of depths is also recognized in the recent NASDAQ regulation of decreasing the minimum depth requirement from 1,000 shares to 100 shares for dealers posting quotes. Finally, our results are consistent with available empirical evidence that shows that specialists actively manage their quoted depths even when prices are not changing.

Our findings are equally compelling from either a theoretical or a practical standpoint. While microstructure theory postulates a specialist price schedule that is complete and continuous (see, for example, Kyle (1985, 1989)), what we observe in practice are two prices and two corresponding sizes the prices are guaranteed for. Understanding the interaction between these posted prices and quantities, and their theoretical counterparts, is important to further our understanding of how new information gets incorporated in subsequent updates of the posted price-quantity schedule. From a practical perspective, posted prices and associated quantities are the information most investors possess when deciding on a trading strategy. Understanding the channel through which new information is reflected first furthers our understanding of how informed traders trade. Finally, our empirical results provide support to 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.

Analysis of the orthoganalized impulse response functions shows that spreads widen initially in response to positive depth shocks but that subsequent tightening occurs within 2 minutes and is a permanent effect. Depths decline in response to positive shocks to the spread but this effect is not permanent. Bid depths and ask depths respond to one another differently. Both eventually increase in response to positive shocks, but ask depth declines initially in response to positive sell-side shocks at the bid whereas bid depth increases continuously in response to positive buy-side shocks.

There are potentially interesting ways of extending our model to develop further insights into the relative importance of depths over spreads in reflecting new information first. While the impulse response analysis focuses on the thirty relatively active (and high profile) stocks at specific times of day and days of week, it does not focus on specific corporate events or on less liquid issues. But we know from extant research that (the degree of) adverse selection is a function of the day of the week (Monday versus Friday), time of day (middle of the trading day versus the beginning or the end) and varies around specific corporate events such as earnings announcements. Additionally, small cap (and thinly traded) stocks are also associated with higher spreads (higher adverse selection). Investigating the relative importance of depths over spreads in each of these cases, to further increase our understanding of the exact channels of information assimilation in prices, should prove to be a fruitful future research agenda.

References

Angel, J.A., 1992, Order placement strategy of informed investors: market versus limit orders, working paper, University of California, Berkeley.

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.

Bacidore, J.M., 1997, The Impact of Decimalization on Market Quality: An Empirical Investigation of the Toronto Stock Exchange, *Journal of Financial Intermediation*, 6, 92-120.

Bacidore, J.M., R. H. Battalio, and R.H. Jennings, 2001, Order submission strategies, liquidity supply, and trading in pennies on the New York Stock Exchange, NYSE working paper.

Ballie, R., G. Booth, Y. Tse, and T. Zabotina, 2002, Price discovery and common factor models, *Journal of Financial Markets*, 5, 309-321.

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

Bollen, N. P. B., and R.E. Whaley, 1998, Are "teenies" better? *Journal of Portfolio Management*, 25, 10-24.
Goldstein, M.A., K.A. Kavajecz, 2000, Eights, sixteenths and market depth: changes in tick size and liquidity provision on the NYSE, *Journal of Financial Economics*, 56, 125-149.

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.

Brock, W.A. and A. Kleidon, 1992, Periodic market closure and trading volume: A model of intraday bids and asks, *Journal of Economc Dynamics and Control*, 16, 451-489.

Campbell, J., A. Lo, and C. MacKinlay, 1997, *The Econometrics of Financial Markets*, Princeton: Princeton University Press.

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., R. Van Ness, and R.A. Wood, 2002, 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.

Chakravarty, S., H. Gulen, and S. Mayhew, 2002, Informed trading in stock and option markets, *Journal of Finance*, forthcoming.

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

Chung, K., B.F., Van Ness and R.A., Van Ness, 2001, "Are Nasdaq stocks more costly to trade than NYSE stocks? Evidence after decimalization, working paper, Kansas State University.

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.

Coppejans, M.L., I. Domowitz, and A. Madhavan, 2001, Liquidity in an automated auction, NBER working paper, May 2001.

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.

DuFour, A. and R Engle, 2000, Time and the price impact of a trade, *Journal of Finance*, 55, 2467-99.

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.

Easley, D., N. Keifer, M. O'Hara, and J. Paperman 1996. Liquidity, Information, and infrequently traded stocks. *Journal of Finance,* 51, 1405-1436.

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

Engle. R. and J. Lunde, 1998, Trades and Quotes: A Bivariate Point Process, Working paper, University of California-San Diego.

Escribano, A., and R. Pascual, 2000, Asymmetries in bid ask responses to innovations in the trading process, working paper, University of Madrid.

Fernando, C., 2003, Commonality in liquidity: Transmission of liquidity shocks across investors and securities, *Journal of Financial Intermediation*, 12(3), 133-154.

Frino, A., F. Harris, T. McInish, and M. Tomas, 2001, Price discovery in the pits: The role of floor brokers on the Sydney Futures Exchange and the CBOT, *Journal of Futures Markets*, forthcoming.

Foucault, T. 1999, "Order flow composition and trading costs in a dynamic limit order market," *Journal of Financial Markets*, 2, 99-134.

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.

Hamilton, J., 1994, *Time-Series Analysis*, Princeton: Princeton University Press.

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.

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, 2002a, DCX trading in New York and Frankfurt: Home bias affects trading costs of international dual-listings, Working paper, Babcock Graduate School of Management, Wake Forest University.

Harris, F. H. deB., McInish, T.H., and R.A. Wood, 2002b, Security price adjustment across exchanges: an investigation of common factor components for Dow stocks, *Journal of Financial Markets,*5, 277-308 and 341-348.

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

Harris, L. E., and V. Panchapagesan, 2002, The information content of the limit order book: Evidence from NYSE specialist trading decisions, working paper, Washington University, St. Louis.

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., 1996, Modeling Microstructure Time-Series, in G.S. Maddala and C. R. Rao, eds., *Statistical Methods in Finance*, New York: North-Holland.

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

Hasbrouck, J., 2002, Stalking the efficient price, *Journal of Financial Markets,* 5, 329-339.

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. and H.R. Stoll, 1997, Components of the bid-ask spread: A general approach, *Review of Financial Studies*, 10, 995-1034.

Huang, R.D., 2002, The quality of ECN and Nasdaq market maker quotes, *Journal of Finance*, 57, 1285-1319.

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.

Jones, C. M., and M.L. Lipson, 2001, Sixteenths: direct evidence on institutional execution costs, *Journal of Financial Economics*, 59, 253-278.

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

Kavajecz, K.A., 1999, A specialist's quoted depth and the limit order book, *Journal of Finance*, 54, 747-71.

Kavajecz, K.A. and E. Odders-White, 2001, An examination of changes in specialist's posted price schedules, *Review of Financial Studies*, 14, 681-704.

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.

Kyle, A.S., 1989, Informed speculation with imperfect competition, *Review of Economic Studies*, 56, 317-355.

Lutkepohl, H. and H. Reimers, 1992, Impulse response analysis of cointegrated systems, *Journal of Economic Dynamics and Control*, 11, 53-78.

Lutkepohl, H., 1993, *An Introduction to Multiple Time-Series Analysis*, New York: Springer-Verlag.

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.

Lehmann, B. N., 2002, Some desiderata for the measurement of price discovery across markets, *Journal of Financial Markets*, 5, 259-276.

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.

Madhavan, A., 2000, Market microstructure: a survey, *Journal of Financial Markets*, 3, 205-258.

Michaely, R., and J. Vila, 1995, Trading volume with private valuation," *Review of Financial Studies*, 9, 471-510.

Michaely, R., J. Vila, and J. Wang, 1996, A model of trading volume with tax-induced heterogeneous valuation and transaction costs, *Journal of Financial Intermediation*, 5, 340-371.

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., 1995, *Market Microstructure Theory*, Oxford: Blackwell.

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.

Ricker, J.P., 1998, Breaking the eighth: sixteenths on the New York Stock Exchange, working paper.

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

Roll, R., 2002, Rational infinitely lived asset prices must be non-stationary, *Journal of Banking and Finance*, 26, 1093-1097.

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.

Tse, Y., 2002, Further examination of price discovery on the NYSE and regional exchanges, *Journal of Financial Research,* 23, 331-351.

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**
St. Dev.			**8.2**	**172.8**	**152.1**			**7.2**	**108.4**	**89.0**

Table 2. Stochastic Properties of Spreads

For DJIA stocks, we present on the left, spreads in closing trades each day in 1998 for all the DJIA stocks. On the right, we present approximately a month of intraday spreads in 1998. Daily spreads mean revert with ADF test statistics of (rho-1) or joint F tests of drift parameters and (rho-1) or drift, time trends, and (rho-1) easily able to reject the unit root hypothesis. Ninety-nine percent critical values for the ADF test of H_0: (rho-1=0) with samples size 250 are -3.99, -3.46, and -2.58 for model specifications with drift and deterministic time trends, wit drift alone, and with neither drift nor time trends. F tests of the linear restrictions have critical values of 6.52 and 8.43 for 99% confidence and samples of size 250 (Hamilton, 1994, p. 76

In contrast, in the intraday data, spreads are non-stationary processes -- specifically, AR(1) random walks reflecting stochastic trends in intraday information or order imbalance. In performing the F tests for a unit root, and drift or time trend in the intraday data, we adjusted the critical values to reflect the enormous number of degrees of freedom in the denominator using Leamer's method (Reject if F > (n-k)/r)((n*r/n) – 1). For example, for AA the critical value for 164,322 observations (n), sixteen variables (k), and three restrictions (r) is ((164,322 16)/3) ((164,322*0.0000183) – 1) = 12.04 or 12.01 for r=1. The comparable critical value for n=10,000, k=16, and r=3 is 9.21 (9.20 for r=1) versus the ∞ sample size augmented Dickey Fuller F statistic for a drift parameter, a time trend, and an AR(1) process of 8.27.

	1998 Daily Closing Spreads							1998 Intraday Spreads						
Stock	**No. Obs.**	**Lags at 0.05**	**Drift/ TimeTrend**	**Rho-1**	**Test Stats ADF**	**F**	**Concl.**	**No. Obs.**	**Lags at 0.05**	**Drift/ T Trend**	**Rho-1**	**Test Stats ADF**	**F**	**Conc**
AA	252	1,4,8	Neg/No	-0.921	-10.16	51.7	I(0)	10,000	1-6,14,15	No/No	-0.009	-4.74	11.09	≈ I(1)
ALD	252	1,4,9,13,15	Neg/No	-0.838	-9.49	42.8	I(0)	10,000	1-6,9,11,15	No/No	-0.005	-3.93	7.20	I(1)
AXP	252	1,3,7	Neg/No	-0.907	-10.46	50.5	I(0)	10,000	1-5,6-9,13,15	No/No	-0.007	-3.94	8.22	I(1)
BA	252	3,7,9,11	Neg/No	-0.994	-14.93	115.4	I(0)	10,000	1-5,7,8,11,15	No/No	-0.005	-3.30	5.41	I(1)
CAT	252	1	Neg/No	-0.866	-10.34	53.4	I(0)	10,000	1-10,12-15	No/No	-0.004	-1.71	1.34	I(1)
CHV	252	8,10,14	Neg/No	-0.968	-15.03	112.9	I(0)	10,000	1-5,7,9-15	No/No	-0.003	-2.12	2.55	I(1)
DD	252	2,3	Neg/No	-0.895	-11.69	68.2	I(0)	10,000	1,2,4-6,13-15	No/No	-0.003	-1.99	2.02	I(1)
DIS	252	1,4,8	Neg/Neg	-0.928	-10.64	37.8	I(0)	10,000	1-5,7,9,12,15	No/No	-0.004	-2.28	2.32	I(1)
EK	252	1,15	Neg/No	-0.881	-9.92	49.2	I(0)	10,000	1-4,6,7,10-15	No/No	-0.004	-2.12	2.46	I(1)
GE	252	1,3,4,8,9,12	Neg/Pos	-0.884	-9.94	32.8	I(0)	10,000	1-5,7,9,12,15	No/No	-0.002	-1.82	1.08	I(1)
GM	252	4,8	Neg/No	-0.940	-14.09	100.3	I(0)	10,000	1-8,10,13-15	No/No	-0.002	-1.58	1.36	I(1)
GT	252	1,3,7	Neg/No	-0.790	-10.47	81.3	I(0)	10,000	1-4,8,9,12,15	No/No	-0.007	-3.40	6.01	I(1)
HWP	252	13,14	Neg/Pos	-1.024	-15.51	80.4	I(0)	10,000	1-7,9,11-15	No/No	-0.003	-1.87	1.89	I(1)
IBM	252	1,2,7,12	Neg/No	-0.806	-7.75	24.3	I(0)	10,000	1-4,6,9-13,15	No/No	-0.003	-1.85	1.70	I(1)
IP	252	2,10,11	Neg/No	-0.951	-14.47	104.4	I(0)	10,000	1-5,7,9,12,15	No/No	-0.004	-2.17	2.31	I(1)
JNJ	252	2,3,8,11	Neg/No	-1.091	-16.70	139.5	I(0)	10,000	1-5,8,9,13-15	No/No	-0.002	-1.42	0.94	I(1)
JPM	252	1,2,9,11,14	Neg/No	-0.877	-8.22	33.8	I(0)	10,000	1-4,6,8,13,15	No/No	-0.008	-3.40	5.60	I(1)
KO	252	1,10,12,14	Neg/No	-0.923	-9.59	46.1	I(0)	10,000	1,2,5,6,11,15	No/No	-0.002	-1.52	1.23	I(1)
MMM	252	6,11	Neg/No	-0.988	-14.01	98.0	I(0)	10,000	1-8,13-15	No/No	-0.005	-2.51	3.07	I(1)
MO	252	3,9,10,14	Neg/No	-1.104	-16.83	141.6	I(0)	10,000	1-4,7,8,11-15	No/No	-0.001	-1.55	0.75	I(1)
MRK	252	3,8	Neg/No	-1.017	-15.46	119.6	I(0)	10,000	1-3,5,13,15	No/No	-0.003	-2.05	2.33	I(1)
MCD	252	4,7	Neg/No	-0.992	-16.50	111.1	I(0)	10,000	1-7,9,11,14,15	No/No	-0.008	-3.04	4.41	I(1)
PG	252	7.8.9	Neg/No	-0.994	-15.08	113.6	I(0)	10,000	1-4,6,9,12-15	No/No	-0.004	-2.39	2.73	I(1)
S	252	4,10	Neg/No	-1.064	-16.28	132.2	I(0)	10,000	1-5,8,10,15	No/No	-0.003	-2.11	2.42	I(1)
T	252	4,5,13	Neg/No	-0.989	-14.68	107.8	I(0)	10,000	1-8,10-15	No/No	-0.002	-1.32	1.05	I(1)
TRV	252	7,12	Neg/No	-1.062	-13.61	92.5	I(0)	10,000	1-4,6-11,13-15	No/No	-0.003	-1.82	1.75	I(1)
UK	252	2,6	Neg/No	-0.975	-14.85	109.9	I(0)	10,000	1-4,6,8,9,14,15	No/No	-0.003	-1.98	1.85	I(1)
UTX	252	1,13	Neg/No	-0.839	- 9.20	42.2	I(0)	10,000	1-4,6,8,9,12,15	No/No	-0.006	-2.78	3.98	I(1)
WMT	252	3,14	Neg/Pos	-1.039	-15.63	80.9	I(0)	10,000	1-6,8-10,12-15	No/No	-0.002	-1.36	0.98	I(1)
XON	252	1,6,8,13	Neg/No	-0.905	- 10.24	52.5	I(0)	10,000	1-12,14,15	No/No	-0.002	-1.50	1.06	I(1)

Table 3. 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 $\gamma_{\perp\,\mathbf{ask}}$ and $\gamma_{\perp\,\mathbf{bid}}$ are common factor weights for the ask and the bid (or the ask size and the bid size), respectively. Note that $\gamma_{\perp\,\mathbf{ask}} + \gamma_{\perp\,\mathbf{bid}} = 1$. 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	$\Sigma\gamma$	$\gamma_{\perp\,\mathbf{ask}}$	$\gamma_{\perp\,\mathbf{bid}}$
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	$\Sigma\gamma$	$\gamma_{\perp\,\mathbf{asz}}$	$\gamma_{\perp\,\mathbf{bsz}}$
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:

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

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

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:

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

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

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

	Hypothesis	Trace	Hmax	Conclusion	Σγ	$\gamma_{\perp S}$	$\gamma_{\perp ½ (asz + bsz)}$
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 4. 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 $r \geq 1$ and of $r = 1$ against $r \geq 2$. 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 thirty cases in 1998 fail to reject the null hypothesis of one cointegrating vector and two common factors. In all sixty cases we can reject the null hypothesis of no cointegrating vectors.

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 5. 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 6. 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 in all 30 cases in 1995 and in 25 of 30 cases in 1998.

	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 7. 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 7 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 8. 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

Figure 1 Own Impulse Response Functions for Spreads and Depths in 1995 and 1998

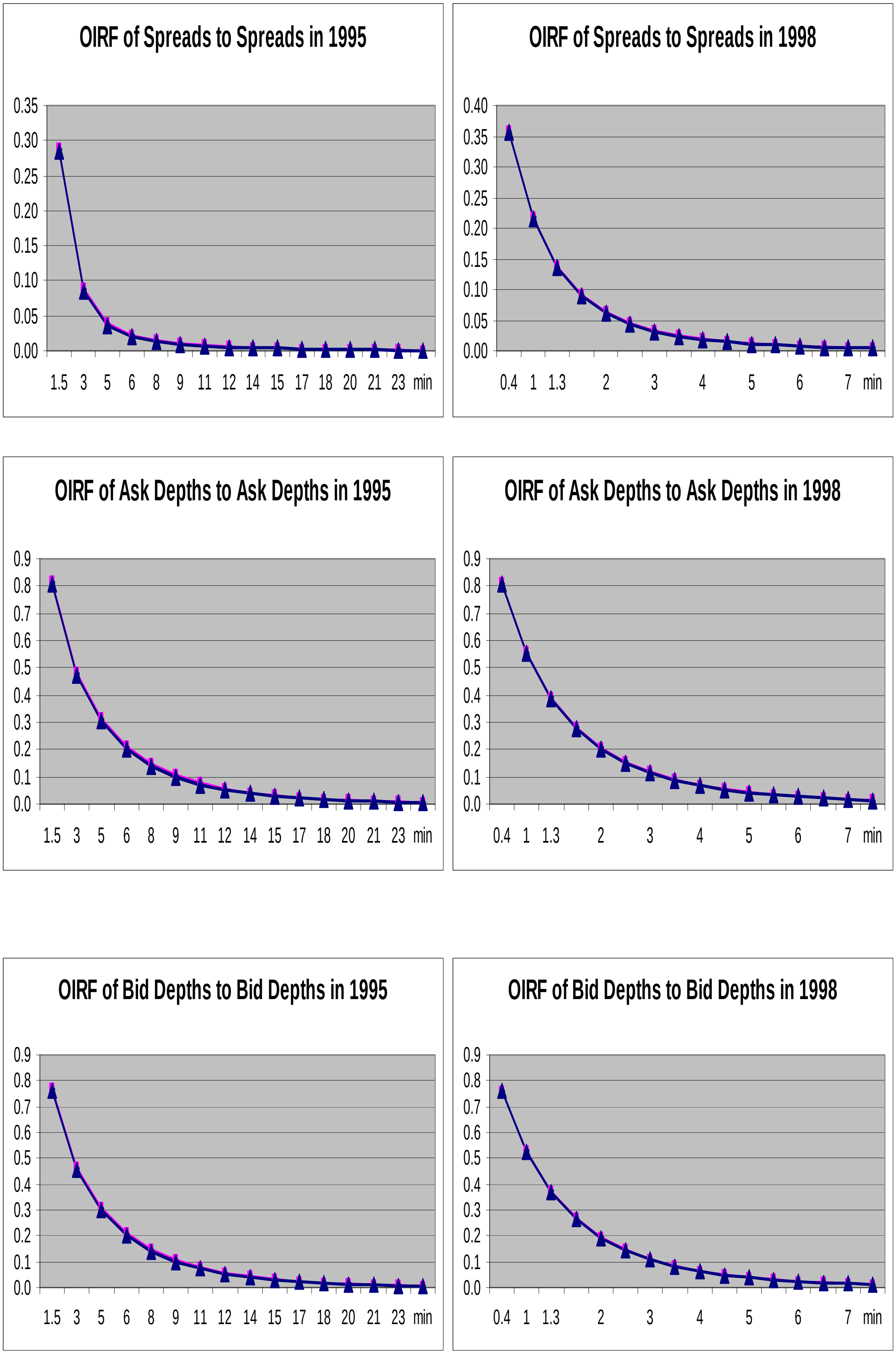


Figure 2 Orthoganalized Impulse Response of Spreads to Depths in 1995 and 1998

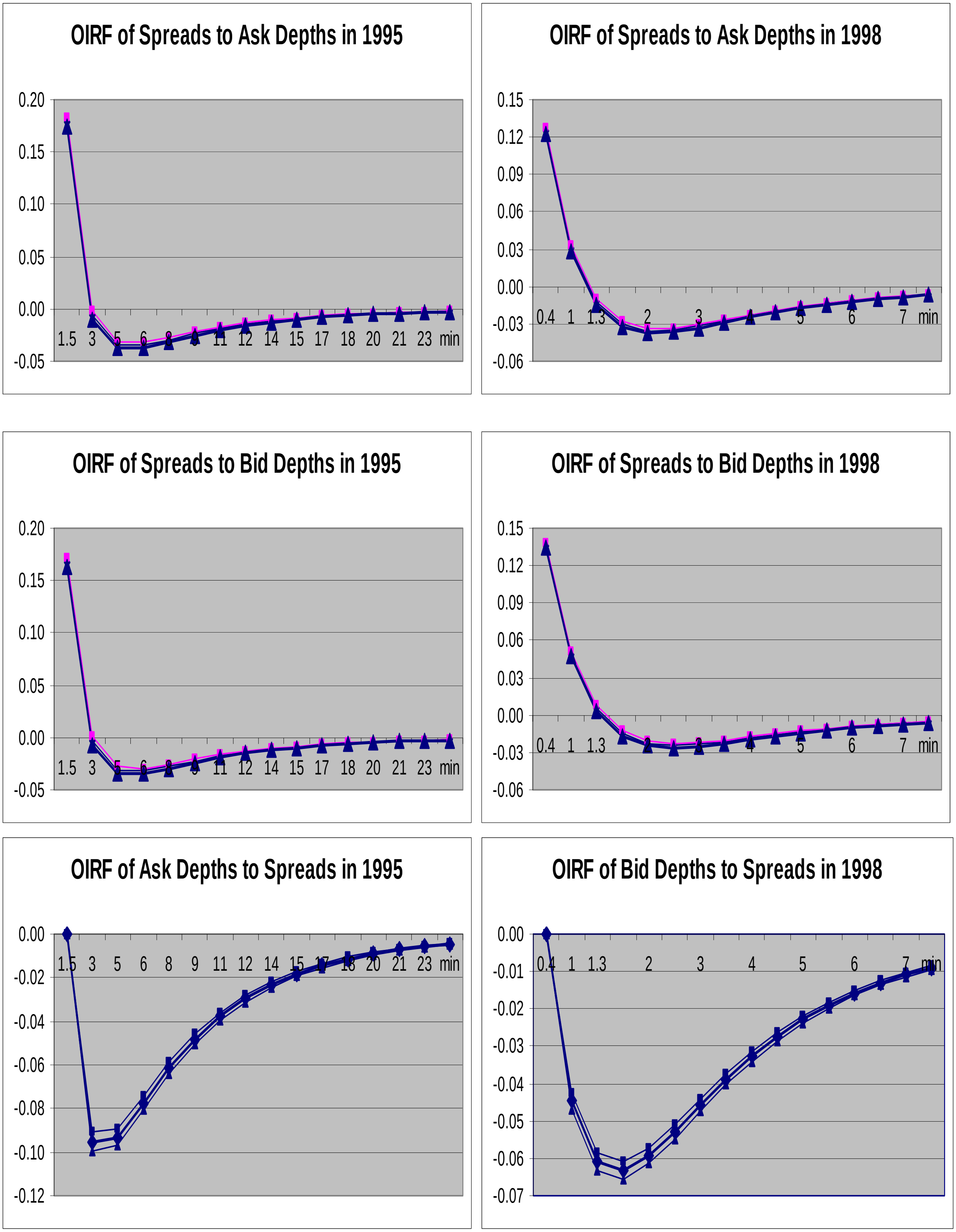


Figure 3 Orthoganalized Impulse Response of Bid Depths to Ask Depths in 1995 and 1998

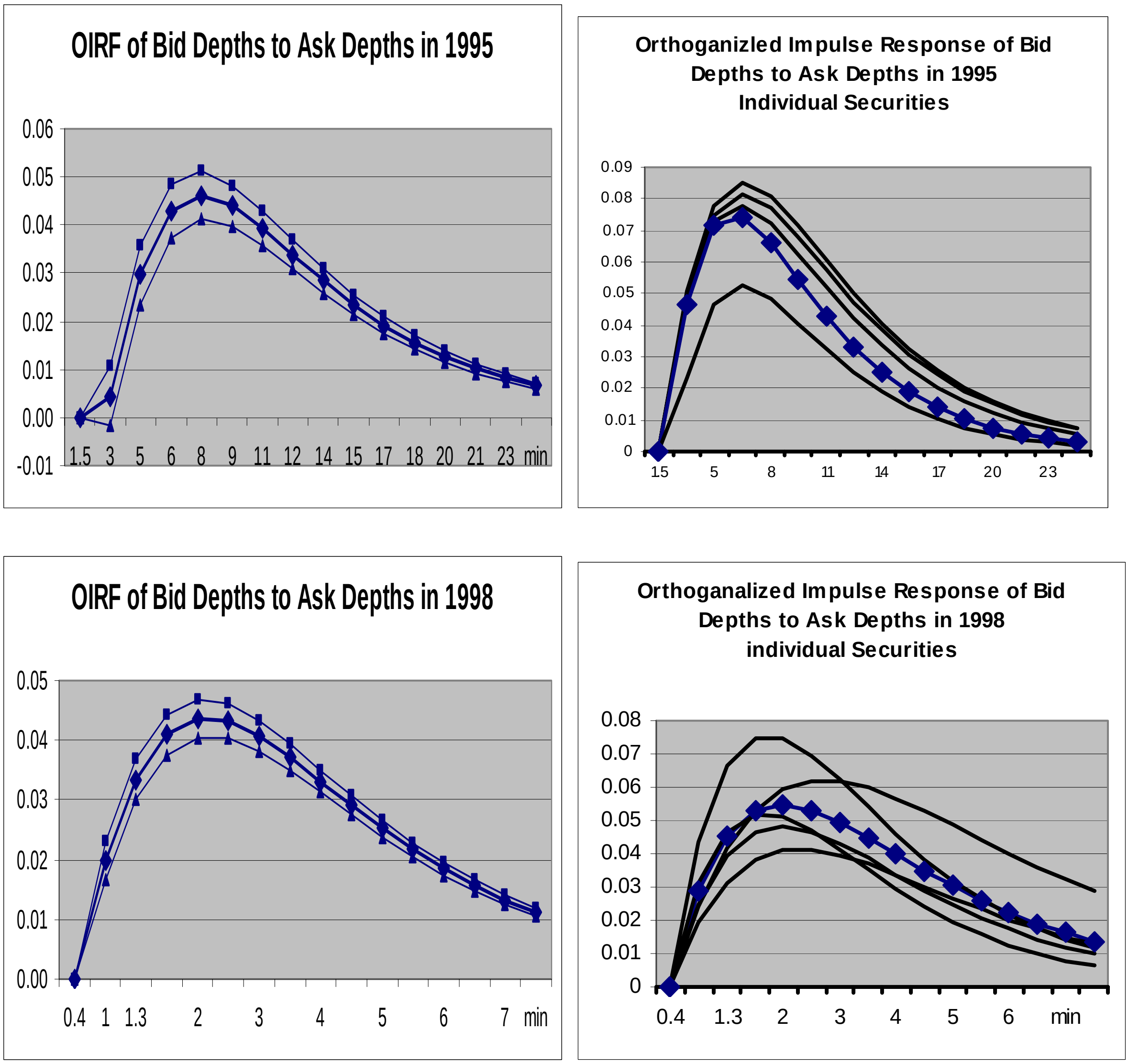


Figure 4 Orthoganalized Impulse Response of Ask Depths to Bid Depths in 1995 and 1998

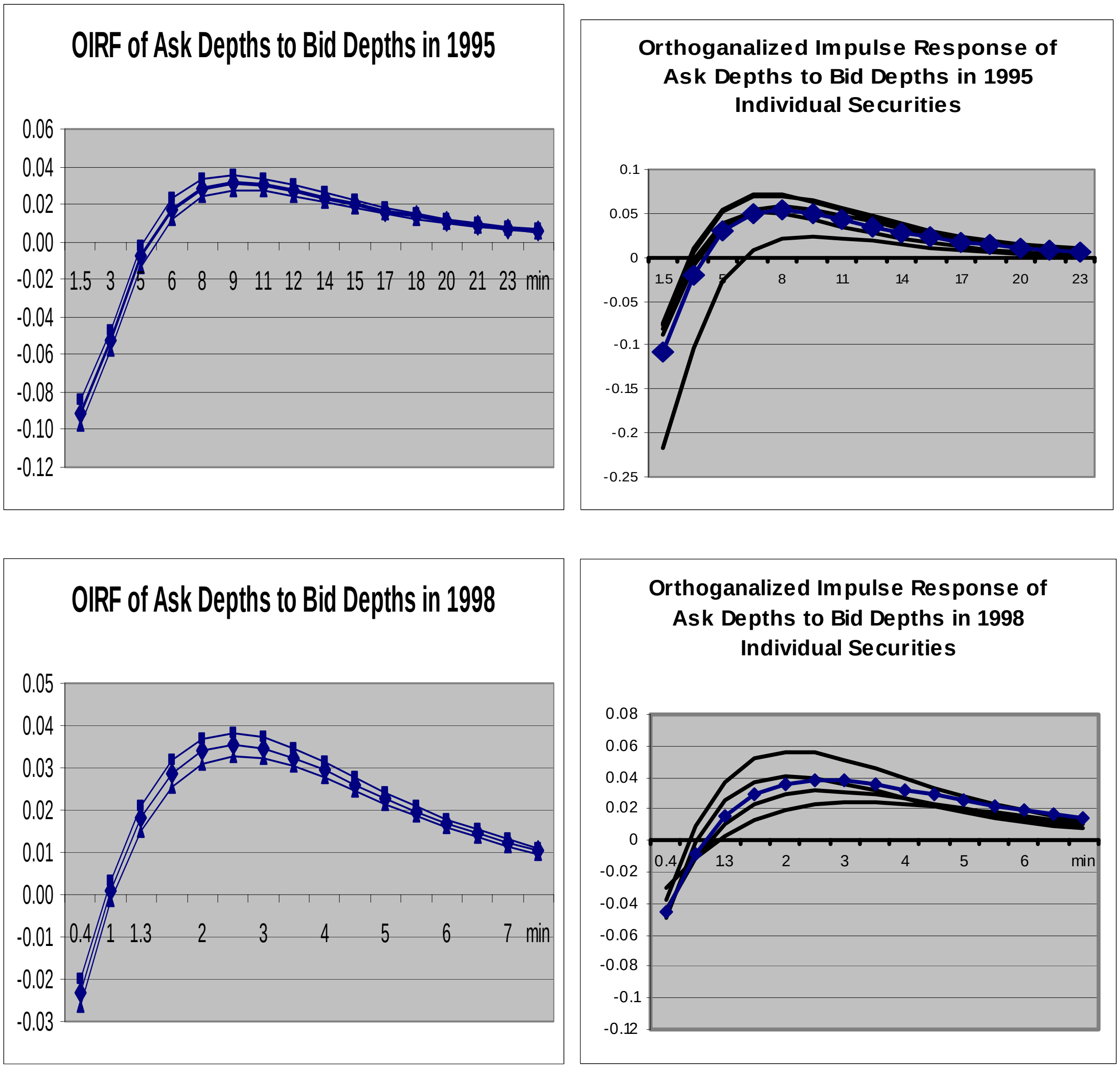
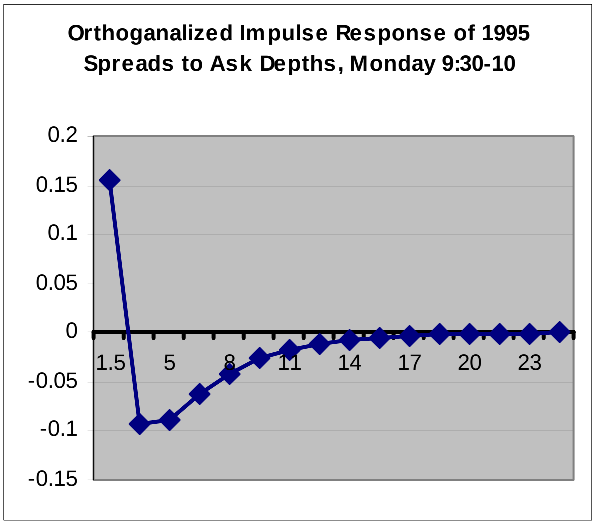
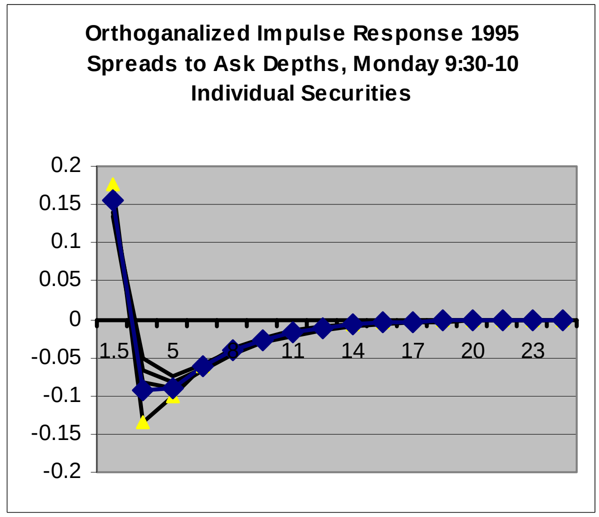
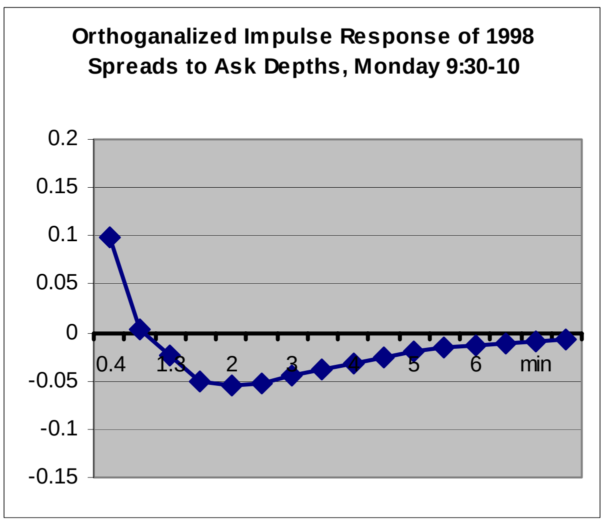
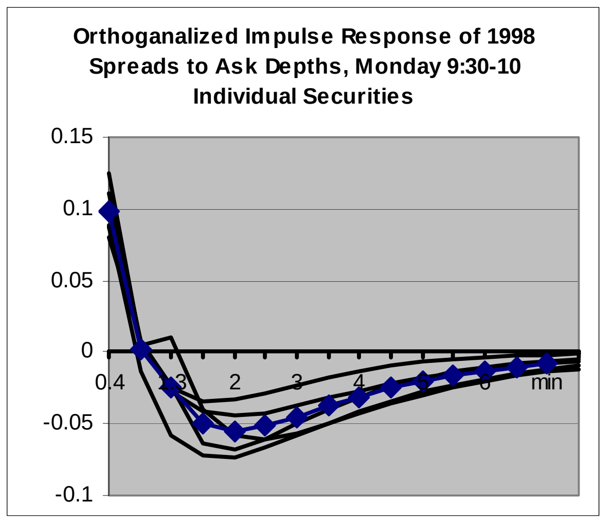


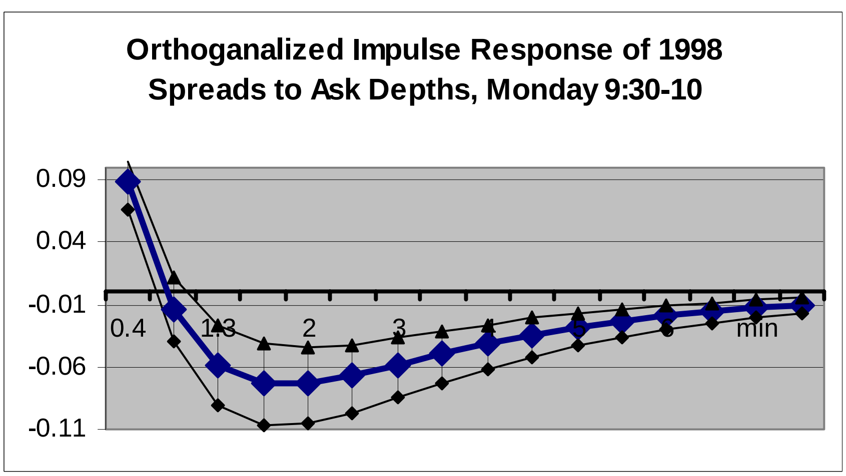
Figure 5 Orthoganalized IRF of Spreads to Ask Depths in 1995 and 1998, Monday 9:30-10:00











APPENDIX A

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

Technical Appendix

The Gonzalo-Granger Decomposition of Co-Integrated Series into Permanent and Transitory Components.

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),

(4) $\mathbf{P}_t = \mathbf{A_1} \mathbf{f}_t + \mathbf{A_2} \mathbf{z}_t$

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

$\mathbf{P}_t$ 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 the above model provide a way to identify the permanent components $\gamma_\perp'\mathbf{P}_t$.

Our information structure incorporates three I(1) variables—i.e., the depth quote at the ask (ASQ), the depth quote at the bid (BSZ), and the spread (S).[24] Consider, for example, the special case in which the spread is totally (100%) responsible for reflecting new information. This would be the case, for example, if informed traders used only market orders and never used limit orders. Further, for simplicity, suppose that the cointegration tests reveal two cointegrating vectors (r = 2), thereby implying that there exists only one common factor—i.e., (k = 3 – 2). With *k = 1*, the rank of the 3 x k loading matrix, $\mathbf{A_1}$ in equation (4'), would be one (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 common factor. The error correction terms of the VECM in equation (4') would then be estimated as

$$(5) \qquad \gamma \ \alpha' \ \mathbf{P}_{t-1} = \begin{bmatrix} \gamma_S & \gamma_S \\ \gamma_{ASZ} & \gamma_{ASZ} \\ \gamma_{BSZ} & \gamma_{BSZ} \end{bmatrix} \begin{bmatrix} \Pi_{1S} & \Pi_{1ASZ} & \Pi_{1BSZ} \\ \Pi_{2S} & \Pi_{2ASZ} & \Pi_{2BSZ} \end{bmatrix} \begin{bmatrix} P_{S,\ t-1} \\ P_{ASZ\ ,\ t-1} \\ P_{BSZ\ ,\ t-1} \end{bmatrix}$$

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

$$(6) \qquad \gamma \ \alpha' \ \mathbf{P}_{t-1} = \begin{bmatrix} 0 & 0 & 0 \\ \gamma_{ASZ}(\Pi_{1S}+\Pi_{2S}) & \gamma_{ASZ}(\Pi_{1ASZ}+\Pi_{2ASZ}) & \gamma_{ASZ}(\Pi_{1BSZ}+\Pi_{2BSZ}) \\ \gamma_{BSZ}(\Pi_{1S}+\Pi_{2S}) & \gamma_{BSZ}(\Pi_{1ASZ}+\Pi_{2ASZ}) & \gamma_{BSZ}(\Pi_{1BSZ}+\Pi_{2BSZ}) \end{bmatrix} \begin{bmatrix} P_{S,\ t-1} \\ P_{ASZ\ ,\ t-1} \\ P_{BSZ\ ,\ t-1} \end{bmatrix}$$

Under this unilateral information discovery hypothesis, spreads do not error correct to changes in ask depths or bid depths (because, by assumption, they are not informative) whereas both depths 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, $\gamma_{\perp\ ,\ S}$, corresponding to the first series in equations (5) and (6) is 1.0; one could therefore conclude spreads are 100% responsible for revealing the common stochastic trend.

Gonzalo and Granger (1995) develop a χ^2 distributed test statistic (Q_{GG}) for the elements of the common factor vector, $\gamma_{\perp\ j}$, interpretable as a vector of factor weights on the underlying time series that together are responsible for the multivariate cointegration. In this paper, we use the common factor weights attributable to spreads and depths to uncover which dimension of the quote adjustment process first conveys new information in DJIA stocks.

[24] Again, recall that our order of integration tests show that the spread is generally not I(0) but I(1) for DJIA stocks during 1995 and 1998 when many features of the security market design were changing.