Price Discovery by ECNs and Nasdaq Market Makers

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First Version: October 25, 1999
This Version: March 29, 2000

I have benefited from discussions with Jim Angel, Cliff Ball, Suzanne Bellezza, Hans Heidle, Tim McCormick, Jeffrey Smith, Hans Stoll, Sunil Wahal, and Simon Wu. Christoph Schenzler provided programming help. This research was supported by the Dean's Fund for Research and by the Financial Markets Research Center at the Owen Graduate School of Management, Vanderbilt University.

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Abstract

This paper examines the discovery of an asset's full-information value by electronic communication networks (ECNs) and Nasdaq market makers. The results show that despite possible market fragmentation due to the addition of alternative trading venues, quotes submitted by ECNs and dealers have information content and quotes on the same asset reflect common information. The evidence also reveals that ECNs are important contributors to the price discovery process, being the dominant venue in eight of the ten most active stocks. Further analysis suggests that structural differences between ECNs and Nasdaq market makers have an impact on price discovery. Specifically, ECNs' share of price discovery is enhanced by informed traders who are enticed by the ability to trade anonymously but is impeded by liquidity traders who are attracted by the possibility of lower trading costs.

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1. Introduction

Trading mechanisms are judged on the basis of their ability to facilitate price discovery and to provide transaction services at low costs.[1] While much research has been devoted to the analysis of trading costs, few studies have investigated the process of price discovery. The purpose of this paper is to examine the price discovery process in the Nasdaq stock market.

The mechanics of price discovery are important to both investors and regulators. Since the trading process may introduce noise that results in inaccurate prices, it has implications for traders interested in avoiding pricing errors and policy makers concerned with market stability. Poor price discovery may lead to heightened price volatility, including bubbles or sudden market crashes, when prices are predominantly influenced by short-run disturbances. A recent concern for market participants is whether the proliferation of alternative trading venues may have adversely affected the price formation process through market fragmentation.[2]

Price discovery is the process of uncovering an asset's full-information or permanent value. The unobservable permanent price reflects the fundamental value of the stock. It is distinct from the observable price, which can be decomposed into its fundamental value and its transitory effects. The latter consists of price movements due to the bid-ask bounce, temporary order imbalances, inventory adjustments, and rounding effects.

The Nasdaq market structure relies on the competition between market makers to keep trading costs low and to promote price discovery. To further enhance the level of competition, the Securities and Exchange Commission (SEC) implemented the Order Handling Rules (OHR) in 1997, consisting of two rules. The Limit Order Display Rule requires a market maker to display a customer's limit order that is priced at or better than

[1] See Schreiber and Schwartz (1985) for a discussion of price discovery objective in trading systems.
[2] Even trading hours have become disjoint with alternative trading venues taking the lead in extending trading beyond the usual time period.

its current quote. This permits customers to directly compete with dealer's quotes.[3] The second rule concerns quotes sent to electronic trading systems that the SEC referred to as electronic communication networks (ECNs). The ECN Rule requires Nasdaq to include the best market makers' quotes submitted to an ECN in the Nasdaq national best bid and offer montage and to make it accessible to all market participants[4]. This paper examines the Nasdaq market after the implementation of the OHR.

How do ECNs compare with the traditional Nasdaq market makers in their contribution to price discovery? The ECNs are computer-mediated markets that widely disseminate buy and sell limit orders from its subscribers and execute trades by matching the order flow. InstiNet (INCA) and Island (ISLD) are the two most popular ECNs. INCA is the earliest ECN and is mainly used by institutional traders and Nasdaq market makers as an alternative-trading venue. ISLD is different from INCA in that it is mainly used by day traders. The distinctive features of these ECNs are the absence of designated market makers and the ability to trade anonymously. These characteristics make studying price discovery in this environment highly attractive. Traders with information prefer anonymous trading environments, potentially contributing to price discovery. On the other hand, liquidity traders don't want to trade with informed traders and the absence of designated market makers may decrease market liquidity, adversely affecting price discovery. However, the uninformed traders may be attracted by the possibility of matched trades in highly liquid ECNs.

The literature on dealer competition and trading costs has grown rapidly in recent years. Christie and Schultz's (1994) conclusion that Nasdaq dealers tacitly collude to maintain wide spreads by avoiding odd-eighth quotes led to numerous academic studies.[5] Their study also prompted lawsuits and government investigations. Studies of the impact of the OHR find that the rules have a profound effect on trading costs. Barclay, Christie, Harris, Kandel, and Schultz (1998) report that following the rule changes, bid-ask spreads decline approximately 30%. Simaan, Weaver, and Whitcomb (1998) examine the

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[3] I use the words market makers and dealers synonymously although, strictly speaking, only the former are registered with Nasdaq and are required to post two-way quotes.
[4] With the implementation of Regulation ATS in 1999, the biggest ECNs, including Instinet, transmit the best bid and offer quotes of all clients, and not just market makers, to Nasdaq quote montage.

quotation behavior of ECNs and Nasdaq market makers. They found that following the tick size reduction from eighths to sixteenths on June 2, 1997, Nasdaq market makers still appear to be avoiding odd ticks (odd-sixteenths) but limit orders from the ECNs do not appear to have such biases.

In contrast to the vast literature on trading costs, there are relatively fewer studies on price discovery. Pure inventory models such as Ho and Stoll (1983) do not consider informed trading and do not consider the role of price discovery by market makers. Adverse selection models of market making such as Kyle (1985) and Admati and Pfleiderer (1988) focus on the behavior of informed traders but in these models, market makers do not actively engage in the price discovery process. In contrast, Leach and Madhavan (1992, 1993) models the price discovery behavior of market makers through intertemporal price experimentation. They note that price experimentation is a feature of a specialist market but is unlikely in competing dealer markets, where a free rider problem arises because other dealers observe the resulting price changes.

The literature on price discovery is more extensive for empirical studies. One branch of the literature addresses the issue of which market moves prices first when an asset is traded on multiple markets. Examples of this work are Stoll and Whaley (1990) and Easley, O'Hara, and Srinivas (1998).

The present paper is most related to the literature on price discovery by various exchanges. An earlier work is by Garbade and Silber (1979) who conclude that regional exchanges contribute to price discovery. Harris, McInish, Shoesmith, and Wood (1995) use an error correction model to examine the discovery of IBM prices by the New York, Midwest, and Pacific Stock Exchanges. Harris, McInish, and Wood (1997) apply the common long-memory procedure of Gonzalo and Granger (1995) to estimate the relative contribution of the NYSE to price discovery. The same methodology is used by Ding, Harris, Lau, and McInish (1998) to compare the contribution to price discovery of a Malaysian firm, Sime Darby Berhad, by the Kuala Lumpur Stock Exchange and Stock Exchange of Singapore.

[5] For example, the theoretical works include Dutta and Madhavan (1997), Kandel and Marx (1999), and Lamoureux and Schnitzlein (1997). For examples of empirical work, see the July 1997 issue of *Journal of Financial Economics*.

Among the papers in the literature on price discovery in multiple markets, the present paper is most related to the work of Hasbrouck (1991, 1995). I adopt Hasbrouck's measure of contribution to price discovery and estimate it in the present context as a Nasdaq quote participant's share of the variance of innovations in the common permanent price. When these innovations are due to information about the fundamental determinants of an asset's value, the participant's contribution is referred to as an information share of the asset. Hasbrouck compares the contribution to price discovery of the New York Stock Exchange (NYSE) and non-NYSE markets. He finds that for the 30 Dow stocks, the NYSE has almost the entire information share of the stocks. The present paper differs from the earlier literature by focusing on the contribution to price discovery by Nasdaq competing dealers and ECNs.

I examine the transactions data of 30 most active stocks on Nasdaq during July 1998 using the econometrics of cointegration. My data identifies the quotes by market participant. The results show that competing Nasdaq market makers and ECNs individually post quotes that are nonstationary, suggesting that they each contain information on the underlying true price. Further analysis suggests that the competitors' posted quotes on each stock have a long-run equilibrium relation with one another. This suggests that despite the proliferation of new trading venues, the quotes are driven by a common trend, as would be the case when the quotes react to the same information on the underlying asset. Next, I examine the contribution to price discovery by various Nasdaq quote participants. The result reveals ECNs to be major contributors, giving them the top information share in eight of the ten most active stocks. Moreover, the information share of ECNs across stocks is positively associated with trading volume and negatively related to the percentage of quotes that are at the inside. This relation is not observed for the traditional Nasdaq market makers. The positive association of volume and information share is consistent with informed traders who are more concerned with the ability to trade in volume than with getting the best price that is limited by its depth. The negative association of best quotes and information share is consistent with uninformed traders who do not contribute to price discovery and focus on trading at the inside quotes.

The remainder of the paper is organized as follows. The next section specifies the various hypotheses for the paper. This is followed in Section 3 by a synopsis of the relevant cointegration econometrics. Section 4 describes the data set. Section 5 presents the results. The paper ends with a conclusion in Section 6.

2. Price Discovery Hypotheses

The Nasdaq market relies on the competition between dealers for price discovery. To promote this competition, Nasdaq makes it easy for dealers to initiate market making in a stock or to withdraw from it. Wahal (1997) documents substantial initiation and withdrawal by market makers over time in Nasdaq stocks, with increases (reductions) in the number of market makers being associated with declines (increases) in spreads.[6]

While easy entrance and withdrawal from the Nasdaq market facilitates price formation, other attributes of the Nasdaq trading structure may conspire against it. Huang and Stoll (1996) find execution costs on Nasdaq to be greater than those on the NYSE, and attribute them to the prevailing institutional arrangements that mitigate incentives for price competition. In particular, before the OHR were implemented in 1997, dealers did not display customers limit orders so that public limit orders could not compete with dealer quotes. In addition, dealers could post one price on Nasdaq while submitting more favorable prices to an alternative trading venue, such as INCA, which are only accessible to the subscribers. These features may have adversely affected price discovery on the Nasdaq system. With the implementation of the OHR, public limit orders that are at the inside are posted and the best ECN quotes are disseminated and may be executed on the Nasdaq system. The integration of public and ECN order flow into the Nasdaq market may have resulted in better price discovery. It also makes possible an examination of whether ECNs or the traditional Nasdaq market makers are more adept at discovering prices.

There are crucial differences between ECNs and traditional Nasdaq market makers. Unlike the traditional market makers, ECNs have no designated market makers who expedite trades. This means that customer orders can be directly crossed with one another.[7] While this feature is especially attractive to liquidity traders, lack of market makers could be a detriment to price discovery in times of order imbalances and market

[6] Huang and Masulis (1999) also find that spreads in the foreign exchange multiple dealer market drop with the entry of more dealers.

illiquidity. This happens when informed traders are unable to find matching orders on the other side of the market.

On ECNs, traders remain anonymous. This facilitates the mingling of informed traders with liquidity traders, as in Admati and Pfleiderer (1988), resulting in better price discovery as information is incorporated into prices. Therefore, the anonymity feature has the potential to substantially increase the ability of ECNs to discover the underlying true value of a stock.

An important characteristic of the Nasdaq market is the existence of payment for order flow. Orders submitted to Nasdaq may be preferenced to a specific dealer through SelectNet. In return for the order flow, which usually consists of retail orders, the dealer provides payment either in cash or service to the broker. Contrary to popular belief, preferenced dealers who do not have the best prices are not obligated to match the best bid or offer available for every order. As discussed in Smith (1999), the obligation for best execution only extends to those with whom the market maker maintains a customer relationship. With the order preferencing arrangements, there is less incentive to compete on price since the market maker posting the best quotes may not receive the order. Moreover, the market maker may maintain a wider spread to discourage preferencing from unwelcomed clients. A natural concern that arises is the information content of prices being posted by the traditional dealers. In contrast, ECNs generally receive payment from brokers for order flow. The fee charged by ECNs may limit the retail order flow from brokers that tend to be uninformed trades.[8]

To determine how ECNs and individual market makers stack up in the price discovery process, I organize my analysis around four hypotheses. I begin with the question of whether the quotes submitted by the different participants contain information about the underlying permanent asset value. This issue is of concern since the addition of new trading venues such as ECNs may fragment the market, resulting in less informative prices. Bid-ask quotes that are nonstationary would constitute evidence against market fragmentation. This is because quotes are nonstationary if the major cause of stock price

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[7] The matching is possible for marketable limit orders.

[8] The only exception to date is ISLD, which pays for (non-marketable) limit orders.

movements is news concerning the fundamental determinants of share values and if stock prices follow a random walk process. This results in my first hypothesis.

H1: The quotes submitted by various Nasdaq participants are nonstationary.

The hypothesis is supported when pricing errors are corrected over time. It is violated when temporary effects such as short-term inventory adjustments or short-run exuberance are the only determinants of a participant's quotes.

The process of trading introduces noise into stock prices. Despite this, quotes from the various participants on a specific stock should be related to one another if they all contain the same information about the underlying true asset value. This relation should be a long-run equilibrium condition that nets out any mispricing. In the language of cointegration, we say that the quotes are cointegrated. More importantly, if all the quotes on a specific stock are driven by one common trend, there should be a total of n-1 linearly independent cointegrating vectors, where n is the number of quote participants. The next section reviews the relevant cointegration econometrics. The testable implication is summarized in the following hypothesis:

H2: The quotes submitted by various Nasdaq participants are cointegrated and there are a total of n-1 linearly independent cointegrating vectors.

Support for the hypothesis would provide further evidence against market fragmentation.

The third hypothesis compares the contribution to price discovery by ECNs and traditional market makers. The ability to trade anonymously on the ECNs may entice informed traders to reveal their true reservation prices, thus contributing to price discovery. Liquidity traders may also be attracted to ECNs if there is adequate order flow that increases the possibility of crossing with another limit order on the network. Even if the limit orders are not matched, under the OHR, the best quotes are disseminated to the entire market by the Nasdaq system. On the other hand, the absence of dealers who commit their own capital to make a market may make ECNs less liquid, resulting in less informative quotes. The third hypothesis specifies that ECNs do not "free ride" off of the price discovery of traditional Nasdaq market makers.

H3: ECNs are important contributors to the price discovery process.

Hypothesis H3 is intentionally vague. This is because, as described in the next section, the determination of information share is ambiguous in that it depends on the method of orthogonalizing the permanent price innovations. However, meaningful comparisons are possible for bounds on the information shares.

The fourth hypothesis investigates the determinants of the price discovery process. Specifically, I analyze the effects of trading volume and inside quotes on price discovery. First, consider the relation for ECNs. Informed traders prefer to trade anonymously and in volume, something ECNs can accommodate. As discussed earlier, ECNs may be very different from one another. Market makers may use INCA to trade anonymously at their true reservation prices. ISLD is popular with day traders. Day traders, who are also referred as SOES bandits, can be considered informed traders who pick off market makers that are slow in updating their quotes.[9] As discussed by Harris and Schultz (1998), SOES traders often lay off their positions using INCA or SelectNet. For day traders, timing is a crucial determinant of the choice of trading venue since their trading strategy calls for rapid buys and sells. With the development of ECNs, a popular alternative to INCA or SelectNet is to trade through ISLD. This often happens when there is heavy order flow on ISLD, thereby increasing the probability of finding an instant match. ISLD also makes available its entire order book on the Web. The discussion suggests that trade volume is positively related to ECN's contribution to price discovery.

The relation between ECN's information share and percentage of quotes at the inside is again best analyzed by considering individual ECNs. INCA also attracts liquidity traders. For example, institutional buy side such as Fidelity typically uses INCA and with the OHR, now has a direct link to Nasdaq through INCA if they do not receive a quick fill on INCA. Liquidity traders prefer to trade at the inside. In contrast, informed traders prefer to remain anonymous and that anonymity is threatened by trading at the inside. This is because of the presence of third party vendors who add bells and whistles to Nasdaq Level II screen. These software often helps identifies those trading at the inside. For example, Tools-of-the-Trade provides information on the number of times a market participant is the only one posting the best bid or offer.[10] This results in game playing, whereby informed traders avoid appearing at the inside. On ISLD, day traders do

[9] The behavior of SOES bandits is analyzed in several papers. For example, Battalio et al. (1997) examine the price volatility around SOES trading and Harris and Schultz (1998) examine their trading profits.

not appear at the inside since their objective is to mop up slow-adjusting market makers to the best quotes. Again this suggests liquidity traders are the primary contributors to the inside spread. Therefore, ECNs' contribution to price discovery may be inversely associated with the percentage of times ECN quotes are at the inside. The differential behavior of informed and uninformed traders also highlights the fact that permanent prices are different from best prices.

Second, consider the same effects for the traditional market makers. I hypothesize that the quantity and price effects noted for ECNs may not materialize for market makers. This is because the process of market making on Nasdaq, in particular the payment for order flow confounds the effects hypothesized for ECNs.

The discussion above motivates my fourth hypothesis:

H4: ECNs', but not traditional market makers', contribution to price discovery is positively associated with trade volume and negatively associated with the frequency of being at the inside.

3. Cointegration Econometrics

This section reviews the pertinent cointegration econometrics.[11] Let p_t be an (nx1) vector of prices from n groups. If the prices are nonstationary, their future time path depends on past effects. Specifically, assume that all prices follow a random walk so that they are integrated of order one or I(1). This means that Δp_t is I(0) and is a stationary process.

Although the various prices are individually nonstationary, we expect them to be related to one another if they are all prices for the same underlying asset. This means that a linear combination of the prices may be stationary. We say that prices are cointegrated if there exists a nonzero vector b such that $b' p_t = e_t$ is stationary. The vector b is called a cointegrating vector and e_t can be interpreted as a deviation from long-run equilibrium.

[10] This information is referred to as "# Best" or "Hammer." The participant that appears most frequently at the inside is called an "Axe" or a leader and day traders' decisions are often based on the behavior of the Axe.

[11] For more detailed reviews see, for example, Campbell and Perron (1991) and Banerjee, Dolado, Galbraith, and Hendry (1993).

When e_t is stationary, prices do not drift too far from one another, suggesting that pricing errors are corrected over time.

There may be also more than one cointegrating vector. For n prices, there may be up to n-1 independent cointegrating vectors. This would be the case if all the prices have the same permanent component that follows a random walk.

The Granger Representation Theorem (Engle and Granger (1987)) proves that cointegrated variables could be equivalently represented as a vector autoregression (VAR) in levels, or as an Error Correction Model (ECM), or as a vector moving average (VMA) representation. Suppose p_t can be expressed as a VAR:

$$p_t = j_0 + j_1 p_{t-1} + \ldots + j_q p_{t-q} + e_t, \qquad (1)$$

where $E(e_t) = 0$

$$E(e_t e_t') = \begin{cases} \Omega & t = t \\ 0 & otherwise \end{cases}.$$

Then there exists an ECM:

$$\Delta p_t = -p\, p_{t-1} + p_1 \Delta p_{t-1} + p_2 \Delta p_{t-1} + \ldots + p_q \Delta p_{t-q+1} + e_t, \qquad (2)$$

where $p_j = -\sum_{i=j+1}^{q} j_i$ for $j=1,\ldots,q-1$

$$p = I_n + \sum_{i=1}^{q} j_i .$$

Alternatively, the cointegrated system can be formulated as a VMA by using the Wold decomposition theorem:

$$\Delta p_t = \Lambda(L) e_t, \qquad (3)$$

where $\Lambda(L) = \sum_{i=0}^{\infty} \Lambda_i L^i$.

The VMA representation can be rewritten as

$$\Delta p_t = \Lambda(1) e_t + (1-L) \sum_{i=0}^{\infty} \left(-\sum_{j=i+1}^{\infty} \Lambda_j \right) L^i e_t, \qquad (4)$$

where $\Lambda(1) = \left(I_n + \sum_{i=1}^{\infty} \Lambda_i \right)$. The matrix $\Lambda(1)$ contains the sums of all the moving average coefficients.[12] Thus, it provides the total impact of innovations on prices from all

[12] It is the (nxn) polynomial matrix $\Lambda(z)$ evaluated at z=1.

the Nasdaq quote participants. It can also be shown that $\Lambda(1)$ has rank n-r where r is the number of cointegrating vectors of p_t .

Integrating (4) leads to the common trends representation proposed by Stock and Watson (1988):

$$p_t = p_0 + \Lambda(1)\sum_{i=1}^{t} e_i + \Lambda^*(L)e_t , \qquad (5)$$

where $\Lambda^*(L)$ is a polynomial matrix with elements which are scalar polynomials in the argument L. The vector p_0 denotes the initial constant prices. The last term in (5) is a stationary process. The second right-hand term captures the stochastic trends common to prices from all dealers and is the driving force that results in cointegration. When p_t has n-1 cointegrating vectors, the loading matrix $\Lambda(1)$ has rank 1. This means that all the rows of $\Lambda(1)$ are identical, showing the common cumulative impact on prices of innovations to the cointegrated system. Campbell and Mankiw (1987) and Cochrane (1988) have proposed alternative measures of persistence in p_t based on the common stochastic trend in (5). I use the duality between the VAR representation (1) and the model (5) to estimate the long-run impact matrix $\Lambda(1)$.

3.1 Contribution to Price Discovery

If price innovations are due to new information the term $\Lambda(1)\sum_{i=1}^{t} e_i$ captures the permanent impact of new information on prices. This impact excludes all transient price effects due to, for example, bid-ask bounce and inventory adjustments. Hasbrouck (1991, 1995) proposes a measure of a market's contribution to price discovery based on this observation. Specifically, the total variance of the common stochastic trend is $\Lambda\Omega\Lambda'$, where Λ is any row in $\Lambda(1)$, and Ω is the (nxn) variance-covariance matrix of the innovations. Therefore, a measure of the share of this total variance that can be attributed to dealer j is

$$S_j \equiv \frac{\Lambda_j^2 \Omega_{jj}}{\Lambda\Omega\Lambda'}, \qquad (6)$$

where Λ_j is the jth element of Λ and Ω_{jj} is the jth diagonal element of Ω .

A complication with the measure (6) is that price innovations are generally correlated across Nasdaq participants so that Ω is not a diagonal matrix. This problem often arises in time series econometrics and a typical approach is to diagonalize the matrix. This is frequently accomplished by finding the Cholesky factorization of Ω:

$$\Omega = FF', \tag{7}$$

where F is a unique lower triangular matrix. Using F, the price innovations can be orthogonalized as

$$e_t = Fu_t, \tag{8}$$

where u_t has mean zero and its covariance is the identity matrix. This is equivalent to making the *i*th element of u_t orthogonal to all the innovations that precede it in the ordering. Therefore, the proportion of the information attributable to a participant would depend on its position in the vector. The first participant in the ordering would have the maximum information share and the last dealer would have the minimum. By changing the ordering, the upper and lower bounds of the information share of each participant can be estimated.

A participant's information share is distinct from the frequency with which the best prices are posted. The information share measures the participant's contribution to permanent movement of prices, presumably towards its unobservable true fundamental value. As such, it is possible for a dealer who often posts the best prices to have minimal contribution to price discovery if the dealer's prices reflect temporary effects.

4. Data

The source for the data is Nastraq, the Nasdaq trade and quote data maintained by the NASD. The data set contains trade data, inside quote data, and individual dealer and ECN quote data. The latter identifies the participant posting bid and ask quotes.[13] The empirical analysis relies only on individual dealer and ECN quote data for July 1998. Use of quote data minimizes the problem of infrequent trading since quote submissions are more frequent than trade occurrences. The more frequent quote submissions also makes possible the choice of a smaller time interval in aligning the data across Nasdaq quote

[13] However, ECNs are not required to post two-way quotes.

participants to estimate information shares of price discovery. A one-minute time interval is selected based on an analysis of time between successive quotes. If instead, a one-minute trade time interval were used, it would lead to severe autocorrelations resulting from frequent occurrences of standing trade prices across the intervals. By specifying a fixed time interval, my comparison of market participants' contribution to price discovery is based on the same number of quotes for all participants.[14]

I examine 30 stocks with the highest share volume traded on Nasdaq. The share volume figures are obtained from the Nasdaq web site. Appendix A lists the names of these stocks. They are mainly technology and Internet stocks.

The large number of dealers in the market precludes analysis of individual dealers. Instead of choosing representative dealers, I opt to group them into categories. I identify the major wholesalers to be NITE, HRZG, MASH, NAWE, SHWD, and TSCO. The big wire houses, which are integrated retail and full discount brokers, are DEAN, MLCO, PRUS, PWJC, and SBSH. The most important institutional brokers are BEST, BTAB, DLJP, GSCO, HMQT, LEHM, MONT, and MSCO. All the remaining Nasdaq market makers are grouped under “other” category. This last category allows an examination of the behavior of small market makers. During the sample period, there are six ECNs: BRUT, BTRD, INCA, ISLD, REDI, and TNTO. Appendix B contains the full names of the dealers and ECNs.

Tables 1 and 2 provide some summary statistics on the data set. Table 1 presents the statistics for the various participant groups in Panel A and for individual ECNs in Panel B. As seen in Panel A, during July 1998, ECNs submit more quotes to the Nasdaq market in the 30 most active stocks than all the traditional market makers combined. Among the market makers, the smaller dealers post more quotes than all the major dealers combined. The difference in the number of quotes between ECNs and Nasdaq dealers is potentially even bigger. The number of quotes submitted to Nasdaq by an ECN is not the total of best bid and ask quotes on the ECN that cannot be crossed internally. This is because OHR require only that quotes from market makers be disseminated on the

[14] As discussed below, the ISLD ECN has much more frequent quote submission in my sample than other participants. This is due to day traders who make rapid quote adjustments.

Nasdaq system. Other participants have the option of having their quotes sent to Nasdaq if necessary.

Panel A also reveals dramatic differences in quoted spreads. The ECNs have the smallest mean and median quoted spreads and the “other” group has the biggest. The differences between the mean and median spreads are due to the existence of very large spreads when the dealer or ECN appears to be interested in only one side of the market. This is especially true for ECNs since they are not required to maintain two-sided quotes. There is much less variation in quoted depth between the groups. Panel A shows no differences in median bid and ask sizes but the mean sizes are highest for ECNs and lowest for smaller dealers.

Panel B reports individual ECN statistics. It shows that the vast majority of the quote submissions come from ISLD and INCA. These ECNs also have the smallest spreads, the others being more than twice as large. The highest mean quote size belongs to INCA. The results suggest that the lack of a market maker on an ECN is not a detriment to tighter spreads. However, a necessary prerequisite is sufficient liquidity. Individual ECNs, with a small number of quote submissions to Nasdaq, have much higher spreads. This also indicates that INCA and ISLD dominate the results for ECNs.

Table 2 provides the number of quotes submitted and mean and median spreads by group for each stock in the sample. The figures show that ECN quote participation in each stock varies across stocks. This suggests that the importance of ECNs in the price discovery process would likely vary across stocks. When one ignores the extreme quotes by examining the medians rather than the means, Table 2 reveals that ECNs are highly competitive: they have the smallest spreads in all 30 stocks. The table also reveals the dominance of ECNs in certain stocks. For example, the ECN median spread for AMZN (Amazon) is $0.375 but is at least $2 for all the Nasdaq dealer groups. Other examples are LCOS, XCIT, and YHOO.

5. Results

Do dealers and ECNs post informative quotes? Do quotes from different participants on the same stock contain common information on the underlying asset value? Do certain participants provide more informative quotes than others? Do differences in trading arrangements between ECNs and Nasdaq market makers affect their share of price discovery? These and related questions are addressed in this section.

5.1 Information Content of Competitive Quotes

The stationarity of prices depends on their information content. In general, prices contain errors that obscure the underlying full-information asset value. The information content of prices renders prices nonstationary and is assumed to follow a random walk process. The latter is an example of a unit root process. Pricing errors tend to be corrected over time and follow stationary processes. The first hypothesis states that quotes from Nasdaq market makers and ECNs contain unit roots.

Hypothesis H1 specifies that Nasdaq quotes are I(1) so that the proliferation of trading platforms has not resulted in fragmented markets. There are numerous unit root tests in the literature. One of the most popular is the Augmented Dickey-Fuller test of unit root. The test involves estimating the following regression:

$$\Delta p_t = g\, p_{t-1} + \sum_{i=2}^{l} b_i \Delta p_{t-i+1} + h_t \,, \qquad (9)$$

where Δp_t is the first difference in prices. The appropriate number of lags (l) can be selected by using the Akaike information criterion (AIC). The null hypothesis of unit root specifies $g = 0$, and Dickey and Fuller (1979) provide the critical values for the "t-tests".

Table 3 presents the test results of bid quotes.[15] It shows the number of lags used in the regression and the "t-statistic" for each stock by different groups of Nasdaq participants. The first five rows of each stock are the results of unit root tests. In almost all cases, the null of unit root is not rejected.

An implication of H1 is that if quotes are I(1), then first differences in quotes are stationary. The last five rows of each stock in Table 3 present the unit root tests of quote changes. In all cases, the null of unit root is strongly rejected.

The results in Table 3 suggest that quotes submitted by various Nasdaq participants contain information content. This is true of ECNs as well as smaller Nasdaq market makers. Therefore, despite the volatile nature of technology and Internet stocks

[15] All the results in the paper are presented only for bid quotes to avoid repeating similar results obtained for ask quotes.

and an increased number of alternative trading systems, the level of competition between the participants has not resulted in uninformative quotes.

5.2 Common Information in Competitive Quotes

Proper price discovery requires quotes from the various participants not only to be informative but also to reflect the common information of the underlying asset. This would provide further evidence that markets have not become fragmented. As stated in H2, this means that quotes on the same asset must be cointegrated. Quotes from individual participants may be mispriced because of trading noise. In the long run, the mispricing attracts orders that correct any persistency in inflated or depressed prices. A cointegrating vector characterizes just such a long-run equilibrium condition.

Hypothesis H2 also states that there are a total of four independent cointegrating vectors since I examine quotes from five sources. This is the maximum possible. Proper price discovery stipulates the maximum because the relevant information driving the permanent price is common to all quotes on the stock. One common stochastic trend means four independent cointegrating vectors, and vice versa.

There are two main approaches to testing for cointegration. The first approach is the Engle-Granger (1987) two-step methodology, which requires the estimation of the ECM. A disadvantage of this approach is that the result of the cointegration test may depend on the participant chosen for normalization of the cointegrating vector. The normalization is done to fix one of the components of the cointegrating vector at unity because the cointegrating vector is not unique. The methodology is also difficult to apply to situations with more than two cointegrating vectors.

The second approach, used in this paper, is the Johansen (1988) maximum likelihood methodology. It does not have the disadvantages noted with the Engle-Granger approach. The estimation uses the duality between the VAR representation (1) and the ECM formulation (2) to test for cointegration. The results reported are based on estimating (1) with four lags.[16]

[16] Experimenting with different lags produces similar results.

Johansen (1988) observes that the rank of the matrix p in (2) determines whether or not the quotes from various participants are cointegrated and the number of cointegrating vectors. Specifically, he provides two test statistics:

$$l_{trace}(r) = -T\sum_{i=r+1}^{n} \ln(1-\hat{l}_i) \qquad (10)$$

and

$$l_{\max}(r, r+1) = -T \ln(1-\hat{l}_{r+1}) \qquad (11),$$

where the n characteristic roots are ordered such that $l_1 > l_2 > ... > l_n$ and T is the number of observations. The statistic l_{trace} tests the null hypothesis that the number of cointegrating vectors is less than or equal to r against the alternative it is greater than r. The statistic $l_{\max}$ tests the null hypothesis that the number of cointegrating vectors equals r against the alternative it is equal to r+1.

The test results for all 30 stocks support H2. I only report the results for the first and the last of the alphabetically arranged 30 stocks in Table 4. The two tests give the same result for the two firms: the quotes from the five groups of participants are cointegrated and the order of cointegration is four as hypothesized by H2.

In Table 5, I present the estimated cointegrating vectors for the two firms shown in Table 4 to illustrate the estimated long-run equilibrium conditions. The four cointegrating vectors for each firm are all normalized by setting the coefficient of the ECN bid quote to unity. The vectors show that quotes from all the participants are intimately related by the underlying common trend.

5.3 Contribution to Price Discovery

This section reports the contribution to price discovery by Nasdaq quote participants. I use the duality between the VAR representation (1) and the VMA formulation (3) to estimate the information share (6) using the covariance matrix of innovations diagonalized by the Cholesky factorization procedure. By varying the ordering of the participants, I obtain the maximum and minimum bounds on the information shares of the participants. Since estimation of the information share's standard error is difficult to obtain, I follow Hasbrouck (1995) in using the cross-sectional variation in the information share to determine the statistical significance of the estimates.

The information shares for the 30 most active stocks are presented in Table 6. The shares represent the participant's relative contribution to the variation in the innovation of long-memory trend. Whether one picks the top contributor based on the upper bound or the lower bound, the same participants are chosen.

Table 6 shows that as hypothesized by H3, ECNs are important contributors to the price discovery process. We expect the information share attributed to ECNs to vary by stock since the reliance on ECNs varies by stock. Yet the table reveals that ECNs are the dominant venue in eight of the ten most active stocks and the biggest contributors in 12 of 30 stocks. The means across 30 stocks show that ECNs have the highest mean. In fact, in six stocks, the ECNs' lower bound is greater than the Nasdaq market makers' upper bounds. The medians give the same inferences. Of the Nasdaq dealers, the major wire houses tend to be top contributors in 8 out of 30 stocks but, on average, do about as well as the big wholesalers and institutional brokers. As for the small market makers, they are not the top contributors to price discovery in any of the 30 stocks. They also have the smallest mean and median information shares.

5.4 Information Share and Institutional Arrangements

The last hypothesis H4 relates the information share of a participant across stocks to differences in institutional arrangements. It also hypothesizes that the observed relation differs between ECNs and non-ECNs. First consider the price discovery behavior of ECNs. Informed traders who are key to the price discovery process may be attracted to ECNs because they can trade anonymously. However, anonymity alone is insufficient since informed traders need somebody to trade with. As Admati and Pfleiderer (1988) pointed out, informed traders prefer to trade during times when liquidity traders are in the market.

Liquidity traders may be attracted to ECNs because of lower trading costs.[17] The quoted spreads presented in Table 2 show that the ECN median spreads are lower than Nasdaq market makers for all 30 stocks. Panel B of Table 1 suggests that the lower ECN spreads are due to the two most liquid ECNs, INCA and ISLD. In ECNs, smaller spreads are due to arrival of more limit orders since there is no market maker expediting trades by posting both bid and ask quotes as in non-ECNs. Limit orders on both sides of the market directly determine the spread in ECNs. The two ECNs with the biggest order flows may be especially attractive to liquidity traders because it increases the probability that their order would be crossed with another counterparty. With the OHR, liquidity traders have the further assurance that their orders would be submitted to Nasdaq quote system in the event their orders cannot be matched.

Summarizing, ECNs may attract both informed traders and liquidity traders. If so, both types of traders would affect the cross-sectional variation in ECNs' contribution to price discovery. My proxy for the strength of informed trading is the level of trading activity. This is because the benefit to informed traders increases the more they are able to trade. Moreover, informed traders trade when there are liquidity traders. Therefore, H4 hypothesizes that the higher the volume of trading the higher the contribution to price discovery. For informed traders the probability of receiving the best price may be of less importance than the ability to trade in size and the probability of being discovered by being at the inside. On the other hand, liquidity traders may be more concerned with receiving the best possible price. If so, being at the inside spread is of more concern to liquidity traders than informed traders. Therefore, H4 hypothesizes that contribution to price discovery is negatively associated with the percentage of times ECNs are at the inside.

The transaction quantity and price associations with price discovery hypothesized for the ECNs may not hold for the Nasdaq market makers. Unlike the ECNs, dealers are a party to all transactions. Consequently, informed traders are more easily exposed as such under the Nasdaq system than in ECNs. Heidle and Huang (1999) find that the probability of trading with an informed trader is higher on Nasdaq than on the NYSE.

[17] This would be the case for limit orders and not market orders. ECNs generally impose a fee for order submission, whereas a participant may receive payment for order flow through preferencing arrangements

Informed traders may respond to a lack of anonymity on Nasdaq by trading less to hide their trades. The preferencing arrangement where dealers make payment for order flow may further confound the associations noted for the ECNs. The preferencing arrangements are typically for retail orders with little information content, further weakening the relation between trading volume and price discovery. Preferenced orders may also play havoc with the relation between price and information share. The orders are executed at the inside quotes irrespective of whether the dealer who's paying for the order flow is quoting at the inside. Thus, I hypothesize that there is no systematic association between price discovery and transaction volume or being at the inside for Nasdaq market makers.

The results for H4 are reported in Table 7. Panel A shows the mean and median of variables used in the analysis. The level of trading activity is measured alternatively by share volume and number of quote submissions. The transaction price association is examined using the percentage of inside bid quotes. This measurement requires imposition of the same time interval for all the groups and the estimates are shown for the one-minute interval. The panel reveals that ECNs are the most active of all the groups in submitting quotes but the quotes do not translate into corresponding trades. ECNs have the smallest percentage of the share volume. ECNs also are not the most frequent at the inside. That position belongs to the major wire houses, but the ECNs are comparable to the wholesalers and the institutional brokers. The small market makers are conspicuous by being rarely at the inside.

Panel B shows the correlation between the variables for each Nasdaq participant. For ECNs, the upper bound and lower bound estimates of information shares are highly correlated. The information shares are in turn correlated with the other variables as hypothesized in H4. They are positively correlated with share volume and number of quote submissions and negatively correlated with percentage of inside quotes. All the correlations are also statistically significant.

Hypothesis H4 is also supported by the correlations for the Nasdaq market makers. The lack of a systematic association between information shares and transaction volumes and prices is apparent for all four Nasdaq groups. For example, for major

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with market makers.

wholesalers, the lower bound correlations with share volume and quote submissions are in the opposite direction to that observed for upper bound estimates. In the case of the big wire houses, the correlations are statistically insignificant.

Table 8 further examines the results for ECNs by conducting a multivariate analysis. Specifically, it shows the results of regressing information share estimates on share volume or number of quote submissions and percentage of inside quotes. All four regressions provide similar inferences. The results support the associations in H4 when information shares are related simultaneously to share volume (number of quote submissions) and percentage of inside quotes.

6. Conclusion

The paper has examined the impact electronic communication networks (ECNs) and Nasdaq market makers have on the process of discovering the full-information value of an asset. The full-information price is unobservable and is net of transitory effects such as trading costs. The analysis yields several results on price discovery.

1. Quotes submitted by all Nasdaq participants, including ECNs, contain information. Despite the predominance of volatile Internet stocks in the sample and the increased possibility of market fragmentation due to the presence of alternative trading venues, bid-ask quotes reflect information on the fundamental value of the assets. This suggests that mispricing due to trading is not serious enough to render the quotes uninformative.
2. Quotes submitted by Nasdaq participants on the same stock are not independent of one another. Individually, they are nonstationary but they are linked to one another by stationary long-run equilibrium conditions. The number of equilibrium relations suggests that they are based on information common to all quotes. This further suggests that markets have not become fragmented with the increase in new trading platforms.
3. Nasdaq quote participants differ in their contribution to price discovery. ECNs are often major contributors, being the dominant venue in eight of ten most active stocks. This suggests that the absence of market makers, who expedite trading by

buying and selling for their own accounts, does not hinder ECNs from discovering the permanent price of an asset.

4. Non-ECN participants' contribution to price discovery is not systematically associated with measures of trading volume and frequency of posting inside quotes. The lack of a systematic relation is consistent with institutional arrangements that obscure the impact of informed trading. The presence of market makers who are on constant alert for informed traders provide incentives for informed traders to hide their trades. Preferencing arrangements where payment for order flow occurs further reduce the information content of trading volume and the incentive to post inside quotes.

5. ECNs' contribution to price discovery is positively associated with measures of trading volume and negatively related to frequency of inside quotes. The positive association is consistent with the anonymous trading feature of ECNs and the absence of dealers with market making responsibilities. These attributes of ECNs permit informed traders to trade in volume without the fear of being discovered. The negative relation shows that having the best price is not the same thing as having discovered the underlying full-information value of the asset. It is consistent with the presence of liquidity traders who are more concerned with obtaining the smallest ask or the biggest bid rather than with the presence of informed traders who are more interested in trading in volume and in remaining anonymous. The presence of uninformed traders in ECNs is consistent with the possibility of lowering trading costs through matched trades in a trading venue without designated market makers.

There is widespread concern with market fragmentation due to the recent proliferation of alternative trading venues. The results of this paper show that the addition of alternative markets may enhance price formation if they have the requisite attributes. The evidence suggests that structural differences between ECNs and Nasdaq market makers translate into differences in their price discovery abilities. The analysis also reveals differences among ECNs and among Nasdaq market makers. This calls for a systematic study of the latter differences in future research.

Appendix A

Stock Symbol

Ticker Symbol	Company Name
AAPL	APPLE COMPUTER INC
AFCI	ADVANCED FIBRE COMMUNCTNS
AMAT	APPLIED MATERIALS INC
AMZN	AMAZON COM INC
ASND	ASCEND COMMUNICATION INC
COMS	3COM CORP
CSCO	CISCO SYSTEMS INC
DELL	DELL COMPUTER CORP
EGGS	EGGHEAD COM INC
ERICY	ERICSSON L.M. TEL ADR-B SEK 10
HBOC	H B O CO
INTC	INTEL CORP
LCOS	LYCOS INC
MCIC	MCI COM CORP
MSFT	MICROSOFT CORP
NOVL	NOVELL INC
NSCP	NETSCAPE COMMUNICATIONS CORP
NXTL	NEXTEL COMMUNICATIONS INC CL-A
ORCL	ORACLE CORPORATION
PMTC	PARAMETRIC TECHNOLOGY CORP
PSFT	PEOPLESOFT INC
QWST	QWEST COMMUNCTNS INTL INC
SPLS	STAPLES INC
SUNW	SUN MICROSYSTEMS INC
TCOMA	TELE-COMMNTSN INC S-A TCI GRP
TLAB	TELLABS INC
WAMU	WASHINGTON MUTUAL INC
WCOM	MCI WORLDCOM INC
XCIT	EXCITE INC
YHOO	YAHOO INC

Appendix B

Market Maker ID

DEALER	FULL NAME
ATTN	ATTAIN-ECN
BEST	BEAR, STEARNS & CO. INC.
BRUT	THE BRASS UTILITY, L.L.C.
BTAB	BT ALEX. BROWN INCORPORATED
BTRD	B-TRADE SERVICES LLC
DEAN	DEAN WITTER REYNOLDS INC.
DLJP	DONALDSON, LUFKIN & JENRETTE SECURITIES CORPORATION
GSCO	GOLDMAN, SACHS & CO.
HMQT	HAMBRECHT & QUIST LLC
HRZG	HERZOG, HEINE, GEDULD, INC.
INCA	INSTINET CORPORATION
ISLD	ISLAND ECN
LEHM	LEHMAN BROTHERS INC.
MASH	MAYER & SCHWEITZER, INC.
MLCO	MERRILL LYNCH, PIERCE, FENNER & SMITH INCORPORATED
MONT	BANC OF AMERICA SECURITIES LLC
MSCO	MORGAN STANLEY & CO., INCORPORATED
NAWE	NASH WEISS**
NITE	KNIGHT/TRIMARK GROUP INC.
NTRD	PIM GLOBAL EQUITIES - ECN
PRUS	PRUDENTIAL SECURITIES INCORPORATED
PWJC	PAINEWEBBER INCORPORATED
REDI	SPEAR, LEEDS & KELLOGG/Redi ECN
SBSH	SALOMON SMITH BARNEY INC
SHWD	SHERWOOD SECURITIES CORP
SLKC	SPEAR LEEDS & KELLOGG CAPITAL MARKETS
STRK	STRIKE TECHNOLOGIES LLC
TNTO	TERRA NOVA TRADING, L.L.C.
TSCO	TROSTER SINGER*
USCT	US CLEARING CORPORATION

* Now owned by Spear, Leeds & Kellogg

** Now owned by US Clearing Corporation.

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Table 1

Summary Statistics on Bid-Ask Quotes

The table presents statistics on number of quote submissions, quoted spreads, and depths by Nasdaq participant group (Panel A) and by ECNs (Panel B). The bid and ask sizes are in hundreds. The sample period is July 1998.

Panel A: Group

Group	Number of Quote Submissions	Mean Quoted Spread	Median Quoted Spread	Mean Ask Size	Median Ask Size	Mean Bid Size	Median Bid Size
ECN	2,885,830	0.5030	0.1875	15	10	14	10
Wholesaler	724,669	0.9599	0.6250	11	10	10	10
Wire house	328,503	0.7799	0.5000	11	10	10	10
Inst. Broker	270,877	1.2712	0.7500	10	10	10	10
Other	1,294,105	1.7551	1.1250	8	10	8	10

Panel B: ECN

ECN	Number of Quote Submissions	Mean Quoted Spread	Median Quoted Spread	Mean Ask Size	Median Ask Size	Mean Bid Size	Median Bid Size
BRUT	23,847	1.1319	0.7500	6	3	5	2
BTRD	109,119	1.0431	0.6875	9	5	9	5
INCA	754,763	0.4078	0.1875	22	10	21	10
ISLD	1,868,350	0.4326	0.1875	13	10	11	10
REDI	49,507	1.4955	0.8750	14	10	13	10
TNTO	80,241	1.5054	0.7500	9	7	9	6

Table 2
Quoted Spreads

The table presents mean and median quoted spreads and number of observations (NOB) used in calculating them by Nasdaq participant group and by stock. The sample period is July 1998.

	ECN			Wholesaler			Wire house			Inst. Broker			Other		
Symbol	NOB	Mean Spread	Median Spread	NOB	Mean Spread	Median Spread	NOB	Mean Spread	Median Spread	NOB	Mean Spread	Median Spread	NOB	Mean Spread	Median Spread
AAPL	49065	0.3498	0.1875	16066	0.4646	0.4375	6187	0.4709	0.4375	6433	0.5450	0.5000	23979	0.9373	0.8750
AFCI	26187	0.4729	0.2500	10177	0.7260	0.6250	3854	0.6269	0.6250	4429	0.7739	0.7500	14616	1.5499	1.8125
AMAT	79909	0.2675	0.1250	24750	0.4449	0.3750	10811	0.4368	0.3750	7709	0.5279	0.5000	32637	1.0343	1.0000
AMZN	250186	0.7137	0.3750	43777	2.3114	2.0000	13690	3.4949	2.8750	12808	4.6150	4.3750	50948	5.1542	4.0000
ASND	82448	0.4331	0.1875	16712	0.7864	0.6250	12168	0.7828	0.5625	10664	0.6608	0.6875	43125	1.0514	0.8750
COMS	57576	0.2480	0.1250	16099	0.4493	0.3750	10261	0.3763	0.3125	7038	0.4971	0.5000	32028	0.8285	0.6250
CSCO	182752	0.3059	0.1875	36109	0.6802	0.6250	25234	0.5500	0.5000	21747	0.7120	0.5000	94438	1.1557	1.0000
DELL	313012	0.3338	0.1875	70338	1.0292	0.7500	35734	0.7073	0.6250	26946	1.0098	1.0000	157609	1.4670	1.0000
EGGS	137066	0.2768	0.1250	59290	0.4983	0.4375	5340	0.8260	0.6250	4701	0.8716	0.8750	56323	1.2236	1.0625
ERICY	34107	0.3814	0.1875	7123	0.5363	0.5000	5961	0.3946	0.3750	2802	0.5468	0.5000	18497	0.9264	0.7500
HBOC	63816	0.4259	0.1875	18350	0.7964	0.6875	7312	0.5314	0.5000	9943	0.6771	0.6250	32417	1.2342	1.0000
INTC	203880	0.2691	0.1250	49804	0.4664	0.3750	29358	0.4242	0.4375	19845	0.6574	0.5000	58651	1.2863	0.8750
LCOS	145734	0.6747	0.3750	33821	1.6146	1.3125	5503	1.8651	1.7500	7169	3.0446	3.0000	91061	2.5200	2.0625
MCIC	22969	3.6167	0.3750	7605	0.9084	0.6875	7732	0.5812	0.5000	5537	0.5634	0.5000	25107	1.1766	1.0625
MSFT	208466	0.2916	0.1875	44117	0.7190	0.6250	29095	0.5175	0.5000	17387	0.7417	0.7500	61661	1.5026	1.1250
NOVL	12184	0.2000	0.1250	6492	0.2402	0.1875	3536	0.2841	0.2500	1621	0.3425	0.3750	9011	0.5831	0.5000
NSCP	147346	0.3684	0.1875	44072	0.6887	0.5000	18981	0.7381	0.5625	13520	1.0199	1.0000	82666	1.6964	1.9375
NXTL	24267	0.7035	0.2500	8113	0.6925	0.6250	5193	0.5525	0.5000	5761	0.6497	0.6875	18386	1.0678	1.0625
ORCL	51503	0.1970	0.1250	19080	0.3635	0.2500	8152	0.3574	0.2500	4873	0.3982	0.3750	25039	0.7595	0.5625
PMTC	31980	0.3297	0.1875	8328	0.4777	0.3750	5258	0.3994	0.3125	4005	0.4339	0.3750	15344	0.9023	0.7500
PSFT	54360	0.5399	0.2500	20980	0.8358	0.6875	9435	0.5071	0.5000	8015	0.7852	0.7500	31139	1.6031	1.8125
QWST	29636	0.7054	0.2500	8997	0.8495	0.7500	5848	0.4552	0.3750	8551	0.6472	0.6250	24342	1.5193	1.8125
SPLS	15088	0.8239	0.3125	4978	0.7197	0.6875	5151	0.4886	0.3750	3226	0.6008	0.5000	12915	1.1844	1.3125
SUNW	69787	0.4433	0.1875	17983	0.5636	0.5000	13798	0.4118	0.3750	8211	0.5590	0.5000	39291	1.1902	1.0000
TCOMA	24212	1.0854	0.3125	5419	0.6204	0.5625	4951	0.4563	0.3750	2820	0.5282	0.5000	10970	1.0537	1.0000
TLAB	59949	1.1806	0.3750	9772	1.2188	1.0625	10360	0.8508	0.7500	6197	0.9628	1.0000	42996	1.3819	1.1250
WAMU	19649	0.7371	0.2500	4456	0.8835	0.7500	5891	0.4627	0.3125	3286	0.5920	0.5000	14160	1.4431	1.8125
WCOM	72591	0.3487	0.1250	16911	0.4817	0.4375	11102	0.3631	0.3125	8691	0.4461	0.3750	29992	0.9634	0.7500
XCIT	169940	0.6350	0.3750	52912	1.5398	1.2500	4055	2.1899	2.0000	6211	3.4064	3.0000	93814	2.8314	2.1250
YHOO	246162	0.8278	0.4375	42036	2.1563	1.8750	8552	3.2253	3.0000	20731	4.0125	3.5000	50943	4.5454	3.0000

Table 3

Tests of Unit Roots

The table shows the Augmented Dickey-Fuller unit root “t-tests” of bid quotes by Nasdaq participant group and by stock. Group A refers to ECNs, B to wholesalers, C to wire houses, D to institutional brokers, and E to other market makers. DA, DB, DC, DD, and DE refer to tests applied to quote changes for the various groups. Lags refer to the number of lags used in the test as determined by the Akaike Information Criterion. The “t-test” 1% critical value is –2.58, 5% critical value is –1.95, and 10% critical value is –1.62.

	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat	Lags	t-stat
Group	AAPL		AMZN		CSCO		ERICY		LCOS		NOVL		ORCL		QWST		TCOMA		WCOM	
A	8	-0.949	3	0.036	12	0.194	18	0.170	4	-0.911	17	-4.655	0	-0.422	20	0.738	12	-0.572	0	0.409
B	5	-0.950	5	-0.004	8	0.192	19	0.209	5	-0.869	0	-4.630	0	-0.429	17	0.873	19	-0.742	0	0.477
C	3	-0.955	20	-0.014	7	0.206	20	0.174	2	-0.812	19	-4.564	0	-0.442	19	0.912	20	-0.773	0	0.560
D	9	-0.922	12	-0.035	20	0.162	18	0.196	12	-0.936	17	-4.493	0	-0.397	17	0.869	18	-0.792	0	0.515
E	18	-0.931	20	-0.041	14	0.179	20	0.138	6	-0.921	6	-4.611	20	-0.472	20	0.797	20	-0.735	17	0.637
DA	2	-60.37	2	-53.02	11	-26.67	18	-31.34	3	-49.45	19	-23.56	3	-61.09	10	-36.61	5	-56.25	5	-42.11
DB	3	-48.58	4	-49.26	7	-39.37	17	-32.73	4	-49.64	16	-26.85	9	-33.40	16	-25.35	19	-21.28	17	-26.65
DC	1	-66.77	19	-26.17	6	-41.08	20	-19.60	1	-71.28	19	-23.48	5	-46.91	19	-21.64	20	-23.29	8	-35.74
DD	2	-55.47	11	-33.34	20	-25.09	18	-20.89	11	-29.19	19	-23.66	18	-27.21	19	-22.47	18	-27.75	18	-26.02
DE	16	-25.73	19	-28.05	13	-33.38	19	-27.62	5	-44.34	4	-42.53	3	-70.15	7	-44.80	19	-26.55	4	-52.90
	AFCI		ASND		DELL		HBOC		MCIC		NSCP		PMTC		SPLS		TLAB		XCIT	
A	17	-1.191	18	-2.286	0	0.764	2	0.039	20	-0.470	0	-3.200	0	0.613	18	-0.807	20	0.484	0	-0.547
B	9	-1.215	0	-2.169	2	0.632	0	-0.052	19	0.560	0	-3.197	1	0.679	0	-0.805	1	0.404	2	-0.549
C	4	-1.152	0	-2.128	0	0.495	0	0.059	20	0.563	0	-3.201	0	0.664	9	-0.844	0	0.342	0	-0.551
D	10	-1.113	18	-2.264	7	0.631	0	-0.099	18	0.580	0	-3.205	0	0.557	17	-0.865	17	0.453	5	-0.593
E	13	-1.199	17	-2.174	10	0.691	13	0.090	20	0.562	9	-3.236	4	0.662	18	-0.866	10	0.469	6	-0.562
DA	20	-22.44	18	-22.11	0	-95.00	1	-77.57	20	-32.34	3	-46.49	17	-21.87	19	-28.48	20	-24.39	7	-30.87
DB	16	-23.95	17	-25.66	0	-128.36	8	-32.01	19	-21.42	9	-29.41	2	-53.57	16	-25.83	19	-24.42	1	-65.09
DC	3	-47.97	20	-34.07	1	-74.64	5	-37.64	20	-20.23	5	-38.01	0	-93.02	16	-27.38	16	-22.55	0	-88.63
DD	3	-48.89	18	-18.99	11	-31.25	10	-29.28	18	-21.50	10	-28.59	1	-66.34	19	-22.99	19	-18.38	2	-55.28
DE	17	-24.24	19	-21.92	9	-33.98	3	-59.33	19	-22.35	3	-47.93	3	-46.99	8	-38.28	7	-35.07	3	-46.63
	AMAT		COMS		EGGS		INTC		MSFT		NXTL		PSFT		SUNW		WAMU		YHOO	
A	5	-0.191	18	-2.026	0	-5.662	0	0.541	0	0.691	18	0.364	2	-1.708	2	0.394	4	-1.721	0	0.320
B	19	-0.258	19	-2.036	0	-5.664	0	0.517	0	0.546	17	0.446	19	-1.857	19	0.906	0	-1.697	2	0.306
C	17	-0.215	20	-1.996	0	-5.732	0	0.517	0	0.612	19	0.454	20	-1.861	20	0.880	0	-1.661	0	0.262
D	11	-0.231	18	-1.980	0	-5.764	0	0.452	0	0.534	17	0.443	18	-1.871	18	0.919	8	-1.800	7	0.242
E	17	-0.232	20	-2.010	10	-5.726	9	0.533	11	0.660	18	0.429	20	-1.898	20	0.914	10	-1.824	20	0.280
DA	4	-51.25	18	-21.75	0	-92.96	4	-40.64	3	-46.45	20	-28.23	4	-47.74	4	-59.29	17	-23.18	17	-22.88
DB	18	-23.29	17	-21.55	8	-30.66	9	-30.51	6	-36.32	16	-24.66	19	-32.83	19	-32.91	19	-22.42	20	-22.47
DC	16	-26.81	20	-18.17	4	-41.73	6	-36.79	5	-37.96	19	-21.96	20	-19.32	20	-27.70	16	-24.15	3	-46.81
DD	10	-33.56	18	-22.25	10	-28.10	17	-24.15	8	-31.72	19	-22.15	18	-33.17	18	-25.01	19	-22.36	4	-45.25
DE	16	-32.82	19	-23.99	1	-66.98	3	-55.24	5	-50.15	7	-41.64	19	-25.30	19	-27.49	7	-35.58	20	-21.46

Table 4

Cointegration Test Examples

The table presents the results of Johansen cointegration tests for the bid quotes of Apple Computer and Yahoo. The sample period is July 1998.

Null H_0	Alternative H_1	Test Value	90% Critical Value
AAPL $l_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\hat{l}_i)$ Test			
$r = 0$	$r > 0$	3468.26	55.54
$r \leq 1$	$r > 1$	2308.35	36.58
$r \leq 2$	$r > 2$	1269.64	21.58
$r \leq 3$	$r > 3$	535.67	10.35
$r \leq 4$	$r > 4$	0.66	2.98
AAPL $l_{\max}(r, r+1) = -T\ln(1-\hat{l}_{r+1})$ Test			
$r = 0$	$r = 1$	1159.91	18.96
$r = 1$	$r = 2$	1038.71	15.00
$r = 2$	$r = 3$	733.97	11.23
$r = 3$	$r = 4$	535.00	7.37
$r = 4$	$r = 5$	0.66	2.98
YHOO $l_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\hat{l}_i)$ Test			
$r = 0$	$r > 0$	3048.27	55.54
$r \leq 1$	$r > 1$	2004.85	36.58
$r \leq 2$	$r > 2$	1057.77	21.58
$r \leq 3$	$r > 3$	323.54	10.35
$r \leq 4$	$r > 4$	0.18	2.98
YHOO $l_{\max}(r, r+1) = -T\ln(1-\hat{l}_{r+1})$ Test			
$r = 0$	$r = 1$	1043.41	18.96
$r = 1$	$r = 2$	947.08	15.00
$r = 2$	$r = 3$	734.24	11.23
$r = 3$	$r = 4$	323.36	7.37
$r = 4$	$r = 5$	0.18	2.98

Table 5

Examples of Cointegrating Relations

The table presents the cointegration vectors identified using Johansen cointegration procedures for bid quotes of Apple Computer and Yahoo. The sample period is July 1998. The superscript A refers to ECNs, B to wholesalers, C to wire houses, D to institutional brokers, and E to other market makers. The vectors are normalized by setting the coefficient for A to unity.

AAPL

$$b_t^A - 0.022b_t^D + 0.425b_t^C + 0.004b_t^B - 1.413b_t^E = 0$$

$$b_t^A - 0.050b_t^D - 0.120b_t^C - 0.995b_t^B + 0.164b_t^E = 0$$

$$b_t^A - 1.877b_t^D - 1.590b_t^C + 2.323b_t^B + 0.139b_t^E = 0$$

$$b_t^A + 9.058b_t^D - 11.359b_t^C + 1.516b_t^B - 0.219b_t^E = 0$$

YHOO

$$b_t^A + 0.014b_t^D + 0.061b_t^C - 1.020b_t^B - 0.058b_t^E = 0$$

$$b_t^A + 0.167b_t^D - 0.219b_t^C + 1.521b_t^B - 2.477b_t^E = 0$$

$$b_t^A - 1.247b_t^D + 0.156b_t^C + 0.100b_t^B - 0.019b_t^E = 0$$

$$b_t^A - 0.004b_t^D - 1.066b_t^C + 0.050b_t^B + 0.013b_t^E = 0$$

Table 6

Contributions to Price Discovery

The table presents the upper bound and lower bound information shares of Nasdaq participant groups for each stock sorted by volume. Volume rank refers to the ranking based on the volume of shares traded, one being the biggest volume. An asterisk identifies the biggest information share among the participating groups. The sample period is July 1998.

Symbol	Volume Rank	ECN	Whole-saler	Wire house	Insti. Broker	Other	ECN	Whole-saler	Wire house	Insti. Broker	Other
		Upper Bound					Lower Bound				
INTC	1	0.898*	0.439	0.340	0.223	0.032	0.338*	0.038	0.017	0.023	0.002
DELL	2	0.987*	0.304	0.434	0.177	0.166	0.386*	0.001	0.009	0.000	0.001
MSFT	3	0.937*	0.243	0.382	0.240	0.031	0.407*	0.008	0.027	0.015	0.002
WCOM	4	0.376	0.401	0.461*	0.305	0.035	0.150	0.151	0.183*	0.096	0.006
HBOC	5	0.301	0.369	0.561*	0.250	0.051	0.124	0.131	0.250*	0.088	0.013
CSCO	6	0.906*	0.304	0.386	0.123	0.062	0.406*	0.021	0.046	0.007	0.002
NSCP	7	0.804*	0.418	0.343	0.195	0.153	0.288*	0.057	0.055	0.020	0.015
EGGS	8	0.852*	0.697	0.151	0.170	0.157	0.244*	0.110	0.001	0.001	0.009
ORCL	9	0.448*	0.339	0.166	0.267	0.064	0.295*	0.197	0.081	0.156	0.034
AMAT	10	0.633*	0.339	0.200	0.249	0.042	0.339*	0.140	0.072	0.082	0.012
PMTC	11	0.381	0.638*	0.579	0.614	0.194	0.051	0.101*	0.064	0.064	0.014
COMS	12	0.622*	0.271	0.266	0.204	0.036	0.375*	0.103	0.113	0.084	0.011
ASND	13	0.427	0.232	0.121	0.555*	0.052	0.210	0.105	0.041	0.319*	0.016
SUNW	14	0.276	0.236	0.511*	0.397	0.099	0.109	0.085	0.242*	0.157	0.028
YHOO	15	0.959*	0.300	0.224	0.065	0.049	0.521*	0.008	0.020	0.003	0.006
TCOMA	16	0.008	0.228	0.330	0.445*	0.119	0.002	0.174	0.264	0.363*	0.077
ERICY	17	0.106	0.438	0.568	0.638*	0.079	0.029	0.084	0.142	0.187*	0.008
AMZN	18	0.967*	0.278	0.101	0.123	0.039	0.576*	0.013	0.007	0.008	0.002
PSFT	19	0.395	0.307	0.614*	0.285	0.025	0.135	0.097	0.250*	0.077	0.000
MCIC	20	0.004	0.085	0.644*	0.438	0.058	0.003	0.039	0.460*	0.269	0.023
XCIT	21	0.890	0.625	0.907*	0.284	0.448	0.057	0.000	0.101*	0.000	0.000
AAPL	22	0.352	0.394	0.347	0.396*	0.058	0.150	0.150	0.128	0.167*	0.011
AFCI	23	0.168	0.159	0.546*	0.378	0.130	0.094	0.055	0.312*	0.191	0.047
LCOS	24	0.937*	0.316	0.310	0.146	0.381	0.357*	0.011	0.010	0.002	0.023
QWST	25	0.105	0.292	0.427	0.427*	0.108	0.056	0.159	0.228	0.229*	0.038
TLAB	26	0.039	0.294	0.333	0.505*	0.253	0.020	0.130	0.151	0.263*	0.107
WAMU	27	0.108	0.174	0.286	0.505*	0.080	0.078	0.110	0.212	0.420*	0.045
NOVL	28	0.281	0.388*	0.195	0.280	0.017	0.215	0.290*	0.139	0.198	0.012
NXTL	29	0.030	0.248	0.444*	0.385	0.120	0.021	0.163	0.307*	0.248	0.062
SPLS	30	0.038	0.438*	0.204	0.380	0.143	0.027	0.302*	0.131	0.276	0.084
Mean		0.474	0.340	0.379	0.322	0.109	0.202	0.101	0.135	0.134	0.024
Median		0.388	0.306	0.345	0.285	0.071	0.150	0.102	0.120	0.092	0.013
Standard Deviation		0.358	0.136	0.183	0.150	0.101	0.165	0.079	0.114	0.122	0.027
Std. Error of Mean		0.065	0.025	0.033	0.027	0.018	0.030	0.014	0.021	0.022	0.005

Table 7

Correlations Between Contributions to Price Discovery and Trading Characteristics

The table presents the summary statistics of variables used in the correlations (Panel A) and the correlations by Nasdaq participant group (panel B). The sample period is July 1998.

Panel A: Summary Statistics

Group	Statistic	Share Volume	Percentage Total Share Volume	Number of Quote Submissions	Percentage of Inside Bid Quotes	Info. Share: Upper Bound	Info. Share: Lower Bound
ECN	Mean	11,330,783	0.068	96,194	0.272	0.474	0.202
	Median	7,212,891	0.059	61,883	0.267	0.388	0.150
Wholesaler	Mean	29,503,080	0.184	24,156	0.267	0.340	0.101
	Median	21,026,483	0.163	17,447	0.260	0.306	0.102
Wire house	Mean	31,012,901	0.203	10,950	0.406	0.379	0.135
	Median	26,084,372	0.211	7,942	0.328	0.345	0.120
Insti. Broker	Mean	36,526,027	0.238	9,029	0.247	0.322	0.134
	Median	31,934,455	0.256	7,104	0.229	0.285	0.092
Other	Mean	48,651,357	0.308	43,137	0.071	0.109	0.024
	Median	41,553,499	0.308	32,223	0.064	0.071	0.013

Panel B: Correlations

The number in parentheses is the p-value for test of the null hypothesis of no correlation.

Upper Triangle: ECN

	Info. Share: Upper Bound	Info. Share: Lower Bound	Share Volume	# of Quote Submissions	% of Inside Bid Quotes
Info. Share: Upper Bound	1	0.853 (0.000)	0.761 (0.000)	0.892 (0.000)	-0.695 (0.000)
Info. Share: Lower Bound		1	0.643 (0.000)	0.779 (0.000)	-0.588 (0.001)
Share Volume			1	0.882 (0.000)	-0.373 (0.042)
# of Quote Submissions				1	-0.613 (0.000)
% of Inside Bid Quotes					1

Table 7 Panel B: Correlations (Continued)

Upper triangle: Wholesaler
Lower triangle: Wire house

	Info. Share: Upper Bound	Info. Share: Lower Bound	Share Volume	# of Quote Submissions	% of Inside Bid Quotes
Info. Share: Upper Bound	1	0.101 (0.595)	0.426 (0.019)	0.347 (0.060)	0.548 (0.002)
Info. Share: Lower Bound	0.485 (0.007)	1	-0.451 (0.012)	-0.641 (0.000)	0.303 (0.104)
Share Volume	0.088 (0.645)	-0.065 (0.733)	1	0.898 (0.000)	0.070 (0.712)
# of Quote Submissions	-0.079 (0.677)	-0.441 (0.015)	0.617 (0.000)	1	-0.074 (0.698)
% of Inside Bid Quotes	0.139 (0.463)	-0.284 (0.129)	-0.499 (0.005)	-0.301 (0.106)	1

Upper triangle: Institutional Broker
Lower triangle: Other

	Info. Share: Upper Bound	Info. Share: Lower Bound	Share Volume	# of Quote Submissions	% of Inside Bid Quotes
Info. Share: Upper Bound	1	0.734 (.000)	-0.069 (0.716)	-0.582 (0.001)	0.205 (0.277)
Info. Share: Lower Bound	0.225 (0.231)	1	-0.223 (0.236)	-0.577 (0.001)	0.113 (0.554)
Share Volume	-0.134 (0.481)	-0.490 (0.006)	1	0.447 (0.013)	-0.343 (0.064)
# of Quote Submissions	0.412 (0.024)	-0.399 (0.029)	0.695 (.000)	1	-0.486 (0.006)
% of Inside Bid Quotes	0.169 (0.372)	0.225 (0.231)	-0.444 (0.014)	-0.440 (0.015)	1

Table 8

ECN Regressions

The table presents regressions of information shares of ECNs on share volume or number of quote submissions and percentage of inside bid quotes. The sample period is July 1998.

Variable	Parameter Estimate	Standard Error	Pr > |t|
	Info. Share: Upper Bound		
Intercept	1.232	0.227	0.000
Share Volume	2.17E-08	3.65E-09	0.000
% Inside Bid Quotes	-3.687	0.758	0.000
$\overline{R}^2$	0.76		
	Info. Share: Lower Bound		
Intercept	0.501	0.149	0.002
Share Volume	8.50E-09	2.39E-09	0.001
% Inside Bid Quotes	-1.451	0.496	0.007
$\overline{R}^2$	0.52		
	Info. Share: Upper Bound		
Intercept	0.665	0.239	0.010
# of Quote Submissions	3.19E-06	4.28E-07	0.000
% Inside Bid Quotes	-1.829	0.773	0.025
$\overline{R}^2$	0.82		
	Info. Share: Lower Bound		
Intercept	0.247	0.165	0.147
# of Quote Submissions	1.33E-06	2.95E-07	0.000
% Inside Bid Quotes	-0.634	0.533	0.245
$\overline{R}^2$	0.60		