Price Discovery and Trading After Hours

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We examine the effects of trading after hours on the amount and timing of price discovery over the 24-hour day. A high volume of liquidity trade facilitates price discovery. Thus prices are more efficient and more information is revealed per hour during the trading day than after hours. However, the low trading volume after hours generates significant, albeit inefficient, price discovery. Individual trades contain more information after hours than during the day. Because information asymmetry declines over the day, price changes are larger, reflect more private information, and are less noisy before the open than after the close.

Technology has dramatically changed the way stock markets operate by allowing investors to trade directly with each other, both during and outside of exchange trading hours. Although it is now relatively easy to trade after hours, in reality most investors do not. Only 4% of Nasdaq trading volume occurs after hours. This article examines how investors' decisions to trade after hours or during the trading day affect the process through which new information is incorporated into security prices. We find that relatively low after-hours trading volume can generate significant price discovery, although prices are noisier after hours, implying that the price discovery is less efficient.

Variation in the amount of informed and uninformed trading is relatively small, both within the trading day [Admati and Pfleiderer (1988), Wood, McInish, and Ord (1985), Madhavan, Richardson, and Roomas (1997)] and across trading days [Foster and Viswanathan (1993)]. In contrast, there are large shifts in the trading process at the open and at the close. These large shifts make it possible to examine price discovery under conditions very different from those studied previously and allow us to address the following four questions regarding the relationship between trading and price discovery. First, how does the trading process affect the

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total amount of information revealed and the timing of that revelation? Second, where do informed traders prefer to trade and, consequently, in which trading venue does most price discovery occur? Third, how does the trading process affect the relative amounts of public and private information incorporated into stock prices? And fourth, how does trading affect the informational efficiency of stock prices?

In addition to improving our general understanding of the interaction between trading and price discovery, answers to these questions have important practical implications for a wide range of market participants. The exchanges must decide when to remain open and when to report trades and quotes. Dealers must decide whether to participate in making an after-hours market. Brokers must decide whether trading after hours is in the best interest of their clients and how to satisfy their fiduciary obligation of best execution. Retail and institutional investors must decide whether to enter the after-hours market or to confine their trades to exchange trading hours. Firms must decide whether to make public announcements, such as earnings announcements, after hours or during the trading day. And regulators must decide on the rules governing all of these activities. Currently these decisions are being made with little information about the characteristics of the after-hours trading environment.

Much of our analysis contrasts the preopen (from 8:00 to 9:30 A.M.) with the postclose (from 4:00 to 6:30 P.M.).[1] We expect trading in these two periods to be very different. A variety of microstructure models predict that information asymmetry will decline over the trading period. Thus we expect less information asymmetry in the postclose than in the preopen. In contrast, portfolio or inventory motives for trade will be greater after the close than before the open because the costs of holding a suboptimal portfolio overnight may be large. Together, these two effects imply that there will be a higher fraction of liquidity-motivated trades in the postclose and a higher fraction of informed trades in the preopen. Because much of our analysis is predicated on this hypothesis, we test it directly. Using the model developed by Easley, Keifer and O'Hara (1996), we find that the probability of an informed trade is significantly greater during the preopen than during the postclose. Starting with this result, we then

[1] Several recent articles have examined the importance of preopening activities in discovering the opening price in financial markets [see Domowitz and Madhavan (2000) for an overview]. Generally these studies focus on preopening price discovery through nonbinding quotes and orders in the absence of trading. For example, Stoll and Whaley (1990) and Madhavan and Panchapagasen (2000) study how the specialist affects the opening on the New York Stock Exchange (NYSE); Davies (2000) analyzes the impact of preopen orders submitted by registered traders on the Toronto Stock Exchange; Biais, Hillion, and Spatt (1999) examine learning and price discovery through nonbinding order placement prior to the opening on the Paris Bourse; Cao, Ghysels, and Hatheway (2000) and Ciccotello and Hatheway (2000) investigate price discovery through nonbinding market-maker quotes prior to the Nasdaq opening; and Flood et al. (1999) study the importance of transparency for opening spreads and price discovery in an experimental market.

proceed to examine our primary research objectives and obtain the following results.

First, there is greater information asymmetry and a higher ratio of informed to uninformed trading in the preopen than at any other time of day. Although the trading day has by far the most price discovery, the preopen has the greatest amount of price discovery per trade. Second, during the postclose, when there is less informed trading and less price discovery than during the preopen, the majority of trades are with market makers. In contrast, the majority of trades and virtually all price discovery during the preopen occur on electronic communications networks (ECNs). This is consistent with Barclay, Hendershott, and McCormick's (2003) findings that informed traders value the speed and anonymity associated with trading on an ECN, while liquidity traders often prefer to negotiate their trades with market makers.

Third, there is a large amount of private information revealed through trades during the preopen. The fraction of the total price discovery that is attributable to private information is similar in the preopen and during the trading day, even though there is a small fraction of the number of trades per hour in the preopen compared with the trading day. However, information asymmetry declines over the day. Thus, despite the fact that there is more trading activity in the postclose than in the preopen, there is less total information revealed in the post close, and a smaller fraction of that information is private.

Finally, stock prices after-hours are less efficient than prices during the day. After the close, there are large bid-ask spreads [Barclay and Hendershott (2003)] thin trading, and little new information. Trades in the postclose cause temporary stock price changes that are subsequently reversed, which results in inefficient stock prices and a low signal:noise ratio for stock price changes. Bid-ask spreads are also large in the preopen. However, the high frequency of informed trades cause stock price changes to have a higher signal:noise ratio in the preopen than during the postclose, although stock prices are still noisier during the preopen than during the trading day.

Overall, our results show that it is possible to generate significant price discovery with very little trading. Both public and private information are incorporated into stock prices before the open with only a fraction of the trading activity that occurs during the trading day. However, larger volumes of liquidity trade facilitate the price discovery process and result in more price discovery and more efficient prices during the trading day.

The remainder of the article is organized as follows: Section 1 describes the after-hours trading environment and provides a description of our data and descriptive statistics on after-hours trading. Section 2 compares the probability of an informed trade in the preopen and in the postclose. Section 3 examines the timing of price discovery after hours and across the

24-hour day. Section 4 investigates the relative share of price discovery attributed to market-maker and ECN trades. Section 5 decomposes price discovery into its public and private components. Section 6 studies the efficiency of after-hours price discovery. Section 7 concludes.

1. The After-Hours Trading Environment, Data, and Descriptive Statistics

The major U.S. stock exchanges have normal trading hours from 9:30 A.M. until 4:00 P.M. Eastern Time. Until recently, the trading of most U.S. stocks was largely confined to these exchange trading hours. A small number of companies are dually listed on foreign exchanges, such as Tokyo or London, and also trade when these foreign exchanges are open. Thus much of the previous work on after-hours trading (i.e., trading outside of U.S. exchange trading hours) focused on the trading of U.S. stocks on foreign exchanges.[2]

Electronic communications networks such as Instinet, Island, Archipelago, and others, are changing the way stock markets operate. ECNs are electronic trading systems based on open limit order books where participants place orders and trade anonymously and directly with one another. This feature of ECNs has significantly expanded the opportunities for after-hours trading. Because these trades do not require an intermediary, they have not been confined to exchange trading hours. As long as the electronic trading system is turned on, trades can occur at any time of day or night.[3]

Currently there are relatively few regulatory differences between trading after hours and trading during the day (a detailed discussion of the after-hours trading environment is available in the appendix). In February 2000, Nasdaq began calculating and disseminating an inside market (best bid and offer) from 4:00 to 6:30 P.M. Eastern Time. In conjunction with the dissemination of the inside market, National Association of Securities Dealers (NASD) members who voluntarily entered quotations during this after-hours session were required to comply with all applicable limit order protection and display rules (e.g., the "Manning" rule and the SEC order handling rules). Market makers are not required to post quotations after 4:00 P.M., and most do not. Nevertheless, these changes provided a nearly uniform regulatory environment on Nasdaq from 9:30 A.M. until 6:30 P.M. Eastern Time. Nasdaq still does not calculate or disseminate an

[2] See, for example, Barclay, Litzenberger, and Warner (1990), Neumark, Tinsley, and Tosini (1991), and Craig, Dravid, and Richardson (1995). Also, Werner and Kleidon (1996) study the integration of multi-market trading in U.K. stocks that are traded in New York.

[3] It has always been possible to trade after hours by negotiating with a market maker over the telephone. Indeed, trades have been executed in this way after the close for many years. ECNs add a dimension to after-hours trading, however, that allows traders to post or hit firm quotes after hours in much the same way as during the trading day.

inside market before the open. Consequently the limit order protection and display rules do not formally apply. Brokers continue to be bound by their fiduciary duties, however, including the duty to obtain the best execution for their customers' orders.

The low trading volume makes trading after hours very different from trading during the day. Market makers seldom submit firm quotes after hours and trading costs are four to five times larger than during the trading day [Barclay and Hendershott (2003)]. Retail brokerage accounts receive warnings about the dangers of trading after hours and retail orders require special instructions for after-hours execution.[4] Thus, although the regulatory differences between the trading day and after hours are now relatively minor, the participation rates of various types of traders are very different. We expect trading after hours to be dominated by professional or quasi-professional traders with strong incentives to trade after hours in spite of the low liquidity and high trading costs.

1.1 Data

Two datasets are used for our analysis. The first contains all after-hours trades and quotes for Nasdaq-listed stocks from March through December 2000 (212 trading days), and was obtained directly from the NASD. For each after-hours trade, we have the ticker symbol, report and execution date and time, share volume, price, and source indicator (e.g., SOES or SelectNet). For each after-hours quote change during times when the Nasdaq trade and quote systems are operating (8:00 A.M. to 6:30 P.M.), we have the ticker symbol, date and time, and bid and ask prices. If there is more than one quote change in a given second, we use the last quote change for that second.

At the close, all market-maker quotes are cleared. If market makers choose to post quotes after the close, these quotes are binding. In our sample period, Knight Securities was the only market maker with significant postclose quoting activity. The other active market participants after the close were ECNs (Instinet and Island had the most quote updates) and the Midwest Stock Exchange. During the preopen, market makers can post quotes, but these quotes are not binding and the inside quotes are often crossed [Cao, Ghysels, and Hatheway (2000)].[5] To construct a series of binding inside quotes, we use only ECN quotes during the preopen.

The second dataset is the Nastraq database compiled by the NASD. For the same time period (March through December 2000), Nastraq data

[4] NASD members are required to disclose the material risks of extended hours trading to their retail customers. According to NASD Regulation, Inc., these risks include lower liquidity, higher volatility, changing prices, unlinked markets, an exaggerated effect from news announcements, and wider spreads.

[5] From 9:20 A.M. until the open, the "trade or move" rule is in effect. This rule requires that if the quotes become crossed, then a trade must occur or the quotes must be revised. Because participants can revise their quotes without trading, the market-maker quotes are not firm.

are used to obtain trades and quotes during the 9:30 A.M. to 4:00 P.M. trading day.[6] Trades are matched with quotes using execution times and the following algorithm that has been found by Nasdaq Economic Research to perform well for the Nasdaq market. SelectNet and SOES are electronic trading systems run by Nasdaq. Because the execution times for these trades are very reliable, we match the trade with the inside quote one second before the trade execution time. For all other trades, we match the trade with the inside quote three seconds before the trade execution time. Using the Lee and Ready (1991) algorithm, trades are classified as buyer initiated if the trade price is greater than the quote midpoint, and seller initiated if the trade price is less than the quote midpoint. Trades executed at the midpoint are classified with the tick rule; midpoint trades on an up-tick are classified as buyer initiated and midpoint trades on a down-tick are classified as seller initiated.

1.2 Sample of the 250 highest-volume Nasdaq stocks

Nasdaq stocks collectively average 25,000 after-hours trades per day, totaling $2 billion or almost 4% of the average trading day volume. We rank the Nasdaq stocks by their total dollar volume during the trading day and focus on the 250 highest-volume stocks (excluding American Depository Receipts) that traded during our entire sample period. These stocks represent 75% of the total after-hours volume and more than half of the after-hours trades for all Nasdaq stocks. After-hours trading in lower-volume stocks is quite thin (i.e., fewer than 20 after-hours trades per day).

Table 1 reports the amount of after-hours trading during three after-hours time periods: the preopen (8:00 to 9:30 A.M.), the postclose (4:00 to 6:30 P.M.), and overnight (6:30 P.M. to 8:00 A.M.).[7] Results are reported for the full sample and for quintiles ranked by dollar trading volume. After-hours trading is concentrated immediately after the close and before the open of the trading day. Trading overnight is largely limited to late-night batch trading systems, the largest of which is Instinet's midnight crossing system.[8] This period also includes some trades between 6:30 and 7:30 P.M. and between 6:30 and 8:00 A.M. on high-volume days. After-hours trading

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[6] We attempt to filter out large data errors in both datasets by eliminating trades and quotes with large price changes that are immediately reversed. We also exclude trades with nonstandard delivery options.

[7] In prior years, many Nasdaq trades were reported late. Block trades in particular were often assembled during the trading day and printed after the close [Porter and Weaver (1998)]. When late reporting of trades was identified as a problem, NASD Regulation, Inc., enacted changes to ensure that trades were reported in a timely fashion. Although it is still possible to report trades late, the surveillance of this activity and disciplinary actions against offenders have reduced late trade reporting to an insignificant amount. The increased use of electronic trading systems (ECNs, SuperSoes, Primex, and SelectNet) and the reduction of phone trades also reduced the excuses for late trade reporting. Therefore we are confident that the vast majority of our after-hours trades were actually executed after hours and are not simply print backs of trades executed during the trading day.

[8] See Hendershott and Mendelson (2000) for details on the operations of crossing networks.

Table 1
After-hours trading for the 250 highest-volume Nasdaq stocks

	Postclose			Overnight			Preopen			Trading day	
Dollar volume quintile	Volume ($000)	Number of trades	days with trading (%)	Volume ($000)	Number of trades	days with trading (%)	Volume ($000)	Number of trades	days with trading (%)	Volume ($000)	Number of trades
Highest	20,036	169	99.1	556	3	52.7	7,747	143	99.9	733,938	17,384
4	4,623	48	99.0	168	1	32.7	1,258	36	98.3	154,664	5,341
3	2,290	31	98.9	102	0	27.4	601	22	91.6	70,723	2,976
2	1,495	16	98.1	83	0	20.3	317	10	80.8	44,046	1,645
Lowest	1,041	12	97.6	65	0	20.2	159	7	72.4	27,812	1,195
Overall	5,926	55	98.5	195	1	30.7	2,028	44	88.6	207,170	5,722

Average dollar volume, number of trades per stock per day, and percentage of days with at least one trade for three after-hours time periods and the trading day from March to December 2000.

volume is skewed toward the highest-volume days. Eleven percent of the after-hours volume occurs on the busiest five days for each stock (of the 212 days in our sample period). Only 4% of the trading-day volume occurs on the busiest five trading days for each stock.

The stocks in the highest-volume quintile average about 150 trades per stock per day in each of the postclose and preopen periods, with average daily trading volumes of $20 million and $8 million per stock, respectively, in these periods. Trading activity falls off quickly in the lower-volume quintiles. The lowest-volume quintile averages about 20 after-hours trades per day (12 in the postclose and 7 in the preopen), with an average daily after-hours trading volume of about $1.2 million. There are many days with little or no preopen trading activity for stocks in the lowest-volume quintile. Stocks below the top 250 (not reported in the table) have very little after-hours trading. Because of the low after-hours trading activity for these stocks, we do not analyze them further.

1.3 Trading volume and volatility

Figure 1 shows the average daily trading volume and average return volatility for each half-hour period from 8:00 A.M. to 6:30 P.M. for the 250 highest-volume Nasdaq stocks. Trading starts off slowly for these stocks, at $170,000 per day from 8:00 to 8:30 A.M. Volume then roughly triples in each subsequent half-hour period during the preopen, reaching $1.5 million from 9:00 to 9:30 A.M. Trading volume in the last half hour

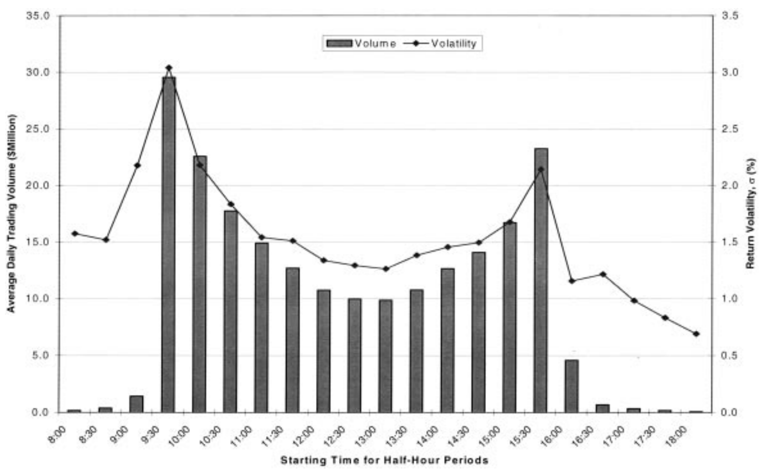

Figure 1
Trading volume and volatility by half-hour period during the trading day and after hours
Average daily trading volume and volatility for each half-hour period from 8:00 A.M. to 6:30 P.M. for the 250 highest-volume Nasdaq stocks from March to December 2000. Volatility, defined as the standard deviation of the half-hour stock return, is calculated for each stock and then averaged across stocks.

before the open (9:00 to 9:30 A.M.) represents about 5% of the trading volume in the first half hour of the trading day, which is the busiest period of the day. Once the market is open, trading volume exhibits the standard U-shape pattern [Chan, Christie, and Schultz (1995) and others]. After the market closes, trading volume falls by 80% from 4:00 to 4:30 P.M., and then again by 85% from 4:30 to 5:00 P.M. After-hours trading is essentially complete by 6:30 P.M.

During the trading day, trading volume and volatility are highly correlated. After hours, trading volume drops off much more quickly than volatility and the correlation between volume and volatility is reduced. Figure 1 illustrates that low levels of trading volume can be associated with relatively high volatility after hours. The last half hour before the open has only 5% of the trading volume, but 72% of the volatility observed in the first half hour of the trading day. Similarly the first half hour after the close has only 20% of the trading volume, but 54% of the volatility observed in the last half hour of the trading day.

Although there are fewer trades after hours than during the trading day, the after-hours trades are much larger. Figure 2 shows the mean and median trade size for each one-minute interval from 8:00 A.M. to 6:30 P.M. Because the variability of mean and median trade size is large after hours, we plot them on a log scale.

Beginning at 8:00 A.M., the mean and median trade sizes are twice as large as they are during the day. Trade size declines as the open approaches and declines sharply in the first minute after the open. Similarly the mean trade size almost triples after the close, from $38,000 during

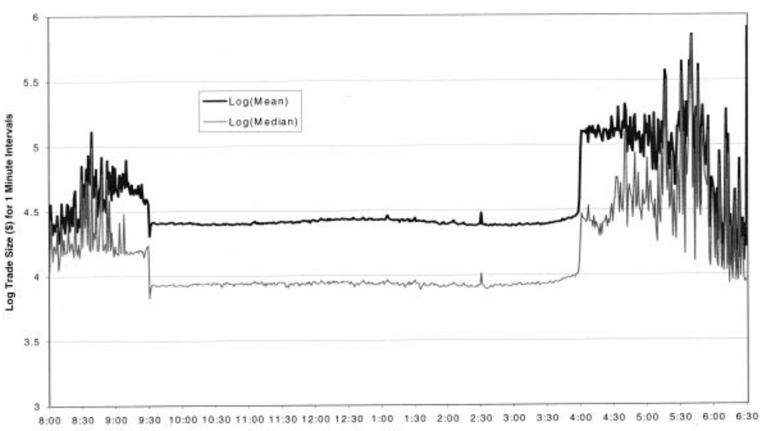

Figure 2
Mean and median trade size by minute during the trading day and after hours
The mean and median trade sizes are calculated each minute from 8:00 A.M. to 6:30 P.M. for the 250 highest-volume Nasdaq stocks from March to December 2000. The log of the mean and median trade size are graphed.

the day to more than $90,000 after the close. The average trade size continues to increase until about 5:00 P.M., where it plateaus at approximately $500,000.

2. Informed and Liquidity Trading After Hours

Given the many impediments to trading after hours, we expect after hours trading to be dominated by professional and quasi-professional traders. Within this set of professional traders, however, it still is natural to question who trades after hours and why. Microstructure models often group traders in two categories: liquidity traders, who trade to rebalance their portfolios and manage their inventories, and informed traders, who trade to profit from their private information. We expect these two types of traders to have very different participation rates in the preopen and postclose periods.

Microstructure models often have the feature that information asymmetry declines over the trading period [see, e.g., Kyle (1985), Glosten and Milgrom (1985), Foster and Viswanathan (1990), and Easley and O'Hara (1992)].[9] Both public and private information accumulate overnight, however, when there is little trading. Thus these studies suggest that information asymmetry will be lowest just after the close and highest before the open.

Liquidity demands follow a quite different pattern. Brock and Kleidon (1992) argue that there are large costs associated with holding a suboptimal portfolio overnight. Traders who are unable to complete their portfolio rebalancing before the close face significant costs of delaying these trades until the open and have large incentives to complete their portfolio rebalancing during the postclose. During the preopen, the opportunity costs of holding a suboptimal portfolio are much less due to the shorter expected delay until the trading day. Because the costs of trading in the preopen are much higher than during the trading day, and the benefits of liquidity trade are small, we expect that there will be more liquidity trades during the postclose than during the preopen. Because there are both fewer liquidity trades and more information asymmetry in the preopen than during the postclose, we expect a higher fraction of informed trades in the preopen than in the postclose.

To test the hypothesis that there is a larger fraction of informed trading during the preopen than during the postclose, and to compare the relative participation rates of informed and liquidity traders throughout the 24-hour trading day, we use Easley, Kiefer, and O'Hara's (1996, 1997a,b)

[9] The decay of private information over the trading period has also been found in laboratory experiments [Bloomfield (1996), Bloomfield and O'Hara (2000) and others] and on the NYSE [Madhavan, Richardson, and Roomas (1997), although they find a slight increase in the last half-hour of the trading day, presumably due to informed traders attempting to trade before the market closes].

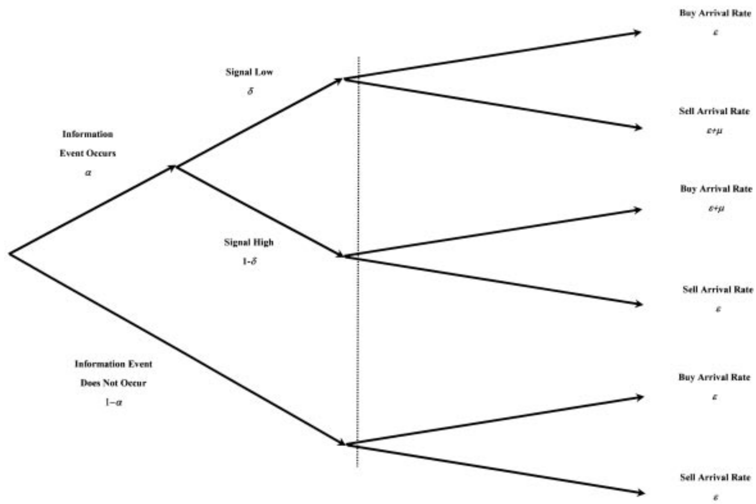

Figure 3
Tree diagram for the trading process in the Easley, Kiefer, and O'Hara model
α is the probability of an information event, δ is the probability of a low signal, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders. Nodes to the left of the dotted line occur once per day.

structural model to estimate the amount of information-based trading. In this model, trading between market makers, informed traders, and liquidity traders is repeated over multiple trading periods. At the start of each period, a private signal regarding the value of the underlying asset is received by the informed traders with probability α. Conditional on the arrival of a private signal, bad news arrives with probability δ, and good news arrives with probability $(1 - \delta)$. The market maker sets prices to buy or sell and executes orders as they arrive. Orders from liquidity traders arrive at the rate ε and, conditional on the arrival of new information, orders from informed traders trades arrive at rate μ.[10] Informed traders buy when they see good news and sell when they see bad news. This process is captured in Figure 3.

The Easley, Kiefer, and O'Hara (EKO) model allows us to use observable data on the number of buys and sells to make inferences about unobservable information events and the division of trade between the informed and uninformed. In effect, the model interprets the normal level of buys and sells in a stock as uninformed trade and it uses this information to identify ε. Abnormal buy or sell volume is interpreted as information-based trade and is used to identify μ. The number of periods during which there is abnormal buy or sell volume is used to identify α and δ. Of course,

[10] Allowing for different arrival rates for uninformed buyers and sellers makes little difference in the estimate of the probability of an informed trade [cf. Easley, Hvidkjaer, and O'Hara (2002)].

the maximum-likelihood estimation does all of this simultaneously. Using this model, the probability of an informed trade (PIN) is given by

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}.$$

Assuming a Poisson arrival process for the informed and uninformed traders, the likelihood function for this model over a single trading period is

$$\begin{aligned} L((B,S)|\theta) = {} & (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} \\ & + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!} \\ & + \alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!}, \end{aligned}$$

where B and S represent total buy trades and sell trades for the period, respectively, and $\theta = (\alpha, \delta, \mu, \varepsilon)$ is the vector of model parameters. This likelihood is a mixture of distributions where the trade outcomes are weighted by the probability of a "good-news day" ($\alpha(1-\delta)$), a "bad-news day" ($\alpha\delta$), or a "no-news day" ($1-\alpha$). EKO assume independence of this process across days and estimate the parameter vector with maximum likelihood. Using the same methodology, we estimate the probability of an informed trade for each of our sample stocks in the preopen, postclose, and trading day periods.

Table 2 reports the cross-sectional mean and standard deviation of the probability of an informed trade by time period and dollar-volume quintile. Consistent with our hypothesis, the probability of an informed trade is greater during the preopen than during the postclose for all five volume quintiles, and this difference is statistically significant at the 0.01 level for four of the five quintiles.[11] In addition, although we did not have a clear prediction about the probability of an informed trade during the trading day, it is interesting to note that for all but the highest-volume quintile, the probability of an informed trade is significantly lower during the trading day than during either after-hours time period. Overall the probability of an informed trade during the trading day is about half of the probability of an informed trade in the preopen, and 60% of the probability of an informed trade in the postclose.

The estimates of the structural parameters of the EKO model appear to be robust and well behaved, even when estimated during the relatively inactive after-hours periods. Consistent with previous estimates, the

[11] We use a nonparametric pairwise Mann–Whitney test to determine one-sided p-values for the differences among time periods.

Table 2
Probability of an informed trade

Dollar volume quintile	Postclose	Preopen	Trading day
Highest	0.09†	0.13†	0.10
	(0.07)	(0.08)	(0.02)
4	0.18†*	0.21†*	0.12
	(0.09)	(0.08)	(0.02)
3	0.22†*	0.26†*	0.14
	(0.09)	(0.12)	(0.02)
2	0.27*	0.30*	0.15
	(0.08)	(0.13)	(0.03)
Lowest	0.31†*	0.37†*	0.16
	(0.10)	(0.11)	(0.04)
Overall	0.21†*	0.25†*	0.13
	(0.12)	(0.13)	(0.03)

The probability of an informed trade as measured by the Easley, Kiefer, and O'Hara model during the postclose, preopen, and trading day for the 250 highest-volume Nasdaq stocks from March to December 2000. Cross-sectional means are reported with standard deviations in parentheses. Pairwise Mann–Whitney tests are used to determine one-sided p-values for the differences among time periods. After-hours values that differ from the trading day at a 0.01 level are denoted with an *. After-hours values that differ from the other after-hours period at a 0.01 level are denoted with a †. For each stock and time period, parameters are estimated by maximizing the following likelihood function:

$$L((B,S)|\alpha,\delta,\mu,\varepsilon) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!},$$

where B and S represent total buy trades and sell trades for the day, respectively, α is the probability of an information event, δ is the probability of a low signal conditional on an information event, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders. The probability of an informed trade is then calculated as:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon}.$$

probability of an informed trade is decreasing in average trading volume in each time period, and the average trading day PIN of 0.13 is comparable to prior estimates. To provide additional evidence on the robustness of the estimation, we report histograms of the estimated model parameters in Figure 4.[12]

For each time period, panel A of Figure 4 provides a histogram of the estimated fraction of informed trades on days with an information event ($\mu/(\mu + 2\varepsilon)$). Consistent with the PINs, the fraction of informed trades is highest in the preopen (65%), followed by the postclose (52%), and lowest during the trading day (32%). The histograms show that the entire cross-sectional distribution of this ratio shifts to the left as we move from the preopen to the postclose and then to the trading day. The distributions are unimodal, relatively smooth, and suggest that the overall results are not driven by outliers. Panel B of Figure 4 provides histograms of the estimated probability of an information event (α). As with the fraction of

[12] Figure 4 is constructed by calculating the fraction of firms in 10 equal-sized bins based on the values of the estimated parameters, and then plotting a smoothed line connecting those fractions.

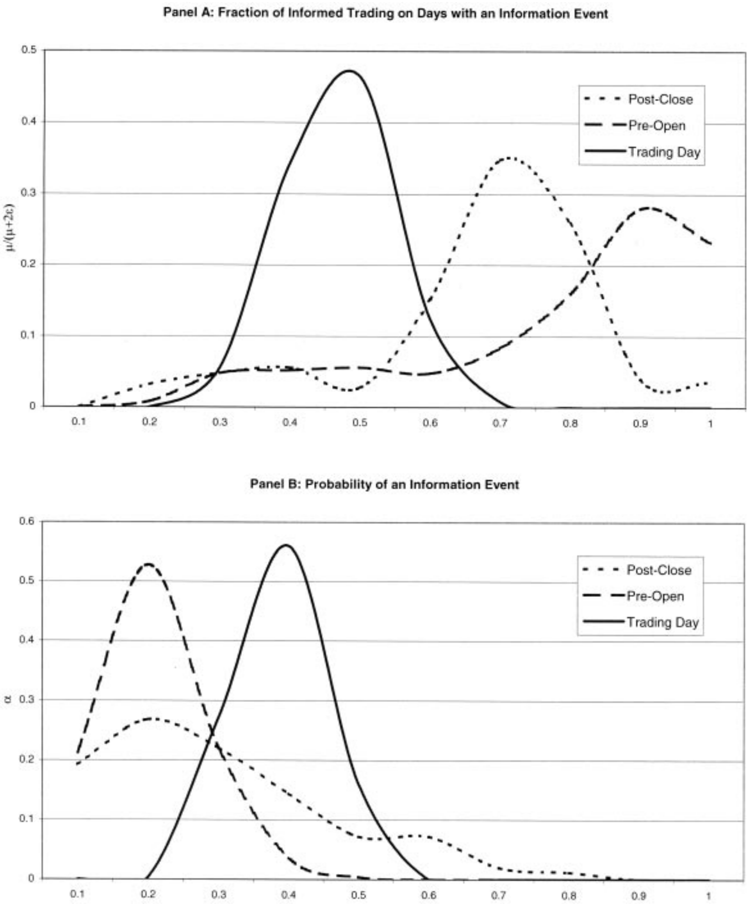

Figure 4
Distributions of the fraction of informed trades and the probability of an information event
Histograms for the fraction of informed trades ($\mu/(\mu+2\varepsilon)$) and the probability of an information event (α) for the 250 highest-volume Nasdaq stocks from March to December 2000. For each stock and time period, parameters are estimated by maximizing the following likelihood function:

$$L((B,S)|\alpha,\delta,\mu,\varepsilon) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^B}{B!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^S}{S!} + \alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^S}{S!}e^{-(\mu+\varepsilon)T}\frac{((\mu+\varepsilon)T)^B}{B!},$$

where B and S represent total buy trades and sell trades for the day, respectively, α is the probability of an information event, δ is the probability of a low signal conditional on an information event, μ is the arrival rate of informed orders, and ε is the arrival rate of uninformed orders.

informed trades, the cross-sectional distributions of α are smooth, unimodal, and without significant outliers, suggesting that the EKO parameters can be estimated even in the less active after-hours time periods.

The estimated probability of an information event is highest during the trading day (0.34), followed by the postclose (0.25), and lowest in the preopen (0.16). Although we had strong priors about the PINs and the ratios of informed to uninformed trades, the theory provides less guidance concerning the probability of an information event. Not surprisingly, the estimated α's suggest that private information is generated more often during the trading day than after hours, because traders have more opportunities to trade on and profit from that information during the day. It is somewhat surprising that an information event is more likely during the postclose than during the preopen, because both public and private information tend to accumulate overnight when there is little or no trading. The higher probability of an information event after the close could either reflect new information discovered after the close or information discovered during the trading day that is not fully incorporated in prices by the end of the day. The likelihood of an information event, however, does not measure the magnitude of those events and, in the following sections, we show that the higher probability of an information event in the postclose does not generate more price discovery.

3. Price Discovery: The Incorporation of New Information in After-Hours Prices

The prior literature shows that price discovery is closely linked with the trading process [see, e.g., French and Roll (1986) and Barclay, Litzenberger, and Warner (1990)]. In the previous sections we showed that the probability of an informed trade is much higher after hours than during the trading day. However, the level of trading activity is also much lower after hours. In this section we study how these competing effects determine the amount and timing of price discovery throughout the 24-hour day.

3.1 Weighted price contribution

We measure the amount of new information incorporated into stock prices during a given time period by the weighted price contribution (WPC), which measures the fraction of the overnight (close-to-open) or 24-hour (close-to-close) stock return that occurs during that period.[13] We divide the close-to-open into three after-hours time periods: preopen, postclose, and overnight. We add a fourth "opening" time period (the last trade before 9:30 A.M. to the first trade after 9:30 A.M.) to separate after-hours trading from the normal opening process.

[13] The WPC has also been used by Barclay and Warner (1993), Cao, Ghysels, and Hatheway (2000), and Huang (2002).

For each day and each time period i, we define the WPC as

$$WPC_i = \sum_{s=1}^{S} \left(\frac{|ret_s|}{\sum_{s=1}^{S} |ret_s|} \right) \times \left(\frac{ret_{i,s}}{ret_s} \right),$$

where $ret_{i,s}$ is the logarithmic return during period i for stock s and ret_s is the close-to-open return for stock s. The first term of WPC is the weighting factor for each stock. The second term is the relative contribution of the return during period i to the total return that day. In the spirit of Fama and MacBeth (1973), we calculate the mean WPC for each day and use the time-series standard error of the daily WPCs for statistical inference.[14]

Table 3 reports WPCs for the close-to-open price change in panel A and the close-to-close price change in panel B. Two primary results emerge from this analysis. First, most after-hours price discovery occurs in the preopen, with a small amount in the postclose, and almost none overnight. For the overall sample, 74% of the close-to-open price discovery occurs in the preopen and 15% occurs in the postclose. Nine percent occurs with the opening trade of the trading day. Second, the price discovery declines rapidly after the close (falling from almost 6% between 4:00 and 4:30 P.M., to only 2% or 3% per half hour after that) and rises dramatically just before the open (over half of the close-to-open price discovery occurs between 9:00 and 9:30 A.M.).

For stocks in the highest-volume quintile, price discovery begins before 8:00 A.M. (8% of price discovery occurs overnight) and is more complete by the open. The final trade before 9:30 A.M. explains more than 99% of the close-to-open price change for this quintile. Price discovery for stocks in the lower-volume quintiles begins later in the morning. For these quintiles, there is more time between the last trade before 9:30 A.M. and the first trade after 9:30 A.M., which causes the opening trade to be more informative. For the lowest-volume quintile, almost 20% of the close-to-open price discovery occurs with the opening trade of the day.

Panel B of Table 3 reports the WPC for the 24-hour (close-to-close) price change and allows an analysis of the fraction of the total price discovery that occurs after hours. The combined after-hours (postclose, overnight, and preopen) price discovery declines from 19% for the highest-volume quintile to 12% for the lowest-volume quintile. The decline in after-hours price discovery across the volume quintiles suggests that the amount of after-hours price discovery is related to the amount of

[14] The WPC is typically calculated stock by stock and then averaged across stocks [cf. Barclay and Warner (1993) and Cao, Ghysels, and Hatheway (2000)]. However, correlation across stocks induced by the common component in stock returns complicates statistical inferences about the mean WPC when it is calculated in this way. For our sample, there are no notable differences in the point estimates when the WPC is calculated for each stock and averaged across stocks, or when it is calculated for each day and averaged across days.

Table 3
Weighted price contribution

Panel A: Weighted price contribution from close to open by time period and trading volume quintile

	Time Periods										
	Postclose					Overnight	Preopen			Open	
Dollar volume quintile	Close–4:30 P.M.	4:30 P.M.–5:00 P.M.	5:00 P.M.–5:30 P.M.	5:30 P.M.–6:00 P.M.	6:00 P.M.–6:30 P.M.	6:30 P.M.–8:00 A.M.	8:00 A.M.–8:30 A.M.	8:30 A.M.–9:00 A.M.	9:00 A.M.–9:30 A.M.	9:30 A.M.–open	Days with zero price change
Highest	0.068*	0.051*	0.041	0.018	0.026	0.077*	0.204*	0.165*	0.349*	0.001	0.020
4	0.055*	0.034	0.038*	0.018	0.019	0.018	0.145*	0.14*	0.512*	0.02	0.035
3	0.053*	0.028	0.028	0.025	0.012	0.016	0.123*	0.114*	0.532*	0.069*	0.051
2	0.048	0.024	0.014	0.011	0.017	0.008	0.082*	0.084*	0.568*	0.145*	0.052
Lowest	0.054	0.02	0.027	0.018	0.014	−0.002	0.046*	0.067*	0.564*	0.192*	0.067
Overall	0.056*	0.031	0.029	0.018	0.018	0.024	0.12*	0.114*	0.505*	0.085*	0.045

Panel B: Weighted price contribution from close to close by time period and trading volume quintile

	Time periods					
Dollar volume quintile	Close–6:30 P.M.	6:30 P.M.–8:00 A.M.	8:00 A.M.–9:30 A.M.	9:30 A.M.–open	Open–close	Days with zero price change
Highest	0.044*	0.025	0.12*	−0.001	0.812*	0.009
4	0.031	0.007	0.119*	0.001	0.841*	0.009
3	0.031	0.004	0.106*	0.003	0.855*	0.013
2	0.021	0.005	0.104*	0.012	0.858*	0.013
Lowest	0.017	0.004	0.086*	0.018	0.875*	0.016
Overall	0.029	0.009	0.107*	0.007	0.848*	0.012

This table provides the weighted price contribution of various after-hours time periods to the close-to-open return (panel A) and the close-to-close return (panel B) for the 250 highest-volume Nasdaq stocks from March to December 2000. For each time period i the weighted price contribution is calculated for each day and then averaged across days:

$$WPC_{i,v} = \sum_{s=1}^{S} \left(\frac{|ret_s|}{\sum_{s=1}^{S} |ret_s|} \right) \times \left(\frac{ret_{i,s}}{ret_s} \right),$$

where $ret_{i,s}$ is the return during period i for stock s and ret_s is the close-to-open return for stock s. Days with zero price change are discarded. The fraction of days with zero price change is provided in the final column. Values that are significantly different from zero at the 0.01 level are denoted with an $*$.

after-hours trading. Higher-volume stocks have a greater percentage of their 24-hour trading in the preopen (Table 1), and increased trading in the preopen shifts price discovery from the trading day to the preopen.

The patterns of price discovery in Table 3 are consistent with the return standard deviations reported in Figure 1. Price discovery and volatility go hand in hand, although volatility measures the total (absolute) price change, while the WPC measures only the permanent component of the price change. The high postclose volatility (Figure 1) combined with the low postclose WPC, suggest that prices are noisy after the close. We return to this issue in Section 6.

3.2 Weighted price contribution per trade

The high probability of an informed trade after hours suggests that, although total price discovery is low, individual trades may reveal more information after hours than during the day. To measure the amount of price discovery per trade, we divide the WPC for each time period by the weighted fraction of trades occurring in that period. We call this normalized measure the weighted price contribution per trade (WPCT).[15] For each day, let $t_{i,s}$ be the number of trades in time period i for stock s, and let t_s be the sum of $t_{i,s}$ across all time periods. The WPCT is then defined as

$$WPCT_i = WPC_i \Bigg/ \left(\sum_{s=1}^{S} \left(\frac{|ret_s|}{\sum_{s=1}^{S} |ret_s|} \right) \times \left(\frac{t_{i,s}}{t_s} \right) \right).$$

Because the WPCT is equal to the fraction of the total price change that occurred in a given time period divided by the fraction of trades that occurred in that time period, the WPCT would be close to one if all trades were equally informative. Table 4 reports WPCTs based on the close-to-open price change in panel A and the close-to-close price change in panel B.

Trades in the first hour after the close contribute least to price discovery. Later in the postclose, the WPCT is often greater than one, but the estimates are noisy and by 5:30 P.M. they typically are not statistically different from zero. In the overnight period the WPCT is greater than three for the highest-volume stocks, but less than one for the other stocks. As noted above, the large overnight WPCT for the high-volume stocks does not reflect informed late-night trading, but rather that preopen trading and price discovery often start before 8:00 A.M. for these stocks.

[15] To calculate the WPCT, we divide the average weighted price contribution (WPC) by the average fraction of trades in that time period. An alternate specification would divide the price contribution by the fraction of trades in that period and then average across trading days. Taking the ratio of the averages or the average of the ratios will yield slightly different results. With the alternate method, however, the WPCT is not defined when there are no trades in a given period, which is a common occurrence for small stocks after hours.

Table 4
Weighted price contribution per trade

Panel A: **Weighted price contribution per trade from close to open by time period and trading volume quintile**

	Time Periods										
	Postclose					Overnight	Preopen			Open	
Dollar volume quintile	Close– 4:30 P.M.	4:30 P.M.– 5:00 P.M.	5:00 P.M.– 5:30 P.M.	5:30 P.M.– 6:00 P.M.	6:00 P.M.– 6:30 P.M.	6:30 P.M.– 8:00 A.M.	8:00 A.M.– 8:30 A.M.	8:30 A.M.– 9:00 A.M.	9:00 A.M.– 9:30 A.M.	9:30 A.M.– open	Days with zero price change
Highest	0.12*	0.57*	0.71*	0.45	0.85	3.24*	2.81*	1.14	0.79*	0.08	0.020
4	0.11	0.62*	1.12*	0.92	0.85	0.61	5.1*	1.9	1.39*	0.9*	0.035
3	0.11	0.69*	1.23*	1.52	1.04	0.36	5.5*	2.27	1.79*	2.04*	0.051
2	0.11	1.05*	0.99	0.55	1.89	0.15	6.7*	3.04	2.25*	3.08*	0.052
Lowest	0.13	0.66*	2.39*	3.6*	1.02	0.03	3.56*	3.34	2.77*	3.68*	0.067
Overall	0.12	0.72*	1.29	1.4	1.13	0.88	4.73*	2.34	1.8*	1.95*	0.045

Panel B: **Weighted price contribution per trade from close to close by time period and trading volume quintile**

	Time periods					
Dollar volume quintile	Close– 6:30 P.M.	6:30 P.M.– 8:00 A.M.	8:00 A.M.– 9:30 A.M.	9:30 A.M.– open	Open– close	Days with zero price change
Highest	4.2*	96.68*	16.74*	–13.4*	0.83	0.009
4	3.44*	18.39*	19.72*	4.47*	0.87	0.009
3	3.02	6.66*	18.88*	6.17*	0.89	0.013
2	2.27	4.02*	22*	11.9*	0.9	0.013
Lowest	1.61	2.89	20.62*	14.27*	0.97	0.016
Overall	2.91	25.73*	19.59*	4.68*	0.89	0.012

This table provides the weighted price contribution per trade for various after-hours time periods using the close-to-open return (panel A) and the close-to-close return (panel B) for the 250 highest-volume Nasdaq stocks from March to December 2000. For each time period i the weighted price contribution per trade is calculated for each day and then averaged across days:

$$WPCT_i = \frac{\sum_{s=1}^{S}\left(|ret_s|/\sum_{s=1}^{S}|ret_s|\right) \times \left(ret_{i,s}/ret_s\right)}{\sum_{s=1}^{S}\left(|ret_s|/\sum_{s=1}^{S}|ret_s|\right) \times \left(t_{i,s}/t_s\right)},$$

where $t_{i,s}$ is the number of trades in stock s each day in time period i and t_s is the sum of $t_{i,s}$ across all i time periods. Days with zero price change are discarded. The fraction of days with zero price change is provided in the final column. Values that are significantly different from zero at the 0.01 level are denoted with an $*$.

The preopen WPCT generally is greater than one, but decreasing as the open approaches. The declining WPCT in the preopen reflects the fact that the first trades of the day are generally the most informative because they reflect the public and private information that has accumulated overnight. As the open approaches, trading volume increases and prices already reflect much of the information that accumulated overnight. Thus individual trades contribute less to price discovery. The opening trade has a WPCT of 1.95 overall, but contains almost no information in the highest-volume quintile. In the highest-volume quintile, trading is very active just before the open and the opening trade itself has little significance.

Panel B of Table 4 shows the WPCT for the close-to-close price change. The trading day (open-close) WPCT is less than one, and more for higher-volume stocks. A trading day WPCT less than one indicates that individual trades are less informative during the trading day than after hours. This result is reasonable given the high volume of uninformed liquidity trades during the day. The preopen WPCTs range from 16 to 20, and the postclose WPCTs range from 1.6 to 4. The relative increase in the preopen WPCTs over the postclose WPCTs is higher when we move from panel A to panel B, indicating again that postclose price changes are noisy and tend to be reversed during the following trading day.

3.3 Preopen price discovery and trading by minute

Tables 3 and 4 demonstrate the importance of the preopen in the price discovery process. These tables also show a distinct pattern in the timing of preopen price discovery across the volume quintiles. During the preopen, price discovery first begins in the high-volume stocks and later spreads to the low-volume stocks. To further examine this phenomenon, and to relate it more closely to the trading process, we examine the preopen WPC on a minute-by-minute basis. Panel A of Figure 5 graphs the minute-by-minute cumulative WPC for each volume quintile in the preopen. For comparison we also calculate the cumulative fraction of trades for each minute in the preopen and graph them in panel B of Figure 5.

Panel A of Figure 5 confirms that at the start of the preopen period, the amount of price discovery increases monotonically across the volume quintiles, with the high-volume stocks moving first, followed by the low-volume stocks. The difference in the amount of price discovery across the quintiles increases from 8:00 A.M. until about 9:00 A.M. By 8:45 A.M., almost 50% of the preopen price discovery has occurred in the highest-volume stocks, while less than 10% has occurred in the lowest-volume stocks. By 9:00 A.M. the gap increases, with the cumulative WPC at 59% for the highest-volume stocks and 18% for the lowest-volume stocks. By construction, all of the cumulative WPCs reach 100% at the open, so the lower-volume stocks eventually catch up. However, much of the

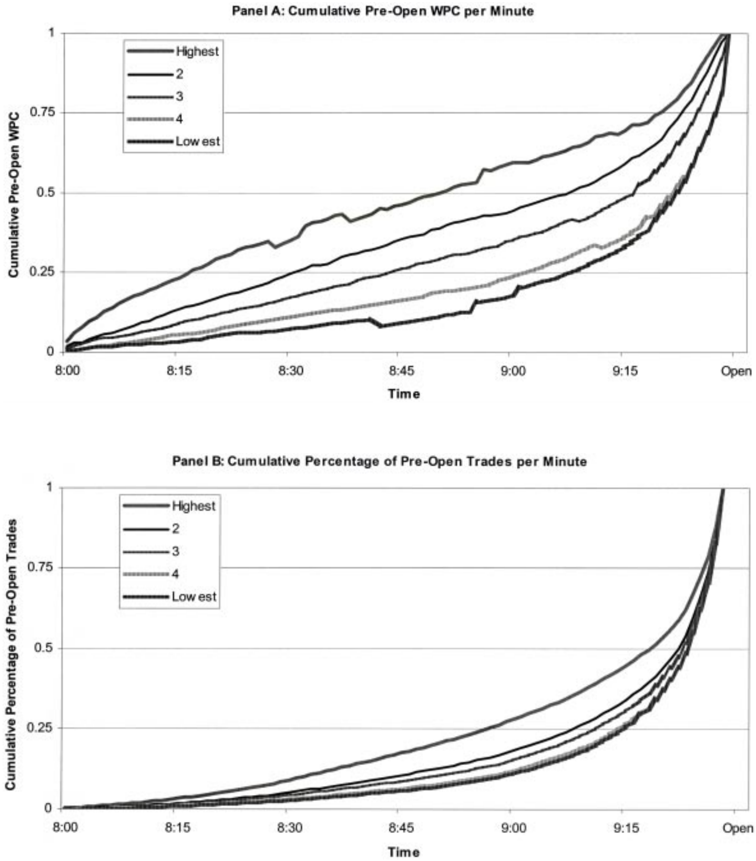

Figure 5
Cumulative preopen WPC and percentage of trades per minute
This chart graphs the preopen cumulative weighted price contribution (panel A) and percentage of trades (panel B) by minute for the 250 highest-volume Nasdaq stocks from March to December 2000. For each day and minute i, the weighted price contribution is calculated as

$$WPC_i = \sum_{s=1}^{S} \left(\frac{|ret_s|}{\sum_{s=1}^{S} |ret_s|} \right) \times \left(\frac{ret_{i,s}}{ret_s} \right),$$

where $ret_{i,s}$ is the return during minute i for stock s and ret_s is the close-to-open return for stock s. The WPC is calculated for each day and then averaged across days. Days with zero preopen price change are discarded. The average fraction of trades in each minute is also calculated for each day and then averaged across days.

catching up occurs in the final 15 minutes of the preopen and with the opening trade.

Panel B of Figure 5 shows the cumulative fraction of preopen trades by minute. The pattern of trading volume in the preopen mirrors the pattern of price discovery. Early in the preopen, the fraction of trades increases monotonically across the volume quintiles, with the high-volume stocks trading first, followed by the low-volume stocks. However, because of the high information content of the first few trades of the day, the cumulative price discovery increases faster than the cumulative fraction of trades. By 8:45 A.M., almost 50% of the preopen price discovery has occurred in the highest-volume stocks on 17% of the preopen trades. By the same time, less than 10% of the price discovery has occurred in the lowest-volume stocks on 5.8% of the preopen trades. Trading in all of the volume quintiles picks up just before the open. More than half of the preopen trades in the highest-volume quintile and more than two-thirds of the preopen trades in the lowest-volume quintile occur between 9:15 and 9:30 A.M.

The minute-by-minute pattern of price discovery during the preopen follows the pattern of trading volume. Preopen trading volume occurs first in the highest-volume stocks and later spreads to the lower-volume stocks. Similarly, preopen price discovery begins in the high-volume stocks and later spreads to the lower-volume stocks. This pattern of information dissemination from high-volume to low-volume stocks has been proposed as an explanation for the pattern of lagged cross-correlations observed in daily stock return data by Lo and MacKinlay (1990), Mech (1993), and others.

4. Price Discovery by Venue: ECN and Market-Maker Trades

The prior analysis examines the overall trading and price discovery processes. However, trading occurs on different venues, both during the trading day and after hours, and trading stocks on an ECN is quite different from the traditional method of trading with a dealer or market maker. Negotiating with market makers after hours typically implies that traders must reveal their identities and trading motives. Liquidity-motivated traders benefit from this lack of anonymity when they attempt to move large positions, and we expect traditional market-maker trades to play a major role in the postclose when relatively little information is discovered. However, information-motivated traders generally seek to protect their anonymity, which is easily shielded on an ECN. Because more price discovery occurs in the preopen, we expect ECNs to capture a larger fraction of the preopen trading volume.

To explore the investors' choice of trading venue, we employ summary data provided by Nasdaq for January to June 1999. For each trading day and after-hours time period, the data contain the percentage of trades, trading volume, and cumulative price change by venue.[16] The mix of ECN

[16] The data provided by the NASD utilizes clearing data to correctly identify and categorize all ECN trades regardless of who reports them. The data does not identify whether individual trades were executed by a market maker or on an ECN, but for each security, day, time period, and trade-size category, aggregate data on price change, number of trades, and trading volume for ECN and market-maker trades were provided.

Table 5
After-hours trading and weighted price contribution by after-hours time period, trade location, and trade size

Panel A: Distribution of after-hours trading activity for ECNs and market makers by time period

	Dollar volume		Trades	
Time period	ECN	Market maker	ECN	Market maker
Preopen	0.682	0.318	0.911	0.089
Postclose	0.246	0.754	0.606	0.394

Panel B: Weighted price contribution for ECN and market maker trades by time period

	Weighted price contribution	
Time period	ECN	Market maker
Preopen	0.955	0.045
Postclose	0.546	0.454

Source: NASD.

For the 250 highest-volume Nasdaq stocks from January to June 1999, the percentage of after-hours dollar volume and number of trades for ECNs and market makers is given in panel A. The weighted price contribution for ECN and market-maker trades is given in panel B. The WPC during period i in venue v is defined as

$$WPC_i = \sum_{s=1}^{S} \left(\frac{|ret_{i,s}|}{\sum_{s=1}^{S} |ret_{i,s}|} \right) \times \left(\frac{ret_{i,s,v}}{ret_{i,s}} \right),$$

where $ret_{i,s,v}$ is the return occurring on trades in venue v during period i for stock s, and $ret_{i,s}$ is the total return during period i for stock s.

and market-maker trades varies noticeably between the preopen and postclose — 75% of postclose trading volume is executed through a market maker and 25% on ECNs. In contrast, only 32% of the preopen trading volume is executed through a market maker, while 68% is executed on an ECN.

To quantify the amount of price discovery by trading venue, we calculate the WPC by venue. Consistent with Huang (2002), for each time period i and trading venue v, we calculate the WPC as

$$WPC_{i,v} = \sum_{s=1}^{S} \left(\frac{|ret_{i,s}|}{\sum_{s=1}^{S} |ret_{i,s}|} \right) \times \left(\frac{ret_{i,s,v}}{ret_{i,s}} \right),$$

where $ret_{i,s,v}$ is the return occurring on trades in venue v during period i for stock s, and $ret_{i,s}$ is the total return during period i for stock s.

Panel B of Table 5 reports the WPC for ECN and market-maker trades in the preopen and postclose periods. During the preopen, ECN trades account for 68% of trading volume and 91% of trades, but more than 95% of the weighted price contribution. Thus, in relation to their dollar volume and, to a lesser extent, in relation to the number of trades, ECN trades are more important than market-maker trades in preopen price discovery.

During the postclose, there is little price discovery overall (Table 3). What little price discovery there is is split evenly between ECN and market-maker trades (53% and 47%, respectively). However, because market-maker trades account for 75% of the trading volume, it appears that large market-maker trades during the postclose contribute less to price discovery.

Together, these results suggest that when there is significant price discovery, traders choose or are compelled to trade anonymously against the firm quotes on ECNs. During these periods, ECN trades contribute more to the price-discovery process than do market-maker trades. This is consistent with Huang (2002), who finds that the ECN quote changes are more informative than market-maker quote changes during the trading day,[17] and with Barclay, Hendershott, and McCormick (2003), who find that ECN trades are more informative than market-maker trades during the trading day.

5. Public versus Private Information

Section 3 focuses on price discovery without distinguishing between public and private information. The PIN measure in Section 2 provides evidence regarding the amount of informed trading, but does not measure the magnitude of information events or the relative amounts of public and private information. To decompose information into its public and private components we use the techniques in Hasbrouck (1991b), which build on the vector autoregression (VAR) in Hasbrouck (1991a).

Following Hasbrouck, we define the time scale (t) as the transaction sequence. We represent a trade at time t by the variable $x_t = +1$ for a buy order and $x_t = -1$ for a sell order. The percentage change (log return) in the quote midpoint subsequent to that trade, but prior to the next trade at $t+1$, is denoted r_t. We then estimate the following VAR of trades and quote changes:[18]

$$r_t = \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=0}^{p} \beta_i x_{t-i} + \varepsilon_{1,t} \text{ and}$$

$$x_t = \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{i=1}^{p} \delta_i x_{t-i} + \varepsilon_{2,t}.$$

The trading process is assumed to restart at the beginning of each time period (preopen, trading day, and postclose), at which time all lagged values of x_t and r_t are set to zero. Because the number of trades per unit

[17] Huang (2002) utilizes both the WPC and the "information share" derived by Hasbrouck (1995) to allocate price discovery across ECN and market-maker quote changes during the trading day. He finds that these two measures provide similar estimates for the proportional contribution of ECN and market-maker quote changes for trading-day price discovery.

[18] Identification also requires the following restrictions on the innovations (as in Hasbrouck, 1991a,b): $E\varepsilon_{1,t} = E\varepsilon_{2,t} = 0$ and $E\varepsilon_{1,t}\varepsilon_{1,s} = E\varepsilon_{2,t}\varepsilon_{2,s} = E\varepsilon_{1,t}\varepsilon_{2,s} = 0$, for $s < t$.

time is more than 20 times greater during the day than after hours, we estimate the system with 100 lagged trades and quote changes (approximately one minute for the highest-volume stocks) during the trading day, and 10 lagged trades and quote changes after hours.[19]

Once estimated, the VAR representation can be inverted to generate the following vector moving average (VMA) model:

$$\begin{pmatrix} r_t \\ x_t \end{pmatrix} = \begin{pmatrix} a(L) & b(L) \\ c(L) & d(L) \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{pmatrix},$$

where $a(L)$, $b(L)$, $c(L)$, and $d(L)$ are the lag polynomial operators. The coefficients of the lag polynomials in this moving average representation are the impulse response functions implied by the VAR. Within the VAR framework, calculating the fraction of total price discovery due to private information revealed through trades is a straightforward variance decomposition. Following Hasbrouck, we decompose the (logarithm) of the bid-ask midpoint, denoted p_t, into a random-walk component m_t and a stationary component s_t:

$$p_t = m_t + s_t,$$

where $m_t = m_{t-1} + v_t$ and $v_t \sim N(0, \sigma_v^2)$ with $Ev_t v_s = 0$ for $t \neq s$. We refer to the random-walk component (m_t) as the permanent component of the price, and we refer to the stationary component (s_t) as the transitory component of the price. Defining $\sigma_{\varepsilon 1}^2 = E\varepsilon_{1,t}^2$ and $\sigma_{\varepsilon 2}^2 = E\varepsilon_{2,t}^2$, we can further decompose the variance of the permanent (or random walk) component of the quote/price changes, ${\sigma_v}^2$, into price changes caused by the arrival of public information and price changes caused by the arrival of private information through trades:

$$\sigma_v^2 = \left(\sum_{i=0}^{\infty} a_i\right)^2 \sigma_{\varepsilon 1}^2 + \left(\sum_{i=0}^{\infty} b_i\right)^2 \sigma_{\varepsilon 2}^2,$$

where the second term in this equation, $\sigma_x^2 = \left(\sum_{i=0}^{\infty} b_i\right)^2 \sigma_{\varepsilon 2}^2$, represents the component of price discovery attributable to private information revealed through trades. Because the preopen, trading-day, and postclose time periods are of different lengths, we normalize and report the variance components on a per hour basis.

Table 6 provides the ratio of private information to total information (${\sigma_x}^2/{\sigma_v}^2$) during the preopen, trading-day, and postclose periods. These results show significant price discovery and private information revealed

[19] We also estimate, but do not present, a model in which x_t is a vector containing signed trade, signed trade volume, and signed trade volume squared [as in Hasbrouck (1991a,b)]. Adding signed trade volume and signed trade volume squared provide little additional explanatory power, primarily because large trades on Nasdaq do not appear to contain more information than do small trades. We also estimate the system using varying numbers of lagged trades and quote changes. Our results are not sensitive to the choice of the number of lags.

Table 6
Public and private information: variance decomposition

Dollar volume quintile	σ_x^2/σ_v^2 Postclose	Preopen	Trading day
Highest	0.22†*	0.33†*	0.41
	(0.06)	(0.07)	(0.07)
4	0.21†*	0.37†	0.37
	(0.08)	(0.06)	(0.07)
3	0.23†*	0.36†	0.36
	(0.08)	(0.08)	(0.07)
2	0.25†*	0.36†	0.32
	(0.12)	(0.16)	(0.06)
Lowest	0.28†	0.36†*	0.31
	(0.16)	(0.16)	(0.07)
Overall	0.24†*	0.36†	0.35
	(0.11)	(0.11)	(0.07)

The variance of the random-walk component of stock prices during the postclose, preopen, and trading day for the 250 highest-volume Nasdaq stocks from March to December 2000 estimated from the following VAR system for quote revisions and trades (with 100 lags for the trading day and 10 lags for the preopen and postclose):

$$r_t = \sum_{i=1}^{p} \alpha_i r_{t-i} + \sum_{i=0}^{p} \beta_i x_{t-i} + \varepsilon_{1,t} \quad \text{and} \quad x_t = \sum_{i=1}^{p} \gamma_i r_{t-i} + \sum_{i=1}^{p} \delta_i x_{t-i} + \varepsilon_{2,t},$$

where x_t is an indicator variable for the trade t ($x_t = +1$ for a buy and -1 for a sell), and r_t is the percentage change in the quote midpoint subsequent to that trade, but prior to the next trade. The VMA coefficients are calculated through step m (where $m = 200$ for the trading day and $m = 20$ for the preopen and postclose) by inverting the VAR representation. Cross-sectional means for the ratio of private information to total information (σ_x^2/σ_v^2) are reported with standard deviations below in parentheses. Pairwise Mann–Whitney tests are used to determine statistical significant of the differences among time periods. After-hours values differing from the trading day at a 0.01 level are denoted with an $*$. After-hours values that differ from the other after-hours period at a 0.01 level are denoted with a †.

through trades during the preopen.[20] The fraction of total price discovery attributable to private information is about 35% in the preopen and during the trading day, even though the number of trades per hour in the preopen is only a small fraction of the number during the trading day. In addition, despite the higher trading activity in the postclose as compared to the preopen, only 24% of the total information discovered in the postclose is private.

Because the variance decomposition and the WPC yield consistent estimates of the total amount of price discovery in the different time periods, we omit the detailed results concerning the total amount or price discovery from the VAR. However, both of these analyses, combined with Figure 1, suggest that price changes in the postclose are noisy

[20] These results suggest that the increase in preopen trading activity has reduced the importance of any preopen signaling activity through market-makers' nonbinding quotes. Because we use only the binding ECN quotes during the preopen, it is possible that we misattribute some price discovery that occurs through market-makers' nonbinding quote changes as described in Cao, Ghysels, and Hatheway (2000). If the market-maker quote changes cause trades to occur before the ECN quotes are updated, the variance decomposition would attribute the subsequent price change to the trades rather than to the market-maker quote changes. This potential misclassification is likely to be small, however.

signals of value that are often reversed. To examine this issue directly, we next measure the efficiency of the price discovery process across periods.

6. The Efficiency of After-Hours Price Discovery

Trades in the postclose are large, and many presumably are liquidity motivated because the amount of information revealed is low. Large liquidity trades often cause temporary price impacts which are subsequently reversed, especially in markets as thin as the after-hours market. The postclose also has large bid-ask spreads that contribute to price reversals. Thus, given the small amount of information in the postclose, we expect postclose stock prices to be noisy and to have a low signal:noise ratio. Bid-ask spreads are also large in the preopen; however, given that the amount of information in the preopen is three times that in the postclose, as measured by the WPC (Table 3), stock price changes in the preopen will have a larger permanent component and a much higher signal:noise ratio.

We estimate the noisiness of stock prices and the efficiency price discovery after hours using what Biais, Hillion, and Spatt (1999) call "unbiasedness regressions." For each stock and each 15-minute time period (i), we regress the close-to-close return (ret_{cc}) on the return from the close to the end of time period i (ret_{ci}):

$$ret_{cc} = \alpha + \beta \times ret_{ci} + \varepsilon_i.$$

We estimate this regression separately for each time period. Although Biais, Hillion, and Spatt refer to these as "unbiasedness regressions," the slope coefficient (β) in these regressions has a natural interpretation as a signal:noise ratio. Consider the standard errors-in-variables problem for regression models [Maddala (1988, p. 381)].[21] If stock returns are serially uncorrelated and measured without error, then the slope coefficient in the unbiasedness regression would equal one. Suppose, however, that the "true" return process is unobserved, and that the observed return is equal to the true return plus noise. Noise in market prices can be related to microstructure effects (e.g., bid-ask spreads) or temporary pricing errors. In particular, suppose we observe $ret_{cc} = RET_{cc} + v$ and $ret_{ci} = RET_{ci} + u$, where RET_{cc} and RET_{ci} are the "true" returns, and u and v have zero mean, and variances equal to u^2 and v^2, respectively. Then, regressing ret_{cc} on ret_{ci} using ordinary least squares produces an estimated slope coefficient, b, where

$$\text{plim } b = \beta\left(\frac{\sigma^2_{RET_{ci}}}{\sigma^2_{RET_{ci}} + \sigma^2_u}\right).$$

[21] See Craig, Dravid, and Richardson (1995) for a related discussion.

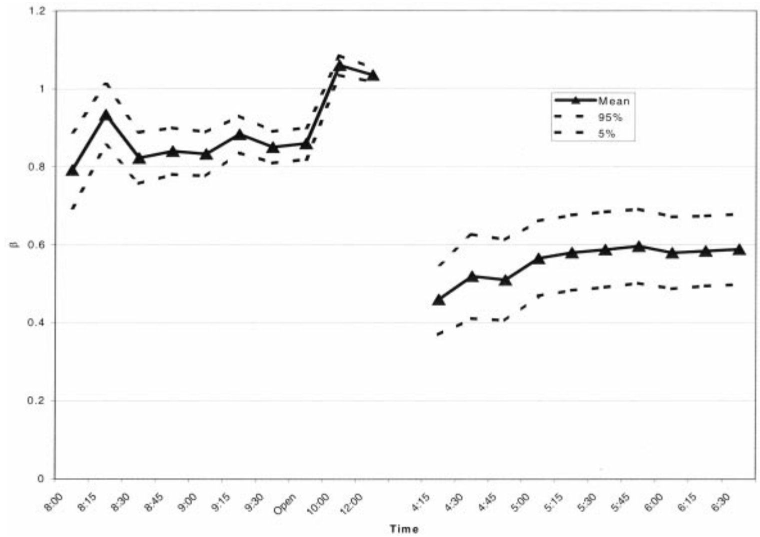

Figure 6
Unbiasedness regressions by time period
The close-to-close return (ret_{cc}) is regressed on the return from close to after-hours time i (ret_{ci}) for 15-minute intervals for the 250 highest-volume Nasdaq stocks from March to December 2000. Cross-sectional OLS regressions are run each day and the mean value of slope coefficient is graphed for each time period. Confidence intervals are calculated using the time-series standard errors of the coefficient estimates.

The term in parentheses can be viewed as the signal:noise ratio, where σ^2_{RETci} measures the information discovered from the close to time i, and σ^2_u is the noise in prices at time i. Although we cannot measure the signal and noise components separately with this technique, the extent to which b is less than one allows us to infer the signal:noise ratio.[22]

The unbiasedness regressions are estimated cross-sectionally for each day and each time period.[23] We then calculate the mean regression coefficient for each time period and use the time-series standard error of the mean for statistical inference [in the spirit of Fama and MacBeth (1973)].[24] The mean coefficient and confidence intervals are graphed in Figure 6.

The signal:noise ratio in the postclose is low, starting at about 0.45 at 4:15 P.M. and increasing to 0.6 as the postclose progresses. During the preopen, the signal:noise ratio is much higher, ranging from 0.8 to 0.9, and increases slightly as the open approaches. By 10:00 A.M., the ratio is

[22] Actually the measure is the ratio of signal to signal plus noise, but this terminology should not be confusing.

[23] The correlation coefficients between the postclose returns and returns to the following open are approximately equal to $\beta - 1$, and are not reported.

[24] Regressions run separately for each stock yield comparable coefficients.

approximately one, and remains at one for the remainder of the trading day. Ciccotello and Hatheway (2000) find similar results for Nasdaq in 1996. These results are quite different from the low preopen coefficients found by Biais, Hillion, and Spatt (1999) for the Paris Bourse. The high preopen signal:noise ratio on Nasdaq, and the low preopen signal:noise ratio on the Paris Bourse (where there is no preopen trading), provide additional evidence that trading activity is an important part of the preopen price discovery process.[25]

The postclose and preopen regression coefficients are both estimated using the same close-to-close return, and consequently are correlated. Thus the statistical significance of the difference between the preopen and postclose coefficients cannot be tested using the time-series standard errors plotted in Figure 6. To account for the contemporaneous correlation, we calculate the difference between the preopen and postclose coefficients each day and use the time-series standard error of this difference to test whether the mean difference is significantly different from zero. The smallest average difference between any postclose coefficient and any preopen coefficient is 0.25, which has a t-statistic of about 6, verifying that the signal:noise ratio is significantly lower in the postclose period than in the preopen period.

7. Conclusion

Trading after hours differs significantly from trading during the day. Trading volume after hours is low, market makers seldom submit firm quotes, and trading costs are four to five times higher than during the trading day. Retail customers are discouraged from trading after hours by warnings of high risk levels and by the special instructions required for after-hours order execution. These impediments suggest that professional or quasi-professional traders with strong incentives to trade will dominate the after-hours session. The large endogenous shifts in the trading process at the open and at the close allow us to investigate the relationship between price discovery, trading volume, and market participants' characteristics and incentives under conditions that are very different from those studied previously. The high frequency of informed trading after hours implies that relatively little trading can generate significant price discovery, although price discovery after hours is less efficient due to noisier prices.

[25] The higher signal:noise ratio in the preopen than in the postclose could be caused in part by the fact that preopen prices include the overnight return, which might increase their signal (independent of noise). To test for this possibility, we reestimate the preopen unbiasedness regressions using the return from the first trade of the day to the close as the dependent variable. These regression coefficients are similar to those reported in Figure 7. Hence the low signal:noise ratios in the postclose do not appear to be caused by their proximity to the close.

Before the open, information asymmetry is high and trades are more likely to be informed than at any other time of day. Most trades before the open are executed anonymously on electronic communications networks and contribute significantly to price discovery. Although the trading day has the most price discovery per hour, the high frequency of informed trades gives the preopen more price discovery per trade. Price changes before the open have a high signal:noise ratio, although prices in the preopen are noisier than trades during the day. The ratio of private to public information in the preopen is comparable to the trading day.

Information asymmetry is lower after the close than before the open, and trades are less likely to be informed. This facilitates direct negotiation of large liquidity trades with market makers and results in stock price changes that are noisy signals of value. Trades after the close contribute little to the price discovery process than do trades during the preopen, and the ratio of private to public information is lower during the postclose than at any other time of day.

In addition to expanding understanding of the interaction of trading and price discovery, our results have practical implications for market participants. We show that individual trades are more informative after hours than trades during the day. Informed traders attempting to camouflage their trades might prefer less transparency, but for investors, brokers, or dealers who rely on the market price as an indicator of value, the immediate reporting of trades and quotes after hours is likely to be more important than during the day.

We also show that trades after hours, particularly after the close, have large temporary price impacts that introduce noise in the stock prices and yield less efficient price discovery. The noisier stock prices and less efficient price discovery after hours could affect firms' decisions about the timing of their public announcements, such as earnings announcements. Announcements made after hours are likely to generate greater volatility and larger price reversals than are announcements made during the trading day.

Finally, our results provide some insight into the reasons why the after-hours market has not developed into a more active trading session. Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) show that uninformed liquidity traders have incentives to bunch their trades to maximize the likelihood that they are trading with other uninformed traders. Given the noisy prices and high information asymmetry after hours, there are few incentives, if any, for liquidity traders to deviate from the current equilibrium in which they trade during the day and refrain from trading after hours. Two of the primary functions of a market are to discover prices and provide liquidity. While this article focuses on price discovery, further analysis of liquidity provision, adverse selection, and trading costs over the 24-hour day may provide insights about the effects of endogenous trading choices on the market's ability to provide liquidity.

Appendix

Table A.1
After-hours trading, quoting, and reporting details for Nasdaq stocks

Timeline for evolution of Nasdaq quote, trade, and reporting systems:

Prior to 1992	SelectNet, ACT (Automated Confirmation Transaction Service), Nasdaq Quotation Dissemination Service (NQDS), and Nasdaq Trade Dissemination Service (NTDS) are open from 9:00 A.M. to 5:15 P.M.[26]
June 15, 1992	Trade reporting required within 90 seconds for all trades executed from 9:30 A.M. to 5:15 P.M.
Dec. 20, 1993	90-second trade reporting requirement extended to 9:00 A.M to 5:15 P.M.
Dec. 12, 1994	90-second trade reporting requirement and ACT, NQDS, and NTDS extended to 8:00 A.M. to 5:15 P.M.
Oct. 25, 1999	ACT, NQDS, NTDS, and SelectNet extended to 8:00 A.M.–6:30 P.M.
Nov. 25, 1999	90-second trade reporting requirement extended to 8:00 A.M.–6:30 P.M.
Feb. 7, 2000	Limit order display and protection rules and dissemination of inside quotes extended to 9:30 A.M.–6:30 P.M.
June 5, 2000	Trade or move rule introduced for quotes from 9:20 A.M. to 9:30 A.M.

After hours trading options

Trading with a market maker — Trades can be negotiated with a market maker over the phone or via SelectNet. Trades between institutions, either directly negotiated or brokered, typically utilize a market maker for settlement and clearing. The reporting rules for these trades are documented above.

Trading on SelectNet — SelectNet communicates trading interest to a single market maker (directed orders) or broadcasts the order to market participants (broadcast orders) who negotiate trade price and quantity. About 15% of after-hours trades in our NASD sample are executed on SelectNet. SelectNet automatically reports trades as they occur.

Trading on an ECN — Prior to July 1999 Instinet was the only ECN operating outside the normal trading day. Since then all ECNs have begun operating outside of the trading day. ECNs typically report trades as they occur.

Trading on a crossing network — Instinet's midnight cross is the only crossing network for Nasdaq stocks operating outside of the trading day. These trades are reported after 8:00 A.M. but have execution times just after midnight.

Trade reporting transparency — Outside of the times when NTDS operates, trades on an ECN are reported in real time only to subscribers of that ECN. Approximately 30,000 after-hours trades in our NASD sample that are reported "ASOF," meaning that they are not reported on the day they occur and are not included in NTDS, Nastraq, or TAQ. Most of these occurred outside of NTDS' hours. There are no reporting requirements, during the trading day or after hours, for trades between parties not involving a NASD member.

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[26] All ACT, NTDS, and NQDS times are approximate because the systems are not activated at an exact time every day.

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