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The dynamics of quote adjustments[#]

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The dynamics of quote adjustments

Abstract

Liquidity providers on the NYSE make faster quote adjustments towards equilibrium spreads and depths than they do on NASDAQ. Liquidity providers in both markets make faster spread and depth adjustments for stocks with more frequent trading, greater return volatility, higher prices, smaller market capitalizations, and smaller trade sizes. We find that stocks with greater information-based trading and in more competitive trading environments exhibit faster quote adjustments. The speed of quote adjustment is faster after decimalization in both markets. These results are robust and not driven by differences in stock attributes between the two markets or time periods. Overall, our results indicate that stock attributes, market structure, and tick size exert a significant impact on the speed of quote adjustment.

JEL classification: G18; G19

Key words: Spreads; Depths; Market structure; Market efficiency; Tick size; Quote revision; Adverse-selection costs

1. Introduction

Traders pay the ask price when they buy shares and receive the bid price when they sell shares. The difference between the bid and ask prices is an important measure of market quality because it represents the cost of trading. The bid-ask spread evolves according to newly placed limit orders as well as new information embedded in order flow, trades, and return volatility. Despite its obvious importance to traders, we know very little about the dynamics of the bid-ask spread.[1] Prior studies offer little evidence as to the speed at which new information is impounded into the bid-ask spread.[2] There is also limited evidence regarding how market structure and trading protocol, such as tick size, affect the speed at which new information is incorporated into the bid-ask spread.

Liquidity providers do not always immediately incorporate the newly arrived information into quotes for a number of reasons. For instance, they may not be able to change quotes because tick size is a binding constraint on spreads or they do not want to change quotes because the minimum feasible quote increment is larger than the desired quote change implied by the new information (see Hasbrouck, 1991a). Furthermore, the speed of quote adjustment is likely to be different across stocks. For example, liquidity providers may make faster quote adjustments to new information (and thereby move more quickly to equilibrium spreads) for stocks with greater adverse-selection risks because the cost of quoting sub-optimal spreads is greater for such stocks.

In this study we address the following questions using a large sample of New York Stock Exchange (NYSE) and NASDAQ stocks: (1) How quickly do specialist/dealer quotes incorporate new information? Do price and depth quotes on the NYSE reflect changes in stock attributes more quickly than those on

[1] Engle and Patton (2004) show that a high spread leads to a decrease in the ask price and an increase in the bid price, moving the spread towards its equilibrium value. The authors also find that the speed of adjustment is faster for frequently traded stocks than infrequently traded stocks.

[2] Numerous studies examine the effects of market structure on market quality. Huang and Stoll (1996), Barclay (1997), and Bessembinder (1999, 2003) compare the execution costs of dealer and auction markets. Others (e.g., Amihud and Mendelson, 1987; Stoll and Whaley, 1990; Masulis and Ng, 1995) investigate the impact of market structure on return volatility. Heidle and Huang (2002) examine the impact of market structure on the probability of trading with an informed trader. Garfinkel and Nimalendran (2003) compare the impact of insider trading on effective spreads between NYSE and NASDAQ stocks. However, none of these studies examine how market structure affects the quote adjustment speed on the NYSE and NASDAQ.

NASDAQ? (2) How is the speed of quote adjustment related to stock attributes? For example, do stocks with greater information-based trading exhibit faster quote adjustments towards equilibrium spreads and depths? Do stocks that are traded in less competitive markets (e.g., fewer dealers) exhibit slower quote adjustments? (3) Does decimal pricing result in faster quote adjustments to new information? (4) What is the relation between the quote adjustment speed and variable measurement intervals? Answers to these questions would be of significant interest to market regulators because they could help design better market structure. Because spreads constitute a part of trading costs, the speed at which liquidity providers adjust their quotes to new information is also of concern to traders.

Hasbrouck (1988, 1991a, 1991b) examines how marketmakers adjust quote midpoints to signed trades. Hasbrouck and Sofianos (1993) show that the trades in which the specialist participates have a greater immediate impact on quote midpoints than those without specialist participation. Madhavan and Smidt (1993) show that quote revisions are negatively related to specialist trades and positively related to the information conveyed by order imbalances. Dufour and Engle (2000) extend Hasbrouck's (1991a) vector autoregression model by incorporating the time interval between trades into empirical estimation. Damodaran (1993) and Brisley and Theobald (1996) estimate the speed of price adjustment using the partial adjustment model of Amihud and Mendelson (1987). Thoebald and Yallup (2004) compare the speed of price adjustments between large and small companies.[3]

While the above studies focus on either how quote midpoints change in response to trades or the speed of price adjustment, our study examines how quickly liquidity providers adjust *quote width* (i.e., the bid-ask spread) and *depth* (i.e., the number of shares at the bid and ask) to their *equilibrium* values in response to new information. Because determinants and information content of spreads and depths are likely different from those of quote midpoints or prices, our study helps better understand the price discovery process. For instance, the quote midpoint reflects the expected value of an asset whereas the

[3] Beja and Goldman (1980) analyze the dynamics of asset prices using a partial adjustment model. Jones and Lipson (1999) show that quotes in NYSE- and AMEX-listed stocks adjust more quickly to the information contained in order flow than quotes in NASDAQ-listed stocks. Theissen (2000) finds that transaction prices in call and continuous auction markets are more efficient than prices in dealer markets. In contrast, Masulis and Shivakumar (2002) show that price adjustments are faster on NASDAQ than on the NYSE.

spread and depth reflect uncertainty about the value of an asset or adverse-selection risks. The quoted depth is an important metric to traders because it is the guaranteed quantity that can be bought or sold at the quoted price.

The speed of quote adjustment on the NYSE is likely to be different from that on NASDAQ for various reasons. For example, NASDAQ dealers may not have strong incentives to make quick quote adjustments in response to information shocks because a significant portion of order flow is either internalized or preferenced. Garfinkel and Nimalendran (2003) find less anonymity on the NYSE specialist system compared to the NASDAQ dealer system. As a result, liquidity providers on the NYSE may respond more quickly to information-based trading than those on NASDAQ. We examine the effect of market structure on quote adjustment process by comparing the speed of quote adjustment between NYSE and NASDAQ stocks.

An important protocol of securities markets is the size of the minimum price variation (i.e., tick size). Although numerous studies examine the effect of tick size on trading costs and return volatility,[4] none of them examine how tick sizes affect the quote adjustment speed. To the extent that the minimum price variation creates frictions in exchange markets, it is likely to affect the speed of quote adjustment. We analyze the effect of tick size on the informational efficiency of spread and depth quotes by comparing the quote adjustment speed before and after decimal pricing.

We employ a simple model of partial adjustment to analyze how quickly liquidity providers on the NYSE and NASDAQ adjust spread and depth quotes in response to new information. We show that the speed of quote adjustment on the NYSE is faster than the speed of quote adjustment on NASDAQ. In both markets, the quote adjustment speed is faster for stocks with a larger number of trades, higher share prices, greater return volatility, smaller market capitalizations, and smaller trade sizes. Our results also indicate that stocks with greater information-based trading and in more competitive trading environments exhibit faster quote adjustments. The speed of quote adjustment after decimal pricing is significantly faster than

[4] See, for example, Harris (1994, 1997), Ahn, Cao, and Choe (1996, 1998), Bacidore (1997), Porter and Weaver (1997), Goldstein and Kavajecz (2000), Bessembinder (2000), and Ronen and Weaver (2001).

the corresponding figure before decimal pricing in both markets, indicating that larger tick sizes slow price discovery. On the whole, our study provides evidence that stock attributes, market structure, and tick size exert a significant impact on the speed of quote adjustment.

The remainder of the paper is organized as follows. Section 2 presents our conjectures on how the speed of quote adjustment may be related to market structure and various stock attributes. Section 3 explains our methodology. Section 4 explains data sources and presents descriptive statistics and Section 5 presents empirical findings. Section 6 analyzes the relation between the quote adjustment speed and the length of variable measurement intervals. Section 7 concludes the paper.

2. Statement of hypotheses

In this section, we present our conjectures on how the speed of quote adjustment is related to market structure and stock attributes, including adverse-selection costs, dealer competition, and tick size.

2.1. Market structure and the speed of quote adjustment

Chung, Chuwonganant, and McCormick (2004) show that a large portion of order flow on NASDAQ is either internalized or preferenced based on payment for order flow agreements. NASDAQ dealers may have little incentives to compete with quotes because aggressive quotes do not necessarily increase market share when a significant portion of order flow is already internalized or preferenced. As a result, NASDAQ dealers may not have strong incentives to make quick quote adjustments in response to information shocks. Although a part of the NYSE volume is also routed to regional exchanges according to preferencing agreements between brokers and dealers, prior studies (see, e.g., Blume and Goldstein, 1997; Bessembinder, 2003) show that NYSE specialists almost always post the most competitive quotes. Consequently, order preferencing between brokers and regional dealers may not significantly compromise quote adjustments on the NYSE. These considerations suggest that the quote adjustment speed on the NYSE is likely to be faster than that on NASDAQ.

Garfinkel and Nimalendran (2003) examine the degree of anonymity–the extent to which a trader is recognized as informed–in alternative market structures and find less anonymity on the NYSE specialist system compared to the NASDAQ dealer system. This result supports the hypothesis advanced by Benveniste, Marcus, and Wilhelm (1992) that the unique relationship between specialists and floor brokers on the NYSE results in less anonymity.[5] The lower degree of anonymity on the NYSE constitutes another reason why liquidity providers on the NYSE are likely to respond more quickly to information-based trading than those on NASDAQ.[6] These considerations lead to our first hypothesis.

Hypothesis 1: The speed of quote adjustment on the NYSE is faster than that on NASDAQ.

2.2. Stock attributes and the speed of quote adjustment

Easley and O'Hara (1992) and Harris and Raviv (1993) analyze the role of trades in price formation and show that the number of trades is positively related to absolute price changes (i.e., return volatility). In Easley and O'Hara (1992), the number of trades is informative with respect to price changes because trades and the lack thereof are both informative to marketmakers. In Harris and Raviv (1993), trading occurs if and only if cumulative information for a particular type of trader switches from favorable to unfavorable or vice versa.

Jones, Kaul, and Lipson (1994) show that the positive relation between return volatility and volume reported in previous studies reflects the positive relation between return volatility and the number of trades. They show that the occurrence of transactions *per se* contains all of the information pertinent to pricing securities. This result is in line with the finding of Dufour and Engle (2000) that the speed of price adjustment in response to trade-related information increases as the time duration between trades decreases. Insofar as trades convey information on asset values and liquidity providers update quotes in response to the

[5] Benveniste, Marcus, and Wilhelm (1992) note that NYSE specialists have continuous face-to-face contact with floor brokers while such contact is not available to NASDAQ dealers because NASDAQ operates on an electronic screen-based system.
[6] Although Battalio and Holden (2001) and Battalio, Jennings, and Selway (2001) suggest that NASDAQ dealers utilize broker identity to distinguish between informed and uninformed order flow, the effect of such behavior on quote adjustment speed has not been shown in previous studies.

newly arrived information, they are likely to update quotes quickly for stocks that are actively traded and have large return volatility. These considerations lead to our second hypothesis:

Hypothesis 2: The speed of quote adjustment is positively related to both the number of trades and return volatility.

Chung and Chuwonganant (2002) show that low-price stocks exhibit fewer quote revisions that accompany a spread change. They interpret this result as evidence that the minimum price variation is more frequently a binding constraint on absolute spreads for low-price stocks. Chung, Charoenwong, and Ding (2004) calculate the proportion of spreads that are equal to one penny to assess the extent to which the penny tick is a binding constraint. They find that although the proportion is much smaller under decimal pricing than under $1/16 pricing, the penny tick is still a significant binding constraint for low-price stocks. We conjecture that liquidity providers make slower adjustments towards equilibrium spreads for low-price stocks because the binding constraint prevents them from making such quote revisions. These considerations lead to our next hypothesis:

Hypothesis 3: The speed of quote adjustment is positively related to share price.

Liquidity providers are likely to make faster quote adjustments to new information (and thereby move more quickly towards optimal spreads) for stocks with greater adverse-selection risks. This is because the cost of quoting sub-optimal spreads is likely to be greater for such stocks. Similarly, we conjecture that liquidity providers make faster quote revisions to equilibrium spreads when competition is higher. These considerations lead to the following hypothesis:

Hypothesis 4: The speed of quote adjustment is positively related to both adverse-selection risks (and costs) and dealer competition.

2.3. Tick size and the speed of quote adjustment

Tick size is an important protocol of securities markets because it affects trading costs and market quality. Tick size affects trading costs because it could be a binding constraint on absolute spreads. Tick size affects market quality also because it limits the prices that marketmakers and traders can quote, thus restricting price competition. Ahn, Cao, and Choe (1996) examine the change in liquidity when the AMEX reduced its tick size. Bacidore (1997), Porter and Weaver (1997), and Ahn, Cao, and Choe (1998) examine the impact of tick size on trading costs using stocks listed on the Toronto Stock Exchange. Goldstein and Kavajecz (2000) examine the effects of the tick-size change on the spreads of NYSE-listed stocks. Ronen and Weaver (2001) examine the effect of tick size on return volatility, spreads, depths, trader behavior, and specialist profits.

Although there is extensive literature on the effect of tick size on market quality, there is little evidence on how tick size affects the speed of quote adjustments. We analyze the impact of tick size on quote adjustment speed using data before and after decimal pricing. We conjecture that the speed of quote adjustments is faster under decimal pricing because the penny tick is less likely to be a binding constraint than the pre-decimal tick size (i.e., $1/16). Also note that a smaller tick size results in greater price competition because it implies a smaller cost of both front running by sell-side intermediaries and stepping ahead of the existing queue by buy-side traders. This is another reason why we expect faster quote adjustments under decimal pricing. These consideration lead to the following hypothesis:

Hypothesis 5: *The speed of quote adjustment during the post-decimalization period is faster than the speed of quote adjustment during the pre-decimalization period.*

3. Methodology

We use the following partial adjustment model to measure the speed of spread adjustment:

$$S_t - S_{t-1} = \pi(S_t^* - S_{t-1}) + u_t; \tag{1}$$

where S_t is the observed spread at time t, π is the partial adjustment coefficient, S_t^* is the equilibrium spread, and u_t is an error term. Prior studies suggest that liquidity providers incur order-processing, inventory-holding, and adverse-selection costs.[7] These studies show that the costs of market-making and,

[7] See, e.g., Stoll (1978), Ho and Stoll (1980, 1981), Glosten and Harris (1988), and Stoll (2000).

by implication, equilibrium spreads vary with select stock attributes such as trade size, number of trades, share price, and return volatility. Accordingly, we assume that the equilibrium spread is a function of four stock attributes in the following manner:

$$S_t^* = \alpha_0 + \alpha_1 \log(NTRADE_t) + \alpha_2 \log(TSIZE_t) + \alpha_3 (1/PRICE_t) + \alpha_4 RISK_t; \tag{2}$$

where $NTRADE_t$ is the number of trades during a time interval that ends at time t, $TSIZE_t$ is the size of the most recent trade prior to or at time t, $PRICE_t$ is the quote midpoint at time t,[8] and $RISK_t$ is the standard deviation of quote-midpoint returns during a time interval that ends at time t.[9] Prior studies usually include measures of competition (e.g., number of dealers, Herfindahl index, or number of markets) and information environment (e.g., firm size) in the spread model.[10] We do not include these variables in our model because we focus on intertemporal variation in the spread (not inter-stock difference) and these variables are unlikely to vary materially between short time intervals.[11]

From Eq. (1) we obtain

$$S_{t+1} - S_t = \pi(S_{t+1}^* - S_t^*) + (1-\pi)(S_t - S_{t-1}) + (u_{t+1} - u_t). \tag{3}$$

Substituting Eq. (2) into Eq. (3), we have

$$S_{t+1} - S_t = \pi(\sum_{i=1}^{4} \alpha_i \Delta X_i) + (1-\pi)(S_t - S_{t-1}) + (u_{t+1} - u_t); \tag{4}$$

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8 Following prior research, we use 1/PRICE as an explanatory variable in the quoted spread model.

9 Our model is analogous to the following partial adjustment model of consumer expenditure behavior (see Judge et al., 1985): $Y_t - Y_{t-1} = \pi(Y_t^* - Y_{t-1}) + \varepsilon_t$; where $Y_t^* = \alpha + \beta X_t$, Y_t = the actual expenditure in period t, Y_t^* = the optimal expenditure, X_t = the disposable income, π = the adjustment coefficient, and ε_t is a random component. Lintner (1956) and Fama and Babiak (1968) employ similar models to analyze corporate dividend policy. Flannery and Rangan (2006) use the model to analyze corporate capital structure changes.

10 See, e.g., McInish and Wood (1992) and Chung, Chuwonganant, and McCormick (2004).

11 Prior studies show that these stock attributes explain a significant portion of cross-sectional variation in the spread. For instance, Stoll (2000) and Chung, Van Ness, and Van Ness (2001) show that they explain about 65% to 85% of cross-sectional variation in the spread. However, prior studies offer little guidance as to how much of the intertemporal variation in the spread of a given stock can be explained by intertemporal variation in these stock attributes. Because our empirical model is concerned with intertemporal variations in the equilibrium and actual spreads, the validity of our partial adjustment model depends on the explanatory power of the equilibrium spread model. As a simple test of the empirical fitness of Eq. (2), we regress the spread on the four stock attributes for each NYSE and NASDAQ stock. We find that about 25% to 35% of intertemporal variation in spreads could be explained by intertemporal variation in these variables. These results suggest that Eq. (2) is a reasonable model of the spread.

where ΔX_i 's denote the changes in stock attributes.

Eq. (4) shows that the spread change between t and t + 1 consists of three components. The first component is the change due to the newly arrived information (thus the change in the equilibrium spread) between t and t + 1 reflected in the changes in stock attributes. The second component is the delayed adjustment in the spread between t and t + 1 for the information arrived prior to time t. The third component is the random noise. If $\pi = 1$, it means that the spread change between t and t + 1 is entirely due to the newly arrived information between the two periods and the random noise. In this case, the new information arrived between t and t + 1 is fully incorporated into the spread at time t + 1. If $\pi < 1$, liquidity providers only partially reflect the newly arrived information between t and t + 1 in the spread at time t + 1. As such, liquidity providers correct this under-adjustment in later periods, slowing down the spread movement towards its equilibrium value. If $\pi > 1$, liquidity providers overreact to the changes in stock attributes between t and t + 1 when they establish the spread at t + 1. Again, liquidity providers correct this over-adjustment in later periods.

We also employ an alternative measure (λ) of quote adjustment speed defined by the following equation:

$$\lambda = 1 - |1 - \pi|; \qquad (5)$$

where π is the partial adjustment coefficient estimated from Eq. (4). Note that if π is equal to one (i.e., when liquidity providers fully incorporate concurrent information into quote update), λ would also be equal to one. If π is either greater or less than one, λ would range between zero and 1.[12] The closer is λ to one, the faster the spread moves towards its equilibrium value. Note that while π measures the absolute speed of quote adjustment, λ measures the speed at which the actual spread moves toward the equilibrium spread. Also note that λ is equal to π whenever π is smaller than or equal to one. We report the results using both π and λ to assess the sensitivity of our results to different measures of quote adjustment speed.

[12] This is true as long as $0 < \pi < 2$. None of our study sample of stocks violated this condition.

Marketmakers post both the price (i.e., the bid and ask prices) and quantity (i.e., the bid and ask depths) of shares that they are willing to trade. To the extent that marketmakers have control over both variables and use them strategically, the analysis of price quotes alone is likely to show an incomplete picture of the quotation behavior of marketmakers.[13] Although prior studies recognize the importance of the quantity dimension of quotes,[14] there is little evidence as to how the depth adjustment speed is related to stock attributes and tick size. Hence, we also analyze how the speed of depth quote adjustments varies with stock attributes and tick size.

Harris (1994) shows that both the spread and depth are related to a common set of stock attributes. Hence, we use the method described above to estimate the speed of depth adjustment. Specifically, we estimate the following regression model:

$$\mathrm{Log}(D_{t+1}) - \mathrm{Log}(D_t) = \pi\left(\sum_{i=1}^{4} \alpha_i \Delta X_i\right) + (1-\pi)(\mathrm{Log}(D_t) - \mathrm{Log}(D_{t-1})) + (u_{t+1} - u_t)\ ; \qquad (6)$$

where D_t is the quoted depth at time t, D_{t-1} is the quoted depth at time t – 1, and all other variables are the same as previously defined. We then obtain the speed of depth adjustment using $\lambda = 1 - |1 - \pi|$.

4. Data sources and sample characteristics

We obtain trade and quote data for the three-month period from October 2005 to December 2005 from the NYSE's Trade and Quote (TAQ) database. We exclude certificates, ADRs (American Depository Receipts), SBIs (Shares of Beneficial Interest), and units from the study sample. We omit the following trades and quotes to minimize data errors: quotes with an ask price or bid price less than or equal to zero; quotes with an ask size or bid size less than or equal to zero; quotes with bid-ask spreads greater than $5 or

[13] Most previous studies focus only on the price quote. See, e.g., Tinic (1972), Tinic and West (1972), Stoll (1978, 1989), Cohen, et al. (1981), Ho and Stoll (1981), Copeland and Galai (1983), Glosten and Milgrom (1985), Glosten and Harris (1988), Glosten (1989), Foster and Viswanathan (1991), and Huang and Stoll (1997).

[14] Lee, Mucklow, and Ready (1993) examine intraday variation in the spread and depth of NYSE-listed stocks and find that spreads widen and depths drop before quarterly earnings announcements. Harris (1994) analyzes the effect of tick size on specialist quotes and finds that tick size affects depths when it is larger than the spread that dealers would otherwise quote (i.e., when tick size is a binding constraint). Kavajecz (1996) suggests that NYSE specialists use depths as a strategic variable to reduce adverse selection risks. Kavajecz (1999) shows that both specialists and limit-order traders quote smaller depths around earnings announcements. Goldstein and Kavajecz (2000) find that both spreads and depths declined after the NYSE's tick size changed from eighths to sixteenths.

less than zero; quotes associated with trading halts or designated order imbalances; before-the-open and after the-close trades and quotes; trades and quotes involving errors or corrections; trades with price or volume less than or equal to zero; trade price, p_t, if $|(p_t - p_{t-1})/p_{t-1}| > 0.10$; ask quote, a_t, if $|(a_t - a_{t-1}) / a_{t-1}| > 0.10$; and bid quote, b_t, if $|(b_t - b_{t-1})/b_{t-1}| > 0.10$. We construct national best bids and offers (NBBOs) using quotes from all exchanges. We obtain data required for calculation of market capitalizations and institutional holding from Standard & Poor's COMPUSTAT and the CDA/Spectrum Institutional (13f) Holdings databases.

We partition each trading day into 390 successive one-minute intervals to calculate the variables used in this study. We measure share price by the quote midpoint at the end of each interval and return volatility by the standard deviation of quote-midpoint returns during each interval. We measure trading frequency by the number of trades during each interval and trade size by the size of the last trade in each interval. We measure the quoted spread of each stock at time t by $(Ask_t - Bid_t)/M_t$; where Ask_t is the ask price, Bid_t is the bid price, and M_t is the mean of Ask_t and Bid_t. The quoted spread is the implicit trading cost for market orders when a trade occurs at the quoted price with no price improvement.[15] To measure the cost of trading when it occurs at prices inside the posted bid and ask quotes, we also measure the effective spread at time t by $2Q_t (P_t - M_t)/M_t$; where P_t is the transaction price at time t, M_t is the midpoint of the most recently posted bid and ask quotes for the stock, and Q_t equals 1 for buyer-initiated trades and –1 for seller-initiated trades. We estimate Q_t using the algorithm in Ellis, Michaely, and O'Hara (2000). We measure the quoted depth of each stock by the combined quoted depth at the bid and ask in round lots. We then calculate the mean values of these variables for each stock during the study period.

Panel A of Table 1 shows descriptive statistics on our study sample of 1,450 NYSE stocks and 2,713 NASDAQ stocks that have complete data required for our empirical analyses. The average share price is $34.79 for the NYSE sample and $17.30 for the NASDAQ sample. The average trade size and

[15] We obtain qualitatively identical results when we replicate our empirical analyses using the quoted dollar spread (i.e., $Ask_t - Bid_t$). Hence, for brevity, we report only the results using the relative spread (i.e., as a proportion of share price).

average number of trades are $12,778 and 4.59 for the NYSE sample, and $4,686 and 5.23 for the NASDAQ sample. The average standard deviation of quote midpoint returns is 0.0003 for the NYSE sample and 0.0008 for the NASDAQ sample. The average market capitalizations for our NYSE and NASDAQ stocks are $8,012 million and $1,166 million, respectively. The average percentage of shares that are held by institutional investors is 69.49% for the NYSE sample and 44.04% for the NASDAQ sample. The average quoted and effective spreads for NYSE stocks are smaller than those of NASDAQ stocks. On the whole, NYSE stocks have higher share prices, larger trade sizes and number of trades, lower return volatility, larger market capitalization, higher institutional ownership, smaller spreads, and smaller depths.

5. Empirical findings

In this section, we present the empirical results regarding our hypotheses 1 through 5 described in Section 2.

5.1. Market structure versus the speed of quote adjustment

We estimate Eq. (4) and Eq. (6) for each stock in our study sample using the one-minute interval data from October 2005 to December 2005.[16] The dynamic nature of Eq. (4) and Eq. (6) makes the usual ordinary least squares method inappropriate. Greene (2003) shows that the Generalized Method of Moments (GMM) yields unbiased estimates of the above model if an instrument could be found that is correlated with the lagged dependent variable but not with the error term. We estimate Eq. (4) and Eq. (6) using the second lag of the dependent variable as an instrument for the first lagged dependent variable.[17]

To determine whether the quote adjustment speed varies with market structure, we calculate the

[16] To assess the extent to which the spread changes between two consecutive one-minute intervals, we calculate the proportion of the spread difference between two consecutive one-minute intervals that is not equal to zero. We find that the proportion of non-zero spread changes is 0.67 for NYSE stocks and 0.58 for NASDAQ stocks when we measure the spread in absolute term (i.e., the ask price – the bid price) and 0.86 for NYSE stocks and 0.79 for NASDAQ stocks when we measure the spread in relative term (i.e., the absolute spread/share price). The latter two figures are greater because the relative spread changes when either the absolute spread or share price changes.

[17] See Section 13.6 of Greene (2003) for a detailed explanation of this method.

mean value of π for our NYSE and NASDAQ stocks, respectively, together with t-statistics for testing the equality of the mean. Because estimates of π (i.e., regression coefficients) for certain stocks are less meaningful (i.e., smaller t-values) than those for other stocks, we calculate the weighted average of π using the reciprocal of the standard error (SE) of each estimated coefficient as weight. Specifically, we multiply each estimated coefficient by the ratio of its own 1/SE to the sum of 1/SE across all NYSE (or NASDAQ) stocks in our study sample and then add up these 'weighted' coefficients across stocks in each market. We consider this approach sensible because it assigns greater weight to the more precise estimates, thereby reducing the effect of measurement errors on our inferences. Similarly, we compare the mean values of λ between our NYSE and NASDAQ stocks.

Panel A of Table 2 shows that the mean value of π estimates from the quoted (effective) spread model is 0.9159 (0.9255) for the NYSE sample and 0.8193 (0.8909) for the NASDAQ sample, and the difference between the two figures is statistically significant at the 1% level. The vast majority of π estimates are smaller than one for both the NYSE and NASDAQ samples. These results indicate that liquidity providers in both markets only partially reflect the newly arrived information between t and t + 1 in the spread at t + 1. The mean value of λ estimates for the NYSE sample is 0.9115 (0.923) in the quoted (effective) spread model, which is significantly greater than the corresponding figures (0.8079 and 0.8871) for the NASDAQ sample. These results indicate that liquidity providers on the NYSE make faster quote adjustments towards the equilibrium spread than their counterparts on NASDAQ. We find qualitatively similar results for the quoted depth model (i.e., Eq. (6)). These results are supportive of our hypothesis 1.

Although our results suggest that liquidity providers on the NYSE make faster spread and depth adjustments, the results could be driven by differences in stock attributes between our NYSE and NASDAQ study samples. As shown in Panel A of Table 1, NYSE stocks have larger transaction sizes than NASDAQ stocks. Furthermore, NYSE stocks have much larger market capitalizations than NASDAQ stocks. Thus, differences in quote adjustment speeds could be due to differences in stock attributes.

To compare the speed of quote adjustment between NYSE and NASDAQ stocks after controlling for differences in their attributes, we obtain matched samples of NYSE and NASDAQ stocks that are similar in trade size, price, return volatility, and market capitalization.[18] We first calculate the matching score (MS) for each NYSE stock against each of the 2,713 NASDAQ stocks in our study sample: MS = $\sqrt{\sum_{i=1}^{4}(X_i^N - X_i^T)^2}$, where X_i represents one of the four stock attributes, superscripts N and T refer to NYSE and NASDAQ, respectively; and Σ denotes the summation over i = 1 to 4. Then, for each NYSE stock, we select the NASDAQ stock with the smallest MS. Once we match a NASDAQ stock with a NYSE issue, that particular NASDAQ stock is no longer considered for subsequent matches. This procedure results in 394 pairs of NASDAQ and NYSE stocks with similar attributes.

Panel B of Table 1 shows descriptive statistics on the matched sample. The average share price for the NYSE sample is $16.31 and the corresponding figure for the NASDAQ sample is $21.3. The average trade size for the NYSE sample is $4,704 and the corresponding figure for the NASDAQ sample is $4,700. The mean value of the standard deviation of quote midpoint returns is 0.0004 for the NYSE sample and 0.0005 for the NASDAQ sample. The average market value of equity for our NYSE and NASDAQ firms is $577 million and $572 million, respectively. The average quoted (effective) spread of NYSE stocks is 0.0034 (0.0016) whereas the corresponding figure for NASDAQ stocks is 0.004 (0.0024). The average quoted depth (16.95 round lots) for NYSE stocks is larger than the corresponding figure (11.57 round lots) for NASDAQ stocks.[19]

Panel D of Table 2 shows the quote adjustment speed comparison results for the matched sample. Similar to the results for the whole sample, liquidity providers on the NYSE make faster quote adjustments than those on NASDAQ. Hence we conclude that our results are not driven by differences in stock attributes between the two markets.

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[18] Although NASDAQ uses the same volume counting rules as the NYSE, the reported number of trades on NASDAQ is not directly comparable to that on the NYSE because there are many interdealer trades and dealer-to-customer interactions on NASDAQ. Hence, we do not use the number of trades as a matching variable.

[19] The TAQ database reports only the size of the first dealer quote at the inside for NASDAQ issues, whereas it reports the aggregate depth (specialist depth plus all the limit orders at the quoted price) for NYSE issues. As a result, the cross-market comparison of quoted depths is not meaningful.

5.2. Stock attributes versus the speed of quote adjustment

5.2.1. Model specification and the measurement of the variables

To examine how the speed of quote adjustment is related to stock attributes, we estimate the following cross-sectional regression model using data for our study sample of 1,450 NYSE stocks and 2,713 NASDAQ stocks (we omit stock subscript for notational simplicity):

$$\pi \text{ or } \lambda = \beta_0 + \sum_{i=1}^{5} \beta_i X_i + \beta_6 \mathrm{GKN/PM} + \beta_7 \mathrm{PIN} + \beta_8 \mathrm{INST} + \beta_9 \mathrm{MM}\ (\mathrm{NASDAQ\ stocks}) + \varepsilon\,; \qquad (7)$$

where π is the partial adjustment coefficient, λ is the speed of quote adjustment, X_i (i = 1 to 5) is one of the five stock attributes (i.e., NTRADE, TSIZE, PRICE, RISK and MVE), Σ denotes the summation over i = 1 to 5, β_0 through β_9 are regression coefficients, and ε is the error term. GKN is the adverse-selection component of the spread estimated from the method in George, Kaul, and Nimalendran (1991),[20] PM is the price impact of trades, PIN is the probability of information-based trading, and MM is the number of marketmakers (for NASDAQ stocks). We include the percentage of shares held by institutions (INST) as a control variable because liquidity providers' reaction to the trades initiated by institutional investors may be different from their reaction to those initiated by individual investors.

George, Kaul, and Nimalendran (1991) use the following regression model to estimate the adverse-selection component:

$$2(TR_t - MR_t) = \rho_0 + \rho_1 s_q (Q_t - Q_{t-1}) + \varepsilon_t; \qquad (8)$$

where TR_t is the transaction return at time t, MR_t is the quote midpoint return calculated from the quote midpoint immediately following the transaction at time t, s_q is the percentage bid-ask spread, Q_t equals 1 for buyer-initiated trades and –1 for seller-initiated trades, ρ_1 measures the order-processing component, $(1 - \rho_1)$ measures the adverse-selection component, and ε_t is the error term.

We calculate the price impact of trades (PM) using the following formula:

$$\text{Price impact}_t = Q_t (M_{t+1} - M_t)\,; \qquad (9)$$

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[20] We obtain qualitatively similar results when we estimate adverse selection costs using the spread component models developed by Glosten and Harris (1988) and Lin, Sanger, and Booth (1995).

where Q_t equals 1 for buyer-initiated trades and –1 for seller-initiated trades and M_{t+1} denotes the first quote midpoint observed at least one minute after the trade for which the price impact is measured.

We use the algorithm in Easley, Hvidkjaer, and O'Hara (2002) to measure the probability of information-based trading (PIN). The Easley, Hvidkjaer, and O'Hara (EHO) model provides the structure necessary to extract information from the observable variables, i.e., the number of buys and sells. The EHO model is represented by the following likelihood function:

$$L(\Theta \mid B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!} + \alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}; \quad (10)$$

where B is the number of buyer-initiated trades, S is the number of seller-initiated trades, α is the probability that an event is information based, δ is the probability that an information event contains good news, 1- δ is the probability that an information event contains bad news, μ is the order arrival rate of informed traders, ε_b is the order arrival rate of uninformed buyers, ε_s is the order arrival rate of uninformed sellers, and $\Theta = (\alpha, \mu, \varepsilon_b, \varepsilon_s, \delta)$ represents the parameter vector. The likelihood function for the estimation period is given by:

$$V = L(\Theta \mid M) = \prod_{d=1}^{D} L(\Theta \mid B_d S_d); \quad (11)$$

where B_d (S_d) is the number of buyer (seller)-initiated trades for day d = 1, 2, ……, D, and M is the data set that contains ((B_1, S_1), ….., (B_d,S_d)). We obtain the probability of information-based trading using PIN = $\alpha\mu/(\alpha\mu + \varepsilon_b + \varepsilon_s)$.

5.2.2. Regression results

As noted earlier, the statistical significance of π estimates varies across stocks. To reflect this feature in our second-pass regression, we estimate Eq. (7) using the weighted regression procedure. We use the reciprocal of the standard error of partial adjustment coefficients (i.e., π) from the first-pass regressions as weight in the second-pass regression (i.e., Eq. (7)). This approach assigns smaller weights to π estimates that are less meaningful (i.e., smaller t-values). We use the log of number of trades, trade size, share price, market value of equity, and MM in the regression.

Panels A, B, and C of Table 3 show the results of the second-pass regressions using π and λ values that are estimated from the quoted spread, effective spread, and quoted depth models. In each panel, the first four columns show the results for NYSE stocks, the next four columns show the results for NASDAQ stocks, and the last four columns show the results for the combined sample of NYSE and NASDAQ stocks.

Panel A shows that both π and λ are significantly and positively related to the number of trades and share price for both NYSE and NASDAQ stocks in most regressions.[21] Both π and λ are also positively related to return volatility for both NYSE and NASDAQ stocks, although the relation is weaker for NASDAQ stocks. These results are consistent with our hypotheses 2 and 3 and support the idea that trades convey information and the penny tick is more likely a binding constraint on the spreads of low-price stocks.[22]

Both π and λ are positively and significantly related to the adverse-selection component of the spread (i.e., GKN) and the price impact of trades. They are also positively related to the probability of information-based trading (PIN) in all regressions. These results are consistent with hypothesis 4, supporting the idea that liquidity providers make faster quote adjustments in response to new information when they face greater adverse-selection costs (risks).

Both π and λ are negatively related to the market value of equity in all regressions. We interpret this result as evidence that liquidity providers face greater adverse-selection risks in stocks of small companies (because less information is available on such stocks) and thus make faster quote adjustments towards equilibrium spreads. Here, firm size may capture dimensions of adverse-selection costs that are not captured by GKN, PM, or PIN.[23] Although π and λ are negatively related to institutional ownership, the

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[21] The positive relation between the speed of quote adjustment and the number of trades is in line with the finding of Nyholm (2002) that private information is incorporated faster in the quotes for high-volume stocks than in the quotes for low-volume stocks.

[22] If the binding constraint is the main reason why quote adjustment speed is positively related to share price, we would expect to find a stronger impact of share price on quote adjustment speed when tick size is larger. To confirm this, we replicate Table 3 using pre-decimalization data. Consistent with our expectation, we find that share price has stronger effects on quote adjustment speed and the speed is generally slower during the pre-decimal periods.

[23] Prior studies report that stocks of large companies exhibit faster price adjustments than stocks of small companies (see, e.g., Damodaran, 1993; Thoebald and Yallup, 2004). One possible explanation for the difference between our

relation is not statistically significant in most regressions. Hence the effect of institutional investors on quote adjustment speed is not clear. Both π and λ are positively and significantly related to the number of marketmakers, supporting our conjecture (i.e., hypothesis 4) that liquidity providers make faster quote adjustments when competition is higher.

Our results show that π and λ are negatively related to trade size in most regressions, although the relation is significant only for NYSE stocks. Because of the ambiguity involved in the relation between trade size and information content, however, it is unclear what drives this relation. Easley, Kiefer, and O'Hara (1997b) show that trade size provides no information content beyond that conveyed by trading frequency. They interpret this result as evidence that informed agents trade both large and small quantities, and therefore trade size is not informative to marketmakers. Such an outcome arises in a pooling equilibrium (see Easley and O'Hara, 1987) in which some informed traders submit small orders and others submit large orders. It is the transaction, not trade size, which conveys information when informed trading occurs in varying quantities.

In a separating equilibrium, however, the preponderance of informed trading in large quantities imparts information content to order size (see Easley, Kiefer, and O'Hara, 1997a). Easley, Kiefer, and O'Hara (1997b) conclude that the role of trade size in information transmission is model-specific. On the other hand, Barclay and Warner (1993) find that informed traders are concentrated in the medium-size category and price movements are due mainly to informed traders' private information. Similarly, Chakravarty (2001) shows that medium-size trades exhibit a larger cumulative price impact than other trade-size categories. Because it is difficult to establish a clear connection between trade size and information content, it is also difficult to interpret the observed relation between trade size and the quote adjustment speed, at least from the perspective of information-based models.

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and their results is that these studies do not control for the effects of stock attributes (e.g., number of trades, trade size, share price, etc.) on price adjustment speed. Indeed, when we regress spread adjustment speed only on MVE, we find that the regression coefficients on MVE are positive and significant for both NYSE and NASDAQ samples, regardless of whether we estimate the speed of adjustment using the dollar or percentage spread.

The results of the second-pass regressions using π and λ values that are estimated from the effective spread model (see Panel B) are generally similar to those in Panel A. For example, both π and λ are positively related to trade size, share price, return volatility, and adverse selection costs, but negatively related to trade size, firm size, and the number of marketmakers. These results indicate that our results are not sensitive to how we measure the spread, i.e., whether we measure spreads using quoted prices or actual transaction prices.

Panel C of Table 3 shows that π and λ values that are estimated from the quoted depth model are positively and significantly related to the number of trades, share price, and return volatility, and negatively related to trade size and firm size on both the NYSE and NASDAQ. We also find that in both markets, liquidity providers make faster depth adjustments for stocks with greater adverse-selection costs. These results are qualitatively similar to those reported in Panel A and Panel B for the speed of spread adjustments. These findings indicate that if liquidity providers make faster spread adjustments for a given stock, they are also likely to make faster depth adjustments for that stock.

Our explanatory variables account for about 47% of cross-sectional variation in the depth adjustment speed of NYSE stocks. In contrast, the same variables explain only about 30% of cross-sectional variation in the depth adjustment speed of NASDAQ stocks. The lower explanatory power of our regression model for NASDAQ stocks may, at least in part, be attributed to the fact that the depth figures for NASDAQ stocks reported in the TAQ database are incomplete measures of actual liquidity at the inside.

5.3. *Relative speed of quote adjustment between NYSE and NASDAQ stocks: a robustness check*

Earlier, we showed that the quote adjustment speed of NYSE stocks is faster than that of NASDAQ stocks. We attributed this result to differences in market structure between the NYSE and NASDAQ. In this section, we examine whether the result can be explained by differences in stock attributes between the two markets. To the extent that the quote adjustment speed is related to stock attributes, a faster speed of quote adjustment in one market relative to the other may simply reflect differences in stock characteristics between the two markets. For example, stocks in one market may have, on average, greater adverse-selection risks or higher share prices and thus exhibit faster quote adjustments.

To test whether quote adjustments are faster on the NYSE after controlling for differences in stock attributes between the two markets, we estimate the following cross-sectional regression model using the pooled sample of NYSE and NASDAQ stocks:

$$\pi \text{ or } \lambda = \beta_0 + \sum_{i=1}^{5}\beta_i X_i + \beta_6 \text{GKN/PM} + \beta_7 \text{PIN} + \beta_8 \text{INST} + \beta_9 \text{NYSE} + \varepsilon\,; \qquad (12)$$

where NYSE is a dummy variable which equals one for NYSE stocks and zero for NASDAQ stocks and all other variables are the same as previously defined.

The last four columns of Table 3 show the regression results. Panels A, B, and C show that estimated coefficients on the NYSE dummy variable are positive and significant in all four regressions, indicating that liquidity providers on the NYSE make faster quote adjustments than those on NASDAQ. This result confirms our earlier finding that the different quote adjustment speeds between NYSE and NASDAQ stocks are not entirely due to differences in stock attributes between the two samples. At least part of the difference could be due to the structural differences (such as order preferencing on NASDAQ and NYSE specialists' interaction with floor traders) between the two markets.

5.4. *Tick size versus the speed of quote adjustment*

For NYSE stocks, we consider the three-month period from May 28, 2000 to August 27, 2000 as the pre-decimal period and January 30, 2001 to April 29, 2001 as the post-decimal period. For NASDAQ stocks, we consider the three-month period from December 12, 2000 to March 11, 2001 as the pre-decimal period and April 10, 2001 to July 9, 2001 as the post-decimal period.[24] For each NYSE and NASDAQ stock, we first estimate the partial adjustment coefficients (π) during the pre- and post-decimal periods, respectively.

[24] The NYSE initiated a pilot decimalization program on August 28, 2000 and converted all 3,525 listed issues to decimal pricing on January 29, 2001. The NASDAQ Stock Market began its decimal test phase with 14 securities on March 12, 2001, followed by another 197 securities on March 26, 2001. All remaining NASDAQ securities converted to decimal trading on April 9, 2001.

We then calculate the mean partial adjustment coefficient during the pre- and post-decimal periods within each market. Similarly, we calculate the mean value of λ during the pre- and post-decimal periods within each market.

Table 4 shows that for NYSE stocks, the mean partial adjustment coefficient (π) in the quoted (effective) spread model is 0.7922 (0.8790) during the pre-decimal period and 0.8231 (0.9315) during the post-decimal period. The differences are all significant at the 1% level. For NASDAQ stocks, the mean partial adjustment coefficients in the quoted (effective) spread model is 0.7780 (0.8755) during the pre-decimal period and 0.811 (0.8922) during the post-decimal period. Again, the differences are all significant at the 1% level. Similarly, the mean quote adjustment speed (λ) during the post-decimal period is significantly greater than the corresponding figure during the pre-decimal period for both NYSE and NASDAQ stocks. We find qualitatively similar results for the depth adjustment speed.[25] These results indicate that liquidity suppliers in both markets make faster quote adjustments after decimalization, which supports our hypothesis 5.

Although the results in Table 4 suggest faster quote adjustments after decimalization, it is possible that the results are driven by differences in the trading environments between the two periods rather than different tick sizes *per se*. To examine this possibility, we estimate the following regression model:

$$\Delta\pi \text{ or } \Delta\lambda = \beta_0 + \sum_{i=1}^{5}\beta_i \Delta X_i + \beta_6 \Delta GKN/\Delta PM + \beta_7 \Delta PIN + \beta_8 \Delta INST + \beta_9 \Delta MM \text{ (NASDAQ stocks)} + \varepsilon\,; \quad (13)$$

where Δ denotes the difference between the post- and pre-decimal values (post – pre) and all other variables are the same as previously defined. If the increases in the quote adjustment speed shown in Table 4 are indeed due to the smaller tick size (rather than due to concurrent changes in stock attributes), we expect the estimated intercept (i.e., β_0) in regression model (13) to be positive and significant.

Panel A of Table 5 shows the results of regression model (13) for NYSE stocks and Panel B shows the results for NASDAQ stocks. In both panels, the first four columns show the regression results using π

[25] Our results also indicate that the mean value of π (λ) estimates is significantly different from one for both NYSE and NASDAQ stocks.

and λ values that are estimated from the quoted spread model. The next four columns show the regression results using π and λ values that are estimated from the effective spread model. The last four columns show the regression results using π and λ values that are estimated from the quoted depth model.

As in Table 3, we estimate the model using the weighted regression procedure, where the weight is the mean value of the reciprocal of the standard error of partial adjustment coefficients from the pre-decimal period and the corresponding value from the post-decimal period. The results show that the estimated intercepts are all positive and significant in most regressions for both the NYSE and NASDAQ samples. Thus, faster quote adjustments during the post-decimal period cannot be attributed to the differences in trading environments between the pre and post decimal periods.

6. Variable measurement intervals and the quote adjustment speed

In this section we examine the effect of variable measurement intervals on quote adjustment speed. From Eq. (4), it can be shown that (see the Appendix for derivation):

$$S_{t+T} - S_t = (S^*_{t+T} - S^*_t) + (u_{t+T} - u_t), \text{ if } \pi = 1 \text{ and} \tag{14}$$

$$= \sum_{i=1}^{T} \pi(1-\pi)^{T-i}(S^*_{t+i} - S^*_{t-T+i}) + (1-\pi)^T (S_t - S_{t-T}) + \sum_{i=1}^{T} (1-\pi)^{T-i}(u_{t+i} - u_{t-T+i}), \text{ if } \pi \neq 1 \tag{15}$$

If π = 1, the newly arrived information between t and t + T is fully incorporated into the spread at t + T. On the other hand, if $\pi \neq 1$, the spread change between t and t + T consists of three components. The first component reflects the change in the equilibrium spread due to the newly arrived information between t and t + T. The second component is the delayed adjustment in the spread between t and t + T for the information arrived prior to t. The third component is the random noise. Eq. (15) shows that the size of delayed quote adjustments becomes smaller as T increases as long as $0 < \pi < 2$. A direct implication of this result is that the size of quote adjustment coefficients increases as we increase the measurement interval of the variables.

To examine the effect of the variable measurement interval on partial adjustment coefficients, we partition each trading day into five- and 30-minute intervals and calculate the variables used in the study during each interval. We then reproduce the results in Panel A of Table 2 with these longer interval data. The results (see Panel B of Table 2) show that the partial adjustment coefficients estimated from the five-minute interval data are all greater than those from the one-minute interval data for both NYSE and NASDAQ stocks. Likewise, the partial adjustment coefficients estimated from the 30-minute interval data are greater than those from the five-minute interval data (see Panel C). For example, the mean partial adjustment coefficient from the five-minute interval data for the quoted spread model is 0.96 for NYSE stocks and 0.8765 for NASDAQ stocks. The mean partial adjustment coefficient increases to 0.9689 for NYSE stocks and 0.9205 for NASDAQ stocks when we estimate it using the 30-minute interval data. These results should not come as a surprise since liquidity providers are more likely to make full adjustments in quotes given longer adjustment periods.

We obtain similar results when we estimate depth adjustment coefficients using the variables measured over longer intervals. We show the results in the last three columns in Panel B and Panel C of Table 2. For NYSE stocks, the mean depth adjustment coefficient (0.9603) estimated from the five-minute interval data is greater than the corresponding figure (0.9050) estimated from the one-minute interval data. The mean depth adjustment coefficient increases to 0.9635 when we calculate it using the 30-minute interval data. For NASDAQ stocks, the depth adjustment coefficient increases from 0.8419 to 0.8930 when the measurement interval increases from one minute to five minutes. The coefficient further increases to 0.9249 when we estimate the variable using the 30-minute measurement interval.

The results in Table 2 also show that liquidity providers on the NYSE make faster spread and depth adjustments than those on NASDAQ when we measure the quote adjustment speed using longer time intervals. For instance, the mean depth adjustment speed (0.9603) of NYSE stocks estimated from the five-minute interval data is significantly greater than the corresponding figure (0.8930) for NASDAQ stocks. We find similar results for the spread adjustment speed.

7. Summary and concluding remarks

Numerous studies have examined the effects of market structure and tick size on measures of market quality such as execution costs, return volatility, and adverse-selection risks. The present study expands this literature by providing evidence on how market structure and tick size affect the quote adjustment speed. Understanding the speed of quote adjustment is important because it likely mirrors the informational efficiency of quoted prices and depths.

Our results show that liquidity providers on the NYSE react more quickly to new information than liquidity providers on NASDAQ. We also find strong cross-sectional regularities in the quote adjustment speed. Liquidity providers make faster quote adjustments for stocks with greater adverse-selection costs and quote competition. In addition, stocks with a greater number of trades, greater return volatility, higher prices, smaller market capitalizations, and smaller trade sizes exhibit faster quote adjustments. Liquidity providers on both the NYSE and NASDAQ react more promptly to new information after decimalization. We interpret the latter result as evidence that large tick sizes create market frictions and delay price discovery. As exchanges around the world search for a better market structure, the speed with which spreads and depths adjust to new information may be one criterion that they should look at in making their choices. In this respect, the finding of the present study that smaller tick sizes and greater transparency about who is trading increase the informational efficiency of quoted spreads and depths should prove useful to regulators, market designers, and exchange officials.

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Appendix
Derivation of Eq. (14) and Eq. (15)

From Eq. (1),

$$S_{t+1} - S_t = \pi(S^*_{t+1} - S_t) + u_{t+1} \quad \text{and} \tag{A1}$$

$$S_t - S_{t-1} = \pi(S^*_t - S_{t-1}) + u_t \,. \tag{A2}$$

Taking the difference between Eq. (A1) and Eq. (A2), we have

$$S_{t+1} - S_t - (S_t - S_{t-1}) = \pi(S^*_{t+1} - S_t) + u_{t+1} - \pi(S^*_t - S_{t-1}) - u_t \,. \tag{A3}$$

After rearrangement, we obtain

$$S_{t+1} - S_t = \pi(S^*_{t+1} - S^*_t) + (1-\pi)(S_t - S_{t-1}) + (u_{t+1} - u_t) \quad \text{and} \tag{A4}$$

$$S_{t+2} - S_{t+1} = \pi(S^*_{t+2} - S^*_{t+1}) + (1-\pi)(S_{t+1} - S_t) + (u_{t+2} - u_{t+1}) \,. \tag{A5}$$

By adding Eq. (A4) and Eq. (A5), we obtain

$$S_{t+2} - S_t = \pi(S^*_{t+2} - S^*_t) + (1-\pi)(S_{t+1} - S_{t-1}) + (u_{t+2} - u_t) \,. \tag{A6}$$

Note that

$$S_{t+3} - S_{t+2} = \pi(S^*_{t+3} - S^*_{t+2}) + (1-\pi)(S_{t+2} - S_{t+1}) + (u_{t+3} - u_{t+2}) \,. \tag{A7}$$

By adding Eq. (A6) and Eq. (A7), we obtain

$$S_{t+3} - S_t = \pi(S^*_{t+3} - S^*_t) + (1-\pi)(S_{t+2} - S_{t-1}) + (u_{t+3} - u_t) \,. \tag{A8}$$

Repeating the above process, we obtain

$$S_{t+T} - S_t = \pi(S^*_{t+T} - S^*_t) + (1-\pi)(S_{t+T-1} - S_{t-1}) + (u_{t+T} - u_t) \,. \tag{A9}$$

From Eq. (A9), we have

$$S_{t+T-1} - S_{t-1} = \pi(S^*_{t+T-1} - S^*_{t-1}) + (1-\pi)(S_{t+T-2} - S_{t-2}) + (u_{t+T-1} - u_{t-1}) \,. \tag{A10}$$

Substituting Eq. (A10) into Eq. (A9), we obtain

$$S_{t+T} - S_t = \pi(S^*_{t+T} - S^*_t) + (1-\pi)[\pi(S^*_{t+T-1} - S^*_{t-1}) + (1-\pi)(S_{t+T-2} - S_{t-2}) + (u_{t+T-1} - u_{t-1})] + (u_{t+T} - u_t)$$

$$= \pi(S^*_{t+T} - S^*_t) + (1-\pi)\pi(S^*_{t+T-1} - S^*_{t-1}) + (1-\pi)^2(S_{t+T-2} - S_{t-2}) + (1-\pi)(u_{t+T-1} - u_{t-1}) + (u_{t+T} - u_t) \,. \tag{A11}$$

From Eq. (A9) again, we obtain

$$S_{t+T-2} - S_{t-2} = \pi(S^*_{t+T-2} - S^*_{t-2}) + (1-\pi)(S_{t+T-3} - S_{t-3}) + (u_{t+T-2} - u_{t-2})\,. \tag{A12}$$

Substituting Eq. (A12) into Eq. (A11), we obtain

$$S_{t+T} - S_t = \pi(S^*_{t+T} - S^*_t) + (1-\pi)\pi(S^*_{t+T-1} - S^*_{t-1}) + (1-\pi)^2[\pi(S^*_{t+T-2} - S^*_{t-2})$$

$$+ (1-\pi)(S_{t+T-3} - S_{t-3}) + (u_{t+T-2} - u_{t-2})] + (1-\pi)(u_{t+T-1} - u_{t-1}) + (u_{t+T} - u_t) \tag{A13}$$

$$= \pi(S^*_{t+T} - S^*_t) + (1-\pi)\pi(S^*_{t+T-1} - S^*_{t-1}) + (1-\pi)^2\pi(S^*_{t+T-2} - S^*_{t-2}) + (1-\pi)^3(S_{t+T-3} - S_{t-3})$$

$$+ (1-\pi)^2(u_{t+T-2} - u_{t-2}) + (1-\pi)(u_{t+T-1} - u_{t-1}) + (u_{t+T} - u_t)\,. \tag{A14}$$

Iterating the above process, we obtain

$$S_{t+T} - S_t = \pi(S^*_{t+T} - S^*_t) + \pi(1-\pi)(S^*_{t+T-1} - S^*_{t-1}) + \pi(1-\pi)^2(S^*_{t+T-2} - S^*_{t-2}) + \ldots\ldots$$

$$+ \pi(1-\pi)^{T-1}(S^*_{t+1} - S^*_{t-T+1}) + (1-\pi)^T(S_t - S_{t-T})$$

$$+ (u_{t+T} - u_t) + (1-\pi)(u_{t+T-1} - u_{t-1}) + (1-\pi)^2(u_{t+T-2} - u_{t-2}) + \ldots\ldots + (1-\pi)^{T-1}(u_{t+1} - u_{t-T+1})\,. \tag{A15}$$

Taking summation on proper terms, we obtain

$$S_{t+T} - S_t = (S^*_{t+T} - S^*_t) + (u_{t+T} - u_t)\,,\ \text{if}\ \ \pi = 1\ \ \text{and} \tag{A16}$$

$$= \sum_{i=1}^{T} \pi(1-\pi)^{T-i}(S^*_{t+i} - S^*_{t-T+i}) + (1-\pi)^T(S_t - S_{t-T}) + \sum_{i=1}^{T}(1-\pi)^{T-i}(u_{t+i} - u_{t-T+i})\,,\ \text{if}\ \pi \neq 1 \tag{A17}$$

which are Eq. (14) and Eq. (15) in the paper.

Table 1
Descriptive statistics

Panel A shows descriptive statistics on our study sample of 1,450 NYSE stocks and 2,713 NASDAQ stocks that have the complete data required for our empirical analyses. We partition each trading day into 390 successive one-minute intervals to calculate the variables used in this study. We measure share price by the mean value of quote midpoints at interval end and return volatility by the standard deviation of quote-midpoint returns during each interval. We measure trading frequency by the average number of trades during each interval, and trade size by the average dollar trade size. We measure firm size by the average market value of equity during the study period. We measure the quoted spread of each stock at time t by $(Ask_t - Bid_t)/M_t$; where Ask_t is the ask price, Bid_t is the bid price, and M_t is the mean of Ask_t and Bid_t. The quoted spread is the implicit trading cost for market orders when a trade occurs at the quoted price with no price improvement. To measure the cost of trading when it occurs at prices inside the posted bid and ask quotes, we also measure the effective spread at time t by $2Q_t (P_t - M_t)/M_t$; where P_t is the transaction price at time t, M_t is the midpoint of the most recently posted bid and ask quotes for the stock, and Q_t equals 1 for buyer-initiated trades and –1 for seller-initiated trades. We measure the quoted depth of each stock by the combined quoted depth at the bid and ask in round lots. We measure institutional holding by the percentage of shares that are held by institutions. Panel B shows descriptive statistics on 394 matched pairs of NYSE and NASDAQ stocks. We obtain matched samples of NYSE and NASDAQ stocks that are similar in trade size, price, return volatility, and market capitalization. We first calculate the matching score (MS) for each NYSE stock against each of the 2,713 NASDAQ stocks in our study sample: MS = $\sqrt{\sum_{i=1}^{4}(X_i^N - X_i^T)^2}$, where X_i represents one of the four stock attributes (i.e., PRICE, NTRADE, TSIZE and RISK), superscripts N and T, refer to NYSE and NASDAQ, respectively; and Σ denotes the summation over i = 1 to 4. Then, for each NYSE stock, we select the NASDAQ stock with the smallest MS.

Panel A: Whole sample

	Exchange	Mean	Standard deviation	Percentile				
				5	25	50	75	95
Share price	NYSE	34.79	31.83	6.61	18.15	29.31	44.85	73.99
(PRICE)	NASDAQ	17.30	16.85	1.59	5.93	13.47	24.11	44.57
Number of trades	NYSE	4.59	4.70	1.44	2.20	3.11	5.20	11.93
(NTRADE)	NASDAQ	5.23	8.96	1.76	2.28	3.06	4.83	13.99
Trade size ($)	NYSE	12,778	9,950	3,179	6,345	9,945	16,192	32,300
(TSIZE)	NASDAQ	4,686	4,262	1,031	2,052	3,701	5,996	11,613
Risk	NYSE	0.0003	0.0001	0.0001	0.0002	0.0002	0.0003	0.0005
(RISK)	NASDAQ	0.0008	0.0009	0.0001	0.0003	0.0004	0.0009	0.0025

Market value (in $1,000)	NYSE	8,012	23,606	173	783	1,867	5,506	31,418
(MVE)	NASDAQ	1,166	7,733	20	82	220	601	3,217
Institutional holding (in %)	NYSE	69.49%	21.11%	29.09%	57.16%	74.31%	85.88%	95.72%
(INST)	NSADAQ	44.04%	28.89%	3.05%	17.73%	41.64%	68.81%	91.66%
Quoted spread	NYSE	0.0016	0.0022	0.0004	0.0006	0.0009	0.0015	0.0048
(QSPRD)	NASDAQ	0.0081	0.0102	0.0007	0.0017	0.0040	0.0110	0.0281
Effective spread	NYSE	0.0007	0.0010	0.0002	0.0003	0.0005	0.0008	0.0021
(ESPRD)	NASDAQ	0.0047	0.0056	0.0005	0.0011	0.0024	0.0066	0.0159
Depth	NYSE	18.4121	93.2465	6.4503	8.8350	12.0571	17.8073	36.4933
(DEPTH)	NASDAQ	23.1604	112.64	4.5166	6.0359	8.3259	13.5848	64.0883

Panel B: Matched sample

	Exchange	Mean	Standard deviation	Percentile 5	25	50	75	95
Share price	NYSE	16.31	10.23	2.93	8.48	14.39	21.31	36.57
(PRICE)	NASDAQ	21.30	11.63	2.93	13.07	18.93	27.80	43.57
Trade size ($)	NYSE	4,704	1,855	2,005	3,352	4,360	5,904	8,131
(TSIZE)	NASDAQ	4,700	1,850	2,012	3,351	4,374	5,936	8,196
Risk	NYSE	0.0004	0.0002	0.0002	0.0003	0.0003	0.0004	0.0008
(RISK)	NASDAQ	0.0005	0.0004	0.0002	0.0003	0.0003	0.0005	0.0013
Market value (in $1,000)	NYSE	577	471	76	223	445	806	1,412
(MVE)	NASDAQ	572	469	68	217	435	774	1,448
Institutional holding (in %)	NYSE	63.37%	23.84%	23.07%	43.56%	65.71%	84.48%	95.35%
(INST)	NSADAQ	56.04%	27.27%	10.13%	34.40%	57.85%	80.91%	94.46%
Quoted spread	NYSE	0.0034	0.0036	0.0010	0.0014	0.0022	0.0034	0.0118
(QSPRD)	NASDAQ	0.0040	0.0050	0.0009	0.0014	0.0021	0.0046	0.0129
Effective spread	NYSE	0.0016	0.0016	0.0005	0.0007	0.0010	0.0016	0.0051
(ESPRD)	NASDAQ	0.0024	0.0028	0.0006	0.0009	0.0013	0.0026	0.0077
Depth	NYSE	16.95	15.76	6.77	8.67	12.11	13.89	46.73
(DEPTH)	NASDAQ	11.57	43.61	4.51	5.49	6.84	9.27	16.77

Table 2
The speed of quote adjustment for NYSE and NASDAQ stocks

This table shows the mean values of partial adjustment coefficients (π) and the mean values of quote adjustment speeds ($\lambda = 1 - |1 - \pi|$) and whether the difference in the mean value between NYSE and NASDAQ stocks is statistically significant. We estimate π and λ using the quoted spread, effective spread, and quoted depth, respectively. This table also shows the percentage of π estimates that are greater than one. We estimate π and λ using one-minute, five-minute, and 30-minute interval data. Panels A, B, and C show the results from the whole study sample of NYSE and NASDAQ stocks, and Panel D shows the results from the matched sample of NYSE and NASDAQ stocks.

Panel A: Whole sample (with one-minute interval data)

	Quoted spread model			Effective spread model			Depth model		
	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)
π	0.9159	0.8193	0.0966** (21.54)	0.9255	0.8909	0.0346** (15.25)	0.9050	0.8419	0.0631** (18.21)
% >1	8.29%	5.61%		4.75%	5.90%		1.27%	4.38%	
λ	0.9115	0.8079	0.1036** (25.24)	0.9230	0.8871	0.0359** (17.03)	0.9043	0.8313	0.0730** (23.71)

Panel B: Whole sample (with five-minute interval data)

	Quoted spread model			Effective spread model			Depth model		
	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)
π	0.9600	0.8765	0.0835** (20.08)	0.9733	0.9328	0.0405** (15.35)	0.9603	0.8930	0.0673** (16.20)
% >1	25.50%	11.98%		32.41%	17.99%		22.50%	12.75%	
λ	0.9431	0.8602	0.0829** (22.44)	0.9498	0.9173	0.0325** (14.82)	0.9484	0.8731	0.0753** (20.45)

**Significant at the 1% level.
*Significant at the 5% level.

Table 2 (continued)
The speed of quote adjustment for NYSE and NASDAQ stocks

Panel C: Whole sample (with 30-minute interval data)

	Quoted spread model			Effective spread model			Depth model		
	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)
π	0.9689	0.9205	0.0484** (10.32)	0.9832	0.9584	0.0248** (6.66)	0.9635	0.9249	0.0386** (8.58)
% >1	38.86%	31.36%		41.04%	33.86%		35.99%	31.31%	
λ	0.9178	0.8740	0.0438** (12.14)	0.9264	0.9008	0.0256** (9.92)	0.9246	0.8776	0.0470** (12.73)

Panel D: Matched sample (with one-minute interval data)

	Quoted spread model			Effective spread model			Depth model		
	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)	NYSE	NASDAQ	Difference (t-value)
π	0.9601	0.8139	0.1462** (26.86)	0.9085	0.8868	0.0217** (4.36)	0.8773	0.8733	0.0040 (0.99)
% >1	7.62%	1.17%		2.64%	1.46%		1.75%	2.05%	
λ	0.9577	0.8128	0.1449** (27.44)	0.9069	0.8851	0.0218** (4.58)	0.8765	0.8725	0.0040 (1.05)

**Significant at the 1% level.
*Significant at the 5% level.

Table 3
The speed of quote adjustment and stock attributes

This table shows the results of the following cross-sectional regression model:

$$\pi \text{ or } \lambda = \beta_0 + \sum_{i=1}^{5} \beta_i X_i + \beta_6 \mathrm{GKN/PM} + \beta_7 \mathrm{PIN} + \beta_8 \mathrm{INST} + \beta_9 \mathrm{MM}\ (\text{NASDAQ stocks}) + \varepsilon$$

where π is the partial adjustment coefficient estimated from the first-pass regression, λ is the quote adjustment speed, X_i (i = 1 to 5) is one of the five stock attributes (i.e., NTRADE, TSIZE, PRICE, RISK and MVE), Σ denotes the summation over i = 1 to 5, β_0 through β_9 are the regression coefficients, and ε is the error term. GKN denotes the adverse-selection component of the spread estimated from the method in George, Kaul and Nimalendran (1991), PM is the price impact of trades, PIN is the probability of information-based trading, INST is the percentage of shares held by institutions, and MM is the number of marketmakers for NASDAQ stocks. We estimate the model using the weighted regression procedure, in which the weight is the reciprocal of the standard error of the partial adjustment coefficient. Panel A shows the results of the second-pass regressions using π and λ values that are estimated from the quoted spread model, Panel B shows the results of the second-pass regressions using π and λ values that are estimated from the effective spread model, and Panel C shows the results of the second-pass regressions using π and λ values that are estimated from the quoted depth model. In each panel, the first four columns show the results for NYSE stocks, the next four columns show the results for NASDAQ stocks, and the last four columns show the results for the combined sample of NYSE and NASDAQ stocks. Numbers in parentheses are t-statistics.

Table 3 (continued)
The speed of quote adjustment and stock attributes

Panel A: Quoted spread model

	NYSE				NASDAQ				Combined			
	π	π	λ	λ	π	π	λ	λ	π	π	λ	λ
Intercept	0.9907**	0.8588**	0.9648**	0.8424**	0.1698	0.4229**	0.3392**	0.6023**	0.9730**	1.0841**	1.0529**	1.1740**
	(6.53)	(5.77)	(6.66)	(5.94)	(1.53)	(3.78)	(3.18)	(5.57)	(14.67)	(16.79)	(16.49)	(18.87)
Log(NTRADE)	0.0280	0.0098	0.0414**	0.0255	0.0522**	0.0213	0.0549**	0.0234*	0.0645**	0.0475**	0.0619**	0.0435**
	(1.72)	(0.66)	(2.66)	(1.80)	(4.70)	(1.94)	(5.14)	(2.20)	(8.02)	(6.28)	(8.00)	(5.97)
Log(TSIZE)	-0.1416**	-0.1321**	-0.1480**	-0.1384**	0.0057	-0.0075	-0.0075	-0.0208	-0.0769**	-0.0790**	-0.0854**	-0.0875**
	(-7.79)	(-7.20)	(-8.52)	(-7.90)	(0.49)	(-0.63)	(-0.67)	(-1.81)	(-8.28)	(-8.50)	(-9.55)	(-9.77)
Log(PRICE)	0.1070**	0.1389**	0.1069**	0.1385	0.0136	0.0365**	0.0250**	0.0514**	0.0589**	0.0778**	0.0644**	0.0857**
	(8.55)	(9.56)	(8.95)	(10.00)	(1.51)	(3.39)	(2.88)	(4.95)	(8.18)	(9.10)	(9.29)	(10.41)
RISK	257.77**	348.69**	275.81**	366.64**	12.81	43.41**	8.76	42.32**	17.35	39.61**	16.47	41.27**
	(3.97)	(5.07)	(4.45)	(5.59)	(1.12)	(3.50)	(0.79)	(3.53)	(1.67)	(3.60)	(1.65)	(3.89)
Log(MVE)	-0.0585**	-0.0490**	-0.0639*	-0.0545**	-0.0008	-0.0054	-0.0078	-0.0132*	-0.0115*	-0.0073	-0.0092*	-0.0044
	(-6.92)	(-5.65)	(-7.92)	(-6.59)	(-0.14)	(-0.88)	(-1.37)	(-2.20)	(-2.49)	(-1.52)	(-2.08)	(-0.97)
GKN	0.1074**		0.0946*		0.3180**		0.3246**		0.1396**		0.1511**	
	(2.75)		(2.54)		(10.49)		(11.10)		(5.71)		(6.42)	
PM		2.0564**		2.0978**		0.9958*		1.2396**		1.4249**		1.6070**
		(3.27)		(3.50)		(2.40)		(3.09)		(4.09)		(4.78)
PIN	0.0915*	0.1195**	0.0823*	0.1102**	0.0491*	0.0471	0.0401	0.0396	0.0517*	0.0583**	0.0431*	0.0506*
	(2.58)	(3.32)	(2.43)	(3.21)	(2.13)	(1.97)	(1.80)	(1.71)	(2.59)	(2.89)	(2.24)	(2.60)
INST	-0.0381	-0.0659*	-0.0299	-0.0563*	-0.0309*	-0.0196	-0.0269	-0.0170	-0.0376**	-0.0352*	-0.0345*	-0.0323*
	(-1.48)	(-2.60)	(-1.22)	(-2.33)	(-1.96)	(-1.19)	(-1.77)	(-1.07)	(-2.74)	(-2.55)	(-2.61)	(-2.42)
Log(MM)					0.1001**	0.1064**	0.0981**	0.1031**				
					(5.51)	(5.64)	(5.56)	(5.66)				
NYSE									0.0435**	0.0796**	0.0455**	0.0843**
									(3.39)	(7.56)	(3.69)	(8.31)
F–value	20.71**	21.15**	23.71**	24.54**	33.25**	20.51**	33.03**	19.24**	33.75**	31.82**	33.61**	31.40**
Adjusted R^2	0.113	0.115	0.127	0.132	0.139	0.089	0.139	0.084	0.089	0.084	0.088	0.083

**Significant at the 1% level.
*Significant at the 5% level.

Table 3 (continued)
The speed of quote adjustment and stock attributes

Panel B: Effective spread model

	NYSE				NASDAQ				Combined			
	π	π	λ	λ	π	π	λ	λ	π	π	λ	λ
Intercept	0.8048**	0.7405**	0.9441**	0.8527**	0.4973**	0.5028**	0.7573**	0.8120**	1.2373**	1.2484**	1.4407**	1.4610**
	(5.68)	(5.44)	(7.12)	(6.69)	(5.41)	(5.53)	(9.12)	(9.87)	(21.57)	(22.33)	(27.23)	(28.40)
Log(NTRADE)	0.0758**	0.0673**	0.0635**	0.0507**	0.0254**	0.0223*	0.0394**	0.0328**	0.0320**	0.0305**	0.0453**	0.0431**
	(4.61)	(4.42)	(4.13)	(3.56)	(2.67)	(2.43)	(4.59)	(3.95)	(4.24)	(4.29)	(6.53)	(6.60)
Log(TSIZE)	-0.0232	-0.0166	-0.0395*	-0.0320*	-0.0117	-0.126	-0.0165	-0.0184*	-0.0647**	-0.0645**	-0.0690**	-0.0679**
	(-1.36)	(-0.98)	(-2.47)	(-2.01)	(-1.21)	(-1.32)	(-1.90)	(-2.12)	(-7.86)	(-7.85)	(-9.09)	(-8.98)
Log(PRICE)	0.0305*	0.0602**	0.0494**	0.0808**	0.0271**	0.0197*	0.0284**	0.0353**	0.0515**	0.0565**	0.0541**	0.0682**
	(2.46)	(4.11)	(4.26)	(5.89)	(3.64)	(2.26)	(4.22)	(4.48)	(8.01)	(7.35)	(9.11)	(9.65)
RISK	102.03	185.07**	133.80*	223.28**	53.59**	48.95**	23.13**	13.71	16.68	21.76*	46.76**	33.38**
	(1.73)	(2.98)	(2.43)	(3.84)	(6.16)	(5.23)	(2.94)	(1.62)	(1.95)	(2.34)	(5.94)	(3.91)
Log(MVE)	-0.0146	-0.0064	-0.0104	-0.0016	0.0000	0.0012	-0.0180**	-0.0192**	-0.0044	-0.0056	-0.0171**	-0.0206**
	(-1.75)	(-0.75)	(-1.34)	(-0.20)	(-0.00)	(0.25)	(-4.00)	(-4.20)	(-1.06)	(-1.30)	(-4.48)	(-5.24)
GKN	0.0404		0.0663		0.0301		0.0657**		0.0101		0.0113	
	(1.11)		(1.94)		(1.24)		(3.01)		(0.48)		(0.58)	
PM		1.9806**		1.9864**		0.5586		0.4577		0.3683		1.0326**
		(3.28)		(3.52)		(1.72)		(1.55)		(1.21)		(3.69)
PIN	0.1687**	0.1862**	0.1578**	0.1758**	0.0331	0.0364	0.0152	0.0122	0.0284	0.0310	0.0318*	0.0390*
	(5.41)	(5.92)	(5.41)	(5.96)	(1.73)	(1.89)	(0.88)	(0.70)	(1.63)	(1.70)	(1.98)	(2.42)
INST	0.0339	0.0177	0.0301	0.0111	-0.0047	0.0010	-0.0099	-0.0099	0.0155	0.0136	0.0060	-0.0004
	(1.45)	(0.76)	(1.37)	(0.51)	(-0.36)	(0.08)	(-0.83)	(-0.82)	(1.28)	(1.12)	(0.54)	(-0.04)
Log(MM)					0.0946**	0.0980**	0.0958**	0.0946**				
					(5.96)	(6.15)	(6.68)	(6.55)				
NYSE									0.0400**	0.0414**	0.0503**	0.0488**
									(3.57)	(4.49)	(4.86)	(5.74)
F–value	15.83**	17.15**	20.38**	21.59**	25.09**	25.26**	40.67**	39.79**	9.91**	10.05**	24.39**	25.97**
Adjusted R^2	0.087	0.094	0.111	0.117	0.108	0.109	0.166	0.163	0.026	0.026	0.065	0.069

**Significant at the 1% level.
*Significant at the 5% level.

Table 3 (continued)
The speed of quote adjustment and stock attributes

Panel C: Depth model

	NYSE				NASDAQ				Combined			
	π	π	λ	λ	π	π	λ	λ	π	π	λ	λ
Intercept	0.7224**	0.7561**	0.7208**	0.7549**	0.8629**	0.9011**	0.8817**	0.9195**	0.7302**	0.7696**	0.7471**	0.7859**
	(18.20)	(19.97)	(18.21)	(20.00)	(13.81)	(14.68)	(14.58)	(15.47)	(23.86)	(25.95)	(25.12)	(27.29)
Log(NTRADE)	0.0402**	0.0321**	0.0399**	0.0318**	0.0177**	0.0128*	0.0174**	0.0127*	0.0178**	0.0121**	0.0180**	0.0124**
	(8.37)	(7.11)	(8.34)	(7.05)	(2.77)	(2.07)	(2.82)	(2.12)	(4.74)	(3.41)	(4.93)	(3.59)
Log(TSIZE)	-0.0188**	-0.0191**	-0.0188**	-0.0192**	-0.0265**	-0.0252**	-0.0319**	-0.0306**	-0.0171**	-0.0163**	-0.0214**	-0.0207**
	(-4.33)	(-4.43)	(-4.35)	(-4.46)	(-4.13)	(-3.94)	(-5.14)	(-4.94)	(-4.11)	(-3.95)	(-5.32)	(-5.15)
Log(PRICE)	0.0490**	0.0587**	0.0490**	0.0586**	0.0651**	0.0764**	0.0659**	0.0772**	0.0560**	0.0679**	0.0564**	0.0684**
	(15.15)	(14.85)	(15.18)	(14.87)	(13.97)	(14.62)	(14.59)	(15.27)	(17.73)	(18.66)	(18.39)	(19.33)
RISK	62.70**	86.35**	63.30**	86.90**	22.53**	35.07**	21.64**	34.18**	29.92**	42.60**	28.56**	41.19**
	(4.15)	(5.29)	(4.20)	(5.34)	(3.90)	(5.77)	(3.86)	(5.82)	(7.35)	(9.91)	(7.22)	(9.87)
Log(MVE)	-0.0059*	-0.0047*	-0.0060**	-0.0048*	-0.0032	-0.0054	-0.0017	-0.0039	-0.0030	-0.0000	-0.0043*	-0.0012
	(-2.57)	(-2.02)	(-2.63)	(-2.08)	(-0.97)	(-1.61)	(-0.53)	(-1.21)	(-1.40)	(-0.00)	(-2.05)	(-0.59)
GKN	0.0465**		0.0469**		0.0455**		0.0448**		0.0443**		0.0434**	
	(4.33)		(4.38)		(3.04)		(3.09)		(4.21)		(4.25)	
PM		0.7519**		0.7526**		1.0248**		1.0307**		0.9968**		0.9968**
		(5.01)		(5.03)		(4.61)		(4.79)		(6.59)		(6.79)
PIN	0.0120	0.0050	0.0123	0.0053	0.0366**	0.0413**	0.0364**	0.0412**	0.0232*	0.0289**	0.0227*	0.0285**
	(1.36)	(0.56)	(1.40)	(0.59)	(2.81)	(3.17)	(2.89)	(3.27)	(2.57)	(3.20)	(2.60)	(3.24)
INST	0.0129*	0.0137*	0.0133*	0.0142*	0.0155	0.0114	0.0192*	0.0150	0.0155*	0.0118	0.0185**	0.0148*
	(2.07)	(2.24)	(2.15)	(2.42)	(1.71)	(1.25)	(2.19)	(1.70)	(2.50)	(1.91)	(3.08)	(2.46)
Log(MM)					0.0002	-0.0031	0.0009	-0.0024				
					(0.01)	(-0.29)	(0.09)	(-0.23)				
NYSE									0.0228**	0.0310**	0.0251**	0.0330**
									(3.99)	(6.49)	(4.52)	(7.12)
F–value	138.99**	140.45**	139.45**	140.86**	83.50**	85.39**	87.77**	89.89**	217.70**	222.37**	230.98**	236.20**
Adjusted R^2	0.469	0.472	0.470	0.472	0.293	0.297	0.303	0.308	0.390	0.395	0.405	0.410

**Significant at the 1% level.
*Significant at the 5% level.

Table 4
Comparisons of the quote adjustment speed between the pre- and post-decimal periods

This table shows the mean value of partial adjustment coefficients (π) and the mean value of quote adjustment speeds ($\lambda = 1 - |1 - \pi|$) for our study sample of NYSE and NASDAQ stocks, respectively, and the results of t-tests on whether the difference in the mean value between the pre- and post-decimal periods within each market is statistically significant. Both π and λ are estimated using the quoted spread model, effective spread model, and quoted depth model, respectively. This table also shows the percentage of π estimates that are greater than one. We estimate π and λ using one-minute interval data. Panel A shows the results for NYSE stocks and Panel B shows the results for NASDAQ stocks. For NYSE stocks, we consider the three-month period from May 28, 2000 to August 27, 2000 as the pre-decimal period and January 30, 2001 to April 29, 2001 as the post-decimal period. For NASDAQ stocks, we consider the three-month period from December 12, 2000 to March 11, 2001 as the pre-decimal period and April 10, 2001 to July 9, 2001 as the post-decimal period.

Panel A: NYSE

	Quoted spread model			Effective spread model			Depth model		
	PRE	POST	Difference (t-value)	PRE	POST	Difference (t-value)	PRE	POST	Difference (t-value)
π	0.7922	0.8231	0.0309** (7.37)	0.8790	0.9315	0.0525** (20.06)	0.8273	0.8335	0.0062* (2.24)
% >1	3.16%	2.77%		4.94%	9.58%		2.61%	2.54%	
λ	0.7849	0.8190	0.0341** (9.10)	0.8749	0.9268	0.0519** (21.99)	0.8262	0.8321	0.0059* (2.25)

Panel B: NASDAQ

	Quoted spread model			Effective spread model			Depth model		
	PRE	POST	Difference (t-value)	PRE	POST	Difference (t-value)	PRE	POST	Difference (t-value)
π	0.7780	0.8110	0.0330** (3.45)	0.8755	0.8922	0.0167** (4.88)	0.8575	0.8791	0.0216** (8.42)
% >1	6.24%	8.43%		9.39%	11.97%		7.96%	7.19%	
λ	0.7320	0.7755	0.0435** (5.01)	0.8668	0.8793	0.0125** (4.07)	0.8503	0.8738	0.0235** (10.35)

**Significant at the 1% level.
*Significant at the 5% level.

Table 5
Effects of decimalization on the speed of quote adjustment for NYSE stocks and NASDAQ stocks

This table shows the results of the following regression model:

$$\Delta\pi \text{ or } \Delta\lambda = \beta_0 + \sum_{i=1}^{5}\beta_i \Delta X_i + \beta_6 \Delta GKN/\Delta PM + \beta_7 \Delta PIN + \beta_8 \Delta INST + \beta_9 \Delta MM \text{ (NASDAQ stocks)} + \varepsilon$$

where Δ indicates the difference between the post- and pre-decimal values (post – pre), π is the partial adjustment coefficient estimated from the first-pass regression, λ is the quote adjustment speed, X_i (i = 1 to 5) is one of the five stock attributes (i.e., NTRADE, TSIZE, PRICE, RISK and MVE), Σ denotes the summation over i = 1 to 5, β_0 through β_9 are the regression coefficients, and ε is an error term. GKN denotes the adverse-selection component of the spread estimated from the method in George, Kaul and Nimalendran (1991), PM is the price impact of trades, PIN is the probability of information-based trading, INST is the percentage of shares held by institutions, and MM is the number of marketmakers for NASDAQ stocks. We estimate the model using the weighted regression procedure, in which the weight is the reciprocal of the standard error of the partial adjustment coefficient. Panel A shows the results for NYSE stocks and Panel B shows the results for NASDAQ stocks. In each panel, we show the regression results using π and λ values that are estimated from the quoted spread model, the effective spread model, and the quoted depth model. Numbers in parentheses are t-statistics.

Table 5 (continued)
Effects of decimalization on the speed of quote adjustment for NYSE stocks and NASDAQ stocks

Panel A: NYSE stocks

	Quoted spread model				Effective spread model				Depth model			
	Δ π	Δ π	Δ λ	Δ λ	Δ π	Δ π	Δ λ	Δ λ	Δ π	Δ π	Δ λ	Δ λ
Intercept	0.0438**	0.0332**	0.0434**	0.0335**	0.0750**	0.0774**	0.0749**	0.0774**	0.0281**	0.0101*	0.0280**	0.0102*
	(6.45)	(6.67)	(6.49)	(6.79)	(10.77)	(15.10)	(11.33)	(15.92)	(5.08)	(2.46)	(5.08)	(2.49)
Δ Log(NTRADE)	0.0501**	0.0337*	0.0494**	0.0341*	0.0577**	0.0510**	0.0539**	0.0464**	0.0522**	0.0245	0.0523**	0.0248
	(2.93)	(2.16)	(2.93)	(2.22)	(3.25)	(3.13)	(3.19)	(3.01)	(3.77)	(1.94)	(3.80)	(1.97)
Δ Log(TSIZE)	-0.0106	-0.0079	-0.0088	-0.0064	-0.0135	-0.0139	-0.0196	-0.0200	-0.0143	-0.0190*	-0.0139	-0.0185*
	(-0.95)	(-0.72)	(-0.81)	(-0.59)	(-1.21)	(-1.25)	(-1.84)	(-1.90)	(-1.57)	(-2.07)	(-1.53)	(-2.02)
Δ log(PRICE)	0.0264*	0.0171	0.0238	0.0152	0.0081	0.0191	0.0005	0.0299*	0.0254*	0.0406**	0.0250*	0.0402**
	(2.11)	(1.16)	(1.93)	(1.05)	(0.62)	(1.25)	(0.04)	(2.07)	(2.50)	(3.32)	(2.47)	(3.31)
Δ RISK	51.8183	38.0623	50.6392	37.8459	123.8706**	91.4105**	118.6882**	83.4843**	33.9816	56.1348*	31.5782	53.8305*
	(1.95)	(1.37)	(1.94)	(1.39)	(4.47)	(3.15)	(4.51)	(3.04)	(1.49)	(2.32)	(1.39)	(2.23)
Δ Log(MVE)	-0.0041	-0.0039	-0.0039	-0.0036	-0.0008	-0.0009	-0.0007	-0.0008	-0.0073*	-0.0070	-0.0072*	-0.0069
	(-0.95)	(-0.89)	(-0.91)	(-0.86)	(-0.19)	(-0.20)	(-0.17)	(-0.18)	(-2.07)	(-1.96)	(-2.05)	(-1.93)
Δ GKN	0.0860*		0.0800*		0.0030		0.0042		0.1458**		0.1447**	
	(2.25)		(2.13)		(0.08)		(0.11)		(4.62)		(4.61)	
Δ PM		0.0218		0.0207		0.7090**		0.7652**		-0.0535		-0.0471
		(0.09)		(0.09)		(2.89)		(3.29)		(-0.27)		(-0.24)
Δ PIN	0.0454**	0.0396*	0.0420*	0.0367*	0.0386*	0.0374*	0.0384*	0.0370*	0.0157	0.0058	0.0163	0.0065
	(2.66)	(2.34)	(2.50)	(2.20)	(2.22)	(2.19)	(2.32)	(2.28)	(1.12)	(0.42)	(1.17)	(0.47)
Δ INST	-0.0462	-0.0401	-0.0493	-0.0436	-0.0096	-0.0246	-0.0130	-0.0291	-0.0006	-0.0095	-0.0014	-0.0086
	(-1.07)	(-0.92)	(-1.16)	(-1.01)	(-0.22)	(-0.56)	(-0.31)	(-0.70)	(-0.02)	(-0.26)	(-0.04)	(-0.24)
F–value	2.10*	1.45	1.98*	1.41	4.47**	5.56**	5.06**	6.47**	7.91**	5.12**	7.83**	5.06**
Adjusted R^2	0.010	0.004	0.009	0.004	0.031	0.041	0.036	0.048	0.060	0.037	0.060	0.036

**Significant at the 1% level.
*Significant at the 5% level.

Table 5 (continued)
Effects of decimalization on the speed of quote adjustment for NYSE stocks and NASDAQ stocks

Panel B: NASDAQ stocks

	Quoted spread model				Effective spread model				Depth model			
	Δ π	Δ π	Δ λ	Δ λ	Δ π	Δ π	Δ λ	Δ λ	Δ π	Δ π	Δ λ	Δ λ
Intercept	0.0084*	0.0149**	0.0090*	0.0173*	0.0068	0.0080*	0.0041*	0.0029*	0.0408**	0.0398**	0.0394**	0.0387**
	(2.03)	(2.78)	(2.13)	(2.10)	(1.94)	(2.07)	(2.60)	(2.41)	(7.49)	(7.07)	(7.40)	(7.05)
Δ Log(NTRADE)	0.0857**	0.0782**	0.0858**	0.0744**	0.0715**	0.0691**	0.0618**	0.0634**	0.0281**	0.0242*	0.0261**	0.0223*
	(5.84)	(5.63)	(5.98)	(5.46)	(5.38)	(5.57)	(4.91)	(5.39)	(2.83)	(2.60)	(2.69)	(2.53)
Δ Log(TSIZE)	0.0280	0.0230	0.0261	0.0210	0.0091	0.0085	0.0100	0.0110	-0.0281*	-0.0280*	-0.0306*	-0.0303*
	(1.50)	(1.22)	(1.44)	(1.14)	(0.56)	(0.51)	(0.65)	(0.70)	(-2.32)	(-2.28)	(-2.59)	(-2.53)
Δ log(PRICE)	0.0196	0.0043	0.0193	0.0041	-0.0169	-0.0154	-0.0214	-0.0244	0.0490**	0.0473**	0.0509**	0.0488**
	(1.24)	(0.24)	(1.25)	(0.23)	(-1.20)	(-0.95)	(-1.60)	(-1.58)	(4.65)	(3.88)	(4.95)	(4.11)
Δ RISK	21.1798	21.9134	17.3969	17.8961	0.4466	0.3572	1.3678	1.1717	4.4146	4.2536	3.1905	3.0104
	(1.83)	(1.90)	(1.54)	(1.58)	(0.04)	(0.04)	(0.14)	(0.12)	(0.59)	(0.57)	(0.44)	(0.41)
Δ Log(MVE)	-0.0010	-0.0021	-0.0007	-0.0014	0.0014	0.0014	0.0008	0.0010	-0.0043	-0.0038	-0.0039	-0.0035
	(-0.25)	(-0.51)	(-0.18)	(-0.35)	(0.38)	(0.38)	(0.23)	(0.29)	(-1.58)	(-1.38)	(-1.49)	(-1.29)
Δ GKN	0.0104		0.0399		0.0141		0.0033		0.0343		0.0292	
	(0.27)		(1.04)		(0.35)		(0.09)		(1.19)		(1.04)	
Δ PM		0.3874		0.3635		0.0245		0.0729		-0.0731		-0.0778
		(1.64)		(1.57)		(0.12)		(0.37)		(-0.47)		(-0.52)
Δ PIN	-0.0315	-0.0310	-0.0320	-0.0312	0.0006	0.0008	0.0045	0.0044	-0.0113	-0.0111	-0.0116	-0.0114
	(-1.40)	(-1.38)	(-1.45)	(-1.42)	(0.03)	(0.04)	(0.24)	(0.24)	(-0.77)	(-0.76)	(-0.81)	(-0.80)
Δ INST	0.0101	0.0203	0.0092	0.0182	0.0555	0.0556	0.0519	0.0500	0.0589	0.0561	0.0592	0.0564
	(0.18)	(0.36)	(0.17)	(0.33)	(1.11)	(1.10)	(1.09)	(1.05)	(1.60)	(1.51)	(1.65)	(1.56)
Δ MM	0.0124	0.0132	0.0131	0.0104	0.0107	0.0096	0.0145	0.0144	0.0399**	0.0363**	0.0375**	0.0564
	(0.83)	(0.93)	(0.90)	(0.75)	(0.82)	(0.76)	(1.17)	(1.20)	(4.10)	(3.86)	(3.95)	(1.56)
F–value	5.54**	5.85**	5.19**	5.36**	4.41**	4.40**	4.20**	4.22**	6.38**	6.23**	6.59**	6.49**
Adjusted R^2	0.043	0.046	0.040	0.041	0.033	0.033	0.031	0.031	0.051	0.049	0.052	0.052

**Significant at the 1% level.
*Significant at the 5% level.