Volatility, Market Structure, and Liquidity[#]

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Abstract

We test the conjecture that the specialist system on the New York Stock Exchange (NYSE) provides more resilient liquidity services than the NASDAQ dealer market for riskier stocks and in times of high return volatility when adverse selection and inventory risks are high. We motivate our conjecture from the observation that there is a designated specialist for each stock on the NYSE who is directly responsible for maintaining a reasonable level of liquidity at all times as the 'liquidity provider of last resort,' whereas there is no such designated dealer on NASDAQ. Empirical evidence is consistent with our conjecture.

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“The possibility that liquidity might disappear from a market, and so not be available when it is needed, is a big source of risk to an investor.” – (The Economist, September 23, 1999)

1. Introduction

Volatility and liquidity are two key attributes of securities markets. Return volatility intrigues both financial economists and investors for a number of reasons. For instance, return volatility changes over time, affects expected stock returns through risk premiums, and determines asset prices. Figure 1 shows the average daily standard deviation of quote-midpoint returns for our study sample of stocks from November 3, 1997 through December 31, 2003. Temporal variation in return volatility is both substantial and dramatic. Market participants care about liquidity because it affects trading costs, stock returns, and the informational efficiency of asset price. Although prior research sheds significant light on volatility and liquidity as separate attributes of the securities markets, the relation between the two measures has received limited attention. In this study we examine how volatility affects liquidity through its impact on the behavior of liquidity suppliers. In particular, we investigate how the impact of volatility on liquidity varies with market structure.

The effect of market structure on liquidity provision and trading costs has been the subject of numerous scholarly endeavors and regulatory investigations. A number of studies compare trading costs between stocks traded on the New York Stock Exchange (NYSE) and on NASDAQ. Huang and Stoll (1996), Bessembinder and Kaufman (1997), Bessembinder (1999), and Chung, Van Ness, and Van Ness (2001) compare trading costs between these two groups of stocks. These studies generally show that traders on NASDAQ pay larger spreads than traders on the NYSE, although some recent studies (see, e.g., Bessembinder, 2003b; Chung, Van Ness, and Van Ness, 2004) show that the results vary with the averaging method. Venkataraman (2001) compares execution costs in an automated trading structure (Paris Bourse) and a floor-based trading structure (NYSE) and shows that execution costs are higher in Paris.

Barclay (1997) finds a significant reduction in spreads when stocks move from NASDAQ to the NYSE. Garfinkel and Nimalendran (2003) examine the degree of anonymity (i.e., the extent to which a trader is recognized as informed) in alternative market structures. They show that there is less anonymity on the NYSE specialist system compared to the NASDAQ dealer system. Heidle and Huang (2002) examine the impact of market structure on the probability of trading with an informed trader and show that the probability of information-based trading is higher on NASDAQ than on the NYSE.

In the present study we perform detailed empirical analyses of how market structure moderates the effects of return volatility on liquidity (bid-ask spreads). Although prior research shows that NASDAQ spreads are on average larger than NYSE spreads, this finding is frequently based on a limited study period of a few weeks to several months because of the enormity of market microstructure data. Also, prior research does not take into consideration the effect of return volatility on the liquidity provision capacity of NYSE specialists and NASDAQ dealers. In this study, we examine such effects.

We test the conjecture that the specialist system on the NYSE provides more resilient liquidity services than the NASDAQ dealer market, particularly for riskier stocks and in times of high return volatility when adverse selection and inventory risks are high.[1] We use data covering more than six years of a large sample of NYSE and NASDAQ stocks. We motivate our conjecture from the observation that there is a designated specialist for each stock on the NYSE who is directly responsible for maintaining a reasonable level of liquidity at all times whereas there is no such designated dealer on NASDAQ. Although there are at least two registered dealers in any NASDAQ stock, no one is in charge of a particular stock. Dealers and public traders may provide adequate liquidity services in normal circumstances. However, they may shy away from liquidity

[1] Prior research shows that both the adverse selection and inventory risks increase with return volatility. See, for example, Stoll (1978) and Stoll (2000).

services in times of high uncertainty and for riskier stocks because there are no regulatory rules that inhibit them from doing so.[2]

Section 11(b) of the Exchange Act, Rule 11b-1 states

> *"Requirements, as a condition of a specialist's registration, that a specialist engage in a course of dealings for his own account to assist in the maintenance, so far as practicable, of a fair and orderly market, and that a finding by the exchange of any substantial or continued failure by a specialist to engage in such a course of dealings will result in the suspension or cancellation of such specialist's registration in one or more of the securities in which such specialist is registered"*

Under Rule 11b-1, specialists have an affirmative obligation to maintain a market presence as well as a fair and orderly market. This obligation requires specialists to provide liquidity when the level of liquidity provided by public traders is inadequate. Indeed, Madhavan and Sofianos (1998) find that specialist participation rate in trading is inversely related to both trading activity and proxies for internal and external competition, and positively related to spreads, indicating that specialists participate more when liquidity is lower. Similarly, Chung, Van Ness, and Van Ness (1999) show that specialists frequently provide liquidity to low-volume stocks when there are no limit orders or when spreads established by limit orders submitted by public traders are too wide. To ensure compliance with the affirmative obligation, the NYSE evaluates the specialists' performance on two measures: whether they maintain narrow spreads and meaningful depths; and whether they provide continuous prices and price stabilization. Poor performance may result in fines, loss of assigned stocks, and ineligibility for new stock allocations.

Although NASDAQ dealers are subject to the rule of best execution, their obligation with respect to liquidity provision is much more lenient.[3] The Limit Order Display Rule requires

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[2] Li, McCormick, and Zhao (2005) show that NASDAQ dealers provide liquidity during extreme return days. However, their study does not compare the NYSE specialist and NASDAQ dealer systems.

[3] NASD rule 2320 provides that a member and persons associated with a member shall use reasonable diligence to ascertain the best inter-dealer market for a security and buy or sell in such market so that the resultant price to the customer is as favorable as possible under prevailing market conditions. Whether a member exercised reasonable diligence to ascertain the best inter-dealer market for the security and bought or sold in that market involves a facts-and-circumstances analysis. Courts have held that the duty of best

NASDAQ dealers to reflect in their quotes the price and size of customer limit orders that would improve upon or equal their bid or offer. However, there is no explicitly stipulated dealer obligation to maintain liquid *inside* markets. The only explicit obligation imposed on dealers by the NASD is that they make two-sided (i.e., bid *and* ask) firm quotes in each security in which they make a market.[4]

Although dealers are required to quote on both sides, evidence suggests that they tend to post competitive quotes (i.e., inside market quotes) on only one side.[5] They are *not* obligated, either collectively or individually, to maintain fair and orderly inside markets as specialists on the NYSE are required to do. Although there may be an implicit presumption among dealers that they should provide reasonable inside market quotes, none of them has direct individual responsibility to do so. Hence, even when the level of liquidity provided by public traders and electronic communications networks (ECNs) is low during high volatility periods and/or for high-risk stocks,[6] NASDAQ dealers may not step up and narrow the inside spread due to the problem of free riding or social loafing.[7]

The common practice of order preferencing for NASDAQ stocks may affect dealer quotation behavior as well. Chung, Chuwonganant, and McCormick (2004) show that a large

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execution requires that a broker/dealer seek to obtain for its customers' orders the most favorable terms reasonably available under the circumstances.

[4] The NASD is the self-regulatory organization of the securities industry responsible for the regulation of the NASDAQ Stock Market and the over-the-counter markets. The NASD operates under the 1938 Maloney Act Amendment to the Securities Exchange Act of 1934.

[5] See, for example, Chan, Christie, and Schultz (1995). Chung and Zhao (2004) also show that NASDAQ dealers frequently quote the minimum required depth (100 shares) when they post noncompetitive price quotes.

[6] Prior research theoretically predicts and finds evidence of the reduction of liquidity provision by limit order traders during times of excessive price uncertainty and adverse selection risk. See, for example, Rock (1990), Grossman (1992) and Seppi (1997) for theoretical predictions, and Lee, Mucklow, and Ready (1993), Bremer, Hiraki, and Sweeney (1997), Kavajecz (1999), Corwin and Lipson (2000), and Goldstein and Kavajecz (2004) for empirical results.

[7] These two terms describe the same basic phenomenon except that the first is an economics term and the second is a social science term. Both terms refer to the observation that people tend to contribute less to a common effort when they are in groups than they do to their individual efforts. When a group of people share the pressure and responsibility, the impact gets divided, and each of them is only faced with a portion of it. As a result, they do not feel as much pressure to perform well as when one person does it alone (see Latane, Williams, and Harkins, 1979).

portion of orders on NASDAQ are preferenced. To the extent that preferenced orders are captive orders that are less likely to be affected by quote aggressiveness than unpreferenced orders, NASDAQ dealers may have little incentives to improve exiting quotes for stocks with large preferenced orders, especially in times of high return volatility and for riskier stocks.

Prior research shows that stock returns and the cost of capital are related to liquidity or return sensitivity to market liquidity (see, e.g., Amihud and Mendelson, 1986, 1989; Amihud, 2002; Pastor and Stambaugh, 2003; Acharya and Pedersen, 2005). Studies also show that the level of stock price is related to return volatility. For example, Haugen, Talmor, and Torous (1991) show that share price declines significantly prior to an increase in return volatility. Schwert (1989) analyzes the relation between return volatility and select macro and micro variables, and concludes that the magnitude of the fluctuations in aggregate stock volatility is difficult to explain based on simple models of stock valuation. However, prior research provides little insight on how volatility affects liquidity provisions and whether market structure plays any role. In this study, we shed some light on these issues.

We take several approaches to analyze how market structure affects the impact of return volatility on liquidity. In the first approach, we classify a large sample of NYSE and NASDAQ stocks into different volatility groups on each day so that each volatility group contains a reasonable number of NYSE and NASDAQ stocks similar in return volatility. We then conduct both cross-sectional and time-series regression analyses to determine whether the difference in spreads between NYSE and NASDAQ stocks is systematically related to return volatility across volatility groups and over time. In the second approach, we calculate the monthly mean volatility of NYSE and NASDAQ stocks and identify both a month with low volatility and a month with high volatility. We then determine whether the difference between the mean NYSE and NASDAQ spreads is significantly greater during the high volatility month. In the third approach, we conduct an event study using data during a time of extreme uncertainty, i.e., surrounding the September 11, 2001 attack. Here, we examine whether the NYSE and NASDAQ responded differently to this extreme event.

Our empirical results lead us to a clear conclusion. The results from all three approaches indicate that the difference in spreads between NASDAQ and NYSE stocks is larger for riskier stocks and in volatile periods. These results are unlikely to be driven by differences in stock characteristics between the two sample groups because we control for such differences in our study. These results are consistent with our thesis that the NYSE specialist system provides more resilient liquidity services than the NASDAQ dealer system for riskier stocks and in volatile periods.

Prior research shows that stocks traded on NASDAQ generally exhibit larger spreads than stocks traded on the NYSE. Researchers have suggested that these results are due to a number of factors, including order preferencing, anticompetitive dealer behavior, and natural quote clustering, among others. Our study provides an alternative explanation: the designated versus non-designated market maker systems. Our results also suggest that the specialist system may serve traders better than pure electronic limit order markets in high volatility periods and for riskier stocks, providing a sound economic rationale for recent discussions in Asian securities markets on whether they should incorporate human intermediation into their otherwise fully automated trading systems.

The remainder of the paper is organized as follows. Section 2 describes data source, variable measurement procedures, and summary statistics. Section 3 presents the results of cross-sectional and time-series regression analyses. Section 4 presents the results of NYSE-NASDAQ spread comparisons during the months of low and high return volatility. Section 5 presents the results of the 9/11 analyses. Section 6 discusses some other possible explanations of our results. Section 7 concludes.

2. Data sources, the measurement of variables, and descriptive statistics

We obtain data from the NYSE's Trade and Quote (TAQ) database. We use the trade and quote data for the seven-year period from November 1997 to December 2003. We use only trades and quotes on the NYSE in NYSE-listed stocks and trades and quotes on both NASDAQ and ECNs (except for 2003) in NASDAQ-listed stocks.[8] We select November 1997 as the first month of our study period in consideration of data homogeneity. On June 2, 1997, the minimum price variation (i.e., tick size) on NASDAQ was reduced from $1/8 to $1/16 for stocks selling at prices greater than or equal to $10. In addition, the Securities and Exchange Commission (SEC) enacted major changes in order handling rules on NASDAQ from January 20, 1997 through October 13, 1997. The new rules allow greater competition between liquidity providers (dealers and public traders) in the quote-setting process. We use data after the implementation of these rule changes.[9]

We omit the following trades and quotes to minimize data errors: quotes with an ask or bid price less than or equal to zero; quotes with an ask or bid size less than or equal to zero; quotes with bid-ask spreads greater than $5 or 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 $|(p_t - p_{t-1})/p_{t-1}| > 0.1$; ask price, a_t, if $|(a_t - a_{t-1})/a_{t-1}| > 0.1$; and bid price, b_t, if $|(b_t - b_{t-1})/b_{t-1}| > 0.1$.

We calculate daily values of the following variables for each NYSE and NASDAQ stock (stock i on day t): share price as measured by the mean value of quote midpoints ($PRICE_{it}$); number of trades ($NTRADE_{it}$); average dollar trade size ($TSIZE_{it}$); return volatility as measured by the standard deviation of quote-midpoint returns ($VOLA_{it}$); and market capitalization as measured by the market value of equity (MVE_{it}).[10]

For each *trade*, we calculate the dollar and percentage effective spreads using the following formulas: \$ESPRD = 2|P – M| and %ESPRD = 2|P – M|/M, where P is the transaction price and M

[8] All ECN quotes and dealer quotes are reported with the exchange code "T" in the TAQ database until 2002. Hence, it is not possible to distinguish between dealer quotes and ECN quotes during most of our study period.

[9] We drop data from January 2001 to April 2001 from the study sample because both the NYSE and NASDAQ went through decimalization during this period.

[10] We obtain the number of shares outstanding from the CRSP. We calculate the market value of equity by multiplying the number of shares outstanding with the daily average quote mid-points.

is the midpoint of the most recently posted bid and ask quotes.[11] The effective spread measures the actual execution cost paid by the trader. For each *quote*, we calculate the dollar and percentage quoted spreads using the following formulas: \$QSPRD = (A − B) and %QSPRD = (A − B)/M, where A and B are the ask and bid prices, respectively. We then calculate for stock i on day t the trade-weighted average dollar and percentage effective spreads ($\$ESPRD_{it}$ and $\%ESPRD_{it}$) and the time-weighted average dollar and percentage quoted spreads ($\$QSPRD_{it}$ and $\%QSPRD_{it}$).

Table 1 shows descriptive statistics for our study sample of 1,924 NYSE stocks and 1,524 NASDAQ stocks that have the complete data required for our empirical analyses. The average share price is \$21.27 for the NYSE sample and \$19.17 for the NASDAQ sample. The average trade size and average daily number of transactions are \$21,100 and 271 for the NYSE sample, and \$13,700 and 597 for the NASDAQ sample. The average standard deviation of quote-midpoint returns is 0.2091 for the NYSE sample and 0.3149 for the NASDAQ sample. The average market capitalizations for our NYSE and NASDAQ stocks are \$2,383 million and \$717 million, respectively. The average dollar effective (quoted) spread of NYSE stocks is 10.23 (12.83) cents, while the corresponding figure for NASDAQ stocks is 15.64 (18.74) cents. The average percentage effective (quoted) spread of NYSE stocks is 0.6909% (0.8755%), while the corresponding figure for NASDAQ stocks is 1.1786% (1.3761%). On the whole, NYSE stocks have higher share prices, larger trade sizes, and larger market capitalizations, but smaller spreads, fewer trades, and lower return volatilities.

3. Empirical analyses and findings

This section presents the results of cross-sectional and time-series regression analyses, NYSE-NASDAQ matched-sample comparisons of trading costs, and the 9/11 event study.

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[11] We use quotes that are at least two seconds older than the trade. Bessembinder (2003a) assesses the sensitivity of trading cost estimates derived from publicly-available trade and quote data to two methodological issues: the time adjustment made before comparing trades to quotes, and the procedure used to designate trades as buyer or seller-initiated. He shows that inference as to whether the NASDAQ dealer market or the NYSE auction market provides lower trade execution costs is not sensitive to these methodological issues.

3.1. Volatility groups

To test our conjecture that the NYSE specialist system provides more resilient liquidity services than the NASDAQ dealer system for riskier stocks and in high volatility periods, we rank our study sample of NYSE and NASDAQ stocks according to return volatility on each day. We then cluster the stocks into 100 groups, where Group 1 consists of stocks with the lowest volatility and Group 100 consists of stocks with the highest volatility. By construction, the number of NYSE stocks and the number of NASDAQ stocks are different in any volatility group as well as across groups and days, although the total number of NYSE and NASDAQ stocks is approximately the same across groups on any given day. The total number of NYSE and NASDAQ stocks in each volatility group differs across days because the number of NYSE and NASDAQ stocks in the TAQ database varies over time. To ensure that each volatility group has a fair representation of both NYSE and NASDAQ stocks, we drop a volatility group from the study sample on each day if either NYSE or NASDAQ stocks constitute less than 20% of the stocks in the volatility group.[12]

Table 2 shows the mean volatility of stocks in Group 10, Group 20, through Group 100, together with the proportion of NASDAQ stocks in each group and the mean values of the variables included in Table 1. For each trading day, we calculate the mean volatility of stocks in each group using two different methods. In the first method, we first calculate the mean volatility of NYSE stocks and the mean volatility of NASDAQ stocks in each group. We then calculate the average of the two mean volatilities, i.e., $MVOLA_{jt}$ = (1/2)(Mean volatility of NYSE stocks in group j on day t + Mean volatility of NASDAQ stocks in group j on day t). In the second method, we calculate the mean volatility of all stocks (NYSE and NASDAQ) in each group, i.e., $MVOLA_{jt}^{S} = (1/N)\sum VOLA_{it}$, where $VOLA_{it}$ is the return volatility of stock i (stock i belongs to group j) on day t. We employ these two averaging methods to assess the sensitivity of our results to averaging methods, given the fact that the proportion of NASDAQ stocks varies almost monotonically across

[12] To check the robustness of our results, we vary the minimum proportion of NASDAQ or NYSE stocks to 5%, 10%, and 35%. Overall, our main results remain the same.

volatility groups. Table 2 shows the time-series mean values of $MVOLA_{jt}$ and $MVOLA_{jt}^{S}$ for groups 10 through 100. We use the second method to calculate the time-series mean values of all other variables (i.e., PRICE, NTRADE, TSIZE, $ESPRD, $QSPRD, %ESPRD, %QSPRD, and MVE).

The results show that the values of $MVOLA_{jt}$ and $MVOLA_{jt}^{S}$ are almost identical within each volatility group, indicating that different averaging methods have little effect. The proportion of NASDAQ stocks generally increases with return volatility, reflecting the fact that NASDAQ stocks have, on average, a higher return volatility than NYSE stocks. Table 2 also shows that stocks with higher return volatilities have smaller trade sizes, fewer trades, lower prices, larger effective and quoted spreads, and smaller market capitalizations.

Figure 1 shows the time-series pattern of return volatility for our entire study sample of stocks and Figure 2 shows the time-series patterns of return volatility for groups 30, 50, and 70. Although there has been a gradual decline in average volatility during our study period, both figures show significant inter-temporal (daily) variations in return volatility. We also note that the overall time-series pattern is quite similar across volatility groups, with somewhat greater variation for riskier groups.

3.2. Cross-sectional regressions

We now test whether the difference in spreads between NASDAQ stocks and NYSE stocks is positively related to return volatility. Our focus here is to find out whether the difference between NASDAQ and NYSE spreads is particularly prominent for riskier stocks. Specifically, we estimate the following regression model using cross-sectional data (across group j) on each day:

$$\$ESPRD_{jt}^{NASD} - \$ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}; \qquad (1)$$

where $\$ESPRD_{jt}^{NASD}$ is the mean dollar effective spread of NASDAQ stocks in group j on day t, $\$ESPRD_{jt}^{NYSE}$ is the mean dollar effective spread of NYSE stocks in group j on day t, $MVOLA_{jt}$ is the mean volatility of (NYSE and NASDAQ) stocks in group j on day t, and Xs are the four stock attributes (i.e., log(NTRADE), log(TSIZE), PRICE, and VOLA).[13] We include these four variables as control variables to account for the possibility that the difference between the NYSE and NASDAQ spreads is due to differences in their attributes.[14] Although we form groups in such a way that stocks in each group are similar in return volatility, difference in return volatility could remain between the NYSE and NASDAQ stocks in each group. We include the difference in VOLA between NYSE and NASDAQ stocks as a control variable to remove the effects (if any) of differential volatilities on differential spreads. We also estimate the above model using $\$QSPRD_{jt}^{NASD} - \$QSPRD_{jt}^{NYSE}$ as the dependent variable.

Similarly, we estimate the model using the percentage spread:

$$\%ESPRD_{jt}^{NASD} - \%ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}; \qquad (2)$$

where $\%ESPRD_{jt}^{NASD}$ is the mean percentage effective spread of NASDAQ stocks in group j on day t, $\%ESPRD_{jt}^{NYSE}$ is the mean percentage effective spread of NYSE stocks in group j on day t, $MVOLA_{jt}$ is the mean volatility of (NYSE and NASDAQ) stocks in group j on day t, and Xs are the four stock attributes (i.e., log(TSIZE), log(NTRADE), 1/PRICE, and VOLA). We also estimate the above model using the percentage quoted spread ($\%QSPRD_{jt}^{NASD} - \%QSPRD_{jt}^{NYSE}$) as the dependent variable.

Table 3 shows the regression results. Because we estimate the regression models above using cross-sectional data for each day, we report the mean value of daily regression coefficients

[13] Trading volume reported for NASDAQ stocks is overstated vis-à-vis NYSE stocks, due to both the dealer's participation in trades as a market maker and inter-dealer trading. Prior research addresses this issue by using an adjustment factor of about 30-50% to make the trading volumes reported by the two exchanges comparable (see, e.g., Chung, Van Ness, and Van Ness, 2001). Such adjustment is not necessary in our regression model. To see this point, suppose that we inflate NYSE volume by 30% to make it comparable to NASDAQ volume. Then, $\beta_t[\log(NTRADE_{jt}^{NASD}) - \log((1.3)NTRADE_{jt}^{NYSE})] = \beta_t[\log(NTRADE_{jt}^{NASD}) - \log(NTRADE_{jt}^{NYSE})] - \beta_t\log(1.3)$. Hence, the volume adjustment changes only the regression intercept. For this reason, we do not make the volume adjustment.

[14] 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.

and its t-statistic for each variable and the mean adjusted R^2. To the extent that the absolute magnitudes of the dependent or independent variables are different across days, estimated regression coefficients are not directly comparable across days. For example, all things being equal, we expect to obtain smaller regression coefficients for log($MVOLA_{jt}$) on those days with larger log($MVOLA_{jt}$). To make regression coefficients comparable across days, we calculate elasticity estimates by dividing regression coefficients for log($MVOLA_{jt}$) by respective mean spreads (i.e., M$ESPRD, M$QSPRD, M%ESPRD, and M%QSPRD).[15]

The results show that the difference in the dollar effective spread between NASDAQ and NYSE stocks is positively and significantly related to MVOLA, indicating that the difference between NASDAQ and NYSE spreads is larger for riskier stocks, after controlling for differences in stock attributes between NYSE and NASDAQ stocks. We obtain qualitatively similar results from the difference in the dollar quoted spread, the percentage effective spread, and the percentage quoted spread between NASDAQ and NYSE stocks, respectively. These results are consistent with our conjecture that NYSE specialists provide better liquidity services than NASDAQ dealers for riskier stocks.

The results show that estimated regression coefficients for control variables are all significant (with an exception of $dVOLA = VOLA^{NASD} - VOLA^{NYSE}$) and have expected signs, indicating that at least a part of the variation in the differential spreads between NASDAQ and NYSE stocks across volatility groups is due to their differential characteristics. The fact that estimated regression coefficients for dVOLA are mostly insignificant indicates that variation in the differential spreads between NASDAQ and NYSE stocks across volatility groups is not likely to be driven by differences in return volatility within each group.

Given the finding that NYSE specialists provide better liquidity services than NASDAQ dealers for *riskier stocks*, we conjecture that this phenomenon would be more prominent *in high*

[15] In regression models (1) and (2), β_{1t} measures changes in differential spreads in response to a 1% change in $MVOLA_{jt}$. By dividing β_{1t} by the mean spreads, we obtain elasticity estimates, i.e., % change in differential spreads (as a fraction of the mean spreads), given a 1% change in the mean volatility.

volatility periods. To test this conjecture, we classify each trading day during our study period (November 1997 through December 2003) as high, medium, or low volatility days according to the average volatility of all stocks (NASDAQ and NYSE) on each day, resulting in 484 low volatility days, 498 medium volatility days, and 485 high volatility days. Table 4 shows the mean value of daily regression coefficients, its t-statistic, and the mean adjusted R^2 for each of the three volatility periods, and Table 5 shows whether the mean elasticity with respect to log(MVOLA) differs significantly between low, medium, and high volatility periods.

Table 4 shows that both the estimated regression coefficients for log(MVOLA) and elasticity estimates are positive and significant during all three volatility periods, with the exception of Model 1 (the dollar effective spread) for the low volatility period. This result is generally consistent with the result from the whole sample. More importantly, Table 5 shows that the mean elasticity with respect to log(MVOLA) differs significantly between low, medium, and high volatility periods. Panel A shows that the mean elasticity during the medium volatility period is significantly greater than the mean elasticity during the low volatility period in all four spread models. Likewise, Panel B and Panel C show that the mean elasticity during the high volatility period is significantly greater than the mean elasticity during the medium and low volatility periods. Overall, these results support our conjecture that the NYSE specialist system provides better liquidity services than the NASDAQ dealer system for riskier stocks, particularly in high volatility periods.

3.3. Comparison of elasticity between the pre- and post-decimal periods

The NYSE converted all 3,525 listed issues to decimal pricing on January 29, 2001, after three pilot implementations during the second half of 2000.[16] The NASDAQ Stock Market began its decimal test phase with 14 securities on March 12, 2001, followed by another 197 securities on

[16] The NYSE initiated a pilot decimalization program on August 28, 2000 with seven listed issues, followed by 57 issues on September 25, 2000, and 94 issues on December 4, 2000.

March 26, 2001. All remaining NASDAQ securities converted to decimal trading on April 9, 2001. To test whether the results differ between the pre- and post-decimal periods, we compare the mean elasticity during the pre-decimal period (from November 1997 through December 2000) with the mean elasticity during the post-decimal period (from May 2001 through December 2003).[17]

The results show that both the estimated regression coefficients for log(MVOLA) and elasticity estimates are positive and significant in all spread models during both the pre- and post-decimal periods (except for model 1 during the post-decimal period).[18] Furthermore, we find that the mean elasticity with respect to log(MVOLA) differs significantly between the two periods. The mean elasticity for the pre-decimal period is significantly greater than the mean elasticity for the post-decimal period in all four spread models. Given the fact that return volatility during the pre-decimal period is higher on average than return volatility during the post-decimal period (see Figure 2 and 3), these results are consistent with our conjecture that the NYSE specialist system provides better liquidity services than the NASDAQ dealer systems for riskier stocks, particularly in times of high volatility.[19]

3.4. Time-series regressions

The cross-sectional regression analyses in the previous sections focus on whether the difference in spreads between NYSE and NASDAQ stocks is larger for riskier stocks *at a point in time* (e.g., on a given day). In this section, we examine whether the difference in spreads between NYSE and NASDAQ stocks is larger on *high volatility days* by looking at the inter-temporal

[17] Tick size is an important protocol of securities markets in that it affects trading costs and market quality. Tick size affects trading costs because it could be a binding constraint on absolute spreads. Also, tick size affects market quality because it limits the prices that dealers and traders can quote, thus restricting price competition.

[18] For space consideration, we do not report these results in the paper. The results are available from the authors upon request.

[19] The Securities and Exchange Commission (SEC) adopted Rule 11Ac1-5 in 2000 to spur more competition among market centers. To the extent that the rule gives broker-dealers and investors meaningful information on execution quality, market centers are expected to attract order flow by providing superior execution. However, it is difficult to disentangle the effect of Rule 11Ac1-5 from the effect of decimal pricing because the SEC initially mandated the rule from April 2001, which coincides with the timing of decimal pricing.

relation between the differential spread and return volatility. For this, we estimate regression models (1) and (2) using time-series data for *each* volatility group.[20] We also estimate these models using $\$QSPRD_{jt}^{NASD} - \$QSPRD_{jt}^{NYSE}$ and $\%QSPRD_{jt}^{NASD} - \%QSPRD_{jt}^{NYSE}$ as the dependent variable.

Table 6 shows the regression results. Because we estimate the above regression models using daily time-series data for each volatility group, we report the mean value (across volatility groups) of regression coefficients and its t-statistic for each variable and the adjusted R^2. As in Table 3, we also calculate elasticity estimates. The results show that the difference in spreads between NASDAQ and NYSE stocks is positively and significantly related to MVOLA, indicating that the difference between NASDAQ and NYSE spreads is larger in times of higher uncertainty, after controlling for differences in stock attributes between NYSE and NASDAQ stocks. These results support our conjecture that NYSE specialists provide better liquidity services than NASDAQ dealers in high volatility periods.[21]

Given the result that NYSE specialists provide better liquidity services than NASDAQ dealers in high volatility periods, we propose that this pattern would be more prominent for riskier stocks. To test this conjecture, we classify each volatility group into high, medium, or low volatility portfolio based on the value of $MVOLA_{jt}$ on each trading day.[22] Table 7 shows the mean value of

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[20] We require that the number of time-series observations for a volatility group should be at minimum 75% of the entire trading days in our sample period, i.e., 0.75 x 1,467 days = 1,100 days. For time series analysis, volatility groups 32 through 87 pass the sample requirements. As mentioned in section 3, we require that a volatility group contains at least 20% of its stocks from both the NYSE and NASDAQ. For a robustness check, we vary the minimum proportion of NYSE or NASDAQ stocks to 5%, 10%, and 35%. For each minimum proportion, we also vary the requirement on the number of time-series observation of stocks to 60%, 75%, 80%, and 90% of entire trading days in our sample period. The results are qualitatively identical.

[21] The results show that estimated regression coefficients for control variables are mostly significant (with an exception of dVOLA) and have expected signs, indicating that at least a part of the variation in the differential spreads between NASDAQ and NYSE stocks over time is due to inter-temporal variation in their characteristics. The fact that estimated regression coefficients for dVOLA are mostly insignificant indicates that the variation in the differential spreads between NASDAQ and NYSE stocks across days is not likely to be driven by differences in return volatility over time.

[22] We form three portfolios of volatility groups according to the time-series average volatility of each group. The high volatility portfolio consists of volatility groups 68 and above, the medium volatility portfolio consists of volatility groups between groups 50 and 67, and the low volatility portfolio consists of volatility groups below group 50.

daily regression coefficients, its t-statistic, and the mean adjusted R^2 for each of the three volatility portfolios, and Table 8 shows whether the mean elasticity with respect to log(MVOLA) differs significantly between the low, medium, and high volatility portfolios.

Table 7 shows that both the estimated regression coefficients for log(MVOLA) and elasticity estimates are positive and significant for all three volatility portfolios. This result is generally consistent with the results from the whole sample. More importantly, Table 8 shows that the mean elasticity with respect to log(MVOLA) differs significantly between low, medium, and high volatility portfolios. Panel A shows that the mean elasticity for the medium volatility portfolio is significantly greater than the mean elasticity for the low volatility portfolio in spread models 2, 3, and 4. Likewise, Panel B and Panel C show that the mean elasticity for the high volatility portfolio is significantly greater than the mean elasticity for the medium or low volatility portfolio. Overall, these results support our conjecture that the NYSE specialist system provides better liquidity services than the NASDAQ dealer system in times of high uncertainty, particularly for risky stocks.

4. Implications for inter-market comparison study

Numerous studies compare trading costs between NYSE and NASDAQ stocks using sample data for a specific study period, which typically spans a few weeks to several months. Our findings in the previous section suggest that the results of such inter-market comparison studies could be sensitive to the selection of particular study periods. Specifically, the relative magnitudes of trading costs on the NYSE and NASDAQ can differ substantially, depending on whether the chosen study period was a high or low volatility period. We expect to observe larger differences between NASDAQ and NYSE spreads during high volatility periods, and little or no difference during low volatility periods.

To test our conjecture, we conduct matching-sample comparisons of NYSE and NASDAQ spreads using data drawn from two months that differ significantly in return volatility but not in average spreads. We choose October 1998 as the high volatility month and July 2000 as the low volatility month. Although there is a significant difference in return volatility between the two months, the difference in mean effective spreads is quite small (see Figure 3). For each month, we match a NASDAQ stock with a NYSE stock in terms of four stock attributes, i.e., trade size, share price, return volatility, and market capitalization. To obtain a matching pair, we calculate the matching score for a NASDAQ stock against each NYSE stock in our sample: $\Sigma[(X_k^{NASD} - X_k^{NYSE})/\{(X_k^{NASD} + X_k^{NYSE})/2\}]^2$, where X_k denotes the *k*th stock attribute (k = 1, 2, 3, and 4) and Σ denotes the summation over *k*. We select, for each NASDAQ stock, the NYSE stock with the smallest matching score. We use the above procedure to obtain 506 matching pairs of NYSE and NASDAQ stocks for October 1998, and 509 matching pairs for July 2000. The maximum matching scores are 0.20 for October 1998 and 0.17 for July 2000, which result in similar numbers of matching pairs between the high and low volatility months.

The matching pairs of NYSE and NASDAQ stocks in each month are similar in their characteristics. For the high volatility month, the mean share price, return volatility, trade size, and market capitalization of NYSE (NASDAQ) stocks are \$19.53 (\$20.19), 0.3576 (0.3948), \$24,600 (\$24,000), and \$992 (\$992), respectively. The corresponding figures for the low volatility month are \$21.49 (\$23.06), 0.2935 (0.3009), \$19,300 (\$17,900), and \$969 (\$975), respectively.

Table 9 shows the mean effective and quoted spreads of NASDAQ stocks and NYSE stocks, respectively, together with the mean differences between NASDAQ and NYSE spreads ($SPRD^{NASD} - SPRD^{NYSE}$) in each month. Table 9 also shows the difference in ($SPRD^{NASD} - SPRD^{NYSE}$) between the high and low volatility months in the third row of each panel. The last two columns report t-statistics for testing the equality of two means and the p-value for the Wilcoxon rank-sum test. The results show that the mean NASDAQ effective and quoted spreads are all significantly larger than the mean NYSE effective and quoted spreads during the high volatility month of October 1998. We find similar results for the low volatility month of July 2000, with an exception of %QSPRD. More importantly, the differences in spreads between NASDAQ and NYSE stocks in October 1998 (i.e., high volatility month) are all significantly greater than the corresponding figures in July 2000 (i.e., low volatility month) according to both the t-test and Wilcoxon rank-sum test.[23] These results are consistent with our expectation that the results of inter-market comparisons can be sensitive to sample period selection.

5. Event study surrounding the September 11, 2001 attack

We conjecture that the difference between the NYSE specialist system and the NASDAQ dealer system is likely to be more prominent during times of catastrophe such as the aftermath of the 9/11 attack. In times of such high uncertainty dealers may not step up their role as liquidity providers because of large adverse selection and inventory risks, even if the liquidity provided by public traders and ECNs is unacceptably low. In contrast, specialists may still provide a reasonable level of liquidity because of their affirmative obligations. To shed some light on this issue, we conduct an event study of liquidity provision using data surrounding the 9/11 attack. After the 9/11 attack, both the NYSE and NASDAQ were closed for four days and reopened on September 17, 2001, ending the longest interruption of U.S. trading since World War II. Figure 4 shows the mean return volatility of our entire sample of NYSE and NASDAQ stocks around the 9/11 attack. As expected, the figure shows significant spikes in return volatility during the first few days after the attack, with a gradual decline in the following weeks.

We define five trading days (days -5 through -1) prior to the 9/11 attack as the pre-9/11 period and ten trading days (days 1 through 10) from the market reopening on September 17 as the post-9/11 period. As in the previous section, we obtain matching samples of NYSE and NASDAQ stocks based on the four stock attributes using data from August 1, 2001 through October 31,

[23] To assess the robustness of our results, we replicate the above analysis after we cluster our matching sample of NYSE and NASDAQ stocks into three groups according to market capitalization. The results are qualitatively identical in all three firm-size groups. The results are available from the authors upon request.

2001.[24] The matching procedure results in a total of 492 pairs of NYSE and NASDAQ stocks that are similar in trade size, share price, return volatility, and market capitalization. We then compare the mean spreads of the NYSE and NASDAQ samples during the pre- and post-event periods. More importantly, we also test whether the differences in spreads between NASDAQ and NYSE stocks during the post-9/11 period are significantly greater than the corresponding figures during the pre-9/11 period.

Panels A through D of Table 10 show the results for $ESPRD, $QSPRD, %ESPRD, and %QSPRD, respectively. Column 1 in each panel shows the mean spread of NASDAQ stocks, the mean spread of NYSE stocks, and the difference (with t-statistic) in the mean spread between NASDAQ and NYSE stocks, i.e., (DIFF = $SPRD^{NASQ} – SPRD^{NYSE}$), during the pre-9/11 period. Columns 2 through 11 show the same variables on each day during the post-9/11 period. Also reported in the fifth row of each panel is the difference in ($SPRD^{NASD} – SPRD^{NYSE}$) between the pre-9/11 period and day *k* in the post-9/11 period (where k = 1 to 10). The t-statistic is for the hypothesis that the difference in the mean is zero. The last row reports the p-value for the Wilcoxon rank-sum test.

The results show that the differences in spreads between NASDAQ and NYSE stocks are all positive and significant during both the pre- and post-9/11 periods, except for two post-9/11 days in Panel D. This result is consistent with the results in the literature that trading costs on NASDAQ are generally higher than those on the NYSE. In addition, we find that the differences in ($SPRD^{NASD} – SPRD^{NYSE}$) between the pre-9/11 period and the first few post-9/11 days are positive and significant, according to both the t-test and Wilcoxon rank-sum test. That is, we find that the differences in spreads between NASDAQ and NYSE stocks during the first few post-9/11 days are significantly larger than the corresponding figures during the pre-9/11 period. These results support our conjecture that the NASDAQ dealer system provides poorer liquidity than the NYSE specialist

[24] The results are qualitatively identical when we obtain matching sample of NYSE and NASDAQ stocks using data from August 1, 2001 through August 31, 2001.

system in high volatility periods. Several days after the market reopening, however, the post-9/11 level of differential spreads is not statistically different from the corresponding value for the pre-9/11 period. NASDAQ dealers resumed their normal liquidity services as the initial shocks of the 9/11 attack waned, although market volatility returned to the pre-9/11 level only after about 30 days.

6. Can the results be driven by other reasons?

Although we attribute the larger difference between NASDAQ spreads and NYSE spreads for riskier stocks and in volatile periods to the fact that there is no liquidity provider of last resort on NASDAQ, we cannot rule out the possibility that our results are driven by some other reasons. For example, we would observe the same pattern if order preferencing, anticompetitive practice, or natural quote clustering on NASDAQ increases with return volatility more so than on the NYSE.

Order preferencing is unlikely to explain our results because order preferencing is likely to *decrease* with return volatility. Dealers are less likely to receive preferenced orders for riskier stocks or in times of high uncertainty because brokers usually preference uninformed orders to dealers and the dealers' adverse selection risk is generally greater for riskier stocks.

Our results may not be explained by anticompetitive behavior because NASDAQ dealers were unlikely to engage in such behavior during our study period. Christie and Schultz (1994) hold that NASDAQ dealers implicitly collude to set wider spreads than their NYSE counterparts. During the summer of 1994, numerous class-action lawsuits were filed in California, Illinois, and New York against dealers.[25] Prompted by renewed debates and also by legal action taken against NASDAQ dealers, both the Department of Justice and the Securities and Exchange Commission undertook regulatory investigations into the issue. The Department of Justice investigation prompted dealers to

[25] These lawsuits were later consolidated into a single class-action suit in the Southern District of New York.

curb the practice of avoiding odd-eighth quotes. It is unlikely that NASDSQ dealers practice anticompetitive behavior in the midst and aftermath of these investigations and regulatory actions.

Chung, Van Ness, and Van Ness (2004) show that the degree of quote clustering increases with return volatility and higher quote clustering results in wider spreads on both the NYSE and NASDAQ. This result suggests that the difference between NASDAQ and NYSE spreads can increase with return volatility if either the elasticity of quote clustering with respect to return volatility or the elasticity of spreads with respect to quote clustering is sufficiently lower for NYSE stocks. The sensitivity of quote clustering to return volatility might be lower for NYSE stocks because of the specialist's affirmative obligations. Whether the elasticity of spreads with respect to quote clustering is lower for NYSE stocks is an interesting empirical question.

7. Summary and concluding remarks

Both NYSE specialists and NASDAQ dealers are likely to be reluctant to provide liquidity in times of high uncertainty and for riskier stocks because of large adverse selection and inventory problems. We show that the NYSE specialist system provides better liquidity than the NASDAQ dealer system in high volatility periods and for riskier stocks. We attribute this result to the fact that there is a designated specialist for each stock on the NYSE who is directly responsible for maintaining a reasonable level of liquidity, whereas there is no such designated dealer on NASDAQ.

Our study sheds light on several issues. Although prior studies show that stocks traded on NASDAQ generally exhibit larger spreads than stocks traded on the NYSE, reasons for the differential spreads have not been well understood. Some suggest order preferencing as a possible explanation while others claim anticompetitive dealer behavior as a probable cause. Yet others suggest natural quote clustering as a possible reason. We propose another explanation for differential spreads: the designated versus non-designated market maker systems.

To the extent that public traders' incentives to provide liquidity through their limit order placements would be weaker in volatile markets, the results of our study suggest that the specialist system may serve traders better than pure electronic limit order markets in high volatility periods and for riskier stocks. In this context, the results of our study offer a sound economic rationale for recent discussions in Asian securities markets on whether they should incorporate human intermediation into their otherwise fully automated trading systems.

We examine only the difference in spreads between NASDAQ and NYSE stocks. As shown in prior research, however, it is important that we consider both the price and quantity dimensions of quotes to accurately measure liquidity. We were not able to perform depth comparison between the two markets because 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. Hence, the inter-market comparison of quoted depths is not meaningful with TAQ data. A fruitful area for future research would be the inter-market comparison of liquidity that considers both dimensions (i.e., spread and depth) of dealer and limit-order quotes.

Another area for future research is to examine how the specialist system, dealer markets, and pure limit order markets respond differently to changes in trading activity. We conjecture that the specialist system may provide better liquidity than either the dealer or pure limit order market for low activity stocks and in times of inactivity for the reasons stipulated in this study. It is well known in most Asian stock markets that liquidity is unacceptably low for inactive stocks that excite little interest of public traders. Research along these lines may demonstrate the value of having 'the liquidity provider of last resort' for those stocks that are not fortunate enough to excite interests from public traders.

References

Acharya, V., Pedersen, L., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375-410.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223–249.

Amihud, Y., Mendelson, H., 1989. The effect of beta, bid-ask spread, residual risk and size on stock returns. Journal of Finance 44, 479–486.

Barclay, M., 1997. Bid-ask spreads and the avoidance of odd-eighth quotes on Nasdaq: An examination of exchange listings. Journal of Financial Economics 45, 35-60.

Bessembinder, H., 1999. Trade execution costs on Nasdaq and the NYSE: A post-reform comparison. Journal of Financial and Quantitative Analysis 34, 387-408.

Bessembinder, H., 2003a. Issues in assessing trade execution costs. Journal of Financial Markets 6, 233-257.

Bessembinder, H., 2003b. Trade execution costs and market quality after decimalization. Journal of Financial and Quantitative Analysis 38, 747-777.

Bessembinder, H., Kaufman, H., 1997. A comparison of trade execution costs for NYSE and Nasdaq-listed stocks. Journal of Financial and Quantitative Analysis 32, 287-310.

Bremer, M., Hiraki, T., Sweeney, R., 1997. Predictable patterns after large stock price changes on the Tokyo Stock Exchange. Journal of Financial and Quantitative Analysis 32, 345–365.

Chan, K., Christie, W., Schultz, P., 1995. Market structure and the intraday pattern of bid-ask spreads for NASDAQ securities. Journal of Business 68, 35-60.

Christie, W., Schultz, P., 1994. Why do NASDAQ market makers avoid odd-eighth quotes? Journal of Finance 49, 1813-1840.

Chung, K.H., Chuwonganant, C., McCormick, D.T., 2004. Order preferencing and market quality on NASDAQ before and after decimalization. Journal of Financial Economics 71, 581-612.

Chung, K.H, Van Ness, B., Van Ness, R., 1999. Limit orders and the bid-ask spread. Journal of Financial Economics 53, 255-287.

Chung, K.H, Van Ness, B., Van Ness, R., 2001. Can the treatment of limit orders reconcile the differences in trading costs between NYSE and NASDAQ issues? Journal of Financial and Quantitative Analysis 36, 267-286.

Chung, K.H, Van Ness, B., Van Ness, R., 2004. Trading costs and quote clustering on the NYSE and NASDAQ after decimalization. Journal of Financial Research 27, 309-328.

Chung, K.H., Zhao, X., 2004. Price and quantity quotes on NASDAQ: A study of dealer quotation behavior. Journal of Financial Research 27, 497-519.

Corwin, S., Lipson, M., 2000. Order flow and liquidity around NYSE trading halts. Journal of Finance 55, 1771–1801.

Garfinkel, J., Nimalendran, M., 2003. Market structure and trader anonymity: An analysis of insider trading. Journal of Financial and Quantitative Analysis 38, 591-610.

Goldstein, M.A., Kavajecz, K.A., 2004. Trading strategies during circuit breakers and extreme market movements. Journal of Financial Markets 7, 301-333.

Grossman, S., 1992. The informational role of upstairs and downstairs trading. Journal of Business 65, 509–528.

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

Haugen, R., Talmor, E., Torous, W., 1991. The effect of volatility changes on the level of stock prices and subsequent expected returns. Journal of Finance 46, 985-1007.

Heidle, H., Huang, R., 2002. Information-based trading in dealer and auction markets: An analysis of exchange listings. Journal of Financial and Quantitative Analysis 37, 391-424.

Kavajecz, K., 1999. A specialist's quoted depth and the limit order book. Journal of Finance 52, 747–771.

Latane, B., Williams, K., Harkins, S., 1979. Many hands make light the work: The causes and consequences of social loafing. Journal of Personality and Social Psychology 37, 822-832.

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

Li, M., McCormick, D.T., Zhao, X., 2005. Order imbalance and liquidity supply: Evidence from the bubble burst of NASDAQ stocks. Journal of Empirical Finance 12, 533-555.

Madhavan, A., Sofianos, G., 1998. An empirical analysis of NYSE specialist trading. Journal of Financial Economics 48, 189-210.

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Rock, K., 1990. The specialist's order book and price anomalies. Unpublished paper, Harvard University.

Schwert, G.W., 1989. Why does stock market volatility change over time? Journal of Finance 44, 1115-1153.

Seppi, D., 1997. Liquidity provision with limit orders and a strategic specialist. Review of Financial Studies 10, 103–150.

Stoll, H., 1978. The pricing of security dealer services: An empirical study of Nasdaq stocks. Journal of Finance 33, 1153-1172.

Stoll, H., 2000. Friction. Journal of Finance 55, 1479-1514.

Venkataraman, K., 2001. Automated versus floor trading: An analysis of execution costs on the Paris and New York exchanges. Journal of Finance 56, 1445-1488.

Table 1
Descriptive statistics

We first calculate daily values of the following variables for each NYSE and NASDAQ stock (stock i on day t): share price as measured by the mean value of quote midpoints ($PRICE_{it}$); number of trades ($NTRADE_{it}$); average dollar trade size ($TSIZE_{it}$); return volatility as measured by the standard deviation of quote-midpoint returns ($VOLA_{it}$); market capitalization as measured by the market value of equity (MVE_{it}), trade-weighted average dollar and percentage effective spreads ($\$ESPRD_{it}$ and $\%ESPRD_{it}$); and time-weighted average dollar and percentage quoted spreads ($\$QSPRD_{it}$ and $\%QSPRD_{it}$). We then calculate the time-series mean values of these variables during our study period (November 1997 through December 2003) for each stock.

	Exchange	Mean	Sandard	Percentile				
			Deviation	5	25	50	75	95
Share price ($)	NYSE	21.27	2.10	4.73	10.42	16.38	26.35	50.39
(PRICE)	NASDAQ	19.17	3.55	3.29	8.06	15.02	25.51	48.95
Number of trades	NYSE	271.4	170.4	5.4	23.7	86.0	263.4	1,085.3
(NTRADE)	NASDAQ	596.5	390.3	8.4	44.1	147.7	453.4	2,337.5
Trade size (in $1,000)	NYSE	21.1	7.1	3.5	8.1	13.8	25.0	61.5
(TSIZE)	NASDAQ	13.7	7.7	2.3	5.2	9.4	17.1	37.9
Return volatility	NYSE	0.2091	0.0833	0.0648	0.1086	0.1573	0.2477	0.5247
(VOLA)	NASDAQ	0.3149	0.1123	0.0861	0.1575	0.2493	0.3984	0.7694
Market value of equity	NYSE	2,383	1,273	54	164	435	1,209	8,270
(in $ million) (MVE)	NASDAQ	717	237	39	115	265	612	2,563
Dollar effective spread	NYSE	0.1023	0.0349	0.0403	0.0582	0.0804	0.1151	0.2139
($ESPRD)	NASDAQ	0.1564	0.0578	0.0429	0.0768	0.1164	0.1853	0.3957
Dollar quoted spread	NYSE	0.1283	0.0489	0.0525	0.0786	0.1062	0.1467	0.2485
($QSPRD)	NASDAQ	0.1874	0.0766	0.0471	0.0863	0.1383	0.2273	0.4819
Percentage effective spread	NYSE	0.6909	0.1816	0.1714	0.3174	0.5022	0.8190	1.8072
(%ESPRD)	NASDAQ	1.1786	0.3452	0.2829	0.5176	0.8397	1.4225	3.1440
Percentage quoted spread	NYSE	0.8755	0.2627	0.2399	0.4199	0.6482	1.0395	2.2725
(%QSPRD)	NASDAQ	1.3761	0.4087	0.3046	0.5958	1.0068	1.7166	3.6717

Table 2
Descriptive statistics for volatility groups

We rank our study sample of NYSE and NASDAQ stocks according to return volatility on each day. We then cluster them into 100 groups, where Group 1 consists of stocks with the lowest volatility and Group 100 consists of stocks with the highest volatility. This table shows the mean volatility of stocks in Group 10 through Group 100, respectively, together with the proportion of NASDAQ stocks in each group (%NASDAQ) and the mean values of the variables included in Table 1. For each trading day, we calculate the mean volatility of stocks in each group using two different methods. In the first method, we first calculate the mean volatility of NYSE stocks and the mean volatility of NASDAQ stocks in each group. We then calculate the average of the two mean volatilities, i.e., $MVOLA_{jt}$ = (1/2)(Mean volatility of NYSE stocks in group j on day t + Mean volatility of NASDAQ stocks in group j on day t). In the second method, we calculate the mean volatility of all stocks (NYSE and NASDAQ) in each group, i.e., $MVOLA_{jt}^{S} = (1/N) \sum VOLA_{it}$, where $VOLA_{it}$ is the return volatility of stock i (stock i belongs to group j) on day t. We show the time-series mean values of $MVOLA_{jt}$ and $MVOLA_{jt}^{S}$ for Group 10 through Group 100. We use the second method to calculate the time-series mean values of all the other variables (i.e., PRICE, NTRADE, TSIZE, $ESPRD, $QSPRD, %ESPRD, %QSPRD, MVE).

Group	%NASDAQ	MVOLA	$MVOLA^{S}$	PRICE	NTRADE	TSIZE	$ESPRD	$QSPRD	%ESPRD	%QSPRD	MVE
10	25.0	0.0521	0.0521	41.42	1,646.4	38.0	0.0887	0.0954	0.23	0.25	7,922
20	26.3	0.0763	0.0763	32.70	846.8	28.6	0.0978	0.1107	0.31	0.36	3,036
30	29.1	0.0991	0.0991	27.13	562.7	23.5	0.1032	0.1199	0.40	0.46	1,535
40	33.5	0.1308	0.1308	23.92	386.7	20.5	0.1137	0.1364	0.50	0.59	922
50	40.1	0.1652	0.1652	21.09	274.0	17.7	0.1235	0.1502	0.61	0.74	629
60	48.6	0.2111	0.2111	18.35	212.4	15.3	0.1341	0.1656	0.77	0.93	439
70	57.2	0.2759	0.2759	15.31	161.1	12.7	0.1421	0.1772	0.99	1.21	312
80	64.5	0.3766	0.3766	11.95	115.0	10.2	0.1495	0.1844	1.35	1.64	206
90	70.1	0.5881	0.5882	8.24	73.0	7.2	0.1523	0.1888	2.06	2.49	123
100	69.7	1.9601	1.9478	3.49	22.1	3.6	0.1656	0.1932	5.69	6.60	39

Table 3
Cross-sectional regression analyses

This table reports the results of the following regressions:

Model 1: $\$ESPRD_{jt}^{NASD} - \$ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

Model 2: $\$QSPRD_{jt}^{NASD} - \$QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

Model 3: $\%ESPRD_{jt}^{NASD} - \%ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$; and

Model 4: $\%QSPRD_{jt}^{NASD} - \%QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

where $\$ESPRD_{jt}^{NASD}$ is the mean dollar effective spread of NASDAQ stocks in group j on day t, $\$QSPRD_{jt}^{NASD}$ is the mean dollar quoted spread of NASDAQ stocks, $\%ESPRD_{jt}^{NASD}$ is the mean percentage effective spread of NASDAQ stocks, $\%QSPRD_{jt}^{NASD}$ is the mean percentage quoted spread of NASDAQ stocks. Variables for NYSE are similarly defined. $MVOLA_{jt}$ is the mean volatility of (NYSE and NASDAQ) stocks in group j on day t, and Xs are the four stock attributes (i.e., log(NTRADE), log(TSIZE), PRICE or 1/PRICE, and VOLA). X_{jtk}^{NASD} is the mean value of the *k*th attribute on day t for NASDAQ stocks in group j (where k = 1, 2, 3, and 4). NTRADE is the total number of trades, TSIZE is the average dollar transaction size, VOLA is the standard deviation of quote-midpoint returns, and PRICE is the mean value of quote midpoints. Elasticity is measured by dividing the regression coefficient for $\log(MVOLA_{jt})$ by the mean spread (i.e., M$ESPRD, M$QSPRD, M%ESPRD, and M%QSPRD). We estimate the above regression models using cross-sectional data on each day, and we report the mean value of daily regression coefficients and its t-statistic for each variable and the mean adjusted R^2. d denotes the difference, e.g., $dPRICE = PRICE^{NASD} - PRICE^{NYSE}$.

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	0.0511**	59.71	0.0831**	59.52	0.362**	52.49	0.323**	42.8
Elasticity	0.0738**	20.51	0.168**	47.75	0.1206**	35.46	0.0985**	33.02
log(MVOLA)	0.0129**	22.83	0.0323**	38.39	0.1295**	40.98	0.1283**	35.2
dlog(NTRADE)	-0.0039**	-13.01	-0.0108**	-39.01	-0.0203**	-12.03	-0.0673**	-45.78
dlog(TSIZE)	0.0059**	10.27	0.0044**	8.77	-0.0338**	-10.23	-0.0587**	-21.71
dPRICE	0.0046**	62.81	0.0054**	72.13	.	.	.	.
d(1/PRICE)	.	.	.	.	2.214**	32.38	2.8048**	40.47
dVOLA	-0.0552	-0.45	-0.0510	-0.46	2.0118*	1.96	1.3580	1.57
Adjusted R^2	0.4155		0.4827		0.3166		0.3634	

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

Table 4
Cross-sectional regression by volatility days

This table reports the results of the following regressions by volatility days:

$$\text{Model 1: } \$ESPRD_{jt}^{NASD} - \$ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt};$$
$$\text{Model 2: } \$QSPRD_{jt}^{NASD} - \$QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt};$$
$$\text{Model 3: } \%ESPRD_{jt}^{NASD} - \%ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}; \text{ and}$$
$$\text{Model 4: } \%QSPRD_{jt}^{NASD} - \%QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}.$$

We classify each trading day during our study period (November 1997 through December 2003) as high, medium, or low volatility days according to the average volatility of all stocks (NASDAQ and NYSE) for each day, resulting in 484 low volatility days, 498 medium volatility days, and 485 high volatility days. We then calculate the mean value of daily regression coefficients, its t-statistic, and the mean adjusted R^2 for each of the three volatility periods from the above regressions, where $\$ESPRD_{jt}^{NASD}$ is the mean dollar effective spread of NASDAQ stocks in group j on day t, $\$QSPRD_{jt}^{NASD}$ is the mean dollar quoted spread of NASDAQ stocks, $\%ESPRD_{jt}^{NASD}$ is the mean percentage effective spread of NASDAQ stocks, $\%QSPRD_{jt}^{NASD}$ is the mean percentage quoted spread of NASDAQ stocks. Variables for NYSE are similarly defined. $MVOLA_{jt}$ is the mean volatility of (NYSE and NASDAQ) stocks in group j on day t, and Xs are the four stock attributes (i.e., log(NTRADE), log(TSIZE), PRICE or 1/PRICE, and VOLA). X_{jtk}^{NASD} is the mean value of the *k*th attribute on day t for NASDAQ stocks in group j (where k = 1, 2, 3, and 4), NTRADE is the total number of trades, TSIZE is the average dollar transaction size, VOLA is the standard deviation of quote-midpoint returns, and PRICE is the mean value of quote midpoints. Elasticity is measured by dividing the regression coefficient for $\log(MVOLA_{jt})$ by the mean spread (i.e., M$ESPRD, M$QSPRD, M%ESPRD, and M%QSPRD). d denotes the difference, e.g., $dPRICE = PRICE^{NASD} - PRICE^{NYSE}$.

Panel A: Results for low volatility days (484 days)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Elasticity	-0.0039	-0.78	0.0724**	18.00	0.0459**	6.34	0.0214**	4.59
log(MVOLA)	-0.0005	-1.36	0.0065**	18.29	0.0478**	9.66	0.0234**	6.24
dlog(NTRADE)	-0.0067**	-17.54	-0.0111**	-31.11	-0.0314**	-11.34	-0.0723**	-30.26
dlog(TSIZE)	0.006**	6.14	0.0002	0.32	-0.0335**	-5.50	-0.0509**	-10.35
dPRICE	0.0024**	48.15	0.0031**	65.02	.	.	.	.
d(1/PRICE)	.	.	.	.	1.383**	14.55	1.7894**	18.39
dVOLA	-0.0405	-0.15	-0.2148	-1.00	2.0192	0.80	0.7074	0.36
Adjusted R^2	0.3276		0.4417		0.2826		0.2891	

Table 4 (Continued)

Panel B: Results for medium volatility days (498 days)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Elasticity	0.0821**	13.22	0.1917**	30.31	0.1469**	30.62	0.1202**	24.77
log(MVOLA)	0.0139**	13.88	0.0374**	25.15	0.1443**	31.23	0.1403**	26.12
dlog(NTRADE)	-0.003**	-6.03	-0.0097**	-20.73	-0.018**	-6.09	-0.0668**	-26.09
dlog(TSIZE)	0.0056**	5.77	0.0053**	6.20	-0.0422**	-8.10	-0.0638**	-13.90
dPRICE	0.0046**	45.84	0.0056**	50.07	.	.	.	.
d(1/PRICE)	.	.	.	.	2.4681**	19.83	3.1323**	25.07
dVOLA	-0.1612	-0.89	0.0799	0.45	2.7604*	2.03	3.3046**	2.76
Adjusted R^2	0.4344		0.4993		0.3437		0.3939	

Panel C: Results for high volatility days (485 days)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Elasticity	0.1427**	26.12	0.2392**	48.17	0.168**	48.91	0.1532**	38.80
log(MVOLA)	0.0251**	24.93	0.0528**	40.20	0.1958**	42.47	0.2208**	36.44
dlog(NTRADE)	-0.002**	-3.22	-0.0116**	-19.92	-0.0115**	-3.90	-0.063**	-23.57
dlog(TSIZE)	0.0061**	5.87	0.0075**	7.91	-0.0255**	-4.35	-0.0613**	-13.53
dPRICE	0.0067**	53.44	0.0075**	59.39	.	.	.	.
d(1/PRICE)	.	.	.	.	2.7825**	22.50	3.4817**	28.61
dVOLA	0.0389	0.22	-0.0221	-0.12	1.2359	1.07	0.0084	0.01
Adjusted R^2	0.4839		0.5064		0.3226		0.4062	

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

Table 5
Testing whether the mean elasticity with respect to return volatility differs between the low, medium, and high volatility days

This table shows whether the mean elasticity with respect to log(MVOLA) differs significantly between low, medium, and high volatility days. Elasticity is measured by dividing the regression coefficient for log($MVOLA_{jt}$) by the mean spread (i.e., M$ESPRD, M$QSPRD, M%ESPRD, and M%QSPRD). We classify each trading day during our study period (November 1997 through December 2003) as high, medium, or low volatility days according to the average volatility of all stocks (NASDAQ and NYSE) for each day, resulting in 484 low volatility days, 498 medium volatility days, and 485 high volatility days.

Panel A: Comparing mean elasticity between the medium and low volatility days

	Model 1	Model 2	Model 3	Model 4
Medium volatility days (M)	0.0821	0.1917	0.1469	0.1202
Low volatility days (L)	-0.0039	0.0724	0.0459	0.0214
Difference: M – L	0.0861**	0.1193**	0.101**	0.0988**
t-statistic	10.73	15.91	11.62	14.66
p-value (Wilcoxon)	0.000	0.000	0.000	0.000

Panel B: Comparing mean elasticity between the high and medium volatility days

	Model 1	Model 2	Model 3	Model 4
High volatility days (H)	0.1427	0.2392	0.1680	0.1532
Medium volatility days (M)	0.0821	0.1917	0.1469	0.1202
Difference: H – M	0.0606**	0.0475**	0.0211**	0.033**
t-statistic	7.31	5.90	3.56	5.27
p-value (Wilcoxon)	0.000	0.000	0.001	0.000

Panel C: Comparing mean elasticity between the high and low volatility days

	Model 1	Model 2	Model 3	Model 4
High volatility days (H)	0.1427	0.2392	0.1680	0.1532
Low volatility days (L)	-0.0039	0.0724	0.0459	0.0214
Difference: H – L	0.1466**	0.1668**	0.1221**	0.1318**
t-statistic	19.65	26.09	15.22	21.53
p-value (Wilcoxon)	0.000	0.000	0.000	0.000

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

Table 6
Time-series regression analyses

This table reports the results of the following regressions:

Model 1: $\$ESPRD_{jt}^{NASD} - \$ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

Model 2: $\$QSPRD_{jt}^{NASD} - \$QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

Model 3: $\%ESPRD_{jt}^{NASD} - \%ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$; and

Model 4: $\%QSPRD_{jt}^{NASD} - \%QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t} \log(MVOLA_{jt}) + \Sigma\beta_{tk} (X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

where $\$ESPRD_{jt}^{NASD}$ is the mean dollar effective spread of NASDAQ stocks in group j on day t, $\$QSPRD_{jt}^{NASD}$ is the mean dollar quoted spread of NASDAQ stocks, $\%ESPRD_{jt}^{NASD}$ is the mean percentage effective spread of NASDAQ stocks, $\%QSPRD_{jt}^{NASD}$ is the mean percentage quoted spread of NASDAQ stocks. Variables for NYSE are similarly defined. $MVOLA_{jt}$ is the mean volatility of (NYSE and NASDAQ) stocks in group j on day t, and Xs are the four stock attributes (i.e., log(NTRADE), log(TSIZE), PRICE or 1/PRICE, and VOLA). X_{jtk}^{NASD} is the mean value of the *k*th attribute on day t for NASDAQ stocks in group j (where k = 1, 2, 3, and 4). NTRADE is the total number of trades, TSIZE is the average dollar transaction size, VOLA is the standard deviation of quote-midpoint returns, and PRICE is the mean value of quote midpoints. Elasticity is measured by dividing the regression coefficient for $\log(MVOLA_{jt})$ by the mean spread (i.e., M\$ESPRD, M\$QSPRD, M%ESPRD, and M%QSPRD). We estimate the above regression models using time-series data for each volatility group, and we report the mean value of regression coefficients and its t-statistic for each variable and the mean adjusted R^2. d denotes the difference, e.g., $dPRICE = PRICE^{NASD} - PRICE^{NYSE}$.

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	0.0970**	83.23	0.1087**	42.48	0.3912**	25.18	0.3080**	13.76
Elasticity	0.3102**	90.75	0.2687**	36.25	0.1552**	50.75	0.0878**	13.21
log(MVOLA)	0.0410**	46.83	0.0445**	24.08	0.1373**	15.37	0.1110**	8.94
dlog(NTRADE)	-0.0055**	-15.74	-0.0141**	-37.44	-0.0452**	-15.96	-0.0875**	-22.03
dlog(TSIZE)	-0.0024**	-2.77	0.0057**	7.11	-0.0135**	-5.40	0.0033	1.24
dPRICE	0.0068**	20.56	0.0075**	28.70	.	.	.	.
d(1/PRICE)	.	.	.	.	2.381**	40.72	2.4466**	38.74
dVOLA	0.4350	1.32	0.6984	1.69	1.7580	1.45	3.4057**	2.50
Adjusted R^2	0.5383		0.5927		0.1249		0.1479	

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

Table 7
Time-series regression by volatility groups

The table shows the average elasticity and average regression coefficient on log(MVOLA) for each volatility group during November 1997-December 2003. Elasticity is measured by dividing the regression coefficient for log($MVOLA_{jt}$) by the mean spread (i.e., M$ESPRD, M$QSPRD, M%ESPRD, and M%QSPRD). We classify each volatility group as the high, medium, or low volatility portfolio according to the average volatility of all stocks (NASDAQ and NYSE) in each group. We then calculate the mean value of regression coefficients and its t-statistic for each of the three volatility portfolios from the following regressions:

Model 1: $\$ESPRD_{jt}^{NASD} - \$ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;
Model 2: $\$QSPRD_{jt}^{NASD} - \$QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;
Model 3: $\%ESPRD_{jt}^{NASD} - \%ESPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$; and
Model 4: $\%QSPRD_{jt}^{NASD} - \%QSPRD_{jt}^{NYSE} = \beta_{0t} + \beta_{1t}\log(MVOLA_{jt}) + \Sigma\beta_{tk}(X_{jtk}^{NASD} - X_{jtk}^{NYSE}) + \varepsilon_{jt}$;

where $\$ESPRD_{jt}^{NASD}$ is the mean dollar effective spread of NASDAQ stocks in group j on day t, $\$QSPRD_{jt}^{NASD}$ is the mean dollar quoted spread of NASDAQ stocks, $\%ESPRD_{jt}^{NASD}$ is the mean percentage effective spread of NASDAQ stocks, $\%QSPRD_{jt}^{NASD}$ is the mean percentage quoted spread of NASDAQ stocks. Variables for NYSE are similarly defined. $MVOLA_{jt}$ is the mean volatility of (NYSE and NASDAQ) stocks in group j on day t, and Xs are the four stock attributes (i.e., log(NTRADE), log(TSIZE), PRICE or 1/PRICE, and VOLA). X_{jtk}^{NASD} is the mean value of the *k*th attribute on day t for NASDAQ stocks in group j (where k = 1, 2, 3, and 4), NTRADE is the total number of trades, TSIZE is the average dollar transaction size, VOLA is the standard deviation of quote-midpoint returns, and PRICE is the mean value of quote midpoints. Nobs denotes the number of observations.

Panel A: Model 1

	Elasticity	t-statistic	log(MVOLA)	t-statistic	Nobs
Low volatility portfolio	0.3023**	63.42	0.0346**	45.17	18
Medium volatility portfolio	0.3046**	56.98	0.0402**	51.88	18
High volatility portfolio	0.3224**	50.25	0.0474**	45.80	20

Panel B: Model 2

	Elasticity	t-statistic	log(MVOLA)	t-statistic	Nobs
Low volatility portfolio	0.2015**	27.70	0.0278**	20.79	18
Medium volatility portfolio	0.2766**	52.34	0.0450**	35.56	18
High volatility portfolio	0.3222**	90.61	0.0590**	72.98	20

Panel C: Model 3

	Elasticity	t-statistic	log(MVOLA)	t-statistic	Nobs
Low volatility portfolio	0.1376**	35.51	0.0701**	21.07	18
Medium volatility portfolio	0.1572**	39.98	0.1182**	25.81	18
High volatility portfolio	0.1693**	33.27	0.2151**	25.43	20

Panel D: Model 4

	Elasticity	t-statistic	log(MVOLA)	t-statistic	Nobs
Low volatility portfolio	0.0288**	5.30	0.0186**	5.23	18
Medium volatility portfolio	0.0889**	18.60	0.0823**	13.04	18
High volatility portfolio	0.1400**	51.45	0.2199**	18.70	20

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

Table 8
Testing whether the mean elasticity with respect to return volatility differs between the low, medium, and high volatility portfolios

This table shows whether the mean elasticity with respect to log(MVOLA) differs significantly between the low, medium, and high volatility portfolios. We classify each volatility group into three portfolios according to the average volatility of all stocks (NASDAQ and NYSE) in each volatility group.

Panel A: Comparing mean elasticity between the medium and low volatility portfolios

	Model 1	Model 2	Model 3	Model 4
Medium volatility portfolio (M)	0.3046	0.2766	0.1572	0.0889
Low volatility portfolio (L)	0.3023	0.2015	0.1376	0.0288
Difference: M – L	0.0023	0.0752**	0.0196**	0.0602**
t-statistic	0.31	8.12	3.46	8.08
p-value (Wilcoxon)	0.877	0.000	0.002	0.000

Panel B: Comparing mean elasticity between the high and medium volatility portfolios

	Model 1	Model 2	Model 3	Model 4
High volatility portfolio (H)	0.3224	0.3222	0.1693	0.1400
Medium volatility portfolio (M)	0.3046	0.2766	0.1572	0.0889
Difference: H – M	0.0178*	0.0456**	0.0121	0.0511**
t-statistic	2.07	6.96	1.83	9.04
p-value (Wilcoxon)	0.042	0.000	0.068	0.000

Panel C: Comparing mean elasticity between the high and low volatility portfolios

	Model 1	Model 2	Model 3	Model 4
High volatility portfolio (H)	0.3224	0.3222	0.1693	0.1400
Low volatility portfolio (L)	0.3023	0.2015	0.1376	0.0288
Difference: H – L	0.0201*	0.1207**	0.0317**	0.1113**
t-statistic	2.45	14.50	4.83	17.82
p-value (Wilcoxon)	0.039	0.000	0.000	0.000

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

Table 9
NASDAQ and NYSE spreads in high volatility and low volatility months

We conduct matching-sample comparisons of NYSE and NASDAQ spreads using data drawn from two months that differ significantly in return volatility but not in average spreads. We choose October 1998 as the high volatility month and July 2000 as the low volatility month. For each month, we match a NASDAQ stock with a NYSE stock in terms of four stock attributes, i.e., trade size, share price, return volatility, and market capitalization. To obtain a matching pair, we calculate the matching score for a NASDAQ stock against each NYSE stock in our sample: $\Sigma[(X_k^{NASD} - X_k^{NYSE})/\{(X_k^{NASD} + X_k^{NYSE})/2\}]^2$; where X_k denotes the k^{th} stock attribute (k = 1, 2, 3, and 4), and Σ denotes the summation over *k*. We select, for each NASDAQ stock, the NYSE stock with the smallest matching score. We use the above procedure to obtain 506 matching pairs of NYSE and NASDAQ stocks for October 1998, and 509 matching pairs for July 2000. This table shows the mean effective and quoted spreads of NASDAQ stocks and NYSE stocks, respectively, together with the mean differences between NASDAQ and NYSE spreads ($SPRD^{NASD} - SPRD^{NYSE}$) during each month. We also show the difference in ($SPRD^{NASD} - SPRD^{NYSE}$) between the high and low volatility months in the third row of each panel. The last two columns show t-statistics for testing the equality of two means and the p-value for the Wilcoxon rank-sum test.

	NASDAQ	NYSE	NASDAQ-NYSE	t-statistic	p-value (Wilcoxon)
Panel A: Dollar effective spread ($ESPRD)					
High volatility month (H)	0.1899	0.1411	0.0488**	17.78	
Low volatility month (L)	0.1656	0.1273	0.0383**	17.10	
Difference: H – L			0.0105**	2.96	0.001
Panel B: Dollar quoted spread ($QSPRD)					
High volatility month (H)	0.2417	0.1825	0.0591**	15.45	
Low volatility month (L)	0.1859	0.1693	0.0167**	5.58	
Difference: H – L			0.0425**	8.75	0.000
Panel C: Percentage effective spread (%ESPRD)					
High volatility month (H)	1.2260	0.9779	0.2481**	16.95	
Low volatility month (L)	1.0050	0.8619	0.1431**	10.63	
Difference: H – L			0.1050**	5.28	0.000
Panel D: Percentage quoted spread (%QSPRD)					
High volatility month (H)	1.5599	1.2846	0.2753**	13.11	
Low volatility month (L)	1.1487	1.1705	-0.0219	-1.10	
Difference: H – L			0.2971**	10.27	0.000

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

Table 10
NASDAQ and NYSE spreads surrounding the September 11, 2001 attack

We define five trading days (days -5 through -1) prior to the 9/11 attack as the pre-9/11 period and ten trading days (days 1 through 10) from the market reopening on September 17 as the post-9/11 period. We obtain matching samples of NYSE and NASDAQ stocks based on the four stock attributes using data from August 1, 2001 through October 31, 2001.The matching procedure results in a total of 492 pairs of NYSE and NASDAQ stocks that are similar in price, trade size, return volatility, and market capitalization. Panels A through D of Table 10 show the results for $ESPRD, $QSPRD, %ESPRD, and %QSPRD, respectively. Column 1 in each panel shows the mean spread of NASDAQ stocks, the mean spread of NYSE stocks, and the difference (with t-statistic) in the mean spread between NASDAQ and NYSE stocks, i.e., (DIFF = $SPRD^{NASQ} – SPRD^{NYSE}$), during the pre-9/11 period (i.e., days -1 through -5). Columns 2 through 11 show the same variables on each day during the post-9/11 period (i.e., days 1 through 10). Also reported in the fifth row of each panel is the difference in ($SPRD^{NASD} – SPRD^{NYSE}$) between the pre-9/11 period and day *k* in the post-9/11 period (where k = 1 to 10). The t-statistic is for the hypothesis that the difference in the mean is zero. The last column reports the p-value for the Wilcoxon rank-sum test.

	Pre-9/11	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
Panel A: $ESPRD											
NASDAQ: (A)	0.1137	0.1763	0.1426	0.1485	0.1359	0.1703	0.1360	0.1317	0.1276	0.1352	0.1324
NYSE: (B)	0.0758	0.1126	0.0878	0.0963	0.1046	0.1057	0.0999	0.1020	0.0851	0.0941	0.0879
DIFF: (A) – (B)	0.0379**	0.0637**	0.0548**	0.0522**	0.0313**	0.0646**	0.0361**	0.0297**	0.0425**	0.0411**	0.0445**
t-statistic	17.30	11.96	11.50	12.75	6.46	11.99	9.31	3.50	10.26	4.91	11.18
Post(DIFF) – Pre(DIFF)		0.0259**	0.0169**	0.0144**	-0.0070	0.0267**	-0.0020	-0.0080	0.0046	0.0033	0.0067
t-statistic		4.49	3.22	3.09	-1.25	4.59	-0.40	-0.93	0.99	0.38	1.47
p-value (Wilcoxon)		0.00	0.44	0.12	0.14	0.00	0.04	0.03	0.19	0.73	0.44
Panel B: $QSPRD	Pre-9/11	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
NASDAQ: (A)	0.1135	0.1775	0.1447	0.1385	0.1360	0.1434	0.1348	0.1303	0.1263	0.1258	0.1248
NYSE: (B)	0.0890	0.1300	0.1090	0.1135	0.1133	0.1206	0.1140	0.1188	0.1024	0.1080	0.1030
DIFF: (A) – (B)	0.0245**	0.0475**	0.0357**	0.025**	0.0227**	0.0228**	0.0208**	0.0115	0.0239**	0.0178*	0.0218**
t-statistic	10.16	8.26	7.70	6.13	6.44	5.98	5.16	1.60	6.19	2.30	5.19
Post(DIFF) – Pre(DIFF)		0.023**	0.0112*	0.0005	-0.0020	-0.0020	-0.0040	-0.0130	-0.0007	-0.0070	-0.0030
t-statistic		3.68	2.14	0.10	-0.42	-0.38	-0.79	-1.72	-0.15	-0.83	-0.56
p-value (Wilcoxon)		0.07	0.36	0.02	0.08	0.00	0.00	0.00	0.01	0.00	0.00

Table 10 (Continued)

Panel C: %ESPRD	Pre-9/11	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
NASDAQ: (A)	0.6291	1.0859	0.8735	0.9637	0.8938	1.1044	0.9019	0.8753	0.8745	0.8896	0.8359
NYSE: (B)	0.4748	0.7408	0.6055	0.6888	0.7795	0.8338	0.7479	0.7022	0.6299	0.6937	0.6290
DIFF: (A) – (B)	0.1542**	0.3451**	0.2680**	0.2749**	0.1143**	0.2706**	0.1540**	0.1730**	0.2446**	0.1958**	0.2069**
t-statistic	10.55	8.04	8.86	9.51	3.05	5.22	4.74	4.34	7.35	4.41	7.75
Post(DIFF) – Pre(DIFF)		0.1909**	0.1137**	0.1207**	-0.040	0.1163*	-0.0003	0.0188	0.0904*	0.0416	0.0527
t-statistic		4.21	3.39	3.73	-0.99	2.16	-0.01	0.44	2.49	0.89	1.73
p-value (Wilcoxon)		0.00	0.04	0.00	0.83	0.00	0.98	0.78	0.76	0.16	0.27
Panel D: %QSPRD	Pre-9/11	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
NASDAQ: (A)	0.6286	1.0682	0.8978	0.8976	0.9004	0.9798	0.8958	0.8759	0.8703	0.8628	0.7947
NYSE: (B)	0.5612	0.8814	0.7549	0.8234	0.8382	0.9242	0.8538	0.8427	0.7605	0.7973	0.7618
DIFF: (A) – (B)	0.0674**	0.1868**	0.1429**	0.0741**	0.0622*	0.0556*	0.0419	0.0332	0.1098**	0.0655	0.0329
t-statistic	4.25	5.93	4.54	2.63	2.23	2.12	1.58	0.91	3.84	1.60	1.17
Post(DIFF) – Pre(DIFF)		0.1193**	0.0755*	0.0067	-0.0050	-0.0120	-0.0250	-0.0340	0.0424	-0.0020	-0.0340
t-statistic		3.38	2.14	0.21	-0.16	-0.39	-0.82	-0.86	1.30	-0.04	-1.07
p-value (Wilcoxon)		0.01	0.65	0.15	0.45	0.06	0.01	0.00	0.10	0.06	0.00

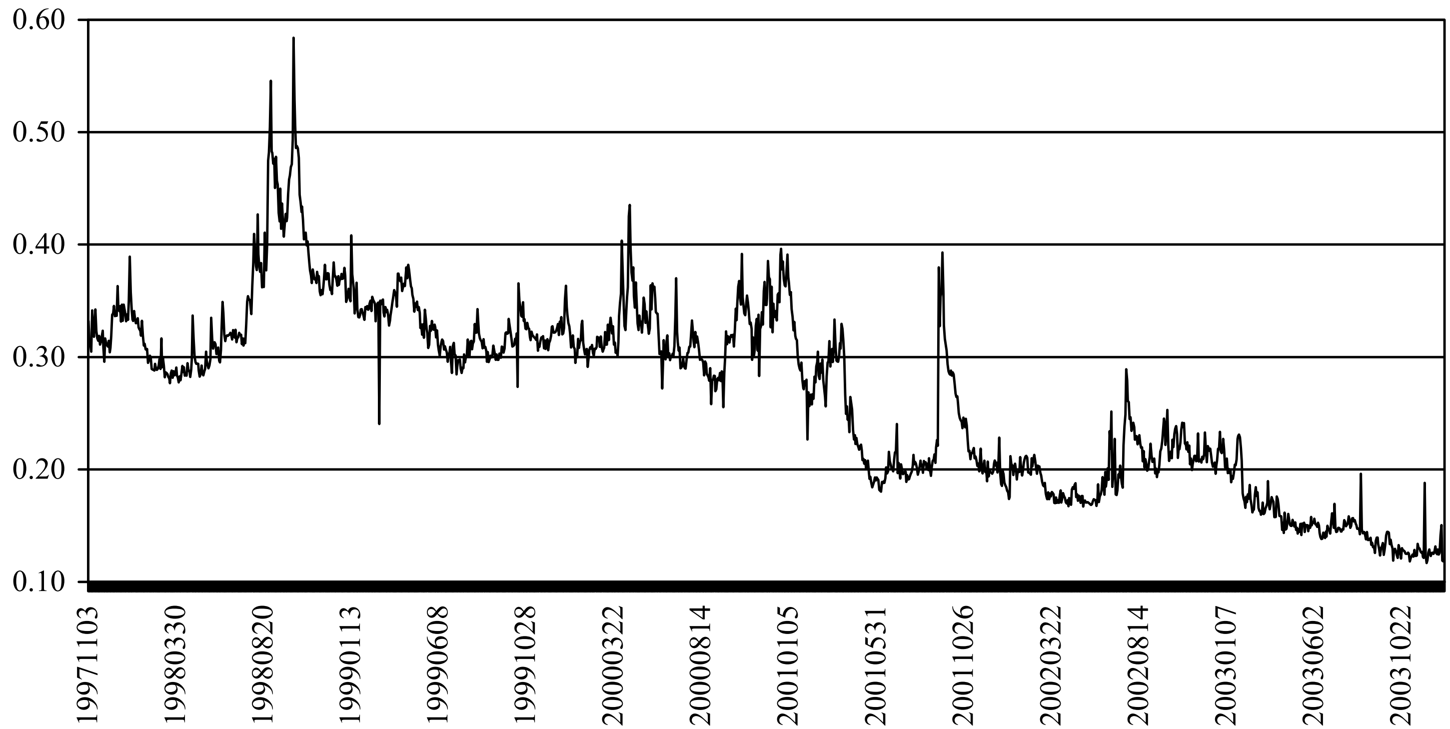

Figure 1. The average daily standard deviation of quote-midpoint returns for our study sample of stocks from November 3, 1997 through December 31, 2003

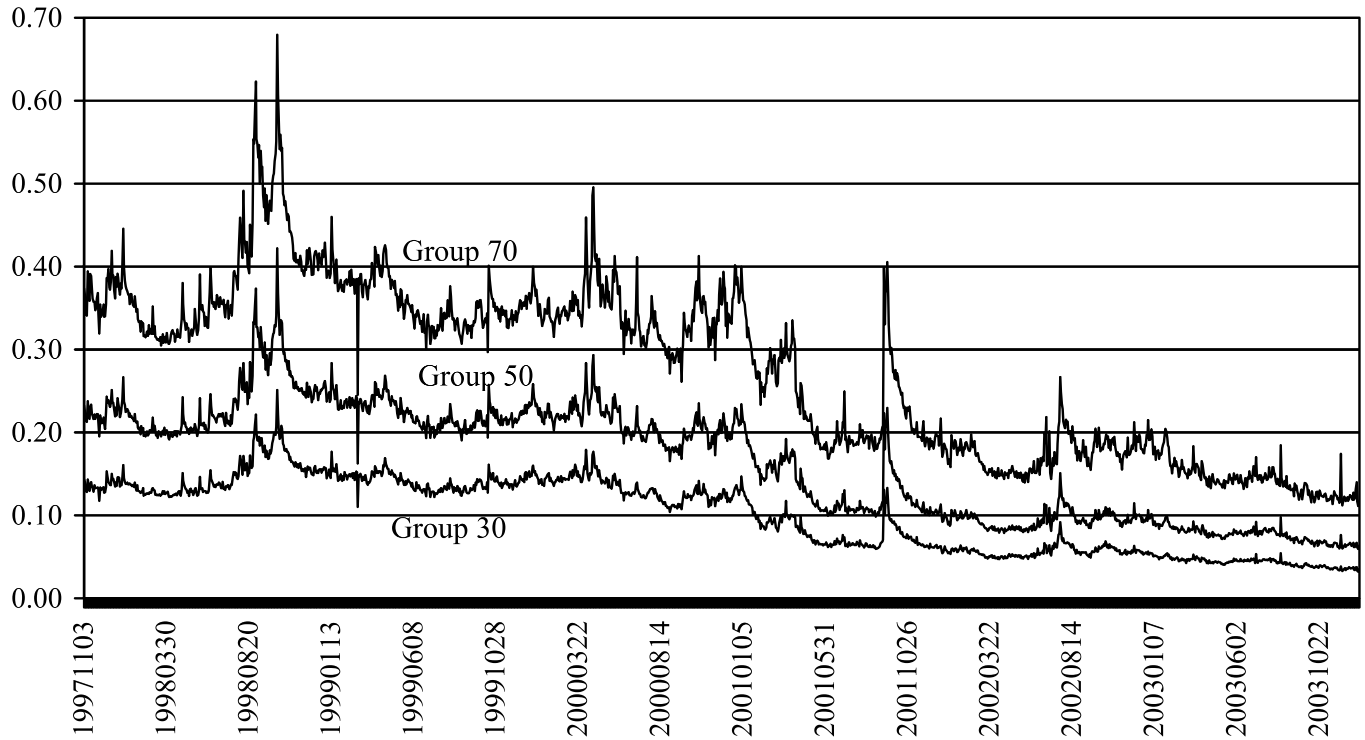

Figure 2. The average daily standard deviation of quote-midpoint returns for our study sample of stocks from November 3, 1997 through December 31, 2003 by volatility group

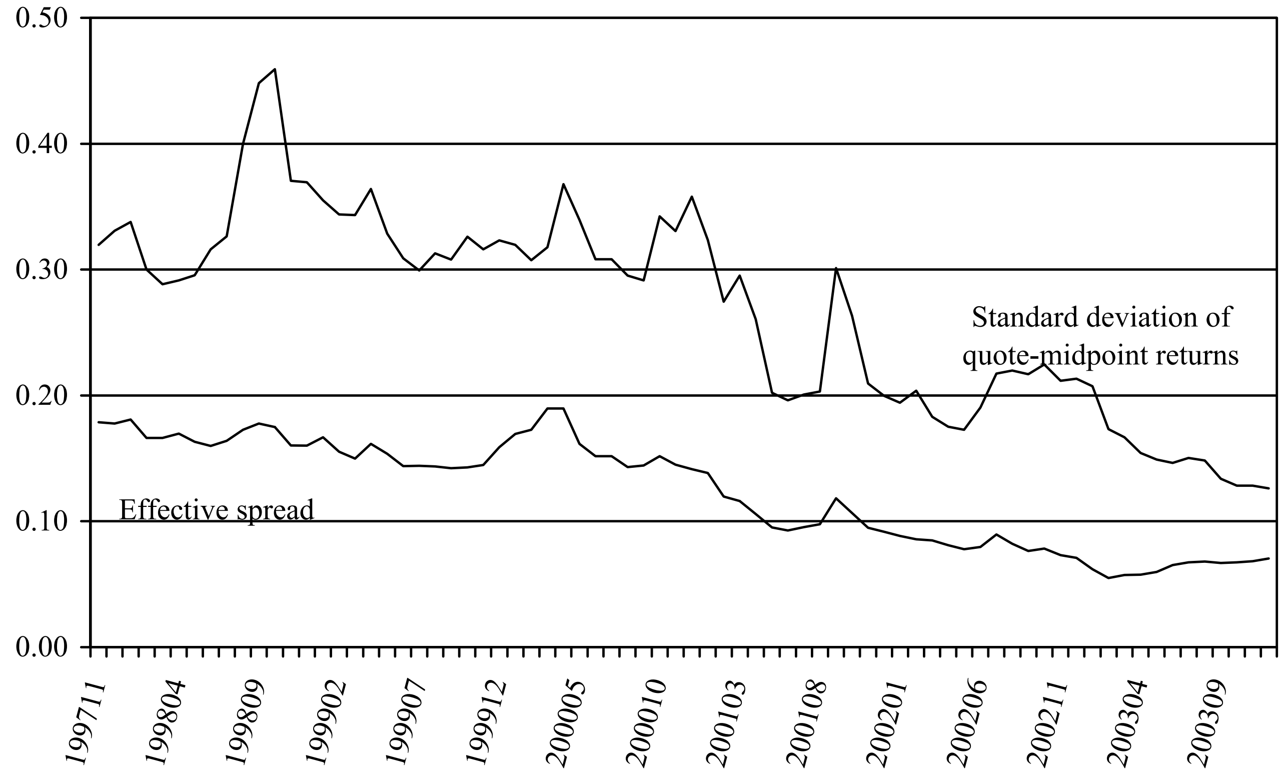

Figure 3. The average monthly effective spread and standard deviation of quote-midpoint returns for our study sample of stocks from November 1997 through December 2003

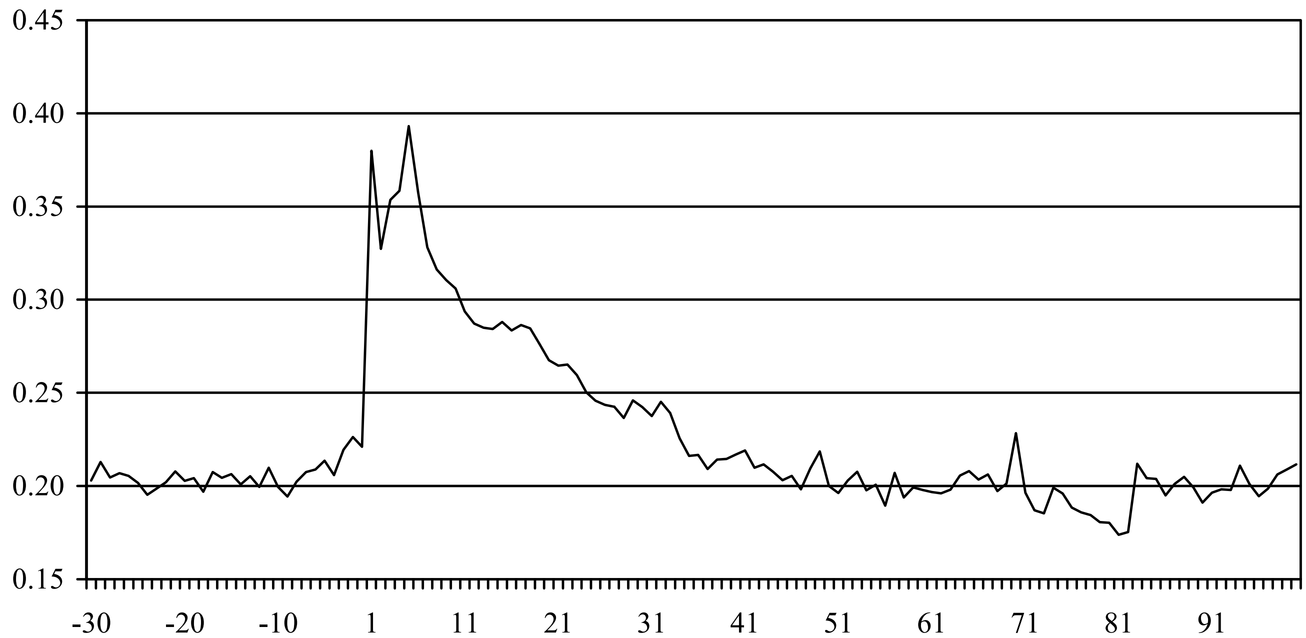

Figure 4. The average daily standard deviation of quote-midpoint returns for our study sample of stocks around September 11, 2001 (from day -30 to day 100)