Volatility, Market Structure, and the Bid-Ask Spread

Abstract

We test the conjecture that the specialist system on the New York Stock Exchange (NYSE) provides better liquidity services than the NASDAQ dealer market 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 (i.e., the bid-ask spread) as the 'liquidity provider of last resort,' whereas there is no such designated dealer on NASDAQ. Empirical evidence is consistent with our conjecture. In a similar vein, we show that the specialist system provides better liquidity than the dealer market in thin markets.

JEL classification: G18; G19
Key words: Dealer; Specialist; Market structure; Bid-ask spreads; Fair and orderly markets

"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)

I. Introduction

Return volatility and the bid-ask spread are two important attributes of securities. 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 two minute quote-midpoint returns for our study sample of stocks from January 2, 1998 through December 31, 2003. Similarly, Figure 2 shows the average standard deviation of daily closing quote-midpoint returns over 20 trading days. Temporal variation in return volatility is both substantial and dramatic, regardless of whether we measure return volatility using returns over short (two minutes) or long (24 hours) intervals. Market participants care about the bid-ask spread because it affects trading costs, stock returns, and the informational efficiency of asset price. Although prior research sheds significant light on return volatility and the bid-ask spread separately, the relation between the two variables has received limited attention. In this study we examine how return volatility affects the bid-ask spread through its impact on the behavior of liquidity suppliers. In particular, we investigate how the impact of return volatility on the bid-ask spread 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 show that traders on NASDAQ pay larger spreads than traders on the NYSE, although 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 between an automated trading structure (Paris Bourse) and a floor-based trading structure (NYSE).

Barclay (1997) finds a significant decrease 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.

In the present study we examine how market structure moderates the effects of return volatility on the bid-ask spread. 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 using data covering six years of a large sample of NYSE and NASDAQ stocks.

We test the conjecture that the specialist system on the NYSE provides better liquidity services than the NASDAQ dealer market in times of high return volatility when adverse selection and inventory risks are high.[1] 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 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 services in times of high uncertainty because there are no regulatory rules that inhibit them from doing so.[2]

---

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

[2] Li, McCormick, and Zhao (2005) show that NASDAQ dealers provide liquidity during extreme return days.

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 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.[3] Poor performance may result in loss of assigned stocks and/or ineligibility for new stock allocations.

The Limit Order Display Rule requires 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

---

However, their study does not compare the NYSE specialist and NASDAQ dealer systems.

[3] Based on all NYSE Hearing panel decisions on specialist disciplinary proceedings and interviews with specialists and senior officials of the NYSE, Panayides (2007) observes that the specialist's affirmative obligation includes three components: the Price Continuity rule, which requires the specialist to avoid large consecutive price changes; the Quotation rule, which requires the specialist to maintain narrow quoted spreads; and the Price Stabilization rule, which requires the specialist to transact against the market trend. Panayides (2007) shows that the specialists are constrained by the Price Continuity rule for both high and low volatility periods and improve the best prices of the limit order book for both periods when they are engaged in price smoothing in compliance with the rule.

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, NASDAQ dealers may not step up and narrow the inside spread due to the problem of free riding.[6]

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 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 existing quotes for stocks with large preferenced orders, especially in times of high return volatility.

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

[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 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, e.g., 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.

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 the bid-ask spread 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 moderates the impact of return volatility on the bid-ask spread. 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 time-series regression analyses to determine whether the difference in spreads between NYSE and NASDAQ stocks is systematically related to return volatility 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 in terms of the bid-ask spread.

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 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 conjecture that the NYSE specialist system provides better liquidity than the NASDAQ dealer system in volatile periods. We also find that the specialist system provides better liquidity than the dealer system in thin markets (both temporally and cross-sectionally). Prior research shows that stocks traded on NASDAQ 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. Our study provides an alternative explanation: the designated versus non-designated market maker systems.

Our empirical results are in line with the findings of Anand and Weaver (2006). Using intraday options data, Anand and Weaver analyze the "natural experiment" of the Chicago Board Options Exchange superimposing a specialist system on an existing multiple market maker system. They show that quoted and effective spreads decrease following the specialist system adoption. The results support hypotheses drawn from theory that a specialist system is better able to ascertain investor demand. Resolving uncertainty regarding investor demand then results in narrower spreads.

Our results corroborate the finding of a recent study by Venkataraman and Waisburd (2007) that stocks with designated dealers exhibit better market quality than stocks without designated dealers from a sample of stocks that trade on the Paris Bourse. In addition, our results suggest that the hybrid trading system may serve traders better than pure electronic limit order markets in high volatility periods, providing a sound economic rationale for the Liquidity Provider (LP) system on Euronext, the Stockholm Stock Exchange, and the Korea Stock Exchange, the Designated Sponsor (DS) system on Deutsche Börse, and the Registered Trader (RT) system on the Toronto Stock Exchange. The LP, DS, and RT systems were added to these otherwise pure electronic limit order markets in an effort to maintain a reasonable level of liquidity for stocks with limited public trading interests.[7]

The NYSE has been implementing the Hybrid Market in phases, starting with Phase I beginning in December 2005. The NYSE's hybrid market consists of the usual floor brokers placing orders through specialists along with a new computerized trading system. The computerized system allows for fast executions on the NYSE similar to those on NASDAQ. The hybrid trading system reduces the role of the floor without removing some of the affirmative obligations of the specialist. Although some market

[7] Another example is the London Stock Exchange's SETSmm trading mechanism launched at the end of 2003. This system replaced the SEAQ (Stock Exchange Automation Quotation) dealer market for FTSE 250 securities which are not liquid enough to be traded on a pure limit order book.

observers predict that the floor may be gone in a few years, the results of the present study suggest that such decision should be made with great caution.

The remainder of the paper is organized as follows. Section II describes data source, variable measurement procedures, and summary statistics. Section III presents the results of time-series regression analyses. Section IV presents the results of NYSE-NASDAQ spread comparisons during the months of low and high return volatility. Section V presents the results of the 9/11 analyses. Section VI discusses some other possible explanations of our results. Section VII examines the effect of trading volume on the spread of NYSE and NASDAQ stocks. Section VIII concludes.

II. Data Sources, Variable Measurement, and Descriptive Statistics

We obtain data from the NYSE's Trade and Quote (TAQ) database. We use the trade and quote data for the six-year period from January 1998 to December 2003. We select January 1998 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.[8]

Prior research (see Blume and Goldstein, 1997; Bessembinder, 2003c) shows that for NYSE-listed stocks, quotes that originate from off the NYSE only occasionally improve NYSE quotes. For example, Bessembinder (2003c) shows that the NYSE is almost always (99.74% of the time and during 99.01% of trades) at the National Best Bid and Offer (NBBO) on at least one side of the market. He also finds that the NYSE is at the NBBO on both sides of the market 89% of the time. Hence, we use only NYSE quotes for NYSE-listed stocks. For NASDAQ-listed stocks, all ECN quotes and dealer quotes

[8] 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.

were reported with exchange code 'T' in the TAQ database until September 12, 2002. Hence, we use quotes with exchange code 'T' for NASDAQ-listed stocks from January 2, 1998 through September 12, 2002.

Island quotes appear on TAQ with exchange code 'C' from September 13, 2002. Also note that, after the implementation of the NASDAQ's SuperMontage system on October 14, 2002,[9] most ECN quotes are posted via the Automatic Display Facility (ADF) with exchange code 'D.' Therefore, we construct the NBBO for NASDAQ-listed stocks using quotes from all major venues, i.e., NASDAQ (T), Cincinnati (C), Pacific (P), and ECNs (D) from September 13, 2002 through December 31, 2003. For the entire study period, we use all trades reported in TAQ for NYSE and NASDAQ stocks, including trades from regional exchanges and ECNs.

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 $|(p_t - p_{t-1})/p_{t-1}| > 0.1$ or if the ratio of the effective spread to the quoted spread is greater than four; 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 drop a stock from our study sample if its average price during our study period is below \$5. We calculate daily values of the following variables for each 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 ($TSIZE_{it}$); and market capitalization as measured by the market value of equity (MVE_{it}).[10]

We measure return volatility using four different methods. First, we measure return volatility by the daily standard deviation of quote-midpoint returns measured over every two minutes interval

[9] The phase-in dates of SuperMontage are 10/14/02, 10/17/02, 10/21/02, 10/28/02, 11/4/02, 11/11/02, 11/18/02, 11/25/02, and 12/2/02.

[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.

(VOLA1).[11] In the second method, we approximate return volatility on day t by the standard deviation of daily closing quote-midpoint returns over previous 20 trading days (VOLA2). An important advantage of VOLA2 over other volatility measures employed in this study is that VOLA2 is not likely to be significantly affected by the NYSE's Price Continuity rule. The Price Continuity rule is likely to have little effect on VOLA2 because we calculate VOLA2 using only *daily* closing quote midpoints.[12] For the same reason, the Price Stabilization rule is likely to have little effect on VOLA2. Panayides (2007) finds evidence of a decrease in volatility and price variance ratios when the specialists are engaged in price smoothing in compliance with the Price Continuity rule. Because the main purpose of our study is to examine how market structure moderates the effect of return volatility on the behavior of marketmakers and thus the bid-ask spread, volatility measures that could be affected by market structure are likely to induce the problem of reverse causality.

We also measure return volatility by the daily standard deviation of quote-midpoint returns using only the quotes at the time of trade (VOLA3) and the daily standard deviation of quote-midpoint returns using all available quotes (VOLA4). Although these measures of return volatility have certain limitations,[13] we use all four metrics to assess the sensitivity our results to different measures of return volatility. Our empirical results indicate that specific methods of calculating return volatility do not

[11] Because we measure return volatility using quote midpoints instead of trade prices, our measure of return volatility is not subject to the bid-ask bounce effect. Hence, our results are not likely to be driven by reverse causality, i.e., the bid-ask spread affecting return volatility instead of return volatility affecting the bid-ask spread.
[12] We account for stock splits and stock dividends in our calculation of daily returns using price adjustment factors from the CRSP.
[13] If two stocks have the same return volatility per unit of time, then the one that trades more frequently would exhibit smaller price changes between trades. Consequently, return volatility calculated from only the quotes at the time of trade (VOLA3) has a built-in negative correlation with the number of trades. To the extent that NYSE specialists and NASDAQ dealers react differently to changes in trading frequency, the relation between differential spreads (between NYSE and NASDAQ stocks) and VOLA3 may reflect at least in part the relation between differential spreads and trading frequency. In addition, the NYSE's Price Continuity rule is likely to have a significant effect on the trade-to-trade return volatility and thus VOLA3 (see Panayides, 2007). We also note that VOLA4 is likely to be affected by market structure. Quote revisions for NASDAQ stocks reflect changes in quotes from multiple dealers and ECNs, whereas quote revisions for NYSE stocks reflect only the quote changes on the NYSE. To the extent that NASDAQ stocks have more frequent quote revisions than NYSE stocks, the variance of quote-midpoint returns for NASDAQ stocks is likely to be greater than that for NYSE stocks.

change our conclusions.[14] For space consideration, therefore, we only report the results using the first two measures (VOLA1 and VOLA2) of return volatility.

For each trade, we calculate the percentage effective spread using the following formula: ESPRD = 2D(P – M)/M, where D is the buy-sell indicator variable (1 for buyer-initiated trades and -1 for seller-initiated trades), P is the transaction price, and M is the midpoint of the most recently posted bid and ask quotes.[15] The effective spread measures the actual execution cost paid by the trader. For each quote, we calculate the percentage quoted spread using the following formula: 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 effective spread ($ESPRD_{it}$) and the time-weighted average quoted spread ($QSPRD_{it}$).[16]

Table 1 shows descriptive statistics on our study sample of 1,841 NYSE stocks and 1,420 NASDAQ stocks that have the complete data. The average share price is $27.89 for the NYSE sample and $23.25 for the NASDAQ sample. The average trade size and average daily number of transactions are $29,000 and 446 for the NYSE sample, and $16,000 and 1,170 for the NASDAQ sample. The average daily standard deviation of two minute quote-midpoint returns (VOLA1) is 0.1362% for the NYSE sample and 0.2259% for the NASDAQ sample. The average standard deviation of daily closing quote-midpoint returns over 20 trading days (VOLA2) is 0.0213 for the NYSE sample and 0.0367 for the NASDAQ sample.

The average market capitalizations for our NYSE and NASDAQ stocks are $5,515 million and $2,085 million, respectively. The average effective (quoted) spread of NYSE stocks is 0.3406% (0.5773%), while the corresponding figure for NASDAQ stocks is 0.7293% (1.0133%). On the whole,

---

[14] The results are available from the authors upon request.

[15] Following the algorithm in Ellis, Michaely, and O'Hara (2000), we use contemporaneous quotes for assigning trade directions and for calculating quote midpoints. Following Lee and Ready (1991), we do not use opening trades not preceded by quotes. 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.

[16] We obtain qualitatively similar results when we replicate our empirical analyses using the *dollar* effective and quoted spreads. The results are available from the authors upon request.

NYSE stocks have higher share prices, larger trade sizes, and larger market capitalizations, but smaller spreads, fewer trades, and lower return volatilities.

III. Methodology and Findings

This section explains our empirical methods and presents the results of time-series regression analyses.

A. Formation of Volatility Groups

To test whether the NYSE specialist system provides better liquidity than the NASDAQ dealer system during high volatility periods, it is necessary to cluster our study sample of NYSE and NASDAQ stocks into groups in such a way that return volatility is similar between the NYSE and NASDAQ stocks within each group but different across groups. We then examine whether the difference in spreads between the NASDAQ and NYSE stocks within each volatility group differs significantly across time.

To form volatility groups, 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.[17]

[17] 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. Price stabilization provided by the specialist is likely to reduce return volatility on the NYSE. Indeed, prior research shows that return volatility of NYSE stocks is

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 volatility groups. 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. Hence, we only report the results that are based on $MVOLA_{jt}$.

Figure 1 shows the time-series pattern of the mean return volatility (MVOLA1) for both our entire study sample of stocks and groups 20, 50, and 80 when return volatility is measured by VOLA1 from January 2, 1998 through December 31, 2003. Similarly, Figure 2 shows the time-series pattern of the mean return volatility (MVOLA2) when return volatility is measured by VOLA2. Although there has been a gradual decline in average volatility during our study period, Figure 1 shows 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.

Panel A of 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 time-series mean values of

---

generally lower than that of comparable NASDAQ stocks (see Bessembinder and Kaufman, 1997; and Weaver, 2005) and return volatility declines when stocks move from NASDAQ to the NYSE (see Bennett and Wei, 2006; Bessembinder and Rath, 2007). Bessembinder and Rath (2007) also show that the highest declines in volatility occur for stocks that experience the highest decline in spreads. Similarly, Bennet and Wei (2006) show that the volatility decline is greater for smaller stocks, and the change in the degree of fragmentation due to the switch is related to the changes in liquidity and volatility. However, the main concern of our study is *not* whether the NYSE specialist system reduces return volatility. Rather, our main question is whether the difference in spreads between the NYSE and NASDAQ stocks that belong to the *same* volatility group increases with return volatility because of the specialist's affirmative obligation. Consequently, the fact that the specialist system reduces return volatility on the NYSE does not confound our research design. In any case, price stabilization is likely to have little effect on VOLA2 because of its long return measurement interval.

the variables included in Table 1 when volatility groups are formed according to VOLA1. Panel B shows the results when volatility groups are formed by VOLA2. Both panels show that the proportion of NASDAQ stocks increases with return volatility, reflecting that NASDAQ stocks have, on average, a higher return volatility than NYSE stocks. The mean volatility of NYSE stocks is almost identical to that of NASDAQ stocks within each volatility group. This result is not surprising given our volatility-group formation method. Consistent with the results reported in previous studies, both the effective and quoted spreads of NASDAQ stocks are larger than those of NYSE stocks across all volatility groups. There are substantial differences in stock attributes (i.e., PRICE, NTRADE, TSIZE, and MVE) between NYSE and NASDAQ stocks across all volatility groups. Although stocks that belong to high return volatility groups (e.g., Groups 80, 90, and 100) have generally smaller trade sizes, more trades, lower prices, and larger effective and quoted spreads than stocks that belong to low return volatility groups (e.g., Groups 10, 20, and 30), the relations between return volatility and these variables are not monotonic.

Table 2 also shows that the relation between return volatility and market capitalization is highly irregular. Regardless of whether we measure return volatility with two minute quote-midpoint returns or daily closing quote-midpoint returns, we find that stocks with smallest market capitalizations exhibit both the lowest and highest return volatility. That is, in both panels, stocks that belong to Groups 10 and 100 have smaller market capitalizations than stocks that belong to other volatility groups (i.e., Groups 20 through 90). Table 2 shows that stocks in the lowest volatility group are those of small companies that are infrequently traded. These stocks do not have the lowest effective and quoted spreads (despite the fact that they exhibit the lowest return volatility) perhaps because of their low trading volume (low volume stocks usually have wide spreads). We conjecture that stocks that belong to the highest volatility group are those of small companies that have high business and financial risks. Not surprisingly, these stocks have the largest effective and quoted spreads, lowest share price, and smallest trade size. Some of the irregular and non-monotonic relations between return volatility and other variables in Table 2 may be interpreted in the similar context.

B. Regression Analyses

In this section we examine whether the difference in spreads between NASDAQ stocks and NYSE stocks is positively related to return volatility. In particular, we test whether the difference in spreads between NYSE and NASDAQ stocks is larger on *high volatility days* by looking at the inter-temporal relation between the differential spread and return volatility.[18] For this, we estimate the following regression models using time-series data for *each* volatility group:[19]

(1) $ESPRD_{jt}^{NASD} - ESPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt}$;

(2) $QSPRD_{jt}^{NASD} - QSPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt}$;

where $ESPRD_{jt}^{NASD}$ is the mean effective spread of NASDAQ stocks in group j on day t, $ESPRD_{jt}^{NYSE}$ is the mean effective spread of NYSE stocks in group j on day t, $QSPRD_{jt}^{NASD}$ is the mean quoted spread of NASDAQ stocks in group j on day t, $QSPRD_{jt}^{NYSE}$ is the mean quoted spread of NYSE stocks in group j on day t, $MVOLA1_{jt}$ is the mean standard deviation of two minute quote-midpoint returns of stocks in group j on day t, and X_{kjt} denotes the mean value of stock attribute k of stocks in group j on day t (where X_{kjt} = log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt})).[20] We include these variables

[18] An alternative test of our hypothesis would be testing whether the difference in spreads between NYSE and NASDAQ stocks is larger for riskier stocks in each month. We believe that the analysis of the time-series relation between the differential spread and return volatility provides a cleaner test of our main conjecture than the analysis of the cross-sectional relation between the two variables because the latter approach requires an assumption that the marketmaker who handles stocks with high return volatility has the same risk aversion as the marketmaker who handles stocks with low return volatility (and thus the former provides poorer liquidity than the latter). If dealers with greater risk tolerance are more likely to make markets in high risk stocks than those with lower risk tolerance, the above behavioral assumption would not hold and thus the validity of the cross-sectional regression approach would be compromised. In addition, as noted earlier, prior theoretical works [see Rock (1990), Grossman (1992), and Seppi (1997)] focus on *temporal variation* in liquidity provision by limit order traders during times of excessive price uncertainty and adverse selection risk.

[19] 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 1,424 days = 1,068 days. We obtain qualitatively similar results when we apply different minimum % values (e.g., 60%, 80%, and 90%).

[20] 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, $\beta_t[\log(NTRADE_{jt}^{NASD}) - \log((1.3)NTRADE_{jt}^{NYSE})] = \beta_t[\log(NTRADE_{jt}^{NASD}) - \log(NTRADE_{jt}^{NYSE})] - \beta_t\log(1.3)$.

to account for the possibility that the difference between the NYSE and NASDAQ spreads is due to differences in their attributes.[21] Although we form groups in such a way that stocks in each group are similar in return volatility, we include the difference in return volatility between NYSE and NASDAQ stocks as a control variable to remove the effects (if any) of differential volatilities on differential spreads.

Note that our main conjecture is that $ESPRD_{jt}^{NASD} = \lambda^{NASD} \bullet VOLA1_{jt}$ and $ESPRD_{jt}^{NYSE} = \lambda^{NYSE} \bullet VOLA1_{jt}$, where $\lambda^{NYSE} < \lambda^{NASD}$ because of the specialist's affirmative obligation. Now letting $\lambda^{NYSE} = \lambda^{NASD} - \beta$ and subtracting $ESPRD_{jt}^{NYSE}$ from $ESPRD_{jt}^{NASD}$, it is easy to show that:

$$ESPRD_{jt}^{NASD} - ESPRD_{jt}^{NYSE} = \beta \bullet VOLA1_{jt}. \tag{3}$$

The main hypothesis of our study is that $\beta > 0$ in equation (3). In essence, testing whether $\beta_{1j} > 0$ in regression model (1) is equivalent to testing whether $\beta > 0$ in equation (3). We do not have any *a priori* reason to believe that share price, firm size, or trade size affects NYSE and NASDAQ spreads differently. Hence, we assume that the parameters for these variables are the same for both groups of stocks. We examine the differential effects of trading volume on NYSE and NASDAQ spreads later in the paper.

We use the reciprocal of share price (instead of share price) because such specification captures more accurately the effect of the tick-size induced binding constraint on spreads when spreads are measured in relative terms [see Harris (1994, p. 160)]. To assess the sensitivity of our results to different model specifications, we also estimate the above models using $\log(MVOLA1_{jt})$, $\log(PRICE_{jt})$, and $\log(VOLA1_{jt})$ in stead of $MVOLA1_{jt}$, $1/PRICE_{jt}$, and $VOLA1_{jt}$.[22]

Panel A of Table 3 shows the regression results. Because we estimate the above regression models using daily time-series data for each volatility group, we report for each explanatory variable the

---

Hence, the volume adjustment changes only the regression intercept. For this reason, we do not make the volume adjustment.

[21] 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.

[22] This model specification is largely in line with the one used by Stoll (2000) as a representative spread model in his survey of the empirical market microstructure literature.

mean value (across volatility groups) of regression coefficients, the Fama-MacBeth t-statistic (Fama and MacBeth, 1973) for testing whether the mean value of regression coefficients is different from zero, and the mean value of adjusted R^2. To the extent that the absolute magnitudes of the dependent or independent variables are different across volatility groups, estimated regression coefficients are not directly comparable across groups. For example, all things being equal, we expect to obtain smaller regression coefficients on $MVOLA1_{jt}$ for volatility groups with larger $MVOLA1_{jt}$. To make regression coefficients comparable across volatility groups, we calculate elasticity estimates by multiplying β_{1j} by the ratio of the mean of $MVOLA1_{jt}$ to the mean of the spread.

The first four columns (under Model 1 and Model 2) show the results of regression models (1) and (2) when we use log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt}) as control variables. The next four columns (under Model 3 and Model 4) show the results of regression models (1) and (2) with the following control variables: log($TSIZE_{jt}$), log($NTRADE_{jt}$), log($PRICE_{jt}$), log($VOLA1_{jt}$), and log(MVE_{jt}). The results show that the difference in spreads (both effective and quoted) between NASDAQ and NYSE stocks is positively and significantly related to both $MVOLA1_{jt}$ and log($MVOLA1_{jt}$), 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. The mean values of elasticity estimates are all significant and positive as well. These results support our conjecture that NYSE specialists provide better liquidity services than NASDAQ dealers in high volatility periods. The results show that estimated regression coefficients for control variables are mostly significant 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.

To assess the sensitivity of our results to different measures of return volatility, we replicate the results in Panel A using the standard deviation of daily closing quote-midpoint returns (from day t – 20 to day t). The results (see Panel B of Table 3) show that the difference in spreads between NASDAQ and

NYSE stocks is also positively and significantly related to both $MVOLA2_{jt}$ and $\log(MVOLA2_{jt})$, indicating that our results are robust to different measures of return volatility.

C. Additional Tests

Although the results in the previous sections are consistent with our conjecture that the NYSE provides better liquidity (i.e., smaller execution costs) than NASDAQ in times of high uncertainty because of its designated liquidity provider system, they could be due to some other reasons. For instance, the results could be a statistical artifact of the portfolio grouping approach employed in this study. To check whether our results are driven by the empirical method instead of differences in market structure between the NYSE and NASDAQ, we replicate the analyses in the previous sections using only NYSE stocks.

On each day we randomly assign our NYSE stocks into two sets: Set A and Set B. We then rank the stocks in both sets according to return volatility and cluster them into 50 groups, where Group 1 consists of stocks with the lowest volatility and Group 50 consists of stocks with the highest volatility. By construction, the number of stocks that belong to Set A and the number of stocks that belong to Set B are different in any volatility group as well as across groups and days. To ensure that each volatility group contains a reasonable number of stocks from both Set A and Set B, we drop a volatility group from the study sample on each day if stocks from either Set A or Set B constitute less than 20% of the stocks in the volatility group.

We then test whether the difference in spreads between stocks that belong to Set A and stocks that belong to Set B is positively related to return volatility by estimating the following regression model using time-series data for each volatility group:

(4) $$ESPRD_{jt}^{A} - ESPRD_{jt}^{B} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{A} - X_{kjt}^{B}) + \varepsilon_{jt};$$

(5) $$QSPRD_{jt}^{A} - QSPRD_{jt}^{B} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{A} - X_{kjt}^{B}) + \varepsilon_{jt};$$

where $ESPRD_{jt}^{A}$ is the mean effective spread of stocks that belong to Set A in group j on day t, $ESPRD_{jt}^{B}$ is the mean effective spread of stocks that belong to Set B in group j on day t, $QSPRD_{jt}^{A}$ is the mean quoted spread of stocks that belong to Set A in group j on day t, $QSPRD_{jt}^{B}$ is the mean quoted spread of stocks that belong to Set B in group j on day t, $MVOLA1_{jt}$ is the mean standard deviation of two minute quote-midpoint returns of stocks in group j on day t, and X_{kjt} denotes the mean value of stock attribute k of stocks in group j on day t. As in Table 3, we also calculate elasticity estimates.

The first four columns (under Model 1 and Model 2) of Panel A in Table 4 show the mean values (and t-statistics) of regression coefficients on $MVOLA1_{jt}$ from regression models (4) and (5) with the following control variables: log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt}). The next four columns (under Model 3 and Model 4) show the mean values (and t-statistics) of regression coefficients on log($MVOLA1_{jt}$) from regression models (4) and (5) with the following control variables: log($TSIZE_{jt}$), log($NTRADE_{jt}$), log($PRICE_{jt}$), log($VOLA1_{jt}$), and log(MVE_{jt}). The results show that the mean values of regression coefficients on $MVOLA1_{jt}$ and log($MVOLA1_{jt}$) and elasticity estimates are not statistically different from zero in the effective and quoted spread models, regardless of different model specifications. When we replicate the results in Panel A using the standard deviation of daily closing quote-midpoint returns (i.e., $VOLA2_{jt}$), we find qualitatively similar results (see Panel B of Table 4).

When we replicate the above analyses with our NASDAQ study sample of stocks, we again find that the mean values of regression coefficients on MVOLA1, log(MVOLA1), MVOLA2, and log(MVOLA1) as well as the mean values of estimated elasticity are not statistically different from zero in the effective and quoted spread models (see Panels C and D of Table 4). Hence, we conclude that the differential spreads between NYSE and NASDAQ stocks in times of high return volatility reported in Table 3 are more likely due to differential market structures than due to a statistical artifact of our portfolio grouping method.

IV. 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 502 matching pairs of NYSE and NASDAQ stocks for October 1998, and 565 matching pairs for July 2000 when we measure return volatility by VOLA1. Similarly, we obtain 509 matching pairs of NYSE and NASDAQ stocks for October 1998 and 517 pairs for July 2000 when we measure return volatility by VOLA2.

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 (VOLA1), trade size, and market capitalization of NYSE (NASDAQ) stocks are \$20.4 (\$21.4), 0.2388 (0.2604), \$25,600

($25,200), and $1,899 million ($1,868 million), respectively. The corresponding figures for the low volatility month are $22.57 ($25.59), 0.1716 (0.2031), $22,700 ($20,400), and $3,123 million ($2,991 million), respectively.

Panels A and B (C and D) of Table 5 show the spread comparison results when we measure return volatility by VOLA1 (VOLA2). Panel A (C) shows the mean effective spread of NASDAQ and NYSE stocks, respectively, together with the difference between the two figures (i.e., $ESPRD^{NASD} - ESPRD^{NYSE}$) in each month. Panel A (C) also shows the difference in ($ESPRD^{NASD} - ESPRD^{NYSE}$) between the high and low volatility months (H – L) in the third row. The last two columns report t-statistics for testing the equality of two means, a t-statistic for testing whether (H – L) is different from zero, and the p-value for the Wilcoxon rank-sum test. Panel B (D) shows the above results for the quoted spread.

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. Although the mean NASDAQ effective spread is significantly larger than the mean NYSE effective spread during the low volatility month of July 2000, the difference in the quoted spread between NYSE and NASDAQ stocks is statistically insignificant. 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.

[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.

V. 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 daily standard deviation of two minute quote-midpoint returns (VOLA1) for 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 for August 2001. The matching procedure results in a total of 401 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 and B of Table 6 show the results for 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 (DIFF) (with t-statistic) in the mean spread between NASDAQ and NYSE stocks 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 fourth row of each panel is the difference in DIFF between the pre-9/11 period and day *k* in the post-9/11 period (where k = 1 to 10).

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. 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 DIFF between the pre-9/11 period and the first post-9/11 day 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 post-9/11 day 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 (i.e., larger execution costs) than the NYSE specialist system in high volatility periods.

Except for the first trading day 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.

VI. Can the Results be Driven by Other Reasons?

Although we attribute the larger difference between NASDAQ spreads and NYSE spreads 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 in times of high uncertainty because brokers usually preference uninformed orders to dealers and the dealers' adverse selection risk is generally greater when uncertainty is higher.

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.[24] 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 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.

VII. Does the Specialist System provide Better Liquidity Services than the Dealer Market in Thin Markets?

In this section we perform an alternative test of our thesis by analyzing whether specialist and dealer markets respond differently to changes in trading activity. We conjecture that the specialist system

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

provides better liquidity services than the dealer market in times of low trading activity for the same reason stipulated in this study. The primary affirmative obligation of NYSE specialists is that they always maintain a reasonable market in their assigned stocks. They must quote two-sided markets and provide additional liquidity when the liquidity provided by public traders is not adequate (e.g., when the bid-ask spread established by public limit orders alone is too wide). Our analysis can shed additional light on the value of having 'the liquidity provider of last resort' when public traders do not provide adequate liquidity.

We cluster our study sample of NYSE and NASDAQ stocks into 100 groups on each day, where Group 1 consists of stocks with the lowest trading volume and Group 100 consists of stocks with the highest trading volume. We use the number of shares traded as our measure of trading volume. We adjust the NASDAQ trading volume, given the result that the NASDAQ trading volume tends to be inflated, relative to the NYSE trading volume.[25] Using the daily mean values of the variables for NYSE stocks and NASDAQ stocks in each group and the average trading volume of the group, we estimate the following time-series regression models:

$$(6) \qquad ESPRD_{jt}^{NASD} - ESPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j}\log(MVOLM_{jt}) + \Sigma\beta_{kj}(X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt};$$

$$(7) \qquad QSPRD_{jt}^{NASD} - QSPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j}\log(MVOLM_{jt}) + \Sigma\beta_{kj}(X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt};$$

where $MVOLM_{jt}$ is the mean trading volume of (NYSE and NASDAQ) stocks in group j on day t and all other variables are the same as previously defined in regression models (1) and (2).

Table 7 shows the regression results.[26] The results show that the difference in effective spreads between NASDAQ and NYSE stocks is negatively and significantly related to $\log(MVOLM_{jt})$, indicating that the difference between NASDAQ and NYSE effective spreads is larger during low-volume periods. The results also show that the mean values of estimated elasticity are all negative and significant. We

---

[25] Following Atkins and Dyl (1997) and Anderson and Dyl (2005), we apply an adjustment factor of 55% for high-volume stocks and 77% for low-volume stocks to account for the reported volume differences between NYSE and NASDAQ stocks.

[26] We report the regression results when we measure return volatility by $VOLA1_{jt}$. The regression results using $VOLA2_{jt}$ are qualitatively similar and available from the authors upon request.

obtain qualitatively similar results for the quoted spread. These results are consistent with our conjecture that NYSE specialists provide better liquidity services than NASDAQ dealers during low-volume periods.[27]

VIII. Summary and Concluding Remarks

Both NYSE specialists and NASDAQ dealers are likely to be reluctant to provide liquidity in times of high uncertainty 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. Our results also indicate that the specialist system provide better liquidity than the NASDAQ dealer system during low-volume periods. We attribute these results 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. In this context,

[27] As an alternative test of our hypothesis, we also estimate regression models (6) and (7) using cross-sectional observations in each month and test whether the time-series mean values of β_{1t} are significantly negative. We find that the mean values of β_{1t} are significantly negative in all four regression models, indicating that the specialist system offers better liquidity than the dealer system for low-volume stocks. We note that the analysis of the cross-sectional relation between the differential spread and trading volume would not be a valid test of our main conjecture if dealers with greater risk tolerance are more likely to make markets in low-volume stocks than those with lower risk tolerance.

the results of our study offer a sound economic rationale for the Liquidity Provider and Designated Sponsor systems adopted in several European and Asian stock markets.

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.

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.

Anand, A., Weaver, D., 2006. The value of the specialist: Empirical evidence from the CBOE. Journal of Financial Markets 9, 100-118.

Anderson, A., Dyl, E., 2005. Market structure and trading volume. Journal of Financial Research 28, 115-131.

Atkins, A., Dyl, E., 1997. Market structure and reported trading volume: NASDAQ versus the NYSE. Journal of Financial Research 20, 291-304.

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.

Bennett, P., Wei, L., 2006, Market structure, fragmentation and market quality. Journal of Financial Markets 9, 49-78.

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., 2003c. Quote-based competition and trade execution costs in NYSE-listed stocks. Journal of Financial Economics 70, 385-422.

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.

Bessembinder, H., S. Rath, S., 2007. Trading costs and return volatility: Evidence from exchange listings. Market Liquidity. Elsevier Publishing, forthcoming.

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.

Blume, M., Goldstein, M., 1997. Quotes, order flow, and price discovery. Journal of Finance 52, 221-244.

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.

Ellis, K., Michaely, R., O'Hara, M., 2000. The accuracy of trade classification rules: Evidence from NASDAQ. Journal of Financial and Quantitative Analysis 35, 529-551.

Fama E., MacBeth J., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

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.

Harris, L., 1994. Minimum price variations, discrete bid-ask spreads, and quotation sizes. Review of Financial Studies 7, 149-178.

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.

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.

Lee, C., Ready, M., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733-746.

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.

Panayides, M., 2007. Affirmative obligations and market making with inventory. Journal of Financial Economics, forthcoming.

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.

Venkataraman, K., Waisburd, A.C., 2007. The value of the designated market maker. Journal of Financial and Quantitative Analysis 42, 735–758.

Weaver, D., 2005. Intraday volatility on the NYSE and Nasdaq. Essays in Market Microstructure, forthcoming.

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 ($NTRADE_{it}$); number of quotes ($NQUOTE_{it}$), average dollar trade size ($TSIZE_{it}$); return volatility as measured by the daily standard deviation of two minute quote-midpoint returns ($VOLA1_{it}$) and the standard deviation of daily closing quote-midpoint returns over 20 trading days ($VOLA2_{it}$); market capitalization as measured by the market value of equity (MVE_{it}), the trade-weighted average effective spread ($ESPRD_{it}$); and the time-weighted average quoted spread ($QSPRD_{it}$). We then calculate the time-series mean values of these variables during our study period (January 1998 through December 2003) for each stock.

	Exchange	Mean	Standard Deviation	Percentile 5	25	50	75	95
Share price ($)	NYSE	27.89	2.53	7.28	13.46	22.11	35.55	65.16
(PRICE)	NASDAQ	23.25	3.98	6.10	10.74	18.04	29.84	57.95
Number of trades	NYSE	446	225	10	48	171	493	1,728
(NTRADE)	NASDAQ	1,170	636	14	60	209	672	4,999
Number of quotes	NYSE	803	635	42	235	559	1,126	2,388
(NQUOTE)	NASDAQ	1,365	1,238	44	189	482	1,269	6,305
Trade size (in $1,000)	NYSE	29.0	10.4	5.4	11.0	19.4	36.9	82.5
(TSIZE)	NASDAQ	16.0	7.7	3.4	6.5	11.2	20.3	43.0
Return volatility (VOLA1)	NYSE	0.1362	0.0252	0.0395	0.0842	0.1211	0.1695	0.2832
(in %)	NASDAQ	0.2259	0.0516	0.0658	0.1341	0.2011	0.2883	0.4688
Return volatility (VOLA2)	NYSE	0.0213	0.0045	0.0057	0.0133	0.0196	0.0271	0.0432
	NASDAQ	0.0367	0.0085	0.0136	0.0239	0.0343	0.0468	0.0685
Market value of equity	NYSE	5,515	548	100	310	859	2,904	22,007
(in $ million) (MVE)	NASDAQ	2,085	627	70	171	373	900	5,648
Effective spread	NYSE	0.3406	0.1450	0.0770	0.1446	0.2515	0.4460	0.8891
(ESPRD)	NASDAQ	0.7293	0.3024	0.1483	0.3231	0.5460	0.9212	1.9207
Quoted spread	NYSE	0.5773	0.2152	0.1500	0.2740	0.4475	0.7388	1.4422
(QSPRD)	NASDAQ	1.0133	0.4453	0.1937	0.4491	0.7683	1.3000	2.6486

Table 2
Stock Attributes by Volatility Groups

This table shows the percentage of NASDAQ stocks and the mean values of the variables for each volatility group. To form volatility groups, we first 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 return volatility and Group 100 consists of stocks with the highest return volatility. We measure return volatility in two ways: (1) the standard deviation of two minute quote-midpoint returns for each day ($VOLA1_{jt}$) and (2) the standard deviation of daily closing quote-midpoint returns over 20 trading days ($VOLA2_{jt}$). Panel A (Panel B) shows the results when volatility groups are formed according to $VOLA1_{jt}$ ($VOLA2_{jt}$). To obtain the mean volatility of stocks in each volatility group, we first calculate the mean volatility of NYSE stocks and the mean volatility of NASDAQ stocks in each group for each day. We then calculate the average of the 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). We show the time-series mean values of $MVOLA_{jt}$ for Group 10 through Group 100. The table also shows the time-series mean values of all the other variables: share price as measured by the mean value of quote midpoints ($PRICE_{it}$); number of trades ($NTRADE_{it}$); number of quotes ($NQUOTE_{it}$), average dollar trade size ($TSIZE_{it}$); market capitalization as measured by the market value of equity (MVE_{it}), the trade-weighted average effective spread ($ESPRD_{it}$); and the time-weighted average quoted spread ($QSPRD_{it}$).

Panel A: Volatility Groups are Formed by the Standard Deviation of Two Minute Quote-Midpoint Returns (VOLA1)

Group	Exchange	Proportion of NASDAQ stocks (%)	MVOLA1	PRICE	NTRADE	NQUOTE	TSIZE	ESPRD	QSPRD	MVE
10	NYSE	72.9	0.0608	29.38	143	368	28.1	0.3554	0.5532	2,565
	NASDAQ	27.1	0.0608	24.81	109	243	20.4	0.7222	0.9416	763
20	NYSE	72.5	0.0857	33.89	309	653	34.1	0.3033	0.5059	6,134
	NASDAQ	27.5	0.0857	25.30	254	391	20.4	0.6696	0.8968	1,689
30	NYSE	72.2	0.1058	33.89	450	843	35.5	0.2855	0.4903	8,512
	NASDAQ	27.8	0.1058	25.63	403	571	20.6	0.6791	0.9368	2,438
40	NYSE	69.8	0.1230	32.10	550	983	33.9	0.2797	0.4886	8,789
	NASDAQ	30.2	0.1231	25.85	702	890	19.0	0.6485	0.8944	3,124
50	NYSE	66.2	0.1425	29.49	573	1,002	31.9	0.2953	0.5161	7,409
	NASDAQ	33.8	0.1425	25.62	934	1,143	18.7	0.6347	0.8859	3,608
60	NYSE	59.6	0.1658	26.09	574	987	29.6	0.3279	0.5787	6,009
	NASDAQ	40.4	0.1658	24.86	1,128	1,357	17.5	0.6480	0.9075	2,879
70	NYSE	50.6	0.1952	22.85	594	958	27.0	0.3799	0.6635	4,544
	NASDAQ	49.4	0.1952	24.17	1,301	1,585	16.6	0.6674	0.9373	2,553
80	NYSE	40.6	0.2355	19.12	573	877	23.7	0.4591	0.7979	3,074
	NASDAQ	59.4	0.2355	23.40	1,446	1,755	15.7	0.7008	0.9889	1,994
90	NYSE	32.8	0.2940	15.70	575	832	20.2	0.5469	0.9476	1,903
	NASDAQ	67.2	0.2941	19.88	1,582	1,960	13.0	0.7710	1.0863	1,194
100	NYSE	28.4	0.6206	11.46	895	961	13.3	0.7270	1.2365	906
	NASDAQ	71.6	0.6287	10.90	1,398	1,643	6.1	1.1471	1.5338	303

Table 2 (Continued)

Panel B: Volatility Groups are Formed by the Standard Deviation of Daily Closing Quote-Midpoint Returns (VOLA2)

Group	Exchange	Proportion of NASDAQ stocks (%)	MVOLA2	PRICE	NTRADE	NQUOTE	TSIZE	ESPRD	QSPRD	MVE
10	NYSE	75.4	0.0094	27.68	164	437	23.0	0.3809	0.5943	2,622
	NASDAQ	24.6	0.0094	25.36	122	310	19.9	0.6678	0.9240	821
20	NYSE	72.7	0.0142	32.24	342	771	29.0	0.3122	0.5329	6,371
	NASDAQ	27.3	0.0142	24.66	248	548	16.5	0.7044	0.9907	1,125
30	NYSE	72.0	0.0174	32.90	463	927	31.4	0.2877	0.5075	7,699
	NASDAQ	28.0	0.0174	24.26	364	767	16.6	0.7430	1.0493	1,439
40	NYSE	69.8	0.0203	32.12	537	1,024	32.8	0.2817	0.5031	7,938
	NASDAQ	30.2	0.0203	24.59	630	919	16.7	0.7429	1.0521	3,116
50	NYSE	66.1	0.0236	30.30	559	1,009	33.0	0.2986	0.5343	7,194
	NASDAQ	33.9	0.0236	24.38	790	1,042	16.8	0.7474	1.0485	3,360
60	NYSE	58.6	0.0273	28.29	585	1,006	31.8	0.3204	0.5708	6,137
	NASDAQ	41.4	0.0273	23.66	987	1,255	16.8	0.7383	1.0405	3,002
70	NYSE	49.0	0.0320	25.55	602	975	29.6	0.3566	0.6294	5,123
	NASDAQ	51.0	0.0320	23.78	1,100	1,373	17.0	0.7119	0.9992	2,604
80	NYSE	37.9	0.0379	23.10	666	974	27.3	0.3811	0.6687	4,228
	NASDAQ	62.1	0.0379	22.46	1,413	1,642	15.7	0.7080	0.9882	2,216
90	NYSE	31.2	0.0458	19.03	835	1,133	23.5	0.3882	0.6824	3,151
	NASDAQ	68.8	0.0458	18.96	1,732	2,198	13.4	0.6900	0.9468	1,440
100	NYSE	29.2	0.0792	11.09	1,658	1,456	15.6	0.3694	0.6615	2,208
	NASDAQ	70.8	0.0778	13.03	2,543	3,021	7.4	0.5800	0.7462	677

Table 3

Testing the Effect of Return Volatility on the Spreads of NYSE and NASDAQ Stocks

Panel A reports the results of the following regression models:

(1) $ESPRD_{jt}^{NASD} - ESPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt}$; and

(2) $QSPRD_{jt}^{NASD} - QSPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt}$;

where $ESPRD_{jt}^{NASD}$ is the mean effective spread of NASDAQ stocks in group j on day t, $ESPRD_{jt}^{NYSE}$ is the mean effective spread of NYSE stocks in group j on day t, $QSPRD_{jt}^{NASD}$ is the mean quoted spread of NASDAQ stocks in group j on day t, $QSPRD_{jt}^{NYSE}$ is the mean quoted spread of NYSE stocks in group j on day t, $MVOLA1_{jt}$ is the mean standard deviation of two minute quote-midpoint returns of stocks in group j on day t, and X_{kjt} denotes the mean value of stock attribute k of stocks in group j on day t (where X_{kjt} = log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt})). Δ denotes the difference between NASDAQ and NYSE values. To assess the sensitivity of our results to different model specifications, we also estimate the above models using log($MVOLA1_{jt}$), log($PRICE_{jt}$), and log($VOLA1_{jt}$) in stead of $MVOLA1_{jt}$, 1/$PRICE_{jt}$, and $VOLA1_{jt}$. $NTRADE_{jt}$ is the total number of trades, $TSIZE_{jt}$ is the average dollar transaction size, $PRICE_{jt}$ is the mean value of quote midpoints, and MVE_{jt} is the market value of equity. Because we estimate the above regression models using daily time-series data for each volatility group, we report for each explanatory variable the mean value (across volatility groups) of regression coefficients, the Fama-MacBeth t-statistic for testing whether the mean value of regression coefficients is different from zero, and the mean value of adjusted R^2. Elasticity is measured by multiplying β_{1j} by the ratio of the mean of $MVOLA1_{jt}$ to the mean of the spread. The first four columns (under Model 1 and Model 2) show the results of regression models (1) and (2) with the following control variables: log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt}). The next four columns (under Model 3 and Model 4) show the results of regression models (1) and (2) with the following control variables: log($TSIZE_{jt}$), log($NTRADE_{jt}$), log($PRICE_{jt}$), log($VOLA1_{jt}$), and log(MVE_{jt}). In Penal B, we replicate the results in Panel A using the mean standard deviation ($VOLA2_{jt}$) of daily closing quote-midpoint returns (from day t – 20 to day t).

Panel A: Regression results using the daily standard deviation of two minute quote-midpoint returns (VOLA1)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	0.1809**	16.38	0.1610**	15.25	0.9389**	33.00	1.1713**	36.64
Elasticity	0.5327**	15.06	0.4497**	17.51	0.6068**	16.92	0.5206**	21.38
MVOLA1	1.4955**	13.64	1.9495**	15.05	.	.	.	.
log(MVOLA1)	.	.	.	.	0.2838**	25.35	0.3833**	35.38
Δlog(NTRADE)	-0.1214**	-82.27	-0.1900**	-86.21	-0.1209**	-79.07	-0.1888**	-82.92
Δlog(TSIZE)	0.0881**	26.36	0.1271**	26.13	0.0911**	30.89	0.1350**	32.38
Δ(1/PRICE)	7.2430**	29.43	10.2266**	39.56	.	.	.	.
ΔVOLA1	3.3604	1.42	2.2613	0.67	.	.	.	.
Δlog(PRICE)	.	.	.	.	-0.3242**	-61.04	-0.4712**	-106.47
Δlog(VOLA1)	.	.	.	.	0.5979	1.65	0.6289	1.20
Δlog(MVE)	0.0529**	20.51	0.0774**	20.30	0.0548**	22.64	0.0805**	22.66
Adjusted R^2	0.320		0.345		0.326		0.355	

Table 3 (Continued)

Panel B: Regression results using the standard deviation of daily closing quote-midpoint returns (VOLA2)

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	0.1139**	11.27	0.0579**	5.01	1.7777**	31.60	2.3559**	29.04
Elasticity	0.6869**	21.24	0.6152**	21.85	0.7516**	20.79	0.6703**	22.13
MVOLA2	12.5777**	17.07	17.4404**	16.60	.	.	.	.
log(MVOLA2)	.	.	.	.	0.3667**	29.26	0.5063**	29.18
Δlog(NTRADE)	-0.1155**	-45.30	-0.1754**	-53.60	-0.1128**	-42.02	-0.1712**	-49.69
Δlog(TSIZE)	0.0471**	13.48	0.0806**	18.65	0.0467**	12.23	0.0825**	19.95
Δ(1/PRICE)	7.8479**	37.58	11.1510**	41.08	.	.	.	.
ΔVOLA2	28.8823	1.49	13.1908	0.51	.	.	.	.
Δlog(PRICE)	.	.	.	.	-0.3424**	-65.39	-0.496**	-66.56
Δlog(VOLA2)	.	.	.	.	0.6415	1.32	0.3295	0.48
Δlog(MVE)	0.0569**	21.95	0.0817**	21.92	0.0567**	22.16	0.0817**	21.97
Adjusted R^2	0.325		0.333		0.331		0.341	

**Significant at the 1% level.

Table 4

Regression Results using Two Sets of Stocks within Each Market

On each day we randomly assign our NYSE stocks into two sets: Set A and Set B. We then rank the stocks in both sets according to return volatility and cluster them into 50 groups, where Group 1 consists of stocks with the lowest volatility and Group 50 consists of stocks with the highest volatility. We then test whether the difference in spreads between stocks that belong to Set A and stocks that belong to Set B is positively related to return volatility by estimating the following regression model using time-series data on each volatility group:

(4) $$ESPRD_{jt}^{A} - ESPRD_{jt}^{B} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{A} - X_{kjt}^{B}) + \varepsilon_{jt};$$

(5) $$QSPRD_{jt}^{A} - QSPRD_{jt}^{B} = \beta_{0j} + \beta_{1j}\, MVOLA1_{jt} + \Sigma\beta_{kj}\,(X_{kjt}^{A} - X_{kjt}^{B}) + \varepsilon_{jt};$$

where $ESPRD_{jt}^{A}$ is the mean effective spread of stocks that belong to Set A in group j on day t, $ESPRD_{jt}^{B}$ is the mean effective spread of stocks that belong to Set B in group j on day t, $QSPRD_{jt}^{A}$ is the mean quoted spread of stocks that belong to Set A in group j on day t, $QSPRD_{jt}^{B}$ is the mean quoted spread of stocks that belong to Set B in group j on day t, $MVOLA1_{jt}$ is the mean standard deviation of two minute quote-midpoint returns of stocks in group j on day t, and X_{kjt} denotes the mean value of stock attribute k of stocks in group j on day t. Elasticity is measured by multiplying β_{1j} by the ratio of the mean of $MVOLA1_{jt}$ to the mean of the spread. The first four columns (under Model 1 and Model 2) of Panel A show the mean values (and t-statistics) of regression coefficients on $MVOLA1_{jt}$ from regression models (4) and (5) with the following control variables: $\log(TSIZE_{jt})$, $\log(NTRADE_{jt})$, $1/PRICE_{jt}$, $VOLA1_{jt}$, and $\log(MVE_{jt})$. The next four columns (under Model 3 and Model 4) show the mean values (and t-statistics) of regression coefficients on $\log(MVOLA1_{jt})$ from regression models (4) and (5) with the following control variables: $\log(TSIZE_{jt})$, $\log(NTRADE_{jt})$, $\log(PRICE_{jt})$, $\log(VOLA1_{jt})$, and $\log(MVE_{jt})$. Panel B shows the results when we measure return volatility by the standard deviation of daily closing quote-midpoint returns (i.e., VOLA2). We repeat the same analyses with our NASDAQ sample and report the results in Panels C and D.

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Panel A: NYSE Regression results using the daily standard deviation of two minute quote-midpoint returns (VOLA1)								
Elasticity	-0.0008	-0.15	0.0037	0.85	0.0000	0.00	0.0044	1.00
MVOLA1	0.0260	1.25	0.0373	1.35	.	.	.	.
log(MVOLA1)	.	.	.	.	0.0004	0.24	0.0024	0.94
Adjusted R^2	0.282		0.318		0.274		0.312	
Panel B: NYSE regression results using the standard deviation of daily closing quote-midpoint returns (VOLA2)								
Elasticity	-0.0031	-0.72	-0.0023	-0.56	-0.0022	-0.48	-0.0012	-0.27
MVOLA2	-0.0858	-0.88	-0.0753	-0.47	.	.	.	.
log(MVOLA2)	.	.	.	.	-0.0010	-0.66	-0.0011	-0.43
Adjusted R^2	0.260		0.294		0.2520		0.287	

Table 4 (Continued)

Panel C: NASDAQ regression results using the daily standard deviation of two minute quote-midpoint returns (VOLA1)

Elasticity	-0.0034	-0.47	-0.0018	-0.3	-0.0024	-0.33	-0.0013	-0.22
MVOLA1	-0.0018	-0.04	0.0016	0.03	.	.	.	.
log(MVOLA1)	.	.	.	.	-0.0010	-0.20	-0.0001	-0.01
Adjusted R^2	0.204		0.203		0.206		0.204	

Panel D: NASDAQ regression results using the standard deviation of daily closing quote-midpoint returns (VOLA2)

Elasticity	-0.0017	-0.25	-0.0019	-0.29	-0.0023	-0.34	-0.0029	-0.44
MVOLA2	-0.0766	-0.39	-0.2028	-0.85	.	.	.	.
log(MVOLA2)	.	.	.	.	-0.0017	-0.35	-0.0031	-0.46
Adjusted R^2	0.215		0.207		0.215		0.207	

Table 5

NASDAQ-NYSE Spread Comparisons between High 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 502 matching pairs of NYSE and NASDAQ stocks for October 1998, and 565 matching pairs for July 2000 when we measure return volatility by VOLA1. Similarly, we obtain 509 matching pairs of NYSE and NASDAQ stocks for October 1998 and 517 pairs for July 2000 when we measure return volatility by VOLA2. Panels A and B (C and D) show the spread comparison results when we measure return volatility by VOLA1 (VOLA2). Panel A (C) shows the mean effective spread of NASDAQ and NYSE stocks, respectively, together with the difference between the two figures (i.e., $ESPRD^{NASDAQ} - ESPRD^{NYSE}$) in each month. Panel A (C) also shows the difference in ($ESPRD^{NASDAQ} - ESPRD^{NYSE}$) between the high and low volatility months (H – L) in the third row. The last two columns report t-statistics for testing the equality of two means, a t-statistic for testing whether (H – L) is different from zero, and the p-value for the Wilcoxon rank-sum test. Panel B (D) shows the above results for the quoted spread.

	NASDAQ	NYSE	NASDAQ-NYSE	t-statistic	p-value (Wilcoxon)
Panel A: Effective spread (ESPRD): Return volatility is measured by VOLA1					
High volatility month (H)	1.0967	0.6788	0.4179**	18.70	
Low volatility month (L)	0.8044	0.6249	0.1794**	11.07	
Difference: H – L			0.2385**	8.64	<.0001
Panel B: Quoted spread (QSPRD): Return volatility is measured by VOLA1					
High volatility month (H)	1.6592	1.1592	0.5000**	13.57	
Low volatility month (L)	1.0713	1.0502	0.0211	0.90	
Difference: H – L			0.4789**	10.95	<.0001
Panel C: Effective spread (ESPRD): Return volatility is measured by VOLA2					
High volatility month (H)	1.1329	0.6400	0.4929**	19.95	
Low volatility month (L)	0.8118	0.6215	0.1903**	11.16	
Difference: H – L			0.3026**	10.08	<.0001
Panel D: Quoted spread (QSPRD): Return volatility is measured by VOLA2					
High volatility month (H)	1.7271	1.0902	0.6369**	15.76	
Low volatility month (L)	1.0890	1.0506	0.0384	1.49	
Difference: H – L			0.5985**	12.5	<.0001

**Significant at the 1% level.

Table 6

Spread Changes around 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. As in the previous section, we obtain matching samples of NYSE and NASDAQ stocks based on the four stock attributes using data for August 2001. The matching procedure results in a total of 401 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. 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 and B show the results for 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 (DIFF) (with t-statistic) in the mean spread between NASDAQ and NYSE stocks 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 fourth row of each panel is the difference in DIFF between the pre-9/11 period and day *k* in the post-9/11 period (where k = 1 to 10). We indicate statistical significance of the difference only when the difference is significant according to both the t-test and Wilcoxon rank-sum test.

Panel A: Effective spread	Pre-911	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
NASDAQ	0.4079	0.7690	0.5448	0.6035	0.5905	0.7033	0.6306	0.5623	0.5477	0.5638	0.5156
NYSE	0.2152	0.4032	0.3292	0.3528	0.3784	0.4100	0.3771	0.3701	0.3132	0.3042	0.3066
DIFF = NASDAQ – NYSE	0.193**	0.366**	0.216**	0.251**	0.212**	0.293**	0.254**	0.192**	0.235**	0.26**	0.21**
DIFF (Post) – DIFF (Pre)		0.173**	0.0228	0.0579	0.0194	0.1005	0.0607	-0.0005	0.0417	0.0667	0.0162

Panel B: Quoted spread	Pre-911	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7	Day 8	Day 9	Day 10
NASDAQ	0.6486	1.1267	0.8598	0.9176	0.9241	0.9957	0.9244	0.8599	0.8310	0.8664	0.8179
NYSE	0.4552	0.7218	0.6222	0.6610	0.7013	0.7680	0.6876	0.7056	0.6153	0.6002	0.5819
DIFF = NASDAQ – NYSE	0.193**	0.405**	0.238**	0.257**	0.223**	0.228**	0.237**	0.154**	0.216**	0.266**	0.24**
DIFF (Post) – DIFF (Pre)		0.212**	0.0443	0.0632	0.0294	0.0343	0.0434	-0.0392	0.0223	0.0728	0.0426

**Significant at the 1% level.

Table 7

Testing the Effect of Trading Volume on the Spreads of NYSE and NASDAQ Stocks

We cluster our study sample of NYSE and NASDAQ stocks into 100 groups on each day, where Group 1 consists of stocks with the lowest trading volume and Group 100 consists of stocks with the highest trading volume. We use the number of shares traded as our measure of trading volume. Using the daily mean of variables for NYSE stocks and NASDAQ stocks in each group, and the average trading volume of the group, we estimate the following time-series regression models:

(6) $ESPRD_{jt}^{NASD} - ESPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j} \log(MVOLM_{jt}) + \Sigma\beta_{kj} (X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt}$;

(7) $QSPRD_{jt}^{NASD} - QSPRD_{jt}^{NYSE} = \beta_{0j} + \beta_{1j} \log(MVOLM_{jt}) + \Sigma\beta_{kj} (X_{kjt}^{NASD} - X_{kjt}^{NYSE}) + \varepsilon_{jt}$;

where $ESPRD_{jt}^{NASD}$ is the mean effective spread of NASDAQ stocks in group j on day t, $ESPRD_{jt}^{NYSE}$ is the mean effective spread of NYSE stocks in group j on day t, $QSPRD_{jt}^{NASD}$ is the mean quoted spread of NASDAQ stocks in group j on day t, $QSPRD_{jt}^{NYSE}$ is the mean quoted spread of NYSE stocks in group j on day t, $MVOLM_{jt}$ is the mean trading volume of (NYSE and NASDAQ) stocks in group j on day t, and X_{kjt} denotes the mean value of stock attribute k of stocks in group j on day t (where X_{kjt} = log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt})). Δ denotes the difference between NASDAQ and NYSE values. To assess the sensitivity of our results to different model specifications, we also estimate the above models using log($PRICE_{jt}$) and log($VOLA1_{jt}$) in stead of 1/$PRICE_{jt}$ and $VOLA1_{jt}$. $NTRADE_{jt}$ is the total number of trades, $TSIZE_{jt}$ is the average dollar transaction size, $PRICE_{jt}$ is the mean value of quote midpoints, $VOLA1_{jt}$ is the standard deviation of two minute quote-midpoint returns, and MVE_{jt} is the market value of equity. Because we estimate the above regression models using daily time-series data for each trading volume group, we report for each explanatory variable the mean value (across trading volume groups) of regression coefficients, the Fama-MacBeth t-statistic for testing whether the mean value of regression coefficients is different from zero, and the mean value of adjusted R^2. Elasticity is measured by dividing the regression coefficient on log($MVOLM_t$) by the mean of the spread. The first four columns (under Model 1 and Model 2) show the results of regression models (6) and (7) with the following control variables: log($TSIZE_{jt}$), log($NTRADE_{jt}$), 1/$PRICE_{jt}$, $VOLA1_{jt}$, and log(MVE_{jt}). The next four columns (under Model 3 and Model 4) show the results of regression models (6) and (7) with the following control variables: log(TSIZE), log(NTRADE), log(PRICE), log(VOLA1), and log(MVE).

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic	Coefficient	t-statistic
Intercept	1.149**	41.59	1.7952**	28.84	1.1099**	37.35	1.6919**	27.26
Elasticity	-0.4775**	-33.43	-0.5396**	-35.35	-0.4588**	-27.08	-0.5098**	-30.79
log(MVOLM)	-0.2406**	-33.06	-0.4377**	-24.15	-0.2254**	-30.91	-0.4051**	-24.64
Δlog(NTRADE)	-0.3372**	-17.57	-0.5539**	-21.16	-0.3295**	-13.35	-0.5244**	-15.78
Δlog(TSIZE)	0.0196**	4.18	0.0262**	4.63	0.0037	0.92	0.0237**	4.41
Δ(1/PRICE)	1.4582**	15.14	1.9199**	14.20	.	.	.	.
ΔVOLA1	2.2411**	17.65	3.697**	15.38	.	.	.	.
Δlog(PRICE)	.	.	.	.	-0.0401**	-8.17	-0.0708**	-8.36
Δlog(VOLA1)	.	.	.	.	0.344**	28.78	0.5944**	23.77
Δlog(MVE)	-0.0248**	-17.75	-0.0169**	-9.01	-0.0355**	-21.10	-0.0255**	-10.94
Adjusted R^2	0.582		0.641		0.502		0.580	

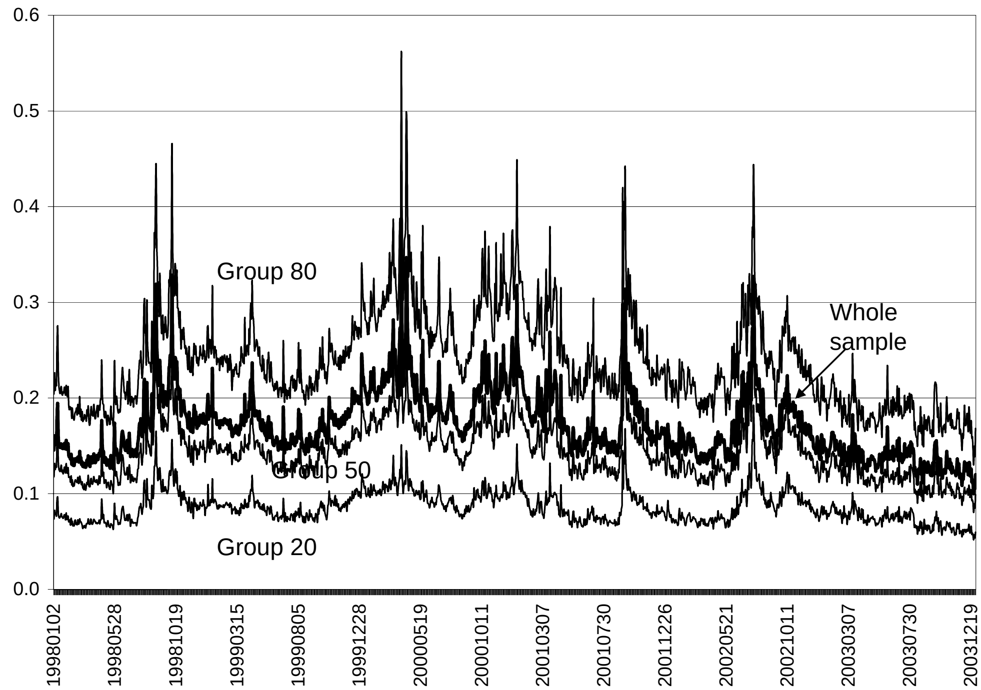

Figure 1: The average daily standard deviation of two minute quote-midpoint returns for our study sample of stocks from January 2, 1998 through December 31, 2003.

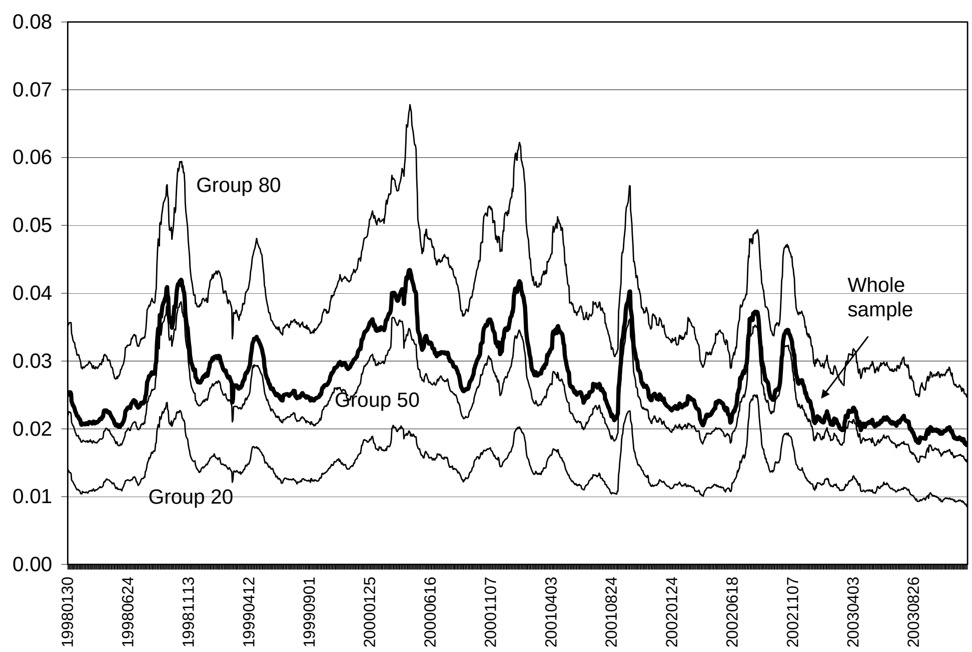

Figure 2: The average standard deviation of daily closing quote-midpoint returns over 20 trading Day s for our study sample of stocks from January 2, 1998 through December 31, 2003.

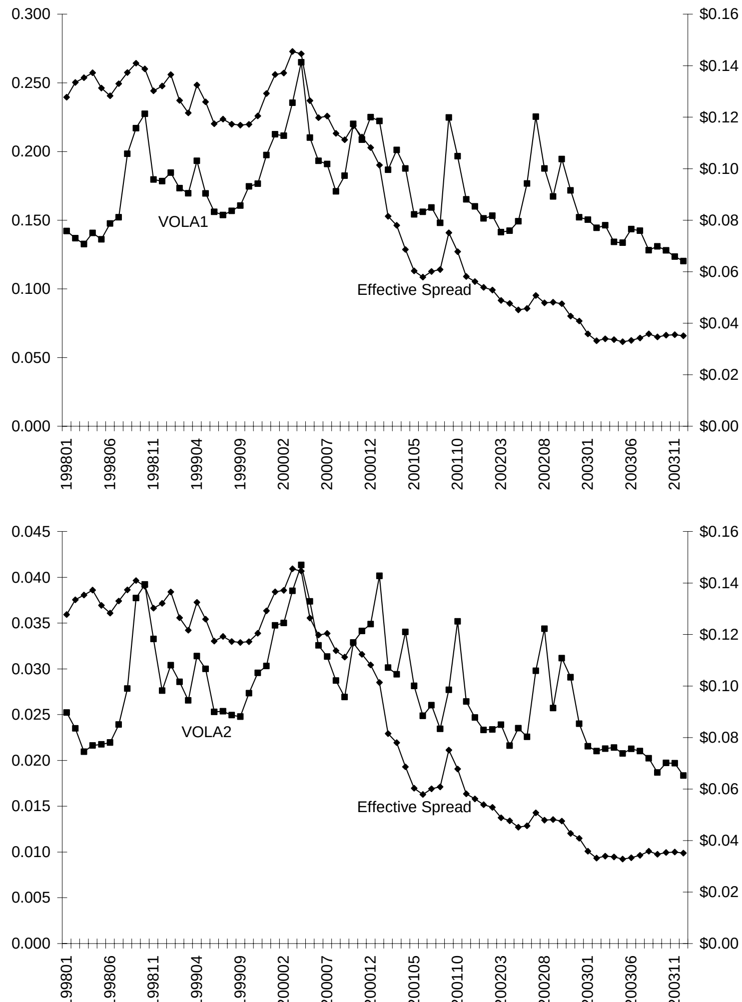

Figure 3: The upper figure shows the average monthly effective spread and standard deviation of two minute quote-midpoint returns (VOLA1) from January 2, 1998 through December 31, 2003. The bottom figure shows the average monthly effective spread and standard deviation of daily closing quote-midpoint returns (VOLA2) for the same period.

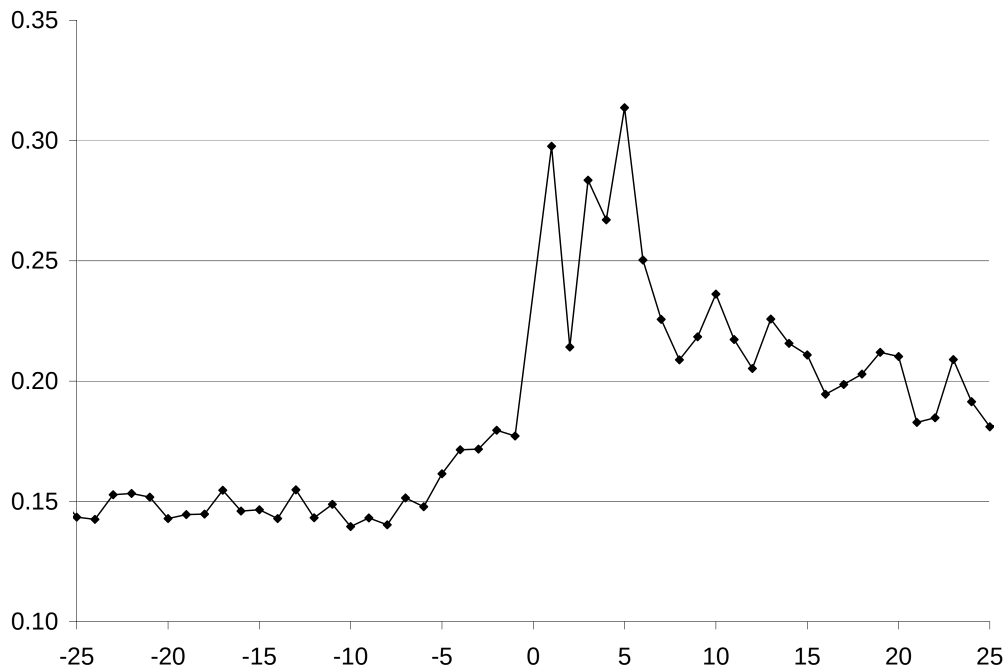

Figure 4: The average daily standard deviation of two minute quote-midpoint returns around September 11, 2001 (from Day -25 to +25)