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TRADING COSTS AND QUOTE CLUSTERING ON THE NYSE AND NASDAQ AFTER DECIMALIZATION

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Abstract

We examine execution costs and quote clustering on the New York Stock Exchange (NYSE) and NASDAQ using 517 matching pairs of stocks after decimalization. We find that the mean spread of NASDAQ stocks is greater than the mean spread of NYSE stocks when spreads are equally weighted across stocks, and the difference is greater for smaller stocks. In contrast, the mean NASDAQ spread is narrower than the mean NYSE spread when spreads are volume weighted, and the difference is statistically significant for large stocks. Both NYSE and NASDAQ stocks exhibit high degrees of quote clustering on nickels and dimes, and quote clustering has a significant effect on spreads in both markets.

JEL Classifications: G14, G18

I. Introduction

The New York Stock Exchange (NYSE) converted all 3,525 listed issues to decimal pricing January 29, 2001, ending the fractional minimum prices whose roots were in the silver coins of the Spanish Empire. The move followed a five-month test during which 159 NYSE stocks traded in price increments of 1 penny instead of one-sixteenth increments. The NASDAQ began its decimal test phase with 14 securities March 12, 2001, followed by another 197 securities March 26, 2001. All remaining NASDAQ securities converted to decimal trading April 9, 2001.

Early evidence indicates that the penny increment has been good for some investors. A preliminary analysis of conversion to decimal pricing indicates a tightening of the bid-ask spread by approximately 37% for a sample of NYSE-listed

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stocks.[1] Similarly, NASDAQ reports that both the quoted and effective spreads fell by an average of 50%.[2] The report also indicates that small retail orders benefited the most from the reduced spreads, whereas the transactions costs for large institutional orders do not appear to have risen. In addition, Chakravarty, Wood, and Van Ness (2004) find a significant decrease in spreads on both the NYSE and NASDAQ after decimalization.

Prior studies show that trading costs on NASDAQ are greater than those on the NYSE. For instance, Huang and Stoll (1996) and Chung, Van Ness, and Van Ness (2001) report that both the quoted and effective spreads of stocks traded on NASDAQ are wider than those of comparable stocks traded on the NYSE. In addition, Barclay (1997) shows that spreads become narrower when stocks move from NASDAQ to the NYSE. Christie and Schultz (1994) maintain that NASDAQ dealers implicitly collude to set wider spreads than their NYSE counterparts based on the finding that stocks listed on NASDAQ exhibit fewer odd-eighth quotes than comparable stocks on the NYSE. Bessembinder (1999) shows that trading costs on NASDAQ are greater than those on the NYSE even after the 1997 NASDAQ market reforms.

In the present study, we compare trading costs between the two markets using post-decimalization data on 517 matching pairs of NASDAQ and NYSE stocks to determine whether investors incur larger trading costs on NASDAQ even after the implementation of decimal pricing. We match each stock in our NYSE sample with a comparable NASDAQ stock on the basis of share price, number of trades, trade size, return volatility, and firm size. This approach enables us to measure differences in spreads between NYSE and NASDAQ stocks after controlling for differences in these attributes.

In a recent study, Bessembinder (Forthcoming) compares execution costs between NYSE and NASDAQ stocks. Our study differs from his study in several important ways. First, we match NYSE and NASDAQ stocks on the basis of five stock attributes, whereas Bessembinder matches stocks based only on market capitalization. Second, we analyze the nature and extent of quote clustering in the post-decimal environment and the effect of quote clustering on spreads, whereas Bessembinder does not perform such investigations. We consider this aspect important because prior studies view quote clustering as both evidence of anticompetitive dealer behavior and a source of supracompetitive spreads. Third, we measure quoted spreads using all available quotes as well as using only those quotes at the time of trade, whereas Bessembinder uses all available quotes. Finally, our sample size is larger (517 matching pairs vs. 300 matching pairs).

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[1]Statement of Catherine R. Kinney, Group Executive Vice President, New York Stock Exchange, Senate Subcommittee on Securities and Investment, May 24, 2001.

[2]"The Impact of Decimalization on the NASDAQ Stock Market," Final report to the Securities and Exchange Commission, NASDAQ Economic Research, The NASDAQ Stock Market, June 11, 2001.

We find that relative sizes of NASDAQ and NYSE spreads after decimalization depend largely on the averaging methods. The mean spread of NYSE stocks is narrower than that of comparable NASDAQ stocks when spreads are equally weighted across stocks, and the difference is greater for smaller stocks. In contrast, the mean spread of large NASDAQ stocks tends to be narrower than that of comparable NYSE stocks when spreads are volume weighted across stocks. These results suggest that the NYSE specialist system offers low-cost executions for small, low-volume stocks, whereas the NASDAQ dealer system offers low-cost executions for large, high-volume stocks. We interpret these results as evidence that the skilled attention of a focused specialist is particularly valuable in reducing execution costs for small, low-volume stocks, whereas the benefits of competing dealers are likely to be greatest for large, high-volume stocks. Finally, we find that both NASDAQ and NYSE stocks exhibit high degrees of quote clustering on nickels and dimes, and stocks with higher levels of quote clustering have wider spreads in both markets.

A better measurement of available liquidity and expected trading costs requires an analysis of both the price and quantity (depth) dimensions of quotes. An analysis of the liquidity supply curve revealed through price and quantity quotes in the limit-order book could be important in the post-decimal environment if liquidity providers spread out their trading interests across different prices given the penny tick increments. Our study focuses only on quoted prices at the inside market; thus, the results should be interpreted with caution.

II. Data Source and Sample Selection

We obtain data for this study from the NYSE Trade and Quote (TAQ) database. We use trade and quote data on matching samples of NYSE and NASDAQ stocks for May 2001—the first month after the full implementation of decimal pricing for both NYSE and NASDAQ stocks. Before matching our NYSE stocks with their counterparts on NASDAQ, we drop preferred stocks, warrants, lower class common stocks (e.g., class B and C common stocks), and NASDAQ issues with five-letter ticker symbols from the study sample.

To minimize errors, we omit trades and quotes if the TAQ database indicates that they are out of time sequence or involve either an error or a correction. We omit quotes if either the ask or bid price is equal to or less than 0, or if the price or volume is equal to or less than 0. As in Huang and Stoll (1996), we omit the following to further minimize data errors: (1) quotes when the spread is greater than \$4 or less than 0; (2) before-the-open and after-the-close trades and quotes; (3) trade price p_t when $|(p_t - p_{t-1})/p_{t-1}| > 0.10$; (4) ask quote a_t when $|(a_t - a_{t-1})/a_{t-1}| > 0.10$; and (5) bid quote b_t when $|(b_t - b_{t-1})/b_{t-1}| > 0.10$.

We match each stock in the NYSE sample with its NASDAQ counterpart based on five stock attributes—share price, number of trades, trade size, return volatility, and firm size—that are believed to determine the interstock differences in spread. This matching method differs from those used in previous studies. Huang and Stoll (1996) match stocks based on the two-digit industry code and firm characteristics identified by Fama and French (1992) as correlated with expected stock returns (i.e., share price, leverage, market value of equity, and the ratio of book to market value of equity). Bessembinder (1999) matches stocks using only market capitalizations. In contrast, we match NYSE and NASDAQ stocks on the basis of stock attributes that are strongly associated with spreads. The main goal of the present study is to obtain matching samples of NASDAQ and NYSE stocks that are similar in these attributes and to test for differences in spread. To the extent that our matching samples of NYSE and NASDAQ stocks have similar attributes, the difference (if any) in spread between the two groups must be due to reasons other than the attributes.

We measure share price by the mean value of the midpoints of quoted bid and ask prices, and return volatility by the standard deviation of daily returns calculated from the daily closing midpoints of bid and ask prices during May 2001. We measure trade size by the average dollar transaction during the study period. We measure firm size by the market value of equity.

We recognize that the reported number of trades on NASDAQ is not directly comparable to that on the NYSE because there are many interdealer trades on NASDAQ. Because interdealer trades exaggerate the reported volume, NASDAQ volume tends to be larger than NYSE volume. We measure the number of trades for NYSE-listed stocks using transactions on both the NYSE and other markets (i.e., regional and over-the-counter markets) to counterbalance the effect of interdealer trades on the reported volume of NASDAQ-listed stocks.

Trades and quotes for NASDAQ-listed stocks originate mostly from the NASDAQ market, whereas many trades and quotes for NYSE-listed stocks reflect activity at regional stock exchanges or NASDAQ InterMarket. Bessembinder (1999) reports that approximately one-third of the trades for NYSE-listed stocks are executed off of the NYSE. Because the recommended adjustment factor for NASDAQ volume that will neutralize the effect of interdealer trades is around 30% to 50% (e.g., see Atkins and Dyl 1997), our volume-counting method appears reasonable. To determine whether our results are sensitive to volume-counting methods, we replicate our analyses using NYSE and NASDAQ stocks that are matched using different methods. For example, we inflate NYSE volume by 30% or 50% before we match NYSE and NASDAQ stocks. We obtain qualitatively identical results from these new samples.

To obtain matching samples of NYSE and NASDAQ stocks, we first calculate the following composite match score (*CMS*) for each NYSE stock in our sample against each of the NASDAQ stocks in the TAQ database:

$$CMS = \Sigma_{k=1 \text{ to } 5}\left[\left(Y_k^N - Y_k^Y\right)/\left\{\left(Y_k^N + Y_k^Y\right)/2\right\}\right]^2, \tag{1}$$

TABLE 1. Descriptive Statistics.

Variable	Exchange	Mean	Standard Deviation	Percentile Min	25	50	75	Max
Share price ($)	NASDAQ	26.89	14.41	2.97	16.68	24.65	33.27	89.94
	NYSE	24.36	13.04	2.93	14.72	22.41	31.14	97.29
Number of trades	NASDAQ	10,725	19,803	32	2,060	5,394	11,518	270,649
	NYSE	8,141	16,225	22	1,858	4,126	8,499	246,198
Trade size ($)	NASDAQ	17,338	8,763	2,577	11,081	16,241	21,734	55,392
	NYSE	21,045	11,737	1,810	12,629	18,470	26,238	73,578
Return volatility	NASDAQ	0.0291	0.0142	0.0033	0.0185	0.0275	0.0376	0.0832
	NYSE	0.0269	0.0129	0.0049	0.0180	0.0251	0.0350	0.1096
Market value of equity (in millions of $)	NASDAQ	1,644	2,839	358	554	854	1,576	34,306
	NYSE	1,567	2,645	301	489	796	1,534	31,158

Note: To obtain matching samples of New York Stock Exchange (NYSE) and NASDAQ stocks, we first calculate the following composite match score (*CMS*) for each NYSE stock in our sample against each of the NASDAQ stocks in the Trade and Quote (TAQ) database:

$$CMS = \Sigma\left[\left(Y_K^N - Y_K^Y\right)/\left\{\left(Y_K^N + Y_K^Y\right)/2\right\}\right]^2,$$

where Y_k represents one of the five stock attributes; the superscripts N and Y refer to NASDAQ and NYSE, respectively; and Σ denotes the summation over $k = 1$ to 5. Then, for each NYSE stock, we pick the NASDAQ stock with the lowest score. Once a NASDAQ stock is matched with a NYSE stock, they are no longer considered for subsequent matches. We find that differences in one or more stock attributes between NYSE and NASDAQ stocks become considerable when the *CMS* exceeds 1. Hence, to ensure the comparability of our matching samples of NYSE and NASDAQ stocks, we include only the 517 pairs with a *CMS* of less than 1 in our study sample. We measure share price by the mean value of the midpoints of quoted bid and ask prices and return volatility by the standard deviation of daily returns calculated from the daily closing midpoints of bid and ask prices during May 2001. We measure trade size by the average dollar transaction during the study period. We measure firm size by the market value of equity.

where Y_k represents one of the five stock attributes, and the superscripts N and Y refer to NASDAQ and NYSE, respectively. Then, for each NYSE stock, we pick the NASDAQ stock with the lowest score. Once a NASDAQ stock is matched with a NYSE stock, it is no longer considered for subsequent matches. We find that differences in one or more stock attributes between NYSE and NASDAQ stocks become considerable when the *CMS* exceeds 1. Hence, to ensure the comparability of our matching samples of NYSE and NASDAQ stocks, we include only those (517) pairs with a *CMS* of less than 1 in our study sample. Intuitively, $CMS < 1$ implies that the mean-adjusted squared difference in each stock attribute between NYSE and NASDAQ stocks is less than 0.20, on average. To assess the sensitivity of our results with respect to different cutoff points, we replicate our analyses with different values (e.g., 0.8, 1.2, and 1.5) of the *CMS*. The results are qualitatively similar to those presented here.

We report summary statistics of our matching samples in Table 1. The average price of our NASDAQ stocks is $26.89, and the corresponding figure for our NYSE sample is $24.36. The average numbers of transactions and trade size for the NASDAQ sample are 10,725 and \$17,338, respectively, and the corresponding figures for the NYSE sample are 8,141 and \$21,045, respectively. The mean values of the standard deviation of daily returns for our NASDAQ and NYSE stocks are 0.0291 and 0.0269, respectively. The average market values of equity for our NASDAQ and NYSE samples are \$1,644 million and \$1,556 million, respectively.

III. Empirical Findings

Measures of Trading Costs

We measure trading costs by quoted and effective spreads.[3] The quoted spreads are calculated as follows:

$$\$Quoted\ spread_{it} = A_{it} - B_{it} \text{ and } \%Quoted\ spread_{it} = (A_{it} - B_{it})/M_{it}, \quad (2)$$

where A_{it} is the posted ask price for stock i at time t, B_{it} is the posted bid price for stock i at time t, and M_{it} is the mean of A_{it} and B_{it}. We calculate the mean quoted spreads of each stock using three averaging methods: (1) the time-weighted average spread using all available quotes during the study period, (2) the equally weighted average spread using only those quotes at the time of trade, and (3) the trade-size-weighted average spread using only those quotes at the time of trade.

To measure the cost of trading when it occurs at prices inside the posted bid and ask quotes, we also calculate the effective spreads as follows:

$$\$Effective\ spread_{it} = 2D_{it}(P_{it} - M_{it}) \text{ and}$$
$$\%Effective\ spread_{it} = 2D_{it}(P_{it} - M_{it})/M_{it}, \quad (3)$$

where P_{it} is the transaction price for security i at time t, M_{it} is the midpoint of the most recently posted bid and ask quotes for security i, and D_{it} is a binary variable that equals 1 for customer buy orders and -1 for customer sell orders. The effective spread measures the actual execution cost paid by the trader. We then calculate the equally weighted and trade-size-weighted average spreads for each stock using only those quotes at the time of trade.

We estimate D_{it} using the algorithm in Lee and Ready (1991). Bessembinder (2003) finds that making no allowance for trade reporting lags is optimal when assessing whether trades are buyer or seller initiated, but comparing trade prices with earlier quotations is optimal when assessing trade-execution

[3]Many quote updates for NYSE-listed stocks originate from off of the NYSE. As Blume and Goldstein (1997) show, however, quotes that originate from off of the NYSE only occasionally are better than NYSE quotes. Hence, we use only NYSE quotes in our study.

costs. Bessembinder also shows that a technique for inferring trade direction recommended by Ellis, Michaely, and O'Hara (2000) leads to significantly smaller estimates of trading costs than the Lee and Ready algorithm. Despite the sensitivity of trading cost measures to these methodological issues, inference as to whether the NASDAQ dealer market or the NYSE auction market provides lower trade execution costs is not sensitive.

Comparison of Quoted Spreads Between NASDAQ and NYSE Stocks

In Table 2 we show the average quoted spreads for our entire sample of NASDAQ and NYSE stocks and for each firm-size quartile. To assess the sensitivity of our results with respect to different averaging methods, we calculate both the equally weighted and volume-weighted average spreads across stocks within each market.

Strictly speaking, the volume-weighted spread is relevant only for investors whose trading volume for each stock is proportional to its total trading volume and who trade all stocks within each group. In contrast, the equally weighted spread is relevant for investors whose trading volume for each stock is equal and who trade all stocks within each group. For investors who trade only a subset of available securities within each group, however, neither metric is a proper measure of trading costs. Nevertheless, for traders whose trading volume for each stock tends to vary with its total volume, the volume-weighted spread is a better measure of trading costs than the equally weighted spread even if they trade only a subset of securities. In contrast, for investors who allocate equal dollar amounts across stocks, the equally weighted spread is a better measure of trading costs.

The volume-weighted spread measures the average cost paid per share traded. Thus, it represents the cost an investor would pay for the average share traded. Or, multiplied by volume, it equals the total costs actually paid by investors over a given period. Unlike the volume-weighted average, the equally weighted average bears no direct relation to actual trading costs paid by investors in aggregate. Consider, for example, that there are only two stocks, A and B, in the market and that the trading volume of each stock is 100 million and 500 million shares, respectively, during a given period. Also, assume that the mean spread of stock A is 2 cents and the mean spread of stock B is 5 cents during the same time period. Then, the equally weighted average spread is $\frac{1}{2}(2 + 5) = 3.5$ cents, whereas the volume-weighted average spread is $[2(100) + 5(500)]/600 = 2700/600 = 4.5$ cents. If we multiply the volume-weighted spread by the total trading volume, we obtain the total cost ($27 million) paid by traders in aggregate. In contrast, the product of the equally weighted spread and the total trading volume underestimates the total cost.

Panel A (Panel B) of Table 2 shows the mean dollar (percentage) spread of NASDAQ stocks, the mean dollar (percentage) spread of NYSE stocks, and

TABLE 2. Comparison of NASDAQ and NYSE Quoted Spreads.

Firm-Size Quartile	Time Weighted Across Quotes and Equally Weighted Across Stocks				Time Weighted Across Quotes and Volume Weighted Across Stocks			
	NASDAQ	NYSE	NASDAQ − NYSE	t-stat	NASDAQ	NYSE	NASDAQ − NYSE	t-stat
Panel A. Dollar Spread Using All Available Quotes								
Q1	0.1770	0.1113	0.0657	4.44***	0.1143	0.0868	0.0275	2.10***
Q2	0.1520	0.1072	0.0448	3.79***	0.0975	0.0824	0.0151	1.46
Q3	0.1248	0.1059	0.0189	1.46	0.0857	0.0710	0.0147	1.92
Q4	0.1042	0.0778	0.0264	2.65***	0.0605	0.0604	0.0001	0.03
Whole sample	0.1394	0.1055	0.0389	6.19***	0.0749	0.0677	0.0072	1.40
Panel B. Percentage Spread Using All Available Quotes								
Q1	0.0088	0.0076	0.0012	2.18***	0.0068	0.0074	−0.0006	−0.51
Q2	0.0073	0.0058	0.0015	2.17***	0.0053	0.0059	−0.0006	−0.60
Q3	0.0045	0.0043	0.0002	0.51	0.0035	0.0037	−0.0002	−0.29
Q4	0.0033	0.0029	0.0004	1.07	0.0020	0.0024	−0.0004	−1.49
Whole sample	0.0060	0.0051	0.0009	2.89***	0.0031	0.0035	−0.0004	−1.48
Panel C. Dollar Spread Using Only Those Quotes at the Time of Trade								
Q1	0.1717	0.1067	0.0650	4.45***	0.1103	0.0924	0.0179	1.36
Q2	0.1438	0.1023	0.0415	3.41***	0.0910	0.0879	0.0031	0.30
Q3	0.1166	0.1035	0.0131	0.88	0.0806	0.0799	0.0007	0.08
Q4	0.0951	0.0777	0.0174	1.91	0.0549	0.0754	−0.0205	−3.14***
Whole sample	0.1317	0.0975	0.0342	5.25***	0.0693	0.0794	−0.0101	−1.72
Panel D. Percentage Spread Using Only Those Quotes at the Time of Trade								
Q1	0.0085	0.0072	0.0013	2.38***	0.0065	0.0078	−0.0013	−1.01
Q2	0.0070	0.0055	0.0015	2.08***	0.0050	0.0062	−0.0012	−1.12
Q3	0.0043	0.0043	0.0000	0.13	0.0033	0.0043	−0.0010	−0.90
Q4	0.0030	0.0029	0.0001	0.40	0.0018	0.0029	−0.0011	−3.38***
Whole sample	0.0057	0.0050	0.0007	2.54***	0.0029	0.0041	−0.0012	−3.19***

Note: Panels A and B show the average quoted spreads for our entire sample of NASDAQ and New York Stock Exchange (NYSE) stocks and for each firm-size quartile based on all available quotes. We calculate the time-weighted average spread of each stock using all available quotes and obtain its cross-sectional mean within each market. To assess the sensitivity of our results with respect to different averaging methods, we calculate the volume-weighted average spreads across stocks within each market. Quartile 1 is the smallest; quartile 4 is the largest. We show the results of paired comparison t-tests. Panels C and D show the average quoted spreads based on only those quotes at the time of trade.

***Significant at the 1% level.

the difference between the two groups when the mean spread of each stock is calculated using all available quotes. In both panels, the left half shows the results when spreads are equally weighted across stocks and the right half shows the results when spreads are volume weighted across stocks. Panel A shows that, for the full sample, the equally weighted NASDAQ spread ($0.1394) is larger than the equally weighted NYSE spread ($0.1055), and the difference (3.89 cents) is statistically significant ($t = 6.19$) at the 1% level. The spread difference (6.57 cents) is largest among stocks in the smallest firm-size quartile (Q1). Similarly, Panel B shows that the equally weighted NASDAQ spread as a fraction of share price (0.0060) is greater than the equally weighted NYSE spread (0.0051), and the difference is statistically significant among stocks with small market capitalization (Q1 and Q2).

In contrast, the volume-weighted NASDAQ dollar spread ($0.0749) for the full sample is only marginally greater than the corresponding figure ($0.0677) for NYSE stocks, and the difference (0.72 cent) is not statistically significant ($t = 1.40$). Similarly, we find that the difference in the volume-weighted percentage spread between the two groups is not statistically significant ($t = -1.48$).

The observed differences in the equally weighted mean spread between NASDAQ and NYSE stocks for the full sample are largely due to the differences for stocks that belong to the two smaller size quartiles. This finding indicates that the NYSE provides better liquidity than does the NASDAQ for stocks of smaller companies. To the extent that the number of dealers in a given stock is positively related to its market capitalization, the large spread of small NASDAQ companies may partly reflect low degree of dealer competition. In addition, NYSE specialists may provide better liquidity services for small, less-active stocks than do NASDAQ dealers for at least two reasons.

First, specialists may face smaller adverse-selection problems in these stocks than do their NASDAQ counterparts because they typically have more information on these stocks than do NASDAQ dealers. Most specialists on the NYSE trade between three and six stocks. Because of this specialization, specialists are usually more knowledgeable about the stocks they trade than are NASDAQ dealers and thus bear smaller adverse-selection costs. Indeed, Heidle and Huang (2002) show that the probability of encountering an informed trader is lower on the NYSE than on the NASDAQ. Second, specialists have affirmative obligations to ensure that a reasonable market always exists in their specialties. They must quote two-sided markets when no one else will, and their quotes must be meaningful in the sense that the bid-ask spread cannot be too wide. Exchanges evaluate how well specialists meet their affirmative obligations by measuring the average width of the quoted spread as well as other market quality measures. These obligations are likely to be more relevant and their effects are likely to be more visible for stocks of smaller companies.

Panel C (Panel D) of Table 2 shows the mean dollar (percentage) spread of NASDAQ stocks, the mean dollar (percentage) spread of NYSE stocks, and the difference between the two groups when the mean spread of each stock is calculated using only those quotes at the time of trade. This metric is a good measure of trading costs for thinly traded stocks because a large proportion of quoted spreads (that are posted when there are no trades) for such stocks are irrelevant to traders. In both panels, the left half shows the results when spreads are equally weighted across trades and across stocks. The right half shows the results when spreads are trade-size weighted within each stock and volume weighted across stocks.

As in Panels A and B for the whole sample, we find that the mean NASDAQ spreads are greater than the mean NYSE spreads when spreads are equally weighted across stocks. For instance, the equally weighted average ($0.1317) of NASDAQ spreads is significantly ($t = 5.25$) greater than the corresponding value ($0.0975) for NYSE stocks. We find that the difference is particularly notable among stocks with small market capitalization (Q1 and Q2). In contrast, we find that the average NASDAQ spread is smaller than the average NYSE spread when spreads are volume weighted across stocks among stocks with large market capitalization (Q4).

We find similar results for the percentage spread. The average NASDAQ spread (0.0057) is significantly ($t = 2.54$) greater than the average NYSE spread (0.0050) when spreads are equally weighted across trades and across stocks. In particular, the NASDAQ spread is greater than the NYSE spread among stocks with small market capitalization (Q1 and Q2). In contrast, the average NASDAQ spread (0.0029) is significantly ($t = -3.19$) smaller than the average NYSE spread (0.0041) when spreads are trade-size weighted across trades and volume weighted across stocks. The difference is most notable for stocks with large market capitalization (Q4).

On the whole, our results indicate that relative sizes of quoted spreads between NASDAQ and NYSE stocks depend critically on the averaging method. The mean NASDAQ spread is wider than the mean NYSE spread for stocks with small market capitalization when spreads are equally weighted across stocks. In contrast, the mean NASDAQ spread tends to be smaller than the mean NYSE spread for stocks with large market capitalization when spreads are volume weighted across stocks. These results are similar to those reported in Bessembinder (Forthcoming) from a sample of NYSE and NASDAQ stocks that are matched based on market capitalization. As noted earlier, the equally weighted spread is germane to those who trade equal dollar amounts across stocks, whereas the volume-weighted spread is more relevant to investors who trade more in high-volume stocks. Our empirical results indicate that the first type of traders are likely to incur smaller trading costs on the NYSE when they trade small capitalization stocks, whereas the second type of traders are likely to incur smaller trading costs on NASDAQ when they trade large capitalization stocks.

Table 3 shows the mean effective spreads of our NASDAQ and NYSE stocks. As in Table 2, relative sizes of the effective spread between NASDAQ and NYSE stocks depend largely on the averaging method. For the whole sample, the equally weighted effective spreads of our NASDAQ stocks are greater than the corresponding figures for the NYSE sample. We find no significant difference in the effective spread between the two markets, however, when spreads are volume weighted. Again, these results are largely driven by wide NASDAQ spreads for small market capitalization stocks. In addition, we find no significant difference in the

TABLE 3. Comparison of NASDAQ and NYSE Effective Spreads.

	Equally Weighted Across Trades and Equally Weighted Across Stocks				Trade-Size Weighted Across Trades and Volume Weighted Across Stocks			
Firm-Size Quartile	NASDAQ	NYSE	NASDAQ − NYSE	*t*-stat	NASDAQ	NYSE	NASDAQ − NYSE	*t*-stat
Panel A. Dollar Spread								
Q1	0.1390	0.0870	0.0520	4.25***	0.1179	0.0823	0.0356	2.05
Q2	0.1195	0.0851	0.0344	3.23***	0.0973	0.0753	0.0220	2.19***
Q3	0.0999	0.0890	0.0109	0.91	0.0937	0.0748	0.0189	2.03
Q4	0.0847	0.1110	−0.0263	−1.55	0.0852	0.1227	−0.0375	−1.59
Whole sample	0.1107	0.0931	0.0176	2.63***	0.0910	0.1027	−0.0117	−0.76
Panel B. Percentage Spread								
Q1	0.0069	0.0058	0.0011	2.02	0.0085	0.0068	0.0017	0.71
Q2	0.0058	0.0045	0.0013	2.22***	0.0057	0.0051	0.0006	0.57
Q3	0.0037	0.0039	−0.0002	−0.43	0.0042	0.0040	0.0002	0.11
Q4	0.0027	0.0046	−0.0019	2.62***	0.0034	0.0057	−0.0023	−1.36
Whole sample	0.0048	0.0047	0.0001	0.23	0.0042	0.0053	−0.0011	−1.07

Note: This table shows the average effective spreads for our entire sample of NASDAQ and New York Stock Exchange (NYSE) stocks and for each firm-size quartile. The first four columns show the results when spreads are equally weighted across trades and across stocks. The next four columns show the results when spreads are trade-size weighted within each stock and equally weighted across stocks. The final four columns show the results when spreads are trade-size weighted within each stock and volume weighted across stocks. Quartile 1 is the smallest; quartile 4 is the largest. We show the results of paired comparison *t*-tests.

*** Significant at the 1% level.

effective spread between NASDAQ and NYSE stocks when spreads are measured as a percentage of share prices, regardless of the averaging method. Overall, our results from the effective spreads are qualitatively similar to those from the quoted spreads.

IV. Quote Clustering and Its Effect on Spreads

Several studies show that stocks with higher degrees of quote clustering exhibit wider spreads (e.g., see Christie and Schultz 1994; Godek 1996; Barclay 1997; Chung, Van Ness, and Van Ness 2001, 2002). In contrast, Bessembinder (1999) reports that the bid-ask spreads of NASDAQ-listed stocks are no longer significantly related to quote clustering after the 1997 NASDAQ market reform. In this section, we analyze the extent and possible causes of quote clustering and provide evidence on the relation between the spread and quote clustering using post-decimal data.

Prior studies advance two competing hypotheses on quote clustering: dealer collusion and natural clustering. Christie and Schultz (1994) and Barclay (1997) show that the frequency of even-eighth quotes for certain stocks on NASDAQ is much higher than the corresponding figure on the NYSE. More significant, Christie and Schultz show that spreads of one-eighth are virtually nonexistent for most of the 100 most actively traded NASDAQ issues, and this lack of one-eighth spreads can largely be accounted for by the absence of odd-eighth quotes for 70 of the 100 stocks. Based on this evidence, they suggest that there exists implicit collusion among NASDAQ dealers, and quote clustering is a means by which dealers maintain supracompetitive levels of spreads. Christie, Harris, and Schultz (1994) and Christie and Schultz (1999) provide additional evidence consistent with collusive behavior.

Others argue that the high frequency of even-eighth quotes does not necessarily imply covert collusion among dealers. For example, Grossman et al. (1997) suggest that the less frequent use of odd-eighth quotes among NASDAQ dealers may be attributed to the natural clustering of price in competitive financial markets. They suggest that market participants use a coarser price grid as protection against informed traders, to compensate for increased inventory risk and to minimize the cost of negotiation. In a similar vein, Huang and Stoll (1996) suggest that collusion is implausible in a market with many competitors and easy entry.

We shed further light on this debate by examining the extent and determinants of quote clustering and the effect (if any) of quote clustering on the bid-ask spread using post-decimalization data. Because the quote-setting mechanisms during our post-decimalization study period differ significantly from those that were effective at the time of previously mentioned studies (because of the 1997 NASDAQ market reforms and different ticks), the present study offers an alternative test of causes and consequences of quote clustering.

Quote Clustering

We report in Table 4 (see also Figure I) the proportion of NASDAQ and NYSE quotes at each quote increment under decimal pricing. The results show strong evidence of quote clustering on \$0.05 and \$0.10. The proportions of quotes that are divisible by 5 cents are about 39% on NASDAQ and 40% on the NYSE, which are almost twice as large as the corresponding figure (20%) in the absence of quote clustering. Similarly, we find that the proportions of quotes that are divisible by 10 cents are around 22% on NASDAQ and 24% on the NYSE, respectively, which are much greater than the corresponding figure (10%) in the absence of quote clustering. These results suggest that liquidity providers on both the NYSE and NASDAQ quote more frequently in nickels and dimes.

Previous studies show that the proportion of even-sixteenth quotes is significantly greater than the proportion of odd-sixteenth quotes on both the NYSE and NASDAQ after the tick-size change in 1997 (e.g., see Simaan, Weaver, and Whitcomb 1998). Indeed, when we calculate the proportions of even- and

TABLE 4. Distribution of Quotes.

	NASDAQ Quotes			NYSE Quotes		
Quote	Bid	Ask	Total	Bid	Ask	Total
Panel A. Average Proportion of Quotes						
x.x0	0.2134	0.2237	0.2186	0.2364	0.2345	0.2354
x.x1	0.1066	0.0645	0.0855	0.1193	0.0859	0.0975
x.x2	0.0785	0.0635	0.0710	0.0728	0.0563	0.0645
x.x3	0.0680	0.0679	0.0679	0.0639	0.0617	0.0628
x.x4	0.0657	0.0917	0.0787	0.0568	0.0891	0.0730
x.x5	0.1691	0.1693	0.1692	0.1666	0.1630	0.1649
x.x6	0.0953	0.0661	0.0806	0.0985	0.0696	0.0840
x.x7	0.0720	0.0673	0.0696	0.0634	0.0592	0.0613
x.x8	0.0667	0.0768	0.0718	0.0618	0.0734	0.0676
x.x9	0.0647	0.1093	0.0870	0.0604	0.1175	0.0889
Panel B. Average Proportion of Quotes Divisible by Nickels, Dimes, and Quarters						
Nickels	0.3826	0.3930	0.3878	0.4031	0.3975	0.4003
Dimes	0.2134	0.2237	0.2186	0.2364	0.2345	0.2354
Quarters	0.1225	0.1324	0.1275	0.1224	0.1295	0.1259

odd-sixteenth quotes using the pre-decimalization data for our matching samples of NASDAQ and NYSE stocks, we find that the proportion of even-sixteenth quotes is much higher (see Figure II).[4] Hence, our results suggest that the high quote clustering on even-sixteenths before decimalization has largely been replaced by the high quote clustering on nickels and dimes after decimalization.

Because NYSE and NASDAQ stocks exhibit high quote clustering during both the pre- and post-decimalization periods and quote clustering is likely to be determined by stock attributes, we expect stocks with high quote clustering before decimalization to exhibit high quote clustering after decimalization. To test this, we regress the extent of quote clustering after decimalization (i.e., the proportion of quotes that are divisible by 5 cents) on the extent of quote clustering before decimalization (i.e., the proportion of even-sixteenth quotes). The results show that for NASDAQ (NYSE) stocks, about 35% (40%) of the variation in the post-decimalization quote clustering can be accounted for by the variation in the pre-decimalization quote clustering.

One might argue that the prevalence of nickel and dime quotes on the NYSE and NASDAQ is due to deliberate attempts by market makers and specialists to widen their spreads. As shown by Chung, Van Ness, and Van Ness (1999), most NYSE quotes reflect the interests of limit-order traders. Similarly, a significant

[4]We calculate these proportions using one-month data just before decimalization.

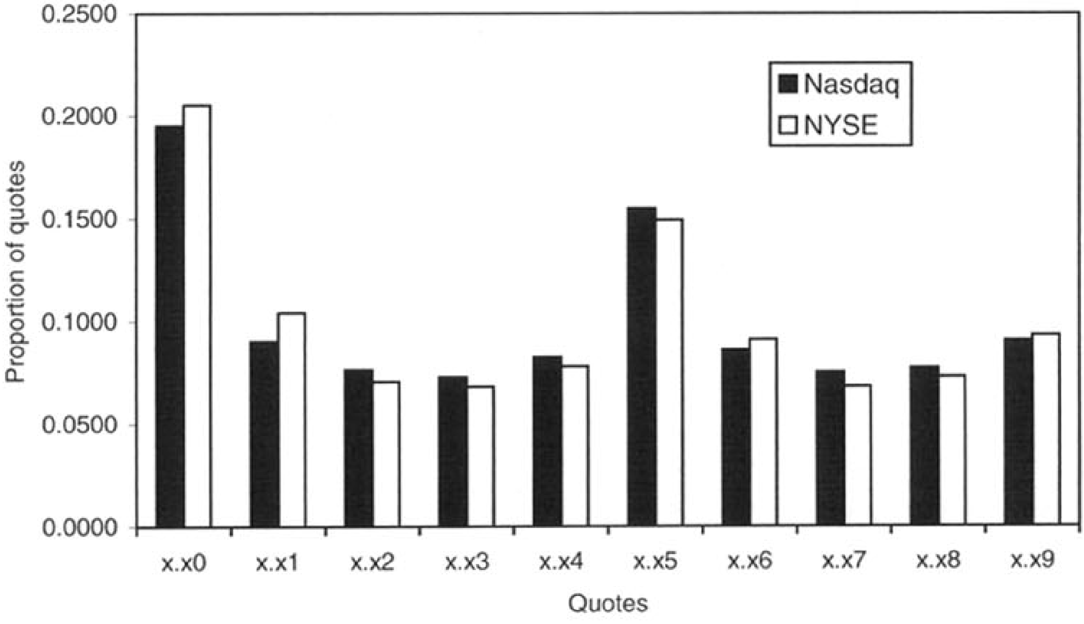

Figure I. Distribution of Quotes by Each Quote Increment After Decimalization.

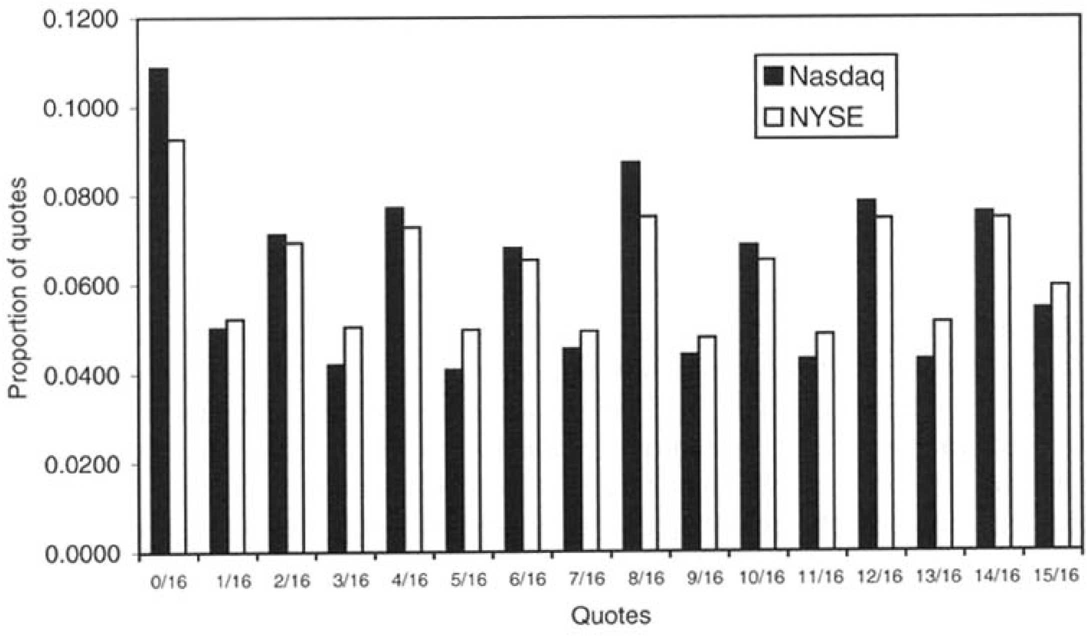

Figure II. Distribution of Quotes by Even- and Odd-Sixteenths Before Decimalization.

portion of NASDAQ quotes may now reflect the interest of limit-order traders. Consequently, attributing more frequent nickel and dime quotes on the NYSE and NASDAQ to specialist and dealer behavior may be fallacious. As suggested by numerous researchers, the observed quote clustering on the NYSE and NASDAQ is likely to be driven by other reasons (e.g., see Laux 1995; Godek 1996; Huang and Stoll 1996; Grossman et al. 1997).

Effect of Quote Clustering on Quoted Spreads

Previous studies show that stocks with higher degrees of quote clustering have wider spreads (e.g., see Christie and Schultz 1994; Godek 1996; Barclay 1997; Chung, Van Ness, and Van Ness 2001). In this section, we examine whether the same pattern exists after decimalization. Specifically, we analyze how the quoted spread is related to quote clustering after controlling for other determinants of the spread that have been suggested in the literature, that is, share price, dollar trading volume, turnover rate (the number of shares traded divided by the number of shares outstanding), return volatility, and market capitalization. We measure the extent of quote clustering by the proportion of quotes that are divisible by 5 cents. Because quote clustering is also likely to be determined by stock attributes, we treat it as an endogenous variable.

Ball, Torous, and Tschoegl (1985), Harris (1991), and Grossman et al. (1997) maintain that traders use discrete price sets to lower the costs of negotiation, and negotiation costs will be low if traders use coarse price sets. If the price set is too coarse (i.e., the set does not include a price that is acceptable to both parties), however, lost gains from trade will be large. Ball, Torous, and Tschoegl suggest that the extent of clustering depends on the trade-off between negotiation costs and lost gains from trade. They suggest that lost gains from trade are likely to be large if little dispersion exists among traders' reservation prices, such as when the underlying security values are well known. Based on these observations, the authors predict that traders will use a fine set of prices when the underlying security values are well known.

We measure the reservation-price dispersion by return volatility, number of trades, trade size, market capitalization, and share price. Harris (1991) holds that stocks with higher return volatility or infrequent trading have larger reservation-price dispersion. We expect stocks with larger trade sizes to exhibit larger reservation-price dispersion because information asymmetry may be greater for such stocks. Stocks of smaller companies are likely to exhibit larger reservation-price dispersion because they are followed by fewer analysts and thus less information is available. Finally, we predict that high-price stocks exhibit larger price variations (and thus more clustering) than low-price stocks because traders are likely to use discrete price sets on the basis of minimum price variations that are constant fractions of price. Thus, we conjecture that quote clustering is positively related to return volatility, trade size, and share price, and negatively related to trading frequency and market capitalization.

Godek (1996) holds that higher quote clustering may be caused by dealers' desire to quote wider spreads to compensate for larger market-making costs, suggesting that quote clustering is likely to be higher for stocks with larger spreads.

Based on these considerations, we employ the following structural model as an empirical representation of the relation between the percentage spread (*SPREAD*) and quote clustering (*QC*):

$$SPREAD = \alpha_0 + \alpha_1(1/PRICE) + \alpha_2 \log(VOLUME) + \alpha_3 TURNOVER + \alpha_4 VOLATILITY + \alpha_5 \log(MVE) + \alpha_6 QC + \varepsilon_1, \quad (4)$$

$$QC = \beta_0 + \beta_1 \log(PRICE) + \beta_2 \log(NTRADE) + \beta_3 \log(TSIZE) + \beta_4 VOLATILITY + \beta_5 \log(MVE) + \beta_6 SPREAD + \varepsilon_2, \quad (5)$$

where *SPREAD* is the time-weighted percentage spread, *QC* is the proportion of quotes that are divisible by 5 cents, *PRICE* is the mean value of the midpoints of quoted bid and ask prices, *VOLUME* is the dollar trading volume, *TURNOVER* is the ratio of the number of shares traded to the number of shares outstanding, *VOLATILITY* is the standard deviation of daily returns calculated from the daily closing midpoints of bid and ask prices, *MVE* is the market value of equity, *NTRADE* is the number of trades, and *TSIZE* is the average dollar transaction size. We include dollar trading volume in lieu of number of trades and trade size in the spread equation to satisfy the rank and order conditions of identification. Note that dollar trading volume captures the joint effect of the latter two variables. Expected signs of regression coefficients are $\alpha_1 > 0$, $\alpha_2 < 0$, $\alpha_3 > 0$, $\alpha_4 > 0$, $\alpha_5 > 0$, $\alpha_6 > 0$, $\beta_1 > 0$, $\beta_2 < 0$, $\beta_3 > 0$, $\beta_4 > 0$, $\beta_5 < 0$, and $\beta_6 > 0$.

We report the three-stage least squares (3SLS) regression results in Table 5. The first two columns show the results for the NASDAQ sample and the next two columns show the results for the NYSE sample. As predicted, the extent of quote clustering is positively related to share price (*PRICE*), return volatility (*VOLATILITY*), and trade size (*TSIZE*), and negatively to the number of trades (*NTRADE*) and firm size (*MVE*) on both the NYSE and NASDAQ. These results are consistent with predictions of the theory of quote clustering advanced by Ball, Torous, and Tschoegl (1985) and Harris (1991). Consistent with the prediction of Godek (1996), we also find that quote clustering (*QC*) is positively and significantly related to the spread (*SPREAD*).

Consistent with the findings of prior studies, we find that the spread is negatively related to dollar trading volume (*VOLUME*) and positively to the reciprocal of share price (*PRICE*) and turnover rate (*TURNOVER*). The less prominent role of share price in the spread equation compared with that reported in Harris (1994) may reflect that the penny tick size is less frequently a binding constraint on spread widths. More important, we find that the percentage spread is significantly and positively related to quote clustering on both the NYSE and NASDAQ. The positive relation between the spread and the extent of quote clustering is consistent

TABLE 5. A Structural Model of the Spread and Quote Clustering.

	NASDAQ		NYSE	
Independent Variable	*SPREAD*	*QC*	*SPREAD*	*QC*
Intercept	0.0072	0.153	0.0101	−0.0393
	(1.45)	(1.12)	(3.50***)	(−0.31)
1/*PRICE*	0.0143		0.0171	
	(1.71)		(3.80***)	
log(*VOLUME*)	−0.0032		−0.0023	
	(−10.91***)		(−12.97***)	
TURNOVER	0.0032		0.0025	
	(2.33**)		(3.39***)	
VOLATILITY	0.0162	1.0197	0.0026	0.9383
	(0.96)	(2.20**)	(0.25)	(2.00**)
log(*NTRADE*)		−0.0632		−0.0804
		(−2.55***)		(−4.16***)
log(*TSIZE*)		0.0752		0.1440
		(3.95***)		(8.25***)
log(*PRICE*)		0.1175		0.1485
		(11.13***)		(7.74***)
log(*MVE*)	0.0039	−0.0265	0.0034	−0.0669
	(4.98***)	(−1.94**)	(7.85***)	(−4.61***)
QC	0.0713		0.0321	
	(16.17***)		(17.78***)	
SPREAD		7.2356		18.2742
		(2.37**)		(5.20***)
System-weighted R^2	0.628		0.676	
System-weighted mean square error	8.323		10.203	

Note: This table shows the three-stage least squares (3SLS) results of the following structural model:

$$SPREAD = \alpha_0 + \alpha_1(1/PRICE) + \alpha_2 \log(VOLUME) + \alpha_3 TURNOVER + \alpha_4 VOLATILITY + \alpha_5 \log(MVE) + \alpha_6 QC + \varepsilon_1,$$

$$QC = \beta_0 + \beta_1 \log(PRICE) + \beta_2 \log(NTRADE) + \beta_3 \log(TSIZE) + \beta_4 VOLATILITY + \beta_5 \log(MVE) + \beta_6 SPREAD + \varepsilon_2,$$

where *SPREAD* is the time-weighted percentage spread, *QC* is the proportion of quotes that are divisible by 5 cents, *PRICE* is the mean value of the midpoints of quoted bid and ask prices, *VOLUME* is the dollar trading volume, *TURNOVER* is the ratio of the number of shares traded to the number of shares outstanding, *VOLATILITY* is the standard deviation of daily returns calculated from the daily closing midpoints of bid and ask prices, *MVE* is the market value of equity, *NTRADE* is the number of trades, and *TSIZE* is the average dollar transaction size. Numbers in parentheses are *t*-statistics.

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

with the finding of Christie and Schultz (1994). This result contradicts the findings of Huang and Stoll (1996) that after controlling for differences in economic factors, no relation exists between quoted spreads and the frequency of odd-eighth quotes among their sample of 66 paired NYSE-NASDAQ stocks.

Although the results of the present study are similar to those of Christie and Schultz (1994) in that the spreads are positively related to the extent of quote clustering, the similarity between the two results may be due to different reasons. In Christie and Schultz, the high frequency of even-eighth quotes is claimed to be a reflection of dealers' collusive behavior to maintain supracompetitive spreads. Hence, in this case, it is the dealers' desire to maintain larger spreads that causes quote clustering. In our framework, the positive correlation between spreads and quote clustering may largely be an unintended outcome of investor preference toward nickel and dime quotes.[5] For example, if all of the market makers and limit-order traders use only nickel and dime quotes, the quoted spread will be at least 5 cents. On the other hand, if these liquidity providers do not exhibit such a preference and thus each quote increment is equally likely, the minimum spread is 1 cent. These considerations suggest that the observed spread is likely to be positively related to the proportion of nickel and dime quotes.

V. Summary and Conclusion

Numerous studies suggest that execution costs on NASDAQ are significantly greater than those on the NYSE. Some researchers maintain that NASDAQ dealers implicitly collude to set larger spreads than their counterparts on the NYSE. Both academic research and anecdotal evidence suggest that execution costs for both NASDAQ and NYSE issues have declined significantly after decimalization. In this study, we perform a post-decimalization comparison of NASDAQ and NYSE trading costs.

Our empirical results show that the mean spreads of small NYSE companies are narrower than those of comparable NASDAQ companies when spreads are equally weighted across stocks. In contrast, the mean spreads of large NASDAQ companies tend to be narrower than those of comparable NYSE companies when spreads are volume weighted across stocks. These results are consistent with the finding of Bessembinder (Forthcoming) from a sample of NYSE and NASDAQ stocks that are matched based on market capitalization. We interpret these results as evidence that NYSE specialists' affirmative obligations to maintain reasonable spreads in their specialties provide low-cost executions for small, low-volume stocks whereas the competitive dealer system provides low-cost executions for large, high-volume NASDAQ stocks. Our results show that the prevalence of even-sixteenth quotes has largely been replaced by ubiquitous nickel and dime quotes after decimalization. We find that stocks with higher degrees of quote clustering have wider

[5] We cannot rule out the possibility that the high proportion of nickel and dime quotes reflects, at least in part, some market makers' desire to maintain wider spreads. We present an alternative theory of quote clustering.

spreads on both the NYSE and NASDAQ. We interpret this result as an unintended outcome of investor preference toward nickel and dime quotes for certain stocks.

We examine only the difference in spread between NASDAQ and NYSE stocks. As shown in Lee, Murklow, and Ready (1993), however, it is important that we consider both the price and quantity dimensions of dealer quotes to accurately measure liquidity. We were not able to perform depth comparison between the two markets because the TAQ database reports only the largest, not the aggregate, depth at the inside market for NASDAQ issues, whereas it reports the aggregate depth (specialist depth plus all of the limit orders at the quoted price) for NYSE issues. Hence, the intermarket comparison of quoted depths is not meaningful with TAQ data. A fruitful area for future research would be the intermarket comparison of liquidity that considers both dimensions (i.e., spread and depth) of dealer and limit-order quotes.

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