

# **Order preferencing and market quality on NASDAQ before and after decimalization**

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## **Abstract**

Despite the widely held belief that order preferencing affects market quality, no hard evidence exists on the extent and determinants of order preferencing and its impact on dealer competition and execution quality. This study shows that the bid-ask spread (dealer quote aggressiveness) is positively (negatively) related to the proportion of internalized trades during both the pre and post decimalization periods. Although decimal pricing led to lower order preferencing on NASDAQ, the proportion of preferenced trades after decimalization is much higher than what some prior studies had predicted. We find that the price impact of preferenced trades is smaller than that of unpreferenced trades and preferenced orders receive greater (smaller) size (price) improvements than unpreferenced trades.

*JEL classification:* G14

*Key words:* Decimalization; Internalization; Payment for order flow; Quote aggressiveness; Spreads; Execution quality

## 1. Introduction

Brokers and dealers on NASDAQ routinely direct or preference customer orders to any dealer who agrees to honor the best quoted price regardless of the price quoted by the dealer to whom the order is directed. In return for the routing of orders, dealers commonly offer either direct monetary payments or in-kind goods and services to brokers. Brokers and dealers also frequently internalize their order flow on NASDAQ. Internalization, a subset of preferencing, is the direction of order flow by a broker-dealer to an affiliated dealer or order flow executed by that broker-dealer as market maker.

Although prior studies offer both analytical predictions and experimental evidence regarding the effects of order preferencing on execution costs,<sup>1</sup> extant studies offer limited evidence on the extent and determinants of preferencing and its impact on market quality. In the present study, we address the following questions using a large sample of NASDAQ-traded stocks:

(1) How extensive is preferencing on NASDAQ? Which stocks, which dealers, and which trades are more likely to be involved in preferencing? (2) How does decimal pricing affect preferencing? (3) How does preferencing affect spreads and dealer quote aggressiveness? (4) Does preferencing allow dealers to separate informed traders from uninformed traders? and (5) Do preferred orders receive better price and size improvements?

Considering the academic and regulatory debates on whether it is anticompetitive behavior or market structure that led to wider spreads on NASDAQ,<sup>2</sup> it may be of great interest to

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<sup>1</sup>Christie and Schultz (1994), Battalio and Holden (1996), Dutta and Madhavan (1997) and Kandel and Marx (1997, 1999) suggest that order preferencing facilitates collusion and thus results in wider bid-ask spreads. Godek (1996) holds that order preferencing weakens the linkage between quote aggressiveness and order flow and diminishes the incentive to narrow the spread. Huang and Stoll (1996) and Bessembinder (1999) suggest that internalization and payment for order flow are likely sources of wider spreads on NASDAQ. Bloomfield and O'Hara (1998) provide experimental evidence regarding the effect of order preferencing on the competitiveness and efficiency of financial markets. The authors show that order preferencing may significantly degrade market performance if preferred orders are a large share of the market, or are received by virtually all market makers. Ackert and Church (1999) examine the effect of verbal communication and order preferencing on bid-ask spreads using laboratory financial markets. The authors conclude that payment for order flow and internalization limit dealers' incentive to improve price.

<sup>2</sup> See Christie and Schultz (1994), Huang and Stoll (1996), and Chung, Van Ness, and Van Ness (2001a).

both regulatory authorities and the general public to know how decimal pricing affects order preferencing and whether order preferencing affects execution quality.

Several studies analyze order preferencing for exchange-listed stocks. Hansch, Naik, and Viswanathan (1999) investigate the effect of preferencing and internalization on spreads and dealer profits for a sample of London Stock Exchange (LSE) stocks.<sup>3</sup> The authors find that while preferenced trades pay higher spreads, they do not generate higher dealer profits. In contrast, they find that internalized trades pay lower spreads. The study finds, however, no evidence of significant relations between the spread and preferencing or internalization across stocks. Although the LSE, like NASDAQ, is primarily a dealer market, the results found on the LSE may not hold on NASDAQ because dealer competition for order flow on the LSE is different from that on NASDAQ. On NASDAQ, there are more than 400 market makers competing for order flow. In contrast, there are only 21 market makers on the LSE and the majority of them compete for business primarily in the large (FTSE-100) stocks. Furthermore, it is illegal on the LSE to make cash payments to purchase the order flow, whereas such payments are allowed on NASDAQ.

Chordia and Subrahmanyam (1995) suggest that brokers may channel customer orders to non-NYSE market makers for order flow payments even if they are aware that NYSE orders execute at better than quoted prices. They find that trades executed on the NYSE have, on average, a higher price improvement rate than trades executed off the NYSE. Battalio, Greene, and Jennings (1997) show that internalization of order flow on regional exchanges has little short-run effect on posted or effective bid-ask spreads at the national level. The authors attribute this result to the degree of market fragmentation being too small. Because the extent of market fragmentation and dealer competition for NASDAQ-traded stocks is greater than that for exchanged-listed stocks, preferencing may exert a stronger impact on NASDAQ.

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<sup>3</sup> The authors define preferencing as “the act of directing an order to a market maker who is not posting the best price but who has agreed in advance to execute the order at best quoted price.”

Peterson and Sirri (2003) conclude that preferencing in exchange-listed stocks has not damaged market quality. The Securities and Exchange Commission also examined the issue of preferencing in detail in a 1997 report. The Commission concludes that while preferencing and internalization may reduce order interaction, it does not inhibit dealers from providing executions of customer orders at the best prices.

Battalio, Jennings, and Selway (2001a, 2001b) examine order preferencing on NASDAQ using proprietary data from Knight Securities. Battalio, Jennings, and Selway (2001a) find that the dealer's gross market-making revenue varies substantially across brokers. The study concludes that payment for order flow may survive decimalization if dealers customize payment schedules by paying some brokers more than others based on the information content of order flow. Battalio, Jennings, and Selway (2001b) examine the division of market-making revenue among dealer, broker, and trader. They find that the net trading cost of the broker refusing order-flow payments does not dominate the net trading cost of all brokers selling order flow to Knight. The study concludes that payment for order flow does not unambiguously harm traders and casts doubt on the conclusions of extant studies using only trade prices to assess market quality.

Although prior studies provide valuable insight into the impact of order preferencing on dealer competition and execution quality, there are still many unanswered questions. In this paper, we provide further evidence on the extent and effect of order preferencing on NASDAQ using data before and after decimalization. Unlike previous studies that utilize data from one market maker, we use quote and trade data for a large number of NASDAQ dealers. While prior research focuses mostly on order preferencing on regional exchanges and the nature of competition between NYSE and non-NYSE market makers, our focus is order preferencing on NASDAQ and competition among NASDAQ dealers. Because the nature and extent of competition among NASDAQ dealers are different from those between NYSE and non-NYSE market makers, our study sheds further light on the effect of order preferencing on market quality.

In addition, our study provides evidence regarding the impact of decimalization on order

preferencing. Prior studies offer conflicting predictions regarding the effect of decimal pricing on order preferencing. Chordia and Subrahmanyam (1995), Kandel and Marx (1999), and Harris (1999) predict that decimal pricing will greatly reduce order preferencing. In contrast, Benveniste, Marcus, and Wilhelm (1992), Battalio and Holden (2001), and Battalio, Jennings, and Selway (2001a) predict that decimalization may have only a marginal effect on preferencing. We shed light on this debate by comparing the extent of preferencing immediately before and after decimalization. We also compare price impact and price/size improvements between preferred and unpreferred trades and thereby determine whether preferred trades have smaller information contents and receive better executions as some researchers suggested.

Our empirical results show that order preferencing is prevalent on NASDAQ during both the pre and post decimalization periods. Although the implementation of decimal pricing lowered the extent of order preferencing, the proportion of preferred trades after decimalization is much higher than what prior studies [e.g., Chordia and Subrahmanyam (1995), Kandel and Marx (1999), and Harris (1999)] had predicted. We find a significant and positive (negative) relation between spreads (dealer quote aggressiveness) and the extent of internalization during both periods. The price impact of preferred trades is significantly smaller than that of unpreferred trades and preferred trades receive greater (smaller) size (price) improvements than unpreferred trades.

The paper is organized as follows. Section 2 describes data sources and sample selection procedures and presents descriptive statistics. Section 3 discusses the extent and determinants of order preferencing and presents evidence on how decimal pricing affects order preferencing and execution costs. Section 4 analyzes the effects of internalization on spreads and dealer quote aggressiveness. Section 5 compares price impact, price improvement, and size improvement between preferred and unpreferred trades. Section 6 provides a brief summary and concluding remarks.

## 2. Data sources and sample characteristics

The NASDAQ Stock Market began its decimal test phase with 14 securities on March 12, 2001, followed by another 197 securities on March 26, 2001. All remaining NASDAQ securities converted to decimal quoting on April 9, 2001. To examine the effects of decimal pricing on order preferencing and execution costs, we use data before and after the implementation of decimal pricing.

We obtain data for this study from NASTRAQ<sup>®</sup> Trade and Quote Data. We use trade, inside quote, and dealer quote data for November 2000 as our study sample for the pre decimalization period. We use corresponding data for June 2001 for the post decimalization period. We use proprietary data from NASDAQ to determine whether each trade is preferenced or not. We include a stock in our study sample if its data are available for both periods. The final study sample consists of 3,242 NASDAQ-listed stocks.

We omit the following to minimize data errors: (1) quotes if either the ask or the bid is less than or equal to zero; (2) quotes if either the ask size or the bid size is less than or equal to zero; (3) quotes if the bid-ask spread is greater than \$5 or less than zero; (4) before-the-open and after-the-close trades and quotes; (5) trades if the price or volume is less than or equal to zero; (6) trade price,  $p_t$ , if  $|(p_t - p_{t-1})/p_{t-1}| > 0.5$ ; (7) ask quote,  $a_t$ , if  $|(a_t - a_{t-1})/a_{t-1}| > 0.5$ ; and (8) bid quote,  $b_t$ , if  $|(b_t - b_{t-1})/b_{t-1}| > 0.5$ .

We measure share price by the mean daily closing quote midpoints and return volatility by the standard deviation of daily returns calculated from daily closing quote midpoints. We measure trade size by the average dollar transaction size. We measure firm size by the market value of equity at the beginning of each study period. We employ the Herfindahl-index as a measure of dealer competition and trading concentration in each stock. We calculate the Herfindahl-index for stock  $i$  using the following formula:

$$\text{H-INDEX}(i) = \sum_j [100V(i,j)/\sum_j V(i,j)]^2, \quad (1)$$

where  $V(i,j)$  is stock  $i$ 's dollar volume executed by dealer  $j$ . The Herfindahl-index increases as the number of dealers decreases or as the proportion of volume by the leading dealer increases. Thus, a high Herfindahl-index is associated with high concentration of trading. Schultz (2000) holds that the Herfindahl-index is a better measure of dealer competition than the number of dealers because the latter tends to overstate the degree of competition.<sup>4</sup>

We report select attributes of our study sample of 3,242 stocks in Table 1. The average share price is \$14.52 before decimalization and \$12.38 after decimalization. The average dollar trade size and the average number of transactions are \$10,752 and 13,340, respectively, before decimalization and \$7,888 and 12,081 after decimalization. The average standard deviation of daily returns is 0.0524 before decimalization and 0.0414 after decimalization. The average market capitalization is \$1,201 millions before decimalization \$685 millions after decimalization. The larger percentage change in market capitalization between the pre and post decimalization periods relative to the corresponding change in share price indicates that the firm with a greater number of shares outstanding experienced a larger reduction in share price.

The average Herfindahl-index based on dollar volume is 2,122 before decimalization and 2,110 after decimalization. We obtain similar results from the Herfindahl-index based on share volume. The Federal Trade Commission (FTC) considers the Herfindahl-index values below 1,000 as characteristics of an unconcentrated industry, the index values between 1,001 and 1,800 as indicative of moderate concentration, and the index values greater than 1,800 as indicative of high concentration. Although the Herfindahl-index is usually applied to broadly defined industries rather than narrowly defined industries like market-making in a specific stock, the FTC guidelines offer

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<sup>4</sup> Using data from May 1997 through February 1998, Schultz finds that the average number of dealers exceeds ten, but the average Herfindahl-index is greater than 2,500. Because the Herfindahl-index of 2,500 would occur if four dealers share all the volume equally, the number of dealers tends to overstate the level of competition. In addition, Ellis, Michaely, and O'Hara (2002) show that there are many dormant market makers for any given stock and entering market makers fail to capture a meaningful share of trading or profits. Thus, the number of market makers alone is unlikely to capture the competitive nature of the market.



some insight on the nature of dealer competition on NASDAQ.

Schultz (2000) shows that the average Herfindahl-index for NASDAQ stocks is 2,883 just prior to the 1997 order handling rule change and 2,756 after the rule change. Our results suggest that there has been a significant decline in the Herfindahl-index since the 1997 rule change: from 2,756 just after the rule change to 2,110 after decimalization, a 23% drop.<sup>5</sup> On the whole, these results indicate that the level of market concentration on NASDAQ has declined considerably during the last several years.

### **3. Order preferencing and execution costs before and after decimalization**

In this section, we first describe how order preferencing and execution costs are measured and compare order preferencing between the pre and post decimalization periods. We then examine how order preferencing is related to stock attributes and dealer types. Finally, we compare execution costs before and after decimal pricing.

#### **3.1. Measurement of order preferencing and execution costs**

Proprietary data from NASDAQ contain information on the quotes and transactions of all market makers that allows us to determine whether a public trade is preferenced. First, we consider a trade internalized (i.e., vertically preferenced) if the reporting market maker is also a contra party in the trade. When the reporting market maker is not a contra party in the trade, we trace the market maker's quote at the time of transaction and consider the trade preferenced if the quote is poorer than the prevailing inside market quote.<sup>6</sup> For example, if a market maker bought 500 shares at the inside market bid price of \$20 while he was posting the bid price of \$19.875, we consider the trade preferenced.

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<sup>5</sup> The average Herfindahl index for our sample of NASDAQ stocks maynot be directly comparable to the corresponding figure in Schultz (2000) unless both study samples include roughly identical stocks.

<sup>6</sup> Blume and Goldstein (1997) and Hansch, Naik, and Viswanathan (1999) employ the same approach to measure the trading volume captured through payment for order flow and other non-price means.

The Securities and Exchange Commission (SEC) notes that in its broadest sense, the term preferencing refers to the direction of order flow by a broker-dealer to a specific market maker or specialist, independent of whether or not some form of affiliation or inducement for the direction of order flow exists between the broker-dealer and the market maker or specialist.<sup>7</sup> Hence, our measure of preferencing is in line with the SEC's definition of preferencing.

Note that stock  $i$ 's volume executed by dealer  $j$  when  $j$  is not an ECN,  $V(i,j)$ , consists of four components:

$$V(i,j) = VINT(i,j) + VINS(i,j) + VNINS(i,j) + VE(i,j); \quad (2)$$

where  $VINT(i,j)$  is stock  $i$ 's internalized volume forwarded to dealer  $j$ ,  $VINS(i,j)$  is stock  $i$ 's non-internalized volume executed by dealer  $j$  when he is at the inside market,<sup>8</sup>  $VNINS(i,j)$  is stock  $i$ 's non-internalized volume executed by dealer  $j$  when he is not at the inside market, and  $VE(i,j)$  is stock  $i$ 's volume on ECNs routed by dealer  $j$ . When  $j = \text{ECN}$ , equation (2) reduces to  $V(i,j) = VINS(i,j) + VNINS(i,j)$  because  $VINT(i,j) = 0$  and  $VE(i,j) = 0$  for  $j = \text{ECN}$ . Although  $VNINS(i,j)$  is likely to be zero or very small for ECNs, we calculate the variable the same way as we do for the market makers for consistency. We measure trading volume both in dollars and number of shares. The results are, however, qualitatively identical between the two measures. Hence, we report only the results based on dollar volume throughout the paper.

From equation (2), we obtain  $\sum_j V(i,j) = \sum_j VINT(i,j) + \sum_j VINS(i,j) + \sum_j VNINS(i,j) + \sum_j VE(i,j)$ ; where  $\sum_j$  denotes summation over  $j$ ,  $\sum_j V(i,j)$  is stock  $i$ 's total volume,  $\sum_j VINT(i,j)$  is stock  $i$ 's internalized volume,  $\sum_j VINS(i,j)$  is stock  $i$ 's non-internalized volume at the inside market,  $\sum_j VNINS(i,j)$  is stock  $i$ 's non-internalized volume at the non-inside market, and  $\sum_j VE(i,j)$  is stock  $i$ 's volume on ECNs routed by dealers. We then measure the extent of preferencing for

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<sup>7</sup> See Securities Exchange Act Release No. 37619A (September 6, 1996), 61 FR 48290 (September 12, 1996) at n.357 (File No. S7-30-95).

<sup>8</sup> Specifically,  $VINS(i,j)$  is defined as customer buy volume when the market maker is at the inside ask plus customer sell volume when the market maker is at the inside bid plus crosses when the market maker is at

stock  $i$ ,  $PREF(i)$ , by the ratio of stock  $i$ 's internalized volume plus any non-internalized volume at the non-inside market to its total volume, i.e.,<sup>9</sup>

$$PREF(i) = \sum_j [VINT(i,j) + VNINS(i,j)] / \sum_j V(i,j). \quad (3)$$

A broker may send customer orders to a market maker with preferencing arrangement when the market maker is posting the inside market quotes. Hence, equation (3) is likely to underestimate the actual level of preferencing. If we assume that preferenced orders arrive at the same rate regardless of whether the market maker is at the inside, we can correct the downward bias by inflating  $VNINS(i,j)$  by the percentage of time during which the market maker is not at the inside.<sup>10</sup> Accordingly, we also calculate the adjusted measure of order preferencing ( $PREF^A(i)$ ) using the following equation:

$$PREF^A(i) = \sum_j [VINT(i,j) + VNINS(i,j) / \{1 - PTINS(i,j)\}] / \sum_j V(i,j), \quad (3a)$$

where  $PTINS(i,j)$  is the percentage of time during which dealer  $j$  is at the inside for stock  $i$ .<sup>11</sup>

Similarly, from equation (2), we obtain  $\sum_i V(i,j) = \sum_i VINT(i,j) + \sum_i VINS(i,j) + \sum_i VNINS(i,j) + \sum_i VE(i,j)$ ; where  $\sum_i$  denotes summation over  $i$ ,  $\sum_i V(i,j)$  is dealer  $j$ 's total volume,  $\sum_i VINT(i,j)$  is dealer  $j$ 's internalized volume,  $\sum_i VINS(i,j)$  is dealer  $j$ 's non-internalized volume at the inside market,  $\sum_i VNINS(i,j)$  is dealer  $j$ 's non-internalized volume at the non-inside market,

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either the inside bid or inside ask, net of any internalized trades.

<sup>9</sup> Non-internalized trades that are executed by dealers whose quotes are away from the inside for a given stock are not necessarily all preferenced trades, especially when orders are sent by a broker who has internalized order flow in the same stock. Dealers generally choose either to internalize or to establish preferencing arrangements for the majority of their order flow in a given stock, but rarely will do both in a given stock. Therefore, some of the preferenced trades we identify may reflect order flow to dealers who do not have any explicit preferencing arrangement with the brokers. In this regard,  $PREF(i)$  is an imperfect measure of order preferencing arrangements. We thank Robert Battalio for the point.

<sup>10</sup> Let  $\Psi$  denote the magnitude of dealer  $j$ 's preferenced volume in stock  $i$ . If preferenced orders arrive randomly over time and the dealer is at the inside 100% of the time, the expected value of non-inside volume ( $VNINS$ ) would be  $\Psi(1 - \lambda)$ . Thus we can estimate the 'unobservable' preferenced volume ( $\Psi$ ) by dividing the non-inside volume by  $(1 - \lambda)$ . We are grateful to an anonymous referee for this suggestion.

<sup>11</sup> We also calculate  $PREF(i)$  using an alternative averaging method:  $PREF(i) = (1/J) \sum_j [VINT(i,j)/V(i,j)] + (1/J) \sum_j [VNINS(i,j)/V(i,j)] / \{1 - PTINS(i,j)\}$ . The results are qualitatively similar to those presented here.

and  $\Sigma iVE(i,j)$  is volume executed on ECNs reported by dealer  $j$ .<sup>12</sup> We then measure the extent of preferencing for dealer  $j$ ,  $PREF(j)$ , by the ratio of dealer  $j$ 's internalized volume plus any non-internalized volume at the non-inside market to his total volume, i.e.,

$$PREF(j) = \Sigma i[VINT(i,j) + VNINS(i,j)]/\Sigma iV(i,j). \quad (4)$$

As in equation (3a), we also calculate the adjusted measure of dealer preferencing using the following equation:

$$PREF^A(j) = \Sigma i[VINT(i,j) + VNINS(i,j)/\{1 - PTINS(i,j)\}]/\Sigma iV(i,j). \quad (4a)$$

We calculate both the time-weighted quoted spread and the trade-weighted effective spread during each period. The quoted spread is calculated as

$$\text{Quoted spread}_{it} = (A_{it} - B_{it})/M_{it}, \quad (5)$$

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  $B_{it}$ .

To measure the cost of trading when it occurs at prices inside the posted bid and ask quotes, we calculate the effective spread using the following formula:

$$\text{Effective spread}_{it} = 2D_{it}(P_{it} - M_{it})/M_{it}, \quad (6)$$

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 which equals one for customer buy orders and negative one for customer sell orders.<sup>13</sup> For each stock, we calculate the time-

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<sup>12</sup> If an ECN such as Instinet does an execution but lets the market maker report the trade, we are likely to find that the market maker is not at the inside (and the ECN probably is). To reflect this possibility, we calculate  $\Sigma iVE(i,j)$  for each market maker.

<sup>13</sup> We estimate  $D_{it}$  using the method in Lee and Ready (1991). We use quotes that are at least onesecond old.

weighted quoted (QSPRD(i)) and the trade-weighted effective spread (ESPRD(i)) using all the time-series observations during each period.

### 3.2. Effect of decimal pricing on order preferencing

Panel A of Table 2 shows the mean and standard deviation of preferred volumes before and after decimalization, together with their percentile values.  $INT(i)$  is the ratio of stock  $i$ 's internalized volume to its total volume,  $NINS(i)$  is the ratio of stock  $i$ 's non-inside volume to its total volume,  $NINS^A(i)$  is the ratio of stock  $i$ 's adjusted non-inside volume to its total volume,  $PREF(i) = INT(i) + NINS(i)$ , and  $PREF^A(i) = INT(i) + NINS^A(i)$ . All else being equal, the probability that a quote is at the inside is likely to be lower with the smaller tick size. This tendency works *against* finding a decrease in our proxy for order preferencing (i.e.,  $PREF^A(i)$ ) after decimalization.

There is wide variation in the proportion of internalized volumes across stocks, ranging from zero to almost 100%, with a mean value of around 25%. The adjusted non-inside volume accounts for more than 50% of the total volume during both the pre and post decimalization periods. Mean proportions of both the internalized and adjusted non-inside volumes after decimalization are smaller than the corresponding figures before decimalization. On average, 79.92% of pre decimalization trades are preferred whereas 75.64% of post decimalization trades are preferred.

Although the observed change (-4.28%) in the proportion of preferred trades is non-trivial and statistically significant ( $t = -14.71$ ), it is not as dramatic as some prior studies had predicted.<sup>14</sup> Chordia and Subrahmanyam (1995) develop a revenue-maximization model that suggests that the tick size reduction will greatly reduce preferencing. The intuition is that finite tick sizes could cause quoted prices to be greater than specialists' and off-floor market makers' reservation prices. By paying a small amount for order flow, off-floor market makers can still earn

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<sup>14</sup> Porter and Weaver (1997) find that the tick size change has a negligible impact on internalization using a

rents in excess of their reservation prices. Kandel and Marx (1999) develop a model that considers the institutional features of the NASDAQ market and show that a decrease in tick size can result in the elimination of preferencing and a reduction in internalized trades. Harris (1999) predicts that payment for order flow will decrease with decimal pricing and probably will cease entirely for stocks for which the decrease in average spreads is greater than the payments currently made for orders. The moderate reduction in preferencing documented in the present study is inconsistent with the predictions of these studies.

Our findings are, however, in line with the result of the several previous studies that predicted the survival of preferencing after decimal pricing. Battalio and Holden (2001) show that order preferencing is viable with competitive dealers quoting in infinitesimal increments if they can use ex ante identifiable attributes to differentiate order flow profitability. Benveniste, Marcus, and Wilhelm (1992) argue that repeatedly dealing with the same brokers allows market makers to learn when brokers exploit private information, suggesting that broker identity may be one such attribute. Building on this insight, Battalio Jennings, and Selway (2001a) claim that order preferencing may survive decimalization if dealers customize payment schedules by paying some brokers more than others based on information content of their orders.

Another possible explanation for our result is that the effects of decimal pricing may take more time to develop since preferencing arrangements are like legal contracts that may take time to re-negotiate or end. The time lapse between the date (April 9, 2001) on which decimalization was completed on NASDAQ and our post decimalization study period (June 2001) may not be long enough, and thus the full impact of decimal pricing on preferencing may yet to be materialized.<sup>15</sup>

Panel B shows the proportions of preferenced trades by *dealers*, where  $INT(j)$  is the ratio of dealer  $j$ 's internalized volume to its total volume,  $NINS(j)$  is the ratio of dealer  $j$ 's non-inside volume to its total volume,  $NINS^A(j)$  is the ratio of dealer  $j$ 's adjusted non-inside volume to its total

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sample of stocks listed on the Toronto Stock Exchange (TSE).

<sup>15</sup> Preferencing may have declined even more with the implementation of SuperSOES in August 2001.

volume,  $PREF(j) = INT(j) + NINS(j)$ , and  $PREF^A(j) = INT(j) + NINS^A(j)$ .

The results show that there is wide variation in the proportion of internalized volumes across dealers as well, ranging from zero to 100%, with a mean value of 35% (30%) during the pre (post) decimalization period. The adjusted non-inside volume accounts for more than 40% of the total volume during both periods. On average, 75.84% of pre decimalization trades are preferenced whereas 71.87% of post decimalization trades are preferenced. The observed change (-3.97%) in the proportion of preferenced trades is non-trivial and statistically significant ( $t = -2.57$ ).

### 3.3. Preferencing as a function of stock attributes and dealer types

Preferencing contracts typically specify the nature of orders the dealer must accept. For example, according to NASD (1991), common qualification includes small orders (usually less than 3,000 shares) and orders on stocks with a certain minimum price. Thus, the proportion of preferenced trades is likely to be higher for stocks with smaller trade sizes and higher share prices. Because trades occurred at the non-inside market are likely to be routed through preferencing arrangements, we expect that the proportion of trades executed at the non-inside ( $NINS^A$ ) is higher for stocks with smaller trade sizes and higher share prices.

Internalized trades are likely to be larger than non-internalized trades because institutional brokers have large internalized volumes and their trade sizes tend to be greater than those of wholesalers or wirehouses. Hence, the proportion of internalized trades ( $INT$ ) is likely to be higher for stocks with larger trade sizes. Similarly,  $INT$  is likely to be higher for stocks with larger trading volumes because institutional brokers are more likely to trade high-volume stocks than low-volume stocks. We expect stocks with concentrated market shares to exhibit lower quote-based competition and thus higher levels of preferenced trades. Hence,  $NINS^A$  is likely to be higher for stocks with a larger H-INDEX.

Because most order flow (75%) on NASDAQ is either internalized or preferenced, stocks with larger preferenced (i.e., non-inside) volumes have smaller internalized volumes and vice

versa. Hence, the expected relations between INT and stock attributes are likely to be opposite to those between NINS<sup>A</sup> and stock attributes. Therefore, NINS<sup>A</sup> is likely to be negatively related to trading volume and INS is likely to be negatively related to share price and H-INDEX.<sup>16</sup>

The extent of order preferencing is likely to depend not only on stock attributes but also on dealer types. Institutional brokers frequently act as both dealer and broker for their clients, who are primarily large institutions. Consequently, institutional brokers are likely to have large internalized volumes. Integrated national firms (i.e., wirehouses) tend to have large retail brokerage forces. Thus, an integrated firm generates substantial order flows that are executed by the market-making arm of the firm. We expect that preferencing arrangements are more likely to be made with wholesalers (relative to institutional brokers and wire houses) because wholesalers tend to specialize in small retail orders. These considerations suggest that INT is likely to be greater for institutional brokers and wirehouses, but smaller for wholesalers. Conversely, NINS<sup>A</sup> is likely to be smaller for institutional brokers and wirehouses, but greater for wholesalers.

We employ the following regression models to examine the relation between order preferencing and stock attributes/dealer types:

$$\text{INT}(i,j) = \alpha_0 + \alpha_1 \log(\text{PRICE}(i)) + \alpha_2 \log(\text{NTRADE}(i)) + \alpha_3 \log(\text{TSIZE}(i)) + \alpha_4 \text{H-INDEX}(i) + \alpha_5 \text{DUMIB}(j) + \alpha_6 \text{DUMWH}(j) + \alpha_7 \text{DUMWS}(j) + \varepsilon_1(i,j); \quad (7)$$

$$\text{NINS}^A(i,j) = \beta_0 + \beta_1 \log(\text{PRICE}(i)) + \beta_2 \log(\text{NTRADE}(i)) + \beta_3 \log(\text{TSIZE}(i)) + \beta_4 \text{H-INDEX}(i) + \beta_5 \text{DUMIB}(j) + \beta_6 \text{DUMWH}(j) + \beta_7 \text{DUMWS}(j) + \varepsilon_2(i,j); \quad (8)$$

$$\text{PREF}^A(i,j) = \gamma_0 + \gamma_1 \log(\text{PRICE}(i)) + \gamma_2 \log(\text{NTRADE}(i)) + \gamma_3 \log(\text{TSIZE}(i)) + \gamma_4 \text{H-INDEX}(i) + \gamma_5 \text{DUMIB}(j) + \gamma_6 \text{DUMWH}(j) + \gamma_7 \text{DUMWS}(j) + \varepsilon_3(i,j); \quad (9)$$

where INT(*i,j*) is the ratio of stock *i*'s internalized volume routed to dealer *j* to its total volume executed by dealer *j*, NINS<sup>A</sup>(*i,j*) is the ratio of stock *i*'s adjusted non-inside volume executed by

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<sup>16</sup> We note that stocks with wide spreads are more likely to be routed through preferencing arrangements than stocks with narrow spreads. We do not include the spread in the NINS<sup>A</sup> equation, however, because



dealer  $j$  to its total volume executed by dealer  $j$ ,  $PREF^A(i,j) = INT(i,j) + NINS^A(i,j)$ ,  $PRICE(i)$  is the average share price of stock  $i$ ,  $NTRADE(i)$  is the number of trades of stock  $i$ ,  $TSIZE(i)$  is the average dollar trade size of stock  $i$ ,  $H-INDEX(i)$  is the Herfindahl-index,  $DUMIB(j)$  equals one for institutional brokers and zero otherwise,  $DUMWH(j)$  equals one for wirehouses and zero otherwise, and  $DUMWS(j)$  equals one for wholesalers and zero otherwise.<sup>17</sup>

We show the regression results in Table 3. The results show that the  $NINS^A(i,j)$  is significantly and positively related to share price and the Herfindahl-index, and negatively to trade size and number of trades during both the pre and post decimalization periods. In contrast, we find that  $INT(i,j)$  is significantly and positively related to trade size and number of trades, and negatively to share price and the Herfindahl-index. We also find that  $INT(i,j)$  is significantly and positively related to the dummy variables for institutional brokers and wirehouses, but negatively to the wholesaler dummy variable. Conversely,  $NINS^A(i,j)$  is negatively related to the dummy variables for institutional brokers and wirehouses, but positively to the dummy variable for wholesalers. These results are consistent with our expectation and support the idea that the extent of order preferencing varies with stock attributes and dealer types.

Note that while the regression model explains 38.6% (30.4%) and 33.6% (24.1%) of variation in  $NINS^A(i,j)$  ( $INT(i,j)$ ) during the pre and post decimalization periods, respectively, it explains only 10.9% and 11.4% of variation in  $PREF^A(i,j)$  during each period. The lower explanatory power for the  $PREF^A(i,j)$  model is largely due to the fact that our common explanatory variables have opposite effects on the two components (i.e.,  $NINS^A(i,j)$  and  $INT(i,j)$ ) of  $PREF^A(i,j)$ .

To the extent that internalization and preferencing are correlated with stock attributes and dealer types, we expect to observe intertemporal stability in internalization and preferencing across

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there is a spurious negative correlation between the spread and  $NINS^A$  (see Section 4 for a detailed discussion of this issue).

<sup>17</sup> We classify dealers into these types according to dealer categories provided in Huang (2002).

stocks and dealers. To examine whether stocks that have high degrees of internalized or preferred (i.e., non-inside) trades before decimal pricing also exhibit similar patterns after decimal pricing, we estimate the following regression models:

$$\text{Post-INT}(i) = \alpha_0 + \alpha_1 \text{Pre-INT}(i) + \varepsilon_1(i); \quad (10)$$

$$\text{Post-NINS}^A(i) = \beta_0 + \beta_1 \text{Pre-NINS}^A(i) + \varepsilon_2(i); \quad (11)$$

$$\text{Post-PREF}^A(i) = \gamma_0 + \gamma_1 \text{Pre-PREF}^A(i) + \varepsilon_3(i); \quad (12)$$

where  $\text{Post-INT}(i)$ ,  $\text{Post-NINS}^A(i)$ , and  $\text{Post-PREF}^A(i)$  are the proportions of internalized, adjusted non-inside, and adjusted preferred trades for stock  $i$ , respectively, during the post decimalization period and  $\text{Pre-INT}(i)$ ,  $\text{Pre-NINS}^A(i)$  and  $\text{Pre-PREF}^A(i)$  are the corresponding figures during the pre decimalization period.

Similarly, we also estimate the above regression models using Pre- and Post- $\text{INT}(j)$ ,  $\text{NINS}^A(j)$ , and  $\text{PREF}^A(j)$ , where  $j$  denotes dealer  $j$  to examine whether dealers with high degrees of internalized, adjusted non-inside, or preferred trades before decimal pricing also exhibit similar patterns after decimal pricing.

Panel A of Table 4 reports the regression results from preferencing data for individual stocks and Panel B reports the results from preferencing data for individual dealers. Panel B shows that there is indeed a high degree of intertemporal stability in INT and  $\text{NINS}^A$  across dealers. The results show that 52.2% (40.9%) of inter-dealer variation in INT ( $\text{NINS}^A$ ) during the post decimalization period can be explained by the corresponding variation during the pre decimalization period. These results should not come as a surprise because both INT and  $\text{NINS}^A$  are strongly correlated to dealer types.<sup>18</sup> Similarly, we find that 32.4% (41.7%) of inter-stock variation in INT ( $\text{NINS}^A$ ) during the post decimalization period can be explained by the corresponding variation

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<sup>18</sup> In addition, the internalized order flow is likely to be routed to the same dealer (i.e., the affiliated dealer) over time. Preferencing arrangements between brokers and dealers may require costly initial setup costs and, as a result, tend to last once they are established.

during the pre decimalization period.<sup>19</sup>

#### 3.4. Execution costs and order preferencing before and after decimalization

Table 5 shows the extent of order preferencing ( $PREF^A(i)$ ) and bid-ask spreads during the pre and post decimalization periods, respectively. We find that decimal pricing has a significant impact on the bid-ask spreads of NASDAQ securities. During the pre decimalization period, the average percentage quoted and effective spreads for our whole sample are 0.0330 and 0.0311, respectively. The corresponding figures are 0.0254 and 0.0224, respectively, after decimalization.<sup>20</sup> Both the quoted and effective spread changes are statistically significant ( $t = -10.12$  and  $-12.75$ ). These results are consistent with the findings of previous studies [see, e.g., Chakravarty, Harris, and Wood (2001), NASDAQ (2001a, 2001b), NYSE (2001), and Bessembinder (2002)].

To examine whether the impact of decimal pricing on order preferencing and spreads differs among stocks, we group our sample of stocks into quartiles based on the average trading volume during the pre decimalization period. We then cluster stocks within each volume quartile into four groups according to the average share price during the pre decimalization period. In Table 5 (Panel B), we show the pre and post decimalization values of preferencing and spreads for the four portfolios: HVHP, HVLP, LVHP, and LVLP, where HVHP includes stocks in the highest volume quartile and the highest price quartile, HVLP includes stocks in the highest volume quartile and the lowest price quartile, LVHP includes stocks in the lowest volume quartile and the highest price quartile, and LVLP includes stocks in the lowest volume quartile and the lowest price quartile.

Consistent with the prediction of Harris (1997, 1999), we find that the impact of the tick size change on spreads is greatest for high-volume and low-price stocks (i.e., HVLP). The mean quoted

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<sup>19</sup> The regression results show that only 7.5% of interstock variation in  $PREF^A$  during the post decimalization period can be explained by the corresponding variation during the pre decimalization period. The low  $\bar{R}^2$  may largely be attributed to the weak correlation between  $PREF^A(i,j)$  and stock attributes. We find that 37.1% of inter-dealer variation in  $PREF^A$  during the post decimalization period can be explained by the corresponding variation during the pre decimalization period. The higher  $\bar{R}^2$  may largely be attributed to the stronger correlation between  $PREF^A(i,j)$  and dealer types during both the pre and post decimalization periods.

and effective spreads for this group declined by 0.0098 ( $t = -9.46$ ) and 0.0107 ( $t = -10.67$ ), respectively, after decimalization. This result suggests that the previous tick size was apparently too large for traders in these stocks. With the relaxation of the binding tick size, liquidity providers start using finer price grids, resulting in narrower spreads. We find that the impact of decimal pricing on preferencing is greatest for high-volume and low-price stocks as well. During the pre decimalization period, about 83% of trades were preferenced for these stocks whereas the corresponding figure is 74% during the post decimalization period.

#### 4. Effects of internalization on spreads and dealer quote aggressiveness

In the previous section, we show that decimalization led to a decline in both order preferencing and bid-ask spreads. In the present section, we examine the cross-sectional relation between bid-ask spreads and the proportion of internalized trades. To examine the effect of internalization on execution costs after controlling for the effects of other variables, we estimate the following regression model:

$$\begin{aligned} \text{QSPRD}(i) \text{ or } \text{ESPRD}(i) = & \beta_0 + \beta_1(1/\text{PRICE}(i)) + \beta_2 \log(\text{NTRADE}(i)) + \beta_3 \log(\text{TSIZE}(i)) \\ & + \beta_4 \text{VOLATILITY}(i) + \beta_5 \log(\text{MVE}(i)) + \beta_6 \text{H-INDEX}(i) + \beta_7 \text{INT}(i) + \varepsilon(i) \end{aligned} \quad (13)$$

where QSPRD( $i$ ) is the time-weighted quoted spread of stock  $i$  (as a percentage of share price), ESPRD( $i$ ) is the trade-weighted effective spread of stock  $i$  (as a percentage of share price), PRICE( $i$ ) is the average share price of stock  $i$ , NTRADE( $i$ ) is the number of trades of stock  $i$ , TSIZE( $i$ ) is the average dollar trade size of stock  $i$ , VOLATILITY( $i$ ) is the standard deviation of stock  $i$ 's daily returns, MVE( $i$ ) is the market value of equity of stock  $i$ , H-INDEX( $i$ ) is the Herfindahl index for stock  $i$ , INT( $i$ ) is the proportion of internalized trades for stock  $i$ , and  $\varepsilon(i)$  is the error term. To assess whether the effects of internalization and other variables on spreads

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<sup>20</sup> The mean and median values of the dollar quoted (effective) spread are \$.2272 (\$.2121) and \$.1729 (\$.1685) before decimalization and \$.1474 (\$.1282) and \$.0944 (\$.0844) after decimalization.

differ between the pre and post decimalization periods, we estimate the above regression model using data for each period.

We use only the proportion of internalized trades as our measure of preferenced volume because the spread is likely to be spuriously correlated to both  $NINS(i)$  and  $NINS^A(i)$ . As noted earlier,  $NINS(i)$  is likely to underestimate the actual level of preferenced trades and the degree of underestimation increases with the dealer's time at the inside market,  $PTINS(i,j)$ . In so far as the bid-ask spread decreases with  $PTINS(i,j)$ , a spurious positive correlation is likely to exist between the spread and  $NINS(i)$ .

Note also that because we measure  $NINS^A(i)$  by  $\sum_j [VNINS(i,j) / \{1 - PTINS(i,j)\}] / \sum_j V(i,j)$ , there exists a built-in positive correlation between  $NINS^A(i,j)$  and  $PTINS(i,j)$ . Hence, to the extent that the bid-ask spread decreases with  $PTINS(i,j)$ , a negative correlation is likely to exist between the spread and  $NINS^A(i)$ , regardless of the true relation between the spread and the proportion of preferenced trades. Indeed, we find that the spread is positively related to  $NINS(i)$  and negatively to  $NINS^A(i)$  in our sample. These results are likely to be driven largely by measurement errors associated with the actual level of preferenced trades.

We report the regression results in Table 6. The results show that both quoted and effective spreads are positively related to return volatility, and negatively to share price, number of trades, and trade size during both the pre and post decimalization periods. These results are all consistent with the findings of prior studies.<sup>21</sup> The spreads are positively and significantly related to the Herfindahl index. This indicates that spreads are wider for stocks with greater inequality in dealer market shares or fewer dealers. This result is consistent with the finding of Klock and McCormick (1999), Schultz (2000), and Ellis, Michaely, and O'Hara (2002).

The quoted and effective spreads are positively and significantly related to the extent of internalization during both the pre and post decimalization periods. Before decimal pricing, the estimated coefficients for  $INT(i)$  in the quoted and effective spread equations are 0.0069 ( $t =$

2.98) and 0.0083 ( $t = 3.97$ ), respectively. The corresponding figures after decimalization are 0.007 ( $t = 2.94$ ) and 0.0092 ( $t = 4.37$ ), respectively. Hence, during the pre decimalization period, an increase in the degree of internalization from 10% to 40% is associated with a corresponding increase of 0.00207 (i.e.,  $0.0069 \times (0.4 - 0.1)$ ) in the quoted spread and 0.00249 (i.e.,  $0.0083 \times (0.4 - 0.1)$ ) in the effective spread. After decimalization, the corresponding figures are 0.0021 (i.e.,  $0.007 \times (0.4 - 0.1)$ ) for the quoted spread and 0.00276 (i.e.,  $0.0092 \times (0.4 - 0.1)$ ) for the effective spread.<sup>22</sup> These results suggest that internalization on NASDAQ may have a significant, detrimental effect on execution costs.<sup>23</sup>

To examine whether the effect of internalization on spreads varies across stocks with different volumes, we estimate the above regression model using only the most active stocks (top quartile based on trading frequency) in our study sample. We find that the estimated coefficients (t-statistics) for INT(i) in the quoted and effective spread equations are 0.0049 (3.26) and 0.0066 (4.93), respectively, before decimal pricing and 0.001 (2.73) and 0.0016 (2.88), respectively, after decimal pricing. Hence, the effect of internalized trades on spreads for high-volume stocks is qualitatively similar to that of our whole sample.<sup>24</sup>

Internalization is likely to affect not only inside spreads but also perhaps more strongly individual dealer spreads. To examine how internalization affects individual dealer spreads, we estimate regression model (13) using the mean value of individual dealer spreads (MDSPRD(i)) for each stock as the dependent variable. The results show that internalization exerts a stronger impact (i.e., greater t-statistics) on dealer spreads than on inside (quoted and effective) spreads.

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<sup>21</sup> See, for example, McNish and Wood (1992), Schultz (2000), and Stoll (2000).

<sup>22</sup> The spread cost differences could be overwhelmed by differences in other costs of trading. For example, a 0.3% difference in effective spread for a \$5,000 trade equals a cost of \$15. Commission costs differences between full-service and discount brokers can easily exceed \$15. Likewise, opportunity cost differences between faster executions of preferred orders and slower executions of unpreferred orders may also exceed the spread costs found.

<sup>23</sup> These results are in line with the finding of Bessembinder (2003) that costs for off-NYSE trades completed when executing market quotes are not at the best price are worse than for matched NYSE trades.

<sup>24</sup> To examine whether the impact of internalization on the effective spread differs between large and small trades, we also estimate regression model (13) using trades that are larger than 2,000 shares and trades that are smaller than 2,000 shares, respectively. We find that the estimated coefficient for INT(i) is significant and

We also find that the estimated coefficients (0.0667 and 0.0705) for INT(i) in the mean dealer spread equation are much larger than the corresponding figures in the inside spread equation. This result should not come as a surprise given the fact that individual dealer spreads are much wider than inside spreads.<sup>25</sup>

The positive relation between the spread and the proportion of internalized trades shown in Table 6 may be driven by reasons other than the one suggested in this study. For example, it may reflect the fact that stocks with larger spreads have more internalized trades because brokers have an incentive to route large-spread stocks to their affiliated dealers. To examine this possibility, we estimate a structural model in which both the spread and the proportion of internalized trades are specified as endogenous variables. As exogenous variables, we include 1/PRICE(i), log(NTRADE(i)), log(TSIZE(i)), VOLATILITY(i), log(MVE(i)), and H-INDEX in the spread equation, and log(PRICE(i)), log(NTRADE(i)), log(TSIZE(i)), and H-INDEX(i) in the INT equation. The result shows that the estimated coefficient for INT(i) in the spread equation and the estimated coefficient for the spread in the INT equation are both positive and significant.<sup>26</sup> This suggests that there is a positive and bi-directional relation between the spread and the proportion of internalized trades.

To further examine the effect of internalization on market quality, we analyze how dealer quote aggressiveness varies with the extent of internalization. We measure dealer j's quote aggressiveness for stock i by: (1) the percentage of time during which dealer j is at the inside (PTINS(i,j)); (2) the percentage of time during which dealer j is at the inside alone (PTINSA(i,j)); and (3) the ratio of dealer j's spread to the average spread across all dealers for stock i (RELSPRD(i,j)). We then estimate the following regression model:

$$QA(i,j) = \beta_0 + \beta_1 INT(i,j) + \text{Control variables} + \varepsilon(i,j); \quad (14)$$

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positive only when we use the large trade size group.

<sup>25</sup> Although the effects of other stock attributes on dealer spreads are generally similar to those on inside spreads, we find that dealer spreads decrease with HINDEX(i).

<sup>26</sup> The results are available from the authors upon request.

where  $QA(i,j)$  is a measure of dealer  $j$ 's quote aggressiveness for stock  $i$  ( $PTINS(i,j)$ ,  $PTINSA(i,j)$ , or  $RELSPRD(i,j)$ ),  $INT(i,j)$  is the proportion of internalized trades for stock  $i$  by dealer  $j$ , and  $\varepsilon(i,j)$  is the error term. To control for the effect of stock attributes on quote aggressiveness, we include  $\log(PRICE(i))$ ,  $\log(NTRADE(i))$ ,  $\log(TSIZE(i))$ ,  $VOLATILITY(i)$ , and  $\log(MVE(i))$  as control variables.

We estimate regression model (14) in three different ways. First, we estimate the model using the panel data of entire stock-dealer quotes. To assess the sensitivity of our results to different estimation methods, we also estimate the model for each stock using individual dealer quote data and calculate the mean  $\beta_1$  coefficient across stocks and the z-statistic.<sup>27</sup> For the panel data regression, we report the estimated  $\beta_1$  coefficient, its t-statistic, F-value, and adjusted  $R^2$  from regression model (14). We also show the panel data regression results when we include a dummy variable for each stock (fixed effects) instead of control variables.<sup>28</sup> For the stock-by-stock regressions, we report the mean  $\beta_1$  coefficient and its z-statistic.

We show the regression results in Table 7. Panel A shows the results for the pre decimalization period and Panel B shows the results for the post decimalization period. In each panel, the first three columns show the results ( $\beta_1$  estimate with its t-statistic, F-value, and adjusted  $R^2$ ) from the panel data regressions with control variables, the next three columns show the results from the panel data regressions with fixed effects, and the last column shows the results (mean  $\beta_1$  coefficient and its z-statistic) from stock-by-stock regressions, respectively.

The results show that internalization has a significant effect on dealer quote aggressiveness. We find that both  $PTINS(i,j)$  and  $PTINSA(i,j)$  are significantly and negatively related to  $INT(i,j)$ , and  $RELSPRD(i,j)$  is significantly and positively related to  $INT(i,j)$ . For the

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<sup>27</sup> In this case, we do not include control variables in the regression model. We obtain the zstatistic by adding individual t-statistics across stocks and then dividing the sum by the square root of the number of coefficients.

<sup>28</sup> Because the number of intercepts exceeds the maximum allowable number of independent variables in SAS, we estimate  $\beta_1$  by applying OLS to the data expressed in terms of deviations from group means.



pre decimalization period, estimates of  $\beta_1$  from the panel data regressions with control variables are  $-0.0156$  ( $t = -19.46$ ),  $-0.0040$  ( $t = -17.02$ ), and  $0.0434$  ( $t = 12.09$ ) when we measure dealer quote aggressiveness by  $PTINS(i,j)$ ,  $PTINSA(i,j)$ , and  $RELSPRD(i,j)$ , respectively. We find similar results from the panel data regressions with fixed effects. The corresponding figures from stock-by-stock regressions are  $-0.0166$  ( $z = -16.81$ ),  $-0.0037$  ( $z = -41.25$ ), and  $0.0583$  ( $z = 10.58$ ). The regression results (see Panel B) for the post decimalization period are qualitatively similar to those for the pre decimalization period.

These results indicate that if a high portion of a dealer's volume on a stock is internalized, the dealer is less likely to post the inside market quote on that stock. Similarly, the dealer is likely to quote wider spreads, relative to other dealers' spread quotes on the stock. The results are quite robust and similar between the pre and post decimalization periods. On the whole, these results are consistent with the notion that internalization discourages dealer quote competition.<sup>29</sup>

## **5. Preferencing, price impact, and execution quality**

In this section, we examine whether the price impact of trades and execution quality differ between preferred and unpreferred trades.

### **5.1. Price impact of preferred and unpreferred trades**

Benveniste, Marcus, and Wilhelm (1992) hold that long-term relationships between brokers and dealers can mitigate the effects of asymmetric information and dealers who actively identify and sanction informed traders can provide low cost services to uninformed traders than dealers who do not make such efforts. Easley, Kiefer, and O'Hara (1996) find a significant

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<sup>29</sup> Our findings are consistent with the observation of Bessembinder (1999, p. 406) that "If, in contrast, a large portion of order flow is subject to preferencing agreements, then posting a better quote may not attract order flow, leaving little incentive to improve quotes." The results are also consistent with Kluger and Wyatt's (2002) recent experimental finding that the average dealer and inside spread are wider when dealers have the opportunity to internalize their order flow.

difference in the information content of orders executed in New York and Cincinnati and interpret the result as evidence that the preferencing arrangements are used to cream skim uninformed liquidity traders. Battalio, Jennings, and Selway (2001a) conjecture that dealers may utilize broker identity to distinguish between profitable and unprofitable order flow and show that NASDAQ dealers' trading gross revenues vary substantially among routing brokers after controlling for order size.

We provide an alternative and *direct* test of the clientele-pricing hypothesis by comparing the information content of preferenced and unpreferenced trades. Trades that convey less private information lead to smaller post-trade price movements and thus are more profitable to execute. If brokers route only those orders with low adverse-selection risks to affiliated dealers (i.e., internalization) or dealers with preferencing arrangements, the price impact of preferenced trades would be smaller than the price impact of unpreferenced trades.<sup>30</sup>

We measure the price impact of trades by  $IMPACT(t) = 100D(t)[\{M(t+5) - M(t)\}/M(t)]$ , where  $M(t)$  and  $M(t + 5)$  are quote midpoints at time  $t$  and  $t + 5$  minutes, respectively, and  $D(t)$  is a trade direction indicator that equals  $+1(-1)$  for buyer (seller) initiated trades. Next, for each stock, we calculate the mean value of  $IMPACT(t)$  for each of the four trade groups (i.e., INS + ECN, INT, NINS, and INT + NINS) by weighting each trade equally within each trade size group. Following SEC Rule 11Ac1-5 Report, we classify trades into the following four size groups: 100–499 shares, 500–1,999 shares, 2,000–4,999 shares, and 5,000+ shares. Finally, we calculate the mean value of  $IMPACT(t)$  across stocks.

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<sup>30</sup>We note that the price impact of preferenced trades could be greater than that of unpreferenced trades if dealers are willing to handle orders with high adverse-selection risks in return for stable order flow guaranteed by internalization or preferencing arrangements and brokers take into consideration of such preference in their order routing decisions. Brokers may also have incentives to route orders with smaller adverse selection risks to dealers without preferencing agreements to build reputation that may help them to earn future business from these dealers. In addition, preferenced trades may exhibit larger price impact if market makers are willing to supply liquidity to affiliated brokers and brokers with preferencing agreements during difficult times (i.e., when prices were moving against them for reasons such as news and market volatility). Hence, whether the price impact of preferenced trades is greater or smaller than the price impact of unpreferenced trades is an empirical question

Panel A of Table 8 shows the mean price impact for each trade size group during the pre and post decimalization periods. For each period, columns 1, 2, and 3 show the average price impact of unpreferred trades (INS + ECN), internalized trades (INT), and non-inside trades (NINS). Column 4 shows the average price impact of all preferred trades (i.e., INT + NINS). To determine whether the average price impact differs significantly between unpreferred and preferred trades, we compare the average price impact of unpreferred trades (INS + ECN) with the average price impact of internalized trades (INT), non-inside trades (NINS), and all preferred trades (INT + NINS), respectively. Column 5 shows the results of paired-comparison t-tests for the equality of mean.

The results show that the price impact of internalized trades is significantly smaller than the price impact of unpreferred trades across all trade-size categories during both the pre and post decimalization period. Similarly, we also find that the price impact of non-inside trades is smaller than the price impact of unpreferred trades in two large trade-size categories during both periods. Overall, these results are consistent with the prediction of the clientele-pricing hypothesis advanced by Battalio and Holden (2001) and others that dealers (brokers) selectively purchase (internalize) orders based on their information content.

To assess the sensitivity of our results, we also employ an alternative empirical method: we regress the price impact of trades on dummy variables for internalized and non-inside trades, dummy variables for trade-size categories two, three, and four, and four stock attributes (share price, number of trades, return volatility, and market capitalization). The regression results show that the estimated coefficients for dummy variables for internalized and non-inside trades are negative and significant at the 1% level during both the pre and post decimalization periods, indicating that the price impact of preferred trades is smaller than the price impact of

unpreferred trades.<sup>31</sup> Hence, our findings are quite robust and not sensitive to different empirical methods.

## 5.2. Preferencing and price/size improvement

Quoted bid and ask prices are not necessarily the prices at which trades take place because it is possible to trade at inside the quoted prices. Quoted prices may simply be viewed as the starting point for a negotiation, not the price at which trades take place. Huang and Stoll (1996) find that the proportion of trades inside the quotes is 0.267 on NASDAQ and 0.379 on the NYSE from a matching sample of NASDAQ and NYSE stocks in 1991.

Hansch, Naik, and Viswanathan (1999) hold that if posting the best price indicates a greater willingness to transact, then dealers who post the best price may offer a better price improvement than dealers who do not post the best price. Because preferred trades are routed to dealers who may or may not be at the inside whereas the unpreferred trades are always routed to dealers who are at the inside market, price improvement is likely to be lower for preferred trades than unpreferred trades.

In contrast, Seppi (1990) holds that the transaction is not anonymous with negotiated price improvements and thus a penalty technology could force repeat customers to trade at the quotes when they are informed and ask for an improvement only when they are uninformed. Barclay and Warner (1993) and Rhodes-Kropf (2001) hold that negotiation allows dealers to assess the customer's information and suggest that informed customers remain anonymous and trade at the quotes while uninformed customers negotiate for price improvements. In so far as preferred orders have lower information content than unpreferred orders, these studies suggest that preferred orders may receive *greater* price improvements than unpreferred orders.

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<sup>31</sup> The results are available from the authors upon request

We measure the price improvement rate for each trade by  $PI(t) = 100\{[IAP(t) - P(t)]/IAP(t)\}$  if  $D(t) = 1$  and  $PI(t) = 100\{[P(t) - IBP(t)]/IBP(t)\}$  if  $D(t) = -1$ , where  $P(t)$  = trade price at time  $t$ ,  $IAP(t)$  = the inside ask price at time  $t$ ,  $IBP(t)$  = the inside bid price at time  $t$ , and  $D(t)$  = a trade direction indicator that equals  $+1(-1)$  for buyer (seller) initiated trades. Next, for each stock, we calculate the mean value of  $PI(t)$  for each of the four trade groups by weighting each trade equally within each trade size group. Finally, we calculate the mean value of  $PI$  across stocks.

Panel B of Table 8 shows the average price improvement rate for each trade size group during the pre and post decimalization periods. Consistent with the result in Bacidore, Battalio, Jennings, and Farkas (2001), the price improvement rates after decimal pricing are smaller than the corresponding figures before decimalization. More importantly, preferred trades generally receive smaller price improvements than unpreferred trades, especially after decimalization. After decimalization, the average price improvement rates for preferred trades (INT + NINS) are significantly smaller than the corresponding figures for unpreferred trades (INS + ECN) in all four trade-size categories. Before decimalization, the average price improvement rate for internalized (non-inside) trades is significantly smaller than the corresponding figure for unpreferred trades for trade-size category 2(4).

Overall, these results are consistent with Hansch, Naik, and Viswanathan's (1999) conjecture that preferred trades receive smaller price improvements than unpreferred trades. The results are in line with Bessembinder's (2003) finding that trades executed at a market displaying inferior quotes receive poorer execution prices, as compared to matched trades in the same stock that are executed on the same market when quotes are competitive. The results are also in line with the finding of Chordia and Subrahmanyam (1995) that trades executed off the NYSE (which are largely preferred) receive smaller price improvements than trades executed on the NYSE.

As in the case of the price impact of trades, we also examine the robustness of our results by regressing the price improvement rate against the same set of explanatory variables. We find that the estimated coefficients for dummy variables for internalized and non-inside trades are both negative and significant during the post decimalization period, indicating smaller price improvements for preferred trades.

Oftentimes, order preferencing is accompanied by execution size guarantees that are larger than the typical size at the inside quotes. As a result, preferred trades are likely to receive greater size improvement. We measure the size improvement rate by  $SI(t) = 100\text{Max}[\{S(t) - IAS(t)\}/IAS(t), 0]$  if  $D(t) = 1$  and  $SI(t) = 100\text{Max}[\{S(t) - IBS(t)\}/IBS(t), 0]$  if  $D(t) = -1$ , where  $S(t)$  = trade size at time  $t$ ,  $IAS(t)$  = the inside ask size at time  $t$ , and  $IBS(t)$  = the inside bid size at time  $t$ .<sup>32</sup> For each stock, we calculate the mean value of  $SI(t)$  for each of the four trade groups by weighting each trade equally and then obtain the mean value of  $SI$  across stocks.

Panel C shows that preferred trades receive greater size improvements than unpreferred trades across all trade-size categories during both periods, with one exception (i.e., NINS after decimalization). The differences are all statistically significant at the 1% level. Not surprisingly, the magnitude of size improvements increases with trade size for both preferred and unpreferred trades. When we employ the regression approach, we find that the estimated coefficients for dummy variables for internalized and non-inside trades are positive and significant at the 1% level. Hence, market makers offer greater size improvements selectively for trades routed by their favored brokers with preferencing arrangements. Market makers also offer greater size improvements for internalized trades. These results are consistent with the clientele-pricing hypothesis addressed in Benveniste, Marcus, and Wilhelm (1992), Huang and Stoll (1996), Battalio and Holden (2001), and Battalio Jennings, and Selway (2001a). In addition to

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<sup>32</sup> As noted by Bacidore, Battalio, and Jennings (2002), the accurate measurement of depth (size) improvement (the order-weighted depth improvement) requires data on order size to obtain the number of shares that are eligible for depth improvement. Our measures of depth improvement are imperfect because we do not use order size information due to our data limitation.

direct payments for order flow to brokers based on information content, market makers may also offer size improvements.

## **6. Summary and concluding remarks**

Despite the widely held notion that order preferencing has detrimental effects on market quality and may have led to wider bid-ask spreads on NASDAQ, there has been no prior direct evidence on the cross-sectional relation between NASDAQ execution costs and the extent of order preferencing. In the present study, we provide new evidence on these issues using a large sample of NASDAQ stocks before and after decimalization.

Our empirical results suggest that order preferencing is prevalent on NASDAQ during both the pre and post decimalization periods. Although decimal pricing results in lower preferencing, the post-decimal proportion of preferenced trades (75.64%) is still much higher than what some people had predicted. Dealer quote aggressiveness (the spread) is significantly and negatively (positively) related to the extent of internalization during both the pre and post decimalization periods. Consistent with the prediction of the clientele-pricing hypothesis advanced in several recent studies, we find that the price impact of preferenced trades is smaller than that of unpreferenced trades. Market makers help affiliated brokers and brokers with preferencing agreements by offering greater size improvements.

Although the present study provides some new evidence regarding the effects of order preferencing on dealer quote competition and execution costs, the net effect of order preferencing on investor welfare is not obvious because order preferencing is likely to have broad and diverse ramifications for investor welfare. For example, order preferencing may reduce broker search costs, allowing the savings to be passed along to customers in the form of reduced commissions. In addition, there are dimensions of market quality other than price competition, such as speed of execution and reliability. Preferencing may improve these areas of market quality also. The accurate quantification of these benefits is likely to be difficult and is well beyond the scope of

the present study. Suffice it to say that the present study adds new evidence to the debate on whether it is dealer collusion or order preferencing that led to wider spreads by providing some credence to the assertion that order preferencing is at least partly responsible for wider quoted spreads on NASDAQ.



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Table 1  
Descriptive statistics

This table shows the attributes of our study sample of 3,242 Nasdaq stocks before and after decimalization. Share price is measured by the mean quote midpoint. Number of trades is the total number of transactions. Trade size is the average dollar transactionsize. Return volatility is measured by the standard deviation of quote midpoint returns. Firm size is measured by the market value of equity. H-INDEX is the Herfindahl-index measured by the sum of squared market share based on dollar volume.

Variable	Decimalization	Mean	Standard deviation	Percentile						
				Min	5	25	50	75	95	Max
Share price (\$)	Before	14.52	17.50	0.31	1.26	3.74	8.89	18.15	47.72	210.48
	After	12.38	13.24	0.13	0.79	2.71	7.99	17.48	37.86	123.60
Number of trades	Before	13,340	73,635	4	56	256	1,039	4,458	37,085	1,428,967
	After	12,081	60,850	3	36	203	1,020	4,610	33,918	1,087,648
Trade size (\$)	Before	10,752	37,845	428	1,277	3,018	6,583	13,722	30,527	2,083,589
	After	7,888	9,001	228	757	2,094	5,189	10,916	22,411	225,104
Return volatility	Before	0.0524	0.0331	0.0001	0.0105	0.0276	0.0471	0.0704	0.1106	0.4208
	After	0.0414	0.0301	0.0002	0.0077	0.0217	0.0359	0.0534	0.0907	0.3593
Market value of equity (\$) (in thousands)	Before	1,200,776	10,555,797	610	8,341	32,084	101,044	387,258	3,114,303	387,360,000
	After	684,600	5,226,588	413	5,894	25,773	80,547	298,393	1,807,287	194,270,000
H-INDEX	Before	2,122	1,294	345	672	1,258	1,808	2,632	4,574	10,000
	After	2,110	1,409	302	587	1,117	1,718	2,697	4,952	10,000

Table 2  
Order preferencing before and after decimalization

Panel A shows the proportions of internalized (INT(i)), non-inside (NINS(i)), adjusted non-inside (NINS<sup>A</sup>(i)), preferred (PREF(i)), and adjusted preferred trades (PREF<sup>A</sup>(i)). INT(i) is the ratio of stock i's internalized volume (i.e.,  $\sum_j VINT(i,j)$ ) to its total volume (i.e.,  $\sum_j V(i,j)$ ), NINS(i) is the ratio of stock i's non-inside volume (i.e.,  $\sum_j VNINS(i,j)$ ) to its total volume, NINS<sup>A</sup>(i) is the ratio of stock i's adjusted non-inside volume (i.e.,  $\sum_j \{VNINS(i,j) / \{1 - PTINS(i,j)\}\}$ ) to its total volume, PREF(i) = INT(i) + NINS(i), and PREF<sup>A</sup>(i) = INT(i) + NINS<sup>A</sup>(i). Panel B shows the proportions of internalized (INT(j)), non-inside (NINS(j)), adjusted non-inside (NINS<sup>A</sup>(j)), preferred (PREF(j)), and adjusted preferred trades (PREF<sup>A</sup>(j)). INT(j) is the ratio of dealer j's internalized volume (i.e.,  $\sum_i VINT(i,j)$ ) to its total volume (i.e.,  $\sum_i V(i,j)$ ), NINS(j) is the ratio of dealer j's non-inside volume (i.e.,  $\sum_i VNINS(i,j)$ ) to its total volume, NINS<sup>A</sup>(j) is the ratio of dealer j's adjusted non-inside volume (i.e.,  $\sum_i \{VNINS(i,j) / \{1 - PTINS(i,j)\}\}$ ) to its total volume, PREF(j) = INT(j) + NINS(j), and PREF<sup>A</sup>(j) = INT(j) + NINS<sup>A</sup>(j). Numbers in parentheses are t-statistics testing the equality of the mean between the pre and post decimalization periods.

A. Stock preferencing

Variable	Decimalization	Mean	Standard deviation	Percentile						
				Min	5	25	50	75	95	Max
INT(i)	Before	26.09	18.82	0	0	9.84	24.93	39.61	57.56	99.98
	After	23.89	18.82	0	0	6.65	22.70	38.02	55.13	99.04
	After – Before	-2.20** (-4.69)								
NINS(i)	Before	37.01	14.11	0	15.71	26.18	36.73	47.27	59.38	100
	After	38.36	16.15	0	14.92	25.47	37.64	50.34	64.87	100
	After – Before	1.35** (3.59)								
NINS <sup>A</sup> (i)	Before	53.83	21.67	0	21.13	35.53	53.34	71.33	88.77	100
	After	51.75	22.42	0	18.82	32.90	51.04	70.22	88.74	100
	After – Before	-2.08** (-3.79)								
PREF(i) (INT(i)+NINS(i))	Before	63.10	11.55	0	43.90	57.66	63.39	68.96	81.68	100
	After	62.25	11.52	0	43.59	56.74	62.24	67.89	82.28	100
	After – Before	-0.85** (-2.94)								
PREF <sup>A</sup> (i) (INT(i)+NINS <sup>A</sup> (i))	Before	79.92	11.01	0	63.18	73.70	80.61	87.96	94.85	100
	After	75.64	12.32	0	58.20	68.03	75.78	83.95	94.55	100
	After – Before	-4.28** (-14.71)								

\*\*Significant at the 1% level.

Table 2 (continued)

## B. Dealer preferencing

Variable	Decimalization	Mean	Standard deviation	Percentile						
				Min	5	25	50	75	95	Max
INT(j)	Before	34.85	25.94	0	0	8.29	37.80	56.33	73.62	100
	After	29.99	24.18	0	0	3.80	30.18	50.33	68.04	100
	After – Before	-4.86* (-2.29)								
NINS(j)	Before	24.17	17.83	0	3.37	10.85	20.41	32.35	60.87	100
	After	25.24	17.65	0	2.93	11.61	20.55	35.18	60.42	80.59
	After – Before	1.07 (0.72)								
NINS <sup>A</sup> (j)	Before	40.98	24.62	0	8.23	21.84	36.04	57.04	88.44	100
	After	41.88	23.80	0	10.07	23.24	37.64	60.08	85.10	100
	After – Before	0.90 (0.44)								
PREF(j) (INT(j)+NINS(j))	Before	59.02	19.64	0	21.57	48.17	62.38	70.10	88.06	100
	After	55.24	18.19	0	17.74	45.93	59.28	66.97	80.21	100
	After – Before	-3.78* (-2.36)								
PREF <sup>A</sup> (j) (INT(j)+NINS <sup>A</sup> (j))	Before	75.84	18.34	0	41.20	69.69	80.45	87.25	98.03	100
	After	71.87	18.01	0	38.50	64.71	74.97	83.25	96.44	100
	After – Before	-3.97** (-2.57)								

\*\*Significant at the 1% level.

\*Significant at the 5% level.

Table 3  
Effects of dealer types and stock attributes on order preferencing

This table reports the results of the following regression model:

$$\text{INT}(i,j) \text{ or } \text{NINS}^A(i,j) \text{ or } \text{PREF}^A(i,j) = \beta_0 + \beta_1 \log(\text{PRICE}(i)) + \beta_2 \log(\text{NTRADE}(i)) + \beta_3 \log(\text{TSIZE}(i)) + \beta_4 \text{H-INDEX}(i) + \beta_5 \text{DUMIB}(j) + \beta_6 \text{DUMWH}(j) + \beta_7 \text{DUMWS}(j) + \varepsilon(i);$$

where  $\text{INT}(i,j)$  is the ratio of stock  $i$ 's internalized volume routed to dealer  $j$  to its total volume executed by dealer  $j$ ,  $\text{NINS}^A(i,j)$  is the ratio of stock  $i$ 's adjusted non-inside volume executed by dealer  $j$  to its total volume executed by dealer  $j$ ,  $\text{PREF}^A(i,j) = \text{INT}(i,j) + \text{NINS}^A(i,j)$ ,  $\text{PRICE}(i)$  is the average quote midpoint of stock  $i$ ,  $\text{NTRADE}(i)$  is the number of trades of stock  $i$ ,  $\text{TSIZE}(i)$  is the average dollar trade size of stock  $i$ ,  $\text{H-INDEX}(i)$  is the Herfindahl-index,  $\text{DUMIB}(j)$  equals one for institutional brokers and zero otherwise,  $\text{DUMWH}(j)$  equals one for wirehouses and zero otherwise, and  $\text{DUMWS}(j)$  equals one for wholesalers and zero otherwise. We report the results for both the pre and post decimalization periods. Numbers in parentheses are  $t$ -statistics.

	Before decimalization			After decimalization		
	INT( $i,j$ )	NINS <sup>A</sup> ( $i,j$ )	PREF <sup>A</sup> ( $i,j$ )	INT( $i,j$ )	NINS <sup>A</sup> ( $i,j$ )	PREF <sup>A</sup> ( $i,j$ )
Intercept	-0.4045** (-20.88)	1.2353** (56.66)	0.8308** (51.22)	-0.4605** (-24.46)	1.2195** (56.61)	0.7590** (46.26)
log(PRICE( $i$ ))	-0.0293** (-12.70)	0.0106** (4.10)	-0.0187** (-9.67)	-0.0286** (-12.53)	0.0111** (4.25)	-0.0175** (-8.80)
log(NTRADE( $i$ ))	0.0012** (4.46)	-0.0084** (-9.14)	-0.0072** (-6.54)	0.0013** (4.62)	-0.0165** (-17.43)	-0.0152** (-14.02)
log(TSIZE( $i$ ))	0.0802** (29.14)	-0.0847** (-27.36)	-0.0045* (-1.97)	0.0837** (29.39)	-0.0783** (-24.02)	0.0054* (2.19)
H-INDEX( $i$ )/10,000	-0.0525** (-3.34)	0.1011** (5.72)	0.0486** (3.70)	-0.0357** (-3.32)	0.1158** (6.58)	0.0801** (5.97)
DUMIB( $j$ )	0.1513** (43.36)	-0.1394** (-35.52)	0.0119** (4.06)	0.1601** (39.70)	-0.1526** (-33.06)	0.0075* (2.15)
DUMWH( $j$ )	0.2420** (51.76)	-0.1665** (-31.66)	0.0755** (19.28)	0.1958** (39.35)	-0.1470** (-25.83)	0.0488** (11.24)
DUMWS( $j$ )	-0.1654** (-70.86)	0.2557** (97.37)	0.0903** (46.24)	-0.1298** (-54.81)	0.2033** (75.02)	0.0735** (35.60)
F-value	2,729.71**	3,930.90**	766.01**	1,927.13**	3,073.87**	780.76**
Adjusted R <sup>2</sup>	0.304	0.386	0.109	0.241	0.336	0.114

\*\*Significant at the 1% level.

\*Significant at the 5% level.

Table 4  
Intertemporal stability in order preferencing

To examine whether stocks (dealers) that have high (low) degrees of internalized, non-inside, or preferred trades before decimal pricing also exhibit similar patterns after decimal pricing, we estimate the following regression models:

$$\begin{aligned} \text{Post-INT} &= \alpha_0 + \alpha_1 \text{Pre-INT} + \varepsilon_1; \\ \text{Post-NINS}^A &= \beta_0 + \beta_1 \text{Pre-NINS}^A + \varepsilon_2; \\ \text{Post-PREF}^A &= \gamma_0 + \gamma_1 \text{Pre-PREF}^A + \varepsilon_3; \end{aligned}$$

where Post-INT, Post-NINS<sup>A</sup>, and Post-PREF<sup>A</sup> are the proportions of internalized, adjusted non-inside, and adjusted preferred trades, respectively, during the post decimalization period and Pre-INT, Pre-NINS<sup>A</sup> and Pre-PREF<sup>A</sup> are the corresponding figures during the pre decimalization period. Panel A reports the regression results from preferencing data for individual stocks and Panel B reports the results from preferencing data for individual dealers. Numbers in parentheses are t-statistics.

Dependent variable	Intercept	Pre-INT(i)	Pre-NINS <sup>A</sup> (i)	Pre-PREF <sup>A</sup> (i)	F-value	Adjusted R <sup>2</sup>
<b>A. Regression results using order preferencing by stocks</b>						
Post-INT(i)	0.0901** (19.36)	0.5707** (39.41)			1,553.02**	0.324
Post-NINS <sup>A</sup> (i)	0.1576** (19.54)		0.6687** (48.11)		2,314.86**	0.417
Post-PREF <sup>A</sup> (i)	0.5106** (33.47)			0.3076** (16.27)	264.59**	0.075
Dependent variable	Intercept	Pre-INT(j)	Pre-NINS <sup>A</sup> (j)	Pre-PREF <sup>A</sup> (j)	F-value	Adjusted R <sup>2</sup>
<b>B. Regression results using order preferencing by dealers</b>						
Post-INT(j)	0.0648** (3.86)	0.6746** (17.42)			303.50**	0.522
Post-NINS <sup>A</sup> (j)	0.1649** (7.73)		0.6194** (13.87)		192.27**	0.409
Post-PREF <sup>A</sup> (j)	0.2640** (7.23)			0.5996** (12.82)	164.24**	0.371

\*\*Significant at the 1% level.



Table 5

## Comparisons of spreads and order preferencing during the pre and post decimalization periods

This table shows the extent of preferencing and bid-ask spreads during the pre and post decimalization periods. For each stock, we first calculate the proportion of adjusted preferenced trades ( $PREF^A(i)$ ), the time-weighted quoted spread ( $QSPRD(i)$ ), and the trade-weighted effective spread ( $ESPRD(i)$ ). Both  $QSPRD(i)$  and  $ESPRD(i)$  are measured as a percentage of share price. We then calculate the cross-sectional mean, median, and standard deviation of  $PREF^A(i)$ ,  $QSPRD(i)$  and  $ESPRD(i)$  for our study sample of 3,242 Nasdaq stocks. Panel A shows the pre and post decimalization values of preferencing and spreads for the whole sample. To examine whether the impact of decimal pricing on preferencing and spreads differs among stocks, we group our sample of stocks into quartiles based on the average trading volume during the pre decimalization period. We then cluster stocks within each volume quartile into four groups according to the average share price during the pre decimalization period. Panel B shows the pre and post decimalization values of preferencing and spreads for the four portfolios: HVHP, HVLP, LVHP, and LVLP, where HVHP includes stocks in the highest volume quartile and the highest price quartile, HVLP includes stocks in the highest volume quartile and the lowest price quartile, LVHP includes stocks in the lowest volume quartile and the highest price quartile, and LVLP includes stocks in the lowest volume quartile and the lowest price quartile.

		Before decimalization			After decimalization			Testing the difference in the mean between the two periods	
		Mean	Median	Standard deviation	Mean	Median	Standard deviation	Difference (after – before)	t-value
<b>A. Results from the whole sample</b>									
	$QSPRD(i)$	0.0330	0.0229	0.0316	0.0254	0.0153	0.0289	-0.0160**	-10.12
	$ESPRD(i)$	0.0311	0.0222	0.0288	0.0224	0.0135	0.0260	-0.0143**	-12.75
	$PREF^A(i)$	0.7992	0.8061	0.1101	0.7564	0.7578	0.1232	-0.0428**	-14.71
<b>B. Results from volume-price portfolios</b>									
HVHP	$QSPRD(i)$	0.0040	0.0037	0.0025	0.0023	0.0014	0.0124	-0.0017**	-4.40
	$ESPRD(i)$	0.0044	0.0041	0.0024	0.0024	0.0012	0.0061	-0.0020**	-6.34
	$PREF^A(i)$	0.7123	0.7098	0.0347	0.6609	0.6573	0.0492	-0.0514**	-12.16
HVLP	$QSPRD(i)$	0.0203	0.0174	0.0110	0.0105	0.0086	0.0098	-0.0098**	-9.46
	$ESPRD(i)$	0.0214	0.0185	0.0107	0.0107	0.0087	0.0092	-0.0107**	-10.67
	$PREF^A(i)$	0.8288	0.8258	0.0459	0.7409	0.7435	0.0624	-0.0879**	-16.13
LVHP	$QSPRD(i)$	0.0295	0.0235	0.0233	0.0244	0.0201	0.0167	-0.0051**	-2.54
	$ESPRD(i)$	0.0254	0.0205	0.0168	0.0209	0.0180	0.0147	-0.0045**	-2.87
	$PREF^A(i)$	0.7804	0.8052	0.1639	0.7837	0.8376	0.1821	0.0033	0.19
LVLP	$QSPRD(i)$	0.0977	0.0897	0.0443	0.0909	0.0817	0.0431	-0.0068**	-3.18
	$ESPRD(i)$	0.0906	0.0830	0.0406	0.0851	0.0726	0.0432	-0.0055**	-3.71
	$PREF^A(i)$	0.7919	0.8358	0.1478	0.7852	0.8139	0.1591	-0.0067	-0.44

\*\*Significant at the 1% level.

Table 6  
Effect of internalization on spreads

This table reports the results of the following regression model:

$$\begin{aligned} \text{QSPRD}(i) \text{ or } \text{ESPRD}(i) \text{ or } \text{MDSPRD}(i) = & \beta_0 + \beta_1(1/\text{PRICE}(i)) + \beta_2 \log(\text{NTRADE}(i)) + \beta_3 \log(\text{TSIZE}(i)) + \beta_4 \text{VOLATILITY}(i) \\ & + \beta_5 \log(\text{MVE}(i)) + \beta_6 \text{H-INDEX}(i) + \beta_7 \text{INT}(i) + \varepsilon(i); \end{aligned}$$

where QSPRD(i) is the quoted inside spread of stock i, ESPRD(i) is the effective inside spread of stock i, MDSPRD(i) is the mean dealer spread of stock i, PRICE(i) is the average quote midpoint of stock i, NTRADE(i) is the number of transactions of stock i, TSIZE(i) is the average dollar trade size of stock i, VOLATILITY(i) is the standard deviation of stock i's quote midpoint returns, MVE(i) is the market value of equity of stock i, HINDEX(i) is the Herfindahl index for stock i, INT(i) is the proportion of internalized trades of stock i, and  $\varepsilon(i)$  is the error term. We report the results for both the pre and post decimalization periods. Numbers in parentheses are t-statistics.

	Before decimalization			After decimalization		
	QSPRD(i)	ESPRD(i)	MDSPRD(i)	QSPRD(i)	ESPRD(i)	MDSPRD(i)
Intercept	0.0977** (17.10)	0.0982** (19.88)	0.5040** (29.83)	0.1021** (22.30)	0.0917** (22.76)	0.5033** (32.51)
1/PRICE(i)	0.0499** (27.03)	0.0372** (23.30)	0.1121** (20.53)	0.0103** (14.09)	0.0077** (11.98)	0.0391** (15.81)
log(NTRADE(i))	-0.0069** (-17.13)	-0.0058** (-16.62)	-0.0125** (-10.53)	-0.0056** (-14.43)	-0.0046** (-13.49)	-0.0122** (-9.25)
log(TSIZE(i))	-0.0073** (-9.94)	-0.0077** (-12.20)	-0.0333** (-15.43)	-0.0094** (-14.55)	-0.0089** (-15.71)	-0.0404** (-18.55)
VOLATILITY(i)	0.2874** (22.40)	0.2319** (20.90)	0.7947** (20.94)	0.2150** (14.70)	0.1797** (13.96)	0.5749** (11.63)
log(MVE(i))	0.0012** (2.67)	0.0010** (2.53)	-0.0064** (-4.78)	0.0017** (3.57)	0.0015** (3.66)	-0.0020 (-1.22)
H-INDEX(i)/10,000	0.0458** (13.19)	0.0337** (11.22)	-0.0575** (-5.59)	0.0469** (13.46)	0.0406** (13.23)	-0.0193 (-1.64)
INT(i)	0.0069** (2.98)	0.0083** (3.97)	0.0667** (9.35)	0.0070** (2.94)	0.0092** (4.37)	0.0705** (8.72)
F-value	1,257.87**	1,152.62**	1,051.47**	820.13**	745.59**	688.56**
Adjusted R <sup>2</sup>	0.731	0.713	0.694	0.639	0.617	0.598

\*\*Significant at the 1% level.

\*Significant at the 5% level.

Table 7  
Effect of internalization on dealer quote aggressiveness

This table reports the results of the following regression model:  $QA(i,j) = \beta_0 + \beta_1 \log(INT(i,j)) + \text{Control variables} + \varepsilon(i,j)$ ; where  $QA(i,j)$  is a measure of dealer  $j$ 's quote aggressiveness for stock  $i$  ( $PTINS(i,j)$ ,  $PTINSA(i,j)$ , or  $RELSPRD(i,j)$ ),  $INT(i,j)$  is the proportion of internalized trades for stock  $i$  by dealer  $j$ , and  $\varepsilon(i,j)$  is the error term. To control for the effect of stock attributes on dealer quote aggressiveness, we include  $\log(PRICE(i))$ ,  $\log(NTRADE(i))$ ,  $\log(TSIZE(i))$ ,  $VOLATILITY(i)$ , and  $\log(MVE(i))$  as control variables.  $PRICE(i)$  is the average quote midpoint of stock  $i$ ,  $NTRADE(i)$  is the number of transactions of stock  $i$ ,  $TSIZE(i)$  is the average dollar tradesize of stock  $i$ ,  $VOLATILITY(i)$  is the standard deviation of stock  $i$ 's quote midpoint returns, and  $MVE(i)$  is the market value of equity of stock  $i$ . We also show the regression results when we include a dummy variable for each stock (fixed effects) in lieu of control variables. To assess the sensitivity of our results to a different estimation method, we estimate the model for each stock using individual dealer quote data and calculate the mean  $\beta_1$  coefficient across stocks and the z-statistic. We obtain the z-statistic by adding individual regression t-statistics across stocks and then dividing the sum by the square root of the number of regression coefficients. For the regression with control variables and fixed effects regression, we report the estimated  $\beta_1$  coefficient, its t-statistic, F-value, and adjusted  $R^2$ . For the stock-by-stock regression, we report the mean  $\beta_1$  coefficient and its z-statistic. Numbers in parentheses are t-statistics or z-statistics.

	Regression with control variable results			Fixed effects regression results			Stock-by-stock regression results
	$\beta_1$ estimate (t-statistic)	F-value	Adj. $R^2$	$\beta_1$ estimate (t-statistic)	F-value	Adj. $R^2$	Mean $\beta_1$ estimate (z-statistic)
<u>A. Before decimalization</u>							
$PTINS(i,j)$	-0.0156** (-19.46)	609.58**	0.152	-0.0129** (-16.59)	275.13**	0.013	-0.0166** (-16.81)
$PTINSA(i,j)$	-0.0040** (-17.02)	1,240.87**	0.268	-0.0041** (-22.24)	494.55**	0.024	-0.0037** (-41.25)
$RELSPRD(i,j)$	0.0434** (12.09)	464.45**	0.120	0.0466** (13.50)	182.34**	0.009	0.0583** (10.58)
<u>B. After decimalization</u>							
$PTINS(i,j)$	-0.0145** (-17.98)	675.67**	0.174	-0.0093** (-11.94)	142.56**	0.007	-0.0086** (-7.45)
$PTINSA(i,j)$	-0.0039** (-15.03)	1,194.19**	0.271	-0.0030** (-14.81)	219.25**	0.011	-0.0017** (-19.47)
$RELSPRD(i,j)$	0.0521** (8.92)	396.33**	0.110	0.0600** (10.52)	110.61**	0.006	0.0610** (6.20)

\*\*Significant at the 1% level.

Table 8

## Comparisons of price impact and price/size improvements between preferred and unpreferred trades

We measure the price impact of trades by  $IMPACT(t) = 100D(t)[\{M(t+5) - M(t)\}/M(t)]$ , where  $M(t)$  and  $M(t+5)$  are quote midpoints at time  $t$  and  $t+5$  minutes, respectively, and  $D(t)$  is a trade direction indicator that equals +1(-1) for buyer (seller) initiated trades. Next, for each stock, we calculate the mean value of  $IMPACT(t)$  for each of the four trade groups (i.e., INS + ECN, INT, NINS, and INT + NINS) by weighting each trade equally within each trade size group. Following SEC Rule 11Ac1-5 Report, we classify trades into the following four size groups: 100-499 shares, 500-1,999 shares, 2,000-4,999 shares, and 5,000+ shares. Finally, we calculate the mean value of  $IMPACT(t)$  across stocks. Panel A shows the mean price impact for each trade size group during the pre and post decimalization periods. For each period, columns 1, 2, and 3 show the average price impact of unpreferred trades (INS + ECN), internalized trades (INT), and non-inside trades (NINS). Column 4 shows the average price impact of all preferred trades (i.e., INT + NINS). To determine whether the average price impact differs significantly between unpreferred and preferred trades, we compare the average price impact of unpreferred trades (INS + ECN) with the average price impact of internalized trades (INT), non-inside trades (NINS), and all preferred trades (INT + NINS), respectively. Column 5 shows the results of paired-comparison t-tests for the equality of mean. Panel B reports the price improvement rates for pre and post decimalization periods. We measure the price improvement rate for each trade by  $PI(t) = 100[\{IAP(t) - P(t)\}/IAP(t)]$  if  $D(t) = 1$  and  $PI(t) = 100[\{P(t) - IBP(t)\}/IBP(t)]$  if  $D(t) = -1$ , where  $P(t)$  = trade price at time  $t$ ,  $IAP(t)$  = the inside ask price at time  $t$ , and  $IBP(t)$  = the inside bid price at time  $t$ . Panel C presents the size improvement rates for pre and post decimalization periods. We measure the size improvement rate by  $SI(t) = 100\text{Max}[\{S(t) - IAS(t)\}/IAS(t), 0]$  if  $D(t) = 1$  and  $SI(t) = 100\text{Max}[\{S(t) - IBS(t)\}/IBS(t), 0]$  if  $D(t) = -1$ , where  $S(t)$  = trade size at time  $t$ ,  $IAS(t)$  = the inside ask size at time  $t$ , and  $IBS(t)$  = the inside bid size at time  $t$ .

## A. Price impact

Trade size category	Before decimalization					After decimalization				
	INS + ECN	INT	NINS	INT + NINS	t-value <sup>a</sup>	INS + ECN	INT	NINS	INT + NINS	t-value <sup>a</sup>
Smallest	0.3925	0.2041**			-6.17	0.2195	0.0958**			-8.07
	0.3925		0.3877		-0.24	0.2195		0.2620		1.66
	0.3925			0.3421**	-2.59	0.2195			0.2254	0.51
2	0.3926	0.2620**			-3.86	0.2244	0.1378**			-4.14
	0.3926		0.4173		1.05	0.2244		0.2588		1.16
	0.3926			0.3730	0.90	0.2244			0.2255	0.07
3	0.3393	0.1120**			-4.51	0.2467	0.0650**			-5.86
	0.3393		0.2730		-1.38	0.2467		0.1328**		-3.85
	0.3393			0.2104**	-2.72	0.2467			0.1018**	-5.17
Largest	0.4369	0.0290**			-11.48	0.2808	0.0052**			-7.78
	0.4369		0.1345**		-5.01	0.2808		0.0414**		-6.62
	0.4369			0.0838**	-8.55	0.2808			0.0231**	-7.66

\*\*Significantly different from the mean price impact for INS + ECN group at the 1% level.

<sup>a</sup>The t-statistic testing the equality of the mean between the two groups.

Table 8 (continued)

## B. Price improvement

Trade size category	Before decimalization					After decimalization				
	INS + ECN	INT	NINS	INT + NINS	t-value <sup>a</sup>	INS + ECN	INT	NINS	INT + NINS	t-value <sup>a</sup>
Smallest	0.2214	0.2838			0.83	0.1133	0.0467**			-6.33
	0.2214		0.2382		1.34	0.1133		0.0954*		-2.07
	0.2214			0.3113	1.18	0.1133			0.0877**	-3.21
2	0.1899	0.1156**			-5.80	0.0990	0.0559**			-3.50
	0.1899		0.1819		-1.29	0.0990		0.0793		-1.91
	0.1899			0.1643**	-4.18	0.0990			0.0745*	-2.42
3	0.1731	0.2171			0.72	0.0838	0.0271**			-3.41
	0.1731		0.1996		1.56	0.0838		0.0457**		-3.14
	0.1731			0.2387	0.97	0.0838			0.0471**	-3.52
Largest	0.1466	0.0612			-0.73	0.0834	-0.1926**			-10.30
	0.1466		0.1052*		-2.41	0.0834		-0.0066		-1.27
	0.1466			0.1186	-0.34	0.0834			-0.0559*	-2.37

\*\*Significantly different from the mean price improvement rate for INS + ECN group at the 1% level.

\*Significantly different from the mean price improvement rate for INS + ECN group at the 5% level.

<sup>a</sup>The t-statistic testing the equality of the mean between the two groups.

Table 8 (continued)

## C. Size improvement

Trade size category	Before decimalization					After decimalization				
	INS + ECN	INT	NINS	INT + NINS	t-value <sup>a</sup>	INS + ECN	INT	NINS	INT + NINS	t-value <sup>a</sup>
Smallest	8,416	9,369**			9.67	9,034	11,612**			21.07
	8,416		8,636**		4.34	9,034		8,860		-1.84
	8,416			8,913**	9.91	9,034			9,533**	10.59
2	34,757	41,351**			15.79	39,937	48,364**			18.15
	34,757		38,475**		17.09	39,937		41,553**		6.90
	34,757			39,446**	22.22	39,937			43,569**	15.88
3	104,373	122,542**			13.38	131,077	146,847**			10.51
	104,373		116,642**		11.07	131,077		141,041**		7.99
	104,373			119,176**	14.96	131,077			143,165**	11.15
Largest	296,022	535,236**			11.25	381,101	722,502**			12.01
	296,022		423,593**		7.86	381,101		502,744**		5.36
	296,022			470,318**	13.67	381,101			593,702**	12.31

\*\*Significantly different from the mean size improvement rate for INS + ECN group at the 1% level.

<sup>a</sup>The t-statistic testing the equality of the mean between the two groups.