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Institutional Trading Patterns and Price Impact Around Decimalization

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Paper No. 1152
Date: December 2001

Institute for Research in the
Behavioral, Economic, and
Management Sciences

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Current Draft: December 2001

Acknowledgements: We thank the Plexus group, including Vinod Pakianathan and Wayne Wagner, for providing us with the data and for related conversations. The usual disclaimer applies.

Abstract

We examine the effect of decimalization on institutional investors using proprietary data. In particular, we examine the time and the number of trades it takes to execute a given trading decision, as well as the price impact of these trades. We use three different benchmarks to determine the price impact of a trade. Unlike the transition of the minimum tick size from eighths to sixteenths, we find no significant changes in the implicit costs of trading for institutional investors following decimalization. Our results survive extensive partitioning of the data and are surprising in light of an oft-repeated complaint among professional traders that liquidity is hard and expensive to find in a post-decimal trading milieu. These findings have important regulatory implications.

1. Introduction

On January 29, 2001, the New York Stock Exchange (NYSE) converted all of its listed issues to decimal pricing, thereby ending a two-hundred-year tradition of trading in fractions. At least four other papers (Chakravarty, Wood and Harris (2001), Charkavarty, Van Ness and Van Ness (2001), Chung, Van Ness and Van Ness (2001) and Bacidore, Battalio and Jennings (2001)) investigate various aspects related to market liquidity and trader behavior around the several pilot rounds that preceded the complete switchover to decimalization. A major result emerging from the above research is that both quoted and effective spreads have decreased significantly as have the corresponding bid and ask depths and adverse selection costs. The direction of these results is not surprising since other researchers report declines in spreads and depths following the conversion of trading in eighths to sixteenths on the NYSE in June 1997 as well as the movement to decimals in foreign stock markets.[1]

What is in debate, however, is the exact nature of trading costs faced by traders - and especially the large institutional traders -- in the wake of decimalization. While a reduction in spreads (as reported by Chakravarty et al. (2001)) implies a reduction in trading costs, a simultaneous reduction in depths at these improved prices further implies that to execute an order of a given size requires deeper forays into the limit order book, relative to the pre-decimal (or sixteenths) world. And nowhere is this problem more likely to be felt than with institutional trades that are characterized by their large sizes, taking multiple transactions, sometimes spanning multiple days, to complete. Thus, if there were a drop off in liquidity available outside the best bid and offer (BBO) prices, then it would cost more to execute large trades while if the supply of liquidity were plentiful in the vicinity of the BBO, then institutional execution costs would remain unchanged (or even improve). Unfortunately, what is unobservable in the publicly available intra-daily transactional databases, such as TAQ (available from the NYSE), is the available supply of liquidity outside the best bid and offer (BBO) prices. TAQ also does not identify the traders behind each reported transaction,

[1] See, for example, Bacidore (1997), Bollen and Whaley (1998), Ricker (1998), Ronen and Weaver (1998), Goldstein and Kavajecz (2000), and Jones and Lipson (2001).

making it impossible to compute transactions costs in protracted trading by a single institutional trader. It is therefore impossible to determine, from such data, if large traders are experiencing greater transactions costs in the wake of decimalization.

In this paper, we add new empirical evidence to this debate by using a proprietary data set of institutional orders and trades to gauge the pattern of their trades and their impact on prices around the time the NYSE switched completely to decimal trading. Specifically, we obtain a sample of institutional trades in NYSE stocks between October 1, 2000, and March 31, 2001. To isolate the specific effect of decimalization on institutional execution costs, we select institutional trades in only those NYSE stocks that were not a part of the decimal pilot (and, hence, trading in sixteenths) over the period of October through January 26, 2001, and then converted to trading in decimals once the entire NYSE went to decimal trading beginning Monday January 29, 2001. To get a perspective of our results, we also obtain institutional trading records in the same stocks over a benchmark period of the first quarter of 2000 (Q1, 2000). Our sample selection procedure therefore eliminates stock-specific effects on the measurement of trade execution costs. Additionally, mindful of Keim and Madhavan's (1996) caution about the importance of the choice of pre-trade benchmark prices in estimating institutional price impact, we perform our analysis with multiple benchmark prices.

Our tests span a number of relevant partitions of the data considered relevant by the extant literature such as the market capitalization of the stocks traded by the institutions, buy versus sell trading decisions, complexity of trading decision and the underlying institutional managers' investments style. We also perform multivariate tests to isolate the potential impact of decimalization after controlling for all relevant determinants of price impact.

Our main result is that even though institutions appear to be taking longer -- in time and in the number of transactions -- to complete a given decision size after decimalization, they are in fact trading more (in terms of trade size and dollar volume) following decimalization and that their implicit trading costs, as measured by the price impact of their trades, show no significant change. An important implication of our finding is that liquidity supply outside the BBO remains unchanged in the wake of decimalization in the NYSE. The latter underscores the fact that the possibility of "penny-jumping" in the NYSE, in the wake of decimalization, discussed by Chakravarty et al. (2001), may not have actually come to pass. Our findings are also consistent with an internal study by the Plexus Group (2001) and appear to contradict popular opinion on Wall Street that institutional investors have been short changed by decimalization[2] thereby nullifying the industry's demand for a nickel price increment[3]. Our results should provide comfort to regulators facing scathing criticism, mostly by practitioners and some academics, related to the possibility of a drop in liquidity supply in a post-decimal trading milieu.

Our research is most closely related to Jones and Lipson (2001) who investigate institutional execution costs around the changeover in minimum ticks from eighths to sixteenths in June of 1997. They find that realized execution costs in their sample of firms increase after the changeover, especially for orders that were not 'worked' by the institutions.[4] While the apparent difference in our results with those of Jones and Lipson is curious, a closer examination of the two samples perhaps explains the difference. First, while they report an average Plexus trade size of about 37,000 (38,000) shares pre-change (post-change), our sample shows an average Plexus trade size of about 53,000 (71,000) shares pre-decimals (post-decimals). Second, while about 14% of the observations in their sample are worked orders (their Table 5, p. 265), over 30% of our observations are worked -- taking either longer than a day or more than one broker to execute. Particularly relevant is the fact that, consistent with our results, they find little changes in execution costs for the unworked orders in their sample.

The plan for the remainder of the paper is as follows. Section 2 discusses the related literature. Section 3 provides the backdrop of our analysis and discusses the data. Section 4 provides multiple ways to measure transactions costs and provides univariate analyses of transactions costs on various partitions of the data. Section 5 extends the analyses to a

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[2] Thus, for example, a recent letter to the Security Industry Association (SIA) claims: *"The execution of large orders has been hampered by reduced depth of the Exchange's limit order book and by increased instances of market participants stepping ahead of orders by increments of as little as one penny, "* while Pete Jenkins, Head Trader at Zurich-Kemper, is quoted as saying, *"The net effect has been for the institutional trader to lose control of his/her order flow, since no effective tools exist in the NYSE listed market to reach the market efficiently."*

[3] See *"Decimal Move Brings Points Of Contention From Traders,"* (Wall Street Journal, February 12, 2001, p. C1) and *"Deals & Deal Makers: Grasso Says NYSE Must Stick to Penny As Trade Increment,"* ((Wall Street Journal, March 22, 2001, p. C18).

[4] Jones and Lipson define an order to be 'worked' if it takes more than a day to execute or if it is executed by more than one broker.

multivariate examination. Section 6 concludes with a discussion.

2. Related Literature

While there has been a longstanding interest among financial economists on the impact of the equity trading process on stock prices, over the last decade an impressive amount of research has been conducted in documenting institutional execution costs under a variety of circumstances. What makes this area of research interesting is the fact that institutions trade large quantities and they trade often, which makes them significantly impact prices. There appear to be two main streams of research involving institutional price impact studies. The first stream investigates the determinants of such price impacts. Thus, for example, Chan and Lakonishok (1995) report that institutional trading impact and trading cost are related to firm capitalization, relative decision size, identity of the management firm behind the trade and the degree of demand for immediacy. Keim and Madhavan (1997) focus on institutional investment styles and its impact on their trading costs. They report that trading costs increase with trading difficulty and that these costs vary with factors like investment styles, order submission strategies and exchange listing.

The second stream of research focuses on the location of trading including upstairs versus downstairs markets as well as across U.S. equity markets. For example, Keim and Madhavan (1996) investigate a sample of "upstairs" trades in the NYSE and report that price movements (up to four weeks prior to the trade date) are significantly positively related to trade size – consistent with information leakage. More importantly, and related to our work, they point out the importance of the choice of pre-trade benchmark prices in estimating institutional price impact. Madhavan and Chang (1997) compare execution costs in both upstairs and downstairs markets and find the economic benefits of upstairs trading are small for the average-sized block trade. Chan and Lakonishok (1997) compare institutional trade execution costs across the NYSE and the NASDAQ and report that, after appropriate controls, costs are lower on NASDAQ (NYSE) for smaller (larger) firms. Jones and Lipson (1999) compare institutional execution costs across major U.S. Exchanges and find that execution costs (including commissions) are indistinguishable across these exchanges.

The third, and emergent, stream of research, and the stream to which the current paper belongs, investigates the impact of minimum tick size reductions on institutional trade execution costs. For example, Jones and Lipson (2001) investigate institutional trading costs around the changeover in minimum tick-size from eighths to sixteenths in the NYSE in June 1997. They find that realized execution costs in their sample of firms increase after the changeover and conclude that smaller tick sizes may actually reduce market liquidity.

3. Background and Data

Theoretical models, such as Kyle (1985), predict that informed investors will trade in a progressive manner such that the full impact of their information will gradually assimilate into market clearing prices. But such stylized models do not account for market frictions and other imperfections that plague actual institutional order executions. Institutions tend to trade large quantities of stock -- each decision to establish or liquidate a position requiring multiple trades over multiple trading days and involving multiple brokers. Traditional measures of transaction costs like the bid-ask spreads are not useful to correctly account for all the costs embedded in such extensive trading activities by a single investor. The most common problem is that of information leakage prior to, and contemporaneous with, the completion of the execution of an order, which moves prices against the ongoing trade. There is also the pure liquidity demand cost, aside from the information effect, associated with finding contra-parties to take the other side of large trades. Thus, information on single quotes and trades is insufficient to correctly capture the full breath of the costs faced by the institution when unloading or building large equity positions.

We are, however, able to directly observe execution details pertaining to a large sample of institutional equity orders provided by the Plexus Group. Plexus is a consulting firm that advises its institutional clients on how to reduce transactions costs. Their clients collectively manage over $2 trillion in equity assets and the firm has access to trading records covering over a quarter of the dollar trading volume in U. S. equity markets. The importance of Plexus data is further evidenced by its use by Keim and Madhavan (1995, 1997), Conrad et al. (1997), and Jones and Lipson (1999, 2001).

3.1 *Data*

The data contain information on equity transactions of institutions complied by the

Plexus Group as part of their advisory services to their institutional clients. Specifically, we obtain records of all valid orders executed for Plexus clients in all NYSE stocks not trading in decimals, over the period October 1, 2000 to January 26, 2001 (BEFORE), and over the period January 30, 2001 - March 31, 2001 (AFTER). Since NYSE went completely decimal on January 29, 2001, AFTER captures the post decimalization period in these stocks while BEFORE captures the pre-decimal period when they were all trading in sixteenths. To properly benchmark our findings, we also obtain all institutional trading records in all NYSE stocks over the first quarter of 2000 (Q1 - 2000).

We classify all stocks in the Plexus data, over the three quarters we study, into three equal market capitalization groups (small, medium and large), based on the closing stock price of the last trading day of September 2000. From each group, we pick the fifty most active stocks based on the average daily trading volume over the month of September 2000. We do this to reduce the sample to a manageable size without compromising valuable information. Any interesting pattern in the data is likely to be contained in the relatively active stocks in each group. [5] From each group we now retain only those stocks that have decision records in each of the three quarters in our study. Out of the 150 stocks in the three groups, 11 had records only on one period, 31 had records in two period and 107 stocks had trading records in all three periods and form the basis of our study.

It should be noted that unlike retail trades, usually completed in a single transaction, these are large orders requiring multiple transactions, sometimes spanning multiple days. We denote each such sequence of trades as a "trading decision". For each trading decision, the data include a) the stock to be traded and the date the decision was made; b) the desired number of shares to be bought or sold; c) whether the decision was to buy or sell; d) the dates the individual components of the trading decision were released to the executing broker; e) the dates and prices at which the various components of the decision were filled; f) the volume weighted average trade price for the stock on each of the days a component of the decision was filled; and g) the manager submitting the orders as belonging to one of three trading styles: value, diversified or growth.

The identification of the underlying manager's style behind each trading decision is

[5] We satisfy ourselves that our results are not an artifact of the number of stocks in each size category.

significant because it enables us to get a glimpse of transactions costs as a function of the aggressiveness of an order. For example, value managers are investors whose trading strategy is based on identification of undervalued stocks with a decidedly longer-term perspective. Growth managers, on the other hand, are expected to have a shorter investment horizon and buy and sell stocks based less on company fundamentals and more on short-term price appreciation. Diversified managers are expected to lie in between growth and value managers and have elements of both in their investment strategy. In terms of their willingness to bear price impact as well as in their desire for immediacy, it is reasonable to expect growth (value) managers to be most (least) aggressive, with diversified managers falling in between.

3.2 *Descriptive Statistics*

Table 1 provides summary statistics of our data. It is designed to provide the backdrop with which to examine the research questions addressed in the paper. For ease of interpretation, the statistics for small (26 stocks), medium (38 stocks) and large (43 stocks), covered by the decisions within our sample period, are reported separately. Market capitalization is based on closing stock prices on September 30, 2000. The average market capitalization of stocks in the three size categories shows an impressive dispersion: \$18M for small stocks, \$97M for medium stocks and \$10,650M for large stocks. Given the well-known correlation between market capitalization and trading volume and, through volume, on the available market liquidity, our classification is designed to highlight differences the parameters of interest across such differences in liquidity. The table highlights several interesting patterns in the data.

First, the frequency of institutional trading activity appears to have significantly declined over the year 2000, mirroring the fall in the stock market.[6] The number of decisions per day has almost halved over the course of the year. It appears that institutions fled the stock market for other safe havens during the market fall following the burst of the technological bubble. Not surprisingly, this precipitous drop is reversed following decimalization. The number of decisions per day increases, especially for small- and

[6] The S&P 500 Index increased by 3 percent in the first quarter of 2000 but fell by 5.7% in the last quarter of 2000 and the twenty-six days in January prior to decimalization. It continued to fall in the first quarter of 2001 by as much as 15 percent after stocks started trading in decimals.

medium-sized stocks, when stocks started trading in decimals. Interestingly, the increase in number of decisions is not followed by a decrease in the average size of these decisions. In fact, the average size of trading decisions also increases indicating that institutions are trading more, rather than less, after decimalization. The average dollar value of trading decisions show an increase following decimalization and approaches the levels of Q1(2000). Institutions appear to buy and sell with similar frequency despite a fall in stock prices. Only in the case of small stocks, do we find an interesting pattern: institutions sell more often prior to decimalization and buy more often after decimalization. Tax selling may partly motivate such behavior.

In summary, relatively fewer trades of larger magnitudes (i.e., larger size trades) are executed by institutional clients following complete decimalization in the NYSE. In most cases, institutional activity appears to be approaching the period of stock market boom just before the bursting of the dot-com bubble.

3.3 *Trading Performance*

Table 2 reports details on the average (and median) number of trades per decision, the average (and median) time to complete a decision and the average (median) number of brokers used in each decision, BEFORE, AFTER and over Q1-2000.[7] The tables are based on fully completed decisions only.[8] We classify our results by market capitalization (panel A), by order type - buys versus sells – (panel B), by complexity of decision (panel C) and by manager style (panel D).

Panel A shows that small and medium size stocks took significantly more transactions to complete a decision following decimalization (1.6 to 2.3 for small and 2 to 2.6 for medium). Transactions in large stocks stayed about the same around decimalization. We also find a significant increase in transaction time for small and medium stocks and no change for large stocks. The numbers for the AFTER period compare favorably with the Q1(2000) period. Finally, the average number of brokers used shows little dispersion between BEFORE and

[7] Institutions often break down a decision into several smaller components and release them individually to the broker. Interestingly, we find that about 95 percent of all releases are filled by the broker in one trade, even after decimalization, thereby making the number of trades per decision roughly equivalent to the number of releases per decision.

[8] Our results appear to be robust to the percentage completion rate of a decision. We successfully replicated our current results with 70%, 75%, 80% and 85% completion rates.

AFTER for stocks of all sizes - although compared to Q1(2000), there appears to be significantly fewer brokers used AFTER, in both small and large stocks.

Panel B indicates that both purchases and sales take more transactions to fully execute following complete decimalization and take a little longer to accomplish with about the same number of brokers. All AFTER numbers compare favorably with Q1(2000).

Panel C partitions the data by complexity of decision defined by the size of the of the trading decision relative to the average daily trading volume in that stock over the month of September 2000. While recognizing that difficult trade versus an easy trade is a multidimensional construct, we follow industry standards in our labeling of trades as easy, moderate and difficult.

The results shows slight increase in the number of trades (per decision) for moderate and difficult trades taking a little longer time to complete with about the same number of brokers, following complete decimalization. These numbers are very similar with the Q1(2000) numbers.

Panel D classifies the data by manager style. On the face of it, we find that the value (growth) managers were the least (most) affected by decimalization. Not apparent though is the fact that the average decision size for value managers halved following decimalization (from 33,400 shares in the period 'BEFORE' to 17,600 shares in the period 'AFTER'), while it doubled for decisions of growth managers (from 92,400 shares to 192,900 shares in the periods BEFORE to AFTER). This suggests that value managers take as much time as before to execute half their decision size, while growth managers take less than twice the amount of time to execute their decisions despite demanding twice the number of shares. This seems reasonable given their trading strategies. Diversified managers show increases lying between those of growth and value managers.

4. Measuring Trading Costs

There are several factors that make capturing institutional trading costs harder than retail trades. Each institutional trading decision involves several transactions, sometimes spanning multiple trading days, to complete. Thus, traditional measures like bid-ask spreads are unable to properly account for all costs associated with such protracted trading strategies. Even the theoretical models of price impact in response to informed (or strategic) trading, such as Kyle (1985) and the significant body of literature in its wake (see O'Hara (1995) for a summary), assume that trades by informed (or strategic) traders are completed in relatively short intervals. There is also the added risk that there may be information leakage when a large institutional order is brought to the upstairs market to be shopped around and prices may move adversely even before this order is exposed to the market. With our sample of realized execution costs for institutional equity trades, however, we are able to bypass such problems.

Arguably, the most difficult component of trading costs to measure is the implicit cost of trading, i.e., the price impact of a trade or the deviation of the transaction price from the unperturbed price that would prevail had the trade not occurred. Thus, price impact can be negative (positive) if the trader buys at a price below (above) the unperturbed price. Thus, liquidity suppliers (demanders) should enjoy negative (positive) costs.

Clearly, how the unperturbed price is measured will determine the magnitude of the implicit costs. In particular, our measure should be such that it is least influenced by the trade itself. Thus, we capture unperturbed price three ways: (1) the prevailing stock price at the time the trading decision was made; (2) the average of (1) and the price of the last trade of the decision; and (3) the value weighted average price (VWAP) on the day the decision was made. While approach (1) follows intuitively since it is the purest form of the unperturbed price and is also the approach followed by Jones and Lipson (2001), in their study of institutional trade execution costs around the changeover to sixteenths, approach (3) assumes that no single trader could influence the value-weighted average price of all trades during a day. The latter was popularized by Perold (1988) who measures trading costs as the difference between a portfolio of trades actually made and a hypothetical paper portfolio whose returns are computed assuming the transactions are executed at prices observed at the time of the trading decision. Keim and Madhavan (1997) also use approach (3) to measure transaction costs.

To mitigate problems that arise when trades span several days, we use approach (2) that averages the price at the time the decision was made and the price at which the last component of the decision (which presumably could be several days after the initial decision was made) was filled. Clearly, this approach is less useful if the last trade price is significantly different from prices at which other components of the decision were filled. To ensure the robustness of our findings, we use other criteria as well, such as the VWAP on the last day and the average VWAP over all days during which the various components of the decision were filled. We find little change in the qualitative nature of our results. For brevity, we do not report those in the paper.

Table 3 provides measures of average (and median) price impact of trades measured as percentage deviation of the value weighted average trade price for each decision from a benchmark price computed as (1), (2) or (3). The deviation is multiplied by –1 if the decision is a sale. Thus, a positive number for the price impact implies that buy (sell) orders were executed at prices higher (lower) than the respective benchmark price. The reverse is true for a negative number. A negative (positive) number, therefore, implies price improvement (deterioration). We concentrate on benchmark measures (1) and (3) in our following discussion as they are least impacted by the trade itself relative to approach (2).

Panel A classifies the data by market capitalization. There appears no statistically significant (differential) price impact following complete decimalization. This is true for the smallest as well as the largest stocks. This suggests that decimalization, in general, does not adversely impact institutional traders. What they lose by staying longer in the market to complete their trades, they seem to gain from lower spreads. In general, it appears that trade executions in small stocks appear to be occurring at inferior prices following complete decimalization.

Panel B classifies the data by decisions that were either a purchase or sale. Interestingly, institutional buyers had lower price impact after decimalization than before, while sellers had no changes in their price impact. We believe that this result has less to do with decimalization than the fact that buyers in a falling market have greater bargaining power than sellers.

Panel C classifies the data by the complexity of decision (as defined before). Ceteris paribus, a larger trade (and, hence, considered more difficult to execute) should have a greater impact on the market than a relatively smaller size trade. As expected, more complex decisions involve higher price impact than relatively easy decisions. Moreover, the price impact is lesser after decimalization - whether it is for easier decisions or for more complex decisions – but these differences are statistically not significant. The implication is that decimalization has not worsened the plight of even the larger traders who are clearly at the greatest disadvantage.

Panel D classifies the data by manager's style of trading (discussed before). Even though value managers have the lowest price impact, there seems little variation, between pre- and post-decimalization levels, in price impact among the different style managers. Though such univariate analysis helps us understand the correlation (if any) between decimalization and trading styles, they fail to control for the fact that other factors, such as the size of their decision and the nature of the stock they trade, may have a bearing on the result. We present a more complete multivariate analysis later in the paper to address such issues.

In sum, price impact investigations using a variety of benchmark prices reveal that institutional traders are neither worse off nor better off following decimalization. Moreover, we find that trades in small size stocks get significantly inferior price executions, while buyers benefit from a falling market through lower price impact.

4.1 Trading Costs and Investment Style

Even though panel D of Table 3 indicates not much activity across manager styles, around complete decimalization in the NYSE, the results could be driven by the fact that the performances of some of the good managers are offset by the performances of the bad managers within each style category. Keim and Madhavan (1997) report significant variations in performance across managers within each trading style. Thus, our results could be driven by a few managers within each group and not indicative of the group overall. To see if this is indeed the case, we partition the data into "good" managers and "bad" managers depending on whether the price impact associated with their trades are negative or positive, respectively. Negative implies that these managers managed to execute their buy (sell) trades at prices below (above) the benchmark while positive implies the reverse. We provide results based on our two benchmark measures (1) and (3) in Panels A and B. We restrict our analysis only to managers who have placed decisions both in the pre- and the post-decimalization periods.

Panel A indicates that an overwhelming majority of managers show no difference in execution costs around complete decimalization. This is true across all styles. For example, the table shows that we had data for 35 value managers both BEFORE and AFTER decimalization. Out of these 35, three managers improved their performance while 1 manager's performance suffered, following decimalization. More importantly, 31 (out of 35) managers showed no change in their execution performance following decimalization. The other style managers' follow similarly. Thus, 60 (out of 68) growth managers showed no statistical difference in their execution performance following decimalization. Panel B exhibits similar results as Panel A and attests to the robustness of our conclusions.

It is well accepted that larger size stocks are usually more liquid and have relatively smaller spreads associated with them while smaller stocks are less liquid and have larger spreads associated with them. The higher spreads could be the result of higher adverse selection and/or lower liquidity. What matters from our perspective is that a manager may have higher costs associated from executing an institutional order on a larger size stock than he would if he were to be trading in a small stock. Here we are interested in the question of whether, for a given manager, there has been a difference in execution costs across the stocks of various sizes following decimalization. To do so, we classify the stocks in our sample into small, medium and large size groups within each style category. These results (not presented for brevity) indicate that regardless of the managers' style and the benchmark used, the vast majority of managers show no statistically significant difference in execution costs around decimalization for any size stocks.

Overall, decimalization appears to have had little or no impact on institutional execution costs -- regardless of how the data are partitioned. The implication is that there appears to be liquidity available out the best bid and offer prices, which should allay the fears of regulators, practitioners and academics.

5. Impact of Decimalization of Institutional Trade Execution: Multivariate Analysis

In Section 3, we see that various factors can impact institutional execution costs. Given that our focus is to see if the act of decimalization itself has impacted execution costs, we need to control for all factors impacting such costs and then isolate the cost attributable to decimalization, if any. In this section, we use a regression analysis to disentangle the effects of decimalization on institutional trade execution costs after controlling for the candidate factors representing information asymmetry through firm size, a measure of return volatility, a measure of the complexity of the trading decision, and inverse price representing the degree of difficulty of executing a trade. Thus, for example, a relatively larger price stock has a lower percentage spread associated with it implying that the cost of front running such stocks is low. We would therefore expect a negative sign on the coefficient corresponding to inverse price. We also add dummy variables to control for managers' styles between value and growth (with diversified representing the omitted category). Finally, the dummy variable AFTER is included to isolate the possible effect of decimalization on institutional execution costs. The formal regression model looks like the following.

$$PI^i = \alpha^i + \beta_1^i LogMktCap + \beta_2^i Volatility + \beta_3^i Complexity + \beta_4^i \text{InversePrice} + \beta_5^i Valuedummy + \beta_6^i Growthdummy + \beta_7^i Afterdummy + \beta_8^i (\text{Valuedummy x Afterdummy}) + \beta_9^i (\text{Growthdummy x Afterdummy}) + \varepsilon$$

Each observation in our regression represents a complete decision. The dependent variable (PI) is the price impact measure discussed in Section 3, measured on the basis of a benchmark price computed one of three ways discussed therein. Hence, the superscript 'i' refers to the price impact measure as computed using one of the benchmark prices (1), (2) or (3).

Among independent variables, *LogMktCap* refers to the natural logarithm of market capitalization of the stock as of September 30, 2000. *Volatility* refers to the average daily standard deviation for the stock in the month of September 2000. *Complexity* is defined as the decision size relative to average daily volume in September 2000, while *InversePrice* is simply the inverse of the stock's price at the time of the decision. We use two dummies to indicate value and growth style manager, while we use the *Afterdummy* to indicate the post-decimalization period. We restrict our analysis only to the periods BEFORE and AFTER that we discuss above. In addition to the three dummies, we use two interaction dummies to capture the effects of decimalization on the value and growth style managers separately. Our main variable of interest is the *Afterdummy*, and we expect the variable to be positive and significant if decimalization has worsened the implicit costs of trading for institutional investors.

Panel A provides the regression coefficient estimates for price impact measured on the basis of the prevailing price at the time of decision (i.e., approach (1)). We find that stocks that are more volatile, decisions that are more complex and decisions of growth managers appear to have a significantly positive price impact. These results are not surprising given that volatile stocks are more difficult to trade, as are decisions to buy or sell large quantities. By nature of their desire to trade quickly in stocks that have either fallen in or out of favor with investors, growth style managers are bound to incur higher price impact than value managers. In other words, they would buy (sell) stocks as their prices are increasing (decreasing). Evaluating their decision against a pre-trade benchmark price, such as (1), would lead to positive price impact costs for these managers. All other variables appear to be non-significant in explaining price impact with most of them carrying signs as expected. More importantly, the *Afterdummy* is negative but not statistically significant. The implication is that after controlling for the standard determinants of institutional execution costs, the act of decimalization itself has not had a significant impact on trade execution costs. This flies in the face of popular wisdom claiming that liquidity has dried up outside the best bid and offer prices thereby leading to costlier executions - especially for large institutional orders - in the wake of decimalization.

Panel B provides the results corresponding to price impacts measured on the basis of the average of the price at the time of decision and the price corresponding to the last trade. Here too, we find that the dummy variable corresponding to after complete decimalization is not statistically significant. Panel C provides similar results based on the benchmark price being measured as the VWAP on the day of the decision. Unlike in Panels A and B, the *Growthdummy* variable is negative but not significant. This is not surprising, as the benchmark is now the average of trade prices during the day rather than the price at the time the decision was taken. Most growth managers appear to be using the VWAP strategy to buy or sell stocks in their portfolios.

Overall, after controlling for the standard determinants of execution costs, we find that decimalization itself had no impact on institutional execution costs. Our results appear robust to standard issues of benchmarking the costs.

To investigate the impact of decimalization on the number of trades per decision and on the number of days needed to complete a trading decision, we re-estimate the above regression model with the same independent variables. Table 6 provides the regression coefficient estimates. Panel A provides results where the dependent variable is the number of trades per decision. Unlike in Table 5, we find the *Afterdummy* to be positive and significant, indicating that decimalization did worsen the search process for a counterparty for institutions. Following decimalization, institutions need 0.3 trades more, or roughly 12.5 percent more trades to complete an average decision in an average stock.[9] Consistent with our expectation, it is the growth style managers who are affected the hardest. They need about 1.4 trades more, or roughly 50 percent more trades after decimalization than before to complete an average decision.[10]

The coefficients of other explanatory variables are as expected. The firm size proxy is positive and significant. Volatility is positive implying that larger number of trades is required on high volatility stocks (or high volatility days for a given stock). Complex trades take more trades to complete while lower priced stocks take more transactions. Value managers execute fewer trades than growth managers and that growth managers have been taking more transactions to compete a decision after decimalization. More importantly, decimalization appears to have increased the number of trades per decision.

In Panel B, the dependent variable is the number of trading days to complete a decision. The independent variables are the same as above. The results indicate that trading in larger stocks take longer to complete while larger size orders (difficult orders) take longer to complete as we would expect. In terms of cross correlations, value managers appear to be taking less time to complete a decision following decimalization. Finally, decimalization appears to have increased the time taken to complete a decision.

Overall, we find that even though the act of decimalization appears to have increased both the number of trades and the number of days necessary to complete a decision, the most important metric, the trading cost, appears to be unaffected by decimalization. This result should be significant to policy makers debating the merits of this historic decision in the face of demands to roll back decimalization by going back to trading in nickel ticks.

5.1 *Execution Costs and Firm Size*

Another extension of our multivariate analysis on the cross sectional determinants of the price impact measure is to partition the data on stock size categories in order to investigate the differential impact of decimalization on transaction costs associated with the

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[9] 2.4 trades are needed to complete an average decision in an average stock prior to decimalization.
[10] 2.8 trades are needed to complete an average decision of a growth style manager in an average stock prior to decimalization.

execution of small, medium or large size stocks. These results (not presented for brevity) indicate that decision complexity is positively correlated with price impact for small and large size stocks, while growth managers appear to be experiencing a price impact inversely related to the underlying stock size. Volatility has a positively related to price impact in large size stocks. More importantly, the AFTER dummy, isolating the possible effect of decimalization, is not statistically significant for any stock size category independent of the benchmark used to capture price impact. Thus, there appears to be no stock size effect on price impact following decimalization. These results remain unchanged when we use different benchmark prices and attest to the robustness of our findings.

Overall, our finding that institutional execution cost is unaffected following decimalization appears to be robust to all reasonable partitions of the data.

6. Concluding Discussion

In the wake of decimalization in the NYSE, there has been considerable speculation that liquidity outside the best bid and offer (BBO) prices may have dried up, which may have increased the implicit trading costs experienced by institutional investors who typically trade large quantities and are therefore unable to take advantage of the smaller spreads and the relatively smaller sizes that are being guaranteed at those improved prices. In related research, Jones and Lipson (2001), investigating institutional trading costs around changeover in minimum tick size from eighths to sixteenths, and using data from the same source as us, report that realized execution costs increase after the changeover.

In contrast, using a large sample of institutional order executions in NYSE stocks around decimalization, we find no evidence that decimalization has not led to increased trading costs. In an effort to discover differential execution costs following decimalization, we also partition our sample into data into managers' styles, underlying stock sizes, and complexity of trading decisions, and find no differences in institutional trading costs in the wake of decimalization. To ensure the robustness of our conclusions, we include different measures of benchmark prices with which to measure price impact. We, however, believe that institutions may face higher explicit costs of trading, as they need to trade more and wait longer to complete their trades in a post-decimal environment. The overall effect of decimalization on the *total* cost of trade executions by institutional investors is, therefore, ambiguous. Our results, relative to those reported by Jones and Lipson (2001), appear to be driven primarily by significantly larger institutional trades taking longer to complete, and to the fact that a significantly larger proportion of our orders are worked orders taking over a day, or more than a single broker, to execute.

Our results have important implications for regulators already battered by professional traders, including mutual fund managers, to roll back decimalization and move to nickel-based minimum price increments.

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Table 1
General Statistics

This table presents the summary statistics of our sample. Using all NYSE stocks that moved to decimal trading on January 29, 2001, we select the fifty most active stocks within each of the three size categories based on the market capitalization as on September 30, 2000. Our final sample includes only those stocks that have institutional orders in the Plexus database in each of the three periods that we examine. The period 'Before' includes all days between October 1, 2000 and January 26, 2001, while 'After' includes all days between January 29, 2001 and March 31, 2001. We use the first quarter of 2000 to provide us with a clean benchmark to compare our post-decimalization results. A trading decision refers to a single decision by an institution to buy or sell stock that may be accomplished by one or more trades.

Variable	Period	Market capitalization as at Sep 30, 2000		
		Small	Medium	Large
Number of stocks		26	38	43
Average market capitalization as at Sep 30, 2000 ($M)		18	97	10,650
Average trading volume in the month of Sep 2000 ('000 shares)		312	1,021	7,487
Number of trading decisions	Q1(2000)	1,720	5,946	30,402
	Before	395	2,597	24,561
	After	271	1,499	9,984
Number of trading decisions per day	Q1(2000)	22.1	76.2	389.8
	Before	3.7	24.3	229.5
	After	6.0	33.3	221.9
Average number of trading decisions per stock	Q1(2000)	66	156	707
	Before	15	68	571
	After	10	39	232
Average size of trading decisions (in'000 shares)	Q1(2000)	58	46	79
	Before	38	45	69
	After	50	66	87
Average dollar value of trading decisions (in $M)	Q1(2000)	4	7	52
	Before	2	4	30
	After	4	6	34
Percentage of trading decisions that were completed up to at least 80% of their original size	Q1(2000)	97	97	99
	Before	92	96	99
	After	93	97	98
Percentage of trading decisions that were purchases	Q1(2000)	52	51	53
	Before	44	54	52
	After	63	54	52

Table 2
Statistics on Institutional Trading Decisions

This table presents statistics on institutional trading decisions in our sample stocks. Using all NYSE stocks that moved to decimal trading on January 29, 2001, we select the fifty most active stocks within each of the three size categories based on the market capitalization as on September 30, 2000. Our final sample includes only those stocks that have institutional orders in the Plexus database in each of the three periods that we examine. A trading decision refers to a single decision by an institution to buy or sell stock that may be accomplished by one or more trades. Each cell in our table represents the cross-sectional average under each period of the time series averages of each stock. We test whether the average measure for either of the two pre-decimalization periods ('Before' and 'Q1(2000)') is statistically different from the average measure after decimalization using a paired t-test. An asterisk denotes significance at 5% level. We report our results using four different partitions based on the market capitalization of the traded stock, order side, complexity of the trading decision and manager style.

Panel A: Classification by market capitalization as on September 30, 2000

Variable	Period	Market capitalization as at Sep 30, 2000		
		Small	Medium	Large
Average (Median) number of trades per decision	Q1(2000)	2.7 (2.1)	2.3 (2.0)	4.7* (4.8)
	Before	1.6* (1.5)	2.0* (1.9)	3.3 (3.2)
	After	*2.3 (2.0)*	*2.6 (2.1)*	*3.4 (3.4)*
Average (Median) number of days to complete a decision	Q1(2000)	2.2 (1.9)	1.8 (1.7)	2.5* (2.5)
	Before	1.6* (1.5)	1.6* (1.5)	2.1 (2.2)
	After	*2.0 (1.9)*	*1.8 (1.7)*	*2.1 (2.1)*
Average (Median) number of brokers used per decision	Q1(2000)	1.7* (1.6)	1.6 (1.5)	3.0* (2.9)
	Before	1.3 (1.3)	1.5 (1.3)	2.4 (2.3)
	After	1.4 (1.4)	1.6 (1.5)	2.3 (2.2)

Table 2 (Continued)

Panel B: Classification by purchases and sales

Variable	Period	Purchases	Sales
Average (Median) number of trades per decision	Q1(2000)	3.6* (2.6)	3.1 (2.8)
	Before	2.5* (2.4)	2.4* (2.4)
	After	2.9 (2.9)	2.8 (2.5)
Average (Median) number of days to complete a decision	Q1(2000)	2.2* (2.1)	2.1* (2.2)
	Before	1.8* (1.9)	1.8 (1.8)
	After	2.0 (2.0)	1.9 (1.8)
Average (Median) number of brokers used per decision	Q1(2000)	2.2* (2.0)	2.1* (1.9)
	Before	1.8 (1.7)	1.8 (1.6)
	After	1.9 (1.8)	1.8 (1.7)

Panel C: Classification by complexity of decision (size of the trading decision relative to the average daily trading volume in September 2000

Variable	Period	Complexity of the trading decision		
		Easy	Moderate	Difficult
Average (Median) number of trades per decision	Q1(2000)	1.2 (1.1)	1.9 (1.4)	6.5* (3.5)
	Before	1.2 (1.2)	1.7* (1.2)	4.0* (3.0)
	After	1.2 (1.3)	2.0 (1.9)	4.8 (4.0)
Average (Median) number of days to complete a decision	Q1(2000)	1.1 (1.1)	1.5 (1.4)	3.3* (2.5)
	Before	1.2 (1.2)	1.4* (1.2)	2.5* (2.4)
	After	1.2 (1.2)	1.6 (1.5)	2.6 (2.4)
Average (Median) number of brokers used per decision	Q1(2000)	1.1* (1.0)	1.4* (1.2)	3.8* (2.2)
	Before	1.1 (1.1)	1.4* (1.1)	2.8 (1.9)
	After	1.1 (1.1)	1.4 (1.2)	2.9 (2.0)

Table 2 (Continued)

Panel D: Classification by manager style

Variable	Period	Manager style		
		Value	Diversified	Growth
Average (Median) number of trades per decision	Q1(2000)	2.8* (2.4)	3.6 (2.7)	3.5 (2.6)
	Before	2.1 (2.0)	2.4* (2.3)	2.8* (2.5)
	After	2.1 (2.0)	3.4 (3.1)	4.2 (3.9)
Average (Median) number of days to complete a decision	Q1(2000)	2.2* (2.0)	2.0 (1.9)	2.5 (2.3)
	Before	1.8* (1.7)	1.7* (1.8)	1.9* (1.8)
	After	1.6 (1.6)	2.2 (2.2)	2.4 (2.3)
Average (Median) number of brokers used per decision	Q1(2000)	1.7* (1.6)	2.2 (1.9)	2.7* (2.1)
	Before	1.3 (1.2)	1.8* (1.7)	2.0* (1.9)
	After	1.3 (1.2)	2.4 (2.4)	2.4 (2.1)

Table 3
Measures of Price Impact of Institutional Trading Decisions

We present three different measures of price impact of institutional trading decisions in our sample stocks. Price impact for each decision is measured as the signed deviation (in percentage) of the value-weighted average trade price for each decision from a benchmark price, where deviation is multiplied by –1 if the decision was a sale. We use three different benchmark prices to best capture the price unperturbed by the decision. Each cell in our table represents the cross-sectional average under each period of the time series averages of each stock. We test whether the average measure for either of the two pre-decimalization periods ('Before' and 'Q1(2000)') is statistically different from the average measure after decimalization using a paired t-test. An asterisk denotes significance at 5% level. We report our results using four different partitions based on the market capitalization of the traded stock, order side, complexity of the trading decision and manager style.

Panel A: Classification by market capitalization as on September 30, 2000

Benchmark Price	Period	Market capitalization as at Sep 30, 2000		
		Small	Medium	Large
Price at the time the trading decision was made	Q1(2000)	1.3 (0.7)	0.5 (0.4)	0.2 (0.2)
	Before	1.2 (1.0)	0.5 (0.6)	0.2 (0.1)
	After	0.2 (0.6)	0.5 (0.4)	0.2 (0.1)
Average of the price at the time the trading decision was made and the price of last trade of the decision	Q1(2000)	-0.1* (-0.0)	0.1 (0.1)	0.1 (0.1)
	Before	-1.0* (-0.6)	0.1 (0.1)	0.1 (0.1)
	After	0.8 (0.7)	0.0 (0.1)	0.1 (0.1)
VWAP (Value-weighted average trade price across all trades) on the day the decision was made	Q1(2000)	0.6* (0.4)	0.2 (0.2)	0.0 (0.0)
	Before	0.4 (0.4)	0.3 (0.3)	0.0 (0.0)
	After	-0.2 (0.1)	0.2 (0.2)	0.1 (0.1)

Table 3 (Continued)

Panel B: Classification by purchases and sales

Benchmark Price	Period	Purchases	Sales
Price at the time the trading decision was made	Q1(2000)	0.6* (0.1)	0.5 (0.4)
	Before	0.5* (0.2)	0.7 (0.4)
	After	-0.2 (-0.1)	0.8 (0.7)
Average of the price at the time the trading decision was made and the price of last trade of the decision	Q1(2000)	1.7 (1.5)	-1.7 (-1.5)
	Before	2.0* (1.8)	-2.4* (-2.0)
	After	1.6 (1.3)	-1.5 (-1.2)
VWAP on the day the decision was made	Q1(2000)	0.3* (0.1)	0.2 (0.1)
	Before	0.1 (0.1)	0.2 (0.2)
	After	-0.1 (-0.0)	0.2 (0.2)

Panel C: Classification by complexity of decision (size of the trading decision relative to the average daily trading volume in September 2000

Benchmark Price	Period	Complexity of the trading decision		
		Easy	Moderate	Difficult
Price at the time the trading decision was made	Q1(2000)	0.1 (0.1)	0.3 (0.1)	0.7 (0.5)
	Before	-0.0 (-0.0)	0.4 (0.2)	0.7 (0.4)
	After	0.1 (0.2)	0.3 (0.1)	0.4 (0.3)
Average of the price at the time the trading decision was made and the price of last trade of the decision	Q1(2000)	-0.0 (0.0)	0.1 (0.1)	0.0 (0.1)
	Before	0.1 (0.0)	-0.2 (0.1)	-0.2 (0.0)
	After	0.0 (-0.0)	0.3 (0.1)	0.2 (0.2)
VWAP on the day the decision was made	Q1(2000)	-0.0 (0.0)	0.1 (0.1)	0.3 (0.2)
	Before	0.1 (0.0)	0.2 (0.1)	0.2 (0.1)
	After	-0.0 (0.0)	-0.0 (0.0)	0.1 (0.1)

Table 3 (Continued)

Panel D: Classification by manager style

Benchmark Price	Period	Manager style		
		Value	Diversified	Growth
Price at the time the trading decision was made	Q1(2000)	0.5* (0.1)	0.6 (0.2)	0.8 (0.5)
	Before	0.4 (0.2)	0.4 (0.2)	1.2 (1.0)
	After	-0.3 (0.1)	0.8 (0.2)	0.9 (0.5)
Average of the price at the time the trading decision was made and the price of last trade of the decision	Q1(2000)	0.3 (0.1)	0.1 (0.1)	0.1 (0.1)
	Before	0.3 (0.1)	-0.2 (0.0)	-0.5 (0.0)
	After	0.1 (0.1)	0.2 (0.1)	0.2 (0.2)
VWAP on the day the decision was made	Q1(2000)	0.0 (0.1)	0.2 (0.0)	0.4 (0.2)
	Before	0.1 (0.1)	0.1 (0.1)	0.3 (0.1)
	After	-0.2 (0.0)	0.2 (0.1)	0.0 (0.2)

Table 4

Comparison of Price Impact (PI) Measures By Manager Before and After Decimalization

We present results on changes in the price impact measures for each manager before and after decimalization. We use the period between October 1, 2000 to January 26, 2001 to represent our pre-decimalization period, and the period between January 29, 2001 to March 31, 2001 to represent our post-decimalization period. Our price impact measure is the signed deviation (in percentage) of the value-weighted average trade price for each decision from a benchmark price, where deviation is multiplied by –1 if the decision was a sale. We use three different benchmark prices to best capture the price unperturbed by the decision. The last two columns represent the number of managers trading stocks within each stock size category whose price impact was lowered or increased significantly (at 5% level) following decimalization. We exclude managers who did not trade in the same stock size category in both the pre- and the post-decimalization periods. Our stock size categories are derived from the cut-offs of the market capitalization as on September 30, 2000. We report results for the three different benchmark prices used in the computation of the price impact measure separately.

Panel A: Using the benchmark price as the price at the time decision was made

Manager style	Variable	Stock size category	Number of Managers		Difference between the price impact measure before and after decimalization by manager	
			Without data in both pre- and post-decimalization periods	With data in both pre- and post-decimalization periods	Number of managers with significant negative difference	Number of managers with significant positive difference
Value	PI (After) – PI (Before)	Small	6	2	1	0
		Medium	15	7	1	1
		Large	14	33	2	0
Diversified	PI (After) – PI (Before)	Small	48	5	0	0
		Medium	137	34	3	2
		Large	288	121	12	12
Growth	PI (After) – PI (Before)	Small	12	2	1	0
		Medium	44	20	0	2
		Large	58	57	5	2

Table 4 (Continued)

Panel B: Using the benchmark price as the average of the price at the time of the decision and the price of the last trade of the decision)

Manager style	Variable	Stock size category	Number of Managers		Difference between the price impact measure before and after decimalization by manager	
			Without data in both pre- and post-decimalization periods	With data in both pre- and post-decimalization periods	Number of managers with significant negative difference	Number of managers with significant positive difference
Value	PI (After) – PI (Before)	Small	6	2	0	1
		Medium	15	7	0	1
		Large	14	33	4	4
Diversified	PI (After) – PI (Before)	Small	48	5	0	0
		Medium	137	34	3	1
		Large	288	121	12	12
Growth	PI (After) – PI (Before)	Small	12	2	0	0
		Medium	44	20	2	0
		Large	58	57	9	5

Table 4 (Continued)

Panel C: Using the benchmark price as the VWAP on the day of the decision

Manager style	Variable	Stock size category	Number of Managers		Difference between the price impact measure before and after decimalization by manager	
			Without data in both pre- and post-decimalization periods	With data in both pre- and post-decimalization periods	Number of managers with significant negative difference	Number of managers with significant positive difference
Value	PI (After) – PI (Before)	Small	6	2	0	0
		Medium	15	7	0	1
		Large	14	33	2	1
Diversified	PI (After) – PI (Before)	Small	48	5	0	0
		Medium	137	34	3	0
		Large	288	121	1	6
Growth	PI (After) – PI (Before)	Small	12	2	0	0
		Medium	44	20	1	1
		Large	58	57	3	6

Table 5
Cross-sectional Regression of Price Impact Measures

This table presents results of cross-sectional regressions of price impact measures within each stock size category. Price impact for each decision is measured as the signed deviation (in percentage) of the value-weighted average trade price for each decision from a benchmark price, where deviation is multiplied by –1 if the decision was a sale. We use three different benchmark prices to best capture the price unperturbed by the decision, as reported in each of the three panels. We include data between October 1, 2000 to March 31, 2001. The After dummy is an indicator variable that takes the value 1 if the decision was placed after January 29, 2001, the date when stocks started trading in decimals. The Value dummy and the Growth dummy are indicator variables to denote manager style. We also use two interaction dummy variables to capture the residual effects of decimalization on manager style. Volatility is the daily return standard deviation in the month of September 2000, while Inverse Price represents the inverse of the price at the time the decision was made. Decision complexity is the size of the decision relative to the average daily volume of the underlying stock. An asterisk means that the coefficient for the variable is significantly different from zero at the 5 percent level.

Panel A: Using the benchmark price as the price at the time decision was made

Stock size category	Intercept	Volatility	Decision complexity	Inverse Price	Value dummy	Growth dummy	After dummy	Value x After dummy	Growth x After dummy	R-square	N
Small	1.17	-0.03	0.01*	0.23	-0.80	2.15	-0.04	-0.30	-1.26	0.03	614
	(0.78)	(0.10)	(0.01)	(1.54)	(0.96)	(1.12)	(1.09)	(1.47)	(2.24)		
Medium	0.33	0.03	-0.00	-0.84	0.09	0.94*	0.46	-0.78	-0.82	0.01	3,958
	(0.29)	(0.07)	(0.00)	(0.76)	(0.30)	(0.34)	(0.32)	(0.46)	(0.63)		
Large	-0.37*	0.14*	0.04*	6.60*	0.01	0.34*	-0.15	0.07	0.07	0.00	34,019
	(0.11)	(0.04)	(0.01)	(2.46)	(0.20)	(0.14)	(0.12)	(0.26)	(0.24)		

Panel B: Using the benchmark price as the average of the price at the time of the decision and the price of the last trade of the decision)

Stock size category	Intercept	Volatility	Decision complexity	Inverse Price	Value dummy	Growth dummy	After dummy	Value x After dummy	Growth x After dummy	R-square	N
Small	-0.08	0.03	-0.00	-2.61*	1.62*	-2.70*	1.81*	-2.44*	2.04	0.11	614
	(0.42)	(0.05)	(0.00)	(0.81)	(0.51)	(0.59)	(0.58)	(0.78)	(1.18)		
Medium	0.18	0.10*	0.00	-3.67*	0.10	-0.28	-0.08	-0.14	0.50	0.02	3,958
	(0.17)	(0.04)	(0.00)	(0.45)	(0.18)	(0.20)	(0.19)	(0.27)	(0.38)		
Large	0.13*	-0.01	-0.01	-1.21	0.04	0.22*	0.02	-0.06	-0.24	0.00	34,019
	(0.06)	(0.02)	(0.00)	(1.26)	(0.10)	(0.07)	(0.06)	(0.13)	(0.13)		

Table 5 (Continued)

Panel C: Using the benchmark price as the VWAP on the day of the decision

Stock size category	Intercept	Volatility	Decision complexity	Inverse Price	Value dummy	Growth dummy	After dummy	Value x After dummy	Growth x After dummy	R-square	N
Small	-0.21	-0.01	0.00	0.92	0.38	2.51*	0.50	-0.81	-3.39*	0.03	614
	(0.54)	(0.07)	(0.00)	(1.07)	(0.66)	(0.77)	(0.75)	(1.01)	(1.54)		
Medium	0.59*	0.02	-0.00	-2.82*	-0.27	-0.16	-0.23	0.03	0.40	0.01	3,958
	(0.17)	(0.04)	(0.00)	(0.44)	(0.18)	(0.20)	(0.19)	(0.27)	(0.37)		
Large	0.00	0.02	0.01*	-1.12	0.17	-0.06	-0.04	-0.14	0.24*	0.00	34,019
	(0.05)	(0.02)	(0.00)	(1.14)	(0.09)	(0.06)	(0.06)	(0.12)	(0.11)		

Table 6
Cross-sectional Regressions of Number of Trades per Decision and the Number of Trading Days to Complete a Decision

This table presents results of a cross-sectional regression model of the number of trades per decision and the number of days it takes to complete a decision. We include data between October 1, 2000 to March 31, 2001. The After dummy is an indicator variable that takes the value 1 if the decision was placed after January 29, 2001, the date when stocks started trading in decimals. The Value dummy and the Growth dummy are indicator variables to denote manager style. We also use two interaction dummy variables to capture the residual effects of decimalization on manager style. Volatility is the daily return standard deviation in the month of September 2000, while Inverse Price represents the inverse of the price at the time the decision was made. Decision complexity is the size of the decision relative to the average daily volume of the underlying stock. An asterisk means that the coefficient for the variable is significantly different from zero at the 5 percent level.

Panel A: Number of Trades per Decision

Stock size category	Intercept	Volatility	Decision Complexity	Inverse Price	Value dummy	Growth dummy	After dummy	Value x After dummy	Growth x After dummy	R-square	N
Small	0.90*	0.10*	0.01*	-0.52	0.54*	0.96*	0.59*	-0.05	-0.58	0.16	614
	(0.21)	(0.02)	(0.00)	(0.42)	(0.26)	(0.31)	(0.30)	(0.40)	(0.61)		
Medium	2.07*	0.00	0.06*	-1.43	-0.34	-0.70*	1.58*	-0.99*	-1.09	0.12	3,958
	(0.28)	(0.06)	(0.00)	(0.73)	(0.29)	(0.33)	(0.31)	(0.44)	(0.61)		
Large	2.95*	0.12*	0.45*	-11.09*	-0.97*	0.07	0.26*	-0.32	0.66*	0.13	34,019
	(0.11)	(0.04)	(0.01)	(2.36)	(0.19)	(0.13)	(0.12)	(0.25)	(0.23)		

Panel B: Number of Trading Days to Complete a Decision

Stock size category	Intercept	Volatility	Decision complexity	Inverse Price	Value dummy	Growth dummy	After dummy	Value x After dummy	Growth x After dummy	R-square	N
Small	1.29*	0.02	0.01*	-0.44	0.48*	0.95*	0.46*	-0.60*	-0.42	0.22	614
	(0.12)	(0.02)	(0.00)	(0.24)	(0.15)	(0.17)	(0.17)	(0.23)	(0.35)		
Medium	1.45*	0.02	0.03*	-0.26	0.01	-0.11	0.38*	-0.40*	0.03	0.28	3,958
	(0.08)	(0.02)	(0.00)	(0.20)	(0.08)	(0.09)	(0.08)	(0.12)	(0.16)		
Large	2.26*	-0.02	0.13*	-4.95*	-0.28*	-0.26*	0.15*	-0.38*	-0.04	0.09	34,019
	(0.04)	(0.01)	(0.00)	(0.83)	(0.07)	(0.05)	(0.04)	(0.09)	(0.08)		

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