Specialist Profits and the Minimum Price Increment

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Abstract

NYSE specialist participation rates and profits are affected by the rules that govern their trades. Lowering the minimum tick from $\$^1/_{16}$ to \$0.01 effectively relaxed the public order precedence rule, gave specialists more price points within the bid-ask spread on which to quote aggressively, and lowered spreads. Due to these offsetting forces, we find that average specialist gross trading profits were not significantly altered, but their participation increased. Cross-sectional analyses reveal that participation rates and high-frequency trading profits increased more for specialists handling stocks where the cost and opportunity of obtaining order precedence were relatively expensive and scarce prior to the tick change.

On January 29, 2001 the New York Stock Exchange changed the minimum price increment, or minimum 'tick,' from $\$^1/_{16}$ to \$0.01. Although the minimum tick size may seem to be a trivial aspect of market design, it is important because it influences execution costs and mediates power among various types of market participants. As a result, changes in many aspects of market quality have been widely reported following decimalization. However, changes in NYSE specialist trading activity and profits have not been studied in detail. In this study, we test cross-sectional hypotheses regarding the change in specialist participation and profits following decimalization. In doing so, our study illuminates the intersection between stock characteristics, NYSE specialist trading behavior, and changes in the rules that govern specialist trades.

Since decimalization, buy-side traders and investment sponsors have argued that specialists became substantially more profitable because the lower minimum price increment allows specialists to gain order precedence at lower cost and at greater frequency. Although many market participants and academics are aware that the concurrent narrowing of spreads would serve to decrease profits, nobody besides the specialists themselves knew which effect dominated. Based on evidence from over 1,800 NYSE-listed stocks, we find that the two effects largely offset each other for most, but not all stocks.

To gain a deeper understanding of the economics driving this result, we measure two separate channels through which narrowed tick sizes may increase specialist participation and profits. The first channel is based on the cost of obtaining order precedence. As noted by Harris (1994, 1999), a smaller tick will induce specialists to trade more often because the cost of gaining order precedence is directly related to the minimum tick. As a result, specialists handling stocks with a larger *relative* minimum tick size prior to decimalization will obtain the largest reduction in the cost of gaining order precedence. Therefore, we expect specialist participation and profits to increase more for specialists that handled stocks with a larger relative minimum tick size, all else constant.

The second channel is based on the opportunities available for specialists to trade. Due to the public order precedence rule, a specialist cannot trade at a price when a public order exists to trade at that price in the same direction. Since NYSE Rule 104 prohibits specialists from taking liquidity from the pubic, a specialist cannot trade when the difference between the best bid and ask quotes equals one tick. Following decimalization, therefore, specialist participation and profits should increase more if they are handling stocks that had a larger increase in intra-spread price points, all else constant.

We recognize that the effect of these two channels should not equally influence all specialist-trading strategies. The ability to obtain order precedence at lower cost primarily benefits short-term specialist trading strategies rather than long-term speculative strategies. We use spectral methods to allocate profits to strategies that vary by time horizon. Following Hasbrouck and Sofianos (1993) we select horizons based on transaction time, but since specialists undoubtedly operate in event time, we generalize their method to decompose profits by calendar time as well. In this manner we ensure that our results identify profits from strategies that operate in either time domain, which is especially critical for the less actively traded securities.

Using our decomposed profit estimates, we analyze the effect of decimalization on profits earned over various trading horizons. Our cross-sectional evidence supports our arguments. While controlling for changes in other relevant stock characteristics, we find that specialist participation and profits earned from high-frequency trading strategies increased most for stocks with a large relative minimum tick size and for stocks that had a greater increase in the number of intra-spread price points. The evidence is robust to the decomposition time domain and to several econometric specifications.

Our study is closely related to Hasbrouck and Sofianos (1993), who decompose specialist profits in 137 stocks across a three-month period ending January 1991 and find that most profits are due to their high frequency (short-term) trading strategies. Our cross-sectional tests are most closely related to Madhavan and Sofianos (1998), who examine all NYSE securities using data from July 1993, and find that listed firm size, block and non-block volume, and return volatility largely explain cross-sectional differences in specialist participation rate levels.

Our study is also related to two recent studies that examine specialist trading after a change in the minimum tick size. Using a sample of 324 AMEX-listed stocks, Ronen and Weaver (2001) report that specialist participation rates increased. Ronen and Weaver also measure gross trading profits and conclude from univariate tests that profits remained unchanged after the minimum tick size decreased from $\$^1/_8$ to $\$^1/_{16}$ in 1997. Edwards and Harris (2003) examine 70 NYSE-listed stocks in a concurrent study and, while testing hypotheses regarding limit order fill rates, report that NYSE specialists increased their participation after price decimalization.[1]

This study presents several unique contributions beyond those already in the literature. Most importantly, we test predictions about the cross-sectional variation of changes in specialist profits. Second, aside from documenting the direction of mean changes in specialist participation, we conduct cross-sectional tests to learn about the determinants of changes in specialist participation rates. Third, we generalize the spectral methods used by Hasbrouck and Sofianos (1993) to recognize that specialist trades and profits are earned in calendar-time. Fourth, we provide a new method for modeling the heteroskedasticity that arises in regressional analyses involving dependent variables estimated from time-series. Less important contributions include corroboration of the importance of high-frequency trading strategies to specialists as first noted by Hasbrouck and Sofianos (1993), and updated information about the level of specialist profits across a relatively large cross-section of stocks.

How trading rules mediate specialist profits and participation is a topic of much recent public debate and intense academic interest. Absent from the literature is empirical evidence relating changes in specialist profits and participation to a change in rules. Following decimalization, we find that specialist participation has increased but specialist gross trading profits did not significantly change. Deeper analysis reveals that specialist participation, and profits from short-term trading strategies, increased most for stocks with larger relative minimum tick sizes and for stocks that had a greater increase in the number of intra-spread price points. These variables are important because they reflect the cost of, and opportunity for, specialists to gain order precedence.

The remainder of this article is organized as follows. Section 1 develops the hypotheses examined in this study. We describe our data in section 2. Results concerning specialist participation rates and specialist profits respectively appear in sections 3 and 4. Section 5 concludes with a short summary and a discussion of public policy implications.

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[1] Bacidore (1997), Bacidore et al. (2003), and Battalio and Jennings (2002) are among others that examine changes in spreads and order characteristics after a tick size change. See also Goldstein and Kavajecz (2000) and Jones and Lipson (2001) for evidence that spreads and depth generally decreased following the change in minimum tick size to sixteenths. Bessembinder (2003a) reports that quoted spreads, effective spreads, and return volatility all decrease following the change in tick size to $0.01.

1. Decimalization and Specialist Profits

Specialists assume special obligations and receive special privileges to facilitate trade. They must quote continuous markets and they must trade when no one else is willing to do so. Specialists provide these services because their unique positions allow them to observe all incoming limit and market orders and to use this private information to their advantage when trading. To ensure that specialists do not abuse these privileges, Exchange rules prevent them from trading at certain times or prices.[2]

The public order precedence rule prohibits specialists from trading at the same price at which standing agency orders could be filled. Specialists who wish to trade ahead of agency orders therefore must trade at superior prices. This rule promotes confidence in the markets by assuring public investors that the trading process is fair. The decrease in tick size associated with decimalization, however, greatly reduced the importance of the public order precedence rule by significantly lowering the cost of obtaining order precedence through price priority.

NYSE Rule 104 prohibits specialists from taking liquidity that public traders could otherwise take. In practice, this rule prevents specialists from trading with limit orders on their books. Consequently, specialists generally trade only when filling incoming marketable orders. When specialists are impatient to trade, they try to attract market orders by quoting aggressively. However, they are not allowed to quote prices that would equate the bid and ask prices and thereby "lock" the market. Specialists therefore cannot quote aggressively when the bid/ask spread in their limit order books is only one tick. Decimalization allows specialists to quote more aggressively by increasing the number of potential price points between the bid and offer.

The most important constraint on specialist trading comes from the competition of other traders who offer liquidity. Like specialists, public traders can quote aggressively by placing limit orders at improved prices. The competition from public limit order traders, coupled with aggressive specialist quoting, has substantially decreased bid/ask spreads.

Decimalization relaxed constraints on specialist trading activity by reducing the importance of the public order precedence rule (for all but the lowest priced stocks and those with one-cent spreads spreads set by agency orders) and by providing additional intra-spread

[2] Chapter 24 of Harris (2003) surveys specialist trading systems, obligations, and privileges.

price points. However, the narrowing of spreads by public liquidity providers tightened an important constraint. Relaxation of the first two constraints should have increased specialist trade participation rates and profitability whereas the tightening of spreads should have had the opposite effect on these variables. The empirical analyses in this study disentangle these conflicting effects by identifying two important stock characteristics that cause the constraints discussed above to vary across stocks.

The first characteristic is the relative minimum tick size, which is the minimum tick divided by stock price. This characteristic is most closely related to the public order precedence constraint. Since the minimum price increment is constant for all stocks, the total cost of obtaining precedence through price priority for a trade of a given dollar size is inversely related to the stock price. Although decimalization lowered this cost for all stocks, the economic impact, measured as a percentage of dollar trade size, was greatest for low price stocks. Accordingly, changes in specialist participation and specialist profits should be directly related to the relative minimum tick size.

The second characteristic, intra-spread price points, is closely related to the Rule 104 constraint. Specialist trading is more constrained when few or no price points are between the best bid and offer than when many such price points exist. Accordingly, changes in specialist participation and specialist profits should be greatest for stocks that formerly were most commonly quoted with a one-tick spread but which now are commonly quoted with a multi-tick spread.

Our analyses explain how changes in specialist participation rates and profits following decimalization depend on price and intra-spread price points, after controlling for changes in spreads and other variables known to affect specialists trading behavior and profits. Controlling for these other effects is important in this one-shot event study. Although these controls allow us to place confidence in our time-series results, we are most confident in our cross-sectional results because of the specificity of our experimental design to the decimalization hypotheses.

2. Data

We obtain our sample by combining NYSE Trade and Quote (TAQ) files with NYSE Consolidated Equity Audit Trail (CAUD) files. Along with many trade details, the CAUD files allow us to determine whether the specialist was a buyer or seller on each trade. Using this information, we measure specialist participation rates and profits in each stock. The TAQ data provides the best quote at the time of each trade, which allows us to determine the rate and degree of specialist price improvement.

The sample includes two three-week periods before and after the final decimalization of prices on January 29, 2001. The pre-decimalization sample contains 15 trading days from December 4 to December 22, 2000, and the post-decimalization sample contains 15 trading days from February 26 to March 16, 2001. The two samples are about one-month removed from January 29 to ensure our results reflect learning by market participants that occurred immediately following decimalization.

The sample includes all NYSE common stocks except foreign listings (ADRs, GDRs, and Canadian stocks), stocks that split between December 4, 2000 and March 16, 2001, stocks for which the average pre- or post-decimalization price exceeded $200, stocks for which we could not explain extreme changes in share volume or returns (7 stocks), and stocks that were included in the pilot decimal trading program.[3] The final sample includes 1,811 common stocks.

2.1 Sample Characterization

The NYSE lists a small number of relatively large stocks and a large number of relatively small stocks. Our sample, which includes most NYSE common stocks, therefore has a similar distribution. The largest one hundred stocks represent roughly 65% of the sample's total capitalization, while the smallest 1,311 stocks represent less than 10% of the total capitalization (Figure 1).

Since specialist-trading strategies depend on the trading activity in their stocks, and since activity is correlated with firm size, we divide our sample into three size categories: large stocks (the top 100), mid-cap stocks (the next 400), and small stocks (the remaining 1,311).[4] The

[3] The decimal pilot stocks traded on pennies in both of our sample periods. We separately analyzed these stocks to confirm that the empirical results reported in this study are not due to unidentified phenomena that are unrelated to decimalization. We discuss the results of these tests below.

[4] We were reluctant to segment by dollar volumes because volumes may be endogenous. The very high cross-sectional correlation between dollar volumes and capitalization ensures that the results would be the same.

segmentation of our analyses by size allows us to identify differential effects of decimalization across large and small stocks.[5]

We compare price, return, spread, and trading activity variable distributions from the pre- and post-decimalization periods in Table 1. We present statistics regarding specialist participation rates and profits in the following sections.

To control for cross-sectional covariation across the stocks, all univariate tests of mean differences between the pre- and post-decimalization sample periods are conducted on a time-series of cross-sectional daily means. This highly conservative procedure ensures that we measure significance with respect to the time-series variation in the daily cross-sectional means and not with respect to the cross-sectional variance in the time-series means for each stock. The former is more appropriate for testing whether the mean of a variable changed between two samples observed at different points in time. The univariate tests thus are based on means for each of the 15 days in each of the two sample periods.

We compute market capitalization as the mean trade price during the December 2000 three-week sample period times the number of shares outstanding. The cross-sectional mean market capitalization ranges from $550 million for small stocks to $63.7 billion for large stocks (Panel A). Since we exclude all stocks that split shares, the post-decimalization change in market capitalization is generally proportional to the post-decimalization change in price.

Price levels rise across the size-sorted stock groups from just under $20 for the small stocks to slightly over $50 for the large stocks. The large stock sample has no stocks priced under $10. Since the cost of stepping ahead decreases with the inverse of price, the cross-sectional variation in this cost is small for high price stocks.[6] The inverse of price therefore should be a relatively less important determinant of post-decimalization changes in specialist participation and in specialist profits for high price stocks.

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[5] We also analyzed the full sample using equal- and value-weighted analyses. The equal-weighted analyses produced results similar to the equal-weighted small stock sample, while the value-weighted analyses produced results similar to the large stock sample. We choose to present size-segmented results instead of these value-weighted results because regulators and practitioners will make better decisions based on segment results than on average results.

[6] Throughout the paper we give the terms ‘step-ahead’ and ‘obtain order precedence’ equivalent interpretations.

The prices of small and mid-cap stocks rose between our two sample periods while the prices of the large stocks fell. These changes reflect different returns earned between our sample periods and should have little effect on our study.

Returns during the post-decimalization period were lower, but not significantly different from the pre-decimalization period. The mean difference in daily mean returns is –29 basis points (from 13 to –16 basis points) for small stocks and –71 basis points (from 27 to –44 points) for large stocks. These price returns, which are not surprising given the time-series volatility of returns, may determine the profitability of some specialist trading strategies—especially long-term strategies. Fortunately, the different returns should not affect our cross-sectional analyses since they largely affect all stocks in each sample. Moreover, our results are less sensitive to the return difference than one might first suspect because we focus on high frequency profits and because we assume inventory is initially zero at the beginning of the sample periods when computing specialist-trading profits.

Daily return standard deviations decreased for each stock group, but by no more than 8 basis points. Although the difference is statistically significant in the cross-section for small and mid-cap stocks, we are reluctant to attribute this change to decimalization because of the substantial time-series variation in volatility. However, we control for this change in the cross-sectional tests since volatility affects the profitability of short term trading strategies.[7]

Average spreads, measured in ticks, increased from 2.3 sixteenth-dollar ticks to 10.7 penny-ticks following decimalization for small stocks and from 2.1 to 8.6 ticks for large stocks (Panel B). The number of prices at which a specialist can gain order precedence by offering a better price thus increased significantly.

As is now well known, absolute dollar and relative spreads declined significantly following decimalization. In our small stock sample, the mean quoted spread fell from 14.2 to 10.7 cents and the mean effective spread dropped from 9.9 to 7.6 cents. For large stocks, quoted spreads fell from 13.3 to 8.6 cents and effective spreads dropped from 8.5 to 5.8 cents. We

[7] Madhavan and Sofianos (1998) find that cross-sectional variation of specialist participation is positively related to volatility. In more volatile markets specialists are more likely to provide liquidity in a one-sided market (an affirmative obligation), and there may be more opportunities to profit from any short-term momentum or reversion.

control for the change in spreads in our cross-sectional regressions because smaller spreads should reduce profits, all else constant.[8]

The average fraction of total trading time that a stock's spread equaled a one sixteenth-dollar tick was 31.1 percent before decimalization for small stocks and 40.9 percent for large stocks (Panel B, last set of rows). Following decimalization, small stocks were quoted with a one-penny spread only 4.3 percent of the time, and large stock spreads were one penny 6.6 percent of the time. For all stocks, specialist trading was far less constrained by the minimum tick following decimalization.

Finally, the mean number of transactions per day increased significantly for each stock group (Panel C). However, small stock share volume decreased significantly while large stock share volume remained essentially unchanged. Together, these results imply that trade size decreased. Consistent with evidence reported by Goldstein and Kavajecz (2000) and Jones and Lipson (2001), these results suggest that traders became more likely to break large orders into small trades.[9] To assess the changes in the composition of trading volume, we follow Madhavan and Sofianos (1998) and partition total volume into block volume (trades ≥ 10,000 shares) and non-block volume (trades < 10,000 shares).[10] While block volume decreased across all stock groups (significantly for the small and mid-cap stocks), non-block volume remained largely unchanged for small stocks but increased significantly for large stocks. We control for changes in block and non-block volume since they are likely to alter specialist participation and profit.

[8] To avoid outliers, we applied typical filters to the data before computing mean spreads. We deleted observations if the quoted spread exceeds $5; if the transaction price is more than 12.5 cents greater (less) than the ask price (bid price); or if the transaction, bid, or ask price is more than 25% larger than (or less than 75% of) the preceding transaction, bid, or ask price respectively. We also deleted trades reported before 9:30 AM or after 4:01 PM, and trades with a CAUD correction code greater than 2 (we use only 'original good,' and 'original corrected' trades). Following Bessembinder (2003b), we match trades to quotes without the time adjustment proposed in Lee and Ready (1991).

[9] We count each CAUD trade record as one transaction. Our transaction count therefore will be greater than the total number of orders. Since share volume largely decreased across the sample periods, the increase in transactions is most likely due to the increased propensity to split orders after a decrease in tick size (e.g. Jones and Lipson, 2001), rather than due to an increase in number of orders.

[10] We also identified block volume as the number of shares originating in each stock's largest 2.5% of orders. All cross-sectional inferences are unaffected by the choice of block definition.

3. Specialist Trade Participation Rates

The specialist trade participation rate is the fraction of all trades in which the specialist either buys or sells. As expected, the average specialist trade participation rate increased from 36.4 percent to 44.4 percent for small stocks following decimalization (Table 2, first set of rows). The large stock participation rate also increased from 24.5 percent to 30.2 percent.[11]

We expect that the post-decimalization change in participation rate should be inversely related to stock price. We provide univariate evidence of this relation by sorting each size-sorted sample into three subsamples based on price. We classify stocks priced $10 or less as low price stocks, those over $25 as high price stocks, and the remainder as mid price stocks. Since the post-decimalization reduction in the cost of stepping ahead was large for the low price stocks but trivial for the high price stocks, the greatest increase in specialist participation should be for the low price stocks. The results confirm this conjecture. For small stocks, the rate of trade participation increased by 11.3 percentage points for stocks priced under $10 whereas it increased only by 5.6 percentage points for stocks priced over $25 (Table 2, Panel A). Similarly, the trade participation rate for mid-cap stocks increases by 14.0 percentage points for stocks priced under $10, but by only 4.0 percentage points for stocks priced over $25. We obtain similar results for the large stocks even though this sample contains no stocks priced under $10 and only six stocks priced under $25.

For each stock we also calculate the percent of specialist trades executed at the current quote, inside the quote, and outside the quote (the sum of which must add to 100%). Specialists trading firms of all size increased their participation rates primarily by trading more often inside the current quote (Table 2, Panel B). Before decimalization, roughly 44% of all specialist trades in small stocks occurred at the quote with virtually all of the remainder inside the quote. After decimalization, specialist trades at the quote fell by roughly 11.1 percentage points, while the fraction inside the quote increased by 10.6%.[12] Interestingly, the change in the distribution was

[11] We also report specialist participation rate by their fraction of all shares traded. This measure produces lower participation rates than does the rate measured as a fraction of transactions, but both measures produce qualitatively identical results in all our analyses.

[12] The increase in percent of specialist trades inside the quote is slightly less than the decrease in specialist trades at the quote, which indicates a slight increase in trades outside the quote. This increase is probably due to greater quote-matching errors caused by "flickering quotes." It may also be due to an increase in trades outside the quotes when there is insufficient depth at the best bid or offer. In these cases, any orders at the quote execute at their limit prices. In any event, the percent of trades outside the quote never exceeds 2%.

roughly the same across stock price and market capitalization levels as well, with the exception of mid-price large stocks whose increase in specialist trades inside the quote exceeded 15%.

We obtain a more rigorous test of the dependence of the post-decimalization change in specialist participation on price level and intra-spread price points by estimating a cross-sectional regression that controls for changes in other determinants of specialist participation. The independent variables of greatest interest are the change in relative minimum tick and the change in step-in-front opportunities.

The change in relative minimum tick, *ΔRelMinTick*, is *.01/Price - .0625/Price = -.0525/Price*. It is proportional to the change in the cost of obtaining precedence. We expect, therefore, to observe a negative relation between the change in the participation rate and *ΔRelMinTick* since specialists handling low price stocks will incur the largest decrease in the cost of stepping ahead.

We measure the change in step-ahead opportunities as the change in the time-weighted average of the inverse spread in ticks, $\Delta InvSpreadInTicks = 1/SpreadInTicks_{Pre} - 1/SpreadInTicks_{Post}$. Therefore if the spread in ticks increased from 1 ticks to 2 ticks, then *ΔInvSpreadInTicks* = 1/1 – 1/2 = 0.5; if the spread in ticks increased from 5 ticks to 6 ticks, then *ΔInvSpreadInTicks* = 1/5 – 1/6 = 0.033. We use the change in the inverse spread (in ticks) instead of the change in spread (in ticks) because a change from one tick to two ticks represents a much more valuable increase in trading opportunity than does a change from five ticks to six ticks. We expect to observe a positive relation between the change in participation and *ΔInvSpreadInTicks*, since this variable increases in the opportunity for a specialist to obtain order precedence.[13]

Madhavan and Sofianos (1998) report that return volatility, block volume, and non-block volume largely determine cross-sectional variation in specialist participation rates. We therefore include changes in these variables to control for variation that is not due to decimalization. We

[13] As an alternative to *ΔInvSpreadInTicks,* we also used *ΔFracTimeOneTick*, which measures the change in percent of time that the spread is at one tick. Both variables measure the change in opportunities available for the specialist to quote aggressively. Since these variables are highly correlated (correlation = 0.89), and since the results are not significantly altered, we report all tests using only the former measure.

also include the change in the total return to determine whether specialist participation might be correlated with market movements. Our full regression model is

$$\text{(1)} \qquad \begin{aligned} \Delta ParticiRate_i = \beta_0 + \beta_1 \Delta RelMinTick_i + \beta_2 \Delta InvSpreadInTicks_i + \beta_3 \Delta Volatility_i + \\ + \beta_4 \Delta NonBlockVolume_i + \beta_5 \Delta BlockVolume_i + \beta_6 \Delta Return_i + \varepsilon_i \end{aligned}$$

where *ΔParticiRate* is the change in specialist participation rate, *ΔVolatility* is the change in daily percent return standard deviation (returns are measured in percent), *ΔReturn* is the change in return, and ε is the regression error term.

The error term in this regression has two components. One component is due to normal variation in the fit of the model while the other component is due to noise in our estimates of the change in specialist participation rates. We therefore assume that the error term is independently distributed with variance

$$\text{(2)} \qquad \sigma_i^2 = \tau^2 + \left(\frac{r_{1,i}\left(1 - r_{1,i}\right)}{N_{1,i}} + \frac{r_{2,i}\left(1 - r_{2,i}\right)}{N_{2,i}} \right).$$

The first term is a standard regression error variance common to all observations while the second term is due to the estimation error associated with computing *ΔParticiRate*. The two terms in parentheses are the binomial error variances of the time-series estimates of the specialist participation rates in the pre- and post-decimalization periods, which we denote by 1 and 2 for brevity. The variables in the numerator are the participation rates and those in the denominator are the total number of trades. The unusual error structure requires that we estimate the model using the maximum likelihood method.

Maximum likelihood coefficient estimates based on each of the three stock size groups appear in Table 3. The negative coefficients for *ΔRelMinTick* indicate that participation rates increased with the decrease in the costs of stepping ahead. This relation is significant for the small and mid-cap stocks, but insignificant for the larger stocks for which their high prices made the change in the step-ahead cost trivial. The significant positive coefficient estimates for *ΔInvSpreadInTicks* in each regression indicate that participation increased with the available number of intra-spread price points. The signs of the estimated coefficients for block volume (-)

and non-block volume (-) are the same as those estimated by Madhavan and Sofianos (1998) in their cross-sectional regression of participation levels.[14]

The change in return variable is negative and significant for mid-cap and large firms. Specialists apparently participated more when prices fell significantly in these stocks in our post-decimalization sample period. The average 15-day holding period returns in this period were –2.5, –3.6, and –6.6 percent respectively for the small, mid-cap and large stocks. Their increased participation while the market was dropping is consistent with their affirmative obligations.

Consistent with our arguments, the increase in participation rates is greatest for stocks with the largest decrease in relative minimum tick and for stocks with the largest increase in the number of intra-spread price points. As a control experiment, we estimated the same regression using the decimal pilot stock sample. In this sample, the change in participation is unrelated to *ΔInvSpreadInTicks* and positively related to *ΔRelMinTick*. The signs and qualitative significance of the control variables are the same as observed for our primary samples. Our primary results thus are not likely due to unidentified phenomena that are unrelated to decimalization.

The estimated intercept coefficients for all three stock group regressions are significantly negative. If the control variables in the regression adequately control for all factors that significantly determine specialist participation, we can interpret this result as follows. Following decimalization, specialist participation rates would have dropped if specialists could not have stepped ahead at decreased cost and if they could not have taken advantage of the additional price points.[15] The drop in specialist participation would have been due to increased competition from limit order traders and their tightening of the spreads. The estimated intercept coefficients indicate by how much specialist participation rates would have decreased if decimalization had not relaxed the negative obligations. Specialist participation would have dropped by roughly 9, 13, and 14 percentage points, respectively for small, mid-cap, and large stocks.

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[14] We also estimated the model using OLS. Our results were qualitatively similar, though statistically somewhat less significant. The maximum likelihood results are more significant because stocks for which the dependent variable is poorly estimated are given less weight.

[15] Analysts usually do not make inferences from regression intercepts because the intercepts depend on the means of the independent variables. In this model, these means are mean changes in the variables that determine profits. The intercept reflects these mean changes, which is exactly what is necessary to control for the effects of these variables.

4. Specialist Profits

We begin this section with a brief analysis of the changes in the effective spreads that specialists earned on their trades. We then discuss the measurement of their actual trading profits and the spectral decomposition of these profits by trade and calendar time horizons. We conclude by presenting our cross-sectional analyses of changes in specialist profits at various time horizons.

4.1 Specialist Effective Spreads and Price Improvement

As discussed above, decimalization decreased quoted spreads and increased the fraction of trades that specialists made inside the quote. These results imply that effective spreads or price improvements that specialists offered traders decreased following decimalization.[16] Both decreased in all three of our stock size groups (Table 4, Panel A). The mean effective spread respectively decreased by 1.0, 1.6 and 1.5 cents for small, mid-cap, and large stocks. The mean price improvement likewise decreased by 3.0, 3.3 cents and 3.9 cents.

Interestingly, the mean effective spread for those trades that occurred inside the spread increased by 1.5, 1.1, and 1.0 cents for small, mid-cap, and large stocks, respectively. Thus, the one-penny price increment allowed specialists to offer less price improvement when stepping in front of the quote.

The effective spread for specialist trades decreased least for low price stocks (Table 4, Panel B). For small stocks, the mean change is –0.4 cents for stocks priced under $10 and –1.5 cents for stocks priced over $25. The difference is due in part to the increase in the effective spread for specialist trades executed inside the quote. This spread increased slightly more for low price small stocks (+1.9 cents) than for high price small stocks (+0.9 cents), while the decrease in dollar price improvement was slightly greater for the low price small stocks (-3.1 cents versus -2.5 cents). The mid-cap and large stock groups also exhibit a similar relation between specialist effective spreads, price improvement, and prices.

[16] The effective spread is twice the difference between the trade price and the midpoint of the bid and ask prices. Price improvement is the difference between the trade price and the bid or ask price that the specialist's customer would have received had the trade occurred at the best bid or offer. The total quoted spread thus is the effective spread plus twice the price improvement.

4.2 Measurement of Specialist Profits

Specialist profits are the difference between their trading profits and any operational costs (labor, telecommunications, …) that they incur making markets. Since their direct costs did not likely change much over the short sample period, any change in profits due to decimalization should be almost exclusively due to a change in their trading profits.

We compute specialist trading profits by tracking changes in the value of their inventories. Following Hasbrouck and Sofianos (1993), we measure trading profits on a mark-to-market basis. Let p_t denote the transaction price at time t, and let n_t denote the number of shares held by the specialist at time t. The mark-to-market profit at time t is the change in the market value of the specialist inventory,

$$\pi_t = n_{t-1}\left(p_t - p_{t-1}\right), \tag{3}$$

so that total profit in any given period is the sum of π_t in that period.

Since we do not know initial inventories, we take them to be zero at the beginning of the pre- and the post-decimalization sample periods. We therefore do not measure actual specialist trading profits, but rather the difference between their actual trading profits and the mark-to-market profits from holding their initial inventory positions. This issue should not seriously affect the results because we expect that decimalization primarily affected high frequency profits. Since we lack data on operational expenses and commission revenue, we examine only trading profits and not net specialist profits.

Following decimalization, the median gross profit per day for specialists handling small stocks decreased insignificantly from \$380 to \$350 (Table 5). Similarly, there was an insignificant decline in the mean gross profit for mid-cap stocks (-\$7,740) and for large cap stocks (-\$22,950). The decline in mean gross profits was also insignificant for all stocks groups. This less-than-dramatic change in gross profits may be the result of offsetting effects of decimalization. While the decrease in cost of trading and increase in trading opportunities was potentially good for specialist profits, the decrease in spreads surely dampened the profitability of their trades.

We do not dwell on gross profits, however, because their variation largely depends on long run phenomena. Since we expect that the reduction in tick size will primarily affect the profitability of short term trading strategies, we turn now to the decomposition of trading profits.

4.3 Decomposition of Specialist Profits

Specialists often engage in long term speculative trading strategies in addition to the high frequency trading strategies normally associated with dealing. Both types of trading contribute to their profits, but decimalization probably only affects profits from their high frequency trading strategies. Accordingly, we use spectral methods to decompose specialist profits into high, medium, and low frequency components following, and expanding upon, Hasbrouck and Sofianos (1993).

4.3.1 The Hasbrouck and Sofianos Decomposition

The appendix to Hasbrouck and Sofianos (1993) provides a detailed description of the spectral decomposition of profits using real analysis. We briefly restate their analysis using linear algebra since many people will find the intuition easier to understand using these methods.

Any data series x_t of length n can be represented as

$$x_t = \sum_{k=0}^{m} \left(\alpha_k \cos\left(\omega_k t\right) + \beta_k \sin\left(\omega_k t\right) \right) \tag{4}$$

where $m = n/2$ if n is even and $(n-1)/2$ otherwise, $\omega_k = 2\pi k/n$ are the Fourier frequencies, k counts the number of waves of the associated frequency that span the sample, and $\{\alpha_k\}$ and $\{\beta_k\}$ are the Fourier coefficients. For expositional convenience, assume that n is even. The Fourier coefficients generally are obtained using specialized algorithms such as the Fast Fourier Transform, but in principle they can be obtained simply by solving the following linear equation:

$$\mathbf{x} = \begin{bmatrix} \mathbf{C} & \mathbf{S} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{bmatrix} \equiv \mathbf{Tc} \tag{5}$$

where $\mathbf{x}$ is the $n \times 1$ data series vector, $\mathbf{C}$ is the $n \times (m+1)$ matrix $\left[\cos\left(\mathbf{t}\boldsymbol{\omega}_k\right)\right]$, $\mathbf{S}$ is the corresponding $n \times (m+1)$ matrix of sines, $\mathbf{t}$ is the $n \times 1$ column vector of the equal-spaced series

$\{1:n\}$, $\boldsymbol{\omega}_k = 2\pi\mathbf{k}/n$ is the $1\times(m+1)$ row vector of the frequencies, $\mathbf{k}$ is the $1\times(m+1)$ row vector of the series $\{1:(m+1)\}$, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $(m+1)\times 1$ vectors of $\{\alpha_k\}$ and $\{\beta_k\}$. The Fourier coefficients thus are simply a linear transform of the data series.[17]

The key to understanding the Hasbrouck and Sofianos profit decomposition is to note that the columns of the trigonometric matrix $\mathbf{T} = [\mathbf{C} \quad \mathbf{S}]$ are orthogonal, so that any dot product of one column with any other is zero.[18] Recall from equation (3) that specialist profits are the product of the change in price with the previous inventory position. Total profit therefore is the dot product of the vector of lagged inventories with the vector of price changes. Let these vectors be called **x** and **y** and let their Fourier transforms be $\mathbf{c}^{\mathbf{x}}$ and $\mathbf{c}^{\mathbf{y}}$ so that $\mathbf{x} = \mathbf{T}\mathbf{c}^{\mathbf{x}}$ and $\mathbf{y} = \mathbf{T}\mathbf{c}^{\mathbf{y}}$. Their dot product is $\mathbf{x}'\mathbf{y} = \mathbf{c}^{\mathbf{x}\prime}\mathbf{T}'\mathbf{T}\mathbf{c}^{\mathbf{y}}$. Since the columns of **T** are orthogonal, the matrix $\mathbf{T}'\mathbf{T}$ is a diagonal matrix so that

$$(6) \qquad \mathbf{x}'\mathbf{y} = \sum_{k=0}^{m} \left(\mathbf{C}_k'\mathbf{C}_k \alpha_k^x \alpha_k^y + \mathbf{S}_k'\mathbf{S}_k \beta_k^x \beta_k^y \right)$$

where $\mathbf{C}_k$ and $\mathbf{S}_k$ are the k^{th} cosine and sine columns of **T**. The dot product $\mathbf{x}'\mathbf{y}$ thus is a weighted sum of the products of the Fourier coefficients of **x** with those of **y** for each *k*. In spectral terminology, these *k* terms constitute the cross-spectrum.

Following Hasbrouck and Sofianos (1993), we identify as high frequency profits the sum of all *k* terms whose corresponding wavelength is less than or equal to 10 trades. We likewise identify medium and low frequency profits as the sums of those *k* terms with corresponding wavelengths of 11 to 100 trades, and more than 100 trades.[19] These identifications derive their

[17] The trigonometric transform matrix **T** is of rank *n*. Since it has *n* + 2 columns if *n* is even and *n* + 1 columns if *n* is odd, the generalized inverse must be used to identify the Fourier coefficients using linear algebraic methods. The additional columns come from the zero frequency components, which are column vectors of ones for the cosine and of zeros for the sine. The zero frequency cosine thus represents the series mean.

[18] The columns are orthogonal because the sine and cosine waves are never in synch with each other (and therefore uncorrelated), they all have different frequencies, they are evaluated at equal intervals, they each cycle a whole number of times over the sample, and the sine and cosine at a given frequency are orthogonal.

[19] These cutoffs occur at $k_{Med} = 2m/10$ and $k_{Low} = 2m/100$. When these formulas do not yield integer values, we interpolate over *k* to sensibly assign the cross-spectral weights of the *k*'s to the two adjacent frequency bands. For example, if $k_{Med} = 50.4$, we assign all cross-spectral weight for $k = 50$ to medium frequency profits, 40 percent of the cross-spectral weight for $k = 51$ to medium frequency profits, and the remainder of the cross-spectral weight for $k = 51$ to high frequency profits.

meaning from the time-structure associated with the Fourier representations of the inventories and the associated price changes. We do not assume that deterministic cyclic processes generate the data. Instead, we use spectral methods only to transform the data to facilitate their useful interpretation.

4.3.2 The Generalized Decomposition

The relation between trading time and calendar time differs substantially across stocks. For the most actively traded stocks, 10 specialist trades may occur within a few minutes or less. For the least actively traded stocks, 10 specialist trades may occur over several days. Since specialist-trading strategies may operate in both trading time and calendar time domains, we also decompose profits by calendar time horizons.[20]

To ensure that our analyses are truly calendar time analyses, we drop the assumption implicit in standard spectral analyses that the observations are equally spaced in time.[21] Unfortunately, although we can compute Fourier transforms in calendar time for unequally spaced data by using the generalized inverse to solve (5) with **T** computed from unequally spaced **t**, the columns of the cosine and sine matrices are not orthogonal when the data are not equally spaced. Since orthogonality is essential to obtain an additive decomposition of profits across frequencies, we cannot use this approach. Instead, we use linear orthogonal projections to generalize the Hasbrouck and Sofianos method to allow for uneven spacing of the trades through time. Our method is a generalization because it exactly produces the Hasbrouck and Sofianos results when the data are equally spaced.

Specifically, we use OLS regression methods to estimate the following model:

$$(7) \qquad x(t) = \sum_{k=1}^{k_{Med}} \left(\alpha_k \cos(\omega_k t) + \beta_k \sin(\omega_k t) \right) + \varepsilon(t)$$

where k_{Med} is the cutoff *k* (specified below) that separates medium frequencies from high frequencies and *t* is now an index that runs from 0 to *n* upon which the trade times are mapped.

[20] Harris (1986 and 1987) and the papers cited therein discuss how trade time and calendar time differ.
[21] We could translate from trading time to calendar time by assuming that the trades are equally spaced in time and identify the cutoff *k* values that correspond, on average, to calendar horizons. This approach transforms a trade time domain approach to calendar domain approach only by varying the cutoff *k* values. The approach described in this section is a true calendar domain approach.

For mapping purposes, t is 0 at 9:30 AM on the first day of the sample period and t is n at 4:00 PM on the last day of the sample period. We concatenate trading days so that 4:00 PM on one trading day and 9:30 AM on the next trading day correspond to the same t.[22] Thus, a trade that takes place at 11:30 AM on the first day of our 15-day sample in a stock that has 300 total specialist trades would be assigned a value of $t = 6.154$ (2 hours into the first day divided by 6.5 hours per day divided by 15 days in the sample period times 300 trades in the sample.)

The linear algebra representation of (7) is

$$(8) \qquad \mathbf{x} = \begin{bmatrix} \mathbf{C}_{Low\&Med} & \mathbf{S}_{Low\&Med} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_{Low\&Med} \\ \boldsymbol{\beta}_{Low\&Med} \end{bmatrix} = \mathbf{T}_{Low\&Med}\mathbf{c}_{Low\&Med} + \boldsymbol{\varepsilon}_{High}$$

where $\mathbf{C}_{Low\&Med}$ and $\mathbf{S}_{Low\&Med}$ consist of the first $k_{Med}+1$ columns of **C** and **S**, which are now computed from the unequally spaced series of times **t**. The OLS estimated residual of this regression, $\hat{\boldsymbol{\varepsilon}}_{High}$, is the high frequency component of **x**. It represents the variation in **x** that cannot be explained by the low and medium frequency sines and cosines in $\mathbf{T}_{Low\&Med}$.

To obtain the medium and low frequency components of **x**, we use OLS to estimate the following model:

$$(9) \qquad \mathbf{x} - \hat{\boldsymbol{\varepsilon}}_{High} = \begin{bmatrix} \mathbf{C}_{Low} & \mathbf{S}_{Low} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_{Low} \\ \boldsymbol{\beta}_{Low} \end{bmatrix} = \mathbf{T}_{Low}\mathbf{c}_{Low} + \boldsymbol{\varepsilon}_{Med}$$

where $\mathbf{C}_{Low}$ and $\mathbf{S}_{Low}$ consist of the first $k_{Low}+1$ columns of **C** and **S**, and k_{Low} is the cutoff k (specified below) that separates low frequencies from medium frequencies. The dependent variable in this regression, $\mathbf{x} - \hat{\boldsymbol{\varepsilon}}_{High}$, is the sum of the low and medium frequency components of **x**. OLS estimation decomposes this sum into the low frequency component $\mathbf{T}_{Low}\hat{\mathbf{c}}_{Low}$ (that depends only on the low frequency sines and cosines) and the medium frequency component $\hat{\boldsymbol{\varepsilon}}_{Med}$ so that $\mathbf{x} = \mathbf{T}_{Low}\hat{\mathbf{c}}_{Low} + \hat{\boldsymbol{\varepsilon}}_{Med} + \hat{\boldsymbol{\varepsilon}}_{High}$. The linear projections ensure that the three components are orthogonal. When the series of times **t** is equally spaced, the regression coefficients

[22] Although our method allows us to map overnight and weekend periods, doing so does not yield significantly different calendar decompositions.

produced in these generalized decomposition method are exactly equal to the Fourier coefficients of **x** described above because the columns of **T** are orthogonal.[23]

We obtain the calendar time low, medium, and high frequency profits for each stock by using this method to decompose the lagged inventory and price change series. The dot products of these two corresponding series provide the low, medium, and high frequency profits. The three types of profit sum to total profits because the decomposed series are orthogonal.

We identify low, medium, and high frequency profits as the sums of all terms whose corresponding wavelengths are less than or equal to ½ day, ½ to 3 days, and over 3 days. The associated cutoff *k*'s are $k_{Med} = 30$ (15 days divided by ½-day period) and $k_{Low} = 5$ (15 days divided by 3-day period). Unlike the trade time decomposition, these cutoff *k*'s are not proportional to the number of observations in the sample. Accordingly, the model estimates zero high frequency profit when the number of observations is 61 or less, and zero medium frequency profit when the number of observations is 11 or less.[24] We therefore dropped such stocks from our cross-sectional analyses.

4.4 Preliminary Profit Characterizations

We initially decompose trading profits using the calendar-time spectral method. The residuals of equations (8) and (9), estimated separately for inventories and price changes, give the respective high and medium frequency components associated with each trade. The low frequency components are given by the predicted values from (9). The product of the inventory and the price change components estimate the profits associated with the frequency components. Following the univariate test procedure described above, we sum each profit component by day for each stock, and then obtain daily cross-sectional averages of each component for each stock group. We then average these time-series of cross-sectional means across days to obtain results that we report in Table 6.

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[23] Although we use our method only to compute orthogonal decompositions for bands of low, medium and high frequencies, the method can be used to create a fully orthogonal transformation of the original series.

[24] The model uses 61 degrees of freedom to compute the low and medium frequency components. The mean accounts for one degree of freedom and the 30 frequencies for *k* between 1 and $k_{Med} = 30$ each account for two degrees of freedom for their sine and cosine terms.

Consistent with Hasbrouck and Sofianos (1993), we find that specialist trading profits largely accrue at high frequencies. When based on calendar time, high frequency (< ½ day) profits are positive for each stock group (Panel A). When based on trade time (Panel B), high frequency (< 10 trades) and medium frequency (10 to 100 trades) profits are positive in each sample period. The difference between the trade- and calendar-time profit decomposition estimates is due primarily to the fact that the number of trades per ½ day typically exceeds 100, especially for the mid-cap and large cap stock groups.

The negative low frequency profits may reflect unprofitable speculation, or the costs of offering liquidity when no one else is willing to offer it. We find that the cross-sectional variance of the low frequency profits is very high, as does Hasbrouck and Sofianos (1993). We also show that the time-series variance of cross-sectional mean daily profits is much higher for low frequency profits than high frequency profits. As expected, the higher frequency trading strategies apparently produce much more regular profits than do low frequency trading profits.[25]

The decomposed results show that the mean post-decimalization decrease in gross profits discussed above (Table 5) for mid cap and large firms, was due primarily to decreases in low frequency profits. The near zero change in gross profits for small firms were due to offsetting increases in low frequency profits. These results suggest that most of the changes in gross profits were not related to decimalization.

Following decimalization, high frequency profits decreased in both time domains for stocks of all sizes. The decrease profits was statistically significant for the mid-cap and large-cap stock groups. However, since this analysis does not control for other factors that affect specialist profits, we cannot yet confidently attribute these results to decimalization. The cross-sectional analyses presented below disentangles the effects of these factors.

4.5 The Change in Specialist Profits Following Decimalization

To obtain a more precise characterization of the cross-sectional effects of decimalization on trading profits, we estimate cross-sectional regression models in which we control for other

[25] Hasbrouck and Sofianos did not examine the time-series properties of their decomposed profits.

factors that may affect specialist profits. In particular, we control for differences in volatility, volume, relative spreads, and returns.

The dependent variables in these regressions are the changes in profit measured at the various frequencies, scaled by a measure of expected total gross trading profit. We scale the change in profit to account for the fact that gross specialist profits are higher for larger stocks than for smaller stocks (see Table 5). This adjustment ensures that the scale of the dependent variable does not vary by firm size.

We scale by expected total gross trading profit instead of pre-decimalization total gross trading profit because trading profits are quite variable. Had we simply examined the percentage change in profits, much of the variation in the dependent variable would have been due to noise in the pre-decimalization profits in the denominator.[26] Instead, we use the predicted value from a non-linear regression of pre-decimalization total profit on market capitalization to estimate expected total trading profit. We assume that expected profit is given by

$$\log \mathrm{E}\left(TotalProfit_t\right) = \alpha + \log \beta\left(MkCap_t\right). \tag{10}$$

Since observed profits are often negative, we estimate

$$TotalProfit_t = \alpha MkCap_t^{\beta} + \varepsilon_t \tag{11}$$

using non-linear ordinary least squares and $\hat{\alpha} MkCap_t^{\hat{\beta}}$ as the expected total profit estimate.

Our cross-sectional regression model is

$$\begin{aligned} Rel\Delta FreqProfit_i = \beta_0 &+ \beta_1 \Delta RelMinTick_i + \beta_2 \Delta InvSpreadInTicks_i + \beta_3 \Delta RelSpread_i \\ &+ \beta_4 \Delta Volatility_i + \beta_5 Rel\Delta NonBlockVolume_i + \beta_6 Rel\Delta BlockVolume_i \\ &+ \beta_7 \Delta Return_i + \varepsilon_i \end{aligned} \tag{12}$$

where *RelΔFreqProfit* is the change in a trading profit at a given frequency, and *RelΔNonBlockVolume*, and *RelΔBlockVolume* are the changes in nonblock and block volumes, all expressed relative to expected total profit. In addition to the control variables that appear in the specialist participation rate regression, we also include the change in the mean relative spread

[26] Scaling by pre-decimalization profits also would have produced meaningless results when the pre-decimalization profits were negative, and extreme percentage changes when the pre-decimalization profits were near zero.

(spread as a fraction of price), *ΔRelSpread*, to account for the narrowing of the spreads due to decimalization. We scale the volume variables to ensure that they conform to the dependent variable. We expect that increases in volatility, non-block volume and relative spreads will increase high frequency profits. We do not expect that block volume will be significant because specialists generally do not participate in blocks to the same extent that they participate in smaller trades, especially with respect to high-frequency trading strategies. Finally, we also include the change in return, *ΔReturn*, to account for systematic effects that price movements may have on specialist profits, especially given the large price drop in the post-decimalization period.

As with the cross-sectional specialist participation regressions, our key variables are *ΔRelMinTick* and *ΔInvSpreadInTicks.* We expect to that high frequency profits should decrease with *ΔRelMinTick* because the relative value of decreasing the minimum price increment is greater for low price stocks. They should increase with *ΔInvSpreadInTicks* because the relative value of decreasing the minimum price increment is greater for stocks with fewer intra-spread price points.[27]

Like the regression model for specialist participation, this regression model has a dependent variable that includes noise from the time-series data from which it was computed. We can derive the standard errors associated with the decomposed profits by assuming that lagged inventories and current price changes are correlated and jointly independently and identically distributed. The formula depends on the variances of the two variables, their correlation, and the sample size. We did not use this approach because the iid assumption is not reasonable. In particular, bid/ask bounce and mean reversion in inventories imparts substantial time structure to the inventories and price changes and thereby inflates their variances. Instead, we assume that the noise in the profit components is proportional to the variance of the total profits, which we estimate as the variance of the mark-to-market profit time-series times its length.[28] In particular, we model the error term variance as a weighted linear sum of a constant

[27] As an alternative to *ΔInvSpreadInTicks,* we also estimated the regression model using *ΔFracTimeOneTick* to measure the change in opportunities to step-ahead, without substantially different results.

[28] We also considered estimating the variances of the three total profit components directly from the mark-to-market profit time series by using spectral methods to decompose the total variance in the mark-to-market profit time series into high, medium and low frequency component variances. Simulation methods confirmed that the variances produced by this decomposition are correct when the lagged inventories and current price changes are correlated and

and the time-series profit variance, and allow the model to estimate the weights. If estimation places all weight on the constant, the resulting model is OLS. If it places all weight on the time-series variances, the resulting model is GLS. The error term for the high frequency change in profit regression model is

$$(13)\qquad \sigma_i^2 = \tau^2 + \gamma^2 \left(\frac{N_1 \operatorname{Var}\left(MarkToMkTradeProfit_{1,i}\right) + N_2 \operatorname{Var}\left(MarkToMkTradeProfit_{2,i}\right)}{\left(\mathrm{E}TotalProfit_i\right)^2} \right)$$

where τ^2 is the regression model error, the term in parentheses is assumed proportional to variance of the estimation error in the dependent variable, $\operatorname{Var}\left(MarkToMkTradeProfit\right)$ is the time-series variance of the mark-to-market profits given by (3), and *N* is the number of specialist trades. We used similar expressions in the regression models of medium and low frequency profit changes. The unusual error structure again requires that we estimate the model using the maximum likelihood method.

We estimate cross-sectional regressions for each stock size group using the change in each trade- and calendar-time profit estimate (Table 7, Panels A and B).[29] In both time domains, the estimated relation between high frequency profits and *ΔRelMinTick* is negative and significant for small and mid-cap stocks, but not for large stocks. The *ΔRelMinTick* coefficient is also negative and significant in the small stock calendar medium frequency (½ day - 3 days) profit regression. Since small stocks are thinly traded, this result may be due to high frequency specialist trading strategies that operate in trade time rather than calendar time. In sum, the estimated coefficients on *ΔRelMinTick* are consistent with the first of our main hypotheses, that higher frequency profits will increase more for low price stocks due to the greater reduction in the cost of stepping ahead.

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jointly independently and identically distributed. However, an examination of our actual cross-sectional results indicates that the mean estimated decomposed profit variance is much larger than the cross-sectional variance of high frequency profits. Since the former should always be smaller than the latter, it is apparent that time structure in the variables is shifting variance among the components. Using simulation methods, we confirmed that this variance decomposition produces highly biases estimates of the profit variances when the data have any interesting time structure. We also found that the mean estimated decomposed profit variance is much smaller than the cross-sectional variance of low frequency profits. Since the component variances have to add up to the total variance, this result is not informative.

[29] The maximum likelihood estimates are at corner solutions with $\tau^2 = 0$ for several regressions. For these models, and for those for which interior solutions were obtained, the reported R^2, and certainly not the adjusted R^2 that we report, is not bounded below at 0.

Similarly, the estimated coefficient for *ΔInvSpreadInTicks* is positive and significant in the high frequency profit regressions for stocks in each size category in the trade time domain (Panel A). It is also positive and significant in the trade time medium frequency (10-100 trades) profit regressions for mid-cap and large stocks. In the calendar time domain it is significant for only the small stocks. This evidence is strongly consistent with our second main hypothesis, that decimalization will increase specialist profits at higher frequencies most in stocks for which the opportunities to step ahead most increase.

In the large stock sample, the estimated coefficient for *ΔInvSpreadInTicks* is positive and significant in the trade time high frequency profit regression, but not the corresponding calendar regression. The difference is probably due to the fact that the high frequency calendar profits (less than ½ day) encompasses many more trades than do the high and medium frequency trade time profits (less than 10 or 100 trades) for these highly active stocks.[30]

We were surprised to discover that the coefficient on *ΔRelSpread* (change in quoted spread as a fraction of price) was not significantly positive in all of the high frequency profit regressions. It is significantly positive in the small stock trade time regressions, otherwise it was near zero. Thus, in several of the regressions, cross-sectional variation in the change in quoted spreads did not substantially explain cross-sectional variation in high frequency specialist profits, after accounting for changes in the cost of stepping ahead and in the opportunities for stepping ahead.[31]

In all of the high frequency regressions, the estimated volatility and non-block volume coefficients were significantly positive, as expected. The return variable generally is not statistically significant.

The estimated intercept coefficient in all the high frequency profit regressions is significantly negative. If the control variables in the regression adequately control for all factors that significantly determine specialist profits, we can interpret this result as we interpreted the parallel result for the specialist trade participation rate. Following decimalization, high

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[30] As a control experiment, we estimated the same regression using the decimal pilot stock sample. In this sample, the change in high frequency profits is unrelated to both *ΔInvSpreadInTicks* and *ΔRelMinTick* and the sign and qualitative significance of the control variables is the same as observed for our primary samples. Our primary results thus are not likely due to unidentified phenomena that are unrelated to decimalization.

[31] We also estimated the model using OLS. Our results were qualitatively similar.

frequency specialist profits would have dropped substantially if specialists could not have stepped ahead at a decreased cost and if they could not have taken advantage of the new price points. The drop in specialist profits would have been due to increased competition from limit order traders and their tightening of the spreads. As it was, specialist profits dropped for the higher priced stocks, but not by as much as they would have if specialist trading opportunities had not increased.

The estimated intercept coefficients indicate by how much high frequency specialist profits rates would have decreased if decimalization had not relaxed the negative obligations. The calendar time regressions indicate that specialist high frequency profits would have dropped by 12.7, 22.1, and 62.6 percent, respectively for small, mid-cap, and large stocks, while the calendar time regressions indicate drops of 8.7, 20, and 45.9 percent. Although the different results suggest that these predictions are noisy, these results clearly suggest that the profits would have dropped without the concurrent relaxation of the public order precedence rule.

5. Conclusion

The role of the specialist is currently being debated by market regulators, market participants, and by individuals within the NYSE. Much of the debate considers the extent special services provided by specialists are worth the profits that specialists earn as an intermediary. However, little is known about specialist profits or the degree regulatory constraints bind their activity. Using proprietary data, our study provides evidence on the degree specialist participation and profits change following decimalization, and what stock characteristics influence this change.

Decimalization had three main effects on specialists. The decrease in the minimum price increment constrained their trading by allowing public limit order traders to tighten spreads, it decreased the costs of stepping ahead, and it increased the number of opportunities to step ahead. These effects had the most significant impact on low price stocks and on stocks that were commonly quoted with one-tick spreads before decimalization.

The results in this study show that specialist participation rates increased following decimalization. As expected, the increases were greatest for low price stocks and stocks for which the number of opportunities to step ahead increased.

The changes in specialist trading opportunities also affected specialist profits. Our cross-sectional evidence indicates that high frequency specialist trading profits were greater for stocks with the largest drop in the relative minimum tick, and for those with a relatively larger increase in the number of opportunities to step ahead.

If decimalization had not relaxed the public precedence rule constraint and given specialists more price points upon which to trade, the increased competition from limit order traders would have decreased specialist participation rates and specialist profits. Anyone who had hoped that decimalization would have shifted power from specialists to public traders probably failed to recognize that decimalization relaxed the negative obligations that constrain specialist trading.

The results of this study are important because regulators must balance the benefits specialists provide to the market with the costs they impose on the market through their special privileges. Therefore, in addition to how decimalization alters overall market quality, regulators need to know how decimalization affected specialist obligations and privileges, and they must understand how these effects vary across stocks. These issues should also interest investors who trade with specialists, dealers who compete with specialists, and academics studying market-making.

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Table 1

Change in price, spread, and trading activity distributions around decimalization

The data come from the NYSE Trade and Quote (TAQ) files and the NYSE Consolidated Equity Audit Trail (CAUD) files. The sample contains two three-week periods that are both roughly one-month removed from the decimalization of prices on January 29, 2001. The pre-decimalization sample contains 15 trading days from December 4 to December 22, 2000. The post-decimalization sample contains 15 trading days from February 26 to March 16, 2001. Stocks do not appear in the sample if they were included in the pilot decimal program, if they are an ADR, GDR, or Canadian issue, if their stock split during or between the sample periods, if the stock mean price exceeds $200, and if large changes in volume or returns could not be verified. The final sample contains 1,811 NYSE-listed common stocks: 1,311 small stocks, 400 mid-cap stocks, and 100 large stocks. For each variable, the reported test statistics consider whether the time-series mean (or median) of the 15 cross-sectional daily means in the pre-decimalization sample equal the time-series mean (or median) for the 15 cross-sectional daily means in the post-decimalization period.

Panel A: Changes in market capitalization, price, and return distributions

		Small stocks		Mid-cap stocks		Large stocks	
Variable	Period	Mean	Median	Mean	Median	Mean	Median
Market cap ($million)	Pre	550.0	359.9	5,813.6	4,523.1	63,765.6	39,834.2
Price ($)	Pre	17.2	17.2	37.4	37.4	55.1	55.3
	Post	18.7	18.7	38.3	38.4	51.9	52.6
	Change	1.5	1.5	0.9	1.0	-3.1	-2.7
	(*t*- or *Z*-value)	(17.9)**	(4.6)**	(3.8)**	(2.9)**	(-7.5)**	(-4.6)**
Return (basis points per day)	Pre	12.6	-14.3	22.2	22.2	26.7	6.0
	Post	-16.4	-24.0	-23.7	-18.2	-44.2	4.3
	Change	-29.0	-38.3	-45.8	-40.4	-70.9	-1.7
	(*t*- or *Z*-value)	(-0.9)	(-0.8)	(-1.0)	(-0.7)	(-1.3)	(-1.1)
Return std. dev. (basis points per day)	Pre	35.8	35.4	11.5	10.7	5.5	5.3
	Post	28.0	28.4	9.5	8.8	5.4	5.0
	Change	-7.8	-7.0	-2.0	-1.9	-0.1	-0.3
	(*t*- or *Z*-value)	(-11.8)**	(-4.6)**	(-2.3)*	(-2.9)**	(-0.2)	(-0.8)

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 1 - continued

Panel B: Changes in spread distributions

		Small stocks		Mid-cap stocks		Large stocks	
Variable	Period	Mean	Median	Mean	Median	Mean	Median
Spread in ticks	Pre	2.3	2.3	2.1	2.1	2.1	2.1
	Post	10.7	10.7	8.5	8.6	8.6	8.5
	Change	8.4	8.4	6.4	6.5	6.5	6.4
	(*t*- or *Z*-value)	(72.2)**	(4.6)**	(63.5)**	(4.6)**	(37.1)**	(4.6)**
Quoted spread (¢)	Pre	14.2	14.1	13.0	13.0	13.3	13.2
	Post	10.7	10.7	8.5	8.6	8.6	8.5
	Change	-3.5	-3.4	-4.5	-4.4	-4.7	-4.7
	(*t*- or *Z*-value)	(-24.9)**	(-4.6)**	(-34.7)**	(-4.6)**	(-22.2)**	(-4.6)**
Effective spread (¢)	Pre	9.9	9.9	8.7	8.7	8.5	8.5
	Post	7.6	7.7	6.0	6.0	5.8	5.8
	Change	-2.3	-2.2	-2.7	-2.7	-2.7	-2.7
	(*t*- or *Z*-value)	(-21.6)**	(-4.6)**	(-31.8)**	(-4.6)**	(-18.6)**	(-4.6)**
Percentage quoted spread (basis points)	Pre	123.4	122.2	41.3	41.2	26.6	26.9
	Post	81.8	81.4	24.9	24.9	17.7	17.3
	Change	-41.6	-40.8	-16.4	-16.3	-8.9	-9.6
	(*t*- or *Z*-value)	(-32.6)**	(-4.6)**	(-34.1)**	(-4.6)**	(-16.1)**	(-4.6)**
Percentage effective spread (basis points)	Pre	86.9	86.4	28.0	28.0	17.0	17.2
	Post	58.2	57.8	17.6	17.7	12.1	11.9
	Change	-28.7	-28.6	-10.4	-10.3	-4.9	-5.3
	(*t*- or *Z*-value)	(-28.9)**	(-4.6)**	(-32.4)**	(-4.6)**	(-13.6)**	(-4.6)**
Time with 1-tick spread (%)	Pre	31.1	31.1	40.2	39.7	40.9	40.1
	Post	4.3	4.3	7.0	6.9	6.6	6.5
	Change	-26.8	-26.8	-33.2	-32.8	-34.3	-33.6
	(*t*- or *Z*-value)	(-81.3)**	(-4.6)**	(-63.0)**	(-4.6)**	(-54.8)**	(-4.6)**

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 1 - continued

Panel C: Changes in trading activity distributions

		Small stocks		Mid-cap stocks		Large stocks	
Variable	Period	Mean	Median	Mean	Median	Mean	Median
Transactions	Pre	112.3	114.5	770.2	783.9	3,029.1	2,890.5
(per day)	Post	129.8	132.0	952.3	963.5	3,518.6	3,478.3
	Change	17.5	17.5	182.2	179.6	489.5	587.8
	(*t*- or *Z*-value)	(4.6)**	(3.4)**	(6.3)**	(4.2)**	(3.6)**	(3.1)**
Share volume	Pre	354.9	356.0	3,266.9	3,336.7	23,735.9	20,873.5
(1,000s per day)	Post	297.6	287.9	2,887.1	2,905.8	25,210.5	22,239.8
	Change	-57.3	-68.1	-379.8	-430.9	1,474.6	1,366.3
	(*t*- or *Z*-value)	(-3.8)**	(-3.1)**	(-2.2)*	(-1.9)*	(0.5)	(0.2)
Block volume	Pre	210.2	206.7	2,160.4	2,159.1	18,317.2	15,820.4
(1,000s per day)	Post	158.2	149.6	1,636.4	1,640.1	18,827.5	15,951.8
	Change	-52.0	-57.1	-524.0	-519.0	510.3	131.4
	(*t*- or *Z*-value)	(-4.1)**	(-3.3)**	(-3.5)**	(-2.8)**	(0.2)	(0.1)
Non-block volume	Pre	144.7	144.2	1,106.5	1,113.6	5,418.7	5,118.8
(1,000s per day)	Post	139.4	141.3	1,250.7	1,254.1	6,382.9	6,288.0
	Change	-5.3	-2.9	144.2	140.5	964.2	1,169.2
	(*t*- or *Z*-value)	(-1.1)	(-1.1)	(3.4)**	(2.8)**	(3.1)**	(2.8)**

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 2

Change in specialist participation rates

Mean percentage of shares traded with specialist participation, and mean percentage of transactions with specialist participation, for all stocks and trades, by stock price level, and by price relative to the prevailing quote. For each variable, the reported *t*-statistics consider whether the time-series mean of the 15 cross-sectional daily means in the pre-decimalization sample equal the time-series mean for the 15 cross-sectional daily means in the post-decimalization period. The sample contains 1,811 NYSE-listed common stocks; the numbers of observations in the price-size sorted subsamples used to calculate daily cross-sectional averages are noted in the table.

Panel A: Change in specialist share and trade participation rates

Sample set		Small stocks		Mid-cap stocks		Large stocks	
		Shares	Trades	Shares	Trades	Shares	Trades
All stocks	Pre	22.1	36.4	11.1	27.5	7.9	24.5
	Post	28.0	44.4	13.7	32.8	9.3	30.2
	Change	5.9	8.0	2.6	5.3	1.4	5.7
	t-stat	(15.5)**	(19.1)**	(10.7)**	(11.5)**	(5.9)**	(13.5)**
	N	1,311	1,311	400	400	100	100
By price level:							
Low	Pre	20.1	33.1	5.4	17.3		
(< $10)	Post	27.8	44.4	11.0	31.3		
	Change	7.7	11.3	5.6	14.0		
	t-stat	(16.8)**	(25.8)**	(14.2)**	(19.8)**		
	N	404	404	9	9	0	0
Mid	Pre	22.8	37.0	8.9	23.8	4.6	18.1
($10-$25)	Post	28.6	44.6	13.1	32.0	7.6	29.0
	Change	5.8	7.6	4.2	8.2	3.0	10.9
	t-stat	(14.4)**	(16.8)**	(16.0)**	(17.5)**	(8.2)**	(17.2)**
	N	647	647	95	95	6	6
High	Pre	23.4	40.3	11.9	29.1	8.1	24.9
(> $25)	Post	26.8	44.1	13.9	33.1	9.4	30.3
	Change	3.4	3.8	2.0	4.0	1.3	5.4
	t-stat	(6.3)**	(5.6)**	(7.7)**	(8.7)**	(5.4)**	(12.5)**
	N	260	260	296	296	94	94

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 2 - continued

Panel B: Change in percentage of specialist trades by trade price relative to quote

Sample set		Small stocks		Mid-cap stocks		Large stocks	
		At quote	Inside quote	At quote	Inside quote	At quote	Inside quote
All stocks	Pre	44.4	55.3	42.9	56.5	39.8	59.2
	Post	33.3	65.9	31.2	67.7	28.2	70.1
	Change	-11.1	10.6	-11.7	11.2	-11.6	10.9
	t-stat	(-35.7)**	(34.3)**	(-45.0)**	(42.0)**	(-43.7)**	(38.3)**
	N	1,311	1,311	400	400	100	100
By price level:							
Low	Pre	45.3	54.5	44.3	55.6		
(< $10)	Post	34.3	65.1	31.5	67.8		
	Change	-11.0	10.6	-12.8	12.2		
	t-stat	(-24.1)**	(23.9)**	(-11.9)**	(11.2)**		
	N	404	404	9	9	0	0
Mid	Pre	43.9	55.8	44.2	55.4	43.1	56.5
($10-$25)	Post	32.9	66.5	30.7	68.3	27.4	71.5
	Change	-11.0	10.7	-13.5	12.9	-15.7	15.0
	t-stat	(-29.4)**	(27.7)**	(-37.5)**	(33.7)**	(-24.7)**	(22.6)**
	N	647	647	95	95	6	6
High	Pre	43.9	55.5	42.5	56.8	39.7	59.3
(> $25)	Post	33.1	66.0	31.3	67.4	28.3	70.1
	Change	-10.8	10.5	-11.2	10.6	-11.4	10.8
	t-stat	(-32.9)**	(31.3)**	(-40.8)**	(38.5)**	(-41.9)**	(36.4)**
	N	260	260	296	296	94	94

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 3

Cross sectional determinants of the change in specialist participation rates

The dependent variable is the change in percentage of transactions with specialist participation. *ΔRelMinTick* = -0.0525/*Price* where *Price* is the mean stock price in the pre-decimalization period, *ΔInvSpreadInTicks* is the change in the time-weighted mean spread in ticks, *ΔVolatility* is the change in mean daily return standard deviation, *ΔReturn* is the change in return, *ΔNonBlockVolume*, and *ΔBlockVolume* are the changes in non-block and block volume, respectively, where a trade greater than 10,000 shares is considered a block. Each cell reports the maximum likelihood estimate and t-statistic estimated from (1).

	Stock sample		
	Small	Mid-cap	Large
Intercept	-0.092	-0.132	-0.141
	(-11.3)**	(-10.8)**	(-5.4)**
ΔRelMinTick	-2.269	-8.791	-3.813
	(-4.3)**	(-3.7)**	(-0.4)
ΔInvSpreadInTicks	0.433	0.449	0.509
	(19.3)**	(12.5)**	(6.7)**
ΔVolatility	0.003	-0.001	-0.005
	(2.3)*	(-1.2)	(-1.7)*
ΔNonBlockVolume	-0.001	-0.001	-0.001
	(-3.9)**	(-2.0)*	(-3.0)**
ΔBlockVolume	-0.000	-0.000	-0.000
	(-0.0)	(-0.78)	(-1.3)
ΔReturn	-0.001	-0.001	-0.001
	(-0.9)	(-2.8)**	(-3.1)**
Adjusted R^2	0.25	0.43	0.46
Observations	1,311	400	100

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 4

The effective spread and price improvement of specialist trades

We provide the mean effective spread (in cents) of all specialist trades, by price relative to the prevailing quote, and by stock price level. For each variable, the reported *t*-statistics consider whether the time-series mean of the 15 cross-sectional daily means in the pre-decimalization sample equal the time-series mean for the 15 cross-sectional daily means in the post-decimalization period. The total sample contains 1,811 stocks. None of the top 100 largest stocks have prices below 10 dollars.

Panel A: Specialist effective spreads by firm size

		Specialist effective spreads (¢)			Price
Sample		All trades	At quote	Inside quote	Improvement
Small stocks	Pre	8.6	13.2	4.8	8.7
N=1,311	Post	7.6	9.7	6.3	5.7
	Change	-1.0	-3.5	1.5	-3.0
	t-stat	(-8.8)**	(-24.8)**	(16.2)**	(-65.1)**
Mid-cap stocks	Pre	7.9	12.3	4.3	8.4
N=400	Post	6.3	7.9	5.4	5.1
	Change	-1.6	-4.4	1.1	-3.3
	t-stat	(-15.5)**	(-39.2)**	(10.9)**	(-42.1)**
Large stocks	Pre	7.3	11.8	3.8	8.2
N=100	Post	5.8	7.6	4.8	4.3
	Change	-1.5	-4.2	1.0	-3.9
	t-stat	(-7.5)**	(-19.9)**	(4.2)**	(-17.9)**

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 4 - continued

Panel B: Specialist effective spreads by firm size and price level

		Specialist effective spreads (¢)			Price
		All trades	At quote	Inside quote	Improvement
Small stocks					
Low	Pre	6.4	10.6	3.0	7.6
(< $10)	Post	6.0	7.7	4.9	4.5
N=404	Change	-0.4	-2.9	1.9	-3.1
	t-stat	(-4.2)**	(-22.3)**	(24.7)**	(-62.8)**
Mid	Pre	8.5	13.2	4.8	8.5
($10 — $25)	Post	7.5	9.6	6.2	5.5
N=647	Change	-1.0	-3.6	1.4	-3.0
	t-stat	(-9.7)**	(-26.6)**	(14.6)**	(-46.1)**
High	Pre	11.8	17.0	7.5	10.6
(> $25)	Post	10.3	12.9	8.4	8.1
N=260	Change	-1.5	-4.1	0.9	-2.5
	t-stat	(-8.4)**	(-15.1)**	(5.5)**	(-23.5)**
Mid-cap stocks					
Low	Pre	3.3	6.9	0.4	6.4
(< $10)	Post	2.5	3.3	2.1	2.5
N=9	Change	-0.8	-3.6	1.7	-3.9
	t-stat	(-7.6)**	(-28.6)**	(22.8)**	(-56.5)**
Medium	Pre	5.8	9.6	2.6	7.5
($10 — $25)	Post	4.7	5.8	4.0	3.9
N=95	Change	-1.1	-3.8	1.4	-3.6
	t-stat	(-12.8)**	(-35.1)**	(18.3)**	(-63.3)**
High	Pre	8.7	13.3	5.0	8.8
(> $25)	Post	7.0	8.7	5.9	5.6
N=296	Change	-1.7	-4.6	0.9	-3.2
	t-stat	(-14.6)**	(-35.7)**	(8.1)**	(-33.1)**

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 4, Panel B - continued

		Specialist effective spreads (¢)			Price
		All trades	At quote	Inside quote	Improvement
Large stocks					
Mid	Pre	4.2	8.2	0.9	6.6
($10 – $25)	Post	3.0	4.4	2.4	2.3
N=6	Change	-1.2	-3.8	1.5	-4.3
	t-stat	(-8.2)**	(-21.0)**	(14.2)**	(-67.1)**
High	Pre	7.5	12.1	4.0	8.3
(> $25)	Post	6.0	7.8	5.0	4.5
N=94	Change	-1.5	-4.3	1.0	-3.8
	t-stat	(-7.3)**	(-19.0)**	(3.8)**	(-16.8)**

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 5

Comparison of gross specialist profit distributions

Profits are measured on a mark-to-market basis assuming zero specialist inventories at the beginning of each sample period using equation (3). Gross profits are the sum of the mark-to-market profits over each period stated on a per day basis. The sample contains 1,811 stocks: 1,311 small stocks, 400 mid-cap stocks, and 100 large stocks. For each variable, the reported *t*-statistics consider whether the time-series mean of the 15 cross-sectional daily means in the pre-decimalization sample equal the time-series mean for the 15 cross-sectional daily means in the post-decimalization period.

		Small stocks		Mid-cap stocks		Large stocks	
	Period	Mean	Median	Mean	Median	Mean	Median
Gross profits	Pre	0.38	0.39	9.25	10.97	33.00	34.20
($1,000 per day)	Post	0.35	0.36	1.78	2.84	10.05	11.78
	Change	-0.03	-0.03	-7.47	-8.13	-22.95	-22.42
	(*t*- or *Z*-value)	(-0.1)	(-0.3)	(-1.3)	(-1.3)	(-1.2)	(-1.4)

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 6

Comparison of specialist profit distributions by frequency

Profits are measured on a mark-to-market basis assuming zero specialist inventories at the beginning of each sample period using equation (3). Gross profits are decomposed into high, medium, and low frequency components using the spectral methods described in Section 4.3. The full samples are used for each panel (1,311 small stocks; 400 mid-cap stocks; 100 large stocks). For each variable, the reported test statistics consider whether the time-series mean (or median) of the 15 cross-sectional daily means in the pre-decimalization sample equal the time-series mean (or median) for the 15 cross-sectional daily means in the post-decimalization period. We also report the standard deviation of each series of 15 cross-sectional daily means.

Panel A: Mean of daily cross-sectional average profits decomposed by calendar frequencies ($1,000)

		Small Stocks			Mid-cap stocks			Large stocks		
Frequency	Period	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
High	Pre	1.55	1.59	0.32	12.64	13.06	2.03	57.69	51.34	12.95
(< ½-day period)	Post	1.48	1.46	0.28	10.36	9.81	1.84	47.93	47.47	9.04
	Change	-0.08	-0.16		-2.29	-3.25		-9.76	-3.87	
	(*t*- or *Z*-value)	(-0.7)	(-0.9)		(-3.2)**	(-2.7)**		(-2.4)*	(-1.9)*	
Medium	Pre	0.13	0.12	0.14	-1.17	-1.05	1.07	-11.15	-9.78	6.73
(½ — 3-day period)	Post	-0.04	0.01	0.13	-1.53	-1.51	0.77	-5.07	-5.27	4.15
	Change	-0.17	-0.11		-0.36	-0.46		6.08	4.51	
	(*t*- or *Z*-value)	(-3.4)**	(-2.9)**		(-1.0)	(-1.0)		(2.9)**	(2.7)**	
Low	Pre	-1.30	-0.73	1.08	-2.21	0.32	20.77	-13.54	-16.40	62.31
(> 3 day-period)	Post	-1.09	-1.12	0.61	-7.05	-5.81	8.07	-32.81	-27.54	41.04
	Change	0.23	-0.38		-4.83	-6.13		-19.27	-11.14	
	(*t*- or *Z*-value)	(0.7)	(-0.0)		(-0.8)	(-0.8)		(-1.0)	(-0.9)	

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 6 – continued

Panel B: Mean of daily cross-sectional average profits decomposed by trade frequencies ($1,000)

		Small Stocks			Mid-cap stocks			Large stocks		
Frequency	Period	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
High	Pre	0.84	0.82	0.15	4.73	4.51	0.94	19.54	20.49	7.27
(< 10 trades)	Post	0.76	0.76	0.09	3.97	3.95	0.83	18.51	17.60	3.63
	Change	-0.08	-0.06		-0.76	-0.56		-1.03	-2.89	
	(*t*- or *Z*-value)	(-1.4)	(-1.2)		(-2.3)*	(-2.4)*		(-0.5)	(-1.4)*	
Medium	Pre	0.72	0.76	0.18	6.10	6.06	1.05	28.36	28.01	6.09
(10 ─ 100 trades)	Post	0.65	0.65	0.10	4.92	4.90	0.53	25.62	26.33	5.97
	Change	-0.07	-0.11		-1.18	-1.16		-2.74	-1.68	
	(*t*- or *Z*-value)	(-1.3)	(-1.1)		(-3.8)**	(-3.2)**		(-1.2)	(-1.0)	
Low	Pre	-1.19	-1.10	0.98	-1.58	-3.49	20.10	-14.90	-23.49	60.92
(> 100 trades)	Post	-1.07	-0.97	0.67	-7.11	-2.64	11.08	-34.08	-26.97	48.81
	Change	0.12	0.13		-5.53	0.85		-19.18	-3.48	
	(*t*- or *Z*-value)	(0.4)	(0.0)		(-0.9)	(-0.3)		(-0.9)	(-0.7)	

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 7

Cross sectional determinants of the change in specialist profits

The dependent variable is the change in specialist profits expressed as a fraction of expected profits estimated using (11). Profits are decomposed into high, medium, and low frequency components using the spectral methods described in Section 4.3. *ΔRelMinTick* = -0.0525/*Price* where *Price* is the mean stock price in the pre-decimalization period. *ΔInvSpreadInTicks* is the change in the inverse time-weighted spread measured in ticks. *ΔRelSpread* is the change in the quoted spread relative to price. *ΔVolatility* is the change in the standard deviation of daily returns. *RelΔNonBlockVolume* and *RelΔBlockVolume* are the changes in non-block and block volume, respectively, expressed as a fraction of expected profits. Trades over 10,000 shares are considered a block. $\hat{\tau}^2$ and $\hat{\gamma}^2$ are the estimated variance component coefficients of equation (13). If $\hat{\tau}^2$ = 0, the estimates are equivalent to GLS estimates. If $\hat{\gamma}^2$ = 0, the estimates are equivalent to OLS estimates, otherwise the estimates are maximum likelihood estimates. Each cell reports the coefficient estimate and *t*-statistic estimated from equation (12).

Panel A: Calendar time profit components

	Small stock sample regressions			Mid-cap stock sample regressions			Large stock sample regressions		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Intercept	-0.127	0.008	-0.009	-0.221	-0.035	0.171	-0.626	0.257	0.183
	(-7.4)**	(0.8)	(-0.5)	(-2.0)**	(-0.8)	(1.2)	(-1.7)*	(0.7)	(0.1)
ΔRelMinTick	-9.452	-2.805	0.741	-74.935	21.012	-145.358	614.871	-227.708	583.182
	(-3.9)**	(-1.9)*	(0.2)	(-2.4)*	(1.0)	(-2.2)*	(2.5)*	(-1.0)	(0.6)
ΔInvSpreadInTicks	0.345	-0.023	0.018	0.307	0.177	-1.277	1.766	-1.140	-1.208
	(8.1)**	(-0.9)	(0.6)	(0.9)	(1.06)	(-2.3)*	(1.5)	(-1.0)	(-0.3)
ΔRelSpread	0.000	0.001	-0.001	0.001	-0.000	0.005	-0.054	0.022	-0.101
	(0.74)	(6.8)**	(-1.8)*	(0.5)	(-0.11)	(0.9)	(-2.5)*	(1.1)	(-1.1)
ΔVolatility	0.025	-0.004	-0.020	0.116	-0.012	-0.078	0.098	-0.132	0.012
	(4.2)**	(-1.0)	(-2.0)*	(4.7)**	(-0.71)	(-1.4)	(2.2)*	(-3.2)**	(0.1)
RelΔNonBlockVolume	4.049	0.385	-0.680	3.073	0.661	-2.366	2.229	1.835	4.001
	(12.5)**	(1.7)*	(-1.8)*	(4.4)**	(1.2)	(-1.3)	(1.9)*	(1.7)*	(0.8)
RelΔBlockVolume	-0.011	-0.866	0.595	0.129	-0.348	0.570	0.201	-0.208	-0.804
	(-0.1)	(-15.6)**	(3.9)**	(1.3)	(-4.2)**	(2.1)*	(1.1)	(-1.2)	(-1.1)
ΔReturn	-0.001	-0.001	0.004	0.001	0.000	0.010	-0.002	-0.014	0.027
	(-2.9)**	(-1.7)*	(3.1)**	(0.7)	(0.16)	(1.9)*	(-0.5)	(-2.9)**	(1.5)
$\hat{\tau}^2$	0.01	0.01	0.00	0.02	0.00	0.00	0.01	0.04	0.00
$\hat{\gamma}^2$	0.13	0.09	1.13	0.09	0.08	0.86	0.04	0.03	0.72
Adjusted R^2	0.21	0.03	-0.01	0.06	0.02	0.03	-0.03	-0.04	0.02
Observations	1,311	1,298	1,180	400	400	400	100	100	100

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 7 - continued

Panel B: Trade time profit components

	Small stock sample regressions			Mid-cap stock sample regressions			Large stock sample regressions		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Intercept	-0.087	-0.003	-0.013	-0.200	-0.248	0.165	-0.459	-0.649	0.778
	(-8.3)**	(-0.3)	(-0.8)	(-4.2)**	(-3.0)**	(1.1)	(-3.5)**	(-3.4)**	(0.5)
ΔRelMinTick	-6.702	0.428	-1.436	-38.929	-24.560	-149.633	8.825	234.643	739.461
	(-4.8)**	(0.3)	(-0.5)	(-3.1)**	(-1.1)	(-2.2)*	(0.1)	(1.8)*	(0.7)
ΔInvSpreadInTicks	0.248	0.027	0.009	0.357	0.487	-1.235	0.981	1.333	-2.454
	(8.9)**	(1.1)	(0.3)	(2.6)**	(2.0)*	(-2.2)*	(2.5)**	(2.3)*	(-0.5)
ΔRelSpread	0.000	0.000	-0.001	0.001	0.000	0.005	-0.004	-0.025	-0.107
	(4.1)**	(0.35)	(-0.7)	(1.1)	(0.0)	(1.11)	(-0.6)	(-2.2)*	(-1.2)
ΔVolatility	0.017	0.008	-0.023	0.051	0.092	-0.084	0.040	0.001	-0.041
	(5.2)**	(2.1)*	(-2.4)*	(5.4)**	(5.7)**	(-1.5)	(2.8)**	(0.05)	(-0.2)
RelΔNonBlockVolume	2.690	0.641	-0.461	1.787	2.541	-2.458	1.012	3.797	3.892
	(12.8)**	(2.8)**	(-1.3)	(7.6)**	(6.3)**	(-1.3)	(2.7)**	(6.4)**	(0.8)
RelΔBlockVolume	-0.003	-0.608	0.381	0.062	-0.085	0.354	0.039	0.075	-0.963
	(-0.1)	(-10.9)**	(2.6)**	(2.0)*	(-1.6)	(1.3)	(0.6)	(0.8)	(-1.3)
ΔReturn	-0.001	-0.001	0.003	-0.001	0.000	0.011	-0.001	-0.001	0.016
	(-1.8)*	(-1.4)	(2.4)*	(-0.87)	(0.52)	(2.2)*	(-0.8)	(-0.4)	(0.9)
$\hat{\tau}^2$	0.01	0.01	0.00	0.01	0.03	0.00	0.01	0.00	0.00
$\hat{\gamma}^2$	0.03	0.09	1.03	0.01	0.02	0.91	0.01	0.01	0.76
Adjusted R^2	0.32	-0.13	-0.01	0.22	0.21	0.03	0.02	0.05	0.02
Observations	1,311	1,311	1,311	400	400	400	100	100	100

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Figure 1

Distribution of market capitalization

The log market value of each stock is plotted in descending order, along with the cumulative market capitalization. Market capitalization is computed using the mean price during the three-week pre-decimalization period and the number of shares outstanding at the end of December 2000. Our sample is divided into three capitalization subsamples, using the 100 and 500 stock ranks as breakpoints. *N*=1,811.