Clustering in U.S. Stock Prices
After Decimalization

David Ikenberry
Department of Finance
University of Illinois
1206 South Sixth Street
Champaign, IL 61820
217.333.6396
daveike@uiuc.edu

and

James P. Weston
Jones Graduate School of Management
Rice University
6100 South Main Street
Houston, Texas 77005-1892
713.348.4480
westonj@rice.edu

November 2005

Abstract

Early in 2001, U.S. equity markets transitioned from trading in multiples of 1/16th and 1/8th of a dollar to a decimal format with a minimum tick size of one penny. This change provides a natural experiment to test whether investors prefer to trade at certain prices when their choices are essentially unconstrained by regulation. Theory suggests that if price discovery is uniform, realized trades should not cluster at particular prices, particularly if the cost of defeating time priority is low. However, we find evidence of widespread and persistent price clustering at increments of five and ten cents (nickels and dimes). For many stocks, these trades account for over half of all transaction prices. While this new evidence is broadly consistent with past studies, the extensive degree of post-decimalization price clustering suggests a more fundamental psychological bias by investors for prominent numbers. Contrary to previous studies, we find no difference in price clustering, *ceteris paribus*, between the Nasdaq and NYSE after decimalization. Overall, our results suggest there may be only minor differences between the transactions prices that would prevail under a tick size of five cents relative to the current system.

Thanks to Jim Angel, Alex Butler, Gustavo Grullon, Narasimhan Jegadeesh, Jeff Norman, and seminar participants at Georgetown University, Rice University, Penn State University, Texas Christian University and the Federal Reserve Bank of New York for helpful comments. Particular thanks are extended to David Scott, Rice University Statistics Dept., and also to and to Scott Baggett for data support.

Clustering in U.S. Stock Prices After Decimalization

Abstract

Early in 2001, U.S. equity markets transitioned from trading in multiples of 1/16th and 1/8th of a dollar to a decimal format with a minimum tick size of one penny. This change provides a natural experiment to test whether investors prefer to trade at certain prices when their choices are essentially unconstrained by regulation. Theory suggests that if price discovery is uniform, realized trades should not cluster at particular prices, particularly if the cost of defeating time priority is low. However, we find evidence of widespread and persistent price clustering at increments of five and ten cents (nickels and dimes). For many stocks, these trades account for over half of all transaction prices. While this new evidence is broadly consistent with past studies, the extensive degree of post-decimalization price clustering suggests a more fundamental psychological bias by investors for prominent numbers. Contrary to previous studies, we find no difference in price clustering, *ceteris paribus*, between the Nasdaq and NYSE after decimalization. Overall, our results suggest there may be only minor differences between the transactions prices that would prevail under a tick size of five cents relative to the current system.

Throughout the 19th and most of the 20th centuries, the smallest allowable change in prices for U.S. equities was set at 1/8th of a dollar or 12.5 cents. After a brief transition to sixteenths of a dollar in 1997, the long anticipated change to decimal pricing was completed in early 2001 when the minimum price variation was set at one penny creating one hundred price bins or ticks per dollar. Rather than quoting and trading in multiples of 1/8 or 1/16, investors and intermediaries may now use a much finer grid of prices to negotiate and facilitate trade. The main impetus for this change highlights a general desire of market participants to simplify trade reporting and to potentially reduce bid-ask spreads to as little as one penny.

Debate over this change in tick size has been both extensive and contentious and reflects a complex tradeoff between the costs of transacting and market quality.[1] While decimalization may well benefit retail investors through a decrease in bid-ask spreads, decimal prices can also cause a deterioration in liquidity along other dimensions which can have an adverse impact on institutional traders. In fact, the SEC has publicly stated that the move to decimalization may not be permanent and that other ticks sizes (such as five cents) may be considered in the future.[2]

Within this important debate lays a fundamental question regarding investor behavior: Do people prefer certain prices? To help answer this question, this paper considers the price clustering, if any, that prevails when investors are essentially unconstrained in their choice of possible prices. While a number of previous studies have documented clustering in U.S. stocks under a 1/8th minimum price increment (see e.g., Harris (1991)), the move to decimal prices provides a natural experiment to test whether predictable patterns in prices result from market microstructure effects or from a deeper preference by investors to trade at certain prices.

Theory suggests that in the absence of any friction or bias, transaction prices should be uniformly distributed across all possible ticks or price bins (Niederhoffer (1965) and DeGrauwe and Decupere

[1] There are many recent studies that analyze the effect of decimalization on different aspects of market quality. See, for example, Ahn, Cao, and Choe (1998), Alexander, and Peterson, (2002), Bacidore (1997, 2001), Chakravarty, Harris, and Wood (2001), Chung, Chuwonganant, and McCormick (2003), Chung, VanNess and VanNess (2004), and Weaver (2002).
[2] New York Times, May 15th 2003, Wall Street Journal May 15th, 2003.

(1992)). Moreover, under decimal pricing, the cost of defeating time priority is relatively low. That is, investors who anticipate natural clustering tendencies can, at low cost, easily change their bid- or ask-prices by a penny to avoid these cluster points.[3] This "pennying" behavior (Jennings (2001)) should diminish predictable clustering patterns in the data.

Yet, we find that investors have strong price preferences in post-decimalization price data. In fact, we see a statistically significant *increase* in clustering after the switch to decimal pricing. Consistent with evidence from the psychology literature, we find that price clustering centers on "prominent" increments of 5 and 10 cents. While this tendency to cluster is consistent with a number of theories, the overall degree of clustering is difficult to explain and appears indicative of a general psychological bias or attraction by investors to trade in prominent numbers. Overall, our results suggest there may be only minor differences between the transactions prices that would prevail under a tick size of five cents relative to those observed under the current system.

Using all transaction prices for a comprehensive sample of NYSE and Nasdaq stocks from the beginning of July to the end of December 2002, we document stark evidence of price clustering at nickels and dimes. Prices are not uniformly distributed over the grid of possible prices; instead, nearly half of all trades occur at only 20 percent of the available price intervals. Compared to 1996, the overall extent of price clustering has increased post-decimalization.

We also consider the cross-sectional properties of price clustering predicted by the negotiation/ price resolution hypothesis. Consistent with previous studies, we find that price clustering decreases with trading intensity and increases with firm size, share price, volatility, and bid ask spreads. While this evidence is consistent with the negotiation/price resolution hypothesis and explains much of the cross-sectional *variation* in price clustering, it fails to explain the systematic and overall pervasive *level* of price clustering evident in the post-decimalization data.

In short, the price clustering we see in markets appears to be more extensive than can be

[3] See Jennings (2001) and Edwards and Harris (2001) for evidence of market participants "stepping-ahead" of limit orders or "pennying" investors.

supported by the conventional negotiation/price resolution hypothesis. For example, price clustering does not change in the periods before, during, or after earnings announcements where, arguably, one might expect to observe changes in the degree of price uncertainty. Further, while share price should be an important determinant of price clustering, we find almost no change in price clustering around stock splits. Moreover, price clustering is seemingly pervasive across almost all stocks; widely held and followed companies such as the Dow 30 stocks also display significant price clustering. Even in these well-known and widely-followed stocks where the costs of market making are low, we continue to see a surprising degree of price clustering. The overall level of clustering in prices suggests that market participants share a common bias towards certain prominent prices that psychologists have identified as natural cluster points.

The balance of the paper is as follows. Section I briefly discusses prior theory and evidence on price clustering. In Section II, we review the data. In Section III, we present new evidence of clustering in stock prices, compare these patterns to pre-decimalization clustering and also consider the cross-sectional properties of price clustering. Section IV, considers the robustness of our results. Section V concludes.

I. Should transaction prices cluster?

Earlier papers have established that in the presence of market frictions and uncertainty, prices may cluster at particular focal points. For example, if valuation is uncertain, investors may cluster at particular prices points to reduce search costs. Ball, Torous and Tschoegl (1985) label this the price resolution hypothesis. Accordingly, the tendency to cluster depends on firm characteristics such as size, liquidity, spreads etc. — attributes that arguably relate to uncertainty about firm value and the difficulty of executing trades. Clustering may also be a practice of convenience to reduce the costs of negotiation (see Harris (1991)). Since the cost traders perceive from any rounding error decreases with price, clustering should also be more prevalent in high-price stocks. If the cost of exploiting these patterns and defeating time priority is high because of a coarse price grid, then clustering may survive in observed transaction prices.

Grossman et al. (1997) and Kleidon and Willig (1995) offer an extension to the negotiation/ price resolution hypothesis related to the costs of maintaining a liquid market. When quotes and trades are infrequent, the value of an asset may be more difficult to gauge. This uncertainty may cause market makers to round quotations which may in turn lead to greater price clustering (Harris (1991)). They suggest that price clustering may exist in the cross section, but should vary over time with volatility and liquidity. Interestingly, Grossman et al. (1997) argue that differences in market structure and firm characteristics lead one to expect more price clustering on Nasdaq compared to the NYSE, particularly given the price continuity requirement imposed on exchange specialists.

In contrast to the negotiation/price resolution hypothesis, another factor contributing to price clustering may be a collective preference by investors to voluntarily trade at particular price levels in order to simplify the trading process. The key distinction here is that investors are choosing to simplify the price grid to particular prominent numbers in order to minimize cognitive processing costs. There is evidence in the psychology literature that some numbers are easier to process than others. For example, Shepard, Kilpatric and Cunningham (1975) find that the "even-ness" or "odd-ness" of numbers affects the time or energy required to process the number. Hornick, Cherian and Zakay (1994) find in surveys of self-reported time-based activities that people display a rounding bias for numbers ending in zero or five. Further, they report this bias increases with value. Loomes (1988) finds under experimental settings that subjects frequently round answers to simplify calculations and that the degree of rounding increases with the difficulty of the calculation. Finally, papers such as Goodhart and Curcio (1991) and Aitken, et al. (1996) argue that investors have a basic "attraction" to certain integers like zero or five. These explanations suggest that, while clustering may indeed vary with value, uncertainty, and search costs, price clustering may also stem from a more fundamental desire to simplify the trading process, thus elevating the observed frequency of particular price points.

Empirical evidence of clustering has a long history. Early studies in the 1960s (Osborn (1962), and Neiderhoffer (1965 and 1966)) report a tendency for U.S. stock prices to cluster at whole integers and at even eighths. More recently, Harris (1991) and others find similar price clustering and argue that this behavior is consistent with the negotiation/price resolution hypothesis.[4] There is also considerable evidence of clustering on bid and ask quotes. For example, Christie and Schultz (1995) find evidence that quotes cluster on even eighths (under a one-eighth tick size) while Chung VanNess and VanNess (2004) find evidence of quote clustering on nickel and dime increments after decimalization.

While all of these studies present compelling evidence of price and quote clustering, such studies do not distinguish whether the results represent a rational response by investors to an arbitrary exchange regulation or whether the results instead reflect a deeper psychological bias toward prominent numbers. We use the change to decimal prices as a natural experiment to test this hypothesis. The contribution of our study therefore is not simply to reiterate the well documented existence of clustering, but rather, to explore whether such clustering can be explained by different existing theories of behavior.

II. Data

U.S. equity markets began the final transition from price fractions to decimals in early 2001. The NYSE completed this task in January while the Nasdaq followed in April 2001. In order to allow investors time to adjust to a new price grid, we delay our sample selection by at least one full year and evaluate data from the last six months of 2002. We draw our sample from the universe of all common stocks listed on the CRSP database. We retain only firms that can be matched to the TAQ database, have a price above $5 and less than $500, and actively trade on at least 50 days during our sample period. Our final sample consists of 1,920 stocks from the NYSE and 1,851 stocks from the Nasdaq.

Table I reports summary statistics for our sample according to their respective market. These results reflect cross-sectional patterns based on time-series averages for each firm. Our sample of NYSE firms has a median market cap of about $770 million and a median share price of roughly $19 per share.

[4] For example, Aitken et.al (1996) report evidence of clustering on prices ending in zero and five for Australian stocks, Goodhart and Curcio (1991) report quote clustering in foreign exchange markets while Kahn, Pennacchi, and Sopranzetti (1999) report clustering in bank deposit rates. See Grossman et.al (1997) for a survey of recent evidence on price and quote clustering in different markets.

The number of Nasdaq firms in our sample is slightly smaller than the NYSE sample; this is largely driven by our screening out of low priced and inactive stocks. Not surprisingly, our Nasdaq firms tend to be much smaller in market-cap (the median is $182 million) and trade at significantly lower price levels (the median is $14.18 per share). Other comparisons between the two markets are generally well-known. Trading activity (as measured by the number of trades per day) is higher on the NYSE compared to the Nasdaq.[5] As expected, daily return volatility on the Nasdaq is roughly double that observed on the NYSE. Average bid-ask spreads also tend to be higher for Nasdaq firms.[6]

III. The Evidence

A. Evidence of price clustering after decimalization

In this section we describe the overall level of price clustering found in post-decimalization transaction prices. We consider several measures of clustering. Regardless of which metric we consider, the results all tend to be the same. Our first measure of price clustering is simply the proportion of all prices that represent a nickel (N%) or a dime (D%). Under the null hypothesis of no price clustering, these two proportions should both be equal to ten percent (their frequency within the grid of possible prices). We also estimate two measures of price "concentration" using a variation of the Hirshmann-Herfindal index.[7] Specifically we construct:

$$H = \sum_{i=1}^{B} (f_i)^2$$

where f_i is the frequency (in percent) of trades that occur at fractions $i=1,2,\ldots B$ possible bins. We estimate H based on both the last penny (H1) and last two digits (H2) of the transaction price, respectively. Under the null hypothesis of no price clustering, these measures should be equal to the sum

---

[5] Of course, volume comparison between the two markets is problematic due to inter-dealer trading on Nasdaq. As a result, we present adjusted volume data for Nasdaq stocks following the common convention of dividing reported Nasdaq volume by two. Any inferences based on Nasdaq/NYSE volume comparisons should, as always, be interpreted with some degree of caution.

[6] See Bessembinder (1999), Barclay, Christie, Harris, Kandel, and Schultz (1999), and Weston (2000).

[7] Huang and Stoll (2001) also use a similar measure of clustering.

of B squared "market shares", all equal to 1/B. That is, with no price clustering at the one-penny level, each digit would have a ten percent market share or a value of H1 equal to 0.10. Similarly, H2 would have a value of 1/100 = 0.01 under the null of no price clustering. In the case of perfect price clustering, H1 and H2 would both equal unity.

To construct our measures of clustering, we use all transaction prices for our sample stocks over the entire sample period. Figure 1a plots a histogram for decimal fractions at the one-penny level (e.g. prices where the last digit ranges from 0 to 9). If price discovery is uniform, we expect to see each of the ten bins to hold roughly one-tenth of the pooled transaction prices. Instead we find *prima facie* evidence of price clustering at zero- and five-penny ticks.

Figure 1b plots this information at the two-penny level. Here we see that this pattern for nickels and dimes is remarkably robust. For each nickel and dime, the observed frequency is roughly double what is expected. Trades at 25, 50 and 75 cents occur at frequencies two to three times greater than expected. Bin 0 reflects the frequency of trades that close at a whole integer value. Consistent with some of the early studies about price clustering in the 1960s (e.g. Osborn (1962)) we see that, post-decimalization, the incidence of whole integer prices is nearly five times greater than what is expected under the null. Table II provides more detail on our measures of price clustering by market-cap, number of trades, volatility, and spread. For each firm attribute, we sort stocks into quintiles from low to high; the analysis is performed separately for NYSE and Nasdaq stocks. The negotiation/price resolution hypothesis suggests that clustering should be highest for smaller firms, firms that trade less frequently, firms with comparatively high volatility and firms with higher spreads.

Looking at each of these attributes, the univariate results in Table II are roughly consistent with this hypothesis. For example, Panel A of Table II shows that the combined frequency of nickels and dimes for NYSE firms ranked in quintile one (smallest firms) is 48.1 percent compared to 31.9 percent for those ranked in quintile 5 (largest firms).[8] For Nasdaq stocks, the difference is larger; 57.1 percent for small stocks compared to 33.9 percent for large firms. Looking at the number of trades and bid-ask

[8] Differences between quintiles one and five are, in all cases, statistically significant at the five percent level.

spreads, the results are again generally consistent with the negotiation/price resolution hypothesis. In contrast however, we see little change in price clustering between high and low volatility firms, a finding inconsistent with the negotiation/price resolution hypothesis.

In sum, with the exception of the volatility results, the cross-sectional evidence is generally consistent with the negotiation/price resolution hypothesis. For firms where value is more uncertain or where trading is more difficult, price clustering tends to increase. Yet recognizing this, the overall degree of clustering seems high. In each of these univariate categorizations, the lowest observed levels of clustering are much higher than that forecast under the null. For example, the frequency of nickels and dimes in very large market-cap firms and in firms rated with highest turnover is still 50 percent higher than expected under the null hypothesis.

B. Comparison of price clustering under eighths vs. decimals

B. 1. Nickels and dimes as a partial explanation for old clustering patterns under fractions

Clustering in U.S. stock prices is not a new phenomenon. However, the change to decimalization does provide a fresh, natural experiment to test whether these older price patterns represent a latent preference for base 5 or base 10 fractions. To test this hypothesis, we take each of the post-decimalization prices in our sample period and reclassify them into one-eighth fractional price bins. To accomplish this, we form a window of one-penny bins pooled about a center value of zero, 12.5, 25 cents, etc. to recreate one-eighth fractions. This procedure essentially simulates the one-eighth ticks we would have observed despite the fact that trades actually occurred under a decimal format. For comparison with clustering patterns made under the one-eighths regime, we consider transaction prices for all NYSE and Nasdaq stocks for July 1996.

Figure 2 presents a comparison of the price clustering observed in one-eighth fractional prices in 1996 and that implied from decimal trading in 2002. Looking first at the old price clustering patterns, we see the familiar tendency for price clustering at whole integer prices followed by a preference for even-eighths over odd-eighths. However using more recent data in 2002, we essentially recreate the same pattern. It is important to note that, if anything, there appears to be more price clustering on zero- and even-ticks in 2002 compared to 1996.

This evidence, while circumstantial in some respects, again raises the specter that the price clustering patterns evident in both the pre- and post-decimalization data are driven by a broader set of issues than those associated with the negotiation/price resolution hypothesis. Specifically, the evidence suggests that some portion of the price clustering we see may be attributable to a fundamental psychological bias by investors toward prominent numbers.

B. 2. Are decimal prices more or less clustered compared to one-eighth fractional prices?

The comparison between new- and old-regime price clustering presented above is somewhat *ad hoc*. In this sub-section we more carefully consider whether the degree or extent of price clustering has changed with the adoption of decimal trading. To make this assessment, we consider a two-step process. We first construct a statistic that under the null hypothesis of a uniform distribution should be below some critical value. To construct such a statistic, we rely on a standard Chi-squared "goodness of fit" statistic. That is, we construct the sum of squared deviations between the observed level of price clustering and the level of clustering expected under the null as:

$$D = \sum_{i=1}^{N} \frac{(O_i - E_i)^2}{E_i}$$

Where O_i is the observed frequency of observations in bin i = 1,…,N and E_i is the expected frequency of observations under the null distribution. Under standard regularity conditions, the statistic D is distributed *Chi-square* with *(N-1)* degrees of freedom. Thus, large values of D signify a significant deviation from the expected distribution, which in our case is uniform.

For this statistic only, we draw a random sample of 10,000 transaction prices from the TAQ database in 1996 and in 2002.[9] We then compute the frequency of each observed eighth-fraction and

[9] As noted above, all of our other measures of clustering are based on all transaction prices over the sample period. We employ random sampling for this test to preserve equal power between the sample periods for any test of a given

compare the observed frequency to the expected frequency under the null (under a uniform distribution we expect 1,250, or one-eighth of 10,000 draws). Similarly, we construct a *D* statistic for the 2002 sample period by selecting 10,000 observations and assigning each price to one of ten bins based on the last digit of the transaction price. Such an approach maintains a "fair race" with respect to the power of the test across sample periods. This sampling is done generally for Nasdaq stocks as a group and for NYSE stocks as a separate group. Within each market, we also resample conditional on price and report evidence separately for low-, medium-, and high-priced stocks.

Table III presents the frequency distribution for these random samples along with their associated Chi-square statistics. Not surprisingly, the price clustering described earlier is apparent and we are, of course, able to reject the hypothesis that the sample is drawn from a uniform distribution. For both the Nasdaq and NYSE, over all price ranges, the observed price clustering is clearly not uniform.

However, this test does not address whether price clustering is more or less prevalent in 2002 than in 1996. To do this, in the second step we compare *D* for both the 1996 (D_1) and 2002 (D_2) regimes. Since both statistics have a centralized Chi-square distribution, we can easily form a test statistic for the difference between the distributions by examining the ratio of D_1 to D_2. Given the standard properties of the Chi-square distribution it follows that:

$$\tilde{D} = \left(\frac{D_2}{D_1}\right) \sim F_{K,N}$$

$$\text{Where } D_1 \sim \chi^2_N \text{ and } D_2 \sim \chi^2_K$$

Thus, $\tilde{D}$ has an $F_{K,N}$ distribution. Large values of $\tilde{D}$ signify that the pattern of price clustering under decimalization is significantly greater compared to that observed under the eighths regime. This statistic allows us to test the hypothesis that the degree to which prices deviate from the uniform distribution is the same under the pre- and post-decimalization regimes.

The last two rows of Table III, Panel B present the F-statistics and associated P-values for our tests. Overall, we reject the hypothesis that the deviation of price fractions from the uniform distribution

---

size.

is the same between 1996 and 2002. From this evidence, it appears that price clustering overall has increased under decimalization. This result holds for low- medium- and high-priced NYSE stocks as well. However, for high-priced Nasdaq stocks, we are not able to reject the hypothesis that the pattern of price clustering is the same.

Overall, our results in this sub-section suggest that price clustering has actually increased under decimalization relative to what was observed under one-eighth fractional prices. This is a surprising result given that the cost of defeating price-time priority has decreased significantly under decimalization. This evidence lends additional support to the hypothesis that previously documented patterns in price clustering were not driven by particular market mechanisms, but rather by a more fundamental psychological preference for prominent base-5 and base-10 numbers.

C. Cross-sectional Determinants of Stock Price Clustering

In this section, we consider the cross-sectional determinants of price clustering in a multivariate framework. While sub-section II.A. analyzes price clustering by various firm characteristics, these inferences may be confounded by cross-correlations in some firm-specific factors. Since the cost of price clustering decreases as share price increases, one expects price level to be an important determinant of price clustering. However, share price is also highly correlated with other important factors such as market-capitalization and trading volume, both of which have a negative correlation with price clustering.

We estimate price clustering at the firm level using all transaction prices over the sample period. We then use firm characteristics to explain cross-sectional patterns of price clustering. Our results are insensitive to the price clustering measure we consider. For ease of interpretation, we focus on the frequency of nickels and dimes (N&D) as our measure of price clustering. In the regressions that follow, this dependant variable is constructed as the observed frequency of price clustering *less* the amount of price clustering expected under the null hypothesis (20%). This transformation implies that, under the null hypothesis, the constant term in the regression should equal zero.

Our choice of explanatory variables is motivated by the negotiation/price resolution hypothesis and generally follows from previous literature.[10] Our estimation equation is:

$$
\begin{aligned}
Clustering - E[Clustering] = \alpha + \beta_1 Size + \beta_2 Price + \beta_3 \frac{1}{\sqrt{NT}} + \beta_4 \sigma^2 \\
+\beta_5 Spread + \beta_6 Average\ Trade\ Size \\
+\beta_6 NasdaqDummy
\end{aligned}
$$

Where *size* is the equity market value of the firm, *Price* is the average share price of the firm over the sample period, *NT* is the number of trades, σ^2 is return volatility, *Spread* is the average bid-ask spread, *Average Trade Size* is the average number of shares per transaction, and the *Nasdaq dummy* is equal to one if the firm trades on the Nasdaq; zero otherwise.

To ease interpretation and reduce skewness, our independent variables are put through two transformations. First, the variables are log-transformed. Second, the independent variables are standardized by subtracting the sample mean and dividing by the standard deviation. In this fashion, we are able to easily compare the relative magnitude and importance of the various coefficients. This also ensures that our constant term captures the expected mean level of clustering for the average firm in our sample.

Table IV presents our multivariate regression results. While all of our control variables have a theoretical justification for inclusion in the empirical model, we successively add our controls simply to demonstrate the incremental contribution of each factor. As we observed above, the evidence is generally consistent with the negotiation/price resolution hypothesis. Firms that are seemingly more difficult to trade or where value is more uncertain tend to show more price clustering. Clustering decreases with firm size and trading activity and increases with price, return volatility, and bid-ask spreads.

The R-squared from each regression along with the relative magnitude of the coefficients shows that the much of the cross-sectional variation in price clustering is explained by price, spreads, trade size, and trading activity. While the sign and significance of the Nasdaq dummy variable varies as the regression is increasingly parameterized, in the final model the economic magnitude of the Nasdaq

[10] See, for example, Harris (1991) and Aitken et al. (1996).

dummy is small and statistically insignificant. This suggests that despite two separate organizational forms and the lack of a continuity requirement for Nasdaq stocks, the overall degree of clustering between the two markets is similar after controlling for firm characteristics. In short, the evidence here does not support the hypothesis that market structure plays a significant role in stock price clustering post-decimalization (e.g. Grossman et al. (1997)).

While our regression is successful in explaining much of the cross-sectional variation in price clustering, the significance of our firm-specific factors hide an economically important feature of the data – specifically, the overwhelming size and significance of the constant term in all specifications. While much of the cross-sectional *variation* in clustering can be explained by firm-specific characteristics, these characteristics appear to explain only a modest amount of the total *level* of price clustering in the data.

For example, the estimated constant term in our final regression model is 22. This magnitude implies that, for the typical firm, the proportion of nickels and dimes is roughly 22 percentage points higher than expected. Absent any variation in price, size, uncertainty, liquidity or market structure, there is *twice* as much price clustering than what is expected under the null.

Clearly, the median firm shows clustering that is well above the null hypothesis. Yet from this evidence alone, one cannot necessarily infer whether the overall level of clustering in the market is large, small, or about right. Perhaps the median firm in our sample has characteristics that are conducive to some positive level of price clustering, characteristics that do not apply to a large portion of the population.

An interesting question is whether *any* firm, after adjusting for its characteristics, shows a trading pattern consistent with the expected naïve level of clustering. To test this, we take each firm's characteristics and calculate an expected level of clustering using regression model (5). When applied to our entire sample, we find that *only two* observations (from 3,771 cases) have a predicted level of price clustering consistent with the null hypothesis. In short, while prices clearly deviate from a uniform distribution, it is hard to avoid the conclusion that the overall level of price clustering among all stocks seems high. While firm characteristics explain a large portion of the differences we see in clustering across stocks, the degree of price clustering appears to be driven by some other factor. This result is consistent with a fundamental psychological bias by investors toward prominent numbers.

D. The importance of share price

According to the price resolution/negotiations hypothesis, nominal share price is an important determinant of clustering. As the nominal share price increases, the minimum tick size becomes a smaller percentage of the price and so the cost haggling over one tick becomes relatively small. Prior empirical work (see e.g., Ball, Tourous and Tschoegl (1985), Harris (1991)) along with our results in Table IV do in fact find that clustering increases with nominal share price. However, while there is a clear statistical relationship between share price and clustering, it is not so clear that these firm-specific factors have a material effect in explaining the overall *magnitude* of clustering.

To investigate this relation between share price and clustering in more depth, we consider firms that executed a stock split during 2002.[11] To the extent that price clustering is related to share price, we expect a large decrease in the level of price clustering after a split. Our post-decimalization sample contains 169 stock splits. Similar to what we did for our estimation of earnings announcement effects, we estimate price clustering for intra-day data for all trades 30 days before and after the split.

Figure 3 plots both the median share price and median combined level of the percentage of nickel and dime trades from 30 days before to 30 days following the split. For the subset of firms that executed a split, nominal prices fall from $41 to about $24 per share reflecting roughly a two-for-one average split factor. The negotiation/price resolution hypothesis suggests that price clustering should fall subsequent to a split. Based on the estimated coefficients from our regression model, we expect that this change in price should lead to an approximately 5.5 percentage point decline in the proportion of nickels and dimes.12 However, the data show only a small decline in price clustering in the post-split period. Table V provides

[11] In order to the sample size and the statistical power of our analysis, we extend our sample period by six months to include all stock splits in 2002.

[12] The change from $41 to $24 represents a 0.91 standard deviation change in log price. Given the estimated coefficient on standardized log price of 5.95, this translates to a 5.45 percentage point change in the proportion of nickels and dimes.

greater detail of this same evidence using all of the various measures of price clustering. Comparing columns 1 and 2 of Table V we again see that while there is a statistically significant decline in overall clustering, the size of the decline is minor in economic terms. For example, while the decline in the proportion of nickels is significant at the 1 percent level, this change represents less than two percentage points.

As a further check, we subdivide this split sample into terciles based on post-split share price. For each of the sub-groups, we see a decrease in post-split clustering yet in no case is the change economically meaningful. For example for high priced stocks, the combined percentage of nickels and dimes decreases from 36.6 percent before the split to 33.9 percent afterwards while prices dropped by over 50 percent.

IV. Robustness

A. Stability

The results to this point show compelling evidence of price clustering. In this section we consider the stability of these findings in a variety of different settings. A basic question is whether clustering is stable over time and whether it may be driven some factor(s) that we have not yet considered. In Table VII, we consider the evidence by day of the week, days when the market is up versus down, days of high versus low volatility and finally days within each month of our sample. Within each pooled set of observations, we then estimate overall price clustering. Further, these tests not only serve as a robustness check, but also provide another chance to reconsider the negotiation/price resolution hypothesis.

Panel A of Table VII presents price clustering by day of the week. Prior studies suggest that mean daily returns differ across the week (Gibbons and Hess (1981)). This has been argued to be due to differences in investor behavior over time (Lakonishok and Maberly (1990), Abraham and Ikenberry (1994)), and Sias and Starks (1995)) or perhaps due to the uneven flow of information across weekdays (Damodaran (1989)). Nevertheless, the results in Panel A suggest no meaningful variation in price clustering across the week.

Panel B sorts the evidence by whether the market is rising or falling. For all days in our sample period, we classify a given day into one of five groups on the basis of that day's return to the S&P 500. The groups are defined such that group one has the worst 20 percent of days when the market was falling while group five has those days with the highest returns. Cases where markets are rising or falling rapidly may be indicative of high news days where uncertainty is high. If trading is more difficult on these days, one might expect a higher tendency to cluster. The results show strong stability; there is no perceptible variation according to whether the market is rising on good news, falling on bad or is relatively calm.

Panel C sorts the evidence by the level of the closing value of the VIX index. This index tracks the implied volatility of the S&P 100 and is a widely followed measure of market uncertainty (Fleming, Ostdiek, Whaley (1995), and Whaley (2000) who characterizes this measure as a "fear gauge"). We sort our sample period on the basis of daily closing values of the VIX – group one represents days when the VIX is low and markets are comparatively calm. When markets are noisy and uncertainty is high, such as days in group five, one might expect trading to be more difficult and search costs to be higher. On these days, the negotiation/price resolution hypothesis suggests that price clustering should be higher. Going from low to high volatility does not show much of a change in the tendency to cluster. For high volatility days ranked in group five, point estimates suggests an elevated tendency to cluster, however the economic effect is mild.13

Finally, we consider the possibility that investors, for some reason, were initially slow to learn to trade in a decimalization environment. To accomplish this, we draw a random sample of trades from the last month of each quarter between September 2001 and December 2002.[14] From these random samples we compute our clustering measures for each time period. Table VI, Panel D presents the results of this analysis. As expected, we find that investors did gradually grow accustomed to trading in decimals and

[13] In addition to this analysis, we also examined changes in clustering surrounding quarterly earnings announcements. Consistent with the volatility evidence, we found no significant changes in clustering around earnings announcements, conditional on turnover, size, or the abnormal return surrounding the announcement. These results also suggest the uncertainty has, at best, a mild effect on the propensity to cluster.

[14] Our sampling procedure weights each firm equally to avoid over-sampling from high volume stocks.

there is a monotonic decrease in clustering over time across all four measures. However, by December 2002, almost two years after implementation of decimals on the NYSE, the combined frequency of nickel is still over 40 percent, more than twice the expected level under the null.

B. Price clustering among Dow Jones Industrial Stocks

Although the pattern of clustering on nickels and dimes shows some consistency with the negotiation/price resolution hypothesis, the overall extent of price clustering appears to be larger than expected. Conceivably there should be some set of stocks that, *ex-ante*, show price distributions that are consistent with uniform price discovery. Thus as an additional check, we consider price clustering among the 30 stocks in the Dow Jones Industrial Average over the sample period. Among all equities, these stocks are generally considered to be the most actively traded, widely followed, transparent, and liquid stocks. While the median share price for these stocks is high compared to our sample (median price of roughly $40 compared to about $20 for all NYSE stocks), other firm characteristics suggest that one should see only minimal price clustering in these stocks. Nevertheless, Figures 4a and 4b show price clustering for Dow 30 stocks to be similar to that observed for the overall sample with obvious peaks on nickel and dime price increments. Overall, over 30 percent of all trades for the Dow Jones stocks occur on nickel or dime increments. We see only limited evidence of traders attempting to step in front of or behind these predictable price points.

In sum, the evidence for price clustering at nickel and dime price bins is robust. Although the price clustering evident here is mildly consistent with the negotiation/price resolution hypothesis, the overall extent of clustering is more pervasive than can be explained by this story alone. Moreover, much of the evidence is seemingly inconsistent with the notion prices cluster when trading is difficult and fair value more uncertain. Price clustering does not appear to directly relate to a rising or falling market, market volatility, liquidity, or any seasonal patterns. Clustering is evident in the 30 stocks comprising the Dow Jones Industrial average and does not vary much by day of the week. These results appear to be robust.

V. Conclusions

In a frictionless market, trade prices should have a uniform distribution. Yet for decades a well-developed literature that evaluates one-eighth fractional prices finds a propensity for prices to cluster at particular focal points. These early studies argue that this tendency is driven by the negotiation/price resolution hypothesis – a theory which suggests that when trading frictions exist, value is uncertain, and the cost of defeating time priority is high, investors may be willing to round to a coarse price grid. An alternative hypothesis (one that is difficult to consider given the coarse nature of an eighths system) is that price clustering may be the result of a deeper psychological bias among investors for prominent numbers in the decimal system.

The recent move by U.S. exchanges to a decimal system provides a natural experiment to test whether investors cluster when their choices are essentially unconstrained by exchange regulation and where the cost of defeating time priority is low. We take a fresh look at this question and reconsider whether price clustering is driven by the costs of negotiating and trading or is also affected by a simple psychological bias or preference to trade at certain price points.

We find that, post-decimalization, investors voluntarily choose to trade using a coarser sub-grid of prices than what pennies allow them to do. This price clustering pattern is quite regular and centers on prices that represent prominent numbers in the decimal system – multiples of nickels and dimes. The overall degree of price clustering at nickels and dimes is striking: on average, clustering is about double what one expects under uniformity. In fact, compared to trading under the old fractional regime, we find evidence that price clustering has increased with the onset of decimalization.

Some portion of this tendency to cluster is consistent with the negotiation/price resolution hypothesis. On the other hand, the overall level of price clustering in market prices appears large and well above what can be explained by the cost of transacting. Many aspects of the data simply do not support the negotiation/price resolution hypothesis. For example, while there is a general price effect evident in the data, we see no economically significant decrease in price clustering around stock splits.

Similarly, we see no decrease in clustering after earnings announcements. Further, price clustering does not change between up and down markets, or between periods of high and low market-wide volatility. We even find a striking propensity for clustering among the 30 stocks in the Dow Jones Industrial Average – a set of the largest, most liquid, and widely followed stocks in the U.S.

Taken as a whole, the evidence suggests that psychology may play some role in why prices cluster. Investors appear to be naturally drawn to certain prominent numbers when faced with making decisions under general uncertainty. Of course, this behavior may be perfectly rational. In fact, the psychology literature provides some support for this contention. Shepard, Kilpatric and Cunningham (1975) find that the “even-ness” or “odd-ness” of numbers affects the time or energy required to process the number. Hornick, Cherian and Zakay (1994) find in surveys of self-reported time based activities a rounding bias for numbers ending in zero or five. Given this cost structure, clustering may be a rational equilibrium response to costly cognitive processing.

It is important to note that this analysis makes no attempt to measure the execution quality of orders that are rounded or clustered in either the pre- or post-decimalization periods. Neither do we consider whether decimalization has improved or reduced overall market quality. The economic costs and benefits of decimalization are beyond the scope of this paper and we cannot say whether the current minimum price variation is either too small or not small enough. Nevertheless, given the voluntary revealed preference of investors to trade at certain prominent numbers, our results highlight the importance of considering psychological effects and investor biases in the optimal design and structure of trading environments. In December 2002, trades that occurred on increments of five or ten cents accounted for over 45 percent of all dollar trading volume. Overall, our results suggest that a policy change to price increments of five cents may not have a major effect on observed transaction prices.

References

Abraham, Abraham and David L. Ikenberry, 1994, The individual investor and the weekend effect, *Journal of Financial and Quantitative Analysis* 29, 263-278.

Ahn, Hee-Joon, Charles Q.Cao, and Hyuk Choe, 1998, Decimalization and competition among stock markets: evidence from the toronto stock exchange cross-listed securities, Journal *of Financial Markets* 1, 51-87.

Aitken, M., P. Brown, C. Buckland, H.Y. Izan, and T. Walter, 1996, Price clustering on the Australian Stock Exchange, *Pacific-Basin Finance Journal* 4, 297-314.

Alexander, Gordon J., and Mark A. Peterson, 2002, Implications of a reduction in tick size on short-sell order execution, *Journal of Financial Intermediation* 11, 37-60.

Bacidore, Jeffrey M., 2001, Decimalization, adverse selection, and market maker rents, *Journal of Banking and Finance* 25, 829-55.

Bacidore, Jeffrey M., 1997, The impact of decimalization on market quality: An empirical investigation of the Toronto stock exchange, *Journal of Financial Intermediation* 6, 92-120.

Barclay, Michael, 1999, Effects of market reform on the trading costs and depths of Nasdaq stocks, *Journal of Finance* 54, 1-34.

Bessembinder, Hendrik, 1999, Trade execution costs on Nasdaq and the NYSE: a post-reform comparison, *Journal of Financial and Quantitative Analysis* 34, 387-407.

Ball, Clifford A., Walter N. Torus and Adrian E. Tschoegl, 1985, The Degree of Price Resolution: The case of The Gold Market, *Journal of Futures Markets* 5, 29-43.

Beaver, William H., 1968, The Information Content Of Annual Earnings Announcements, *Journal of Accounting Research* 6, 67-92.

Cahart, Mark M., Ron Kaniel, David K. Musto and Adam V. Reed, 2002, Leaning for the tape: Evidence of gaming behavior in equity mutual funds, *Journal of Finance* 57, 661-693.

Chakravarty, Sugato, Stephen P. Harris and Robert A. Wood, 2001, Decimal Trading and Market Impact, Purdue University working paper.

Chung, Kee H., Chairat Chuwonganant, and D. Timothy McCormick, 2003, Order preferencing and market quality on Nasdaq before and after decimalization, forthcoming *Journal of Financial Economics*.

Chung, Kee H., Bonnie F. VanNess, and Robert A. VanNess, 2004, Trading costs and quote clustering on the NYSE and Nasdaq after decimalization, forthcoming *Journal of Financial Research*.

Damodaran, Aswath, 1989, The weekend effect in information releases: A study of earnings and dividend announcements, *Review of Financial Studies* 2, 607-623.

De Grauwe, Paul and Danny Decupere, 1992, Psychological Barriers in the Foreign Exchange Market, Centre for Economic Policy Research Discussion Paper: 621.

Edwards, A., and J. Harris, 2002, Stepping ahead of the book, working paper, Securities and Exchange Commission.

Fleming, Jeff, Barbara Ostdiek and Robert E. Whaley, 1995, Predicting Stock Market Volatility: A New Measure, *Journal of Futures Markets* 15, 265-302.

Gibbons, Michael R. and Patrick Hess, 1981, Day of the week effects and asset returns, Journal of Business, 54, 579-596.

Goodhart, C., and R. Curcio, 1991, The clustering of bid/ask prices and the spread in the foreign exchange market, Dicussion Paper No. 110, LSE Financial Markets Group Discussion Paper Series.

Grossman, Sanford J. et al., 1997, Clustering and Competition in Asset Markets, *Journal of Law and Economics* 40, 23-60.

Harris, Lawrence, 1991, “Price Clustering and Discreteness” *Review of Financial Studies* 4, 389- 415.

Hornick, Cherian and Zakay, 1994, The influence of prototypic values on the validity of studies using time estimates, *Journal of Market Research Society* 36, 145-147.

Huang R.D., and H.R. Stoll, Tick size, bid-ask spreads, and market structure, *Journal of Financial and Quantitative Analysis* 36, 503-522.

Jennings, Robert, 2001, Getting “Pennied”: The effect of decimalization on traders’ willingness to lean on the limit order book at the New York Stock Exchange, NYSE working paper 2001-01.

Kahn, Charles, George Pennacchi, Ben Sopranzetti, 1999, Bank Deposit Rate Clustering: Theory and Empirical Evidence, *Journal of Finance* 54, 2185-2214.

Kleidon, A. and R. Willig, 1995, Why do Christie and Schultz infer collusion from their data? Working Paper, Cornerstone Research, New York.

Lakonishok, Josef and Edwin Maberly, 1990, The weekend effect: Trading patterns of individual and institutional investors, *Journal of Finance*, 1990 45, 231-244.

Loomes, G., 1988, Different Experimental Procedures For Obtaining Valuations Of Risky Actions – Implications For Utility-Theory, *Theory and Decision* 25, 1-23.

New York Times, “Penny Wise at the NYSE,”, May 15th 2003

Niederhoffer, V., 1965, Clustering in Stock Prices, *Operations Research* 13, 258-265.

Niederhoffer, V., 1966, A new look at clustering in stock prices, *Journal of Business* 39, 309-313.

Osborne, M. F. M., 1962, Periodic Structure in the Brownian Motion of Stock Prices, *Operations Research*, 345-379.

Patell, James M., 1976, Corporate Forecasts Of Earnings Per Share And Stock Price Behavior: Empirical

Tests, *Journal of Accounting Research* 14, 246-276.

Patell, James M. and Mark A. Wolfson, 1979, Anticipated Information Releases Reflected In Call Option Prices, *Journal of Accounting and Economics* 1, 117-140.

Patell, James M. and Mark A. Wolfson, 1981, The Ex Ante And Ex Post Price Effects Of Quarterly Earnings Announcements Reflected In Option And Stock Prices, *Journal of Accounting Research* 19, 434-458.

Shepard R.N., D. Kilpatric and, J.P. Cunningham, 1975, Internal representation of numbers, *Cognitive Psychology* 7, 82-138.

Sias, Richard W. and Laura T. Starks, 1995, The day-of-the-week anomaly: The role of institutional investors, *Financial Analyst Journal*, 51, 57-66.

Wall Street Journal, "SEC Aide Urges Look at Decimal Trading," May 15th, 2003.

Weaver, Daniel G., 2002, Decimalization and market quality, Working Paper, CUNY.

Weston, James P., 2000, Competition on the Nasdaq and the impact of recent market reforms, *Journal of Finance* 55, 2565-98.

Whaley, Robert E., 2000, The investor fear gauge, *Journal of Portfolio Management* 26, no. 3, 12-17.

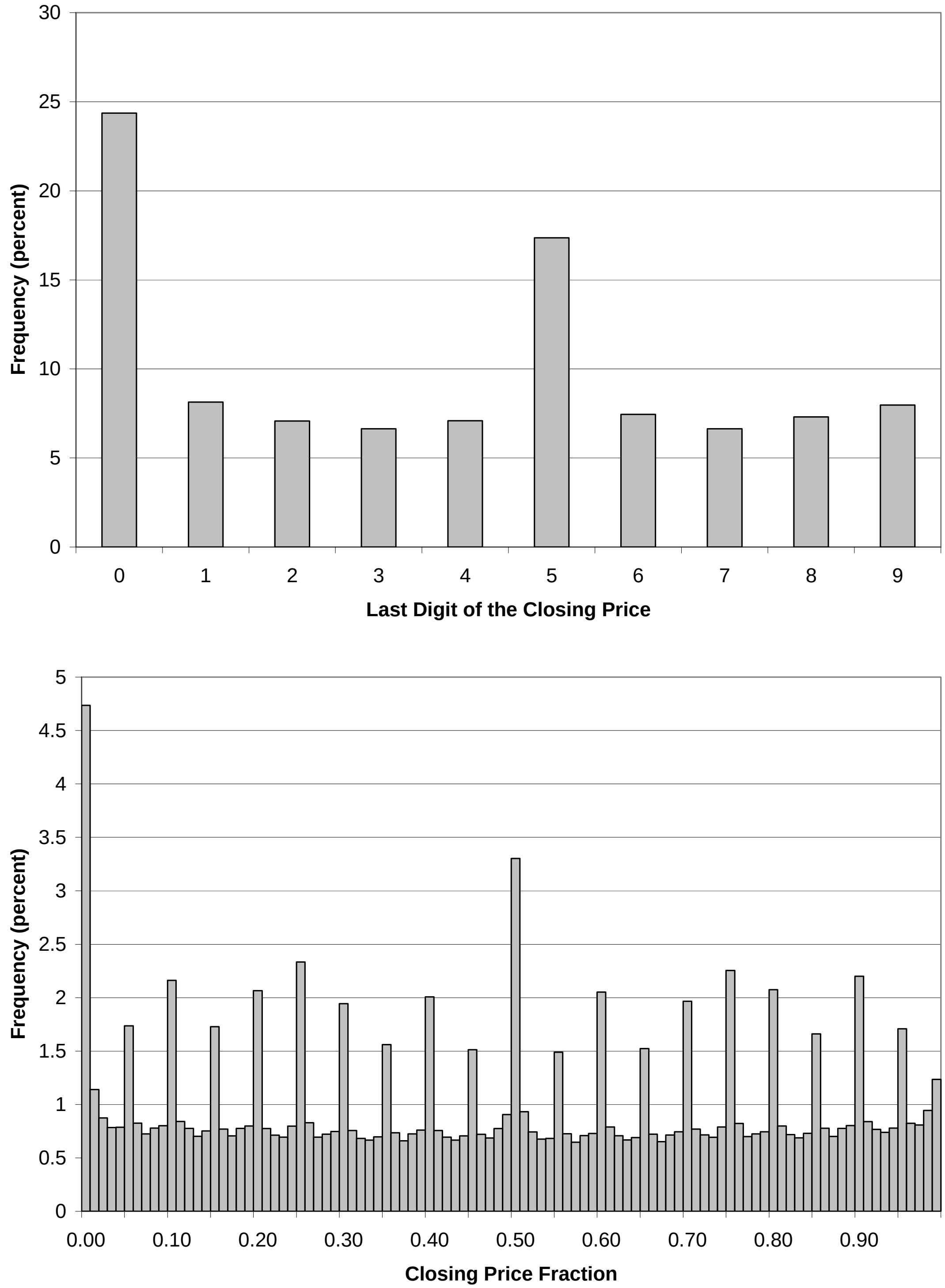

Figure 1. **The post-decimalization distribution of transaction prices**. The top panel plots a histogram of transaction prices based on the frequency of the last digit of the transaction price. The bottom panel plots a similar histogram based on the last two digits of the transaction price. Reported frequencies are computed over all transaction prices for sample stocks between July 2002 to December 2002.

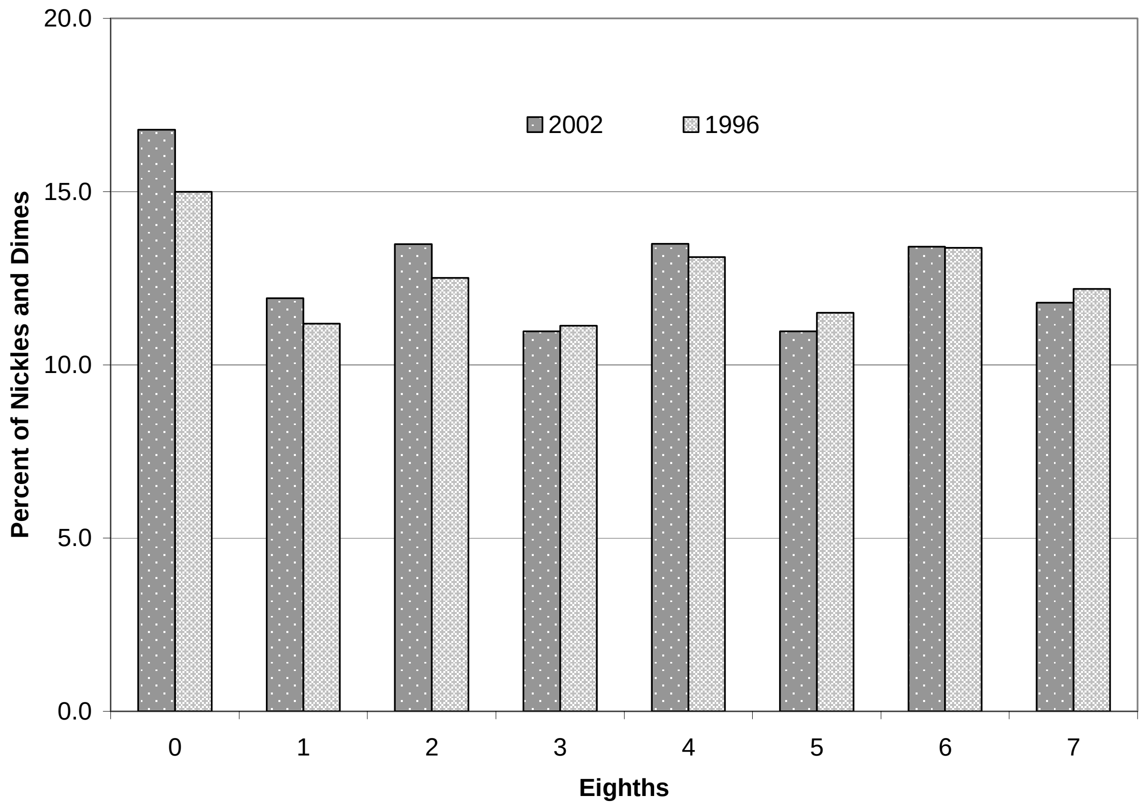

Figure 2. Comparison of price clustering on eighths: 1996 vs. 2002 (simulated). This figure presents a comparison of clustering on eighths between 1996 and 2002. Reported frequencies for eighths for 1996 are based on all transaction prices from TAQ during July 1996. For 2002, reported frequencies of eighths are based on simulated eighths which reflect, for each decimal price, the nearest eighth bin that would have occurred under a minimum tick size of one-eighth.

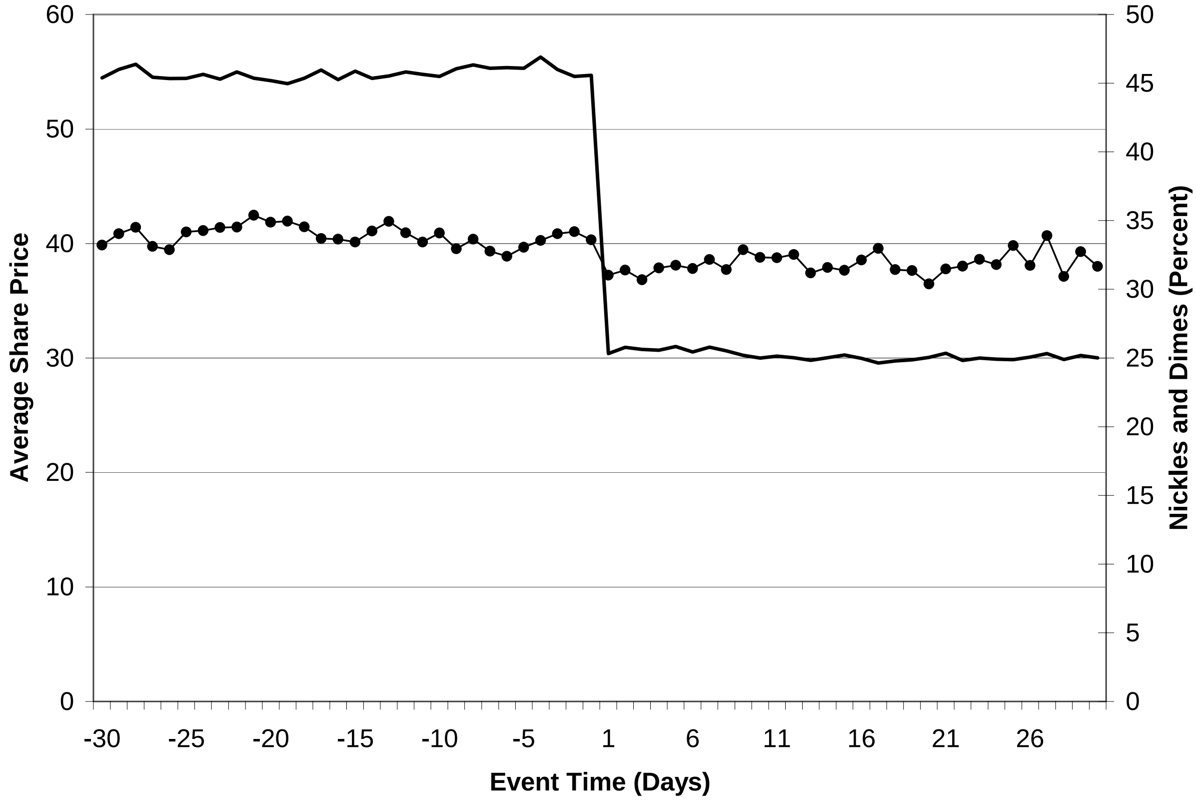

Figure 3. Price clustering around stock splits. This figure presents a time series of average stock prices and the average frequency of prices ending in increments of five or ten cents from 30 days before to 30 days after a stock split. Our sample includes 168 stock splits during 2002. Average prices are based on the equally-weighted cross-sectional mean of all closing prices each day (in event time). The average proportion of nickels and dimes is computed using all transactions (from the TAQ database) for each stock on each event day.

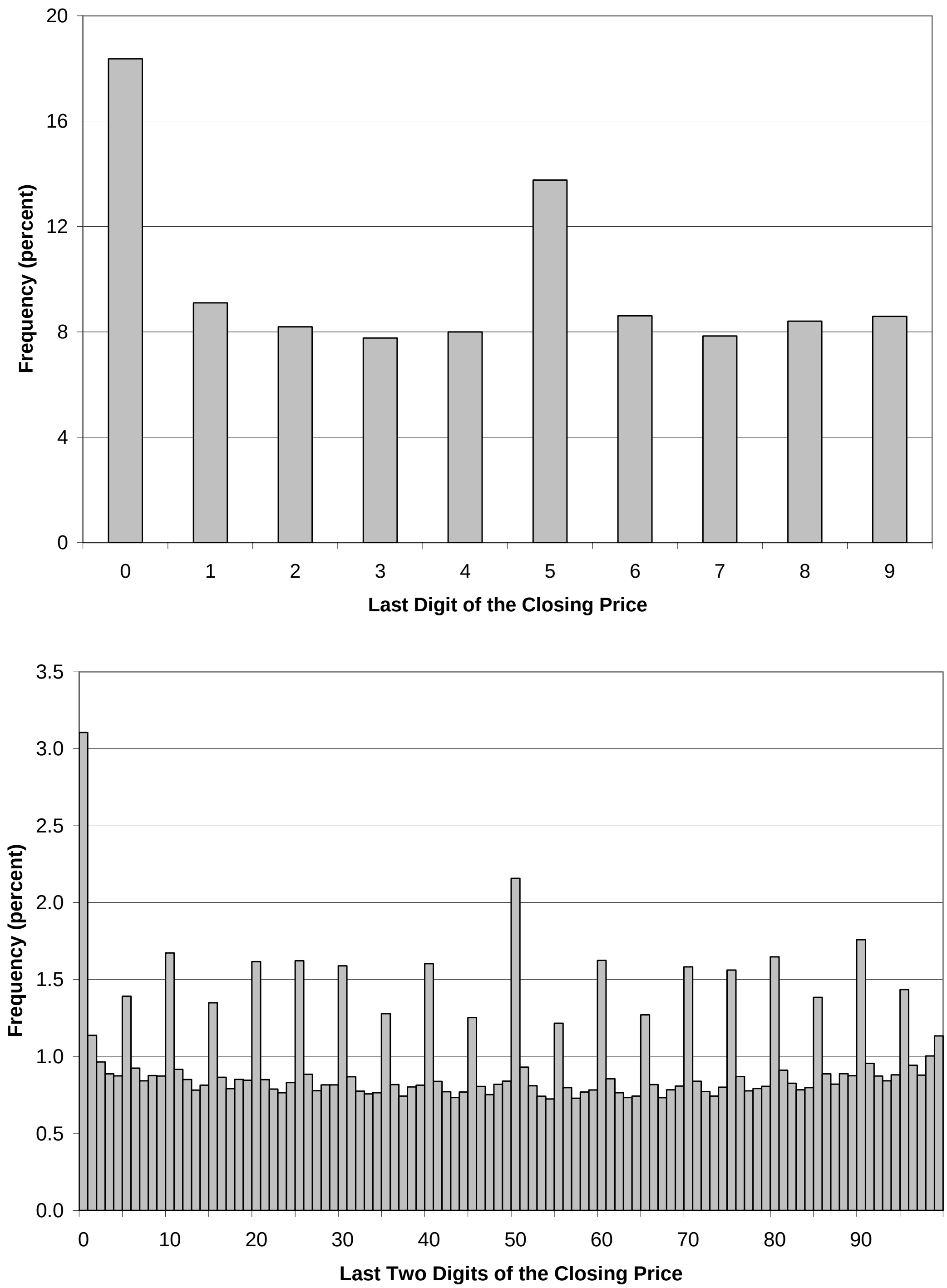

Figure 4. The post-decimalization distribution of transaction prices for stock in the Dow Jones 30. The top panel plots a histogram of transaction prices based on the frequency of the last digit of the transaction price. The bottom panel plots a similar histogram based on the last two digits of the transaction price. Reported frequencies are computed over all transactions (from the TAQ database) for the 30 stocks in the Dow Jones Industrial Average between July 2002 to December 2002.

Table I

Descriptive Statistics

This table provides descriptive information regarding our sample of firms. This information is provided separately for NYSE (Panel A) and Nasdaq (Panel B) firms. Statistics for each firm are constructed based on all transaction prices from July to December 2002. The summary statistics are based on equally weighted cross-sectional averages over all firms in each sample. Market value is constructed for each firm as the number of shares outstanding times the closing price. Average price is based on average daily closing prices. Volume is average daily trading volume in millions of shares. Number of trades is the average total number of transactions per day. Share turnover is constructed as share volume divided by shares outstanding. Return volatility is computed for each firm as the standard deviation of returns over the sample period. Quoted spreads are constructed for each stock as the equally-weighted average ask minus bid price over all quotations on the firm's primary exchange. Relative spreads are quoted spreads divided by the midpoint of the spread.

Panel A: NYSE Listed Stocks

	N	Mean	Std. Dev.	25^{th} %	Median	75%
Market Value	1,920	4,345	15,937	259	770	2,473
Price	1,920	23.30	16.80	12.39	19.13	30.38
Volume	1,920	7.19	18.35	0.38	1.60	6.04
Number of Trades	1,920	66	88	7	31	91
Share Turnover	1,920	0.011	0.013	0.004	0.008	0.013
Return Volatility	1,920	0.028	0.013	0.020	0.027	0.034
Quoted Spread	1,920	0.081	0.119	0.047	0.063	0.094
Relative Spread (%)	1,920	0.510	0.515	0.185	0.334	0.672

Panel B: Nasdaq Stocks

	N	Mean	Std. Dev.	25^{th} %	Median	75%
Market Value	1,851	915	7,753	72	182	469
Price	1,851	17.09	12.99	8.65	14.18	21.68
Volume	1,851	5.56	34.35	0.07	0.41	2.34
Number of Trades	1,851	100	409	2	10	61
Share Turnover	1,851	0.014	0.020	0.003	0.006	0.017
Return Volatility	1,851	0.036	0.015	0.024	0.034	0.046
Quoted Spread	1,851	1.191	2.289	0.148	0.368	1.132
Relative Spread (%)	1,851	1.781	1.587	0.590	1.338	2.501

Table II

Clustering by Firm Characteristic

This table reports measures of clustering observed in transaction prices for NYSE and Nasdaq firms based on all transaction prices from July to December 2002. H1 and H2 are measures of clustering at the one- and two-digit levels respectively. N% and D% represent the observed frequency of transaction prices that fall increments of nickels or dimes This is reported overall and conditional on market-cap, share turnover, volatility and bid-ask spread. Quintiles are defined separately for NYSE and Nasdaq stocks.

	NYSE					Nasdaq				
Market-Cap	1	2	3	4	5	1	2	3	4	5
N%	0.203	0.170	0.154	0.141	0.139	0.224	0.211	0.184	0.167	0.145
D%	0.278	0.228	0.202	0.186	0.180	0.347	0.325	0.267	0.234	0.194
H2	0.022	0.016	0.013	0.013	0.011	0.037	0.031	0.019	0.015	0.013
H1	0.167	0.132	0.119	0.114	0.111	0.207	0.188	0.147	0.131	0.116
Number of Trades										
N%	0.204	0.170	0.152	0.143	0.139	0.226	0.208	0.187	0.165	0.144
D%	0.280	0.228	0.201	0.186	0.179	0.371	0.314	0.268	0.226	0.188
H2	0.025	0.015	0.013	0.012	0.011	0.046	0.025	0.018	0.014	0.012
H1	0.171	0.131	0.118	0.113	0.111	0.226	0.177	0.147	0.127	0.113
Volatility										
N%	0.176	0.162	0.157	0.156	0.157	0.211	0.189	0.182	0.179	0.170
D%	0.228	0.216	0.211	0.211	0.208	0.319	0.285	0.268	0.260	0.235
H2	0.020	0.014	0.014	0.013	0.014	0.034	0.025	0.021	0.019	0.017
H1	0.139	0.130	0.126	0.125	0.124	0.189	0.165	0.153	0.147	0.136
Spread										
N%	0.135	0.143	0.153	0.169	0.208	0.145	0.170	0.193	0.212	0.211
D%	0.167	0.182	0.198	0.224	0.302	0.186	0.231	0.275	0.311	0.365
H2	0.012	0.012	0.014	0.015	0.023	0.012	0.015	0.020	0.028	0.041
H1	0.108	0.112	0.117	0.129	0.179	0.113	0.130	0.154	0.179	0.215

Table III
Comparison of clustering between 1996 (eighths) and 2002 (Decimals)

This table presents a comparison of trade price clustering between 1996 and 2002. Panel A presents a frequency distribution for 10,000 randomly drawn transaction prices for each category for 1996. Cell frequencies are determined based on the price fraction (number of eigths). Chi-square "goodness of fit" statistics are constructed as the sum of squared deviations of the cell frequencies from the expected frequency under the null hypothesis of a uniform distribution (i.e., one-eighth). P-values are based on a Chi-square distribution with 7 degrees of freedom. Panel B is similarly constructed using 10,000 random draws from based on all transaction prices from July to December 2002.. Cell frequencies are based on the last digit of the transaction price fractions. Chi-square "goodness of fit" statistics are constructed for Panel B as the sum of squared deviations of the cell frequencies from the expected frequency under the null hypothesis of a uniform distribution (i.e., one-tenth). P-values are based on a Chi-square distribution with 9 degrees of freedom. In the bottom sets of rows, F-statistics are constructed as the ratio of the two Chi-square statistics. Reported p-values are based on an F-distribution with 9 and 7 degrees of freedom for the case where 1996 clustering is compared to 2002 clustering at the one-digit level.

Panel A: Observed frequencies of price fractions (eighths) in 1996.

			Clustering by Nominal Price Category					
	All Prices		NYSE			Nasdaq		
Eighths	NYSE	Nasdaq	$5<P<$10	$10<P<$30	P>$30	$5<P<$10	$10<P<$30	P>$30
0	0.148	0.192	0.154	0.145	0.153	0.169	0.191	0.228
1	0.116	0.080	0.120	0.115	0.112	0.101	0.077	0.059
2	0.122	0.156	0.116	0.121	0.125	0.136	0.169	0.171
3	0.112	0.084	0.114	0.113	0.111	0.099	0.078	0.056
4	0.129	0.172	0.119	0.131	0.131	0.155	0.169	0.208
5	0.120	0.078	0.120	0.115	0.116	0.098	0.071	0.053
6	0.128	0.157	0.132	0.134	0.133	0.139	0.167	0.170
7	0.125	0.080	0.126	0.126	0.118	0.103	0.079	0.056
N	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
χ^2_7	66.9	1332.9	95.1	70.7	109.6	454.3	1554.0	3251.0
P-Value	0.000	0.000	0.000	0.000	0. 000	0.000	0.000	0.000

Panel B: Observed frequencies of price fractions (decimals) in July-December 2002.

			Clustering by Nominal Price Category					
	All Prices		NYSE			Nasdaq		
Last Digit	NYSE	Nasdaq	$5<P<$10	$10<P<$30	P>$30	$5<P<$10	$10<P<$30	P>$30
0	0.215	0.274	0.219	0.215	0.212	0.269	0.279	0.259
1	0.084	0.078	0.079	0.084	0.089	0.077	0.078	0.081
2	0.077	0.064	0.077	0.077	0.077	0.065	0.063	0.069
3	0.073	0.060	0.073	0.073	0.073	0.059	0.059	0.066
4	0.076	0.066	0.074	0.076	0.077	0.066	0.065	0.071
5	0.162	0.186	0.170	0.163	0.153	0.192	0.188	0.162
6	0.079	0.070	0.077	0.078	0.082	0.069	0.069	0.074
7	0.072	0.061	0.071	0.072	0.073	0.061	0.060	0.067
8	0.081	0.065	0.081	0.081	0.080	0.066	0.063	0.071
9	0.082	0.077	0.079	0.083	0.084	0.076	0.076	0.082
N	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
χ^2_9	2096.92	4632.58	2372.13	2108.12	1912.86	4588.36	4899.98	3519.63
P-Value	0.000	0.0000	0.000	0.000	0.000	0.000	0.000	0.000
F-Statistic$_{9,7}$	31.4	3.5	25.0	29.8	17.5	10.1	3.2	1.1
P-value	0.000	0.057	0.000	0.000	0.001	0.003	0.072	0.469

Table IV
Cross-sectional Determinates of Clustering

This table reports regression evidence where various measures of clustering are regressed on firm specific characteristics. Clustering is constructed based on all transaction prices from July to December 2002.. N&D represents the observed frequency of transaction prices that fall on either nickels or a dimes. Size (market-cap) and Price are calculated as daily averages over the sample period. Sigma calculated as the time-series standard deviation of daily returns over the sample period. The bid ask spread is constructed as the average difference between the bid and asked prices divided by the midpoint of the spread. Each variable (except the Nasdaq dummy) is log-transformed and standardized to have a zero mean and unit variance. T-statistics are reported in parentheses below coefficient estimates.

	(1) N&D	(2) N&D	(3) N&D	(4) N&D	(5) N&D	(6) N&D
Constant	20.691 (94.392)	20.619 (103.277)	20.390 (109.886)	20.882 (115.323)	22.085 (119.538)	21.872 (110.620)
Size	-7.634 (-40.408)	-9.693 (-45.225)	-5.595 (-23.408)	-5.634 (-23.878)	-2.648 (-9.122)	-3.706 (-11.550)
Price	. .	3.839 (22.582)	2.780 (17.514)	3.285 (19.764)	4.757 (27.103)	5.949 (26.78)
1/sqrt(NT)	. .	. .	4.929 (20.010)	5.642 (20.988)	3.868 (13.516)	3.236 (10.770)
Sigma	. .	. .	. .	1.571 (9.172)	1.147 (7.111)	1.287 (7.860)
Spread	. .	. .	. .	. .	6.278 (18.279)	6.612 (19.563)
Trade Size	. .	. .	. .	. .	. .	1.715 (9.240)
Nasdaq	2.121 (6.815)	2.268 (7.928)	2.735 (10.384)	1.732 (6.496)	-0.718 (-2.646)	0.327 (1.080)
Obs	3,771	3,771	3,771	3,771	3,771	3,771
Adj R^2	0.486	0.562	0.648	0.660	0.699	0.710

Table V

Clustering Before and After Stock Splits

This table reports median pre- and post-split share prices and measures of clustering before and after stock splits for sample firms which split their shares during 2002. The median price before and after the split is determined using the last closing price on the day preceding the split and the first closing price after the split has taken effect. Measures of price clustering are reported overall and also conditional on the post-split share price. Here the closing prices on the first day of trading after the split is compared to the nominal price of all shares in the market in which that firms trades. H1 and H2 are measures of clustering at the one- and two-digit levels respectively. N% and D% represent the observed frequency of transaction prices that fall either on an increment of a nickels or dimes. O% represents the observed frequency of "odd-penny" (exclusive of nickels) transaction prices. a, b, and c denote differences in mean clustering before compared to after at the 1%, 5% and 10% levels respectively.

			Post-Split Share Price					
	Overall		**1 (low prices)**		**2**		**3 (High prices)**	
	Before	After	Before	After	Before	After	Before	After
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Median Price	40.60	24.25	24.79	16.40	39.59	24.25	67.60	36.20
H2	0.012	0.011[c]	0.014	0.014	0.014	0.014	0.013	0.012[a]
H1	0.113	0.109[b]	0.121	0.118[b]	0.121	0.118[c]	0.118	0.113[a]
N%	0.207	0.194[a]	0.178	0.175[a]	0.178	0.175[b]	0.167	0.157[a]
D%	0.158	0.150[a]	0.200	0.189[a]	0.200	0.189[b]	0.199	0.182[a]

Table VI

Robustness

This table reports evidence of clustering in transaction prices by pooling NYSE and NASAQ stocks on a given day satisfying a certain condition. Panel A reports evidence by day of the week. Panel B sorts days into five equal size groups conditional on the S&P daily return. Panel C sorts days according by market volatility into high versus low volatility days. Here, market volatility is measured as the closing value that day of the VIX index. Panel D reports evidence by four month intervals from August 2001 to December 2002.

	NYSE				Nasdaq			
Day of the week	H2	H1	N%	D%	H2	H1	N%	D%
Monday	0.011	0.111	18.2	14.4	0.011	0.108	17.1	13.5
Tuesday	0.012	0.112	18.6	14.2	0.011	0.108	17.2	13.5
Wednesday	0.012	0.113	19.2	14.5	0.011	0.109	17.3	13.8
Thursday	0.012	0.113	18.9	14.6	0.011	0.108	17.2	13.6
Friday	0.012	0.112	18.5	14.3	0.011	0.108	17.3	13.5
Daily S& P Return								
Loser	0.012	0.114	19.2	14.6	0.011	0.108	17.3	13.6
2	0.011	0.111	18.3	14.1	0.011	0.108	17.0	13.5
3	0.011	0.110	18.0	14.1	0.011	0.108	16.9	13.5
4	0.012	0.112	18.5	14.4	0.011	0.108	17.3	13.6
Winner	0.012	0.114	19.3	14.7	0.011	0.109	17.5	13.7
VIX index								
Low	0.011	0.109	17.5	14.0	0.011	0.108	17.1	13.5
2	0.011	0.111	18.2	14.1	0.011	0.108	17.2	13.6
3	0.012	0.112	18.8	14.4	0.011	0.108	17.3	13.6
4	0.012	0.113	19.1	14.6	0.011	0.108	17.1	13.6
High	0.012	0.115	19.7	14.7	0.011	0.109	17.4	13.6
By month over time								
September 2001	0.017	0.162	21.4	29.3	0.019	0.159	19.9	29.5
December 2001	0.016	0.152	20.6	27.6	0.017	0.147	18.7	27.3
March 2002	0.015	0.150	20.5	27.1	0.018	0.152	18.9	28.4
June 2002	0.014	0.141	19.0	25.7	0.017	0.140	17.2	26.5
September 2002	0.014	0.138	19.0	25.1	0.016	0.135	16.5	25.6
December 2002	0.014	0.134	18.4	24.2	0.016	0.129	15.9	24.2