

Clustering in U.S. Stock Prices After Decimalization

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Abstract

Early in 2001, U.S. equity markets transitioned from trading in multiples of $1/16^{\text{th}}$ and $1/8^{\text{th}}$ 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 unconstrained by regulation. Theory suggests that if price discovery is uniform, realized trades should not cluster at particular prices. 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 closing 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 round 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 those observed under decimal pricing.

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 to simplify trade reporting and to potentially reduce bid-ask spreads to as little as one penny.

The debate over this change in tick size is 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 psychology: Do people prefer certain prices? To help answer this question, this paper considers the price clustering 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 (1992)). Moreover, under decimal pricing, the cost of defeating time priority is relatively low. That is,

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 (2002), and Weaver (2002).

² New York Times, May 15th 2003, Wall Street Journal May 15th, 2003.

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 decimal pricing.

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

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

makers to round quotations which may in turn lead to greater price clustering (Harris (1991)). They suggest that price clustering may increase when markets are more volatile and less liquid. In fact, 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, Kilpatrick 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 price 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 While these

⁴For 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

studies present compelling evidence of price clustering, such studies cannot 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.

Using daily closing prices for all NYSE and Nasdaq stocks from the beginning of May to the end of October 2001 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, bid ask spreads, and institutional ownership. 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 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

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.

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. In Section I, we review the data. In Section II, we present evidence of clustering in stock prices, compare these patterns to pre-decimalization clustering and also consider the cross-sectional properties of price clustering. Section III, considers the robustness of our results. Section IV concludes.

I. 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. Our sample consists of daily closing prices for all stocks traded on either Nasdaq or NYSE that had closing prices available on CRSP throughout the six-month interval from May through October 2001. We focus on daily closing prices for most of our work. However for some tests, using daily data would be quite limiting. For these tests, we also use intra-day trade prices. As a result, we also restrict our sample to stocks we can also identify in the TAQ database.⁵ Our final sample consists of 2,011 stocks from the NYSE and 3,606 stocks from the Nasdaq over 125 trading days for a total of roughly 650,000 observations of post-decimalization closing prices.

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 \$750 million and a median share price of roughly \$22 per share. The number of Nasdaq firms in our sample is about 60 percent larger. Not surprisingly, these firms tend

⁵The use of daily closing prices may raise concern if investors, dealers, or specialists place special emphasis or care in setting closing prices compared to other transactions over the day. Our motivation for focusing on closing prices is to make the data more tractable. Further, there is a substantial amount of volume at this time of the day. Liquidity tends to be high and these prices are less likely to be affected by infrequent trading. However as a check, we do consider intra-day evidence for some tests. Further, as a robustness check in Section III, we consider intra-day evidence for one month in our sample period. All of these checks suggest that intra-day and closing prices show a qualitatively similar level of clustering.

to be much smaller in market-cap (the median is about \$73 million) and trade at significantly lower price levels (median is about \$7.70 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.⁶ 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.⁷

II. 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.⁸ 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 $i=1,2,\dots,B$ 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 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

⁶ 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.

⁷ See Bessembinder (1999), Barclay, Christie, Harris, Kandel, and Schultz (1999), and Weston (2000).

⁸ Huang and Stoll (2001) also use a similar measure of clustering.

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. Finally, to test for any even digit vs. odd digit clustering, we also report the percentage of odd penny bins that are not nickels (O%).

To construct our measures, we begin by pooling daily closing prices for all firms across days and plotting the frequency observed in each price bin. 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 closing trades. 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 roughly four 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 8 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 49.6 percent compared to 34.7 percent for those ranked in quintile 5 (largest firms).⁹ For Nasdaq stocks, the difference is larger; 63.2 percent for small stocks compared to 38.5 percent for large firms. Looking at the number of trades and bid-ask spreads, the results are again generally consistent with the negotiation/price resolution hypothesis. In

⁹ Differences between quintiles one and five are, in all cases, statistically significant at the five percent level.

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 nearly double that suggested by 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 numbers. 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 closing 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 2001. 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 2001, 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 2001 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 $i = 1, \dots, N$ 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.

To construct this statistic, we draw a random sample of 10,000 closing prices from the CRSP database in 1996. We then compute the frequency of each observed eighth-fraction and 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 2001 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. We also repeat this test at the two-digit level using all 100 possible bins. As before, we draw a random sample of 10,000 observations from the 2001 sample. 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 2001 than in 1996. To do this, in the second step we compare D for both the 1996 (D_1) and 2001 (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:

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

Where $D_1 \sim \chi_N^2$ and $D_2 \sim \chi_K^2$

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 four 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 is the same between 1996 and 2001. This holds true whether we bin prices based on the last digit (ten bins) or the entire fraction (100 bins). 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 finding 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 closing 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:

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

$$Clustering - E[Clustering] = \alpha + \beta_1 Size + \beta_2 Price + \beta_3 \frac{1}{\sqrt{NT}} + \beta_4 \sigma^2 + \beta_5 Spread + \beta_6 Inst. + \beta_7 NasdaqDummy$$

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, *Inst.* is the level of institutional ownership, 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 a step-wise analysis of our multivariate regression results. 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, bid-ask spreads and institutional ownership.

The R-squared from each step-wise regression along with the relative magnitude of the coefficients shows that the majority of the cross-sectional variation in price clustering is explained by three factors: price, spreads, 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 dummy is small. 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 regression is about 25. This magnitude implies that, for the typical firm, the proportion of nickels and dimes is roughly 25 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 shows a trading pattern consistent with the expected level of clustering at nickels and dimes of 20 percent. Thus we take each firm's characteristics and calculate an expected level of clustering from the regression model. When applied to our entire sample, we find that *only two* observations (from 5,606 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. Information resolution

As a further check on the magnitude of the negotiation/price resolution hypothesis, this subsection examines the role of information uncertainty in greater detail. One implication of the negotiation/price resolution hypothesis is that price clustering should decrease with the quality and precision of information about firm value. As the market receives information that reduces uncertainty, clustering should decrease. Developing a precise test of this inference is difficult. As a proxy, we estimate clustering at the firm level in the days preceding and following an earnings announcement. To the extent that earnings announcements are informative and reduce uncertainty, one might expect to see an overall decline in price clustering after such an information revelation. To accomplish this, we collect data on price clustering for 30 days before and after earnings announcements. Our final sample includes 1,763 earnings announcements for our NYSE sample and 2,372 for Nasdaq. Because the sample period is too small to rely on closing prices for accurate measures of clustering, we instead use all transactions (from the TAQ database) to calculate our measures of clustering for the 61-day event windows.

Table V presents a comparison of price clustering between the pre- and post-announcement periods broken out by quintiles of firm size, share turnover, and three-day cumulative abnormal returns (a proxy for the information content of the announcement).¹¹ For both NYSE and Nasdaq firms, we find no evidence of a decrease in clustering following an earnings announcement. Panel B considers the evidence by turnover quintile. Although one might expect earnings to have more information content in low turnover stocks, there is no meaningful difference in pre- versus post-earnings announcement price clustering in any of the turnover quintiles.

Panels A and B of Table V show evidence that is pooled across all classes of earnings and earnings surprises. Thus in Table V Panel C, we sort firms on the basis of earnings surprise. Here we estimate the three-day cumulative abnormal return (calculated as the three-day holding period return relative to the concurrent return on the CRSP value-weighted index). These returns are pooled and then

¹¹ While Table IV presents results only for the percentage of nickels and dimes, similar results obtain for our other measures of clustering.

sorted into quintiles from large negative surprises in quintile 1 to large positive surprises in quintile 5. Consistent with the findings in Panels A and B, we see no evidence that price clustering differs in any meaningful way around earnings announcements.

Of course this evidence might be interpreted in a variety of ways. One possibility is that earnings provide investors with little resolution toward understanding fair value. On the surface, this would not seem to be the case as earnings and earnings forecasts are widely followed in the press and appear to affect market prices and a rich literature suggests otherwise (e.g., Beaver (1968), Patell (1976) and Womack (1996)). Another interpretation might be that while the overall level of earnings affects prices, the overall information content of earnings announcements is low and has little impact on resolving uncertainty. While a possibility, here too the accounting literature suggests that earnings resolve uncertainty at the margin. For example, Patell and Wolfson (1979 and 1981) find evidence that that risk, as measured by implied equity volatility, decreases subsequent to earnings announcement. A third interpretation is that earnings are informative and that the level of price clustering may not be so consistent with the notion that clustering is affected by the resolution of informational uncertainty.

E. The importance of share price

We see evidence of price clustering in closing prices for both NYSE and Nasdaq stocks. However, this practice of rounding comes at a cost that decreases with price. Ball, Torous and Tschoegl (1985) consider this hypothesis in the context of gold prices. Harris (1991) later considers price clustering in the context of pre-decimalization share prices. These papers as well as our regression results reported in Table IV find that price clustering increases with share price, a result consistent with the notion that the degree of clustering relates to its relative cost. 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 the sample period May to October 2001. 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 109 stock splits. Similar to our earnings announcement analysis above, we construct our measures of price clustering based on intra-day data from the TAQ database for 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 \$50 to about \$35 per share reflecting roughly a three-for-two average split factor. The negotiation/price resolution hypothesis suggests that price clustering should fall subsequent to a split, yet we see only a small decline in price clustering in the post-split period. Table VI provides greater detail of this same evidence using all of the various measures of price clustering. Comparing columns 1 and 2 of Table VI we again see that while there is a statistically significant decline in 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 tenths of one percentage point.

Finally, we subdivide this split sample into terciles based on pre-split share price. Both overall and in each of the sub-groups, we see a decrease in post-split clustering yet in no case are these changes economically meaningful. For example for high priced stocks, the combined percentage of nickels and dimes decreases from 46.8 percent before the split to 43.9 percent afterwards. These frequencies are both more than double what is suggested under the null hypothesis of no price clustering.

III. Robustness

A. Stability

The results to this point show compelling evidence of price clustering. In this section of the paper, 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. Our approach is to sort each day's set of closing price data according to some criteria. In Table VII, we consider sorts 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 sorts allow us to check for any further support for 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)). 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.

Finally, we consider the possibility that investors, for some reason, were initially slow to learn to trade in a decimalization environment. Thus in Panel D, we sort the data by month. Again, we find that there is considerable stability over the sample period. For example, the combined frequency of nickels and dimes in May 2001 is 42.6 percent. In October 2001, the combined frequency is 41.1 percent.

B. The integrity of closing prices to estimate price clustering

In our examination of price clustering to this point, we have focused primarily on end-of-day closing prices. This was done in an attempt to keep the data set reasonably tractable. However closing prices may not be a clean measure of market tendencies. While a substantial fraction of daily volume occurs at the close, this price may have unusual properties, particularly on the NYSE where the specialist may play a larger role in setting the closing price. Moreover, closing prices are unusually important in settling certain transactions such as derivative contracts or in establishing mutual fund NAVs and may be prone to manipulation (Carhart, Kaniel, Musto and Reed (2002)).

To consider the sensitivity of our results to the use of closing prices, we replicate our results using all transaction prices for both Nasdaq and NYSE stocks for the month of July 2001. For brevity, we do not report these findings here however the results are essentially the same. For example, the overall combined fraction of nickel and dime transactions for all trades on the NYSE during July was 39 percent. This compares to 40.8 percent as reported in Table VII using only closing trades during that month. For Nasdaq firms, the combined nickel and dime percentage during July is 43 percent. The comparable percentage using closing trades for that month is 45.9 percent.

C. 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 for the period May 2001 to October 2001.¹² 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 \$46 compared to \$22 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, roughly 40 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 consistent with the negotiation/price resolution hypothesis, the overall extent of clustering is more pervasive than can be explained by this story alone. Moreover, we see some evidence inconsistent with the notion prices cluster when trading is difficult and fair value more uncertain. Price clustering does not appear to directly relate to closing prices, 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. Price clustering does not vary much by day of the week nor do investors appear to be learning from these patterns over time. These results appear to be robust.

IV. Conclusions

In a frictionless market, trade prices should have a uniform distribution. Yet a well-developed literature using one-eighth fractional prices reports 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 and value is uncertain, investors may be willing to round to a coarse price grid. An alternative hypothesis (one difficult to consider under

¹² In order to have enough observations to compute accurate frequency distributions for these 30 stocks, we collect transaction prices from the TAQ database for the first 1,000 trades for each stock on each day over the six-month sample period. Results are qualitatively similar using only closing prices for these stocks.

fractional trading) 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. In this paper, 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. 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, roughly half of the closing prices for U.S. firms occur at either a nickel or dime. 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 indeed consistent with the negotiation/price resolution hypothesis. On the other hand, the overall level of price clustering in market prices appears large. Moreover, observed patterns in clustering do not always behave in ways as forecast by 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. In short, the overall extent of price clustering appears to exceed what can be economically supported by the negotiation/price resolution hypothesis. 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. The psychology literature provides some support for this contention. The literature reports that some numbers are more difficult to process than others. 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.

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. Overall, our results suggest that a policy change to price increments of five cents may not have a major effect on observed transaction prices.

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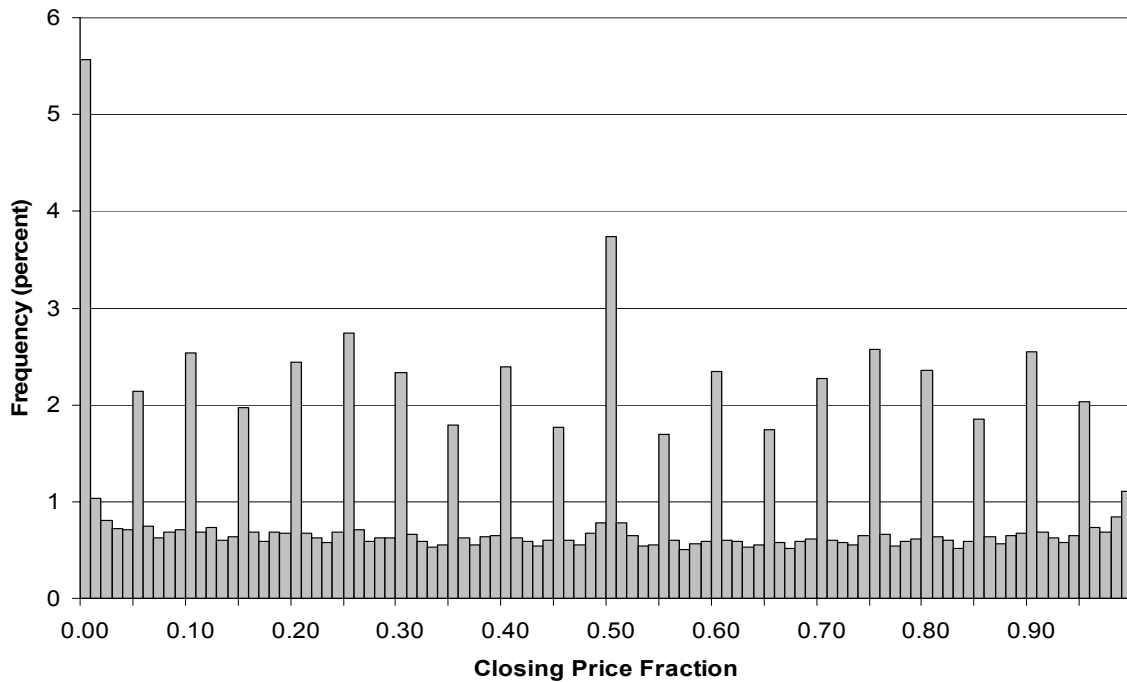
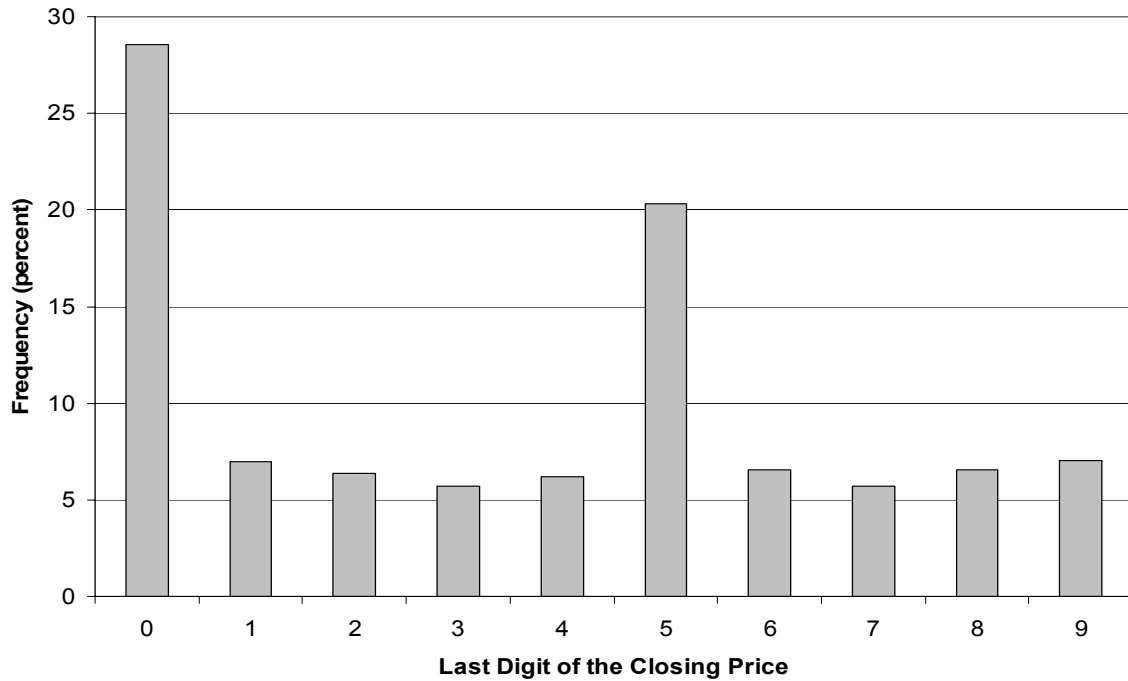


Figure 1. The post-decimalization distribution of transaction prices. The top panel plots a histogram of closing prices based on the frequency of the last digit of the transaction price. The bottom panel plots a similar histogram based on the last two digits of the closing price. Reported frequencies are computed over all daily closing prices for all CRSP stocks between May 2001 to October 2001.

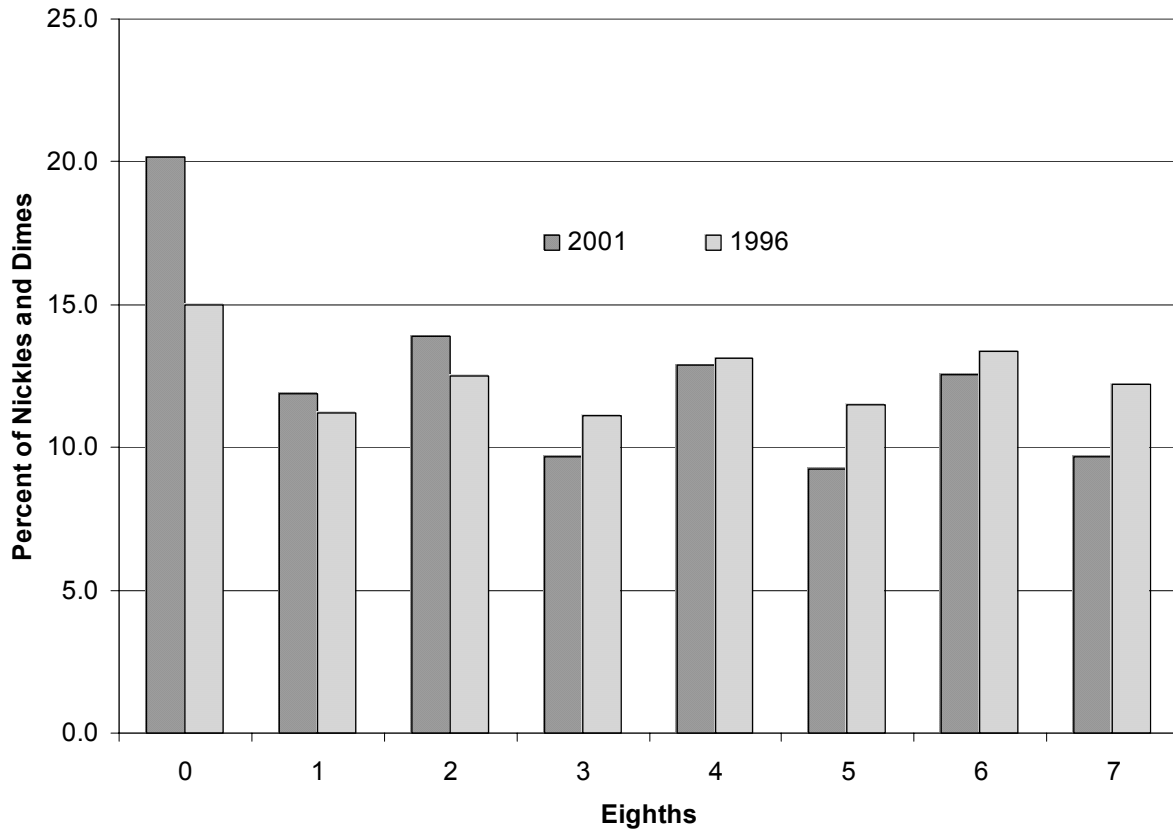


Figure 2. Comparison of price clustering on eighths: 1996 vs. 2001 (simulated). This figure presents a comparison of clustering on eighths between 1996 and 2001. Reported frequencies for eighths for 1996 are based on all closing prices from CRSP during July 1996. For 2001, reported frequencies of eighths 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.

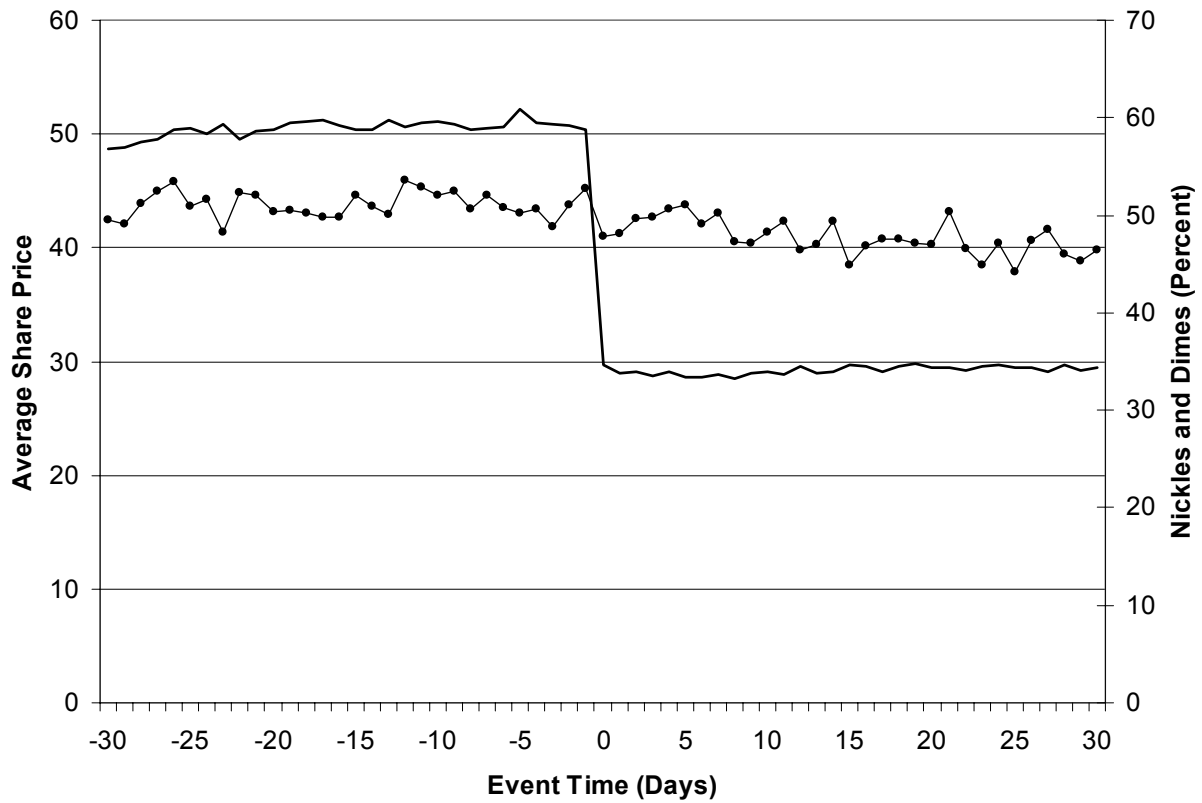


Figure 3. Price clustering around stock splits. This figure presents a time series of average stock prices and the average frequency of prices ending in increments of five or ten cents from 30 days before to 30 days after a stock split. Our sample includes 109 stock splits between May and October 2001. 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 day (in event time).

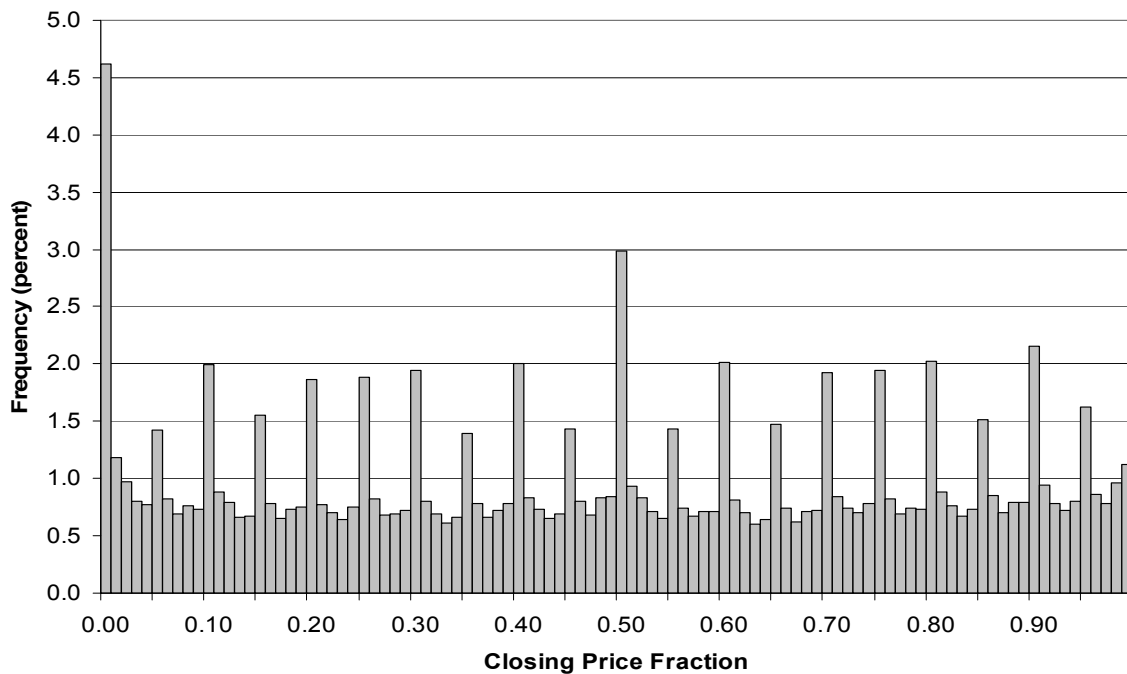
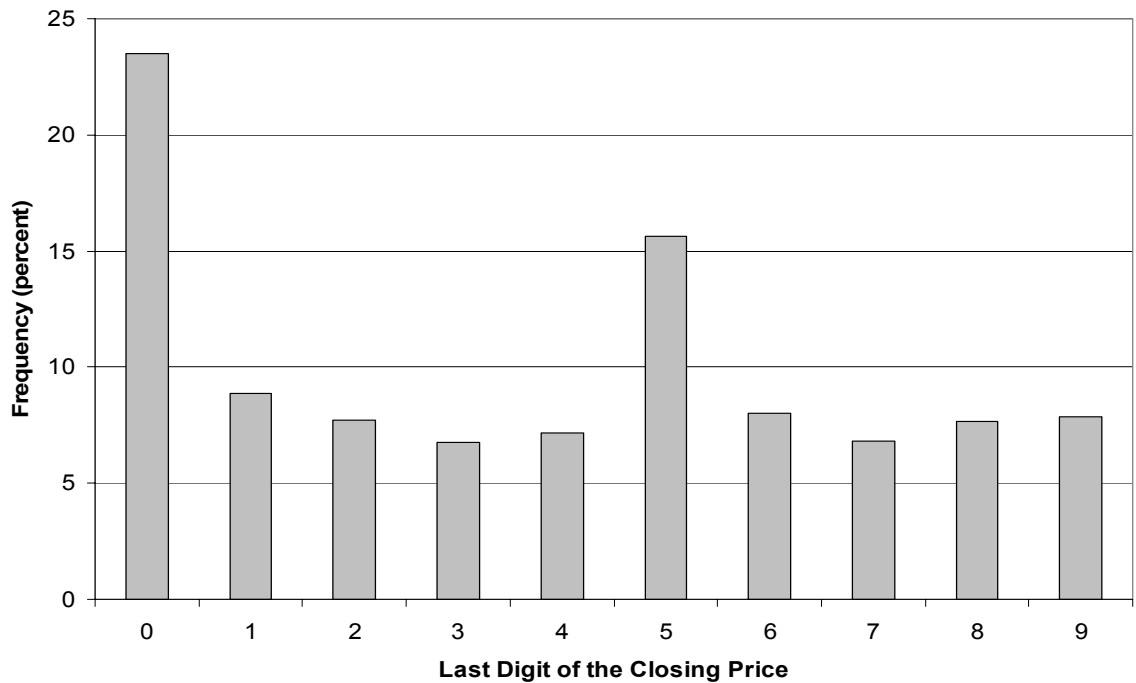


Figure 4. The post-decimalization distribution of transaction prices for stock in the Dow Jones 30. The top panel plots a histogram of closing prices based on the frequency of the last digit of the transaction price. The bottom panel plots a similar histogram based on the last two digits of the closing price. Reported frequencies are computed over all transactions (from the TAQ database) for the 30 stocks in the Dow Jones Industrial Average between May 2001 to October 2001.

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 daily observations from May to October 2001. Presented statistics are then 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	2,011	5,239	20,651	238	754	2,667
Price	2,011	26.30	32.02	11.98	21.81	34.58
Volume	2,011	6.406	16.608	0.371	1.422	5.035
Number of Trades	2,011	413	826	44	147	433
Share Turnover	2,011	0.124	0.202	0.049	0.089	0.145
Return Volatility	2,011	0.028	0.015	0.018	0.025	0.034
Quoted Spread	2,011	0.111	0.102	0.068	0.090	0.123
Relative Spread	2,011	0.008	0.010	0.003	0.005	0.009

Panel B: Nasdaq Stocks

	N	Mean	Std. Dev.	25 th %	Median	75%
Market Value	3,606	732	7,461	22	73	288
Price	3,606	11.89	16.35	2.56	7.69	16.57
Volume	3,606	4.43	25.17	0.07	0.36	1.76
Number of Trades	3,606	596	3,171	11	42	199
Share Turnover	3,606	0.155	0.253	0.030	0.070	0.181
Return Volatility	3,606	0.055	0.032	0.033	0.049	0.070
Quoted Spread	3,606	0.178	0.234	0.072	0.118	0.211
Relative Spread	3,606	0.027	0.018	0.011	0.024	0.042

Table II**Clustering by Firm Characteristic**

This table reports measures of clustering observed in closing prices for NYSE and Nasdaq firms over the period April through September 2001. H1 and H2 are measures of clustering at the one- and two-digit levels respectively. N% and D% represent the observed frequency of closing prices that fall increments of nickels or dimes. O% represents the observed frequency of “odd-penny” (exclusive of nickels) closing prices. 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%	0.177	0.166	0.150	0.139	0.129	0.172	0.184	0.185	0.171	0.155
D%	0.319	0.290	0.268	0.232	0.218	0.294	0.319	0.321	0.292	0.246
H1	0.169	0.152	0.139	0.124	0.119	0.154	0.169	0.171	0.153	0.131
H2	0.021	0.017	0.015	0.013	0.012	0.018	0.021	0.022	0.019	0.014
O%	0.266	0.290	0.316	0.341	0.359	0.287	0.268	0.263	0.289	0.322
Number of Trades										
N%	0.184	0.159	0.150	0.139	0.129	0.218	0.187	0.168	0.160	0.151
D%	0.343	0.280	0.254	0.235	0.216	0.414	0.326	0.285	0.257	0.234
H1	0.185	0.146	0.133	0.125	0.118	0.240	0.174	0.149	0.136	0.126
H2	0.023	0.017	0.014	0.013	0.012	0.039	0.023	0.018	0.015	0.013
O%	0.247	0.300	0.323	0.340	0.361	0.197	0.259	0.294	0.314	0.331
Volatility										
N%	0.149	0.150	0.152	0.153	0.156	0.197	0.180	0.170	0.167	0.152
D%	0.253	0.260	0.266	0.271	0.273	0.349	0.311	0.286	0.271	0.249
H1	0.132	0.135	0.138	0.140	0.142	0.189	0.164	0.150	0.143	0.132
H2	0.014	0.015	0.015	0.015	0.015	0.027	0.021	0.018	0.016	0.014
O%	0.324	0.318	0.314	0.312	0.308	0.241	0.273	0.292	0.303	0.323
Spread										
N%	0.131	0.140	0.149	0.163	0.178	0.155	0.173	0.181	0.184	0.175
D%	0.221	0.235	0.264	0.298	0.309	0.243	0.291	0.317	0.318	0.307
H1	0.120	0.125	0.137	0.155	0.164	0.130	0.153	0.167	0.168	0.161
H2	0.012	0.013	0.015	0.018	0.020	0.014	0.019	0.021	0.022	0.019
O%	0.356	0.343	0.315	0.288	0.272	0.323	0.287	0.270	0.268	0.278

Table III
Comparison of clustering between 1996 (eighths) and 2001 (Decimals)

This table presents a comparison of trade price clustering between 1996 and 2001. Panel A presents a frequency distribution for 10,000 randomly drawn CRSP closing prices for each category for 1996. Cell frequencies are determined based on the price fraction (number of eighths). 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 closing prices on the CRSP database during May-October 2001. Cell frequencies are based on the last digit of the closing 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 2001 clustering at the one-digit level. At the two-digit level, p-values are based on an F-distribution with 99 and 7 degrees of freedom.

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

Eighths	All Prices		Clustering by Nominal Price Category					
			NYSE			Nasdaq		
	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 May-October 2001.

Last Digit	All Prices		Clustering by Nominal Price Category					
			NYSE			Nasdaq		
	NYSE	Nasdaq	\$5<P<\$10	\$10<P<\$30	P>\$30	\$5<P<\$10	\$10<P<\$30	P>\$30
0	0.285	0.310	0.269	0.283	0.297	0.318	0.324	0.290
1	0.072	0.065	0.063	0.069	0.076	0.064	0.063	0.077
2	0.062	0.053	0.065	0.063	0.064	0.057	0.051	0.061
3	0.058	0.052	0.056	0.058	0.055	0.053	0.048	0.056
4	0.062	0.059	0.063	0.062	0.060	0.057	0.053	0.067
5	0.200	0.232	0.210	0.209	0.194	0.228	0.235	0.186
6	0.060	0.057	0.065	0.061	0.063	0.056	0.056	0.070
7	0.058	0.052	0.059	0.053	0.055	0.048	0.053	0.057
8	0.073	0.056	0.079	0.073	0.068	0.056	0.057	0.062
9	0.069	0.065	0.071	0.070	0.067	0.064	0.060	0.075
N	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
χ^2_9	5458.33	7601.13	5083.88	5611.39	5848.62	7932.21	8472.28	5333.22
P-Value	0.000	0.0000	0.000	0.000	0.000	0.000	0.000	0.000
F-Statistic _{9,7}	81.6	5.7	53.5	79.4	53.4	17.5	5.5	1.6
P-value	0.000	0.0159	0.000	0.000	0.000	0.001	0.018	0.263
F-Statistic _{99,7}	96.6	8.8	61.0	83.1	69.5	23.1	8.1	2.1
P-value	0.000	0.003	0.000	0.000	0.000	0.000	0.003	0.150

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 estimated at the firm level over the period May to October 2001. N&D represents the observed frequency of closing prices that fall 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.

	N&D	N&D	N&D	N&D	N&D	N&D
Constant	25.183 (94.26)	24.281 (99.30)	23.230 (109.89)	24.071 (107.21)	25.900 (123.11)	25.960 (123.66)
Size	-4.849 (-26.22)	-13.147 (-54.83)	-4.472 (-16.07)	-4.035 (-14.62)	0.853 (2.54)	0.634 (1.850)
Price		11.209 (46.94)	7.577 (36.78)	8.819 (38.65)	11.900 (44.98)	11.797 (44.27)
1/sqrt(NT)			7.766 (33.83)	8.731 (36.02)	5.902 (22.76)	6.120 (23.30)
Sigma				2.213 (10.48)	1.289 (6.41)	1.324 (6.59)
Spread					11.158 (24.59)	11.110 (24.51)
Inst. ownership						0.062 (4.05)
Nasdaq	0.838 (2.48)	2.243 (7.27)	3.871 (14.09)	2.571 (8.66)	-0.279 (-0.970)	-0.333 (-1.16)
Obs	5,617	5,617	5,617	5,617	5,617	5,617
Adj R ²	0.146	0.435	0.573	0.584	0.640	0.641

Table V
Clustering Before and After Earnings Announcements

This table summarizes clustering in the 30 days before and 30 days following an earnings announcement for sample firms overall and by market cap, volatility, and 3-day CAR quintiles surrounding the earnings announcement. Earnings announcement dates during the period April to September 2001 are obtained from Compustat. N% and D%, respectively, are defined as the observed frequency of closing prices that fall either on an increment of a nickel or a dime. 3-day CAR is defined as the three-day holding period return from day -1 to +1 relative to the Compustat reporting date, less the concurrent three-day holding period return to the CRSP value-weighted index of NYSE and NASDAQ stocks.

		NYSE					Nasdaq				
		Low	2	3	4	High	Low	2	3	4	High
Panel A: Market Cap											
Nickels (%)	Before	0.231	0.193	0.176	0.161	0.152	0.268	0.252	0.209	0.198	0.177
Nickels (%)	After	0.237	0.197	0.177	0.162	0.152	0.265	0.257	0.211	0.195	0.172
Dimes (%)	Before	0.349	0.278	0.247	0.228	0.211	0.441	0.397	0.292	0.279	0.232
Dimes (%)	After	0.354	0.283	0.251	0.232	0.211	0.439	0.393	0.303	0.273	0.222
Panel B: Turnover											
Nickels (%)	Before	0.213	0.180	0.171	0.172	0.176	0.272	0.239	0.210	0.195	0.188
Nickels (%)	After	0.217	0.186	0.172	0.174	0.176	0.267	0.241	0.212	0.196	0.184
Dimes (%)	Before	0.322	0.252	0.234	0.242	0.264	0.463	0.360	0.297	0.266	0.256
Dimes (%)	After	0.330	0.259	0.241	0.244	0.257	0.453	0.366	0.302	0.265	0.243
Panel C: CAR-Surprise											
Nickels (%)	Before	0.187	0.179	0.183	0.178	0.185	0.201	0.227	0.231	0.225	0.220
Nickels (%)	After	0.188	0.183	0.184	0.184	0.186	0.204	0.224	0.229	0.229	0.214
Dimes (%)	Before	0.276	0.257	0.262	0.255	0.263	0.294	0.337	0.353	0.351	0.307
Dimes (%)	After	0.277	0.257	0.265	0.263	0.268	0.285	0.335	0.352	0.344	0.314

Table VI**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 the period May to October 2001. 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 closing prices that fall either on an increment of a nickels or dimes. O% represents the observed frequency of “odd-penny” (exclusive of nickels) closing prices. ***, **, and * 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	44.54	26.21	26.63	15.42	46.12	26.29	72.61	39.48
H1	0.107	0.105	0.195	0.199	0.084	0.077	0.041	0.038**
H2	0.240	0.227*	0.333	0.321	0.209	0.196	0.174	0.164***
N%	0.207	0.194***	0.239	0.216*	0.199	0.192	0.180	0.173**
D%	0.311	0.294**	0.355	0.340	0.287	0.275	0.288	0.266***
O%	0.452	0.454	0.445	0.444	0.460	0.462	0.451	0.458

Table VII
Robustness

This table reports evidence of clustering in closing prices by pooling NYSE and NASDAQ 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 month over the interval May to October 2001.

Day of the week	NYSE				Nasdaq			
	H1	H2	N%	D%	H1	H2	N%	D%
Monday	0.015	0.136	0.155	0.260	0.018	0.153	0.172	0.293
Tuesday	0.015	0.138	0.148	0.267	0.019	0.155	0.174	0.295
Wednesday	0.015	0.139	0.151	0.269	0.018	0.153	0.175	0.292
Thursday	0.015	0.138	0.152	0.266	0.018	0.153	0.172	0.292
Friday	0.015	0.137	0.154	0.262	0.018	0.153	0.172	0.293
Daily S& P Return								
Loser	0.015	0.140	0.155	0.270	0.018	0.155	0.171	0.296
2	0.015	0.138	0.153	0.265	0.018	0.153	0.173	0.293
3	0.015	0.135	0.150	0.259	0.018	0.152	0.173	0.289
4	0.015	0.137	0.150	0.263	0.018	0.153	0.173	0.292
Winner	0.015	0.138	0.150	0.267	0.019	0.154	0.176	0.294
VIX index								
Low	0.015	0.135	0.151	0.259	0.018	0.152	0.171	0.292
2	0.015	0.135	0.150	0.260	0.018	0.152	0.173	0.290
3	0.015	0.136	0.152	0.261	0.018	0.152	0.173	0.290
4	0.015	0.137	0.151	0.265	0.018	0.153	0.172	0.292
High	0.016	0.144	0.155	0.280	0.019	0.158	0.176	0.300
By month over time								
May	0.015	0.141	0.154	0.272	0.018	0.153	0.174	0.291
June	0.015	0.136	0.151	0.262	0.018	0.151	0.171	0.289
July	0.014	0.134	0.151	0.257	0.018	0.151	0.173	0.286
August	0.014	0.133	0.150	0.254	0.019	0.156	0.171	0.300
September	0.016	0.149	0.158	0.290	0.020	0.162	0.181	0.306
October	0.014	0.136	0.150	0.261	0.018	0.152	0.171	0.290