Pricing Response Biases in Financial Products

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Abstract

The biases of investor behavior in the stock market are examined. Interest in this topic is motivated by the notion of the stock market as a marketplace in which investors, as consumers, buy and sell (i.e., exchange) financial products such as stocks. Specifically, the ‘price-end phenomenon’ in financial markets is explored. A price-end refers to the last digit of a price and the ‘price-end phenomenon’ refers to the finding that most trades and quotes are at prices that end in only a few specific digits, despite the availability of numerous other digits. Drawing on the behavioral finance, marketing and psychology literature we develop and investigate four propositions regarding market-level intra-day trading on the New York Stock Exchange. The Trade and Quote database of this exchange was used to analyze trades across three separate three-month periods within a three-year time span. Three of the propositions address expected relative frequencies of 0, 5 and 9 price ends. The fourth proposition addresses different patterns of these price-end trades expected between institutional and retail investors. Implications of the findings are discussed and suggestions are offered for avenues of future research.
Price-End Biases in Financial Products

There is a small, but growing literature that links marketing and finance (e.g., Srivastava, Shervani, and Fahey, 1998; Rust, Moorman, and Dickson, 2002; Aaker and Jacobson, 1994). Such research has been advanced under calls for increased interdisciplinary research (e.g., Karmarkar, 1996; Malhotra, 1999). In Srivastava et al. (1998), the authors develop a theoretical framework that shows how marketing activities create relational and intellectual market-based assets that influence cash flows such that shareholder value is positively impacted. In turn, Rust, Moorman, and Dickson (2002) empirically examine the effect that specific managerial initiatives such as quality improvement have on a firm’s return on assets and stock returns.

In our paper, we take a different approach to exploring the link between the disciplines of marketing and finance. Instead of examining the impact of marketing activities and its contribution to market valuations, we examine the influence of consumer behavior biases on investor behavior in the stock market. This focus on investor behavior is motivated by our expanded notion of the stock market as a market place in which investors, as consumers, buy and sell (i.e., exchange) financial products such as stocks. In this context, the New York Stock Exchange (NYSE) and other such stock exchanges can be seen as providing a financial service in the sense of facilitating exchanges between buyers and sellers. Thus, our study of investor psychology using traditional research in marketing and psychology is simply an extension of the study of consumer behavior in a non-traditional, but consequential, market place such as the stock market.
In our paper, we examine in particular how pricing studies in marketing and experimental psychology help explain the ‘price-end phenomenon’ in financial markets. A price-end refers to the last digit in a price. For example, 42.15 has a price-end of 5. The ‘price-end phenomenon’ refers to the finding that most trades and quotes are at prices whose last digits are a 0 or a 5, despite the availability of other digits. This clustering of trades and quotes around price-ends of 0 and 5 has been found in markets as varied as the foreign exchange market (Goodhart and Figliuoli, 1991; Olser, 2000), the S&P futures market (Schwartz, Van Ness, and Van Ness, 2004), the equity market (Harris, 1991), and the London gold market (Ball, Torous, and Tschoegl, 1985).

In our paper, we integrate the work in behavioral finance with the relevant literature from marketing and psychology. Further, in comparison to earlier work that has solely focused on frequency of trades at price-ends of 0 and 5, we look at trading volume, which incorporates both trade frequency and trade size. Specifically, we examine whether price-ends of 9 are associated with larger trade sizes or greater frequency of trades, given the prevalence of such price-ends in most retail markets and the studies in marketing that have claimed that price-ends of 9 are associated with “bumps” in demand (e.g., Gendall, Holdershaw, and Garland, 1997). We then examine whether even price-ends such as the dime-ending of 0 attracts more trading volume than the odd price-endings of 5 and 9, given the pricing and experimental psychology literature which suggests that the processing of even numbers is faster. This issue, of whether the evenness or oddness of a price-end makes a difference, has not been addressed in the prior literature. Lastly, we examine whether large institutional investors exhibit the same psychological bias as retail investors. This is because institutional investors are known to
rely on considerable proprietary research and formal market models in their decision making, and accordingly, one would not expect institutional trades to exhibit the same cognitive bias as individual, retail investors. This issue also has not been specifically examined in the prior literature.

Our research provides an interesting illustration of how consumers’ cognitive processes affect the functioning of an otherwise efficient financial market. One of the major motivations for the decimalization of the US stock market was to lower the transaction cost for investors by providing investors with a finer pricing grid. However, to the extent that investors continue to prefer a coarse pricing grid with a distinct preference for price-ends of 0 and 5, this objective is trumped by investors’ biases that lead to the continued use of a coarse pricing grid. This situation is not unlike that of a marketing researcher who introduces ever-finer scales for capturing respondent differences, only to find that the respondents still tend to use only certain portions of the scale.

The rest of this paper is organized as follows. First, we provide our rationale for price-end effects and develop a set of propositions. Second, we describe the methodology we employed to test these propositions. Third, we present the results of our analysis, and last, we conclude with a discussion of our results and directions for future research.

**Proposition Development**

In this section, we develop theoretical support for the price-end phenomenon. We argue that the preference that investors exhibit towards certain price-ends such as those of 0 and 5 result from the desire of investors to avoid significant deliberation costs when
retrieving and processing numerical information (cf. Kahneman and Tversky, 1974; cf. Monroe and Lee, 1999). This desire derives from the principle articulated in Shugan’s (1980) article on the ‘cost of thinking,’ namely, that consumers willingly trade off the benefits of accuracy against the mental cost of achieving that accuracy. The behavioral finance literature has well documented that, investors, as decision-makers, tend to follow heuristic shortcuts, because of the high cost of deliberation. This departure from the behavior of “Homo Economicus,” whom Thaler (2000) describes as an animal that strictly follows the axiomatic tenets of economic behavior outlined in introductory economic textbooks, has been successfully used to explain why investors value losses differently from gains, as opposed to equally (Odean, 2000), hold onto losses and cash gains early (Shefrin and Statman, 1985), are more risk averse following a loss as opposed to after a gain (Barberis and Huang, 2001; Thaler and Johnson, 1990), and extrapolate from small samples with greater confidence than is warranted (Rabin, 2002). As Stracca (2004) notes, when consumers with ‘bounded rationality’ are faced with massive quantities of information, they tend to adopt heuristic rules and zero in on salient information.

In this context, the salient information that investors tend to focus on is the price-ending of stocks. The history of counting reveals the reason why 0’s and 5’s figure prominently in the processing of numerical information. As Dehaene (1997) and Ifrah (1985) note, most human societies since time immemorial have tended to pay special significance to the number 5 and its immediate multiples, since body extremities such as hands and toes are often used for basic counting. Tzelgov, Meyer, and Henik (1992) argue (and find experimental support) for their thesis that the digit ‘5’ is of special
significance to humans, because humans use it to separate “larger” numbers from
“smaller” numbers when approximating numerical information. Thus, digits of 4 and less
are considered “smaller” and digits of 6 and above are considered “larger” numbers
during autonomic processing of numerical information.

Still, the question is whether a price-end alone is enough to influence choice. In
this context, Stiving and Winer (1997), in an interesting experiment using actual scanner
data, show that price-ends do indeed influence consumer decisions. Based on a body of
literature from applied psychology, Stiving and Winer put to test the proposition that
consumers tend to process digits from left to right, and that consumers focus on the dimes
and pennies digits, when the integer component of prices are the same. Using choice
information from a scanner panel data, Stiving and Winer find evidence that price-ends
have a separate (and significant) effect on consumers’ choice, over and above a simple,
holistic representation of price in the choice model.

Consequently, we propose that if price-ends of 0 and 5 are more salient to
consumers than price-ends of other digits, and that price-ends influence choice, then this
should result in increased trading at these price-ends. Thus, in *intra-day* trades one
would expect increased trading at these price ends. This is different from earlier findings
in two respects. Earlier papers such as Harris (1991) have demonstrated the clustering
around price ends of 0 and 5 using end-of-day trades across several years. Also, the focus
in these earlier papers has been on showing greater trading frequency at price ends of 0
and 5, whereas our emphasis is on showing greater trading volume at these price ends,
keeping in mind that trading volume is a function of trading frequency and trade size.
Accordingly, we propose that
**Proposition 1:** In intra-day trading, greater *trading volume* will be associated with price-ends of 0 and 5.

In marketing, price-endings of 9 dominate in ordinary retail markets (Stiving and Winer, 1997). Two arguments have been advanced in the literature for the prevalence of such price-endings (Schindler and Kirby, 1997, Stiving and Winer, 1997). First, the idea is that when consumers confront a price like 19.99, they see it as a “gain” of 1 cent (from the reference price of 20 dollars) as per the tenets of prospect theory, and this “gain” results in a small spike in demand at 19.99. Second, the belief is that consumers’ process information from left to right, resulting in the price of 19.99 being remembered as a price of “19.00 something” rather than a price of 20 dollars because of consumers’ cognitive constraints. Consequently, in “off-line” processing of this numerical information (Coulter 2001), the advantage is to the retailer in the form of increased demand.

If the above idea also applies to traders in the stock market, one would expect to see more sell orders at price-ends of 9. However, most databases (e.g., Trade and Quote database from the New York Stock Exchange) do not differentiate trades by whether the trades are buy-side or sell-side trades. Therefore, it is difficult to verify whether there are more sell orders at price-ends of 9 (i.e., sellers using odd-even pricing) or buy orders at price-ends of 9 (i.e., buyers responding positively to odd-even pricing). Still, if price-ends of 9 are favored in terms of either buy or sell, one would still expect to see increased volume at price-ends of 9. Accordingly, we propose that:
Proposition 2: Greater trading volume will be associated with price-ends of 9, in addition to the price-ends of 0 and 5.

Of the different price-ends, the price-end of 0 (an immediate multiple of the price-end of 5) has the additional advantage that it is a round, even number (i.e., divisible by 2). This is in contrast to the “oddness” of price-ends of 5 and 9. In a series of experiments in experimental psychology, Hines (1990) noted that humans encode, retrieve, and process even numbers faster than odd numbers. In support of his thesis that humans store and process even numbers better than odd numbers and exhibit a preference for the same, Hines (1990) cites early research in math education which has shown that from an early age, school children exhibit greater facility with even numbers in ordinary mathematical operations such as addition and subtraction than they do with odd numbers (e.g., Clapp 1924; Knight and Behrens, 1928).

Dawes, Faus, and Meehl (1989) report that experimental subjects tend to use simplifying heuristics rather than precise quantitative judgments when engaged in numerical judgment tasks in order to reduce the demand on their cognitive resources. An experiment by Schindler and Wiman (1989) suggests the manner in which consumers cope with such cognitive demands. They found that, in the context of pricing, consumers tend to disproportionately over-represent 0- and 5-ending numbers in price recall tasks, with 0-ending prices being overrepresented the most. This was interpreted to mean that conversion of actual price ends to 0-ending representations in memory did most to alleviate cognitive workload.
Additional evidence is provided by Estelami (1999) who investigated subjects’ behavior in computational tasks involving multidimensional prices (those having more than one component, such as price plus a shipping charge). He found that the cognitive difficulty was a function of price ends, with 0 price-ends requiring the least amount of computational effort. This influence was also apparent in Estelami’s study (2001) of the effect of price ends on consumers’ reactions to credit amounts. This experiment demonstrated that when consumer credit amounts were presented in disaggregated format (a listing of component prices), there were marked differences in consumers’ perceived discount rates between prices presented in odd ends and even ends. His interpretation was that the odd-ended presentation of disaggregated prices likely overwhelmed subjects processing capacity compared to the simpler cognitive demands required by even-ended prices.

Finally, Monroe and Lee (1999, p. 219), in their review of the pricing literature on odd and even numbers, suggest a human bias towards even prices and concluded that “prices that end in even numbers may be more likely to be processed non-consciously.” Dehaene, Bossini, and Giraux (1993, p. 45) also find that “even digits are processed faster and/or more accurately than odd digits.” In addition, Dehaene et al. allude to the special significance of endings of 0. In their experimental probe of the mental architecture of number representation and processing, they find support for the internal representation of numbers in a base 10 system. Evidence of this can be found in the natural practice of “rounding,” which is typically towards a zero.

Together, the conceptual arguments and empirical support for the computational simplicity of even-ended numbers (especially of 0-ended prices) leads us to propose that:
**Proposition 3:** The trading volume at the even price-ends of 0 will exceed the trading volume at the odd price-ends of 5 and 9.

Typically, a trade size of 10,000 shares or more is regarded as a block trade made by institutional investors (see, for example, Bacidore et al., 2001; Bodie, Kane, and Marcus, 2001; and Oppenheimer and Sabherwal 2003). Institutional investors include large hedge funds, mutual funds, and other corporate entities. This is in contrast to the retail trader or individual investor who buys and sells for his/her personal account. Since institutional trades are large trades, one would assume that such trades would be placed after significant deliberation. Also, since large institutions have vast resources, it is not uncommon for them to routinely employ sophisticated market models and other technical resources to assist them in their deliberations (Harris 2003). By contrast, a retail investor has limited access to the research and other resources of the institutional investor. Accordingly, one would expect institutional accounts to be indifferent to price-ends in their purchase/sale decisions, because of their more systematic, rational, and informed approach to investing. Accordingly, we propose that:

**Proposition 4:** Institutional investors will exhibit less of a price-end bias than retail investors.
Methodology

To determine whether the price-ends of 0 and 5 result in increased trading volume relative to the other price-ends, we analyzed the Trade and Quote (TAQ) database available from the New York Stock Exchange (NYSE). TAQ data lists the prices and number of shares traded at each point in time during the day across the various US exchanges.

We employed TAQ data for all 30 Dow stocks from three different quarters, spanning three different years. The Dow stocks were chosen because they represent some of the most widely held and traded stocks, and collectively, are regarded as a premier indicator of the health of the stock market. The three time periods analyzed were May 1–July 31, 2001, October 1–December 31, 2002, and January 1–March 2003. The number of trades over this period ranged from a low of around 300,000 trades for Eastman Kodak to a high of around 10 million for Microsoft. These huge numbers are the result of our analysis of intra-day trading data.

Since stock prices and trading volumes are subject to influences such as earnings releases, analyst upgrades/downgrades, rumors, etc., the total volume of shares traded each day can be expected to vary. To control for these daily volume fluctuations when determining whether the price-ends of 0, 5, and 9 are associated with significant volume spikes, we chose to compute the percentage volume traded at each of the price-ends ranging from 0 to 9 for each of the 30 Dow stocks. The percentage volume at each price-end for each stock is determined by dividing the number of shares transacted at a particular price-end by the total number of shares traded during the day for that stock. Thus, the daily percentage volume at each of the 10 price-ends was computed. Also, we
tracked the percentage number of trades that were made at these different price-ends. The percentage number of trades at each price-end for each stock was determined by dividing the number of trades made at a particular price-end by the total number of trades made during the day in the stock.

The analysis of the data was done via dummy variable regression, with the percentage daily volume traded at each of the 10 price-ends as the dependent variable. The independent variables were the dummy variables for the various price-ends. This regression was then followed by a separate regression with percentage daily number of trades as the dependent variable.

The dummy coding scheme employed was effects coding, which is also known as deviation coding (Judd and McClelland, 1989). The reason for choosing deviation coding (as opposed to indicator coding) was to highlight the effects of the various price-ends as a deviation from the grand mean. By contrast, an indicator coding scheme would have expressed the various price-end effects as a deviation from the mean of a chosen reference category. Note that in deviation coding with M categories, the coefficient estimates for Mth reference category are derived from the estimates of the other M-1 coefficients. This is possible because the deviation coefficient estimates are constrained to add up to zero by definition (Greene 1993).

**Analysis**

Table 1 presents the estimates for all price-ends across all 30 Dow stocks, with percentage daily volume and percentage daily number of trades as the dependent variables, respectively. Table 2 reports the estimates with trade size as the dependent
variable. Tables 3 and 4 present the results for retail and block trades for percentage daily volume and percentage daily number of trades, respectively.

**take in Table I**

**Percentage Daily Volume**

In Table I, under the column of ‘Percentage Daily Volume,’ one sees that the coefficients against the price-ends of 0 and 5 are significantly positive, implying that the percentage daily volume traded at these price-ends is considerably more than the mean. The estimates for all other price-ends, including that for the price-end of 9, are significantly negative, thereby implying that the volumes traded at these price-ends are significantly below the mean. Thus, Proposition 1 is supported, whereas Proposition 2 is not supported. Figure 1 displays the distribution of the percentage daily volume across the various price-ends for all the stocks, with the heights of the individual bars adding to a 100 as one would expect. It is clear from the figure that the trading volume is greater at price-ends of 0 and 5 than at other price-ends, including the price-end of 9.

**take in Figure 1**

Examining Table I, one finds that the percentage volume traded at the price-end of 0 is approximately 14% higher than the mean, whereas for the price-end of 5 it is approximately 7% higher. Thus, though the percentage volumes traded at the price-ends of 0 and 5 are significantly higher than that at other price-ends, the percentage volume
traded at the price-end of 0 is nearly double that at 5. This supports Proposition 3 that the even price-end of 0 is more strongly favored by investors.

**Percentage Daily Trades**

Referring to the price-end effects reported in Table I, under the column of ‘Percentage Daily Number of Trades,’ we see that the aggregate percentage by which the number of trades is greater than the mean is 6% in case of price-ends of 0 and 3% in the case of price-ends of 5. By comparison, the number of trades at the price-end of 9 is 1% less than the average. Figure 2 displays the distribution of the percentage daily number of trades across the various price-ends for all the stocks. Clearly, the number of trades at price-ends of 0 and 5 substantially exceed those at other price-ends, including those at the price-end of 9.

**take in Figure 2**

**Trade Size**

To determine whether the increased trading volume is not only due to an increased number of trades but also due to an increased trade size, we directly regressed trade size against the dummy variables for the various price-ends. This regression is possible since TAQ data contains the time of trade and the size of the trade (trade size). However, since trade sizes could vary by day depending upon the market conditions and news for that day, we scaled the trade sizes at the various price-ends by dividing the daily average trade size at each of the price-ends by the overall average trade size for that day across all price-ends.
The results of this regression are presented in Table II which shows that besides increased number of trades at price-ends of 0 and 5, there is also increased order size at these price-ends. Thus, not only do investors trade more frequently at these price-ends, they also do so more aggressively. However, the price-end of 9 is associated with trade sizes that are significantly below the mean. Figure 3 displays the data plot of trade size at each of the various price-ends relative to a mean trade size indexed at one. Thus, bar heights greater than one indicate trade sizes greater than the mean trade size and bar heights lower than one represent trade sizes less than the mean trade size. The mean trade size is the overall average of the average daily trade size across all the price-ends, and it is indexed at one.

take in Table II

take in Figure 3

Block Trades Vs. Retail Trades

Tables III and IV compare the price-end estimates when the analysis is restricted to either all block trades or all retail trades. As mentioned earlier, trades of 10,000 shares or more are regarded as block trades, which are typically made by institutional accounts (Bodie, Kane, and Marcus, 2001), whereas trades of less than 10,000 shares are regarded as retail trades.

Table III presents the results when percentage daily volume is the dependent variable, and Table IV presents the results when percentage daily number of trades is the dependent variable. From Table III, one can see that the percentage daily volume is 8%
and 4% more than the mean at the price-ends of 0 and 5 for retail accounts, whereas the corresponding estimates are 26% and 13% for institutional accounts. (By contrast, the percentage daily volume traded at the price-end of 9 is 2% less than the mean for retail accounts, whereas for institutional accounts, it is 6% less than the mean.)

**take in Table III**

Similarly, in Table IV, one can see that while the percentage daily number of trades is 6% and 3% more than the mean at the price-ends of 0 and 5 for retail accounts, the corresponding estimates for institutional accounts are 23% and 12%. (By contrast, the percentage daily number of trades at the price-end of 9 is 1% less than the mean for retail accounts, whereas for institutional accounts, it is 5% less than the mean.) These results strongly reject proposition 4 in that the price-end bias is much stronger among institutional trades both in terms of its effect on percentage daily volume and percentage daily number of trades.

**take in Table IV**

**Discussion and Future Research**

In this paper, we empirically examine the influence of cognitive biases on investor behavior in the stock market. This focus on investor behavior is motivated by our expanded notion of the stock market as a market place in which investors, as consumers, buy and sell (i.e., exchange) financial products such as stocks. Thus, our
study of investor psychology using traditional research in marketing and psychology is an extension of the study of consumer behavior in a non-traditional, but consequential, market place such as the stock market.

Our research reveals that the price-ends of 0 are strongly favored by investors, followed by price-ends of 5. Unlike other retail markets, though, price-ends of 9 are not associated with significant increases in trading volume. This bias could be the result of a tendency of buyers and sellers to negotiate towards price-ends of 0 or 5. Alternatively, this bias could be the result of an intrinsic, cognitive bias of traders to quote in price-ends of 0 or 5, which results in more trades at price-ends of 0 or 5. To further explore this issue, we analyzed the bid and ask quotes of all the Dow 30 stocks to see if the quote data itself exhibited price clustering around price-ends of 0 and 5. As shown in Figures 4 and 5, there is a strong clustering of quotes around price ends of 0 and 5, both in bid (buyer) and ask (seller) quotes. Since quotes are put out by individual traders, this evidence suggests that the price-end bias in trades probably results from an intrinsic cognitive bias towards price-ends of 0 and 5, rather than a tendency to negotiate towards a price-end of 0 or 5 in a fast moving market.

**take in Figures 4 and 5**

It is also interesting that the price-ends of 0 and 5 are favored compared to the price-ends of 9, which are so prevalent in ordinary retail markets. One explanation for this discrepancy in the price-end effect could be the structural difference between ordinary retail markets and the stock market. In ordinary retail markets, the clustering of prices around price-ends of 9 is driven in part by the fact that manufacturers/retailers
offer products at price-ends of 9 and consumers are constrained to buy at the offered price (cf. Schindler, 2001). By contrast, prices in the retail stock market are determined as in an auction-market, with prices constantly changing in relation to the number of interested buyers and sellers in a stock at any given moment in time. Thus, it would appear that the lack of a clear wholesaler for a stock for a period of time detracts from finding a clustering effect around price-ends of 9.

Another interesting finding is that institutional investors appear equally susceptible to a cognitive bias in favor of price-ends of 0 and 5. This is surprising, since a-priori one would not have expected institutional investors to favor price-ends of 0 and 5 over other possible price-ends, given their access to sophisticated models for program trading and advanced forms of custom research.

Again, the structure of the retail stock market could possibly explain these contrary findings. In the stock market, investors actively utilize limit orders (as opposed to market orders), and though precise figures of the percentage of orders that are limit orders are unknown, it is commonly believed that most orders are limit orders (Harris, 2003; Rosu, 2003). Buy limit orders are orders to buy a certain set price or better (i.e., lower), while sell limit orders are orders to sell at a certain price or better (i.e., higher). Thus, if most of the trades are the result of the triggering of preset limit orders, it is possible that institutional traders are exhibiting their bias when encoding their market model outputs in the form of limit prices. This human intervention would then explain the increased volume of trades at price-ends of 0 and 5 among institutional trades.

A strength of this study is that it uses market-level data to gain insights into the cognitive process of the individual investor, in addition to teasing out specific biases that
have not been identified earlier in the literature. These biases shed light on how consumers’ cognitive processes affect the functioning of an otherwise efficient financial market. For example, investors’ continued preference for a coarse pricing grid anchored in nickel and dime endings, rather than the fine pricing grid of a penny, detracts from the purpose of decimalization, namely, to lower transaction costs.

Several interesting avenues for future research exist. Currently, TAQ data (or for that matter, most commercial financial services we are aware of) does not break out individual trades by whether they are buy-trades or sell-trades. Thus, one is constrained to report at best that there is an increased level of buying and selling at price-ends of 0 and 5. If one could gain access to the books of a large brokerage house, one would potentially be able to break down the trading volume by type of trade, buy or sell. With this information in hand, one could then test whether ‘even’ prices favor selling and ‘odd’ prices favor buying, since in marketing it is generally assumed that prices have a signaling effect, with even prices generally signaling higher price (and quality), and odd prices signaling lower price (e.g., Lamb, Hair, and McDaniel, 2004). Also, one could examine cultural influences on investor behavior. For example, it is well-known that Asian cultures ascribe special meanings to certain digits based on the shape and sound of such numbers, and this could influence how consumers react to certain trades. As Heeler and Nguyen (2001) note, the digit ‘8’ sounds like ‘multiply’ in Chinese and this evokes favorable connotations among the Chinese. Similarly, the digit ‘8’ is represented in the form of a mountain in Japanese characters, which in turn evokes positive associations of ‘growth’ and ‘prosperity’ among the Japanese. Not surprisingly, Heeler and Nguyen observe that ‘8’ is the most common price-end in Chinese and Japanese retail markets.
Thus, it is possible that investors in the Chinese and Japanese equity markets may also favor limit prices that end in 8, as opposed to 0 and 5. Lastly, our study could be extended to see if similar psychological biases exist in other non-traditional electronic (auction) markets such as Ebay, where consumers regularly post bid and ask prices online for items they want to buy/sell.
References


Knight, F. and M. Behrens (1928), *The Learning of the 100 addition and 100 subtraction combinations*, New York: Longmans, Green.


Table I
Percentage Daily Volume and Percentage Daily Number of Trades for All Dow Stocks

<table>
<thead>
<tr>
<th></th>
<th>Percentage Daily Volume</th>
<th>Percentage Daily Number of Trades</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-value</td>
</tr>
<tr>
<td>constant</td>
<td>.10</td>
<td>587.35</td>
</tr>
<tr>
<td>price-ending of 0</td>
<td>.14</td>
<td>271.37</td>
</tr>
<tr>
<td>price-ending of 1</td>
<td>-.03</td>
<td>-49.90</td>
</tr>
<tr>
<td>price-ending of 2</td>
<td>-.02</td>
<td>-45.87</td>
</tr>
<tr>
<td>price-ending of 3</td>
<td>-.03</td>
<td>-56.17</td>
</tr>
<tr>
<td>price-ending of 4</td>
<td>-.03</td>
<td>-59.81</td>
</tr>
<tr>
<td>price-ending of 5</td>
<td>.07</td>
<td>139.35</td>
</tr>
<tr>
<td>price-ending of 6</td>
<td>-.02</td>
<td>-50.70</td>
</tr>
<tr>
<td>price-ending of 7</td>
<td>-.03</td>
<td>-55.08</td>
</tr>
<tr>
<td>price-ending of 8</td>
<td>-.02</td>
<td>-38.40</td>
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<tr>
<td>price-ending of 9**</td>
<td>-.03</td>
<td>-54.67</td>
</tr>
</tbody>
</table>

Notes:

1. All t-values are significant at the .01 level.
2. The estimates give the extent to which the percentage volume at the price-end deviates from the unweighted grand mean (intercept). Thus, the percentage daily volume at price-end of 0 is .14 (or 14%) above the grand mean of .10.
3. **The estimate and t-value for the price-end of 9 are derived from the constraint that all price-end estimates that measure deviation from the grand mean sum to 0 (Greene 1993).
Table II
Trade Size for Each Price-End for All Dow Stocks

<table>
<thead>
<tr>
<th>Price-End</th>
<th>Relative Trade size</th>
<th>Estimate</th>
<th>t-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>constant</td>
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<td>1.00</td>
<td>923.82</td>
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<td>price-end of 0</td>
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<td>.57</td>
<td>177.59</td>
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<td></td>
<td>-.13</td>
<td>-42.30</td>
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<td>price-end of 2</td>
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<td>-.08</td>
<td>-24.53</td>
</tr>
<tr>
<td>price-end of 3</td>
<td></td>
<td>-.12</td>
<td>-36.06</td>
</tr>
<tr>
<td>price-end of 4</td>
<td></td>
<td>-.15</td>
<td>-47.11</td>
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<tr>
<td>price-end of 5</td>
<td></td>
<td>.40</td>
<td>123.28</td>
</tr>
<tr>
<td>price-end of 6</td>
<td></td>
<td>-.13</td>
<td>-40.39</td>
</tr>
<tr>
<td>price-end of 7</td>
<td></td>
<td>-.12</td>
<td>-37.97</td>
</tr>
<tr>
<td>price-end of 8</td>
<td></td>
<td>-.07</td>
<td>-21.67</td>
</tr>
<tr>
<td>price-end of 9**</td>
<td></td>
<td>-.17</td>
<td>-51.08</td>
</tr>
</tbody>
</table>

Notes:

1. All t-values are significant at the .01 level.
2. The estimates give the extent to which the trade size at a particular price-end deviates from the unweighted grand mean (intercept). For example, the trade size at the price-end of 0 is 0.57 above the unweighted grand mean, which is indexed at 1.
3. ** The estimate and t-value for the price-end of 9 are derived from the constraint that all price-end estimates that measure deviation from the grand mean sum to 0 (Greene 1993).
Table III  
Percentage Daily Volume of Trades for All Dow Stocks by Type of Account

<table>
<thead>
<tr>
<th></th>
<th>Retail Accounts</th>
<th></th>
<th>Institutional Accounts</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-value</td>
<td>Estimate</td>
<td>t-value</td>
</tr>
<tr>
<td>constant</td>
<td>0.10</td>
<td>825.76</td>
<td>0.10</td>
<td>281.55</td>
</tr>
<tr>
<td>price-ending of 0</td>
<td>0.08</td>
<td>231.96</td>
<td>0.26</td>
<td>241.15</td>
</tr>
<tr>
<td>price-ending of 1</td>
<td>-0.01</td>
<td>-38.62</td>
<td>-0.05</td>
<td>-47.08</td>
</tr>
<tr>
<td>price-ending of 2</td>
<td>-0.01</td>
<td>-42.23</td>
<td>-0.04</td>
<td>-39.39</td>
</tr>
<tr>
<td>price-ending of 3</td>
<td>-0.02</td>
<td>-54.13</td>
<td>-0.05</td>
<td>-45.85</td>
</tr>
<tr>
<td>price-ending of 4</td>
<td>-0.02</td>
<td>-52.02</td>
<td>-0.05</td>
<td>-51.90</td>
</tr>
<tr>
<td>price-ending of 5</td>
<td>0.04</td>
<td>121.46</td>
<td>0.13</td>
<td>123.42</td>
</tr>
<tr>
<td>price-ending of 6</td>
<td>-0.01</td>
<td>-40.80</td>
<td>-0.05</td>
<td>-46.39</td>
</tr>
<tr>
<td>price-ending of 7</td>
<td>-0.02</td>
<td>-51.89</td>
<td>-0.05</td>
<td>-46.42</td>
</tr>
<tr>
<td>price-ending of 8</td>
<td>-0.01</td>
<td>-31.48</td>
<td>-0.04</td>
<td>-35.23</td>
</tr>
<tr>
<td>price-ending of 9**</td>
<td>-0.02</td>
<td>-42.25</td>
<td>-0.06</td>
<td>-52.19</td>
</tr>
</tbody>
</table>

Notes:

1. All t-values are significant at the .01 level.
2. ** The estimate and t-value for the price-end of 9 are derived from the constraint that all price-end estimates that measure deviation from the grand mean sum to 0 (Greene 1993).
### Table IV
Percentage Daily Number of Trades for All Dow Stocks by Type of Account

<table>
<thead>
<tr>
<th></th>
<th>Retail Accounts</th>
<th></th>
<th>Institutional Accounts</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-value</td>
<td>Estimate</td>
<td>t-value</td>
</tr>
<tr>
<td>constant</td>
<td>0.10</td>
<td>953.577</td>
<td>0.10</td>
<td>325.72</td>
</tr>
<tr>
<td>price-ending of 0</td>
<td>0.06</td>
<td>183.92</td>
<td>0.23</td>
<td>247.78</td>
</tr>
<tr>
<td>price-ending of 1</td>
<td>-0.01</td>
<td>-26.10</td>
<td>-0.05</td>
<td>-48.61</td>
</tr>
<tr>
<td>price-ending of 2</td>
<td>-0.01</td>
<td>-37.26</td>
<td>-0.04</td>
<td>-40.61</td>
</tr>
<tr>
<td>price-ending of 3</td>
<td>-0.01</td>
<td>-45.88</td>
<td>-0.04</td>
<td>-47.93</td>
</tr>
<tr>
<td>price-ending of 4</td>
<td>-0.02</td>
<td>-41.00</td>
<td>-0.05</td>
<td>-54.43</td>
</tr>
<tr>
<td>price-ending of 5</td>
<td>0.03</td>
<td>89.53</td>
<td>0.12</td>
<td>128.93</td>
</tr>
<tr>
<td>price-ending of 6</td>
<td>-0.01</td>
<td>-29.57</td>
<td>-0.04</td>
<td>-47.26</td>
</tr>
<tr>
<td>price-ending of 7</td>
<td>-0.01</td>
<td>-41.67</td>
<td>-0.05</td>
<td>-48.92</td>
</tr>
<tr>
<td>price-ending of 8</td>
<td>-0.01</td>
<td>-25.90</td>
<td>-0.03</td>
<td>-34.60</td>
</tr>
<tr>
<td>price-ending of 9**</td>
<td>-0.01</td>
<td>-26.04</td>
<td>-0.05</td>
<td>-54.33</td>
</tr>
</tbody>
</table>

Notes:

1. All t-values are significant at the .01 level.
2. ** The estimate and t-value for the price-end of 9 are derived from the constraint that all price-end estimates that measure deviation from the grand mean sum to 0 (Greene 1993).
Figure 1: Distribution of Volume across Price-Ends for All Dow 30 Stocks
Figure 2: Distribution of Number of Trades across Price-Ends for All Dow 30 Stocks
Figure 3: Distribution of Relative Trade size across Price-Ends for All Dow 30 Stocks
Figure 4: Distribution of Bid Quotes across Price-Ends for All Dow 30 Stocks
Figure 5: Distribution of Ask Quotes across Price-Ends for All Dow 30 Stocks
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