Limit Order Clustering and Stock Price Movements

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Abstract

Stocks with prices slightly above round numbers (e.g., \$6.1) tend to increase in the next period, while those slightly below (e.g., \$5.9) tend to decrease. A long-short strategy based on daily closing prices yields a daily return of 24.6 basis points (or 61% per annum). This pattern is extremely robust across different stock price levels, sizes, liquidity, exchanges, sub-periods, intraday half-hour periods, and international samples. We demonstrate that an excessively large volume of limit orders, which tend to cluster at round numbers (e.g., \$6.0), supports stocks with prices just above and resists those just below these round levels, resulting in differential subsequent price movements. Our findings highlight the profound impact of investors placing orders at psychologically appealing round numbers on random price movements and market efficiency.

Key Words: Limit Order Clustering, Stock Price Movements, Round Numbers, Return Predictability
JEL Codes: G12, G14

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1 Introduction

Price clustering is a widespread phenomenon in financial markets, where asset prices tend to converge at salient points such as round numbers. This has attracted significant attention since it was first observed by Osborne (1962). The reason why asset prices cluster has been extensively studied in the literature. This is largely because investors are more likely to place orders at these psychologically appealing round numbers (see Harris (1991) and Kuo, Lin, and Zhao (2015) among others). However, how an excessive distribution of orders affects stock price movements around these clustering points remains unclear.

This paper documents a distinct price movement pattern where a stock's price tends to move up when it is slightly above a round number, but tends to move down when it is below a round number. To explain this pattern, we demonstrate that a relatively large volume of bid (buy) orders clustering at the round number (e.g., \$6.0) supports the stock with a price just above (e.g., \$6.1) from dropping, leading to a more likely upward movement. Conversely, a significant volume of ask (sell) orders concentrated at the round number resists the stock just below (e.g., \$5.9) from rising, leading to a downward movement.

The financial practitioners have also long anecdotally observed "support and resistance" effects at significant price levels, such as \$100, which tend to buoy stocks above these levels and restrain those below, particularly among technical traders. Our findings substantiate these observations, demonstrating that clustering of limit orders plays a critical role in the formation of these support and resistance levels. This paper sheds light on the underlying market microstructure mechanisms, offering practical insights for traders.

To analyze stock price movements around round numbers, we examine the subsequent daily returns of stocks based on their proximity to round numbers, utilizing the first digit after the decimal point in their previous closing prices. For instance, a stock closing at $6.13 would be categorized into a group denoted by $X.1, where the first digit after the decimal point is 1, while another closing at $5.92 would be classified into the group denoted by $X.9, with the first decimal digit being 9. Analyzing U.S. individual stocks from 1963 to 2021, we find that stocks with a previous closing price at $X.1 tend to exhibit upward movement the following day, in contrast to those closing at $X.9, which tend to move downward. The average daily return difference between these two groups is approximately 24.6 basis points (bps), with a t-statistic of 32.5, translating to an annualized return of 61%. A similar pattern is observed with stocks around the half-dollar prices (e.g., $5.5), where those slightly above the half-dollar prices tend to outperform those just below.

This distinctive price movements pattern is extremely robust and remarkbly pervasive. It remains consistent across diverse price levels, market capitalizations, liquidity levels, equity exchanges, as well as over various subperiods. Notably, this pattern is observed not only at market close but throughout the trading day in the U.S. market. Furthermore, this effect is prevalent in the majority of the 22 foreign equity markets we examined.

We hypothesize that this pattern arises from investors clustering their limit orders at psychologically appealing round numbers, such as $X.0 or $X.5. This behavior creates an imbalance in the depth of the order book at the best bid versus best ask prices around these levels, as depicted in Figure 4. For example, a significant volume of buy orders (best bid) may cluster at a round number (e.g., $X.0), compared to sell orders (best ask), which are typically placed at a slightly higher but non-round price, such as $X.1. This imbalance tends to favor stocks with current prices just above round numbers, like $X.1, by preventing them from dropping, thereby leading to higher returns in the subsequent period. Conversely, stocks trading just below round prices, like $[X-1].9, may experience a larger volume of sell orders at round numbers compared to buy orders at lower non-round prices. This disparity could impede price increases, resulting in lower future returns. A similar dynamic is observed for stocks at $X.6 and $X.4 when there is a clustering of limit orders at the half-dollar price, $X.5.

To validate our hypothesis, we begin by examining evidence of price clustering at round numbers using Trade and Quote (TAQ) data. In an ideal market without any frictions, one would expect a random distribution of prices, with each digit after the decimal point occurring with equal probability, theoretically at 10%[1]. However, contrary to this expectation and in alignment with previous research, such as that by Harris (1991), our analysis uncovers a significant deviation from this pattern. Specifically, we observed that 16.7% of trades, 15.4% of bids, and 14.8% of asks were executed at round dollar prices ($X.0) over the period from 1993 to 2014. Additionally, 12.4% of trades, 12.2% of bids, and 12.1% of asks occurred at half-dollar prices ($X.5).

Our study reveals an asymmetric effect of limit order clustering on the imbalance between the best bid and best ask, particularly when one is positioned at a round level and the other is not. On average, at any given moment, the depth of the best bids at a round price ($X.0) surpasses that of the best asks—which are typically set higher than the bid price—by 2.4%. This difference is economically large, representing a substantial percentage of the total volume of all bids and asks in that day. Consequently, when the best bid price reaches a round number (e.g., $X.0) and the current trade price is slightly above this bid (e.g., $X.1), there is often a larger volume of bid (buy) orders compared to ask (sell) orders. This supports the stock with price above the round level, preventing it from decreasing. Conversely, when there is a larger volume of best ask (sell) orders at a round price compared to real-time best bid (buy) orders at a lower non-round price, it tends to suppress the prices of stocks just below this threshold, such as $[X-1].9.

More importantly, we establish a direct link between the imbalance of bid and ask

[1]The expected probability should be 12.5% in period of orders bid in one-eighth, and be 10% in post-decimalization period.

orders, resulting from order clustering, and the observed pattern of price movements by analyzing the distribution of trade prices on the day following the close. The distribution of intraday trade-by-trade prices explains why stock prices move in opposite directions after closing at $X.1 or $X.9, respectively. As shown in Figure 7, stocks that closed at $X.1 typically see a higher concentration of trades at the round price below ($X.0) and fewer at further lower prices such as $[X-1].9, $[X-1].8, etc., on the following day. This distribution is attributed to a large volume of best bid orders at the round number $X.0, surpassing real-time best ask orders at slightly higher but non-round prices, like $X.1. This excess of bid (buy) orders supports the current price, preventing it from declining and thus leading to positive returns the next day. Conversely, stocks that closed at $X.9 exhibit more trades at the round price above ($[X+1].0) and fewer at higher non-round prices such as $[X+1].1, $[X+1].2, etc., the following day. This pattern arises from a larger volume of ask orders clustering at the round number $[X+1].0 compared to bid orders at lower non-round numbers ($X.9), thereby restraining the price from increasing further and resulting in negative returns.

We further test a prediction derived from the limit order clustering hypothesis by exploiting the variations in price clustering intensity among stocks. Consistent with our hypothesis, we found that stocks exhibiting the highest level of price clustering at round numbers in the previous year demonstrated a more substantial next-day return difference, with a disparity of approximately 31.2 bps between stocks at $X.1 and $X.9. In contrast, stocks with minimal price clustering exhibited a smaller return gap of 19.9 bps. These findings reinforce the notion that limit order clustering at round numbers significantly influences the directional price movements of stocks positioned above or below these critical points.

We conducted a placebo test on Exchange-Traded Funds (ETFs) to investigate whether trading associated with limit order clustering within ETFs could influence the price movements of their underlying assets. Although the daily closing prices of ETFs show a slight tendency towards clustering at round numbers, the difference in daily returns between ETFs closing at $X.1 and $X.9 is minimal, amounting to only 2 basis points (bps). This is in stark contrast to the significant 20.3 bps return difference observed in individual stocks over the same period. These placebo findings indicate that limit order clustering in ETF trading has a minimal impact on the price movement of underlying assets, likely due to the segmentation between ETF trading and the trading of underlying assets.

Furthermore, we examine two alternative explanations for the observed return patterns: the bid-ask bounce[2], and the delta hedging of option trading at round strike prices[3]. After adjusting the next-day returns for changes in mid-quote prices, the return difference between stocks priced at $X.1 and $X.9 remains highly significant, indicating a limited impact of the bid-ask bounce on this pattern. Additionally, stocks with minimal or no option trading volume show a more pronounced return difference between $X.1 and $X.9 compared to those with significant option trading volume. This finding is hard to square with the notion that delta hedging at round strike prices significantly influences the observed daily return patterns.

This paper extends the literature on price clustering by demonstrating the pronounced impact of order clustering on price dynamics around clustering levels. Previous research, including seminal works by Osborne (1962), Niederhoffer (1965), Niederhoffer (1966), Ball, Torous, and Tschoegl (1985), and Harris (1991), primarily examined the static distribution of asset prices and the determinants of clustering behavior. Our analysis goes a step further to demonstrate the pronounced impact of this disproportionate distribution on price dynamics. Specifically, we identify how price clustering creates barriers that impede the smooth movement of prices across clustering points, leading to distinct price trajectories for stocks situated above and below these thresholds. This finding traces the

[2]See discussion in Blume and Stambaugh (1983) and Subrahmanyam (2005).

[3]Ni, Pearson, and Poteshman (2005) show that individual stock price tends to close at option strike price.

root of this detrimental effect to the cognitive biases of retail investors, who are chiefly responsible for the clustering of limit orders, as explored in the studies by Kuo, Lin, and Zhao (2015) and Chiao and Wang (2009).

This paper also expands upon existing research on the pattern of daily returns for stocks priced around round numbers. While not the first to observe these patterns, our study identifies the limit order clustering as the primary cause of the observed price effects. Previous studies, such as those by Johnson, Johnson, and Shanthikumar (2007) and Bagnoli, Park, and Watts (2006), have noted differences in returns for stocks priced above or below round numbers without pinpointing the mechanisms at play. Moreover, these prior analyses were confined to the initial years following decimalization. Our study broadens the scope of investigation to cover an extensive period starting from 1963, demonstrating the consistency of this return pattern throughout the trading day and across 22 foreign markets based on a standard portfolio sorting method.

This paper closely relates to existing research on price dynamics around psychological pricing thresholds, specifically round numbers. While Sonnemans (2006) identified the presence of price clustering at these thresholds and their role as price barriers, it did not explore their impact on subsequent price movements and daily return patterns. Bhattacharya, Holden, and Jacobsen (2012) analyzed the surge in trading activity by liquidity seekers as prices reach and cross these round numbers, without delving into the price dynamics in proximity to these levels. Our research aims to fill this gap by focusing on how prices, when nearing these round numbers from either direction, are influenced by the heightened concentration of limit orders at these levels.

The impediment to price movement across round levels introduces a specific type of trading friction. This also suggests that prices tend to wobble between adjacent round numbers, leading to increased price volatility[4]. The negative consequence of limit

[4]This might explain why price clustering results in more volatile market in Blau and Griffith (2016) from a trading perspective.

order clustering prompts the consideration of regulatory policy such as decimalization to mitigate such behavior. Decimalization not only reduces transaction costs[5], but also encourages investors to consider decimal points more carefully when placing limit orders, promoting a uniform price distribution[6].

The price dynamics around round numbers also provides an alternative explanation for short-term reversal[7], which are traditionally ascribed to the liquidity shock or market overreaction[8]. We demonstrate that stocks closing at $X.1 generally exhibit a downward trend in the preceding week towards a support level at $X.0, only to reverse upwards in the subsequent week. In contrast, stocks ending the day at $X.9 show an initial upward trend towards the resistance level at $[X+1].0, followed by a downward correction the next week.

The limit order clustering and the resulting price movements contribute to further herding behavior and increased limit order clustering. For example, stocks priced at $X.9 are likely to face downward pressure due to a larger ask orders at the next round price level of $[X+1].0. This anticipation may lead investors to place additional ask orders at $[X+1].0, expecting a negative return. Such anticipatory actions by investors further amplify the clustering of limit orders at round price points. Thus, our analysis provides an alternative explanation for limit order clustering, suggesting that investors strategically engage in clustering, anticipating its impact on subsequent price movements.

The remainder of this paper is structured as follows: Section 2 details our data sample and methodology. Section 3 examines the empirical return pattern based on the previous closing price. Section 4 illustrates the pervasiveness of this empirical pattern. Section 5 proposes a hypothesis regarding the asymmetric effect of limit order clustering and

[5]See Graham, Michaely, and Roberts (2003) and Chakravarty, Wood, and Van Ness (2004) for discussion of the effect of decimalization.

[6]Although Ikenberry and Weston (2008) finds that the magnitude of clustering does not significantly declines immediately after decimalization, the recent sample shows little evidence of price clustering.

[7]See Fama (1965), Jegadeesh (1990), and Lehmann (1990) among others.

[8]See, for example, the disscussion in Da, Liu, and Schaumburg (2014) among others.

provides supporting evidence. Section 6 explores two alternative hypotheses: the bid-ask bound and option trading. Section 7 discuses the relevance and implications of these findings. Finally, Section 8 concludes the paper.

2 Data and methodology

2.1 Data

This study utilizes five databases: CRSP, TAQ, Datastream, OptionMetrics, and Thomson/Refinitiv 13F database. We obtain individual stocks' daily closing prices, returns, mid-quotes, market capitalization, and exchanges information from CRSP. Similar data for ETFs, identified by a share code of 73, are also sourced from CRSP. All trades and quotes information come from TAQ. We obtain individual stocks' daily closing prices, returns, and market capitalization in 22 foreign countries from Datastream. Our sample for individual stocks in U.S. equity market includes all stocks listed on NYSE, Amex, and NASDAQ with daily closing price (either last trade price or mid-quote price) and spans from 1963 to 2021. The intraday analysis of trade prices, quote price, and half-hour returns extends from 1993 to 2014. The data for foreign equity markets starts in different years, ranging from 1970 to 2002, depending on the specific markets, and all end in 2021. The analysis based on option trading activity covers the periods from 1996 to 2021 due to the data availability in OptionMetrics. The institutional holdings data starts from 1980 to 2021 from the Thomson/Refinitiv 13F institutional holdings database. s

2.2 Methodology

Our primary method to assess the relationship between the previous closing price and subsequent price movement involves sorting individual stocks into ten portfolios based on the first decimal number of their previous closing price. We then calculate the average next-day return for these stocks with the same first decimal number in each portfolio, using either equal weight or value weight based on market-cap at the end of previous month. To estimate the return pattern, we calculate the average return difference between portfolios of stocks priced at $X.1 and $X.9, along with its t-statistics. In alternative analyses, we also use the percentage change in last mid-quotes price to calculate daily returns for robustness check.

For the analysis of intraday trade price distribution or best bid and best ask (called ”bid1-ask1” hereafter) shares imbalance at different first decimal numbers, we first calculate the distribution or quotes shares imbalance at stock-day level. These daily values are then aggregated to the stock-year level, averaged across all stocks for each year, and finally averaged across years. For the analysis of next-day trades price distribution and bid1-ask1 shares imbalance conditional on the previous closing price, we calculate the trade price distribution or bid1-ask1 shares imbalance at the stock-day level, then average these values across stocks with the same first decimal number each day, and then obtain the average value across all days in the sample.

3 Empirical Pattern

In this section, we first present the baseline pattern of the next-day return for ten portfolios based on the first decimal number of the previous closing price, covering a period from 1963 through 2021. We also calculate the cumulative returns around the day of closing price to explore the price dynamics for stocks closing above or below round numbers. Additionally, we examine the next-day return pattern based on the second decimal numbers of the previous closing price in the post-decimalization period.

Our main finding indicates that stocks with a previous closing price at $X.1 exhibit higher returns than those at $X.9 in the following day and week. Stocks hitting $X.1 today have, on average, already experienced a downward movement in the previous day and week. In contrast, those at $X.9 have typically seen an upward movement in the preceding days. This pattern is also evident around the half-dollar price of $X.5. In the post-decimalization era, the second decimal number show a similar pattern around round first decimal numbers.

3.1 Price's first decimal digit and next one-day return

Figure 1 illustrates the next one-day return in relation to the previous closing price's first decimal digit number. There are two noticeable declining trends: one from $X.0 to $X.4, and another from $X.5 to $X.9. We observe that stocks with a previous price at $X.1 and $X.6 yield higher returns, in contrast to the lower returns from stocks at $X.9 and $X.4. Both equal-weight and value-weight returns follow similar patterns, but the magnitude is greater for equal-weight returns.

Table 1 offers specific statistics and returns for stocks with different first decimal numbers. The first two columns report the average number of stocks (as a percentage of the total) and the average size percentile for stocks in each decimal category. From 1963 to 2021, fewer stocks had daily closing price at $X.4 and $X.9, likely due to the one-eighth or one-sixteenth order regulations in the early period. Conversely, more stocks were priced at round numbers and half-dollar numbers, such as $X.0 and $X.5, which aligns with the price clustering extensively documented in literature[9]. It is also noted that the size of stocks at $X.4 and $X.9 is smaller than average, influenced by the one-sixteenth regulation for low-priced stocks that are more usually smaller and by more mid-quotes closing prices at $X.4 and $X.9 from NASDAQ where stocks are on average smaller as well[10].

Columns (3) and (4) of table 1 present the average equal-weight and value-weight daily returns for each first decimal number. The return difference between stocks at $X.1 and $X.9 is economically significant: 24.6 bps, translating to an annual return of 61%,

[9]See Osborne (1962), Niederhoffer (1965), Niederhoffer (1966), Harris (1991) among others.

[10]We will discuss the distribution of stocks with closing price at $X.4 or $X.9 in next section.

with a t-stat of 32.5 based on equal-weighting. The value-weighted return difference is also notable, at 11.8 bps with a t-stat of 12.9.

3.2 Price dynamics before and after price closing at different first decimal numbers

We investigate the price dynamics surrounding the closing day by examining the cumulative return before and after that day. Figure 2 shows that stocks with a closing price at $X.1 typically experienced a downward movement beforehand, with an average negative return of 7.9 bps and 18.8 bps for the previous one day and one week, respectively. Subsequently, they exhibit an upward trend, with an average positive return of 4.7 bps and 12.8 bps for the following one day and one week, respectively. In contrast, stocks closing at $X.9 display an upward movement before and a downward trend after, with average positive returns of 18.2 bps and 29.5 bps in the preceding one day and one week, and negative returns of 21.9 bps and 37.0 bps in the subsequent one day and one week, respectively. Similar patterns are observed for value-weighted cumulative returns, though with a smaller magnitude. We adjust each stock's cumulative return for the market and size effects by subtracting the average returns of stocks in the same size decile group.

These distinct dynamic patterns for stocks closing at $X.1 and $X.9 suggest that stock prices tend to rebound when approaching round numbers. This observation leads us to consider limit order clustering at round numbers as a potential explanation for this pattern. It also implies that this return pattern around round numbers contributes to short-term reversal, which we will discuss in a later section.

We also show in appendix Table A.1 that the stocks with a previous closing price at $X.X1 yield higher returns than those at $X.X9 the next day. The daily return difference between them is approximately 14.4 bps, with a t-stat of 28.3. The value-weighted returns show a similar pattern. We also observe more stocks with closing prices at round first decimal prices ($X.X0) and half first decimal price ($X.X5), which can be attributed to the price clustering at these round first decimal numbers.

4 This pattern is pervasive

Based on the return pattern outlined in the previous section, we conducted a comprehensive analysis on its pervasiveness. This return pattern is found to be prevalent across various price levels, among small, medium, and large stocks, across three different exchanges, and during three subperiods. Additionally, we discovered that this pattern is not limited to market closing prices in the U.S. equity market but also exists for any intraday half-hour prices and persists across most foreign equity markets.

4.1 Price level and last digit of integer part

Panel A of table 2 displays the daily return difference between stocks with first decimal at $X.1 and $X.9 within different price level groups, such as $0-10, $10-20, ..., $90-100, and above $100. The results show a positive and significant return difference across almost all price levels. The pattern is generally stronger for lower-priced stocks and weaker for higher-priced stocks. The value-weighted return difference aligns with the equal-weight results.

Panel B of table 2 displays the daily return difference between stocks at $X.1 and $X.9 with different last digit number of the price integer part, such as $ X0., $X1., ..., $X9.. The results show a positive and significant return difference for stocks with different last digit numbers in the integer part. The pattern is on average stronger for stocks with price at $X0., and weaker for stocks at $X9.. We know the price $X0. are multiples of 10 such as $10, $20, $30, ..., which are more pronounced round numbers. This result is consistent with the prediction in support and resistance technical analysis which usually focus on those specific price at multiples of 10. The value-weighted return difference is also consistent with the equal-weighted results.

4.2 Size and liquidity

Panel C of table 2 details the daily return pattern for stocks with varying market-caps. We classify stocks into three subgroups based on their market cap as of the previous day. The results indicate that the return difference between $X.1 and $X.9 is larger for smaller stocks. However, the returns are economically large and statistically significant for all groups, regardless of value weight or equal weight.

Panel D of table 2 reports the daily return pattern for stocks with different liquidity. We sort stocks into three subgroups based on their previous one-month liquidity measure, which is calculated as the previous one-month trading volumes scaled by the total number of shares outstanding. The results indicate that the return difference between $X.1 and $X.9 is larger for less liquid stocks. But the returns are economically large and statistically significant for all subgroups, regardless of value- or equal- weighting.

4.3 Different exchanges and subperiods

Panel E and F of table 2 report on the pattern across three exchanges and during three distinct subperiods, respectively. A stronger pattern is observed on Amex compared to NASDAQ. And a larger return difference between $X.1 and $X.9 occurred during earlier periods than in more recent times.

Figure A.1 in the appendix demonstrates the specific distribution of daily closing prices at $X.4 or $X.9 and other decimal numbers across the three exchanges each year from 1993 to 2021. The chart includes the number of closing prices based on the last trade price or the mid-price of bid and ask. It reveals that in the period before 1996, when most exchanges did not permit one-sixteenth orders, most daily closing prices at \$X.4 and \$X.9 were based on mid-quotes prices, predominantly from NASDAQ and to a lesser extent from Amex. This explains why the stocks priced at \$X.4 and \$X.9 are, on average, smaller in size, as indicated in table 1.

4.4 Price anytime: Half-hour price and next half-hour return

All our previous results are based on daily closing prices around the market closing time. We have delved deeper into intraday prices at half-hour intervals using TAQ data. Table 3 presents the average half-hour return for stocks with varying first decimal numbers of the last trade price in the previous half-hour period and the first trade price in the current half-hour period, respectively. It reveals that stocks with a closing price at \$X.1 at the end of the last half-hour period exhibit higher returns than those at \$X.9 in the subsequent half-hour period. The results are similar, albeit weaker, when based on the first trade price of the current half-hour period. This might be due to the first trade price being less representative than the last trade price to be a reference price for investors to place limit order. In panel B, we display the return difference between stocks at \$X.1 and \$X.9 for each of the 12 half-hour periods within a day. The results are strongest in the first half-hour but remain persistent and significant at any time of the day.

4.5 Price anywhere: International market

Beyond the U.S. equity market, we have examined the daily return pattern for individual stocks in many foreign equity markets. Table 4 shows the average daily return different between stocks at \$X.1 and \$X.9 in 22 different equity markets.A significant return difference is observed in most of these 22 countries, with the exceptions of Israel and Japan. We know in Japanese equity market, most equity prices are quoted on round number or on basis of ten Yens, leading to no variation on the decimal part. The results are robust using both equal-weight and value-weight methods. The magnitude of the return different in these countries is comparable to that in the U.S. market.

5 A hypothesis: Asymmetric effect of limit order clustering on round number

In this section, we propose a hypothesis regarding limit order clustering around round numbers to explain the pervasive return pattern documented in previous sections. This clustering leads to an asymmetric effect on stocks with closing prices above and below these round numbers. Initially, we provide evidence documenting the trades and quotes price clustering. Subsequently, We demonstrate snapshot-level real-time bid1-ask1 shares imbalance at different first decimal numbers of price. Moreover, we offer direct evidence about the next-day trades distribution and bid1-ask1 shares imbalance following different previous closing prices.

Additionally, we conduct a placebo test on ETFs and test a prediction based on stocks with varying levels of limit order clustering. The results consistently support our limit order clustering hypothesis.

5.1 Limit order clustering

Price clustering has been documented for a long history since first paper by Osborne (1962). Subsequent studies, such as Niederhoffer (1965), Niederhoffer (1966), Ball, Torous, and Tschoegl (1985), Harris (1991), Hausman, Lo, and MacKinlay (1992), and Ahn, Cai, and Cheung (2005), have further analyzed the distribution of trades or quotes price, providing potential explanations for price clustering. Here, we present the distribution pattern for trades and quotes prices from 1993 to 2014 based on TAQ data.

Figure 3 panel A plots the overall trades price distribution on different first decimal numbers from 1993 to 2014. We observe more trades at \$X.0 and \$X.5, indicative of price clustering, and fewer trades at \$X.4 and \$X.9, due to the one-eighth and one-sixteenth regulations before decimalization. The clustering pattern persists, albeit less intensively, even after the decimalization in 2001.

Figure 3 panel B and C show the quotes price distribution, plotting the bid and ask prices separately. A similar distribution pattern emerges: more quotes (both bid and ask) at \$X.0 and \$X.5, and fewer at \$X.4 and \$X.9. Each trade's price is predetermined by the corresponding limit order (quote) price, rather than by the market orders, which are not required to specify the price. Therefore, the trade's price distribution mechanically mirrors the quotes price distribution.

5.2 Asymmetric effect of order clustering on the price above and below round numbers

Assume more limit order (quotes) clustering occurs at round numbers, such as \$6.0, we expect more bid (buy) orders at \$6.0 than ask (sell) orders at \$6.2 when a stock is being traded at a price above the round numbers, like \$6.1, which is the midpoint of bid order and ask order. This leads to a positive bid1-ask1 imbalance where bid1 exceeds ask1 in shares and predicts an upward price movement. Conversely, when a stock is being traded below the round number, like \$5.9, we expect more ask (sell) orders at the round price of \$6.0 than bid (buy) orders at \$5.8, resulting in a negative bid1-ask1 imbalance and a downward price movement.

Thus, limit order clustering at round numbers results in an asymmetric effect for stocks priced above and below the round number, leading to opposite price movements and a predictable return pattern in the subsequent period. Figure 4 illustrates this concept in a general case with limit order clustering at price \$X.0. We expect a similar asymmetric effect around half-dollar price \$X.5 given order clustering at \$X.5.

Figure 5 provides evidence of this asymmetric effect on bid1-ask1 shares imbalance when the bid price or ask price reaches different points around round numbers. We define the bid1-ask1 shares imbalance as the difference between the bid1 shares and the ask1 shares in the same snapshot, scaled by the total bid1 and ask1 shares that day. As discussed in previous example, a positive bid1-ask1 imbalance means that the bid1 shares exceed the ask1 shares and therefore predicts a upwards price movement, and vice versa. Panel A shows that the average bid1-ask1 shares imbalance is positive and larger when the bid price is exactly at $X.0 and $X.5, due to more bid orders clustering at these round or half-dollar prices, than real-time counterpart ask orders at higher price levels such as $X.1 and $X.6. Conversely, a smaller bid1-ask1 shares imbalance is observed when the bid price is at $X.9 and $X.4, where there are more ask orders clustering at higher prices, typically the round or half-dollar prices like $X.0 and $X.5.

Panel B of figure 5 shows inverse results when focusing on ask order prices. When the ask order price is at $X.0 and $X.5, the bid1-ask1 shares imbalance is negative or smaller due to more ask orders clustering at these round or half-dollar prices than bid orders at lower prices such as $X.9 and $X.4. Meanwhile, a positive and higher bid1-ask1 shares imbalance is noted when the ask price is at $X.1 and $X.6, due to more bid orders clustering at lower prices, typically round or half-dollar prices like $X.0 and $X.5.

5.3 Evidence: Next-day intraday trade price distribution conditional on previous closing price

We analyze the next-day trades' price distribution after different previous closing prices to explain the next-day return pattern. Figure 6 presents the next-day intraday trades price distribution for stocks with previous closing prices at $X.0, $X.9, $X.1, $X.8, and $X.2, respectively. Comparing the next-day trades distribution between stocks with previous closing price at $X.9 and $X.1 in panel B and C, we observe that more trades occurs at $X.0 for both groups, due to limit order clustering. However, this clustering impacts stocks at $X.9 and $X.1 in opposite ways. For stocks priced at $X.9, more trades occur at $[X+1].0 but fewer at higher prices like $[X+1].1, $[X+1].2, etc., implying a negative impact on next-day returns. Conversely, for stocks priced at $X.1, more trades happen on $X.0 but fewer at lower prices like $[X-1].9, $[X-1].8, etc., leading to a positive effect on next-day returns.

This mechanism also explains why stocks at $X.9 exhibit lower returns than those at $X.8, and why stocks at $X.1 show higher returns than those at $X.2. As demonstrated in panel B and D, compared to those at $X.9, stocks at $X.8 experience less negative impact from the shift of trades from higher prices ($X.1, $X.2, ...) to the lower clustering price of $X.0, since stocks previously closed at price of $X.8 are farther from the round price of $X.0 than those closed at $X.9. Additionally, stocks at $X.8 benefit from a positive impact of fewer trades at the lower price of $X.9 and more trades at the higher round price of $X.0, unlike those at $X.9. Less negative impact and additional positive impact together explain the higher return for stocks at $X.8 than those at $X.9. A similar comparison applies to stocks at $X.2 and $X.1 in panel C and E. Stocks at $X.2 show less positive impact and additional negative effects compared to those at $X.1, resulting in lower returns for stocks at $X.2 than for those at $X.1.

5.4 Evidence: Next-day bid1-ask1 imbalance conditional on previous closing price

The trade price distribution can explain the next-day return pattern for stocks with different previous closing price. A follow-up question is what leads to the differential trade price distribution for stocks with different previous closing prices. The answer is the limit order clustering at round prices. In this part, we use the real-time bid1-ask1 shares imbalance to proxy the asymmetric effect of limit order clustering when the bid1 or ask1 is at round price. We then examine the next-day bid1-ask1 shares imbalance following different previous closing prices to explain the next-day trades distribution.

Figure 7 retains the trades distribution for stocks at $X.1 and $X.9 from figure 6 as a reference. It demonstrates in panel C that for stocks previously priced at $X.9, there is a negative bid1-ask1 shares imbalance when the bid price is $X.9 next day because the counterpart ask price is more likely to be a round price $X.0, which will see excessive shares due to order clustering at $X.0. This excessive ask orders at price of $X.0 prevent the current stock price of $X.9 from moving upward and across the round price, resulting more trade distribution at or below this round price and less distribution at higher price levels. Panel E displays a more obvious negative bid1-ask1 shares imbalance when the ask price is exactly at round price of $X.0, which shows more clustering and excessive shares compared to the counterpart bid orders at lower prices. Therefore, the clustering of ask orders at the round number $X.0 prevents the trade price from further upward movement, leading to a next-day negative return for stocks with a previous closing price at $X.9. Panel D and E present opposite results for stocks with previous closing price at $X.1 where the bid price is exactly at the round price of $X.0 and see excessive clustering shares and larger bid1-ask1 shares imbalance, preventing the price from further moving down. This explains the next-day trade distribution and the next-day positive return for stocks previously closed at $X.1.

5.5 Prediction: Stocks with more clustering exhibits stronger pattern

We test a prediction directly related to our limit order clustering hypothesis. We anticipate that stocks with more pronounced clustering behavior at round number $X.0 will show a larger return difference between stocks with closing prices at $X.1 and $X.9. We use the probability of a stock's daily closing price being at round number $X.0 in the prior year as a measure of clustering level for each stock.

Table 5 panel A presents the return difference between \$X.1 and \$X.9 for stocks with varying clustering levels in the prior year. It reveals that stocks with the highest clustering level exhibit the largest return difference between stocks at \$X.1 and \$X.9, compared to those with lower clustering levels. This result aligns with our limit order clustering explanation of the return pattern. Stocks with a higher likelihood of their daily price closing at round numbers \$X.0 in the past year are more likely to be subject to limit order clustering on round numbers. This leads to a more asymmetric impact on stocks priced above and below these round numbers, resulting in a larger return difference between these stocks.

We can imagine that the stocks with more price clustering in the prior year might be less liquid stocks, and thus show a stronger return difference next day. To control the impact of liquidity, we present the results under subgroups of liquidity in panel B of table 5. After controlling for the liquidity measure, we can still see that the past price clustering predicts a stronger return difference for stocks at \$X.1 and \$X.9. This result mitigates the concern of the potential impact of liquidity on return pattern.

5.6 Placebo test on ETF

We conducted a placebo test using the daily closing price of ETFs. Our expectation is that ETF prices also exhibit a clustering pattern, but the order clustering in ETFs have much less impact on their next-day returns. This is because the value of the ETFs primarily depends on the trading on the underlying assets, not on the trading on the ETFs themselves.

Table 6 panel A shows the average next-day return for ETFs with different first decimal numbers of the previous closing price. We observe less significant return difference for ETFs with price at \$X.1 and \$X.9, contrasting with the large and significant return difference observed in individual stocks over the same periods in panel B. This placebo test suggests that limit order clustering affects price movement only when the order with price clustering can directly influence the price movement of the underlying asset.

6 Alternative hypothesis

In this section, we discuss two alternative explanations for the return pattern and test these hypotheses using the data. The first potential explanation is the bid-ask bounce: the stocks with a previous closing price at $X.9 might stem from a last trade on the ask order at $X.9, with a corresponding bid order at $X.8. This could lead to a bounce back to the bid price at $X.8, resulting in a negative return the next day. An opposite bid-ask bounce could occur for stocks with a previous closing price at $X.1, leading to a positive return. The second potential explanation involves option trading around round strike prices. Specifically, delta hedging trading on individual stocks might lead to more orders in individual stocks, but with prices related to the option striking price. Our tests indicate that both explanations have a limited effect on the daily return pattern based on the previous closing price.

6.1 Bid-ask bounce

Table 7 presents the previous closing price's first decimal and the next one-day return based on mid-quotes price or regular daily return, respectively. The return difference between stocks at $X.1 and $X.9 decreases from 25.1 bps based on daily return to 22.2 bps based on mid-quotes price. The latter is still high and significant. However, the return difference based on value weight decreases more then half from 5.3 bps to 2.4 bps, which is still statistically significant. This suggests that the bid-ask bounce play a more important role in the larger stocks.

We also see in figure 2 that the first decimal pattern is not merely a daily effect, but also persist over one week. This one-week pattern is less likely to be driven by the bid-ask bounce which usually occurs in a short period less then one day.

6.2 Option trading with round striking price and delta hedging

Table 8 panel A reports the next-day return pattern for stocks with different levels of option trading activity on the previous day. Stocks without any options trading shows a larger return difference between $X.1 and $X.9. However, stocks with more option trading volume see the least return difference. This implies that option trading has a limited effect on the order price clustering and thus a lesser impact on the daily return pattern around round numbers.

One might suspect that the stocks with more option trading volume might be those larger and liquid stocks, and thus show a weaker return difference next day. To control the impact of liquidity, we present the results under subgroups of liquidity in panel B of table 8. After controlling for the liquidity measure, we can still see that the more option trading volume predicts a smaller return difference for stocks at $X.1 and $X.9. This result alleviates the concern of the potential negative impact of liquidity on return pattern.

7 Discussion and implications

7.1 Who places orders on round prices?

Our hypothesis suggests that limit ordering clustering explains the daily return pattern, creating friction and a hurdle for random price movement in financial market. The question then arises: who is placing these orders with clustered prices on round numbers? We analyze the size of order with different decimal numbers. Larger orders are more likely to be placed by institutional investors[11], especially in earlier periods before the widespread use of algorithms to split orders.

Figure A.2 in the appendix plots the average size of trades with prices at different first decimal numbers. Orders at \$X.4 and \$X.9 are relatively larger, while the size at round numbers \$X.0 is similar to the average level. This indicates that instructional investors do not place more orders on round prices. Kuo, Lin, and Zhao (2015) reveal that more orders with round prices are submitted by retail inventors.

To further identify whether institutional or retail investors are more likely to be responsible for this return pattern, we present the daily return pattern for subgroups with different institutional trading activities. Table 9 panel A shows that the stocks with high institutional trading volumes exhibits smaller return difference at \$X.1 and \$X.9. This implies that institutional investors are less likely to the reason behind the pattern. These results are consistent even when we control for the impact of liquidity which might be positively related to the institutional trading volume.

7.2 Short-term reversal

Based on the price dynamics of stocks with closing prices at \$X.1 and \$X.9 in figure 2, we see a strong short-term reversal pattern between the return in previous week and the following week. Thus, limit order clustering on round and half-dollar numbers creates hurdles at these numbers for the random movement of asset price, which leads the price to move back and forth between these hurdles, resulting in a distinct short-term reversal.

Table A.2 in the appendix presents the benchmark short-term reversal results based on past 1-day or 5-day returns, and the intersection effect with the price first decimal number. We can see that in the past loser group, stocks with price at \$X.1 and \$X.6 are more likely to reverse and exhibit higher next-day return. On the other hand, in the past

[11]See discussion in Lee and Radhakrishna (2000).

winner group, stocks at $X.9 and $X.4 are more likely to reverse and show lower next-day return. The combined effect of short-term reversal and first decimal number, measured by the return difference between 1B and 3B, is 47.2 bps, compared to the raw short-term reversal effect, which is return difference between 1A and 3A, 34.1 bps, in equal weight. The comparison is much more obvious, 6.3 bps versus 2.3 bps, in value weight.

The results for the 5-day short-term reversal are similar. The equal-weighted return difference for benchmark reversal effect is 9.5 bps, compared to the combined effect, 14.3 bps. And the value-weighted return difference is 5.0 bps versus 5.9 bps, for benchmark reversal and combine effect of reversal and first decimal number.

7.3 Herding: Enhanced clustering due to predictable movement

The predictable daily return pattern is initially due to limit order clustering. However, once investors anticipate that the price will move away from those round numbers, they will place more orders at those round numbers, enhancing the order clustering at round numbers. Therefore, this finding provides an alternative rationale for limit order clustering. The dynamic between the limit order clustering the consequent herding behavior in the orderbook requires more direct evidence based on high-frequency trade and quote orders.

8 Conclusion

This paper investigates the price dynamics when the daily closing price reaches different points of the first decimal. It reveals a distinctive pattern where stocks with previous closing price above the round numbers are more likely to move up than those below. We show that this pattern is pervasive in U.S. equity market, prevalent across various international markets, and persistent throughout the trading day. This challenges the notion that support and resistance in technical analysis are merely illusions.

Our hypothesis explains this pattern by demonstrating that limit order clustering at round numbers leads to an asymmetric effect on stocks priced above and below these round numbers. We also explore two alternative explanations, finding that both have limited effects on the return pattern.

This research sheds new light on the profound adverse impact of limit order clustering on the random movement of prices. It also partially leads to the short-term reversal that is widely studied and usually attributed to liquidity explanations. A further implication is that predictable price movements exacerbate limit order clustering behavior, thereby enhancing the daily return pattern.

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Figure 1: **Next-day daily return by sorting stocks based on first decimal number of previous closing price**

This figure displays the average next-day return for stocks daily sorted based on the first decimal number of their previous closing prices from 1963 through 2021. It includes all individual stocks with daily closing price (either last trade price or bid-ask mid-price) from the NYSE, Amex, and NASDAQ. The blue lines depict the equal-weighted returns and the orange lines the value-weighted returns.

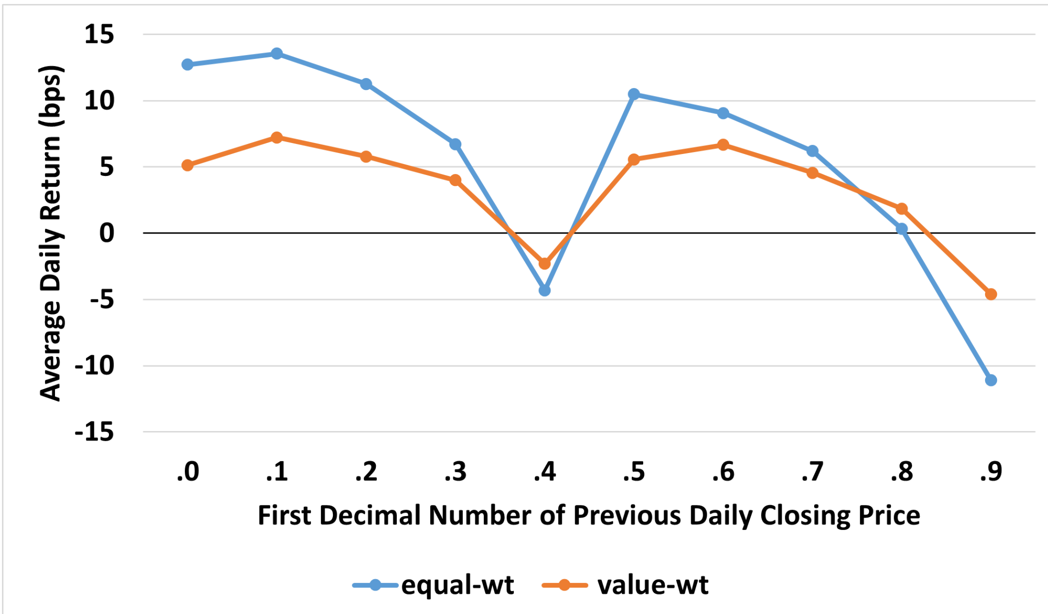


Figure 2: **Cumulative return over 10 days around closing day for stocks with price at \$X.1 and \$X.9**

This figure illustrates the cumulative returns of portfolios constructed based on the first decimal number of the closing price on day 0. It focuses only on stocks priced at \$X.1 (shown with a blue line) and \$X.9 (shown with an orange line). The individual stocks' cumulative returns are normalizaed to zero on day 0 and then compounded from day 0 to day 5, and from day -5 to day -1. The cumulative return is adjusted for size and market returns by subtracting the average return of stocks in the same size decile portfolio. Panels A and B present the equal-weighted and value-weighted returns, respectively.

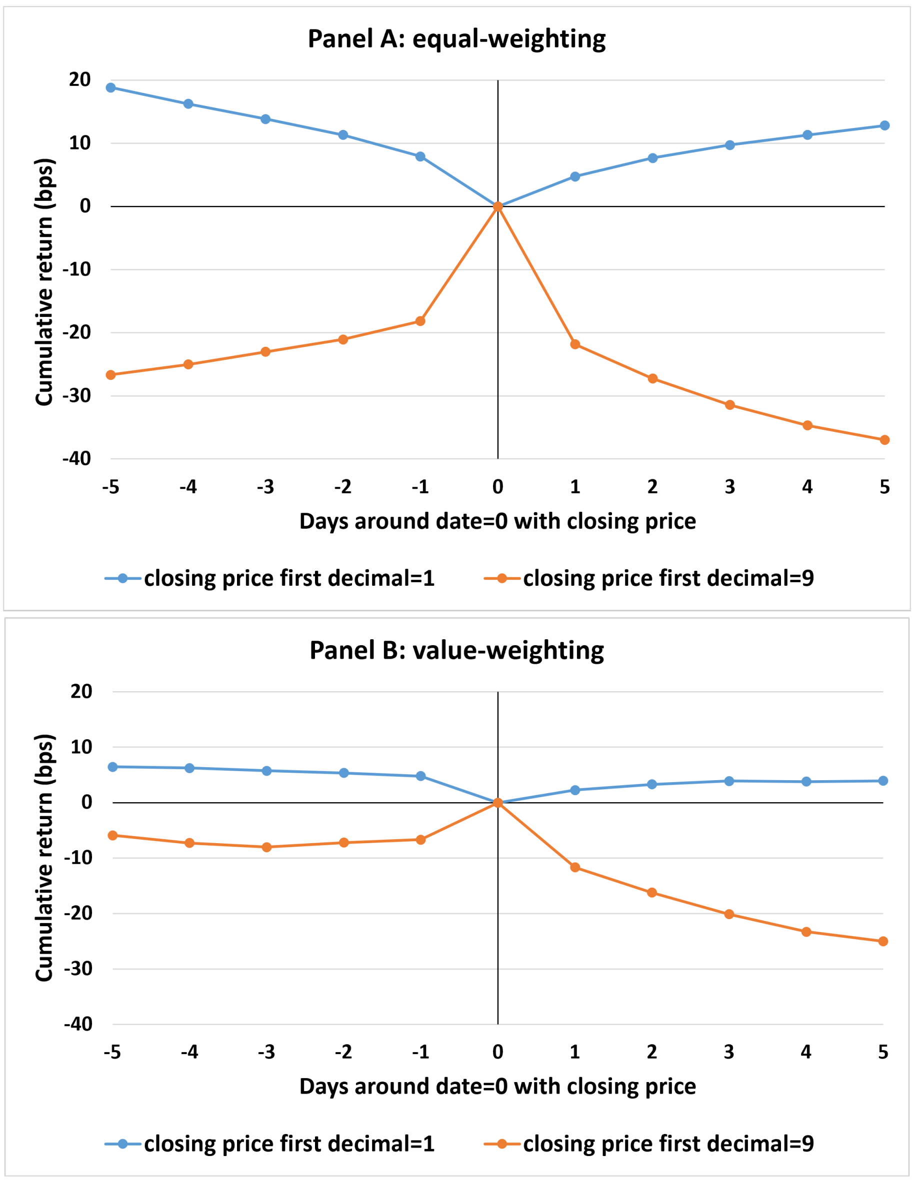
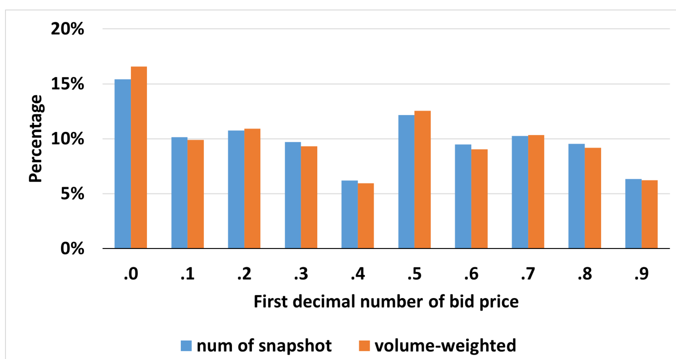


Figure 3: **Price clustering: Trade, bid, and ask price distribution**

This graph presents the price's first decimal number distribution of intraday trades and quotes from 1993 through 2014 based on TAQ data. Panels A, B, and C present the trade, bid, and ask price distribution respectively. The frequency of each decimal number of trades or quotes price is either equally weighted (shown in blue bars) or volume-weighted (shown in orange bars). Frequencies (in percentage) of each decimal number are first calculated for each individual stock within each year and then averaged across all stocks in one year. Finally, the frequencies are averaged across years.

Panel A: Trade

Panel B: Bid



Panel C: Ask

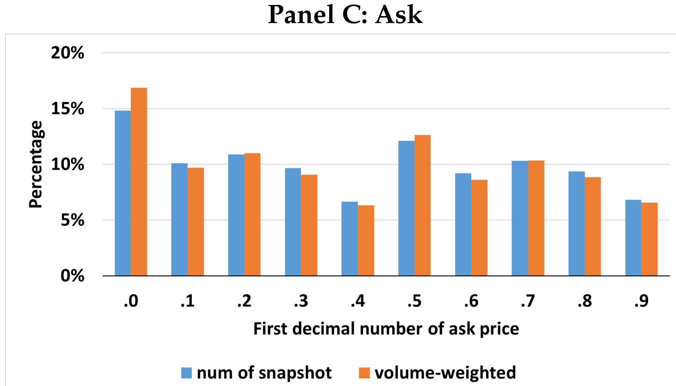


Figure 4: **Illustration: Limit order clustering and asymmetric effect on price above and below round numbers**

This graph first presents an example of limit order clustering with more shares at price $X.0 and $X.5 (or $[X-1].5). We then illustrate its asymmetric effect on bid1-ask1 shares imbalance for two cases: when the current trade price is $[X-1].9, $X.1, respectively. We assume the trade price is the midpoint of bid1 and ask1 prices and the bid-ask spread is always $.2. We expect the pattern to be similar around price $X.5 or $[X-1].5, but with a smaller asymmetric effect due to less concentration at these half-dollar prices compared to round prices.

Limit Order Clustering at X.0		**Case 1: Price=[X-1].9**		**Case 2: Price=X.1**	
Order Price	**Shares**	**Order Price**	**Shares**	**Order Price**	**Shares**
X.5	5	Sell=X.5	5	Sell=X.5	5
X.4	1	Sell=X.4	1	Sell=X.4	1
X.3	1	Sell=X.3	1	Sell=X.3	1
X.2	1	Sell=X.2	1	**Sell=X.2**	**1**
X.1	1	Sell=X.1	1	**X.1**	
X.0	10	**Sell=X.0**	**10**	**Buy=X.0**	**10**
[X-1].9	1	**[X-1].9**		Buy=[X-1].9	1
[X-1].8	1	**Buy=[X-1].8**	**1**	Buy=[X-1].8	1
[X-1].7	1	Buy=[X-1].7	1	Buy=[X-1].7	1
[X-1].6	1	Buy=[X-1].6	1	Buy=[X-1].6	1
[X-1].5	5	Buy=[X-1].5	5	Buy=[X-1].5	5

Figure 5: **Bid1-ask1 shares imbalance at different bid or ask prices**

This figure presents the bid1-ask1 shares imbalance in real-time snapshot, conditional on the first decimal number of the bid1 price or ask1 price, from 1993 to 2014 based on TAQ data. The bid1-ask1 shares imbalance for a specific first decimal number of bid1 or ask1 price is calculated as the difference between the real-time bid1 and ask1 shares at same snapshot, and aggregate across all snapshots with bid1's or ask1's price at that number in a day. This shares difference is then scaled by the total shares of all bid1 and ask1 quotes regardless of their prices on that day for each stock, and then averaged among stocks and across days. A positive bid1-ask1 shares imbalance indicates that on average there are more bid1 orders than ask1 orders in the real-time snapshot, and vice versa. Panel A and B display the average bid1-ask1 shares imbalance conditional on the first decimal number of bid1 and ask1 prices, respectively.

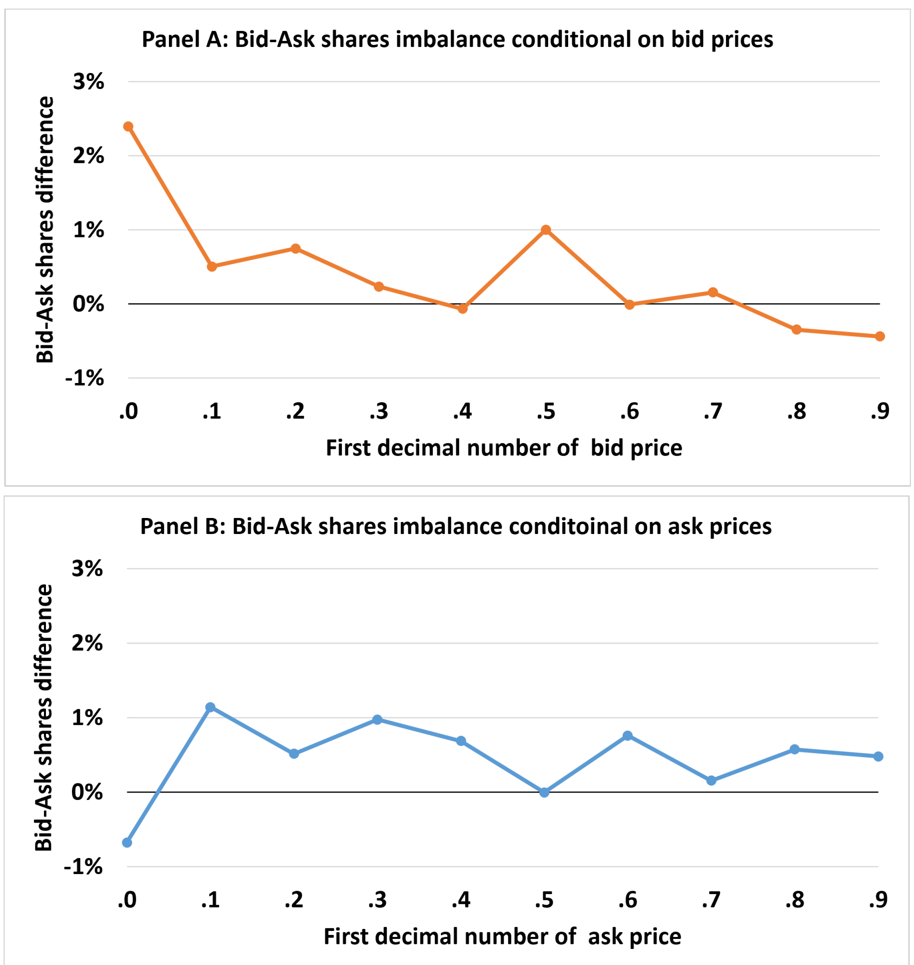


Figure 6: **Next-day intraday trade price distribution conditional on previous closing price**

This graph shows the average distribution of next-day intraday trade prices on each decimal number within a \$1.2 range of the previous closing price among stocks with previous closing prices at \$X.8, \$X.9, \$X.0, \$X.1, and \$X.2, respectively. The sample includes all trades from TAQ from 1993 through 2014 for all individual stocks in the NYSE, Amex, and NASDAQ. The blue bars depict the equal-weighted frequencies in percentage, and the orange bars depict the volume-weighted frequencies in percentage.

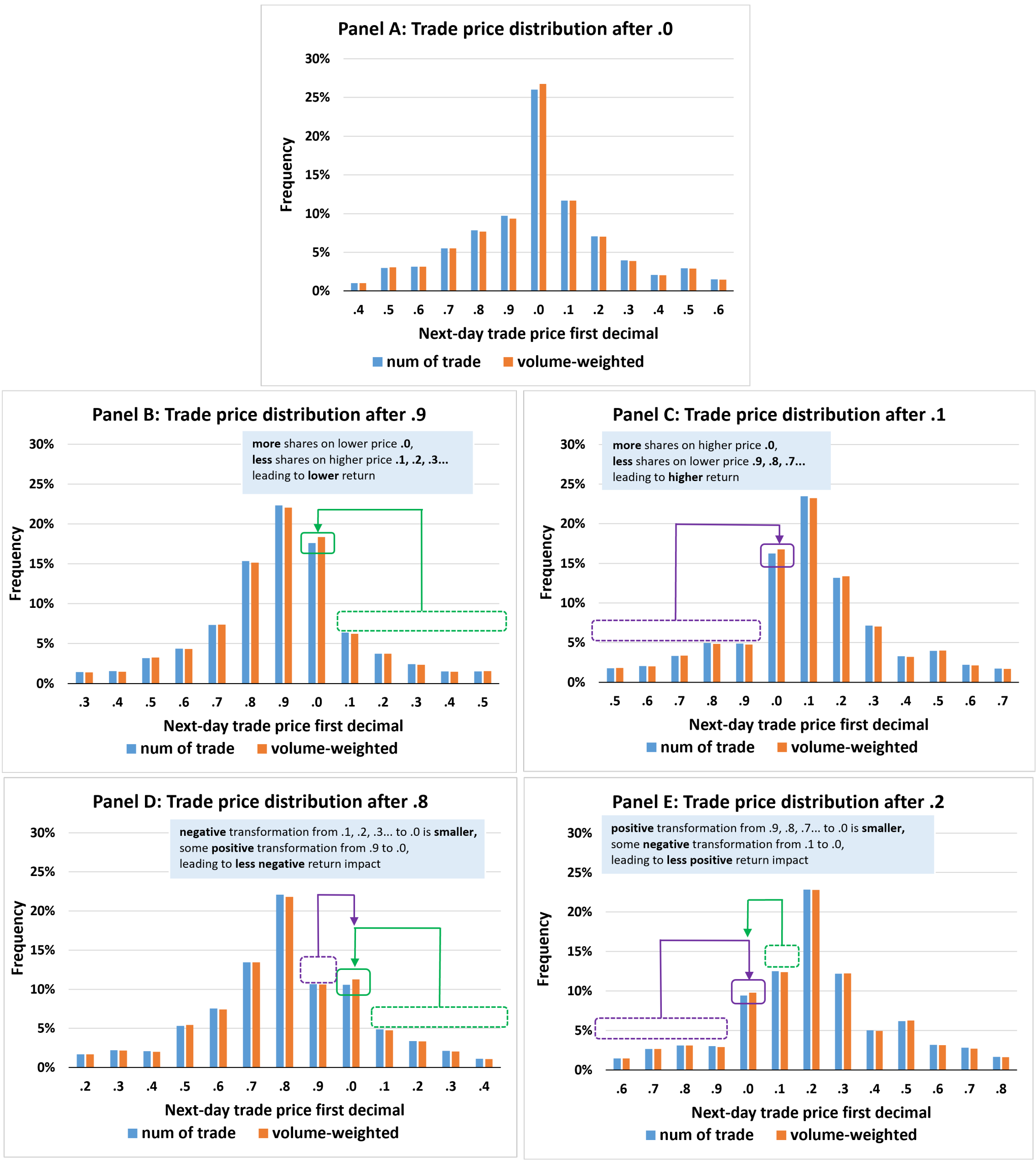


Figure 7: **Next-day intraday bid1-ask1 shares imbalance conditional on previous closing price**

This graph first shows the distribution of next-day intraday trades price on each decimal numbers within a \$1.2 range of the previous closing price among stocks with previous closing prices at \$X.9 and \$X.1 in panel A and B, as shown in figure 6. The panels below show the average bid1-ask1 shares imbalance conditional on bid1's or ask1's first decimal number on the next day. The bid1-ask1 shares imbalance for a specific first decimal number of bid1 or ask1 price is calculated as the difference in total shares between bid1 and ask1 across all snapshots with bid1's or ask1's price at that number in a day. This shares difference is then scaled by the total shares of all bid1 and ask1 quotes regardless of their prices on that day for each stock, and then averaged among stocks and days. Panel C and D present the bid1-ask1 shares imbalance conditional on the first decimal of bid1 price for stocks with closing price at \$X.9 and \$X.1, respectively. Panel E and F present the bid1-ask1 shares imbalance conditional on the first decimal of ask1 price for stocks with closing price at \$X.9 and \$X.1, respectively. The sample includes all trades and quotes from TAQ from 1993 through 2014 for all individual stocks in the NYSE, Amex, and NASDAQ.

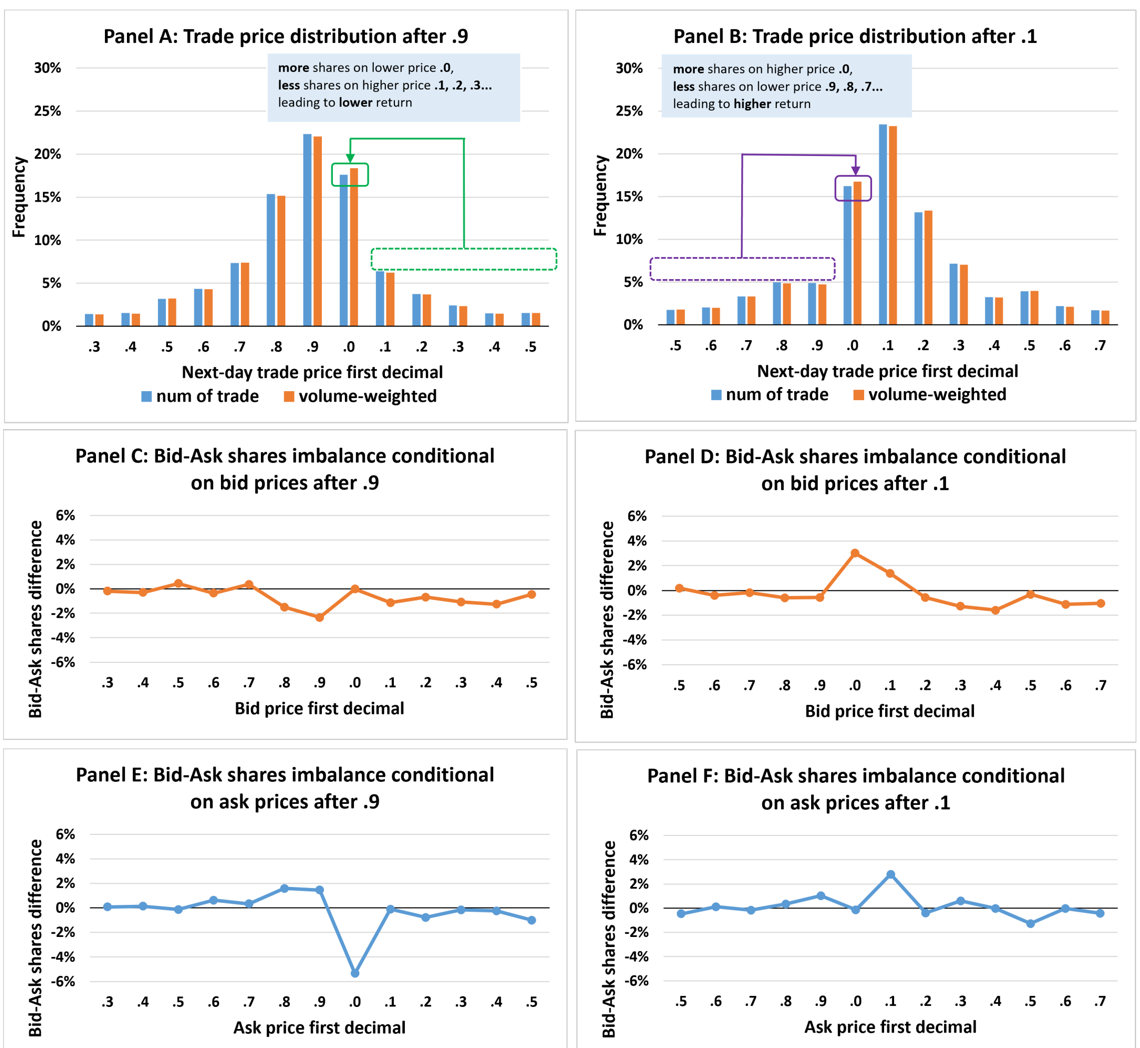


Table 1: **Average next-day daily return based on first decimal number of previous closing price**

This table presents the average next-day daily return for stocks, categorized by the different first decimal numbers of their previous closing price. Columns (1) and (2) show the percentage of stocks and the average size percentile in the cross-section for each first decimal number portfolio. Columns (3) and (4) present the equal-weighted and value-weighted returns in basis points, respectively. In the last three rows, we display the return difference between the portfolios with first decimal numbers at $X.1 and $X.9, along with their t-statistics and annualized returns. Our sample includes all individual stocks with daily closing prices (either last trade price or bid-ask mid-price) from the NYSE, Amex, and NASDAQ from 1963 through 2021.

	(1)	(2)	(3)	(4)
first decimal	# stocks (percent)	size (percentile)	daily return eq-wt (bps)	daily return val-wt (bps)
.0	15%	51%	12.7	5.1
.1	10%	48%	13.5	7.2
.2	12%	51%	11.3	5.8
.3	10%	49%	6.7	4.0
.4	4%	35%	-4.3	-2.3
.5	13%	51%	10.5	5.6
.6	10%	49%	9.1	6.7
.7	12%	52%	6.2	4.6
.8	10%	50%	0.3	1.9
.9	4%	36%	-11.1	-4.6
.1 - .9			24.6	11.8
t-stat			(32.5)	(12.9)
annual			61%	29%

Table 2: **Robustness: Daily return pattern under different subsamples**

This table presents the average next-day daily return for stocks with different first decimal numbers of their previous closing price, under various subsamples. Panel A presents the return difference between stocks at $X.1 and $X.9 across difference price levels: $0-10, $10-20, ..., $90-100, and above $100, respectively. Panel B presents the return difference between stocks at $X.1 and $X.9 with different last dignit numebrs of price integer part such as $X0., $X1., ..., and $X9., respectively. Columns (1) and (2) show the percentage of stocks and the average size percentile; Columns (3) to (6) present the equal-weight and value-weight daily returns and their corresponding t-stats. Our sample includes all individual stocks with daily closing prices (either last trade price or bid-ask mid-price) from the NYSE, Amex, and NASDAQ from 1963 through 2021.

Panel A: Price levels

	(1)	(2)	(3)	(4)	(5)	(6)
Price level	# stocks (percent)	size (percentile)	.1 - .9 (eq-wt)	t-stat (eq-wt)	.1 - .9 (val-wt)	t-stat (val-wt)
$0-10	41%	25%	34.3	(34.7)	21.8	(17.3)
$10-20	23%	51%	15.1	(18.2)	12.2	(10.8)
$20-30	14%	65%	10.9	(11.0)	9.1	(7.0)
$30-40	9%	73%	9.2	(9.3)	6.2	(4.6)
$40-50	5%	79%	5.7	(5.0)	4.6	(2.9)
$50-60	3%	82%	6.7	(5.1)	7.9	(4.7)
$60-70	2%	84%	3.1	(1.9)	2.3	(1.2)
$70-80	2%	86%	2.3	(1.1)	-0.5	-(0.2)
$80-90	1%	86%	5.6	(2.3)	3.4	(1.3)
$90-100	1%	86%	6.0	(1.9)	1.7	(0.5)
>$100	4%	88%	9.2	(4.1)	7.6	(3.1)

Panel B: Last digits of integer part

	(1)	(2)	(3)	(4)	(5)	(6)
last digit of integer	# stocks (percent)	size (percentile)	.1 - .9 (eq-wt)	t-stat (eq-wt)	.1 - .9 (val-wt)	t-stat (val-wt)
X0.	12%	36%	50.4	(25.8)	15.4	(7.8)
X1.	12%	35%	30.9	(24.2)	13.4	(8.7)
X2.	12%	39%	23.4	(18.7)	13.2	(8.2)
X3.	11%	42%	20.1	(16.4)	14.3	(9.0)
X4.	10%	46%	16.8	(13.6)	10.1	(6.4)
X5.	10%	49%	16.3	(12.5)	10.2	(6.1)
X6.	9%	51%	16.7	(12.3)	12.8	(7.7)
X7.	9%	54%	15.7	(11.7)	13.5	(8.2)
X8.	8%	55%	13.1	(10.3)	8.6	(5.5)
X9.	8%	57%	11.0	(8.5)	8.6	(5.1)

Table 2: **Robustness: Daily return pattern under different subsamples (continued)**

Panel C displays the average daily return for stocks with different first decimal within small, medium, and large market-cap subgroups, respectively. Panel D displays the average daily return for stocks with different first decimal numbers of previous closing price within illiquid, medium, and liquid stocks subgroups, respectively. The liquidity measure is calculated as the previous one-month trading volumes scaled by total number of shares outstanding. Panel E presents the average daily return for stocks with different first decimal numbers from the NYSE, NASDAQ, and Amex, respectively. Panel F shows the average daily return for stocks with different first decimal numbers during three subperiods: (1) 1963-1979; (2) 1980-2000; and (3) 2001-2021, respectively.

Panel C: Size

size	small		medium		large	
first decimal	eq-wt	val-wt	eq-wt	val-wt	eq-wt	val-wt
.1	23.0	16.7	8.2	9.3	8.4	7.1
.9	-15.6	-12.8	-8.7	-7.6	-0.7	0.1
.1 - .9	38.4	29.5	16.7	16.7	8.7	6.9
t-stat	(38.5)	(29.7)	(20.6)	(19.5)	(7.1)	(5.1)

Panel D: Liquidity

liquididy	illiquid		medium		liquid	
first decimal	eq-wt	val-wt	eq-wt	val-wt	eq-wt	val-wt
.1	16.2	7.8	13.9	7.7	12.5	7.6
.9	-20.9	-12.6	-15.8	-9.8	-14.0	-8.4
.1 - .9	37.1	20.3	29.4	17.5	26.4	16.2
t-stat	(37.4)	(17.8)	(22.2)	(12.2)	(16.9)	(9.5)

Panel E: Exchanges

exchanges	NYSE		NASDAQ		AMEX	
first decimal	eq-wt	val-wt	eq-wt	val-wt	eq-wt	val-wt
.1	10.5	7.2	13.6	6.4	20.6	9.9
.9	-16.6	-13.7	-7.1	0.3	-19.6	-16.1
.1 - .9	27.0	21.0	20.7	6.1	40.0	25.8
t-stat	(11.2)	(8.7)	(35.2)	(6.6)	(27.1)	(15.5)

Panel F: Subperiods

subperiods	P1: 1963-1979		P2: 1980-2000		P3: 2001-2021	
first decimal	eq-wt	val-wt	eq-wt	val-wt	eq-wt	val-wt
.1	11.9	8.3	14.9	8.1	14.0	5.4
.9	-12.0	-9.3	-17.7	-7.6	-4.8	2.4
.1 - .9	23.8	17.4	32.6	15.8	18.9	3.0
t-stat	(12.4)	(8.3)	(32.3)	(9.6)	(38.7)	(4.4)

Table 3: **Intraday half-hour: Half-hour price and next half-hour return**

This table presents the half-hour return for stocks sorted by the first decimal number of the price of the last trade of the previous half-hour period or the price of the first trade of the current half-hour period. When sorting stocks by the last trade price, we calculate the half-hour return based on the price difference between the last trade in the previous half-hour period and this half-hour period. When sorting stocks by the first trade price, we calculate the half-hour return based on the price difference between the first trade in this half-hour period and the next half-hour period. Panel A presents the average half-hour return for stocks with prices at ten decimal numbers and the return difference between stocks at \$X.1 and \$X.9. Panel B reports the average half-hour return difference between stocks with prices at \$X.1 and \$X.9 for each of the 12 half-hours periods within a day. For example, the first half-hour period is from 9:30-10:00 am when sorting by the price of the first trade in this period, but it is from 10:00-10:30 am when sorting by the price of the last trade in the previous period of 9:30-10:00 am. The sample covers all stocks from the NYSE, Amex, and NASDAQ from 1993 through 2021 based on CRSP and TAQ data.

Panel A: Last or first half-hour price and the next half-hour return

	by last trade price		by first trade price	
first decimal	last to last half-hour return	t-stat	first to first half-hour return	t-stat
.0	5.8	(26.7)	1.5	(7.2)
.1	2.2	(11.9)	0.8	(4.5)
.2	1.7	(9.8)	0.7	(4.4)
.3	2.1	(12.8)	0.9	(5.4)
.4	0.1	(0.4)	-0.7	-(3.1)
.5	5.8	(31.1)	2.3	(14.1)
.6	3.9	(20.5)	1.5	(8.8)
.7	-4.5	-(23.3)	-0.8	-(4.6)
.8	-4.7	-(26.1)	-1.2	-(6.9)
.9	-11.0	-(48.1)	-3.3	-(15.7)
.1 - .9	13.2	(48.0)	4.1	(16.7)

Panel B: Return difference for each half-hour period within a day

	by last trade price		by first trade price	
half-hour	.1 - .9 last to last ret difference	t-stat	.1 - .9 first to first ret difference	t-stat
1	19.4	(19.6)	6.6	(6.9)
2	14.3	(14.9)	5.3	(6.3)
3	14.7	(15.8)	3.7	(4.5)
4	12.5	(13.0)	3.4	(4.1)
5	13.0	(14.0)	4.3	(5.2)
6	13.2	(14.2)	3.4	(4.0)
7	11.9	(12.9)	3.9	(4.6)
8	10.9	(11.6)	3.0	(3.6)
9	12.2	(13.2)	4.1	(5.0)
10	10.0	(11.5)	3.7	(4.4)
11	13.4	(11.5)	4.3	(5.2)
12	12.6	(14.9)	3.3	(3.9)

Table 4: **International Markets: Next-day return pattern in 22 foreign markets**

This table presents the next-day return difference between stocks with previous closing prices at $X.1 and $X.9 withing each of 22 countries or regions. Columns (1) and (2) report the average number and average size of stocks with prices at $X.1 and $X.9. Columns (3) and (5) show the equal-weighted and value-weighted returns, respectively. Columns (4) and (6) report the corresponding t-stats. The sample period for each country differs in the starting year, ranging from 1970 to 2002 due to the data availability, and all end in 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Country	# stocks (percent)	size (percentile)	.1 - .9 (eq-wt)	t-stat (eq-wt)	.1 - .9 (val-wt)	t-stat (val-wt)
AT	9%	51%	14.8	(5.5)	10.1	(4.6)
AU	9%	51%	17.1	(14.0)	9.8	(6.9)
BE	9%	48%	50.8	(27.4)	13.6	(6.2)
CA	5%	48%	41.9	(12.8)	18.3	(5.6)
CN	10%	50%	0.9	(1.5)	2.3	(2.4)
DE	9%	51%	14.7	(9.0)	2.7	(2.0)
DK	4%	41%	43.3	(7.9)	25.9	(5.1)
ES	10%	51%	8.4	(7.3)	5.0	(3.6)
FI	10%	50%	8.4	(4.5)	4.3	(1.9)
FR	10%	50%	14.9	(18.8)	6.1	(5.7)
GB	9%	54%	1.7	(2.8)	1.5	(1.6)
HK	10%	51%	6.1	(4.6)	5.7	(4.2)
IL	10%	50%	12.1	(7.8)	10.7	(4.7)
IS	12%	48%	0.4	(0.1)	0.9	(0.2)
IT	10%	51%	3.9	(3.7)	1.1	(0.8)
JP	0%	98%	-0.8	-(0.2)	-1.0	-(0.2)
NL	10%	50%	1.7	(0.4)	3.5	(2.2)
NO	6%	41%	39.2	(10.2)	28.1	(7.4)
NZ	10%	51%	8.4	(5.0)	3.7	(2.2)
PT	12%	52%	11.4	(4.9)	7.1	(3.0)
SE	5%	38%	58.3	(16.1)	22.2	(7.5)
SG	10%	57%	6.7	(5.4)	7.5	(5.6)

Table 5: **Prediction: Next-day return pattern with different price clustering intensity**

This table presents the average next-day return difference between stocks with previous closing prices at \$X.1 and \$X.9, under subgroups with different price clustering levels in the prior year. The clustering level is the probability of the daily price closing at integer numbers \$X.0 in the previous year. We calculate the excess probability of the closing price at \$X.0 by subtracting the expected average probability at each first decimal number, which is the reciprocal of the total number of different first decimal numbers occurring for the daily closing prices in the prior year. In panel A, stocks are sorted into ten subgroups based on the excess probability of the closing price at \$X.0 in the prior year. The average next-day return difference for stocks at \$X.1 and \$X.9 within each clustering level subgroup is reported. In panel B, stocks are independently sorted into three groups based on previous 1-month liquidity (1-month trading volumes scaled by total number of shares outstanding), and into three groups based on prior 1-year clustering levels. The return difference for stocks at \$X.1 and \$X.9 within 3×3 liquidity & clustering level subgroup is calculated. Both the equal-weight and value-weight return difference are presented. The sample includes all individual stocks with positive excess probability of daily closing prices at \$X.0 listed on the NYSE, Amex, and NASDAQ from 1996 to 2021.

Panel A: Return difference with different price clustering intensity

Clustering intersity group	Excess prob of closing prices at .0	.1-.9 (eq-wt)	t-stat (eq-wt)	.1-.9 (val-wt)	t-stat (val-wt)
1	0.7%	19.9	(15.6)	5.1	(3.2)
2	1.6%	18.6	(14.0)	4.3	(2.5)
3	2.3%	17.8	(13.1)	4.8	(2.7)
4	3.0%	17.1	(13.2)	6.4	(3.7)
5	3.7%	18.1	(13.3)	3.9	(2.2)
6	4.4%	19.4	(13.6)	5.4	(2.9)
7	5.3%	22.5	(15.6)	7.9	(4.0)
8	6.5%	22.8	(12.1)	5.7	(2.8)
9	8.2%	27.6	(17.3)	16.2	(7.3)
10	14.9%	31.2	(17.6)	20.4	(8.2)

Panel B: Pattern with control of liquidity

liquidity	clustering intensity	.1 - .9 (eq-wt)	t-stat (eq-wt)	.1 - .9 (val-wt)	t-stat (val-wt)
illiquid	low	24.9	(16.1)	11.2	(6.4)
	median	25.8	(17.2)	12.3	(7.1)
	high	32.3	(22.2)	18.6	(11.9)
medium	low	16.7	(15.0)	5.2	(3.9)
	median	16.9	(14.9)	5.3	(3.6)
	high	22.1	(14.6)	9.5	(5.1)
liquid	low	17.9	(14.5)	4.3	(2.5)
	median	14.7	(11.1)	4.8	(2.8)
	high	21.4	(11.4)	9.6	(4.5)

Table 6: **Placebo test: Next-day return pattern for ETFs**

This table reports the next-day daily return for ETFs with different first decimal numbers of previous closing prices. Columns (1) and (2) in panel A show the average number and size of EFTs with different first decimal numbers of closing prices. Columns (3) and (4) present the average returns based on equal-weighting and value-weighting, respectively. The last three rows present the return difference between ETFs priced at $X.1 and $X.9, along with their t-stats and annualized returns. Panel B presents the results based on individual stocks from the same period, from 2001 to 2021. The sample starts in 2001 due to the availability of ETF data.

Panel A: Daily return pattern for ETFs: 2000-2021

	(1)	(2)	(3)	(4)
first decimal	# stocks (percent)	size (percentile)	daily return eq-wt (bps)	daily return val-wt (bps)
.0	11%	51%	3.6	3.5
.1	10%	50%	3.2	2.6
.2	10%	50%	2.6	1.5
.3	10%	50%	2.7	2.1
.4	9%	51%	2.2	1.3
.5	11%	51%	3.1	1.9
.6	10%	50%	3.0	2.6
.7	10%	50%	3.4	3.3
.8	10%	50%	3.3	2.6
.9	9%	50%	1.1	2.5
.1 - .9			2.0	0.1
t-stat			(2.3)	(0.0)
annual			5%	0%

Panel B: Daily return pattern for individual stocks: 2000-2021

	(1)	(2)	(3)	(4)
first decimal	# stocks (percent)	size (percentile)	daily return eq-wt (bps)	daily return val-wt (bps)
.0	12%	50%	14.0	5.5
.1	10%	49%	14.2	5.1
.2	10%	49%	11.7	4.4
.3	10%	49%	9.2	3.7
.4	9%	50%	2.4	2.8
.5	11%	50%	10.1	4.2
.6	9%	50%	6.4	3.8
.7	10%	51%	3.3	3.9
.8	10%	50%	1.2	2.4
.9	9%	51%	-6.1	1.5
.1 - .9			20.3	3.6
t-stat			(41.5)	(4.8)
annual			51%	9%

Table 7: **Next-day return pattern based on mid-quotes price**

This table reports the next-day average return for stocks with different first decimal numbers of previous mid-quotes price based on mid-quotes price change, and of previous daily closing prices based on regular daily return, respectively. The mid-quotes price return is calculated as the percentage change in the average of the bid and ask prices from one day to the next (last bid and ask prices are provided in CRSP). The regular daily return is directly provided in CRSP. Both the equal-weight and value-weight average returns are presented. The last three rows present the return difference between stocks priced at $X.1 and $X.9, along with their t-stats and annualized returns. The sample are identical for two results based on different type of returns. It includes all stocks with daily last bid and ask prices in CRSP from the NYSE, AMex, and NASDAQ from 1993 to 2021. The sample starts in 1993 due to the availability of bid and ask prices in CRSP.

			mid-quotes ret		daily ret	
first decimal	# stocks (percent)	size (percentile)	eq-wt (bps)	val-wt (bps)	eq-wt (bps)	val-wt (bps)
.0	14%	50%	17.6	4.2	15.4	6.4
.1	10%	49%	22.2	3.8	15.4	6.4
.2	11%	50%	20.0	3.3	12.8	5.6
.3	10%	49%	14.3	2.8	10.3	5.0
.4	7%	46%	10.8	1.4	1.0	2.8
.5	12%	50%	10.7	3.7	11.8	5.3
.6	10%	50%	7.3	2.6	8.2	5.2
.7	11%	51%	4.3	2.5	5.0	5.2
.8	10%	50%	2.6	0.4	1.0	3.5
.9	8%	47%	0.6	1.3	-9.7	1.1
.1 - .9			21.6	2.4	25.1	5.3
t-stat			(15.9)	(3.0)	(46.8)	(6.1)
annual			54%	6%	63%	13%

Table 8: **Next-day return pattern for stocks with different option trading activity**

This table presents the average next-day return for stocks with previous closing prices at \$X.1 and \$X.9, and their return difference, under subgroups with different option trading volumes. In panel A, the first group, marked by 0, consist of stocks without any option trading volumes that day or without any listed options in the option markets. Groups 1, 2, and 3 are formed by equally sorting stocks with option trading volumes into three subgroups. The average number and size of stocks with different first decimal numbers within each subgroup are presented. In panel B, stocks are independently sorted into three groups based on previous 1-month liquidity (1-month trading volumes scaled by total number of shares outstanding), and into fours groups based on daily option trading volumes. The return difference for stocks at \$X.1 and \$X.9 within 3×4 liquidity & option trading activity subgroup is calculated. The equal-weight and value-weight daily returns and their t-stats are reported in the last four columns, respectively. The sample includes all stocks from the NYSE, AMex, and NASDAQ from 1996 to 2021. The sample starts in 1996 due to the availability of options trading data in OptionMetrics.

Panel A: Return pattern for stocks with different option trading volumes

option trading volume group	first decimal	# stocks (percent)	size (percentile)	daily ret (eq-wt)	t-stat (eq-wt)	daily ret (val-wt)	t-stat (val-wt)
0	.1	10%	49%	20.8	(15.8)	11.8	(7.6)
	.9	8%	50%	-14.4	-(11.6)	-6.9	-(4.4)
	.1 - .9			35.2	(40.1)	18.7	(20.9)
1	.1	10%	49%	9.5	(5.2)	6.9	(4.3)
	.9	9%	49%	-4.3	-(2.3)	-0.2	-(0.1)
	.1 - .9			13.8	(14.2)	7.0	(8.9)
2	.1	10%	49%	9.6	(5.0)	7.1	(4.5)
	.9	9%	49%	-0.4	-(0.2)	3.1	(1.8)
	.1 - .9			10.1	(9.5)	4.1	(4.0)
3	.1	10%	49%	8.2	(4.0)	6.3	(3.8)
	.9	9%	49%	0.3	(0.1)	3.3	(1.7)
	.1 - .9			7.8	(7.5)	3.0	(2.4)

Panel B: Pattern with control of liquidity

liquidity	option trading volume group	.1 - .9 ret dif (eq-wt)	t-stat (eq-wt)	.1 - .9 ret dif (val-wt)	t-stat (val-wt)
illiquid	0	37.4	(35.4)	20.4	(20.7)
	1	17.2	(6.9)	14.8	(6.8)
	2	10.4	(2.9)	7.5	(2.2)
	3	8.2	(2.1)	1.1	(0.3)
medium	0	28.7	(15.5)	14.1	(8.3)
	1	13.2	(12.1)	7.6	(7.8)
	2	9.5	(7.5)	4.2	(3.8)
	3	7.0	(5.1)	2.8	(2.0)
liquid	0	35.0	(10.6)	19.4	(6.4)
	1	17.0	(8.6)	9.7	(6.4)
	2	11.9	(8.8)	6.6	(5.0)
	3	7.8	(6.3)	2.5	(1.7)

Table 9: **Next-day return pattern for stocks with different institutional trading**

This table presents the average next-day return for stocks with different previous closing prices under subgroups with low, medium, and high institutional trading activity. The institutional trading activity is measured as the sum of the absolute change in holdings of shares across all institutional investors in 13F database, scaled by the total number of shares outstanding. Panel A presents the average next-day return for stocks with ten different first decimal numbers within each of three institutional trading subgroups. In panel B, stocks are independently sorted into three groups based on previous 1-month liquidity (1-month trading volumes scaled by total number of shares outstanding), and into three groups based on contemporaneous institutional trading activity. The return difference for stocks at $X.1 and $X.9 within 3 × 3 liquidity & institutional trading subgroup is calculated. Both the equal-weight and value-weight return difference are presented. The sample includes all stocks held by institutional investors and from the NYSE, AMex, and NASDAQ from 1980 to 2021. The sample starts in 1980 due to the availability of institutional holdings data in 13F database.

Panel A: Return pattern for stocks with different institutional trading volumes

institutional trading	low		medium		high	
first decimal	eq-wt	val-wt	eq-wt	val-wt	eq-wt	val-wt
.0	16.8	4.9	12.0	4.9	9.1	5.5
.1	16.2	7.8	13.9	7.7	12.5	7.6
.2	14.3	6.4	11.5	6.5	9.4	5.9
.3	6.7	3.7	6.2	4.3	6.1	4.6
.4	-11.5	-8.2	-6.5	-6.3	-2.1	-2.1
.5	12.9	5.9	10.9	5.6	9.4	6.4
.6	9.3	6.3	10.7	7.0	9.4	7.1
.7	7.4	4.1	6.6	4.6	5.5	5.3
.8	-2.3	0.4	0.2	1.9	0.3	2.2
.9	-20.9	-12.6	-15.8	-9.8	-14.0	-8.4
.1 - .9	37.1	20.3	29.4	17.5	26.4	16.2
t-stat	(37.4)	(17.8)	(22.2)	(12.2)	(16.9)	(9.5)
annual	93%	51%	74%	44%	66%	40%

Panel B: Pattern with control of liquidity

liquidity	institutional trading	.1 - .9 ret dif (eq-wt)	t-stat (eq-wt)	.1 - .9 ret dif (val-wt)	t-stat (val-wt)
illiquid	low	40.0	(33.2)	19.7	(13.9)
	medium	22.7	(14.9)	13.8	(8.4)
	high	28.4	(6.7)	20.5	(5.3)
medium	low	34.6	(19.0)	16.3	(8.8)
	medium	15.7	(10.5)	7.9	(4.6)
	high	16.0	(7.1)	11.1	(4.7)
liquid	low	39.4	(13.0)	27.2	(8.2)
	medium	14.3	(8.0)	4.4	(2.1)
	high	10.6	(5.6)	4.7	(2.3)

Appendix

Figure A.1: **Historical distribution of daily closing prices on three exchanges**

This figure plots the distribution of daily closing prices with the first decimal at $X.4 or $X.9 (in the left column), in contrast to other numbers (in the right column), for each year from 1963 to 2021. It presents the closing price distribution under three exchanges, based on bid-ask mid-quotes (shown with a blue solid line) or on the last trade price (shown with an orange dashed line). All distribution frequencies are scaled by the total number of daily closing prices within that year.

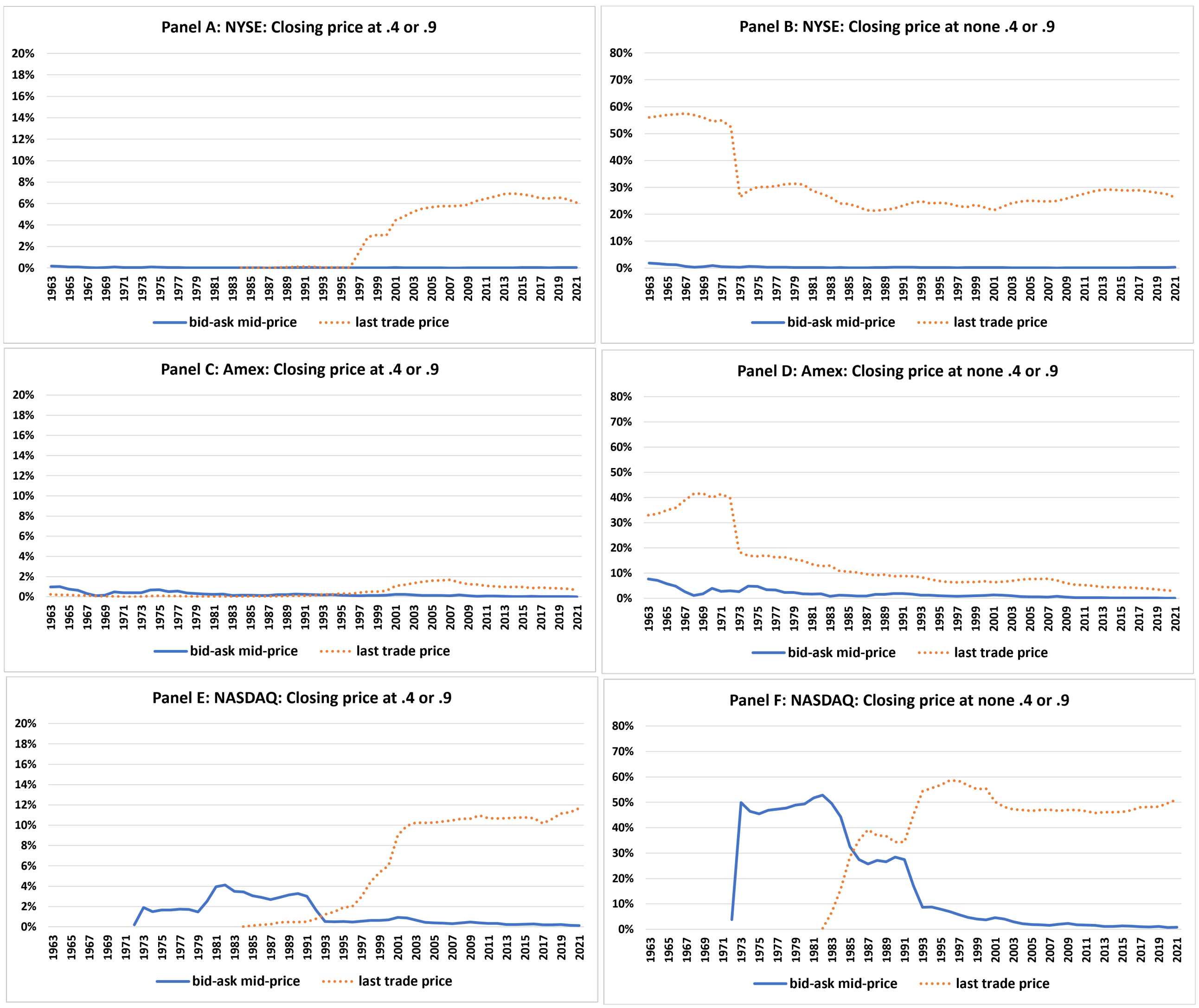


Figure A.2: **Trade size conditional on trade price's first decimal number**

The first top panel shows the average size in shares or dollars for trades in TAQ with different price's first decimal numbers from 1993 through 2014. The average size in shares or dollars for trades at a specific decimal number is divided by the average size in shares or dollars from all trades within a day for a stock. The average size in shares and dollars is presented with blue and orange lines, respectively, based on the left-axis. The frequencies of trades with different prices are depicted on grey bar based on the right-axis. In the four panels below, we present by-year results for 1993, 1997, 1998, and 2014, respectively.

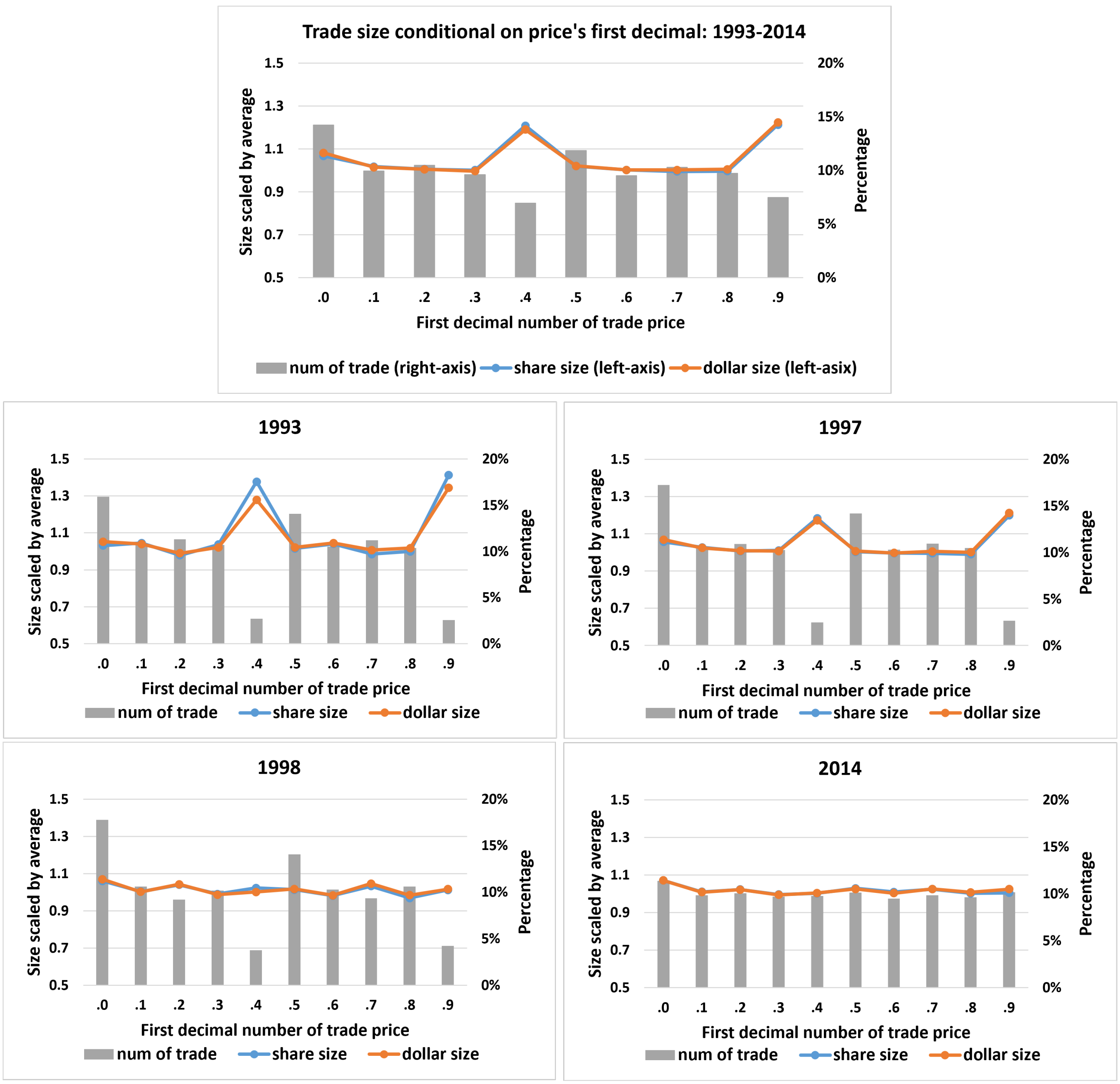


Table A.1: **Average next-day daily return based on second decimal number of previous closing price**

This table presents the average next-day daily return for stocks with different second decimal numbers of their previous closing price. Columns (1) and (2) display the percentage of stocks and the average size percentile in the cross-section for each second decimal number portfolio. Columns (3) and (4) present the equal-weighted and value-weighted returns in basis points, respectively. The last three rows show the return difference between portfolios with second decimal numbers at $X.1 and $X.9, including their t-statistics and annualized returns. Our sample includes all individual stocks with daily closing prices (either last trade price or bid-ask mid-price) from the NYSE, Amex, and NASDAQ in the post-decimalization period from 2001 through 2021.

	(1)	(2)	(3)	(4)
second decimal	# stocks (percent)	size (percentile)	daily return eq-wt (bps)	daily return val-wt (bps)
.X0	15%	48%	11.1	4.8
.X1	9%	51%	16.6	5.8
.X2	9%	51%	9.2	5.3
.X3	8%	51%	4.1	4.2
.X4	10%	50%	4.4	4.3
.X5	13%	49%	11.2	4.6
.X6	8%	52%	9.7	5.5
.X7	9%	50%	5.0	3.9
.X8	9%	51%	-1.7	2.3
.X9	11%	49%	2.2	3.2
.X1 - .X9			14.4	2.6
t-stat			(28.3)	(3.5)
annual			36%	6%

Table A.2: **Short-term reversal and price first decimal effect**

This table presents the average next 1-day or 5-day return for stocks with different previous 1-day or 5-day returns, and with different first decimal number of previous closing prices. The 1-day and 5-day results are presented in panel A and B, respectively. The 5-day returns are the average daily return in the next five days. The left half table presents the benchmark short-term reversal effect: calculating the average daily return in next 1 day or 5 days by sorting stocks into three groups based on previous 1-day or 5-day returns. The return difference between past loser (group 1) and winner (group 3) and its t-stat are presented in last two rows. The right half table shows the double sorting results that first sort stocks into three groups based on past 1-day or 5-day returns, and then the first loser group 1 into $X.1 & $X.6 first decimal number subgroup 1B and non-$X.1 & $X.6 subgroup 1A, the third winner group 3 into $X.9 & $X.4 first decimal number subgroup 3B and non-$X.9 & $X.4 subgroup 3A, respectively. The return differences between 1A and 3A, and between 1B and 3B, and their t-stats are reported in the last four rows. The sample includes all stocks from the NYSE, AMex, and NASDAQ from 2001 to 2021. The sample starts in 2001, which is post-decimalization period, to cover enough and balanced stocks for price at $X.1 and $X.9, and at $X.6 and $X.4, respectively.

Panel A: 1-day return reversal and price's first decimal effect

1-day short-term reversal					1-day short-term reversal and price first decimal				
group by past 1-day return	# stocks (percent)	size (percentile)	1-day ret eq-wt (bps)	1-day ret val-wt (bps)	group by past 1-day return & first decimal	# stocks (percent)	size (percentile)	1-day ret eq-wt (bps)	1-day ret val-wt (bps)
					1B (.1 & .6)	6%	45%	31.3	7.2
1	33%	45%	27.4	6.2	1A (not .1 & .6)	26%	45%	26.4	6.1
2	33%	57%	4.7	4.1	2	33%	57%	4.7	4.1
3	34%	48%	-9.2	3.3	3A (not .9 & .4)	28%	48%	-7.7	3.8
					3B (.9 & .4)	6%	48%	-15.9	0.9
1 - 3			36.6	2.9	1A - 3A			34.1	2.3
t-stat			(34.4)	(2.2)	t-stat			(32.2)	(1.8)
					1B - 3B			47.2	6.3
					t-stat			(38.2)	(4.2)

Panel B: 5-day return reversal and price's first decimal effect

5-day short-term reversal					5-day short-term reversal and price first decimal				
group by past 5-day return	# stocks (percent)	size (percentile)	5-day ret eq-wt (bps)	5-day ret val-wt (bps)	group by past 5-day return & first decimal	# stocks (percent)	size (percentile)	5-day ret eq-wt (bps)	5-day ret val-wt (bps)
					1B (.1 & .6)	6%	44%	13.4	7.5
1	33%	45%	11.8	7.1	1A (not .1 & .6)	27%	45%	11.4	6.9
2	33%	56%	5.4	4.1	2	33%	56%	5.4	4.1
3	34%	50%	1.4	1.9	3A (not .9 & .4)	28%	50%	1.9	2.0
					3B (.9 & .4)	6%	50%	-0.9	1.6
1 - 3			10.4	5.2	1A - 3A			9.5	5.0
t-stat			(20.4)	(8.4)	t-stat			(18.8)	(8.1)
					1B - 3B			14.3	5.9
					t-stat			(24.6)	(8.1)