Round Number Price Barriers in U.S. Stock Market

Ammon Lam

First Draft: April 28, 2018
This Draft: May 31, 2018

Abstract

This paper examines the existence of round number price barriers in the U.S. stock market. I show that stock prices clusters around multiples of $10 as a result of the price barriers. The price barriers results in abnormal future return pattern; a long-short portfolio formed around the barrier held for a week produces 17 basis point weekly return (8% annually). Such abnormal return does not change in magnitude after controlling for varies factors. I present supportive evidence for the left-digit-bias barrier channel.

1. Introduction

Under efficient market hypothesis, current stock price should give no information towards predicting future return. Using current price level to predict future return is a violation of the Semi-Strong form efficient market hypothesis. In this paper I present evidence for price barriers at multiples of $10, and that simply using the integer digit of stock price, one could predict future return.

The findings are motivated by a widely observed behavioral bias: the left digit bias. The left digit bias has been observed in many instances including car market (citation), housing market (citation) , and many more. It would not be surprising that investors are faced with the same bias when making decisions regarding buying and selling of stocks. The important question is whether the left digit bias could lead to predictable stock return. This relates to whether investors can withhold themselves from the bias and whether arbitragers' force are strong enough the correct the mispricing caused by the bias.

An important and related phenomenon that has been studied extensively is asset prices clustering. Asset prices clustering (at penny, dime and integer level) has been observed repeatedly in various markets. Price clustering implies that investors treat particular price levels different than other. A natural question to ask if whether such differential treatment of certain price levels would result in predictable future return. This paper examines the channels for price clustering around multiples of ten and the corresponding return implication.

Previous literature has documented price clustering in the U.S. equity market *(Osborne (1962), Nierderhoffer (1965 and 1966), Harris (1991), Christie and Schult (1994), Grossman et. al. (1997), Cooney, VanNess and VanNess (2003)).* Some of the recent literature has studied price clustering on varies commodities markets such as water markets (Brooks 2013) and Carbon markets (Palao 2012), as well as option market (Capelle-Blancard 2007).

However none of the literature explored the return implications of price clustering, except for (Johnson, Johnson and Shanthikumar 2008), where they showed that at penny, dime and integer level, a just above round number closing price is followed by a higher return. Johnson focused on predicting the next day return base on the past day closing price, and showing that investors are insensitive to the penny and dime digits in stock price. In this paper I specifically examine the round number bias abnormal return around multiples of ten (at the integer level), and examine the return pattern through a longer horizon of up to two weeks. A one day abnormal return from a penny or dime level bias is not very tradable, but a two week return resulting from an integer level bias should be large enough to be implemented in a portfolio. Existence of a large and long lasting abnormal return simply using information from previous price level raise the question why the profit is not arbitraged away.

2. Data

My primary data sample is from CRSP. Common stock for US firms trading on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) or NASDAQ are included.

3. **Main Results**

Clustering in stock prices has been established by several papers in the past (Citations). Since clustering is an essential feature of psychological barrier in prices, I present specific price clustering results around multiples of tens. Such result reaffirms previous studies that shows clusterings in stock price.

[Figure 1]

Figure 1 plots the distribution of prices of all U.S. stocks between $5 and $45 from 1960 to 2017. Prices are grouped into bins of 0.5. There are a visible drop in frequency occurring at multiples of 10. This is anecdotal evidence for clustering around tens.

[Figure 2]

To understand more clearly how price clustering occurs, I look at the distribution of prices starting with an initial price. Condition on several initial price (9.3, 9.4, 9.5, 9.6, 9.7, 9.8), I plot out the distribution of prices 5 days later on figure 2. We again observe a discontinuity in frequency occurring at $10 for all those initial prices. A more formal test for the discontinuity is presented in table A.

[Table A (to be included)]

In table A we simply look at the difference in frequency between bin [9.8,9.9), [9.9,10), [10,10.1) and [10.1,10.2). Assuming that stock return are roughly normally distributed, the frequency function should be concave and decreasing in prices to the right side of the mean i.e. the initial price. If normality assumption holds, we expect to see that the $d\_9.9>d\_10>d\_10.1$ for all of the initial values. However as shown in table A, d_10 is significantly large than $d\_9.9$ and $d\_10.1$. This provide evidence that prices starting below multiples of ten clusters BEFORE the barrier. To access the likelihood of seeing this discontinuity in distribution, I simulated the distribution of prices with same number of observations as our empirical sample, assuming a normal distribution with mean and standard deviation calibrated to fit our empirical sample. Taking the distribution with initial price 9.3 for example, the probability of seeing a discontinuity as large as observed in our empirical distribution is less than 0.001%. This again confirms that prices are not smoothly distributed at round numbers, and indirectly implies that $10 has special significance in affecting the distribution of prices (and return).

With the clustering of prices around multiples of $10 as motivation, we go on to check whether one could find predictable return for stocks with prices near multiple of $10.

[Figure 3]

In figure 3 I plot out the one day equal weighted portfolio return of stocks base on their previous day closing prices. We can see a visible jump in average return going from prices with ending integer digit 9 to prices with ending integer digit 0.

[Figure 4]

In figure 4 I plot out the buy-and-hold one week equal weighted portfolio return of stocks base on their previous week closing prices. The pattern is pretty striking here. We see a visible jump in average return going from prices with integer digit 9 to prices with integer digit 0, as well as a gradual decrease in return from digit 0 to digit 4. (We see a significant but weaker pattern around integer digit 5)

Figure 4 gives evidence that price level (around multiples of $10) does lead to some predictable returns pattern. I now go on to form a portfolio that exploits the return pattern in figure 4. The round number portfolio allows us to measure the size of the abnormal return as well as to check whether the abnormal return can be explained by known risks.

To quantify and provide benchmark for the abnormal return resulted from left digit bias, I form a portfolio that exploits the bias. The portfolio is constructed in the following way: at the end of each day, I long stocks with prices $[20,21)∩[30,31)∩[40,41), and short stocks with prices $[19,20)∩[29,30)∩[39,40). The portfolio is then held for a week. I excluded $10 stocks because stocks with such small prices could potentially introduce some bias. I also excluded stock with prices greater than $50 because the number of stocks decreases as the price gets larger. In the Appendix I repeat the portfolio construction while including all decile prices within $100 and the results remain unchanged.

[Table 1]

Table 1 gives the summary statistics of the long portfolio versus the short portfolio. We do not see any significant difference in market cap or volume between the long and short side[1]. In fact, assuming returns are distributed normally, stocks in the short side at one time could easily switch to be in the long side in the future. With a long enough sample horizon, the number of days a stock resides in the long side would be roughly the same as the number of days a stock resides in the short side[2]. The difference in next week return between the long and short side is the focus of this paper and will be discussed in detail. Notice that we also see a difference in previous week return between the long and short side. With the assumption that price level does influence future price movement, it is not surprising to see that the conditional previous week return is different provided that a stock is in the long or short side today. Given that the previous week return if different between the long and short side, one might worry that weekly momentum is a confounding factoriugyi here. In the appendix I show a long short portfolio construction conditioned on same past week return to and the effect remains unchanged.

[Table 2]

Table 2 gives the buy-and-hold one week portfolio return over the subsample period of 1980-2010. Average daily return is reported for ease of comparison. Column 1 is the net portfolio return without adjusting for any risk. A 3.3 basis point daily return is equivalent to 8.3% annual return. Column 2 gives the portfolio return adjusted for market risk. Column 3 gives the portfolio return adjusted for

[1] We do expect the long side to be slightly larger in marketcap because their prices is on average $1 higher than the short side

[2] See Appendix. A stock with over 10 years history on the stock market has roughly the same number of days of being in the long side and in the short side.

Fama-French three factors. As we can see, the correlation coefficient with each of the three factors are less than 1%, and the alpha is largely unchanged when adjusted for risk. We rule out the hypothesis that the round prices bias can be explained by the three factor risk.

Testing Round Price Bias with Other Cross-sectional Characteristics

We go on to examine the round prices effect under some cross-sectional characteristics. I first examine whether the bias is stronger among the top quartile of firms in terms of market capitalization.

[Figure 5]

Figure 5 shows the effect among the top quartile size firms. Surprisingly, we observe a stronger (6 basis point) return premium among the top quartile size firms.

The round prices effect is about the same during recession vs the good times. It's stronger (~4bp) with stocks that has more positive past return, and weaker (~2bp) with stocks that has a more negative past return. The effect appears to be the same between stocks with high and low past trading volume

4. Potential Channels

I propose the left-digit-bias induced psychological barriers as a channel that explains the observed price clustering and the abnormal return. The channel implications are consistent with the empirical results. After discussing the left-digit-bias channel I'll look at other potential channels and whether they fit with the empirical observations.

Left-Digit-Bias Induced Barriers

This channel begins with assuming that investors suffers from left digit bias; Specifically, the tens digit is more salient than the integer digit to an investor. Put it in other words, investors mentally put stocks into bins base on their tens digit, where stocks with price $[10,20) is in one bin and stocks with price $[20,30) is in another bin, etc. A $20 stock appears to be substantially higher in value than a $19 stock because it is in a higher value bin (while a $17 stock appears similar in value to a $16 stock, being from the same bin). Such mental binning of stocks results in a discontinuous jump in the perceived value of a stock at multiples of $10, thus creating stock prices barriers at tens ($10, $20, $30, etc), making it harder for stock price to move from $19 to $20 (and vice versa).

The first consequence of barriers at multiples of $10 are clustering of stock prices. Looking at the empirical distribution of prices in figure 2, we observe a discontinuous drop in frequency at $10, consistent with barriers blocking price movements from above. The second consequence is that barriers prevents information from incorporating into prices. Imagine good news arrives for a stock at $19, and normally such news would push its price above $20. Due to the barrier at $20 however, investors are reluctant to buy with a price above $20. This creates a temporary underpricing for the stock. The good news eventually prevails and push the price through the $20 barrier. Now there is no long a barrier above and the underpricing are being corrected, resulting in an abnormal high return of stocks just above $20. Again this fits well with the empirical observation that stocks with integer digit 9 earns an abnormal low return while stocks with integer digit 0 earns an abnormal high return.

There are some potential secondary implications of the left-digit-bias channel. We expect more sophisticated investors/ institutional investors to be less subjected to the left-digit-bias[3]. Therefore we should find a smaller abnormal return if we form the round number portfolio using stocks with a higher institution ownership.

Given how easy it is to form the round number portfolio (using only past price level), it should be fairly easy for investors to incorporate the strategy into their existing portfolio. I expect the abnormal return to be

[3] Institutional investors has been shown to be subject to various behavioral bias too. It is not clear how immune institutional investors are towards the left digit bias.

arbitraged away once investors/arbitragers became aware of investor's left-digit-bias in stock prices. Looking at the round number portfolio return over the years in figure 6, the premium is consistently high until around 2001, then it gradually reduced to around 1 basis point on 2006 and less than 1 basis point since 2011. This is consistent with investors/arbitragers becoming aware of the bias since 2001 and the premium effect slows dies down.

Another channel propose in the literature to explain price clustering is that round numbers serves as focal points to make price discrete and minimize negotiation cost . Ball et al. [1985] and Harris [1991] argued that the level of price clustering depends on how well the true value of the security is known by investors. This argument, denoted as the price resolution hypothesis, suggests that, when the true value of a security is unknown, investors will prefer to use a discrete set of prices to minimize negotiation costs. In this case, clustering will occur. This explains the clustering at penny and dime digits well, however it become less helpful on dollar digit because the uncertainty towards a stock's true value is a lot smaller at integer level. Furthermore, such channel has difficulty explaining the abnormal low return for stocks with integer digit 9 and abnormal high return for stocks with integer digit 0.

Conclusion

Reference

Table 1: Summary statistics

Summary statistics for the long and short portfolio

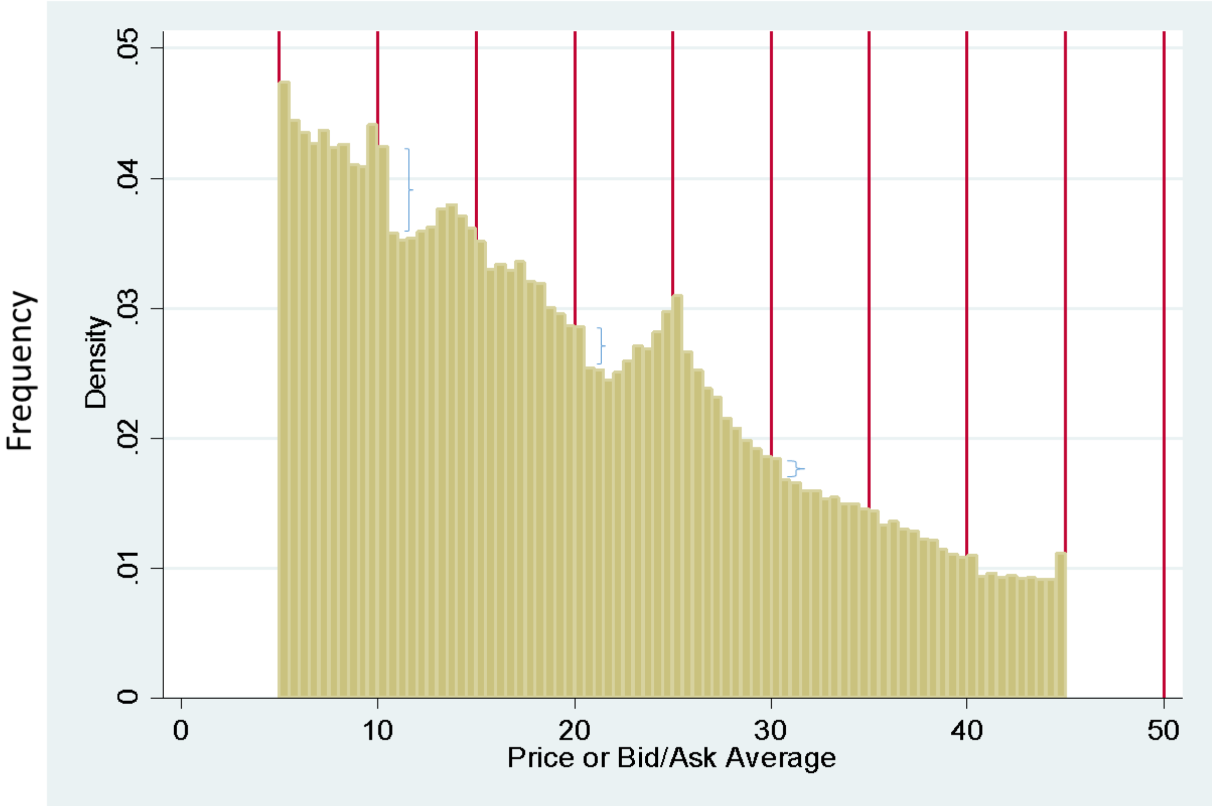
	Next week (daily) return		Past week (daily) return		marketcap		volume	
	long	short	long	short	long	short	long	short
Mean	.0008245	.0004925	.0010143	.0013428	1895624	1707718	377186	357778
std	.0129276	.0128183	.0137478	.0133481	8928671	7722465	1981542	1918264

Table 2

Test of the CAPM over the subsample period of 1980-2010

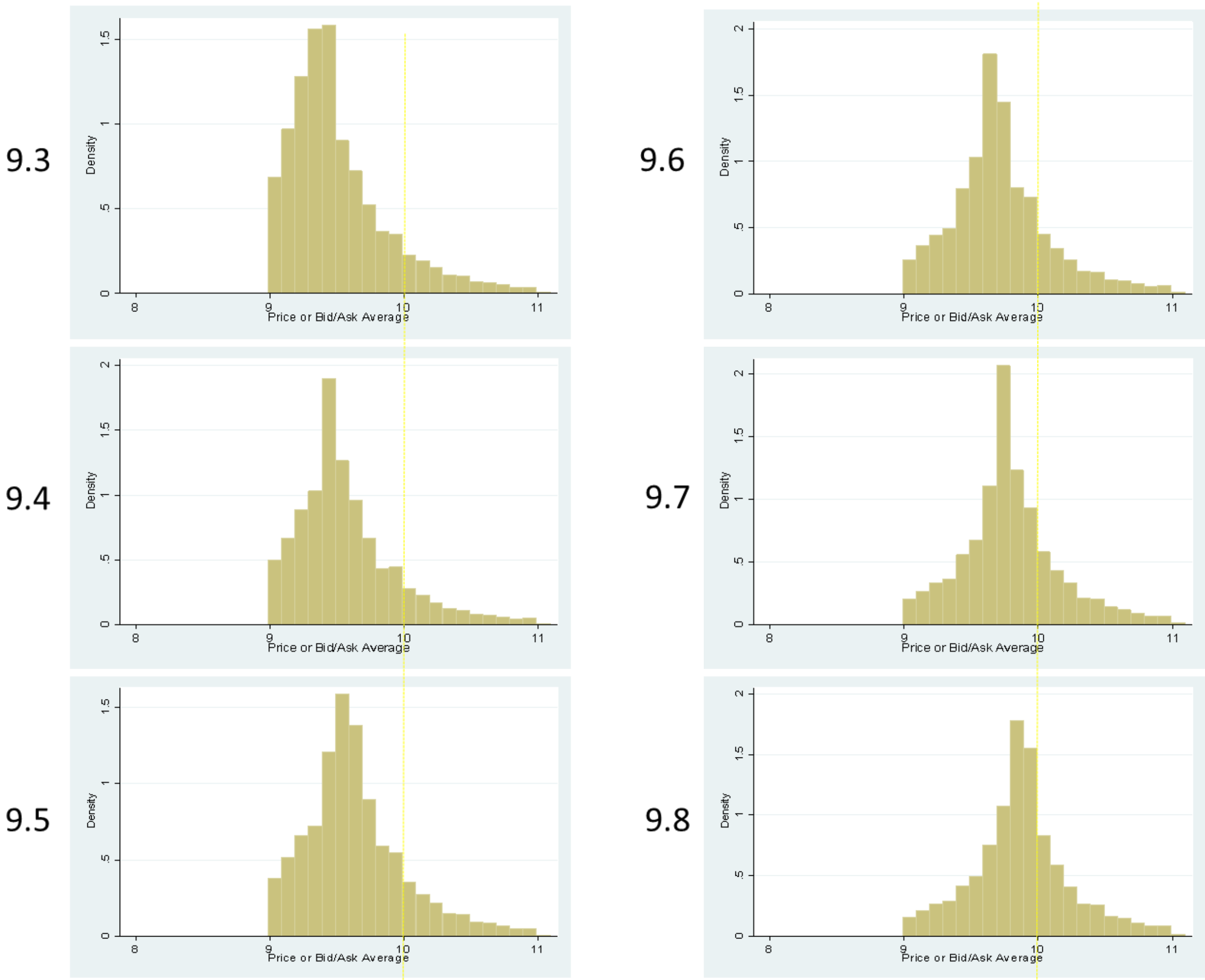
	(1)	(2)	(3)
constant	.00033 (.00002)	.00031 (.00002)	.00032 (.00002)
Market		.020 (.005)	.019 (.005)
HML			.0089 (.0076)
SMB			.0049 (.0099)
R-square			0.0065
N	2,514	2,514	2,514

Figure 1: Distribution of U.S. Stock Prices



This graph plots the distribution of prices of all U.S. stocks with price between \$5 and \$45 for the sample period 1960-2017. Prices are grouped into bins of 0.5. Difference in frequency at \$10, \$20, \$30 etc are highlighted.

Figure 2: Distribution of Stock Prices Condition on 5 Days Ago Prices.



Condition on initial price indicated on the left, I plot out the distribution of stock prices 5 days later. Prices are grouped into bins of \$0.1. A yellow line is added at \$10 to highlight the discontinuity in distribution of prices.

Figure 3: Average Next Day Returns Across Stocks Prices

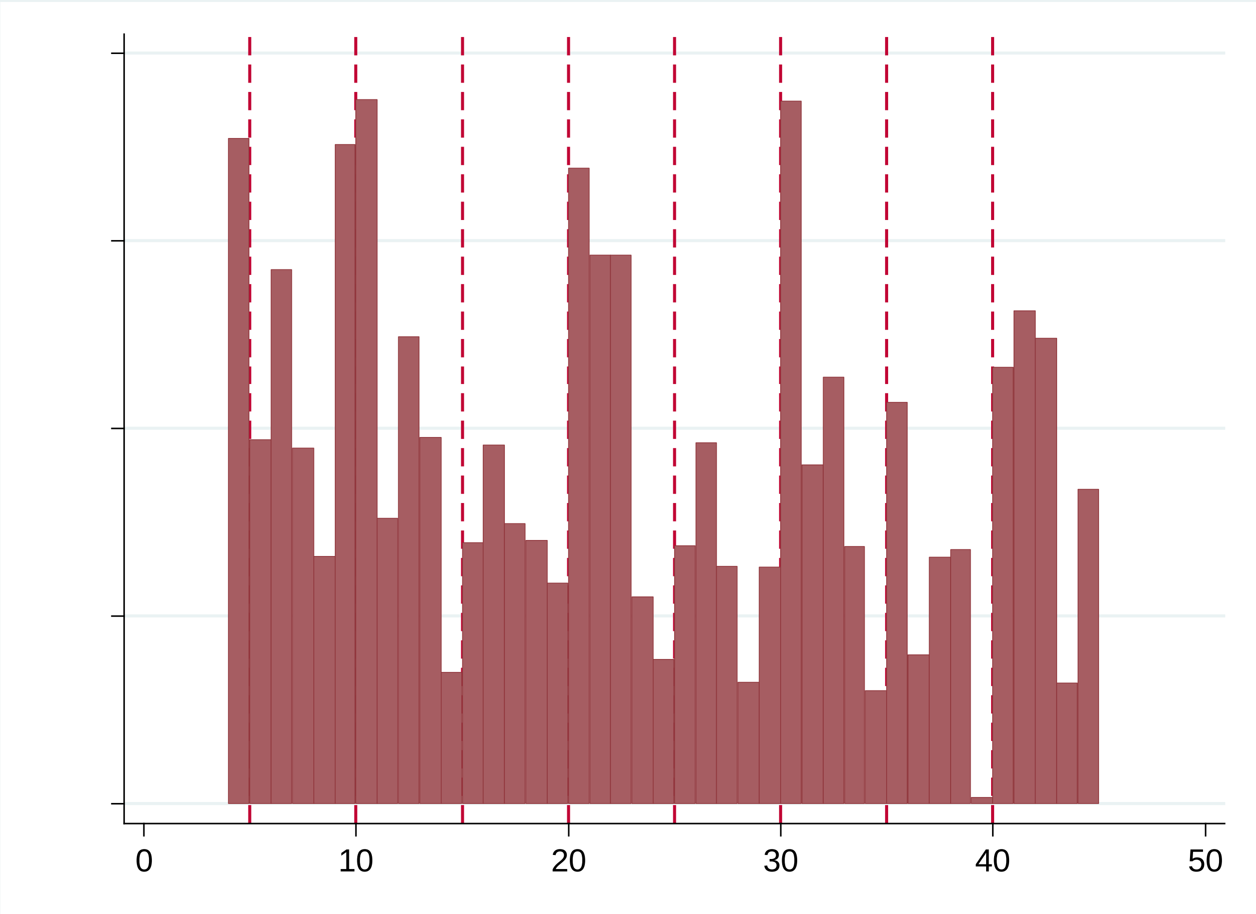


Figure 3 plots out the average next day return of stocks across prices from $5 to $45. Prices are grouped into integer bins.

Figure 4: Average Next Week Returns Across Stocks Prices

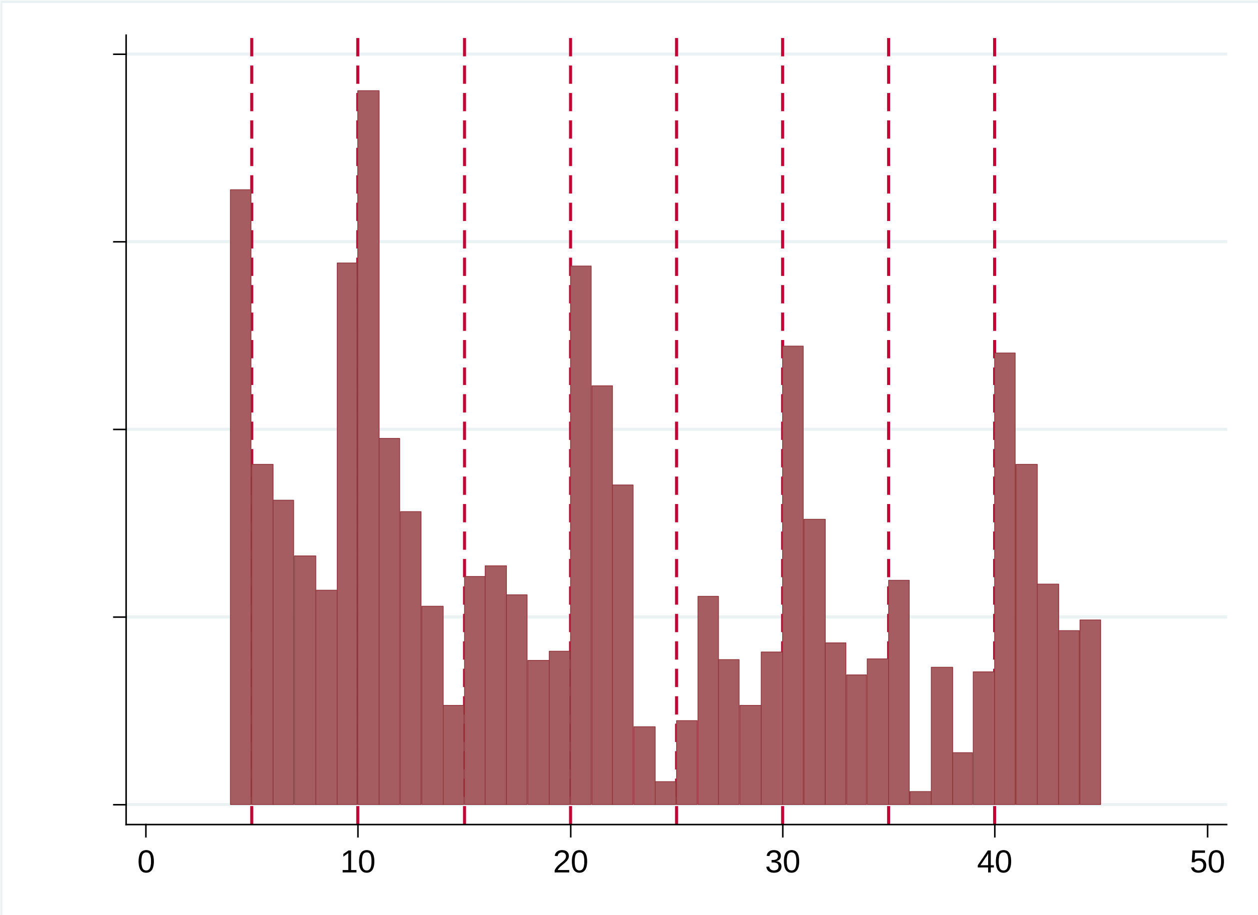


Figure 4 plots out the average next week return of stocks across prices from \$5 to \$45. Prices are grouped into integer bins.

Figure 5: Average Next Week Returns for top quartile market cap

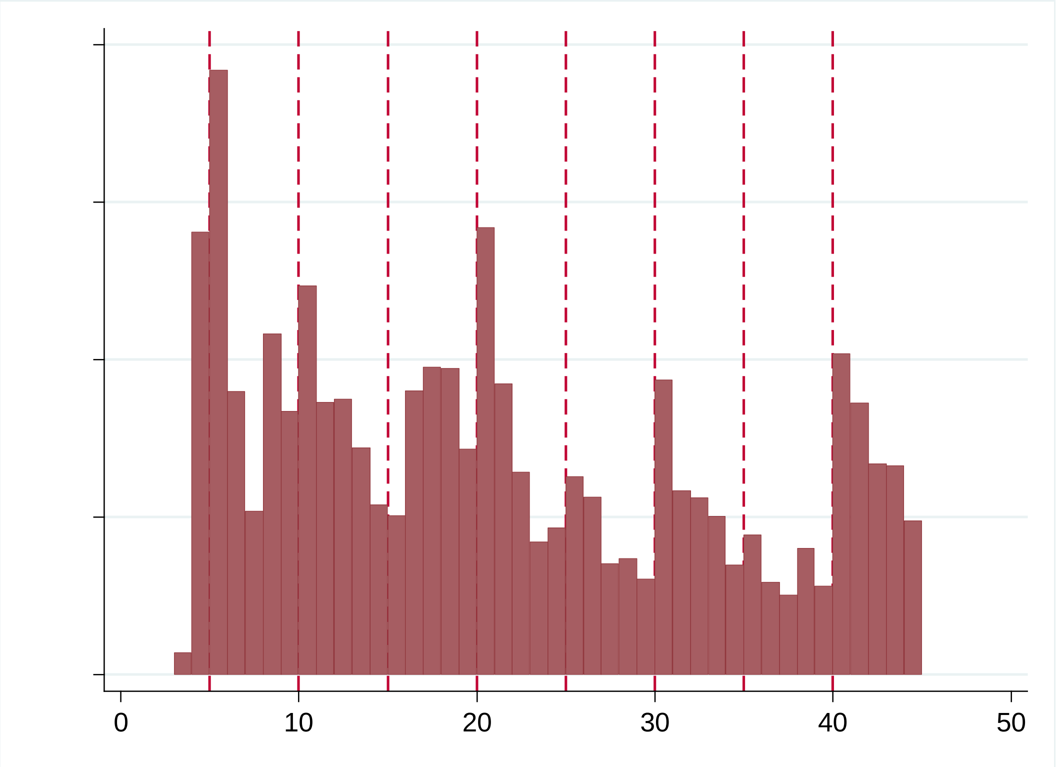


Figure 5 plots out the average next week return of stocks across prices from $5 to $45 for the top quartile market cap stocks only. Prices are grouped into integer bins.

Figure 6: Portfolio return across the years

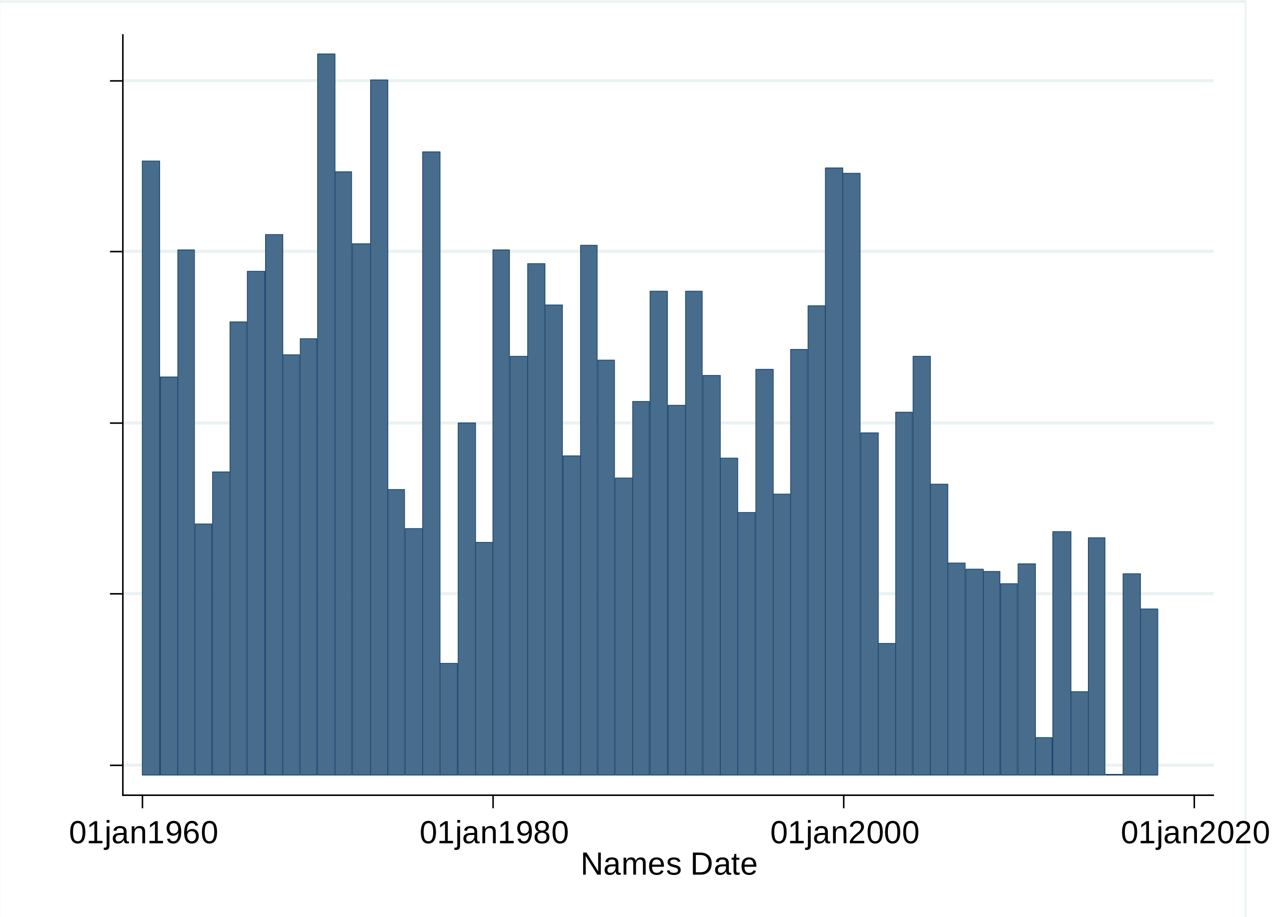


Figure 6 plots out round number portfolio average daily return. To form the round number portfolio, I long stocks with prices $[20,21) ∩ [30,31) ∩ [40,41), and short stocks with prices $[19,20) ∩ [29,30) ∩ [39,40). The portfolio is then held for a week and average daily return is calculated by dividing the weekly return by 5.