Psychological Anchors, Underreaction, Overreaction, and Asset Prices *

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Abstract

Motivated by both statistical and psychological evidence on underreaction and overreaction, we propose two measures, the nearness to the 52-week high and the nearness to the historical high, as proxies for the degree of good news that traders have overreacted and underreacted in the past, respectively. For aggregate market returns, the nearness to the 52-week high positively predicts future returns, while the nearness to the historical high negatively predicts future market returns. The predictive power from these two proxies is stronger than traditional macro variables. Together with macro variables, these two proxies predict market returns up to 46% at annual horizon. On the cross-sectional analysis, for stocks that have more likely experienced underreaction (to either good news or bad news) in the past, the momentum effect is 2 to 3 times stronger. Similarly, for stocks that have more likely experienced overreaction in the past, the value premium is much stronger.

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1 Introduction

Both psychological and statistical evidence[1] show that stock market underreacts to some types of news and overreacts to other types of news. Daniel et. al (1998), Hong and Stein (1999), and Barberis, Shleifer, and Vishny (1998) among others develop behavioral models that can account for both overreaction and underreaction in stock market. For example, Barberis, Shleifer, and Vishny (1998) provide a model to explain how investors might form beliefs that lead to both underreaction and overreaction. In the model, investors underreact to sporadic news. However, investors overreact to a prolonged record of extreme performance, whether good or bad.

Further support for on over- and underreation comes from the evidence that when making decision, human beings are subject to "adjustment and anchoring bias" (e.g. Kahneman, Slovic, and Tversky (1982)). They report on experiments in which subjects are asked to estimate a quantity as an increment to a random number that the subject observes. The estimates are positively correlated with the random numbers. George and Hwang (2004) suggest that traders might use the 52-week high as an "anchor," like the random number in the experiments when assessing the increment in stock value implied by new information. George and Hwang (2004) argue that a stock whose price is at or near its 52-week high is a stock for which good news has recently arrived. This may be the time when biases in how traders underreact to news are at their peaks. Indeed, They find that profits to a momentum strategy based on nearness to the 52-week high are superior to those strategies based past returns. Specifically, the nearness to the 52-week high is positively associated with expected returns. We further conjecture that traders might also use the historical high as another anchor when evaluating information. However, the effect of this anchor is the opposite of the 52-week high anchor. When the current price is far from its historical high, this may be the time when biases in how traders overreact to the bad news are at their peaks[2]. Hence,

[1]See section 2 for a brief review on this literature. A partial list includes De Bondt and Thaler (1985), Rosenberg et al (1985), Poterba and Summers (1988), Bernard and Thomas (1990), Cutler et al. (1991), Fama and French (1992), Jegadeesh and Titman (1993), and Lakonishok et al (1994), Loughran and Ritter (1995), and Daniel et al. (1998).

[2]This overreaction hypothesis can also be justified as follows. Because in this case, it is likely that there are a series of bad news in the past, traders overreact to prolonged news as in the model of Barberis, Shleifer,

the nearness to the historical high should negatively predict future returns.

Motivated by the psychological and statistical evidence mentioned above, we propose two proxies[3] for overreaction and underreaction - the nearness to the 52-week high, and the nearness to the historical high - to predict the aggregate market returns. We show that our measures have strong predictive power for aggregate market index. Traditional macro such as cay and dividend yield have strong predictive ability at longer horizons. Our proposed predictors have a stronger predictive ability at shorter horizons (typically less than 1 year). Since most of the strong empirical evidence on over- and underreaction comes from the cross-sectional analysis and long-horizon time-series analysis, our results complements previous studies.

Specifically, from Dow Jones index, we compute the nearness to the 52-week high and the nearness to the historical high. We first show that there is no momentum in aggregate market when we regress future market returns on past market returns alone. However, after we control the nearness to the historical high, the past market returns can positively predict future returns at a marginally significant level. This indicates that the nearness to the historical high contaminates the relationship between future returns and the past performance. Furthermore, when the nearness to the 52-week high is included in the regression along with the nearness to historical high and past returns, past returns can't predict future returns at all while the nearness to the 52-week high can positively predict future market returns. This indicates that the predictive ability of the past market return is dominated by the nearness to the 52-week high, confirming the cross-sectional findings of George and Hwang (2004). In a horse race regression where future market returns are regressed on the nearness to the 52-week high, the nearness to the historical high, default premium, term premium, real interest rate, inflation rate, wealth-consumption ratio, and dividend yield, our proposed predictors have the biggest power and are stable across sub-samples. Furthermore, together with the traditional macroeconomic predictors, the nearness to the 52-week high and the nearness to the historical high can predict market returns with astonishingly high R-squared of 46% at one year horizon.

and Vishny (1998). See section 2 for more details.

[3]See section 2 for more detailed discussion on the intuition and justification behind these proxies.

The negative predictive power for the nearness to the historical high could also be consistent with a rational model with a mean-reverting state variable. However, if we replace the Dow index with the market cap from NYSE/AMEX, the predictive power from the nearness to the historical high is actually much lower. This suggests the special role for the Dow index, probably due to its visibility. Consequently, the unobservable mean-reverting state variable is unlikely to account for all the predictive power for the nearness to the historical high. Lin and Xiong (2006) show that investors with limited attention tend to process more market and sector-wide information than firm-specific information. Dow index is probably the most readily available information about market. Hence, investors tend to use Dow index as a benchmark while evaluating new information.

Given the vast literature on the predictability of market returns, it may be surprising that the highly predictive variables, the nearness to 52-week high and the nearness to historical high- are missed by the previous studies. This may due to three reasons. First, if the past performance is measured by past market returns, past performance can't predict future returns in aggregate. Second, the nearness to the 52-week high and the historical high need be measured against Dow index. If it is measured against the market capitalization from NYSE/AMEX, the predictive ability is much weaker. Third, the nearness to the 52-week high has a small power to predict future returns if the nearness to the historical high is not controlled in the regression. This highlights the importance of the psychological anchoring and the opposite effect of these two anchors.

We provide further support for our proxies by cross-sectional analysis. We first identify a group of firms who have less likely experienced overreaction in the past. Specifically, we show that, for stocks with only one anchor, that is, the 52-week high equals to historical high, the momentum effect is 2 to 3 times stronger[4]. For stocks with two anchors, the momentum effect is not significant anymore in a simple one-way sorting by the nearness to the 52-week high. However, after controlling for the nearness to the historical high, momentum effect re-emerges significantly. A similar pattern is found for historical high. When controlling for the nearness to the 52-week high, the nearness to the historical high is positively associated

[4]see section 2 for more discussion on the intuition behind this. Basically, in section 2, we argue that, for stocks whose 52-week high equals to the historical high, it is less likely that there is overreaction in the past.

with expected returns. However, this effect is insignificant in a simple one-way sorting by the nearness to the historical high. We also demonstrate the link between the historical high and value investing. In particular, we show that the value premium is much weaker among firms where the overreaction is less likely, that is, the 52-week high equals to the historical high.

Recently, Chen and Zhang (2009) proposed a 3-neoclassical-factor model that can successfully explain a number of anomalies including momentum profit and value premium. However, when we form the momentum and book-to-market portfolios by controlling the historical high anchor, the 3-neoclassical-factor model has difficulty in explaining either the momentum profit or the value premium. As a consequence, we demonstrate that the psychological anchoring has important implications in asset price movements, which is hard to fit in a traditional rational asset pricing framework.

Our contribution is two-fold. First, we propose two predictors for market returns and show that the nearness to the 52-week high and the historical high are important predictors for future market returns. These predictors based on psychological anchors are more robust than the traditional macroeconomic predictors. Unlike dividend yield, our predictors have strongest power in horizons less than one year. Hence, we are not subject to the criticisms on long-run predictability. Unlike the wealth consumption ratio, our predictors have no look-ahead bias. In addition, it is very easy to construct our predictors from any major newspaper. Second, we find that the historical high is also an anchor investors use when evaluating information. This anchor has an opposite effect with the 52-week high anchor. Controlling for the historical high, momentum effect is 2 to 3 times bigger. On the other hand, controlling for the 52-week high, the value premium is much stronger. Our findings suggest that models in which agents' valuations depend on the nearness of the share price to anchors will be successful in explaining price dynamics.

The rest of the paper is organized as follows. The next section describes the psychological and statistical evidence on over- and underreaction and provides intuitions behind our proxies. Section III describes the empirical results from time-series analysis. Section IV provides further evidence from cross-sectional analysis. Section V concludes.

2 Underreaction, overreaction, statistical and psychological evidence

This section summarizes the statistical and psychological evidence on underreaction and overreaction and provides motivations for our proposed predictors for expected returns. The empirical work pointing to overreaction or underreaction is so vast, we only list a few most relevant ones for our purpose here. Barberis et al (1998), Daniel et al. (1998), and Fama (1998) summarize a large number of studies related to under/overreaction. Below, we follow Barberis et al (1998) to describe the evidences on over- and underreaction, then provide intuition for our proposed proxies.

Recent empirical research in finance has identified two robust phenomena in asset market: underreaction of stock prices to news such as earnings announcements, and overreaction of stock prices to a series of news, either good or bad. Cutler, Poterba, and Summers (1991) find positive autocorrelations in excess stock returns over horizons of 1-12 months. This is consistent with with the underreaction hypothesis that stock price underreact to new information and hence incorporate information slowly, leading to trends in subsequent returns in short horizons. Stronger support for the underreaction hypothesis comes from the cross-section of stock returns. Jegadeesh and Titman (1993) show that stock returns exhibit momentum behavior at intermediate horizons. They interpret their finding as underreaction to information and slow incorporation of information into prices.

On the other hand, Cutler, Poterba, and Summers (1991) find slight negative autocorrelations in stock returns over horizons between 3 years and 5 years. The studies on long-run predictability of aggregate index is numerous, starting with Campbell and Shiller (1988), Fama and French (1988), and Poterba and Summers (1988). Overall, previous studies find that some measures of stock valuation, such as dividend yield, can positively predict future market returns, esp. in longer horizons[5]. This group of studies are consistent with the overreaction hypothesis that stock price overreacts to a series of news, leading to reversal in subsequent returns in longer horizons. Again, the stronger evidence for overreaction comes

[5]Due to difficulty in dealing with overlapped data and persistent predictors, there is still an ongoing debate about the long-run predictability of the aggregate stock returns

from the study of the cross-section of stock returns. De Bondt and Thaler (1985) discover that portfolios of stocks with extremely poor returns over the previous five years significantly outperform portfolios of stocks with extremely high returns. In the case of earnings, Zarowin (1989) finds that firms that have had a sequence of good earnings realizations subsequently underperform firms with a sequence of bad earnings. This evidence suggests that stocks with a prolonged record of good news, and hence extremely high past returns, are overvalued. Further evidence comes from the analysis by sorting stocks into portfolios by valuation ratio such as book to market, earnings/price, and cash flow/price (e.g. Fama and French (1992), and Lakonishok, Shleifer and Vishny (1994)). This type of sorting typically generates a large return spread across two extreme portfolios. However, the economic interpretation is more controversial. Some authors argue for a risk-based explanation, others argue for explanations based on behavior bias, such as overreaction.

Apart from the statistical evidence on over- and underreaction in asset market, the psychological studies related to over- and underreaction are also extremely numerous. One important phenomenon known as conservatism has been identified by many psychologists, including Edwards (1968). Conservatism states that individuals are reluctant or slow to change their prior beliefs in the face of new information. In experiments, it is found that individuals adjust their posteriors in the same direction with Bayesian update, but much smaller in magnitude. This, of course, is what underreaction is all about. Tversky and Kahneman (1974) document another important phenomenon - the representativeness -that is the tendency of human beings to view events as representative of some specific class and to ignore the laws of probability. An important aspect of the representativeness is that people think they see patterns in truly random sequences. This is extremely suggestive of the overreaction evidence from the stock market described above. When investors see a series of high earning growth for a company, they may classify this company as growth firm, and ignore the probability that very few companies can keep growing. To unify conservatism and representativeness, Griffin and Tversky (1992) suggests that people might underreact to intermittent news, while overreact to a prolonged record of salient performance.

In a nutshell, there are plenty of psychological and statistical evidence on over- and underreaction. However, most of the anomalous statistical evidence comes from the cross-section of stock returns, and the efficient market hypothesis is generally not rejected by the data, especially for short horizons. For example, past returns only have a very limited power to predict future returns in aggregate market, in the short and long horizons. In this paper, motivated by both the psychological and statistical evidence, we propose the nearness to the 52-week high as a proxy for underreaction, and the nearness to the historical high as a proxy for overreaction. We show that, unlike past returns, our predictors have strong power to predict future market returns, especially for short horizons of 1-12 months. We also provide further support from cross-sectional analysis.

One possible justification for our proxies is based on stock market's underreaction to intermittent news, and overreaction to a prolonged series of news. By comparing the current price to the 52-week high, it is more likely that this would pick up the overreaction to sporadic past recent news. For example, if the nearness to the 52-week is high, on average, it is more likely that there is some sporadic good news in the recent past. Based on psychological evidence on conservatism, traders tend to have underreacted to the news. Similarly, if the current price is much below its 52-week high, it is more likely that the firm has experienced some intermittent bad news in the recent past (one year at maximum), again based on conservatism for isolated news, it is more likely that traders have underreacted to the bad news in the recent past. We use the nearness to the 52-week high to summarize the degree of good news market has underreacted in the past year. Analogously, if the current price level is far from the historical high, it is more likely that there is a series of bad news in the past. Hence, based on representativeness, traders may have overreacted the bad news, and hence the subsequent returns should be higher. As a consequence. we can use the nearness to the historical high to summarize the degree of good news to which market has overreacted in the past. Therefore, the nearness to the historical high should be positively associated with future returns.

Another possible justification for our proxies for over- and underreaction comes from the experimental research on "adjustment and anchoring bias" (e.g. Kahneman, Slovic, and Tversky ((1982)). They report on experiments in which subjects are asked to estimate a quantity as an increment to a number that the subject observes was generated randomly. Estimates are higher (lower) for subjects that start with higher (lower) random numbers.

George and Hwang (2004) suggest that traders might use the 52-week high as an anchor against which they evaluate the potential impact of news. When intermittent good news in the past year has pushed a stock's price near or to a new 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it. The information eventually prevails and the price moves up, leading to a continuation. Similarly, when intermittent bad news in the past year pushes a stock's price far from its 52-week high, traders are initially unwilling to sell the stock at prices that are as low as the information implies. That is, they underreact to the news. The information eventually prevails and the price falls subsequently. As a consequence, the nearness to the 52-week high summarizes the degree of underreaction to news in the past. If the current price is close to its 52-week high, it is more like that this stock has underreacted to some good news.

On the other hand, if the current price is far from its 52-week high, it is more like that this stock has underreacted to some bad news. Therefore, the nearness to the 52-week high should positively predict future returns. On the other hand, based on the psychological evidence on overreaction to a series of salient news, we further conjecture that traders may use the historical high as another anchor against which they evaluate information. When a prolonged bad news has push the stock price much below its historical high, traders may sell the stock at prices that are lower than the news would imply. That is, traders overreact to prolonged salient news. The information eventually prevails and the price moves up, resulting in a higher subsequent returns when the current price is far below is distant historical high. Hence, the nerness to the historical high can summarize the degree of overreaction to news in the past. Therefore, anchoring effect provides an additional way to justify our proxies to under- and overreaction.

Of course, these proxies are undeniably imperfect in some sense, and there could be a lot of common component in these two proxies. For example the nearness to the 52-week high could also include information on overreaction since there might be some salient news in the past if the stock is very close or far from its 52-week high. However, by controlling the information from the nearness to the historical high, the nearness to the 52-week high should be a purer proxy for underreaction. Therefore, by putting both proxies on the right side of regression, they should pick up more information on expected returns resulting from over- and underreaction. Furthermore, we simulate a variation of the model by Barberis, Shleifer and Vishny (1998) where investors underreact to sporadic news and overreact to a prolonged record of extreme performance, whether good or bad. The simulation results support our claim here. That is, in the model simulation, the nearness to the historical high is a proxy for overreaction and negatively predict future returns, while the nearness to the 52-week high is a proxy for underreaction and positively associated with future returns.

Because there tends to be a upward trend in stock prices in general, we need to consider especially for the case where the historical high equals to 52-week high. For one reason, when historical equals to the 52-week high, investors only have one anchor against which evaluating information. We argue that, in this case, investors tend to ignore the historical anchor in general because 52-week is psychologically more recent and more importantly, because there is probably only a limited good news, not a prolonged good news in the past. Furthermore, when the 52-week high equals to the historical high, firms have unlikely experienced a series of bad news in the past, and hence overreaction. Hence, comparing with the rest of stocks, there should be less overreaction in the past among these stocks. As a result, we argue that for firms with the same 52-week high and historical high, the nearness to 52-week high captures the underreaction effect better. That is, the nearness to the 52-week high should predict future return more strongly among those stocks. We use cross-section of returns to test this hypothesis in section 4 and indeed find strong support.

3 Anchors and Aggregate Market Behavior

3.1 Data and Notation

In this section, we describe the data used in this paper, and introduce notations for our predictive variables. The daily and monthly value-weighted CRSP return from 1926-2008 is obtain from CRSP. The daily Dow Jones Industrial Index data from 1928-2008 is obtained from Dow Jones. Here, we focus on Dow index instead of aggregate market capitalization due to its high visibility. Lin and Xiong (2006) show that investors with limited attention tend to process more market and sector-wide information than firm-specific information. Dow index is probably the most readily available information about market. Hence, investors tend to use Dow index as a benchmark while evaluating new information.

Several macroeconomic variables known in the literature that can predict stock returns are used as control variables in this paper. Specifically, we use monthly default premium (DEF), monthly term premium ($TERM$), monthly real interest rate (r_t), monthly inflation (π_t), and Lettau and Ludvigson's quarterly consumption wealth ratio, *cay*. The DEF is define as the yield spread between BAA and AAA bonds obtained from St. Louis FED. The $TERM$ premium is defined as the difference between 30-year treasury bond yield and 30-day t-bill yield, obtained from CRSP. *cay* is defined as in Lettau and Ludvigson (2001), obtained from Martin Lettau and Sydney Ludvigson's website. Since it is in quarterly frequency, we convert it into monthly frequency by assigning the same to all the three months in the same quarter. The inflation rate (π_t) is converted from monthly CPI, obtained from CRSP. The real interest rate (r_t^f) is defined as the difference between 30-day t-bill rate and the inflation. The monthly dividend yield is calculated as the difference between the log of the last 12 month dividends and the log of the current level of the CRSP valued-weighted index. Previous studies have shown that each of the above variables has predictive power for the stock market.

We use these variables as our control variables for the nearness to the 52-week high and the historical high in the predictive regressions. In daily regression, we simply assume that the macro variables have the same value for each day in the same month. We shall focus on our main analysis on the data sample from 1963-2008 since many of the previous studies using samples after 1963 and our cross-section analysis also starts with year 1963. Therefore, for comparison with previous literature, we use data sample from 1963 to 2008 for most of our regressions. More importantly, Dow Jones 30-stock Industrial Index starts late 1928, its visibility is not big in early days. Hence, we discard the first few decades for Dow index to build its reputation and to attract attention. Furthermore, there is a great depression and two world wars in early sample, Dow index has not return to his pre-depression level until the thanksgiving in 1954. Therefore, with that in mind, the historical high probably don't mean much to investors and may not be a good anchor. However, we use the full sample 1928-2008 as a robustness check, and the results are still significant, but smaller in magnitude.

Let p_t denote the Dow Jones Industrial Average level at the end of day t. $p_{max,t}$ and $p_{52,t}$ denote its historical high and 52-week high of the Dow level until the end of day t. We now can define our main predictive variables. The nearness to the 52-week high is computed as the ratio of the current Dow index and its 52-week high

$$x_{52,t} = p_t / p_{52,t},$$

and the nearness to the historical high is calculated as the ratio of the current Dow index and its historical high

$$x_{max,t} = p_t / p_{max,t}.$$

We also define two new indicator D_t and I_t. The Dow historical high indicator D_t is one when Dow reaches a record high at day t, zero otherwise. I_t is defined to be one when the historical high at day t equals to its 52-week high at day t, zero otherwise. Yuan (2008) uses D_t as proxy for attention-grabbing events, and finds that D_t negatively predicts next days returns because of the selling pressure in the next day after investors realize their gains following the attention-grabbing event.

As discussed in the section 2, if traders underreact to current good news when the current price level is close to his 52-week high, then we expect that x_{52} can positively predict future market returns. On the other hand, when traders overreact to bad news when the current price level is far below to its historical high/or is close to its historical low, then we expect x_{max} negatively predict future market returns. As discussed before, when historical high equals to 52-week high, trades would only have on anchor in his mind, and traders would be more likely to underreact to current good news. Hence, we should take special care of the case where $I_t = 1$. In this section, we examine the predictive ability of the nearness to the 52-week high and the historical high at aggregate level. In the next section, we shall explore their implications on the cross-section of expected returns, especially on the momentum and value premium.

3.2 Main time-series regression

The Dow Jones Industrial Average Index is the oldest continuing US market index. It represents the average of 30 stocks from various important American industries. The Dow Index is the most widely used and most visible index. The top panel of figure 1 plots the Dow Jones Industrial Average Index (in logs) from 1963 to 2008, along with its 52-week high and its historical high. Due to inflation and the high equity market return, the index shows a strong positive trend. The lower panel of figure 1 plots the nearness to the 52-week high and the historical high. Not surprisingly, these quantities are close to one on average, highly correlated, and actually identical in about half of the time. However, as we will show later, the predictive power of these two proxies has a opposite sign. The reason that we use Dow index is that it is more visible than the total market value from NYSE/AMEX stocks or other index. Hence, it should have stronger predictive power resulted from anchoring and limited attention. We use NYSE/AMEX market value as robustness checks as well, and the results are similar, but much weaker, consistent with our arguments.

Panel A of Table 1 reports the summary statistics of our proposed predictors, along with other main predictors noticed by previous literature. Because Dow index is increasing over time, the average value of x_{52}, and x_{max} is high and close to one. As expected, the nearness to 52-week high, x_{52} and the nearness to historical high x_{max} are quite persistent, but less persistent than the traditional predictors, such as wealth-consumption ratio and dividend yields. Our predictors are quite negatively skewed because it is up bounded by 1.

Panel B of Table 1 shows that the nearness to the 52-week high and the nearness to the historical high are not much correlated with other macro variables. Among all the macro variables, dividend yield is most correlated with the nearness to the historical high, with a correlation of -0.39. As we expected, the correlation between x_{52} and x_{max} is as high as 84%. However, as we show later, they have opposite predictive ability for future market returns.

We now explore the linkage between the market return and the nearness to the 52-week high and the nearness to the historical high. Because there is momentum effect in the the cross-section of stocks, it is interesting to examine if high past market returns can predict high future returns at aggregate level. In table 2, we regress realized market returns (at different horizons) onto a set of lagged predictors. For the top part of the table, future daily, monthly, 6-month, and annul realized returns are regression on the past daily, monthly, 6-month, and annual returns, respectively. It is seen that past market returns (r_t) do not predict future market returns except at daily horizon, which, we believe, could derive from market microstructure reasons. Hence, if we measure performance by past realized returns, we do not observe momentum at aggregate level, in contrast to the strong cross-sectional momentum effect. Since as argued in last section, the nearness to the historical high could serve an opposite effect as past returns, we control the nearness to the historical high in the middle of table 2. In this case, past market returns indeed have a marginally positive predictive power at 6-month horizon which is consistent with the momentum effect from the cross-section literature. Furthermore, the nearness to the historical high has a strong ability to negatively predict future returns.

At the bottom part of table 2, we regress (daily, monthly, 6-month, and annual) CRSP value-weighted returns onto corresponding past returns r_t, the nearness to the 52-week high x_{52}, the nearness to the historical high x_{max}, Dow historical high indicator D_t, and Dow 52-week high equal historical high indicator I_t. Again, D_t is defined to be one when Dow reaches a record high at day t, zero otherwise. I_t is one when the historical high at day t equals to its 52-week high at day t, zero otherwise. We can see that once we include the nearness to the 52-week high as control, the t-stat of the past performance measured by returns is significantly lowered. However, the nearness to the 52-week high positively predicts future market returns at horizons up to one year. Else equal, if the nearness to the 52-week high increases 1%, the next year's expected return increases for about 1% too, which is economically highly significant. The economic magnitude for the nearness to the historical high is similar. In the same time, if the Dow index is reached its historical high, that is $D_t = 1$, the next days return is likely to be lower. This confirms the result from Yuan (2008) who argues that this is due to the selling pressure from the investors after the attention-grabbing event. However, we show that in long-horizons, D_t predicts positively future market returns. This is consistent with the naive trend-chasing investment strategy at the market level. Based on the above regression results, the market is most likely to go up when the current Dow index is close to its 52-week high, but far below its historical high. This is the time when the underreaction to recent good news is at its peak while its overreaction to prolonged bad news in the past is also at its peak. At this time, investors can ride on the current momentum, and the market still has a lot of potential to go up.

Because there tends to be an upward trend in stock prices, reaching a historical may not be a good proxy for a prolonged good news. For this reason, we need to control the indicator variable where the 52-week high equals to the historical high. Table 2 shows that when the 52-week high equal to the historical high, investors indeed tend to have just underreacted to recent past good news because there is probably no prolonged good news in the past, and hence no overreation. It is also consistent with the interpretation that investors just use the 52-week high anchor and ignore the historical high anchor, and hence mostly just underreact to past good news.

One potential issue for our findings is the multicollinearity. The nearness to the 52-week high pct_{52} and the nearness to the historical high pct_{max} is highly correlated (about 84%). However, this can't explain our results since multicollinearity usually leads to a small t-statistics. In contrast, our t-statistics is always big across different specifications. Variance inflation factor (VIF) for our predictors is about 3.4, much less than the critical cutoff of 10 suggested by Kutner, Nachtsheim, and Neter (2004). This confirms that the multicollinearity is unlikely to plague our results.

As discussed in section 2, one possible explanation for our findings is that investors underreact to sporadic news while overreact to prolonged/salient news. As a consequence, the nearness to the 52-week high is a proxy for the degree of good news to which the investors have underreacted, and the nearness to the historical high is proxy for the degree of prolonged good news to which investors have overreacted. The other possible explanation for our findings is that traders use the both 52-week high and historical high as a reference point against which they evaluate the potential impact of news. Investor tend to underreact to news when they use the 52-week high anchor, and tend to overreact while using the historical high anchor, as discussed in section 2.

3.3 Controlling For the Business Cycle

One potential explanation for our finding is that the nearness to the 52-week high and the nearness to the historical high are correlated with some commonly used predictive variables, in particular, macro variables related to business cycle fluctuations. Indeed, table 1 shows that the nearness to the two anchors is related to business-cycle variables. At the same time, Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988, 1989), Fama (1990), Campbell (1991), and Ferson and Harvey (1991), Lettau and Ludvigson (2001, 2003) find evidence that stock market can be predicted by variables related to business cycle, such as the default spread, the term spread, the interest rate, inflation rate, dividend yield, and the wealth-consumption ratio. Hence, to make sure our predictive ability is not due to their correlation to traditional predictor of stock market returns, we examine the relation between future market returns and the nearness to 52-week high ad historical high using macro variables as controls for business cycle fluctuation. Here, we denote default premium as DEF_t, term premium as $TERM_t$, real interest rate as r_t^f, inflation rate as π_t, consumption wealth ratio as cay_t, and dividend yield as dp_t.

In table 3, we use overlapped daily sampled data. The New-West t-stat for x_{max} ranges from -3.42 to -5.18 for horizons from daily to annual. By contrast, the t-stat for the nearness to 52-week high, is always positive and ranging from 2.04 to 3.83. In table 4 we run a non-overlapped regression, the results stay similar. In this case, we can predict one-year stock market return up to a stunning R-squared of 46%. Furthermore, the nearness to the 52-week high and the nearness to the historical high appears to be the most important predictor from weekly to annual horizon. Notice that our predictors x_{52} and x_{max} is less persistent than the traditional predictors, consumption wealth ratio cay_t and dividend yield dp_t. It is interesting that the naive momentum investing and contrarian investing at aggregate level have a grain of truth. They indeed generate significant positive returns at aggregate level.

One may argue that the predictive ability of x_{max} is due to its ability to pick up some unobserved mean-reverting state variable in the economy. As a robustness check, we also replace Dow Jones Index with NYSE-AMEX total market value to obtain new measures of the nearness to the 52-week high and to the historical high. The table 5 shows that the predictive ability of the nearness to the 52-week high and the historical high is still significant for shorter horizons, but with much smaller magnitude. Overall, the predictive power is much smaller than that from Dow index. Hence, the unobserved mean-reverting state variable from a rational model can't explain our findings. On the other hand, our findings are consistent with our anchoring hypothesis since Dow Index is more visible information than NYSE-AMEX total market value. The Dow Jones Industrial Average Index is the oldest and most visible market indicator in the United States. News of the Dow reaching a record level attracts heavy media coverage and investor attention. Hence, it is a better anchor than the market cap of NYSE-AMEX stocks. Yuan (2008) shows that the record-breaking events of the Dow index predict the trading behavior of investors and market returns due to its attention-grabbing ability.

3.4 Sub-sample Analysis and Monthly Regression Analysis

The predictive power of our proposed variables can be best manifested by comparing with other main predictors through sub-sample analysis. We separate the whole sample into two equal sub-samples, one from 1963 to 1985, and the other from 1986 to 2008. Table 7 reports the regression result for these two sub-samples. The predictive ability for most of the macroeconomic variables is not stable across these two sub-samples. For example, there is no predictive power for wealth-consumption ratio in sub-samples, and its sign flips. The predictive ability of dividend yield is much weaker in the second sub-sample, and the sign flips at short horizons. The predictive ability of term premium mostly derives from the early sub-sample. The predictive ability of default premium changes sign completely across two sub-samples. By contrast, the predictive ability of x_{max} and x_{52} is very consistent across two sub-samples, although the predictive ability for x_{52} is weaker for the second sub-sample. At intermediate horizons where the traditional momentum is the strongest, x_{52} also has significant predictive power in the second sub-sample.

So far we have focused our analysis on the daily regression of total market return. As a robustness check, we also use monthly data to run the same type of predictive regressions for excess market returns. Table 8 reports the monthly regression analysis and the results are very similar. That is, the nearness to the 52-week high and the nearness to the historical high have the strongest predictive power among all the predictors. We also use the long-sample from 1928 to 2008 to repeat our analysis. The results are similar. In a unreported table, the predictive power from the nearness to historical high is still significant, but slightly weaker than that in the short sample. The predictive power from the nearness to the 52-week high is also less significant in the long-sample. This is probably due to the period of great depression. The price level does not reach its pre-depression level after many years. Hence, the historical high is not really a psychological anchor, and the nearness to the historical high have weaker ability as proxy to underreaction.

Instead of using the nearness to the 52-week high, we also tried the nearness to the 26-week high, the results are less significant, but on the same direction. More importantly, when both the nearness to the 52-week high and the nearness to the 26-week high are included in the regression, the nearness to the 52-week high drives out the predictive power of the nearness to the 26-week high for most of the horizons. Similar results obtained when we use 13-week high, 4-week high. Since Dow rarely reaches its historical low, we do not use historical low as a reference point in our analysis.

4 Further Evidence from Cross-Section of Stock Returns

We have shown that both the nearness to the 52-week high and the nearness to the historical high have significant power to predict future market returns, and they function on the opposite directions. Although we view our time-series analysis as our main empirical findings, in this section, we shall provide further evidence by investigating their implications on the cross-section of expected stock returns, especially on the momentum strategy and value investing strategy.

In last section, our time-series results show that when the 52-week high equals to the historical high, investors tend to just interpret it as a 52-week high anchor. As argued in section 2 and 3, for firms with the same 52-week high and historical high, they have unlikely experienced a series of bad news in the past, and hence overreaction. Therefore, comparing with other stocks, there should be less overreaction in the past among these stocks. Hence, we expect that for firms with identical 52-week high and historical high, the nearness to the 52-week high should predict future returns more strongly. Similarly, for the firms with different 52-week high and historical high, they should have experienced less underreaction in the past, hence a higher value premium. Hence, to control these effects in cross-section, for each month, we separate the whole sample into two sub-samples, one with equal 52-week high and historical high, the other with different 52-week high and historical high. We then investigate the momentum and value premium in each sub-samples.

In the tests that follow, we examine the impact of the nearness to the historical high on the momentum strategies of Jegadeesh and Titman (1993) (hereafter JT) and George and Hwang (2004) (hereafter GH), and the effect of the nearness to the 52-week high on the value investment strategy of Fama and French (1992). To get rid of the potential effect from small stocks, we use all the common shares from NYSE/AMEX from 1963 to 2008. For momentum strategies, we adopt the same approach as JT and GH to calculate monthly returns. Both JF and GH focus on strategies that hold the portfolio for 6 months. Specifically, each month investors form a portfolio based on past 6-month returns (or the nearness to the 52-week high), and hold the position for 6 months.

In the following we consider momentum strategy conditional on the case where the 52-week high equal to the historical high. We construct our momentum strategy by following GH with some variations. At the beginning of each month t, we select a set of stocks with the same 52-week high and historical high at the end of month $t-1$. Then the selected stocks are ranked in ascending order according to their past 6-month returns, or their nearness to the 52-week high, $x_{52,i,t} = p_{i,t-1}/p_{i,52,t-1}$, where $p_{i,t-1}$ is the price of stock i at the end of month $t-1$ and $p_{i,52,t-1}$ denotes the highest price of stock i from month $t-12$ to month $t-1$. Based on these ranking, 5 portfolios are formed. Stocks ranked in the top 20% is considered as the winner portfolios, stocks in the bottom 20% is regarded as the loser portfolio. Following the tradition in the momentum literature, we form equally-weighted portfolio. The strategy is to hold, for 6 months, a self-financing portfolio that is long the top quintile portfolio (the winners) and short the bottom quintile portfolio (the losers). Hence, in any particular month t, the return to winners is computed as the equally weighted average of the month t returns from six separate winner portfolios, each formed in one of the 6 prior months $t-6$ to $t-1$. The same procedure can be applied to calculate the returns to losers and other quintile portfolios in month t. We also consider momentum strategy conditional on the case where the 52-week high is less than the historical high. The strategy is the same with before except that we only form portfolios based on a subset of stocks at the beginning of month t for which their 52-week high is less to their historical high at the end of month $t-1$. Later we also form quintile portfolios by ranking on the nearness to the historical high by a similar procedure. In addition to momentum portfolios, we also form quintile portfolios based on book-to-market ratio following Fama and French (1996).

Table 9 shows that the average return from the momentum strategy conditional on the firms with the same 52-week high and historical high is about 3 times bigger than the return from the momentum strategy conditional on the firms with different 52-week high and historical high. Furthermore, although the alpha from Chen and Zhang's 3-neoclassical-factor model is very small for the stocks with two anchors, the momentum strategies still generate a monthly alpha of 0.87 for JT strategy, and an alpha of 0.41 for GH strategy. Because the sample is shorter for Chen and Zhang's factors, the t-stat for GH strategy is less significant. However the magnititude is big. Not surprisingly, the Fama-French 3-factor yields a large alpha for momentum strategy. However, the alpha is much bigger conditional on the stocks with only one anchor. This is true when we use either past returns (JT strategy) or its nearness to the 52-week high (GH sttretegy) as past performance measure. On the opposite, Table 10 shows that the return spread from the value investing strategy conditional on the case where the 52 week high is less than the historical high is much bigger than the return spread from the value investing strategy conditional on the case where the 52 week high equals to the historical high. The effect is especially stronger when we use value-weighted returns following the tradition in the value premium literature. These results indicate that psychological anchoring is part of the force behind both momentum and value premium.

Table 9 indicates that the average return to the momentum strategy (sorted by the nearness to the 52-week high) conditional on the stocks with different 52 week high and historical high is not significantly different from zero. However, if at the beginning of each month t, after we selected the same set of stocks, we first rank this set of stocks by the nearness to the historical high, $x_{max,i,t} = p_{i,t-1}/p_{i,max,t-1}$, where $p_{i,max,t-1}$ denotes the highest price of stock i from until the end of month $t-1$. Based on this ranking, we obtain five subgroup of stocks. In each subgroup, we form 5 portfolios as before. This way, we can form 25 portfolios each month, and hold them for 6-month. We then calculate the momentum spread for each of the 5 subgroups sorted by the nearness to the historical high, then average the spreads across the 5 subgroups. This way, we obtain the spread for the nearness to the 52-week high by controlling for the nearness to the historical high. Comparing table 11 with table 9, it can be seen that this double-sort momentum strategy can generate significantly larger spread comparing with the simple one-way sorting on past performance. This further indicates that the nearness to the historical high works against momentum strategy and it is important to control for this effect.

A similar result is obtained when we sort on historical high. Table 12 show that conditional on the set of stocks with different 52-week high and historical high, a simple one-way sort strategy based on historical high generate an insignificant spread of 0.26 per month. However, in a double-sorting, after controlling for the nearness to the 52-week high, the portfolio longing bottom 20% nearness to the historical high and shorting top 20% nearness to the historical high results in a return spread of 0.48 per month which is also statistically significant with t-value of 3.22.

One last interesting observation is that the nearness to the historical high have stronger predictive power than the nearness to the 52-week high in time-series while it is the opposite in the cross-sectional analysis. This might suggest that, at aggregate level, the mean-reverting state variable plays some roles, while at individual stock level, the psychological underreaction/overreaction is the main driving force, and the importance of the mean-reverting state variable is negligible.

The results from this section also point to the importance to separate the role of the 52-week high and the historical high, confirming the findings from the time-series regressions in section 3.

5 Conclusion

In this paper, we have proposed two predictors for aggregate market returns. In time-series regression, we show that the nearness to the 52-week high positively predicts future returns, while the nearness to the historical high negatively predicts future market returns. The predictive power for these two variables is stronger than traditional macro variables. Together with macro variables, these two anchors predict market returns up to about 50% at annual horizon. On the cross-section side, for stocks where overreaction is less likely in the past, we show that the momentum effect is 2 to 3 times stronger. On the other hand, for stocks where underreaction is less likely, the momentum effect is not significant anymore in a simple one-way sorting based on either past 6-month returns or the nearness to the 52-week high. However, after controlling for the second anchor - the historical high, momentum effect re-emerges significantly. A similar pattern is found for the historical high anchor. We also show that the value premium is 2 to 3 times stronger among stocks where the underreaction is less likely in the past. Our findings suggest that models (e.g. Grinblatt and Han (2002) and Klein (2001))in which agents' valuations depend on the nearness of the share price to anchors will be successful in explaining price dynamics.

Table 1: Summary Statistics: Panel A of this table reports the mean, standard deviation, autocorrelation, skewness, and kurtosis of predictive variables. The predictive variables are the past 1-month (log) excess returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal historical high indicator I_t, default premium DEF_t, term premium $TERM_t$, real interest rate r_t^f, inflation rate π_t, consumption wealth ratio cay_t, and dividend yield dp_t. The summary statistics is for monthly frequency. The mean and standard deviation of log monthly returns, DEF, TERM, interest rate, inflation, cay, and dividend yield are in terms of percentage. Panel B reports the correlation matrix for the same 11 predictive variables except that the past return r_t is measured over the past 6-month instead of one month. The data sample is from 1963 to 2008.

Panel A: Summary Statistics											
	r_t	x_{52}	x_{max}	D_t	I_t	DEF_t	$TERM_t$	π_t	r_t^f	Cay_t	dp_t
$mean$	0.29	0.93	0.90	0.04	0.51	1.02	0.20	0.35	0.11	-0.03	2.97
std	4.50	0.07	0.09	0.19	0.50	0.45	3.16	0.36	0.33	1.54	1.07
$AC(1)$	0.10	0.88	0.93	0.07	0.95	0.97	0.10	0.59	0.48	0.96	0.99
$Skewness$	-0.89	-1.45	-0.91	4.96	-0.04	1.50	0.58	-0.11	0.23	0.34	0.18
$Kurtosis$	6.31	4.75	3.25	25.64	1.00	6.13	5.73	6.81	5.31	2.54	2.30

Panel B: Correlation Matrix											
	r_t	x_{52}	x_{max}	D_t	I_t	DEF_t	$TERM_t$	π_t	r_t^f	Cay_t	dp_t
r_t	1.00	0.75	0.56	0.17	0.12	0.04	-0.03	-0.12	0.11	0.00	-0.11
x_{52}	0.75	1.00	0.84	0.24	0.23	-0.17	-0.05	-0.22	0.14	0.04	-0.29
x_{max}	0.56	0.84	1.00	0.28	0.57	-0.30	-0.04	-0.33	0.25	0.16	-0.39
D_t	0.17	0.24	0.28	1.00	0.24	-0.10	0.04	-0.11	0.08	0.10	-0.11
I_t	0.12	0.23	0.57	0.24	1.00	-0.27	0.02	-0.28	0.23	0.39	-0.27
DEF_t	0.04	-0.17	-0.30	-0.10	-0.27	1.00	0.09	0.18	0.17	-0.09	0.52
$TERM_t$	-0.03	-0.05	-0.04	0.04	0.02	0.09	1.00	-0.16	0.17	0.06	-0.02
π_t	-0.12	-0.22	-0.33	-0.11	-0.28	0.18	-0.16	1.00	-0.76	-0.09	0.43
r_t^f	0.11	0.14	0.25	0.08	0.23	0.17	0.17	-0.76	1.00	0.14	0.04
cay_t	0.00	0.04	0.16	0.10	0.39	-0.09	0.06	-0.09	0.14	1.00	0.13
dp_t	-0.11	-0.29	-0.39	-0.11	-0.27	0.52	-0.02	0.43	0.04	0.13	1.00

Table 2: Daily Overlapping Regression: we regress future (daily, monthly, 6-month, and annual) CRSP value-weighted return onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, and Dow 52-week high equal historical high indicator I_t. We use overlapped daily sampled data. The Newey-West t-stat is given in the parentheses. We use daily CRSP value-weighted return data and Dow index from 1963 to 2008.

horizon	r_t	x_{52}	x_{max}	D_t	I_t	R^2
day	0.0862					0.0074
	(4.5192)					
month	0.0320					0.0010
	(0.8093)					
6-month	-0.0112					0.0001
	(-0.1193)					
year	-1.1544					0.0169
	(-0.1376)					
day	0.0875		-0.0018			0.0077
	(4.6178)		(-1.1954)			
month	0.0561		-0.0394			0.0064
	(1.4000)		(-1.7885)			
6-month	0.1501		-0.3426			0.0491
	(1.6443)		(-3.3940)			
year	0.1291		-0.6240			0.0806
	(0.8195)		(-2.9988)			
day	0.0882	0.0075	-0.0085	-0.000	0.0006	0.0087
	(4.6045)	(2.2830)	(-3.5592)	(-2.595)	(2.5198)	
month	0.0202	0.1808	-0.2005	0.000	0.0130	0.0221
	(0.5121)	(3.2832)	(-4.1420)	(0.068)	(2.7818)	
6-month	0.0358	0.8294	-1.0890	0.007	0.0781	0.1119
	(0.3378)	(3.4669)	(-5.4487)	(0.620)	(3.2589)	
year	0.0511	0.9905	-1.5875	0.031	0.1098	0.1463
	(0.3401)	(2.8797)	(-4.5045)	(1.541)	(2.3044)	

Table 3: Daily Overlapping Regression: we regress future (daily, weekly. monthly, quarterly, 6-month, and annual) CRSP value-weighted return onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal historical high indicator I_t, default premium DEF_t, term premium $TERM_t$, real interest rate r_t^f, inflation rate π_t, consumption wealth ratio cay_t, and dividend yield dp_t. We use overlapped daily sampled data. The macro variables are monthly (or quarterly) sampled. We assign the same monthly (quarterly) value for each day in that month (quarter) for those macro variables. The Newey-West t-stat is given in the parentheses. The coefficients for D_t, I_t, and DEF are in terms of percentage. We use daily CRSP value-weighted return data and Dow index from 1963 to 2008.

horizon	r_t	x_{52}	x_{max}	D_t	I_t	DEF_t	$TERM_t$	π_t	r_t^f	Cay_t	dp_t	R^2
day	0.09	0.01	-0.01	-0.08	0.04	-0.01	0.00	-0.06	0.01	0.01	0.02	0.01
	(4.55)	(2.34)	(-3.42)	(-2.87)	(1.56)	(-0.26)	(1.42)	(-0.86)	(0.18)	(1.64)	(1.17)	
week	-0.03	0.06	-0.06	-0.08	0.25	-0.04	0.01	-0.43	0.11	0.09	0.13	0.02
	(-1.15)	(3.49)	(-4.02)	(-0.64)	(1.49)	(-0.23)	(0.70)	(-1.11)	(0.32)	(2.50)	(1.74)	
month	-0.01	0.18	-0.19	-0.04	0.86	-0.01	0.05	-1.32	0.02	0.28	0.41	0.05
	(-0.27)	(3.45)	(-4.15)	(-0.13)	(1.63)	(-0.02)	(0.92)	(-1.11)	(0.02)	(2.51)	(1.83)	
quarter	-0.05	0.56	-0.58	-0.14	2.64	0.33	0.07	-3.96	0.07	0.80	1.12	0.13
	(-0.73)	(3.83)	(-4.70)	(-0.18)	(1.82)	(0.17)	(0.74)	(-1.26)	(0.02)	(2.75)	(1.99)	
6-month	-0.01	0.81	-1.01	0.26	5.39	0.05	0.37	-6.27	0.77	1.27	2.08	0.22
	(-0.08)	(3.58)	(-5.18)	(0.23)	(2.14)	(0.02)	(3.03)	(-1.23)	(0.13)	(2.30)	(1.97)	
year	0.06	0.74	-1.29	2.51	4.84	2.09	0.22	-9.40	-2.34	3.42	2.78	0.32
	(0.41)	(2.04)	(-3.53)	(1.56)	(0.88)	(0.58)	(1.42)	(-1.27)	(-0.32)	(2.57)	(1.31)	

Table 4: Non-overlapping Regression: we regress future (daily, weekly. monthly, quarterly, 6-month, and annual) CRSP value-weighted return onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal historical high indicator I_t, default premium DEF_t, term premium $TERM_t$, real interest rate r_t^f, inflation rate π_t, consumption wealth ratio cay_t, and dividend yield dp_t. We use non-overlapped data in the regression. The Newey-West t-stat is given in the parentheses. The coefficients for D_t, I_t, and DEF are in terms of percentage. We use daily CRSP value-weighted return data and Dow index from 1963-2008.

horizon	r_t	x_{52}	x_{max}	D_t	I_t	DEF_t	$TERM_t$	π_t	r_t^f	Cay_t	dp_t	R^2
day	0.09	0.01	-0.01	-0.08	0.04	-0.01	0.00	-0.06	0.01	0.01	0.02	0.01
	(5.14)	(2.73)	(-3.55)	(-2.93)	(1.74)	(-0.29)	(1.57)	(-0.98)	(0.19)	(1.88)	(1.28)	
week	0.03	0.06	-0.06	-0.47	0.28	0.00	-0.01	-0.50	0.03	0.09	0.14	0.02
	(1.01)	(2.90)	(-3.50)	(-2.61)	(1.62)	(0.00)	(-0.48)	(-1.12)	(0.07)	(2.40)	(1.79)	
month	-0.02	0.20	-0.20	-0.10	0.96	0.07	0.06	-1.26	0.36	0.29	0.37	0.05
	(-0.29)	(2.89)	(-3.69)	(-0.20)	(1.56)	(0.11)	(1.04)	(-0.86)	(0.29)	(2.30)	(1.59)	
quarter	-0.17	0.72	-0.66	2.51	2.11	0.47	0.13	-7.98	-0.06	0.85	1.57	0.19
	(-1.90)	(4.26)	(-5.83)	(1.60)	(1.24)	(0.19)	(0.64)	(-1.66)	(-0.01)	(2.17)	(1.77)	
6-month	0.15	0.58	-0.88	-0.51	4.22	3.66	0.12	-11.04	-5.72	1.84	1.95	0.26
	(1.44)	(2.74)	(-4.36)	(-0.20)	(1.54)	(1.21)	(0.65)	(-1.54)	(-0.80)	(3.27)	(1.27)	
year	0.20	0.95	-1.63	5.80	3.21	-0.10	-0.48	-16.98	6.77	4.36	4.18	0.46
	(1.16)	(1.98)	(-4.13)	(1.23)	(0.57)	(-0.04)	(-1.13)	(-1.37)	(0.45)	(3.91)	(1.85)	

Table 5: Daily Overlapping Regression: we regress future (daily, weekly. monthly, quarterly, 6-month, and annual) CRSP value-weighted return onto corresponding past returns r_t, current NYSE/AMEX index divided by its 52-week high x_{52}^{NY}, current NYSE/AMEX index divided by its historical high x_{max}^{NY}, NYSE/AMEX historical high indicator D_t, NYSE/AMEX 52-week high equal historical high indicator I_t, default premium DEF_t, term premium $TERM_t$, real interest rate r_t^f, inflation rate π_t, consumption wealth ratio cay_t, and dividend yield dp_t. We use overlapped daily sampled data. The macro variables are monthly (or quarterly) sampled. We assign the same monthly (quarterly) value for each day in that month (quarter) for those macro variables. The Newey-West t-stat is given in the parentheses. We use daily CRSP value-weighted return data and NYSE/AMEX market capitalization data from 1963 to 2008.

horizon	r_t	x_{52}^{NY}	x_{max}^{NY}	D_t	I_t	R^2
Panel A: without macro variables as control						
day	0.0860	0.0064	-0.0069	-0.0000	0.0004	0.0079
	(4.4635)	(1.4618)	(-2.1007)	(-0.0014)	(1.2619)	
month	0.0293	0.1638	-0.1735	-0.0031	0.0113	0.0125
	(0.7310)	(2.0961)	(-2.5629)	(-1.1875)	(1.6948)	
6-month	0.1205	0.1838	-0.4869	0.0084	0.0188	0.0377
	(1.2173)	(0.5152)	(-1.6619)	(0.8647)	(0.5194)	
year	0.0952	-0.0956	-0.4509	0.0288	-0.0132	0.0611
	(0.6544)	(-0.2140)	(-1.0963)	(1.9144)	(-0.2349)	
Panel B: with macro variables as control						
day	0.0846	0.0075	-0.0078	-0.0000	0.0004	0.0090
	(4.3708)	(1.7446)	(-2.2773)	(-0.1256)	(1.3617)	
month	0.0078	0.1904	-0.1811	-0.0038	0.0140	0.0454
	(0.1805)	(2.4424)	(-2.6382)	(-1.4444)	(2.2104)	
6-month	0.0750	0.1980	-0.4067	0.0059	0.0261	0.1665
	(0.7948)	(0.6518)	(-1.4565)	(0.6716)	(0.7761)	
year	0.0323	-0.1350	-0.1959	0.0244	-0.0035	0.2416
	(0.2284)	(-0.3196)	(-0.4849)	(1.8575)	(-0.0693)	

Table 6: Daily Overlapping Regression: we regress future (daily, weekly. monthly, quarterly, 6-month, and annual) CRSP value-weighted return onto corresponding past returns r_t, current NYSE/AMEX index divided by its 52-week high x_{52}, current NYSE/AMEX index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal historical high indicator I_t, We use overlapped daily sampled data. The macro variables are monthly (or quarterly) sampled. We assign the same monthly (quarterly) value for each day in that month (quarter) for those macro variables. The Newey-West t-stat is given in the parentheses. We use daily CRSP value-weighted return data and NYSE/AMEX market capitalization data from 1963 to 2008.

horizon	r_t	x_{52}	x_{max}	D_t	I_t	x_{52}^{NY}	x_{max}^{NY}	R^2
day	0.09	0.00	-0.01	-0.00	0.00	-0.00	0.01	0.01
	(4.59)	(0.78)	(-3.03)	(-2.55)	(2.56)	(-0.06)	(0.88)	
week	-0.02	0.03	-0.07	-0.00	0.00	-0.00	0.04	0.01
	(-0.86)	(1.10)	(-3.46)	(-0.20)	(2.80)	(-0.15)	(1.09)	
month	0.01	0.12	-0.21	0.00	0.01	-0.01	0.08	0.02
	(0.25)	(1.38)	(-3.43)	(0.27)	(2.95)	(-0.09)	(0.83)	
quarter	0.01	0.55	-0.63	0.00	0.04	0.03	-0.01	0.06
	(0.15)	(2.47)	(-4.05)	(0.07)	(2.95)	(0.17)	(-0.02)	
6-month	0.05	0.95	-1.16	0.01	0.08	0.13	-0.21	0.11
	(0.51)	(2.46)	(-4.70)	(0.62)	(3.19)	(0.68)	(-0.46)	
year	0.06	1.29	-1.70	0.03	0.11	0.22	-0.46	0.15
	(0.41)	(2.93)	(-4.81)	(1.53)	(2.31)	(1.42)	(-0.92)	

Table 7: Daily Overlapping Regression: we regress future (daily, weekly. monthly, quarterly, 6-month, and annual) CRSP value-weighted return onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal historical high indicator I_t, default premium DEF_t, term premium $TERM_t$, real interest rate r_t^f, inflation rate π_t, consumption wealth ratio cay_t, and dividend yield dp_t. We use overlapped daily sampled data. The macro variables are monthly (or quarterly) sampled. We assign the same monthly (quarterly) value for each day in that month (quarter) for those macro variables. The Newey-West t-stat is given in the parentheses. The coefficients for D_t and DEF are in terms of percentage. Panel A use data from 1963-1985 while panel B uses data from 1985 to 2008.

horizon	r_t	x_{52}	x_{max}	D_t	I_t	DEF_t	$TERM_t$	π_t	r_t^f	Cay_t	dp_t	R^2
Panel A: Sub-sample 1963-1985												
week	-0.02	0.06	-0.08	0.04	0.28	0.33	0.01	-1.60	-0.69	0.13	0.24	0.04
	(-0.60)	(2.34)	(-3.26)	(0.23)	(1.35)	(1.59)	(0.45)	(-3.24)	(-1.35)	(1.18)	(1.11)	
month	-0.07	0.19	-0.22	-0.03	0.99	1.17	0.02	-5.06	-2.81	0.40	0.83	0.11
	(-1.39)	(2.30)	(-3.29)	(-0.08)	(1.57)	(2.00)	(0.25)	(-3.57)	(-2.09)	(1.26)	(1.37)	
quarter	-0.12	0.49	-0.57	-0.11	3.86	4.72	-0.09	-15.01	-11.73	0.79	2.55	0.27
	(-1.45)	(2.15)	(-2.71)	(-0.11)	(2.57)	(2.98)	(-0.68)	(-4.30)	(-3.40)	(1.01)	(1.61)	
6-month	-0.19	0.79	-0.87	0.64	5.70	5.09	0.29	-23.82	-16.70	0.88	6.63	0.40
	(-1.44)	(2.54)	(-2.87)	(0.40)	(2.36)	(2.34)	(1.92)	(-3.74)	(-2.74)	(0.63)	(2.76)	
year	-0.02	0.66	-1.21	2.23	3.02	1.22	0.20	-24.91	-10.91	2.83	10.41	0.57
	(-0.12)	(1.57)	(-2.63)	(0.87)	(0.52)	(0.35)	(1.05)	(-2.80)	(-1.38)	(1.11)	(2.48)	
Panel B: Sub-sample 1986-2008												
week	-0.04	0.03	-0.04	-0.05	0.08	-1.14	0.01	0.35	0.71	0.01	0.23	0.02
	(-0.97)	(1.06)	(-1.84)	(-0.32)	(0.29)	(-2.40)	(0.27)	(0.53)	(1.28)	(0.20)	(1.48)	
month	0.04	0.09	-0.16	-0.02	0.48	-3.67	0.03	1.57	2.22	0.04	0.60	0.05
	(0.71)	(1.44)	(-2.63)	(-0.04)	(0.58)	(-2.77)	(0.45)	(0.71)	(1.27)	(0.25)	(1.41)	
quarter	-0.04	0.39	-0.55	-0.18	1.07	-12.96	0.00	3.30	6.74	0.02	2.18	0.17
	(-0.51)	(2.15)	(-2.85)	(-0.21)	(0.48)	(-2.73)	(0.03)	(0.74)	(1.49)	(0.06)	(2.08)	
6-month	0.07	0.61	-1.04	0.04	3.51	-21.44	0.17	2.09	8.10	0.04	3.83	0.28
	(0.52)	(1.81)	(-2.91)	(0.03)	(0.86)	(-2.51)	(1.11)	(0.29)	(1.01)	(0.05)	(1.85)	
year	0.08	0.51	-1.23	3.11	1.89	-26.05	-0.20	-7.04	-7.22	2.42	3.58	0.30
	(0.53)	(0.79)	(-1.71)	(1.90)	(0.20)	(-3.62)	(-0.87)	(-0.53)	(-0.52)	(1.34)	(0.88)	

Table 8: Monthly Overlapping Regression: we regress future (1-, 3-, 6-, and 9-month, 1-year) CRSP value-weighted excess return onto corresponding past returns r_t, current Dow index divided by its 52-week high x_{52}, current Dow index divided by its historical high x_{max}, Dow historical high indicator D_t, Dow 52-week high equal historical high indicator I_t, default premium DEF_t, term premium $TERM_t$, real interest rate r_t^f, inflation rate π_t, consumption wealth ratio cay_t, and dividend yield dp_t. We use overlapped daily sampled data. The macro variables are monthly (or quarterly) sampled. We assign the same monthly (quarterly) value for each day in that month (quarter) for those macro variables. The Newey-West t-stat is given in the parentheses. The coefficients for D_t and DEF are in terms of percentage. We use daily CRSP value-weighted return data and Dow index from 1963 to 2008.

horizon	r_t	x_{52}	x_{max}	D_t	I_t	DEF_t	$TERM_t$	π_t	r_t^f	Cay_t	dp_t	R^2
1-month	0.06	0.17	-0.18	-0.28	0.85	-0.20	0.11	-2.24	-0.81	0.25	0.45	0.06
	(1.02)	(2.97)	(-3.83)	(-0.37)	(1.58)	(-0.28)	(1.63)	(-1.61)	(-0.68)	(2.13)	(1.72)	
3-month	-0.06	0.56	-0.54	-1.73	2.47	0.28	0.19	-8.17	-4.17	0.80	1.42	0.13
	(-0.90)	(3.43)	(-4.33)	(-0.99)	(1.55)	(0.13)	(1.82)	(-2.09)	(-1.10)	(2.44)	(1.89)	
6-month	0.04	0.72	-0.91	-3.34	4.53	0.62	0.46	-13.84	-6.55	1.48	2.39	0.23
	(0.39)	(2.89)	(-4.32)	(-1.70)	(1.64)	(0.18)	(4.19)	(-2.48)	(-0.97)	(2.22)	(1.59)	
9-month	0.08	0.77	-1.12	1.15	4.73	1.36	0.32	-18.60	-10.58	2.44	3.07	0.27
	(0.72)	(2.66)	(-4.20)	(0.56)	(1.15)	(0.40)	(2.47)	(-2.47)	(-1.33)	(2.38)	(1.33)	
1-year	0.11	0.61	-1.18	3.34	3.10	2.81	0.35	-22.03	-13.11	3.77	3.11	0.32
	(0.57)	(1.79)	(-3.69)	(1.31)	(0.57)	(1.02)	(2.13)	(-2.68)	(-1.55)	(2.75)	(1.06)	

Table 9: Momentum investing strategies under samples of one anchor and two anchors. This table reports momentum strategies and the corresponding asset pricing test results. Jegadeesh and Titman (JT) quintile portfolios are formed based on past 6-month returns, and George and Hwang (GH)quintile portfolios are based on the ratio of current price to the past 52-week high price. All portfolios are held for 6 months. Panel A reports results for sample where the 52 week high price is less than historical high price, that is, there are two reference points (anchors). Panel B reports results for sample where the 52 week high price is equal to historical high price, that is, there is only one reference point (anchor). Returns are equally weighted, t-stats are reported inside the parenthesis. α^{FF3F} is the abnormal return of the Winner-Loser portfolio in Fama-French(1993) three factor model test, and α^{CZ} is the abnormal return of the Winner-Loser portfolio in Chen and Zhang (2009) new three-factor model test. The data sample is from January 1963 to December 2008.

Panel A: Two-Anchor Sample: 52 Week High<Historical High

Return	Loser	2	3	4	Winner	Winner-Loser	α^{FF3F}	α^{CZ}
JT Strategy	1.06	1.23	1.26	1.30	1.48	0.42	0.68	-0.08
	(3.07)	(4.74)	(5.48)	(5.90)	(5.81)	(2.38)	(4.24)	(-0.26)
GH Strategy	1.08	1.20	1.31	1.36	1.35	0.28	0.75	-0.18
	(2.91)	(4.19)	(5.32)	(6.43)	(7.04)	(1.20)	(4.65)	(-0.57)

Panel B: One-Anchor Sample: 52 Week High=Historical High

Return	Loser	2	3	4	Winner	Winner-Loser	α^{FF3F}	α^{CZ}
JT Strategy	0.61	1.20	1.41	1.52	1.79	1.19	1.29	0.87
	(1.95)	(4.45)	(5.61)	(5.83)	(5.98)	(6.96)	(6.85)	(2.66)
GH Strategy	0.84	0.98	1.37	1.56	1.67	0.83	0.90	0.41
	(2.68)	(3.18)	(4.65)	(5.84)	(6.93)	(5.15)	(5.39)	(1.28)

Table 10: Value investing strategy under samples of one anchor and two anchors. This table reports value investing strategy and the corresponding asset pricing test results. Book-to-Market quintile portfolios are formed based by following Fama-French (1996). Panel A reports results for sample where the 52 week high price is less than historical high price, that is, there are two reference points (anchors). Panel B reports results for sample where the 52 week high price is equal to historical high price, that is, there is only one reference point (anchor). Both equal-weighted and value-weighted returns are presented, t-stats are reported inside the parenthesis. α^{FF3F} is the abnormal return of the Value-Growth portfolio in Fama-French(1993) three factor model test, and α^{CZ} is the abnormal return of the Value-Growth portfolio in Chen and Zhang (2009) new three factor model test. The data sample is from January 1963 to December 2008.

Panel A: Two-Anchor Sample: 52 Week High<Historical High

Return	Growth	2	3	4	Value	Value-Growth	α^{FF3F}	α^{CZ}
EW	0.85	1.03	1.18	1.38	1.65	0.80	0.37	0.80
	(3.14)	(4.30)	(5.09)	(5.62)	(5.50)	(5.20)	(3.81)	(4.38)
VW	0.83	0.96	1.00	1.15	1.33	0.50	-0.17	0.55
	(4.27)	(5.04)	(5.87)	(6.22)	(6.07)	(2.96)	(-1.67)	(2.93)

Panel B: One-Anchor Sample: 52 Week High=Historical High

Return	Growth	2	3	4	Value	Value-Growth	α^{FF3F}	α^{CZ}
EW	1.15	1.14	1.55	1.54	1.64	0.49	0.15	0.48
	(3.91)	(3.94)	(5.59)	(5.77)	(6.00)	(2.89)	(1.05)	(2.24)
VW	1.38	1.08	1.35	1.57	1.48	0.10	-0.45	-0.06
	(5.43)	(4.09)	(5.16)	(6.34)	(5.86)	(0.45)	(-2.38)	(-0.24)

Table 11: Double-sorted portfolios on historical high and then momentum(or 52-week high) on two-anchor sample, i.e. 52 week high is less than historical high. This table reports equal-weighted returns of portfolios on sample with two anchors, that is, the 52-week high is less than the historical high. Firms are first sorted by the ratio of current price to historical high price into quintile and then, among each quintile, sorted into either Jegadeesh and Titman (JT) quintile portfolios (Panel A), or into George and Hwang (GH) quintile portfolios (Panel B). The data sample is from January 1963 to December 2008.

Panel A: First Sorted by Historical High, then Sorted by Past 6-Month Return (JT)

Return	Loser	2	Mom	4	Winner	Winner-Loser	Ave.(Winner-Loser)
Low	1.44	1.41	1.54	1.53	1.63	0.18	
	(2.87)	(3.74)	(4.62)	(4.89)	(4.87)	(0.69)	
2	0.73	1.17	1.27	1.33	1.47	0.74	
	(2.18)	(4.18)	(5.02)	(5.57)	(5.56)	(4.83)	
Hist. High	0.81	1.18	1.16	1.25	1.39	0.59	
	(2.72)	(4.79)	(5.15)	(5.81)	(5.66)	(4.31)	
4	0.93	1.16	1.19	1.26	1.46	0.53	
	(3.43)	(4.99)	(5.53)	(5.97)	(6.04)	(4.20)	
High	1.03	1.19	1.25	1.34	1.57	0.54	0.52
	(4.55)	(5.86)	(6.20)	(6.35)	(6.52)	(4.61)	(3.91)

Panel B: First Sorted by Historical High, then Sorted by 52 Week High(GH)

Return	Loser	2	3	4	Winner	Winner-Loser	Ave.(Winner-Loser)
Low	1.48	1.34	1.56	1.58	1.64	0.16	
	(2.76)	(3.23)	(4.33)	(5.11)	(6.26)	(0.46)	
2	0.71	1.09	1.31	1.39	1.45	0.74	
	(2.07)	(3.55)	(4.79)	(5.82)	(6.88)	(4.09)	
Hist. High	0.78	1.11	1.28	1.29	1.29	0.51	
	(2.57)	(4.01)	(5.23)	(6.16)	(6.85)	(3.30)	
4	0.87	1.18	1.29	1.33	1.29	0.42	
	(3.02)	(4.51)	(5.62)	(6.61)	(6.90)	(2.92)	
High	0.99	1.23	1.34	1.35	1.40	0.41	0.45
	(3.91)	(5.47)	(6.50)	(6.97)	(7.33)	(3.93)	(2.76)

Table 12: Historical high portfolios for sample with two anchors, i.e. 52-week high less than historical high. Panel A reports the equal-weighted return of one-way sorted quintile portfolios based on the ratio of current price to historical high price. Panel B reports the equal-weighted return of five-by-five portfolios by first sorting firms into quintile portfolios by the ratio of current price to 52-week high price, and then inside each portfolio, sorting into quintile portfolios by the ratio of current price to historical high price. t-stat is presented inside the parentheses. The data sample is from January 1963 to December 2008.

Panel A: One-way Sorting by Historical High

	Low	2	3	4	High	High-Low
Return	1.52	1.19	1.15	1.19	1.26	-0.26
	(4.20)	(4.43)	(4.80)	(5.20)	(5.94)	(-1.19)

Panel B: Two-way Sorting First by 52-week High and then by Historical High

Return	Low	2	Hist. High	4	High	High-Low	Average(High-Low)
Loser	2.00	1.02	0.83	0.79	0.80	-1.20	
	(3.63)	(2.47)	(2.30)	(2.44)	(2.69)	(-3.05)	
2	1.58	1.18	1.13	1.05	1.07	-0.51	
	(4.62)	(3.97)	(4.09)	(3.78)	(3.99)	(-3.26)	
52-week	1.54	1.32	1.29	1.24	1.17	-0.37	
	(5.39)	(5.26)	(5.44)	(5.15)	(4.95)	(-3.16)	
4	1.56	1.32	1.31	1.33	1.32	-0.24	
	(6.31)	(6.28)	(6.48)	(6.36)	(6.20)	(-2.39)	
Winner	1.49	1.25	1.30	1.34	1.40	-0.10	-0.48
	(6.90)	(6.76)	(6.85)	(6.94)	(7.22)	(-1.04)	(-3.22)

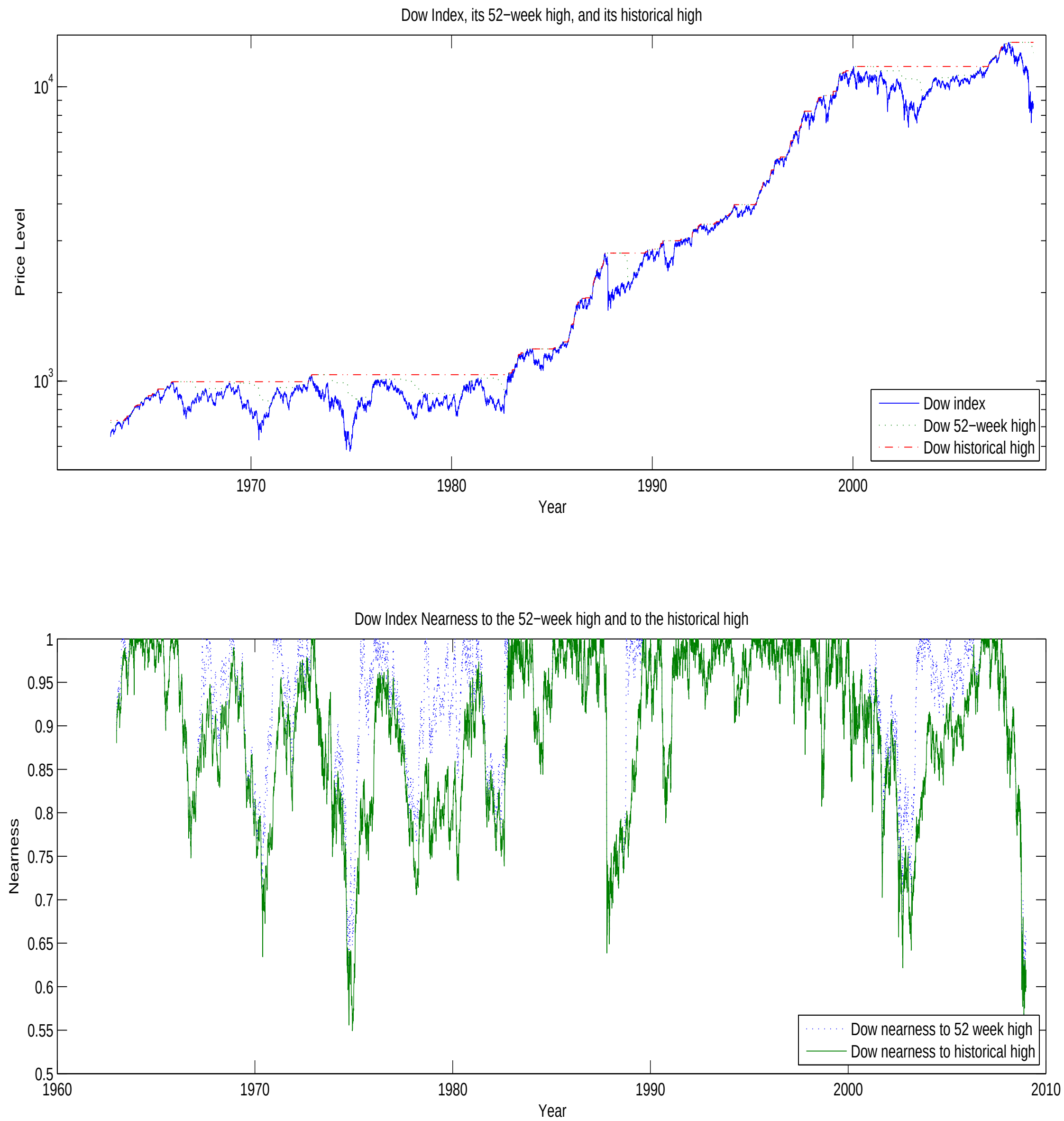

Figure 1: The Dow Jones Index and Proxies for Under- and Overreaction

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