Journal of Financial Economics 104 (2012) 401–419

Contents lists available at SciVerse ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Investor attention, psychological anchors, and stock return predictability☆

Jun Li, Jianfeng Yu*

University of Minnesota, Department of Finance, 3-133 Carlson School of Management, 321 19th Avenue South, Minneapolis, MN 55455, United States

ARTICLE INFO

Article history:
Received 28 September 2010
Received in revised form
4 March 2011
Accepted 18 April 2011
Available online 14 September 2011

JEL classification:
G12
G14

Keywords:
Attention
Anchor
Overreaction
Underreaction
52-week high

ABSTRACT

Motivated by psychological evidence on limited investor attention and anchoring, we propose two proxies for the degree to which traders under- and overreact to news, namely, the nearness to the Dow 52-week high and the nearness to the Dow historical high, respectively. We find that nearness to the 52-week high positively predicts future aggregate market returns, while nearness to the historical high negatively predicts future market returns. We further show that our proxies contain information about future market returns that is not captured by traditional macroeconomic variables and that our results are robust across G7 countries. Comprehensive Monte Carlo simulations and comparisons with the NYSE/Amex market cap index confirm the significance of these findings.

1. Introduction

Financial economists have sought to identify variables that forecast aggregate stock market returns. This article investigates the ability of the nearness to the Dow 52-week high and the nearness to the Dow historical high to predict market returns. The predictors we propose in this study are motivated by empirical evidence on psychological anchoring and limited investor attention.

In an intriguing study, George and Hwang (2004) suggest that traders might use the 52-week high as an anchor when assessing the increment in stock value implied by new information. They argue that a stock whose price is at or near its 52-week high is a stock for which good news has recently arrived, and that this may be precisely the time when traders' underreaction to good news is at its peak. Hence, nearness to the 52-week high is positively associated with expected returns in the cross-section. On the other hand, Peng and Xiong (2006) show that limited investor attention leads to category-learning behavior, i.e., investors tend to process more market-wide information than firm-specific information. Because the Dow index is arguably the most widely available information about the market, investors are likely to use the Dow index as a benchmark when evaluating new market-wide information. Taken together, we conjecture that nearness to the Dow 52-week high captures the extent of underreaction, and it should forecast aggregate market returns.

Griffin and Tversky (1992) suggest that individuals might underreact to sporadic news, but overreact to a prolonged record of salient performance, regardless of

☆ First draft: October 2009. We would like to thank an anonymous referee, Santiago Bazdresch, Frederico Belo, John Boyd, Murray Frank, Bob Goldstein, Felix Meschke, Stavros Panageas, William Schwert, Jian Wang, and seminar participants at the University of Minnesota and the 2010 Econometric Society World Congress for comments. Of course any errors are our own.

* Corresponding author. Tel.: +1 612 625 5498; fax: +1 612 626 1335.
E-mail addresses: lixxx353@umn.edu (J. Li), jianfeng@umn.edu (J. Yu).

0304-405X/$ - see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.jfineco.2011.04.003

whether good or bad. Motivated by Griffin and Tversky (1992), George and Hwang (2004), and Peng and Xiong (2006), we further conjecture that traders might also use the Dow historical high as an anchor when evaluating information. However, the effect of this anchor is expected to be opposite that of the Dow 52-week high anchor. In particular, when the current price is far from its historical high, this may be precisely the time when traders' overreaction to bad news is at its peak. Because, in this case, it is likely that there has been a series of bad news in the past, traders overreact to prolonged news. Hence, we hypothesize that nearness to the Dow historical high captures the extent of overreaction, and that it should be negatively associated with future market returns.

Armed with these two psychologically motivated proxies for under- and overreaction, we then empirically explore their ability to forecast aggregate excess market returns. Using the Dow Jones Industrial Average index, we compute nearness to the 52-week high and nearness to the historical high. We show that there is no momentum in aggregate market returns when we regress future excess market returns on past excess market returns alone. However, after we control for nearness to the historical high, past excess market returns significantly predict future excess market returns. This indicates that nearness to the historical high contaminates the relationship between future returns and past performance. Furthermore, when nearness to the 52-week high is included in the regression along with nearness to the historical high and past returns, the predictive ability of past returns weakens substantially while nearness to the 52-week high significantly predicts future excess market returns. This indicates that the predictive ability of past market returns is dominated by nearness to the 52-week high, confirming the cross-sectional findings of George and Hwang (2004). In a horse race regression in which future excess market returns are regressed on the nearness to the 52-week high, nearness to the historical high, and a set of macro variables, our proposed predictors have the greatest power and are stable across subsamples and other G7 countries.

Note that the negative predictive power of nearness to the historical high could also be consistent with a rational model with a mean-reverting state variable. Hence, to differentiate our limited-attention explanation with the unobservable-state-variable explanation, we replace the *most visible* Dow index with the *economically more meaningful* market cap from NYSE/Amex, and we find that the predictive power from the nearness to the historical high is much lower. This suggests a special role for the Dow index, probably due to its visibility and investors' limited attention, consistent with Peng and Xiong (2006). Consequently, an unobservable mean-reverting state variable is unlikely to account for the predictive power of nearness to the historical high. We also perform comprehensive Monte Carlo simulations to confirm the significance of these findings.

We provide further support for our hypotheses in cross-sectional analysis. We first identify a group of firms that are less likely to have experienced overreaction in the past. Specifically, we find that for stocks with only one anchor, that is, for which the 52-week high equals the historical high, the momentum effect is about three times stronger.[1] For stocks with two anchors, the momentum effect is no longer significant in a simple one-way sorting by nearness to the 52-week high. However, after controlling for nearness to the historical high, the momentum effect re-emerges significantly. A similar pattern is found for the historical high. When controlling for nearness to the 52-week high, nearness to the historical high is positively associated with expected returns. However, this effect is insignificant in a simple one-way sorting by nearness to the historical high. We also demonstrate a link between the historical high and value investing. In particular, we show that the value premium is much weaker among firms for which overreaction is less likely, that is, for which the 52-week high equals the historical high.

Our paper's main contribution to the literature is at least threefold. First, we propose two novel predictors based on the visible Dow index and show that these variables are important predictors for future aggregate market returns. Indeed, these predictors, which are based on psychological anchors, have a few advantages compared with the traditional macroeconomic predictors. For instance, unlike dividend yield, our predictors have the greatest power at horizons of less than one year. Our proxies are therefore not subject to criticisms on long-run predictability. In addition, unlike the consumption–wealth ratio, our predictors have no look-ahead bias. Second, we show that the historical high is also an anchor that investors use when evaluating information. This anchor has an effect that is opposite that of the 52-week high anchor. Controlling for the historical high, the momentum effect is two to three times larger. On the other hand, controlling for the 52-week high, the value premium is much stronger. Finally, although there is abundant evidence on stock market over- and underreaction, most of the statistical evidence comes from the cross-section of stock returns. Whether behavioral biases can affect the aggregate market return is still under debate. We add to the literature by showing that two behavioral-bias-motivated variables have strong power to forecast future *aggregate market* returns.

In addition, this paper contributes to the price barrier literature,[2] led by Donaldson (1990a, 1990b) and Donaldson and Kim (1993). The concept of psychological barriers is closely related to the issue of anchoring and heuristic simplification. Donaldson and Kim (1993) find that multiples of 100 and 1,000 in the Dow index are difficult to break through, and hence, these levels are approached as well as transgressed relatively infrequently. Many subsequent studies confirm the existence of price barriers in other asset classes. Despite the strong evidence of psychological barriers in asset prices, the evidence of the induced return predictability by price barriers is limited and mixed. This paper adds to the barrier literature by showing that two other psychological

[1] See Section 2 for more discussion on the intuition behind this. In short, in Section 2 we argue that, for stocks whose 52-week high equals the historical high, it is less likely that there has been overreaction in the past.

[2] We are grateful to the referee for bringing this interesting earlier literature to our attention.

anchors, the 52-week high and the historical high, induce strong predictability in aggregate market returns. In this sense, our evidence complements the price barrier literature.

The rest of the paper is organized as follows. Section 2 describes the psychological and statistical evidence on under- and overreaction and provides the intuition behind our proxies. Section 3 presents the empirical evidence on return predictability induced by psychological anchors. Section 4 concludes.

2. Related literature and motivation

This section summarizes the statistical and psychological evidence on under- and overreaction and provides the intuition for our proposed predictors of expected returns. The empirical work pointing to under- or overreaction in asset markets is vast, so that it is impossible to provide a comprehensive review here. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Fama (1998) provide excellent summaries of this literature.

Psychological studies related to over- and underreaction are also extremely numerous. One important phenomenon that has been identified by many psychologists (e.g., Edwards, 1968) is conservatism. Conservatism refers to the tendency of individuals to be reluctant or slow to change their prior beliefs in the face of new information. This, of course, is consistent with underreaction in the stock market where high past returns predict high future returns (e.g., Cutler, Poterba, and Summers, 1991; Jegadeesh and Titman, 1993). Tversky and Kahneman (1974) document another important phenomenon, the representativeness, which is the tendency of human beings to view events as representative of some specific class and to ignore the laws of probability. For example, when investors see that a company displays a series of high earnings growth, they may classify this company as a growth firm and ignore the probability that very few companies can keep growing. This is in line with the overreaction evidence from the stock market where long-term past performance is negatively associated with future returns (e.g., De Bondt and Thaler, 1985; Zarowin, 1989). Finally, to unify conservatism and representativeness, Griffin and Tversky (1992) suggest that individuals might underreact to intermittent news, but overreact to a prolonged record of salient performance.

In a nutshell, previous empirical studies suggest that stock prices tend to underreact to intermittent news such as earnings announcements, and overreact to a series of news, either good or bad. However, most of the strong evidence comes from the cross-section of stock returns, and whether behavioral biases can affect the aggregate market return is still under debate. In this paper, as mentioned in the introduction, we propose nearness to the 52-week high as a proxy for underreaction, and nearness to the historical high as a proxy for overreaction. In the data, we find that our behavioral-bias-motivated variables have strong power to predict future aggregate market returns, especially for short horizons of 1–12 months. Below we provide two potential justifications for our hypothesis that our proxies capture under- and overreaction in the stock market.

One possible justification is based on the 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 underreaction to sporadic past recent news. For example, if nearness to the 52-week high is high, it is more likely that the firm has experienced sporadic good news in the recent past. Psychological evidence on conservatism suggests that traders tend to underreact to this good news in the recent past. Similarly, if the current price is far below its 52-week high, it is more likely that the firm has experienced intermittent bad news in the recent past. Again, conservatism suggests that traders underreact to this bad news in the recent past. We therefore use nearness to the 52-week high to summarize the degree of good news that the market has underreacted to in the past year, where nearness to the 52-week high is expected to be positively associated with future returns. Analogously, if the current price level is far from the historical high, it is more likely that the firm has experienced a series of bad news in the past. As representativeness suggests, traders tend to overreact to a series of bad news, and hence subsequent returns should be higher. As a consequence, we use the distance to the historical high to summarize the degree of bad news that the market has overreacted to in the past.

Another possible justification comes from the experimental research on "adjustment and anchoring bias". Kahneman, Slovic, and Tversky (1982) report on experiments in which subjects are asked to estimate a quantity as an increment to a randomly generated number that the subject observes. Estimates are higher (lower) for subjects that start with higher (lower) random numbers. Based upon this idea, 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 good news in the past year pushes a stock's price near a new 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it, that is, they underreact to the news. However, the information eventually prevails and the price moves up, leading to a continuation. Similarly, when bad news in the past year pushes a stock's price far from its 52-week high, traders are reluctant 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, however, and the price falls. As a consequence, nearness to the 52-week high summarizes the degree of good news that the market has underreacted to in the past year.

On the other hand, we further conjecture that traders may use the historical high as another anchor against which they evaluate information. However, this anchor tends to generate overreaction. Representativeness provides a natural account for this overreaction. When prolonged bad news pushes a stock's price far below its historical high, traders may sell the stock at prices that are lower than the news would imply, that is, traders may overreact. However, the information eventually prevails and the price moves up, resulting in higher subsequent returns when the current price is far below its distant historical high. Hence, the distance to the historical high can summarize the degree of bad news that the market has overreacted to in the past. Therefore, psychological anchoring provides an additional possible way to justify our proxies to under- and overreaction.

Peng and Xiong (2006) show that investors with limited attention tend to process more market- and sector-wide information than firm-specific information. Because the Dow index is arguably the most widely available information about the market, investors are likely to use the Dow index as a benchmark when evaluating new market-wide information. Taken together, nearness to the Dow 52-week high and nearness to the Dow historical high should both forecast future aggregate market returns, but with a different sign. Furthermore, nearness to the Dow index should be better at capturing information than nearness to the total market capitalization index (e.g., NYSE/Amex market cap).

Of course, there could be a common component in these two proxies. For example, nearness to the 52-week high may also include information on overreaction since there might be some salient information in past news, especially when the stock is very close to or very far from its 52-week high. However, by controlling for nearness to the historical high, nearness to the 52-week high should be a more pure proxy for underreaction. Therefore, by putting both proxies on the right side of the regression, they should pick up more information on expected returns resulting from under- and overreaction. Furthermore, in unreported analysis, we simulate a variant of the model by Barberis, Shleifer, and Vishny (1998) where investors underreact to sporadic news and overreact to a prolonged record of extreme performance. The simulation results are consistent with our predictions. Specifically, in the model simulation, nearness to the historical high is a proxy for overreaction and negatively predicts future returns, while nearness to the 52-week high is a proxy for underreaction and positively associated with future returns.

For the cross-section of stocks, we consider the special case in which the historical high equals the 52-week high. In this case, investors only have one anchor against which to evaluate information. We conjecture that, in this case, investors tend to ignore the historical anchor because the 52-week high is psychologically more recent. More importantly, when the 52-week high equals the historical high, firms are unlikely to have experienced a series of bad news in the past, and hence are less likely to have experienced an overreaction.[3] Thus, compared with other stocks, there should be less overreaction in the past among these stocks. We therefore argue that for firms with the same 52-week high and historical high, nearness to the 52-week high captures the underreaction effect better. That is, nearness to the 52-week high should predict future returns more strongly among those stocks. On the other hand, if book-to-market captures overreaction as suggested by Lakonishok, Shleifer, and Vishny (1994), then it may be better at capturing information on overreaction among the rest of the firms. Hence, we conjecture that the value premium should be stronger among the firms with two anchors.

Our paper is related to George and Hwang (2004) which shows that nearness to the 52-week high is positively associated with future stock returns in the cross-section. However, we focus on the predictability of the aggregate market. Moreover, we highlight the importance of the historical high anchor and the visibility of the Dow index. The Dow index and the historical high anchor are two key ingredients for our predictability results. In addition to George and Hwang (2004), other notable papers which study the effect of anchoring include Odean (1998) and Grinblatt and Keloharju (2001) on individual trading, Ljungqvist and Wilhelm (2005) on IPO underpricing, Hart and Moore (2008) on contracting, and Baker, Pan, and Wurgler (2009) on mergers and acquisitions, among others.

Our paper is also related to the price barrier literature. The concept of psychological barriers was introduced into finance by Donaldson and Kim (1993), who show that price barriers are often associated with levels that are multiples of 100 or especially 1,000. In particular, the Dow index appears to close, on average, less frequently around multiples of 100 and more frequently away from these levels. Subsequent studies demonstrate that price barriers also exist in other asset classes, such as Aggarwal and Lucey (2007) in gold prices; Koedijk and Stork (1994) and Cyree, Domian, Louton, and Yobaccio (1999) in international stock indexes; De Grauwe and Decupere (1992) and Westerhoff (2003) in currency markets; and Burke (2001) on bond markets. Ley and Varian (1994) and De Ceuster, Dhaene, and Schatteman (1998) criticize some testing methods on the hypothesis of uniformity of digital distribution in the earlier studies. Overall, evidence of price barriers in various asset classes is fairly robust.

One key difference between our anchors and the price barriers is that the price barriers are typically pre-fixed, whereas our anchors move along with the rising index. Hence, nearness to the 52-week high and nearness to the historical high are stationary. More importantly, despite strong ex post evidence of psychological barriers in the Dow index, there is generally no strong evidence of *ex ante predictability* of stock returns induced by the presence of pre-fixed psychological barriers (see, e.g., Donaldson and Kim, 1993; Koedijk and Stork, 1994; Ley and Varian, 1994). For example, there is no significant relationship between returns in period t and the last two digits of the closing price in period $t-1$. In contrast, the focus of this paper is the return predictability induced by anchoring on the 52-week high and the historical high, and the evidence suggests that these two anchors induce strong return predictability in the aggregate stock market. Finally, we have used several simulation methods originally developed in the barrier literature to address many potential statistical concerns for our empirical results.

3. Anchors and stock market behavior

3.1. Data and notation

In this section, we describe the data used in this paper, and introduce our predictive variables. We obtain monthly

[3] Because there is an upward trend in prices, even if the 52-week high equals the historical high, there is probably only limited good news, rather than prolonged good news in the past. Hence, the probability of overreaction to a series of good news is still very low.

value-weighted NYSE/Amex returns from the Center for Research in Security Prices (CRSP). Excess returns are formed by subtracting the return on the 30-day T-bill from the actual stock return. Daily Dow Jones 30-stock Industrial Average Index data for 1928–2009 come from Dow Jones. Several macroeconomic variables shown by the literature to predict stock returns are used as control variables in this paper. Specifically, we use monthly default premium (def_t), monthly term premium ($term_t$), monthly real interest rate (r_t), monthly inflation (π_t), Lettau and Ludvigson's (2001a) quarterly consumption–wealth ratio, cay_t, Campbell and Cochrane's (1999) surplus ratio (s_t), and dividend yield (dp_t). Previous studies have shown that each of the above variables has predictive power for the stock market.

def_t is defined as the yield spread between BAA and AAA bonds obtained from the St. Louis Federal Reserve. *term* is defined as the difference between the 20-year Treasury bond yield and the 1-year yield, obtained from the St. Louis Federal Reserve. The inflation rate (π_t) is calculated from the monthly Consumer Price Index (CPI), obtained from CRSP. The real interest rate (r_t^f) is defined as the difference between the 30-day T-bill rate and inflation. cay_t is defined as in Lettau and Ludvigson (2001a), obtained from Martin Lettau's Web site. cay_t spans from 1951Q2–2009Q3. Campbell and Cochrane's (1999) surplus ratio is approximated by a smoothed average of the past 40-quarter consumption growth as in Wachter (2006). As a result, the surplus ratio spans from 1957Q2 to 2009Q4. Finally, the monthly dividend yield is calculated as the difference between the log of the last 12-month dividend and the log of the current level of the CRSP valued-weighted index. Since cay_t and surplus ratio are available at a quarterly frequency, we convert them into monthly frequency by assigning the most recent quarterly value to each month.

We use these variables as our control variables for nearness to the 52-week high and the historical high in the predictive regressions. Our aggregate analysis uses the sample period 1958–2009 and our cross-sectional analysis starts with 1963. Our aggregate sample starts with 1958 for several reasons. First, and most importantly, while the Dow Jones 30-stock Industrial Average index starts in late 1928, its visibility was not large in its early days. Hence, we discard the first three decades of the Dow index. Second, there was a great depression and two world wars in the early part of the Dow sample, and the Dow index did not return to its pre-depression level until November of 1954. As such, the historical high probably would not mean much to investors, and this would not be a good anchor in the Dow's early years. Third, one of our macro control variables starts with 1957Q2, which also makes 1958 a natural choice.

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

$$x_{52,t} = \frac{p_t}{p_{52,t}} \tag{1}$$

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

$$x_{max,t} = \frac{p_t}{p_{max,t}}. \tag{2}$$

We also define two indicators D_t and I_t. The Dow historical high indicator D_t equals one when the Dow reaches a record high at day t, and zero otherwise. Similarly, I_t is defined to equal one when the historical high at day t equals its 52-week high at day t, and zero otherwise. Yuan (2008) uses D_t as a proxy for attention-grabbing events, and finds that D_t negatively predicts next-day returns because of the selling pressure in the next day, after investors realize their gains following the attention-grabbing event. Instead of using daily data, for the majority of our analysis, we use monthly observations to reduce statistical concerns from overlapping observations. The value at month t is just defined as the value at the last trading day of month t.

The Dow Jones Industrial Average index is the oldest continuing U.S. market index. It represents the average of 30 stocks from various important American industries and is arguably the most widely used and visible index. The reason that we use the Dow index is that it is more visible than the total market value of NYSE/Amex stocks or other indexes. Hence, it should have stronger predictive power resulting from anchoring and limited attention.

Panel A of Table 1 reports summary statistics of our proposed predictors, along with those of other predictors suggested by previous literature. Because the Dow index is increasing over time, the average value of x_{52} and x_{max} is high and close to 1.0. As expected, nearness to the 52-week high, x_{52}, and nearness to the historical high, x_{max}, are quite persistent, but less persistent than the traditional macro predictors, such as the consumption–wealth ratio or dividend yield. Our predictors are quite negatively skewed because they are bounded from above by one.

Panel B of Table 1 shows that nearness to the 52-week high and nearness to the historical high are not strongly correlated with traditional macro predictors. Among all the macro variables, dividend yield is most correlated with nearness to the historical high, with a correlation of -0.32. As expected, the correlation between x_{52} and x_{max} is as high as 86%. However, as discussed in Section 2, the predictive ability of these variables with respect to future market returns runs in opposite directions. Hence, it is important to include both variables into our predictive regressions. Furthermore, when the historical high is equal to the 52-week high, traders would have only one anchor in mind, and hence, we shall take special care in the case in which $I_t = 1$.

We first examine the predictive ability of nearness to the 52-week high and the historical high at an aggregate level. In Section 3.8, we then explore their implications for the cross-section of expected returns, especially with respect to momentum and the value premium.

3.2. Main time-series regression

We now explore the link between market returns and nearness to the 52-week high and nearness to the historical

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 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, dividend yield dp_t, and surplus ratio s_t. The mean and standard deviation of log monthly returns, def_t (annualized), $term_t$, interest rate, inflation, and dividend yield are in terms of percentage. Panel B reports the correlation matrix for the same 12 predictive variables except that the past return r_t is measured over the past 6-month instead of 1-month interval. Our sample is monthly from 1958.01 to 2009.12.

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	s_t
Mean	0.49	0.93	0.90	0.04	0.53	1.01	1.10	0.32	0.10	0.06	3.01	0.10
Std	4.28	0.08	0.10	0.20	0.50	0.46	1.40	0.36	0.32	1.56	1.03	0.03
AC(1)	0.09	0.89	0.94	0.04	0.94	0.97	0.96	0.55	0.44	0.96	0.99	0.99
Skewness	−0.55	−1.61	−1.11	4.59	−0.12	1.75	−0.02	0.04	0.18	−0.02	0.12	−0.11
Kurtosis	5.30	5.73	3.99	22.04	1.01	7.02	2.91	6.31	5.27	2.64	2.43	2.49

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	s_t
r_t	1.00											
x_{52}	0.36	1.00										
x_{max}	0.24	0.86	1.00									
D_t	0.13	0.19	0.23	1.00								
I_t	0.00	0.23	0.54	0.20	1.00							
def_t	0.04	−0.33	−0.42	−0.10	−0.30	1.00						
$term_t$	0.10	0.00	−0.03	0.00	0.08	0.20	1.00					
π_t	−0.12	−0.12	−0.23	−0.07	−0.25	0.07	−0.33	1.00				
r_t^f	0.08	0.13	0.24	0.05	0.22	0.14	−0.04	−0.77	1.00			
cay_t	0.12	0.03	0.13	0.10	0.35	−0.02	0.31	−0.17	0.17	1.00		
dp_t	−0.06	−0.26	−0.32	−0.03	−0.25	0.43	−0.30	0.36	0.01	0.12	1.00	
s_t	−0.02	0.08	0.22	0.09	0.16	−0.65	−0.25	−0.17	−0.08	0.00	−0.24	1.00

high. Jegadeesh and Titman (1993) show that past short-term returns predict future returns in the cross-section, and Cutler, Poterba, and Summers (1991) find positive autocorrelations in excess index returns over horizons between one month and one year. It is interesting to examine whether high past market returns can predict high future returns at an aggregate level. In Table 2, we regress realized excess value-weighted market returns (at different horizons) on a set of lagged predictors. We use overlapping monthly sampled data. In the top part of the table, future monthly, quarterly, 6-month, and annual realized returns are regressed on past monthly, quarterly, 6-month, and annual returns, respectively. We find that past market returns (r_t) do not predict future market returns except at the monthly horizon at which the predictive power is marginally significant. Hence, if we measure performance by past realized market returns, we do not observe significant momentum at an aggregate level, in contrast to the strong cross-sectional momentum effect.

Since, as we argued in the prior section, nearness to the historical high could have an effect that is opposite that of recent past returns, we control for nearness to the Dow historical high in the middle of Table 2. In this case, past market returns indeed have significant positive predictive power over intermediate horizons, which is consistent with the momentum effect from the cross-section literature. At 6-month and 1-year horizons, without controlling for nearness to the historical high, past returns are negatively associated with future returns. However, after controlling for nearness to the historical high, past returns are positively associated with future returns, consistent with momentum. Furthermore, nearness to the historical high strongly negatively forecasts future market returns, consistent with our hypothesis.

At the bottom part of Table 2, we regress (monthly, quarterly, 6-month, and annual) excess value-weighted market returns on corresponding past returns r_t, nearness to the 52-week high x_{52}, nearness to the historical high x_{max}, the Dow historical high indicator D_t, and the Dow 52-week high equal-historical high indicator I_t. We can see that once we include nearness to the 52-week high as a control, the t-statistic of past performance as measured by returns is significantly lower. However, nearness to the 52-week high positively predicts future market returns at horizons up to one year. The predictive power of our variables is not only statistically significant, but economically important. All else equal, if nearness to the historical high increases 1%, next year's expected return decreases more than 1%, which is economically highly significant. The economic magnitude of nearness to the 52-week high is similar.

Because there tends to be an upward trend in stock prices, reaching a historical high may not be a good proxy for prolonged good news. For this reason, we need to control for the case in which the 52-week high equals the historical high. Table 2 shows that when the 52-week high is equal to the historical high, future market returns tend to be significantly higher. This is consistent with the notion that investors underreact to recent intermittent good news, because the stock probably has not experienced prolonged good news in the past, and hence, there is no overreaction. This finding is also consistent with the interpretation that investors use the 52-week high anchor but ignore the role of the historical high, and hence, mostly underreact to past good news. Finally, the Dow record high variable, D_t, has no predictive power in our monthly regression, although D_t predicts returns in the daily regression as in Yuan (2008).

One potential issue with our findings concerns multicollinearity. Nearness to the 52-week high x_{52} and nearness to the historical high x_{max} are highly correlated (about 86%). However, this cannot explain our results since multicollinearity usually leads to small t-statistics, whereas, our t-statistics are always large across the different specifications. Furthermore, our predictors are significant when only one of these two variables is included in the predictive regression as show in the middle of Table 2. In addition, the variance inflation factor (VIF) for our predictors is about 3.4, much less than the critical cutoff of 10.0 suggested by Kutner, Nachtsheim, and Neter (2004). This confirms that multicollinearity is unlikely to plague our results. We provide further support with Monte Carlo simulation in Section 3.5 when we examine small sample properties.

In untabulated analysis, we also predict aggregate excess returns at 2- to 5-year horizons. We find that our variables lose predictive power for horizons longer than one year. Hence, our predictors provide a nice complement to traditional predictors which usually have stronger forecasting power over longer horizons.

Table 2
Monthly overlapping regression.

In this table, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex 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, and Dow 52-week high equal-historical high indicator I_t. We use overlapped monthly sampled data. The Newey–West t-stats given in parentheses control for heteroskedasticity and autocorrelation. Our sample is monthly from 1958.01 to 2009.12.

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	R^2
1-Month	0.09					0.01
	(1.82)					
3-Month	0.08					0.01
	(1.10)					
6-Month	−0.05					0.00
	(−0.53)					
1-Year	−0.16					0.02
	(−1.51)					
1-Month	0.12		−0.05			0.02
	(2.35)		(−2.15)			
3-Month	0.16		−0.18			0.04
	(2.49)		(−3.30)			
6-Month	0.14		−0.37			0.06
	(1.63)		(−3.69)			
1-Year	0.05		−0.52			0.07
	(0.37)		(−2.68)			
1-Month	0.11	0.10	−0.15	−0.49	0.93	0.03
	(2.06)	(1.86)	(−3.19)	(−0.73)	(2.01)	
3-Month	0.13	0.32	−0.48	−1.29	3.20	0.07
	(1.96)	(2.09)	(−3.79)	(−0.97)	(2.55)	
6-Month	0.07	0.60	−0.93	−0.96	5.85	0.09
	(0.75)	(2.39)	(−4.52)	(−0.54)	(2.44)	
1-Year	−0.05	0.93	−1.31	3.89	7.76	0.11
	(−0.31)	(2.86)	(−4.08)	(1.17)	(1.70)	

Table 3
Monthly overlapping regression with macro control.

In this table, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex value-weighted excess returns 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, dividend yield dp_t, and surplus ratio s_t. We use overlapped monthly sampled data, except for cay_t and s_t, which are only available at quarterly frequency. The Newey–West t-stat given in parentheses control for heteroskedasticity and autocorrelation. The coefficients for D_t, I_t, and def_t are in terms of percentage. Our sample data are monthly from 1958.01 to 2009.12.

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	s_t	R^2
1-Month	0.08	0.12	−0.15	−0.66	0.54	−0.39	0.26	−0.80	0.15	0.20	0.44	0.04	0.05
	(1.52)	(2.21)	(−3.54)	(−0.99)	(1.14)	(−0.48)	(1.06)	(−0.44)	(0.09)	(1.50)	(1.98)	(0.44)	
3-Month	0.07	0.37	−0.47	−1.93	2.01	−0.19	0.07	−5.39	−3.7	0.86	1.14	0.00	0.13
	(0.76)	(2.36)	(−3.69)	(−1.54)	(1.48)	(−0.10)	(0.12)	(−1.05)	(−0.82)	(2.49)	(1.80)	(−0.01)	
6-Month	0.02	0.68	−0.87	−2.23	3.24	0.65	−0.30	−11.52	−6.66	1.86	1.84	−0.11	0.21
	(0.18)	(2.84)	(−4.06)	(−1.44)	(1.19)	(0.24)	(−0.32)	(−1.59)	(−0.93)	(2.53)	(1.50)	(−0.23)	
1-Year	0.00	0.74	−1.23	2.83	1.39	−5.20	0.47	−11.91	−0.65	3.44	2.81	−0.59	0.32
	(0.03)	(2.33)	(−4.00)	(1.12)	(0.28)	(−1.00)	(0.29)	(−0.96)	(−0.05)	(2.59)	(1.13)	(−0.73)	

As discussed in Section 2, one possible explanation for our findings is that investors underreact to sporadic news while they overreact to prolonged (a series) news. As a consequence, nearness to the 52-week high is a proxy for the degree to which investors have underreacted to good news, and nearness to the historical high is a proxy for the degree to which investors have overreacted to prolonged good news. Another possible explanation for our findings is that traders use both the 52-week high and the historical high as reference points against which they evaluate the potential impact of news. Investors tend to underreact to news when they use the 52-week high anchor, and tend to overreact when using the historical high anchor. George and Hwang (2004) first propose that investors may use the 52-week high as a reference point while evaluating information. Here, we further highlight the importance of the historical high anchor and that controlling for the historical high anchor also raises the predictive power of the 52-week high anchor.

3.3. Controlling for the business cycle and NYSE/Amex index

Another potential explanation for our finding is that nearness to the 52-week high and 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 nearness to the two anchors is related to business cycle variables. Furthermore, Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988), Campbell (1991), Ferson and Harvey (1991), Lettau and Ludvigson (2001a, 2001b), and Li (2001) find evidence that the stock market can be predicted by variables related to the business cycle, such as the default spread, term spread, interest rate, inflation rate, dividend yield, consumption–wealth ratio, and surplus ratio. Hence, to ensure our variables' predictive ability is not due to their correlation with traditional predictors of stock market returns, we examine the relation between future market returns and nearness to the 52-week high and the historical high using macro variables as controls for business cycle fluctuations.

In Table 3, we use overlapping monthly sampled data. The Newey and West (1987) t-statistic for x_{max} ranges from −3.54 to −4.06 from monthly to annual horizons. By contrast, the t-statistic for nearness to the 52-week high is always positive and remains significant at horizons less than one year. Hence, our predictors contain information about future market returns that is not captured by the traditional macroeconomic variables. The coefficients on *cay* and dividend yield are also significant, but the magnitude is smaller than that of our predictors. Notice, however, that our predictors are less persistent than *cay* and dividend yield. In summary, nearness to the 52-week high and nearness to the historical high appear to be the most significant predictors at horizons less than one year.

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 replace the visible Dow index with the economically more meaningful NYSE/Amex total market value to obtain new measures of nearness to the 52-week high and the historical high. Panel A of Table 4 shows that nearness to the historical high is still a significant predictor over shorter horizons, but with much smaller magnitudes. On the other hand, nearness to the 52-week high is not significant anymore. Overall, the predictive power of our predictors using NYSE/Amex total market value is much smaller than that using the Dow index. Furthermore, we run a horse race regression between the Dow index and the NYSE/Amex market value index. Panel B of Table 4 shows that once we control for nearness to the Dow 52-week high and nearness to the Dow historical high, the predictors constructed from NYSE/Amex total market value completely lose their power in forecasting future market returns. In addition, the regression coefficients flip signs.[4] Hence, an unobserved mean-reverting

[4] In Panel B of Table 4, we used macro variables as control. If we do not control for macro variables and just run a horse race between the Dow index and the NYSE/Amex total market value, all the t-statistics of the variables constructed from NYSE/Amex are less than 0.6 (absolute value).

Table 4
Monthly overlapping regression.
In Panel A of this table, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex value-weighted excess returns 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^{NY}, and NYSE/Amex 52-week high equal-historical high indicator I_t^{NY}. In Panel B, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex value-weighted returns 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, current NYSE/Amex index divided by its 52-week high x_{52}^{NY}, current NYSE/Amex index divided by it historical high x_{max}^{NY}, default premium def_t, term premium $term_t$, real interest rate r_t^f, inflation rate π_t, consumption–wealth ratio cay_t, dividend yield dp_t, and surplus ratio s_t. We do not report the coefficients and t-statistics for the macro control variables to save space. The Newey–West t-stats in parentheses control for heteroskedasticity and autocorrelation. Our sample data are monthly from 1958.01 to 2009.12.

Panel A: NYSE/Amex market cap as benchmark

Horizon	r_t	x_{52}^{NY}	x_{max}^{NY}	D_t^{NY}	I_t^{NY}	R^2
1-Month	0.13	0.09	−0.13	−1.14	0.99	0.03
	(2.59)	(1.39)	(−2.29)	(−2.47)	(1.52)	
3-Month	0.16	0.24	−0.41	−1.56	3.08	0.05
	(2.17)	(1.08)	(−2.21)	(−1.95)	(1.50)	
6-Month	0.12	0.26	−0.61	0.63	2.94	0.06
	(1.17)	(0.74)	(−2.01)	(0.57)	(0.92)	
1-Year	−0.06	0.32	−0.56	4.09	−0.81	0.06
	(−0.38)	(0.81)	(−1.54)	(2.68)	(−0.16)	

Panel B: Horse race between the Dow index and NYSE/Amex market cap

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	x_{52}^{NY}	x_{max}^{NY}	R^2
1-Month	0.08	0.14	−0.19	−0.62	0.62	−0.04	0.06	0.05
	(1.47)	(1.65)	(−3.32)	(−0.94)	(1.26)	(−0.42)	(1.10)	
3-Month	0.08	0.51	−0.56	−1.95	2.04	−0.22	0.17	0.13
	(0.87)	(2.01)	(−3.13)	(−1.55)	(1.48)	(−0.81)	(1.09)	
6-Month	0.04	0.96	−1.06	−2.31	3.23	−0.48	0.34	0.21
	(0.45)	(2.26)	(−3.69)	(−1.44)	(1.28)	(−1.17)	(1.40)	
1-Year	0.00	1.11	−1.56	2.97	1.59	−0.62	0.57	0.33
	(0.01)	(2.40)	(−5.05)	(1.18)	(0.35)	(−1.12)	(1.71)	

state variable corresponding to a rational model cannot explain our findings.

These findings are consistent with our hypothesis on anchoring and limited attention since the Dow index is more visible than NYSE/Amex total market value—news on the Dow index attracts heavy media coverage and investor attention, and hence, the Dow is a better anchor than the market cap of NYSE/Amex stocks. These finding are also consistent with Yuan (2008), who shows that record-breaking events of the Dow index predict both the trading behavior of investors and next-day market returns due to their attention-grabbing ability.[5]

3.4. Subsample analysis

The predictive power of our proposed variables can be illustrated by comparison with other main predictors through subsample analysis. We separate the full sample into three equally sized subsamples, 1958–1974, 1975–1992, and 1993–2009. Table 5 reports the regression results for these three subsamples.

The predictive ability of most of the business cycle variables is not stable across the three subsamples. For example, there is no predictive power for the consumption–wealth ratio in the first two subsamples at horizons less than or equal to one year. Surprisingly, while the predictive power of dividend yield is only marginally significant in the full sample, its power is strong across all three subsamples. This suggests a structural break for dividend yield (see, e.g., Goyal and Welch, 2008; Lettau and Van Nieuwerburgh, 2008). In fact, if we add a few more earlier years into the last subsample, dividend yield loses most of its forecasting power and becomes insignificant, while our predictors remain significant.

The predictive ability of term premium mostly derives from the early subsample and the sign flips across subsamples; the predictive ability of default premium changes sign across the three subsamples; the forecasting ability of inflation is weak across all subsamples and the sign flips as well; and the surplus ratio has strong predictive power in the second subsample, but the sign is wrong. By contrast, the predictive ability of x_{max} and x_{52} is consistent across the three subsamples, although the statistical significance varies a bit across the three subsamples. In summary, although many business cycle variables can predict excess returns in single-variable regressions, their forecasting power is not robust in multivariate horse race regressions. However, our behavioral-bias-motivated predictors are fairly robust.

[5] In a related study, Pontiff and Schall (1998) show that the book-to-market ratio of the Dow Jones Industrial Average predicts total market returns.

Table 5
Monthly overlapping regression for subsamples.

In this table, we regress future (1-month, 3-month, 6-month, and 1-year) NYSE/Amex value-weighted excess returns 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, dividend yield dp_t, and surplus ratio s_t. We use overlapped monthly sampled data, except for cay_t and s_t, which are only available at quarterly frequency. The Newey–West t-stat in parentheses control for heteroskedasticity and autocorrelation. The coefficients for D_t, I_t, and def_t are in terms of percentage. Panel A uses data from 1958.01 to 1974.12, while Panel B uses data from 1975.01 to 1992.12, and Panel C uses data from 1993.01 to 2009.12.

Horizon	r_t	x_{52}	x_{max}	D_t	I_t	def_t	$term_t$	π_t	r_t^f	cay_t	dp_t	s_t	R^2
Panel A: Subsample: 1958.01–1974.12													
1-Month	0.02	0.21	−0.23	−0.53	0.62	−1.36	1.51	0.10	1.56	0.06	1.62	0.37	0.14
	(0.27)	(1.71)	(−1.83)	(−0.64)	(0.84)	(−0.83)	(1.40)	(0.01)	(0.21)	(0.16)	(1.15)	(1.23)	
3-Month	0.17	0.58	−0.93	0.14	1.95	−0.52	0.33	−28.01	−23.77	−0.47	3.38	0.39	0.38
	(1.33)	(1.81)	(−4.00)	(0.11)	(1.16)	(−0.14)	(0.28)	(−3.21)	(−2.71)	(−0.64)	(1.53)	(0.72)	
6-Month	0.00	0.90	−1.29	0.76	1.67	−1.27	1.69	−37.77	−30.82	0.29	10.27	0.58	0.53
	(0.02)	(1.46)	(−3.31)	(0.39)	(0.65)	(−0.16)	(1.17)	(−2.67)	(−2.32)	(0.23)	(2.94)	(0.76)	
1-Year	0.22	0.73	−1.91	0.08	−4.13	−23.09	5.30	−44.66	−35.25	1.55	17.29	1.29	0.75
	(1.11)	(1.75)	(−5.22)	(0.05)	(−1.54)	(−4.02)	(4.34)	(−5.32)	(−4.06)	(1.04)	(3.76)	(1.56)	
Panel B: Subsample: 1975.01–1992.12													
1-Month	−0.01	0.11	−0.08	−0.47	0.31	2.23	0.43	−3.36	−1.47	0.20	2.90	0.59	0.12
	(−0.09)	(1.19)	(−0.86)	(−0.35)	(0.33)	(2.14)	(1.02)	(−1.22)	(−0.55)	(0.52)	(2.48)	(1.98)	
3-Month	−0.12	0.37	−0.20	−5.08	3.33	6.88	0.89	−9.09	−7.17	0.14	9.01	1.88	0.30
	(−1.64)	(1.88)	(−1.02)	(−1.88)	(1.38)	(3.52)	(1.24)	(−1.72)	(−1.46)	(0.16)	(4.45)	(2.84)	
6-Month	−0.07	0.54	−0.21	−4.29	6.09	13.64	1.95	−7.76	−7.41	−0.87	16.94	4.25	0.49
	(−0.54)	(3.07)	(−0.87)	(−2.15)	(1.73)	(6.50)	(1.81)	(−1.26)	(−1.22)	(−0.62)	(6.48)	(5.53)	
1-Year	−0.09	0.65	−0.60	7.70	8.51	13.15	3.86	−0.68	6.66	−0.81	22.97	5.48	0.65
	(−0.94)	(2.76)	(−2.16)	(4.68)	(2.11)	(4.65)	(2.18)	(−0.07)	(0.76)	(−0.70)	(4.85)	(4.46)	
Panel C: Subsample: 1993.01–2009.12													
1-Month	0.17	0.15	−0.33	−0.69	0.37	−4.18	−0.01	8.03	8.40	−0.03	1.65	−0.08	0.12
	(1.92)	(1.41)	(−3.68)	(−0.59)	(0.39)	(−3.07)	(−0.03)	(1.41)	(1.54)	(−0.18)	(2.05)	(−0.23)	
3-Month	−0.04	0.74	−1.04	−1.24	0.56	−14.22	−0.28	19.30	19.76	0.20	3.54	−0.30	0.35
	(−0.33)	(2.59)	(−5.36)	(−0.97)	(0.27)	(−5.00)	(−0.37)	(1.89)	(1.92)	(0.48)	(1.89)	(−0.36)	
6-Month	0.15	1.21	−1.80	−6.24	−1.32	−19.91	−1.07	30.92	37.26	0.61	9.10	−0.17	0.50
	(0.92)	(2.84)	(−7.37)	(−2.12)	(−0.34)	(−4.33)	(−0.62)	(1.29)	(1.56)	(1.05)	(2.61)	(−0.1)	
1-Year	0.49	1.46	−2.63	−0.21	−7.58	−11.93	−4.39	29.84	35.91	3.30	18.12	0.77	0.57
	(1.77)	(2.28)	(−5.05)	(−0.06)	(−0.99)	(−1.46)	(−1.58)	(0.87)	(1.03)	(3.51)	(2.51)	(0.24)	

3.5. *Small sample bias and out-of-sample R^2*

A large literature has shown that the standard t-statistics based on asymptotic theory can have poor finite sample properties. In particular, when predictor variables are persistent and the innovations in the predictors are highly correlated with the variable being predicted, the small sample biases can be severe (see, for example, Stambaugh, 1986, 1999; Valkanov, 2003; Campbell and Yogo, 2006). More recently, based on simulation, Ang and Bekaert (2007) show that there are substantial size distortions with the Newey–West t-statistics when forecasting stock returns using persistent variables.

To address this issue when predicting stock returns with nearness to the 52-week high and the historical high, we follow Ang and Bekaert (2007) to perform a Monte Carlo experiment to investigate whether the statistical inference based on Newey–West t-statistics is affected by size distortions. Specifically, we simulate the return data for the Monte Carlo experiment under the null hypothesis of no predictability:

$$r_t = \gamma_0 + \varepsilon_{0,t}, \tag{3}$$

where γ_0 is a constant and $\varepsilon_{0,t}$ is independent and identically distributed (i.i.d.) normal. In addition, we specify the following vector autoregression (VAR) system for our predictors, x_{52} and x_{max}[6]:

$$x_{52} = a_1 + \rho_{11} x_{52,t-1} + \rho_{12} x_{max,t-1} + \varepsilon_{1,t}, \tag{4}$$

$$x_{max} = a_2 + \rho_{21} x_{52,t-1} + \rho_{22} x_{max,t-1} + \varepsilon_{2,t}. \tag{5}$$

The error terms are again jointly normal. The parameter values we use for our Monte Carlo experiment are estimated from the observed data for x_{52} and x_{max}. Finally, we estimate the sample covariance matrix for the joint residual vector $\overline{\varepsilon}_t \equiv (\varepsilon_{0,t}, \varepsilon_{1,t}, \varepsilon_{2,t})$ from the actual data, we then use the estimated sample covariance as the covariance matrix for the innovation vector $\overline{\varepsilon}_t$. This way, we explicitly take account of the small sample bias in Stambaugh (1986, 1999).

For each experiment, we simulate $100+T$ observations, where T is the sample size for the actual data. We then use the last T observations to run the following

[6] Since our predictors are bounded between zero and one, we also specified a VAR(1) for log-transformed variables, and the results are essentially the same.

predictive regression:

$$r_t = \gamma_0 + \gamma_1 x_{52,t-1} + \gamma_2 x_{max,t-1} + \varepsilon_{0,t}. \quad (6)$$

We repeat this procedure for 10,000 times. This gives us the distribution of the t-statistics testing the null hypotheses that $\gamma_1 = 0$ and that $\gamma_2 = 0$, along with the distribution of the regression R^2. To assess whether there are any size distortions with the Newey–West t-statistics, we compare its empirical size generated from the Monte Carlo experiment against a 5% nominal size. The empirical size is defined as the percentage of times the relevant absolute t-statistics are greater than 1.96. If the empirical size of the t-statistics is greater than 5%, the Newey–West t-statistics tend to overreject the null hypotheses. We report our results in Panel A of Table 6.

For one-month-ahead forecasting regressions, the Newey–West t-statistics have reasonable size properties. It is 4.98% for the null that $\gamma_1 = 0$ and 5.82% for the null that $\gamma_2 = 0$ from simulation, as opposed to the nominal 5% value. Therefore, the size distortion is small for the 1-month horizon. However, when we increase the forecast horizon, the size distortion is bigger. For a 12-month horizon, the size from simulation is 10.53% for the null that $\gamma_1 = 0$ compared to the nominal 5%. Hence, we indeed find overrejections by using Newey–West t-statistics, consistent with the findings in Ang and Bekaert (2007).

To evaluate how severe the size distortions are, we provide the 97.5% quantile of the simulated t-statistics for x_{52} and the 2.5% quantile of the simulated t-statistics for x_{max}. The asymptotic critical values for the t-statistics are 1.96 or -1.96 for a two-sided test at all horizons. In our Monte Carlo experiments, the 97.5% (2.5%) quantiles for the t-statistics are above (below) the asymptotic values of 1.96 (-1.96) and increase (decrease) to 2.45 (-2.80) as the forecast horizon increases to one year. These results indicate that for long-horizon forecast regressions, we need a t-statistic higher than standard critical value (in absolute value) to reject the null hypotheses. However, these findings do not alter our earlier conclusion about the significant forecast ability of x_{52} and x_{max}. For example, the t-statistics for x_{max} in Table 3 are between -3.54 and -4.06 at 1-, 3-, 6-, and 12-month horizons, as opposed to two-sided empirical t-statistics of -2.23, -2.44, -2.59, and -2.80 at the 1-, 3-, 6-, and 12-month horizons, respectively, in Table 6. The t-statistics for x_{52} in Table 3 is also usually slightly higher than the corresponding two-sided empirical t-statistics from our Monte Carlo experiments. Finally, since the regressors are highly correlated in the Monte Carlo experiments as in our actual data, the simulation results also confirm that multicollinearity is unlikely to plague our statistical inference.

We now turn to the out-of-sample analysis for our predictive variables. In a comprehensive study, Goyal and Welch (2008) show that many traditional forecast variables perform poorly out of sample. To examine the out-of-sample performance of a predictor, x_t, they first run a regression $r_{t+1} = a + bx_t + \varepsilon_{t+1}$ using data up to time τ, and use $\hat{r}_{t+1} \equiv \hat{a} + \hat{b}x_\tau$ to forecast the return at time $\tau+1$. They then compare the mean squared error of the forecast $\hat{r}_{t+1}$ with that of the other forecast, the sample mean

Table 6
Small sample bias and out-of-sample analysis.

Panel A of this table reports the results on small sample properties by Monte Carlo experiments. Size(52-week) is the percentage of times the absolute value of the t-statistics for x_{52} is greater than 1.96; Size(max) is the percentage of times the absolute value of the t-statistics for x_{max} is greater than 1.96; Size(52-week + max) is the percentage of times the absolute value of the t-statistics for both x_{52} and x_{max} is greater than 1.96. t(52-week) is the 97.5% quantile of the t-statistics for x_{52} in Monte Carlo experiments. t(max) is the 2.5% quantile of the t-statistics for x_{max} in Monte Carlo experiments. The $\overline{R}^2$ is the 95% confidence interval for the Monte Carlo-generated R^2. Panel B reports the results on out-of-sample forecasts. At each month t, 1-month, 3-month, 6-month, and 1-year cumulative future excess returns are regressed on past nearness to the 52-week high and nearness to the historical high and the coefficients are estimated with data up to month t. We use the first 20 years of data for initial estimation, and then add one month each time and re-estimate recursively. We perform out-of-sample analysis for two strategies: one uses nearness to the historical high as the only predictor, the other uses both nearness to the historical high and nearness to the 52-week high as predictors. We compare both strategies against the strategy using historical mean as forecast for the next period's equity premium and we report the out-of-sample R^2 by comparing the mean-squared-errors of the two strategies above with the historical mean forecaster. Our full sample is monthly from 1958.01 to 2009.12.

Panel A: Small sample bias

	1-Month	3-Month	6-Month	1-Year
Size(52-week)	4.98%	7.29%	8.57%	10.53%
Size(max)	5.82%	8.11%	9.78%	11.54%
Size(52-week + max)	2.64%	3.84%	4.59%	5.90%
t(52-week)	2.03	2.22	2.34	2.45
t(max)	−2.23	−2.44	−2.59	−2.80
$\overline{R}^2$	−0.00, 0.01	−0.00,0.03	−0.00, 0.06	−0.00,0.09

Panel B: Out-of-sample R^2

Predictive variables	1-Month	3-Month	6-Month	1-Year
x_{max}	0.003	0.012	0.032	0.026
$x_{52}+x_{max}$	0.001	0.008	0.034	0.027

return, $\bar{r}_\tau$, up to time τ. Following Goyal and Welch (2008), we define the out-of-sample R^2, R^2_{oos} as

$$R^2_{oos} = 1 - \frac{\sum_{\tau=1}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=1}^{T}(r_\tau - \bar{r}_\tau)^2}. \tag{7}$$

Goyal and Welch (2008) find that R^2_{oos} is generally less than zero for many return forecast variables. However, Campbell and Thompson (2008) show that R^2_{oos} is usually positive by imposing sensible restrictions on the out-of-sample forecasting exercise. One of the restrictions is to rule out a negative equity premium forecast. We follow this restriction, and provide our out-of-sample R^2s in Panel B of Table 6.

Since nearness to the 52-week high cannot predict aggregate market returns alone, we do not perform out-of-sample analysis for nearness to the 52-week high. We perform out-of-sample analysis for two strategies: one uses nearness to the historical high as the only predictor, the other uses both nearness to the historical high and nearness to the 52-week high as predictors. We compare both strategies against the strategy using the historical mean as forecast for the next period's equity premium. The first 20 years of data are used for initial estimation. Panel B of Table 6 reports the out-of-sample R^2s. They are positive, with similar magnitude as those reported by Campbell and Thompson (2008).

The positive R^2_{oos} implies that our predictors beat the historical mean forecast. However, the small magnitude implies that the gain is relatively small. Cochrane (2008) shows through simulation that small or even negative R^2_{oos} is expected even if returns are *truly forecastable*. He shows that poor out-of-sample R^2 is exactly what we expect given the persistence of our regressors and the relatively short samples we have for estimating the relation between returns and our predictors. Hence, a small (or even negative) out-of-sample R^2 does not necessarily reject the hypothesis that returns are predictable by our variables (see, e.g., Inoue and Kilian, 2004; Cochrane, 2008).

3.6. *Evidence from Monte Carlo simulations*

The tests in the preceding subsections indicate the existence of anchor-induced return predictability in the aggregate stock market. To give readers maximum confidence in our conclusions, in this subsection we further examine the strength of the results by using Monte Carlo simulations.

A skeptical reader might be concerned with the distribution of our predictors. For example, since the Dow index is rising over time, both nearness to the 52-week high and nearness to the historical high are highly skewed. This nonstandard nature of the distribution involved in our predictors may change the true statistical significance of our tests, and hence, poses a potential concern. To address this potential issue, we use several Monte Carlo simulation methods developed in the price barrier literature (see, e.g., Donaldson and Kim, 1993) to determine the true statistical significance of our return predictability tests.

If our predictability results are purely due to time-series regularities in an index of rising prices, the results should remain if we randomly reorder the Dow index. When we randomly reorder the Dow series, the shape and the rising feature of the Dow index remain, and hence, the predictability results should remain as well. On the other hand, if the predictability results are due to psychological anchoring and limited investor attention, then random reordering should destroy the anchoring effect, and hence, there should be no or weak predictability in returns. For example, after reordering, the 52-week high in the reordered series is not a psychological anchor anymore and should not capture underreaction information either. Thus, the nearness to the 52-week high should show no predictive power in forecasting future market returns.

In the first return-randomization simulation, we first calculate the (log) return of the Dow index, $r_t^{Dow} = \log(p_t/p_{t-1})$, from the Dow index level, p_t, for each day. We then randomly reorder daily returns on the Dow index and daily market excess returns simultaneously,[7] so that the returns for the Dow index and the market on the same day occur on the same day again after randomization. A new sequence of Dow prices is then produced using the true starting value of the Dow index and the subsequent price levels implied by the reordered returns series. Moreover, the ending level of the reordered Dow index is the same as the one in the true Dow index, and hence, the shape of the simulated Dow index is similar to the true Dow index. Armed with the simulated Dow price level and the simulated market excess returns, we then perform the same regression as the last one shown in Table 2. This procedure is repeated 1,000 times to obtain the distribution of the regression coefficients on x_{52} and x_{max}.

The distribution for coefficients on x_{52} is roughly symmetric but slightly fat-tailed. For example, the kurtosis of the distribution is 3.796, 3.574, 3.450, and 3.511 for predictive horizons at 1, 3, 6, and 12 months, respectively. Compared with the distribution of the coefficients on x_{52}, the distribution of the coefficients on x_{max} is more negatively skewed and more fat-tailed. Therefore, to determine the p-value for nearness to the 52-week high, we calculate the portion of the coefficients from the simulation that are higher than the corresponding coefficients in Table 2. Similarly, to determine the significance level of nearness to the historical high, we compute the portion of the coefficients from the simulation that are smaller than the corresponding coefficients in Table 2. Panel A of Table 7 reports the results and shows that the coefficients for the nearness to the 52-week high and to the historical high remain highly significant. In particular, the p-values for x_{52} are 0.40%, 0.20%, 0.60%, and 1.10% for predictive regression horizons at 1, 3, 6, and 12 months, respectively, and the p-values for x_{max} are 0.30%, 0.20%, 0.10%, and 0.20%, for horizons at 1, 3, 6, and 12 months, respectively. Moreover, out of the 1,000 repeated simulations, less than three produce a coefficient

[7] The daily riskfree rate is inferred from the monthly riskfree rate (obtained from the database in Kenneth French's Web site), assuming it to be constant over the month.

Table 7
Monte Carlo simulations.

In Panel A, we randomly reorder the realized daily returns on the Dow index and NYSE/Amex excess returns from the sample period 1958.01–2009.12. We redo the tests in the last regression in Table 2 based on the simulated data. The procedure is repeated 1,000 times to obtain the distribution of the coefficients on x_{52} and x_{max}. Panel A reports the p-values from the reordered simulation. We use starred values to denote the coefficients on that variable from the estimation based on real data. For example, the p-value for x_{52}, denoted as $x_{52} > x^*_{52}$ in the table, is calculated as the percentage of times the estimated coefficients on x_{52} are greater than their empirical counterparts in Table 2. Other p-values are calculated in a similar manner. Panel B reports the p-values from the bootstrap simulation. Panel C reports the p-values from the reordering simulation by taking account of the weekend effect. In particular, we reorder returns separately among Mondays and non-Mondays. Panel D reports the results for the bootstrap simulation by accounting for the weekend effect. In Panel E, we first estimate a VAR(1) process for returns on the Dow index and NYSE/Amex returns jointly. The simulated Dow price series is then constructed based on the initial Dow price and subsequent Dow prices implied by the return processes generated using the estimated VAR(1) parameters. Based on the simulated data, the p-values are obtained the same way as in previous simulations. In Panel F, we further estimate the conditional covariance using bivariate GARCH(1,1) based on the innovations from the VAR(1) estimation. All simulations are repeated 1,000 times.

p-Value	1-Month	3-Month	6-Month	1-Year
Panel A: Reordering simulation				
$x_{52} > x^*_{52}$	0.40%	0.20%	0.60%	1.10%
$x_{max} < x^*_{max}$	0.30%	0.20%	0.10%	0.20%
$x_{52} > x^*_{52}$ and $x_{max} < x^*_{max}$	0.20%	0.00%	0.00%	0.10%
Panel B: Bootstrap				
$x_{52} > x^*_{52}$	1.60%	0.90%	1.50%	2.00%
$x_{max} < x^*_{max}$	0.40%	0.10%	0.10%	0.60%
$x_{52} > x^*_{52}$ and $x_{max} < x^*_{max}$	0.40%	0.10%	0.10%	0.60%
Panel C: Reordering with weekend effect				
$x_{52} > x^*_{52}$	0.70%	1.00%	0.90%	1.80%
$x_{max} < x^*_{max}$	0.20%	0.00%	0.00%	0.50%
$x_{52} > x^*_{52}$ and $x_{max} < x^*_{max}$	0.10%	0.00%	0.00%	0.30%
Panel D: Bootstrap with weekend effect				
$x_{52} > x^*_{52}$	1.70%	1.80%	1.10%	2.10%
$x_{max} < x^*_{max}$	0.30%	0.30%	0.30%	0.80%
$x_{52} > x^*_{52}$ and $x_{max} < x^*_{max}$	0.30%	0.20%	0.20%	0.40%
Panel E: VAR(1)				
$x_{52} > x^*_{52}$	1.70%	1.40%	1.70%	2.60%
$x_{max} < x^*_{max}$	1.00%	0.60%	0.10%	1.20%
$x_{52} > x^*_{52}$ and $x_{max} < x^*_{max}$	0.80%	0.40%	0.10%	0.80%
Panel F: VAR(1)-GARCH(1,1)				
$x_{52} > x^*_{52}$	2.00%	1.90%	2.00%	2.30%
$x_{max} < x^*_{max}$	1.10%	0.70%	0.30%	0.90%
$x_{52} > x^*_{52}$ and $x_{max} < x^*_{max}$	0.80%	0.60%	0.30%	0.60%

on x_{52} higher than the corresponding counterpart in Table 2, and a coefficient on x_{max} smaller than the counterpart in Table 2 simultaneously. In sum, the low p-values from the return-randomization experiment strongly suggest that our return predictability results are unlikely due to the statistical property of the Dow index.[8]

The second return-randomization simulation is similar to the first one and differs only in that the returns are resampled with replacement. Hence, it replicates the traditional "bootstrap" approach. Specifically, in the second simulation, the same number of observations of returns on the Dow and market excess returns are sampled simultaneously from the corresponding empirical distributions with replacement. Then a new sequence of Dow prices is produced the same way as before. The resulting Dow index has the same number of observations as in the data, and is still increasing over time, but the ending level is usually different from the true one in the data. Again, this procedure is repeated 1,000 times to obtain the distribution of the coefficients on x_{52} and x_{max}. The results are reported in Panel B of Table 7, which shows that coefficients of the predictive regression remain highly significant.

To account for the weekend effect in the daily returns, the third simulation repeats the first simulation by separately reordering the returns on Mondays and non-Mondays. In particular, we randomly reorder all the Mondays using the returns on Mondays, and reorder non-Mondays using the returns on non-Mondays. The results for the third simulation, reported in Panel C of Table 7, are very similar to the first simulation. The fourth simulation repeats the second "bootstrap" simulation by sampling Monday returns from the historical Monday returns with replacement and by sampling non-Monday returns from the historical non-Monday returns. The results are reported in Panel D of Table 7. Overall, accounting for the weekend effect has no significant impact on the p-values.

To further ensure that the results in previous subsections are not simply a product of the general rising shape traced by the Dow index, we perform two additional simulations based on the modeling of returns of the Dow index and excess market returns as a VAR(1) process and as a vector autoregression(1)-generalized autoregressive conditional heteroskedasticity(1,1) (VAR(1)-GARCH(1,1)) process.

In the fifth return-randomization simulation, we first estimate a VAR(1) for the daily return on the Dow and the daily aggregate excess market return. As with the previous four simulations, 1,000 simulated price series are constructed based on the initial Dow price and subsequent Dow prices implied by the return processes generated using the estimated VAR(1) parameters, each with the same number of observations as in the data. The resulting Dow index is still increasing over time. We then perform the same regressions as before and report the results for the coefficient distributions in Panel E of Table 7. The results remain similar to the previous simulations. For example, in the 3-month predictive regression, the p-values for the coefficients on nearness to the 52-week

[8] In unreported analysis, we also obtain the distribution of t-statistics for both x_{52} and x_{max}, and compare the corresponding t-statistics in Table 2 with the Monte Carlo distribution. The results based on t-statistics are also very significant. Moveover, the distribution of t-statistics also confirms the results in Table 6 on the small sample bias.

high and nearness to the historical high implied by the VAR(1) simulation are 1.4% and 0.6%, respectively.

To account for the volatility cluster in return data, in the last return-randomization simulation, we further model the residuals in the previous VAR(1) as a bivariate GARCH(1,1) process. We follow the two-step approach of Pagan and Schwert (1990), Gallant, Rossi, and Tauchen (1992), Engle and Ng (1993), and Kroner and Ng (1998) in estimating the VAR-GARCH model.[9] To save space, we do not report the estimation here since it is a fairly standard estimation method and the results are in line with existing empirical studies. Again, 1,000 simulated price series are constructed based on the initial Dow price and subsequent Dow prices implied by the return processes generated using the estimated VAR(1)-GARCH(1,1) parameters, each with the same number of observations as in the data. The Monte Carlo distributions of coefficients are obtained from these 1,000 simulated series. As shown in Panel F of Table 7, the significance levels are very similar to the previous simulations.

In untabulated analysis, we have performed several additional simulation tests. For example, instead of predicting excess market returns, we forecast total market returns or returns on the Dow index directly.[10] The p-values based on these simulations remain similar. We have also tried a different way to account for the weekend effect by dividing the (log) return on Monday by a factor of three. Those tests yield essentially the same significance level as we reported in Table 7. In sum, the results based on our extensive simulations in this subsection appear to confirm the statistical significance of the results in previous subsections. We therefore conclude that neither the general rising shape of the Dow index nor the statistical properties of our predictors can account for the apparent return predictability in the aggregate market.

3.7. Evidence from international data

Given the strong predictive ability of our proxies in the United States, it is interesting to examine whether these results can carry to other countries around the world. In this subsection, we extend our analysis to six other G7 countries. We choose these countries because their stock markets are more developed and stable.

The benchmark indexes for these countries are: FTSE100 for United Kingdom, DAXINDX for Germany, FRCAC40 for France, NIKKEI for Japan, SPTSX for Canada, and FTSEMIB for Italy. The month-end data for these indexes are obtained from DataStream. From these indexes, we calculate nearness to the 52-week high, x_{52}, and nearness to the historical high, x_{max}, at the end of each month for each country. We also create D_t dummy and I_t dummy the same way as before. We then investigate the predictive ability of x_{52} and x_{max} on future market returns in each country.

One issue with the benchmark indexes is their visibility. For example, France launched its index AC40 on 1987. However, the AC40 index is unlikely to be visible in the year of 1987. Hence, we eliminate the first five years of observations in our predictive regressions. We implicitly assume that five years after the launching of an index, it becomes a visible benchmark in that country.[11] The only exception is Italy, where its benchmark was created in 1998. To keep its sample as long as possible, we do not make such adjustment. All results reported here are robust even if we use the full sample.

For each country, we run the monthly time-series overlapping regression of future market returns on past market returns, x_{52}, x_{max}, D_t, and I_t. The results are presented in Table 8. Panel A reports the regression of 6-month future returns on lagged predictors and Panel B reports the regression of 1-year future returns on lagged predictors. For all the six countries, the coefficients on x_{52} and x_{max} always have the correct sign. Despite the short sample period and issues with the indexes' visibility, many of the coefficients are statistically significant. For both U.K. and Italy, nearness to the 52-week high and nearness the historical high are highly significant predictors. Nearness to the historical high is also significant for Germany at the one-year horizon and nearness to the 52-week high is significant for France and Canada at the one-year horizon. Overall, the evidence from international data is very supportive.

Furthermore, Wang, Yu, and Yuan (2010) find that nearness to the 52-week high exchange rate and nearness to the historical high exchange rate in the foreign exchange market can predict exchange rate changes and returns on foreign exchange for most of the currencies in industrial countries against the U.S. dollar. This finding is especially striking given that the foreign exchange market is often regarded as the largest and most liquid/efficient financial market in the world. The foreign exchange market is unique because of its trading volume, the extreme liquidity of the market, its geographical dispersion, its long trading hours, and its use of leverage. As such, it has been referred to as the market closest to the ideal perfect competition. Hence, the evidence from the currency markets renders an "out-of-sample" support to our predictors.

3.8. Further evidence from the cross-section of stock returns

We have shown that both nearness to the 52-week high and nearness to the historical high have significant power to predict future market returns, and that their predictive power works in opposite directions. Although

[9] In particular, first we estimate the mean equation, the VAR(1), to obtain the residuals, and then we estimate a bivariate GARCH(1,1) process for the residuals using maximum likelihood, treating the residuals from the VAR(1) as observable. The details on the estimation are available upon request.

[10] For a regression with horizons less than six months, the difference between using the Dow return and the market return as the dependent variable is negligible. For forecast horizons longer than six months, the results using the Dow return as the dependent variable are slightly less significant than those using the market excess return as the dependent variable. This is reasonable, since the Dow index is a price index without dividends. Hence, for return predictability regressions at longer horizons, we should employ the market return series to include dividends.

[11] Of course, another benefit from omitting the first five years of data is to calculate the historical high using those five years of data.

Table 8
International evidence with monthly overlapping regressions.

This table reports predictive regressions for aggregate market returns in six other G7 countries. We construct nearness to the 52-week high and the historical high from visible market indexes for the G7 countries. Sample starts in 1983 for UK, 1976 for Germany, 1992 for France, 1976 for Japan, 1983 for Canada, and 1998 for Italy, and ends at 2008. Indexes are the benchmark index for each country obtained from DataStream. The observations are at monthly intervals. All variables except D_t and I_t are in terms of percentage. Panel A presents the predictability results for the 6-month horizon and Panel B presents the predictability results for the 1-year horizon. The Newey–West t-stats in parentheses control for heteroskedasticity and autocorrelation.

Country	Index	r_t	x_{52}	x_{max}	D_t	I_t	R^2
Panel A: Predictability of 6-month horizon							
UK	FTSE100	−0.24	0.77	−0.37	−0.02	0.12	0.13
		(−1.24)	(2.34)	(−2.25)	(−1.74)	(2.36)	
Germany	DAXINDX	0.12	0.10	−0.15	0.05	−0.01	0.03
		(0.94)	(0.37)	(−1.63)	(1.17)	(−0.27)	
France	FRCAC40	0.01	0.59	−0.17	−0.02	0.05	0.12
		(0.04)	(1.60)	(−1.10)	(−0.54)	(0.61)	
Japan	NIKKEI	0.06	0.16	−0.10	−0.01	0.12	0.09
		(0.41)	(0.60)	(−0.83)	(−0.59)	(2.01)	
Canada	SPTSX	0.05	0.07	0.00	−0.02	−0.03	0.03
		(0.35)	(0.29)	(0.00)	(−0.88)	(−0.68)	
Italy	FTSEMIB	−0.21	1.01	−0.72	−0.02	0.23	0.35
		(−1.10)	(2.73)	(−6.05)	(−0.44)	(3.06)	
Panel B: Predictability of 12-month horizon							
UK	FTSE100	−0.03	0.89	−0.81	−0.03	0.24	0.22
		(−0.11)	(2.46)	(−3.12)	(−0.62)	(4.09)	
Germany	DAXINDX	−0.06	0.46	−0.38	0.13	−0.01	0.06
		(−0.28)	(0.92)	(−2.99)	(2.90)	(−0.07)	
France	FRCAC40	−0.02	0.97	−0.40	−0.01	0.08	0.11
		(−0.15)	(1.98)	(−1.12)	(−0.15)	(0.58)	
Japan	NIKKEI	−0.10	0.48	−0.18	−0.03	0.23	0.13
		(−0.64)	(1.38)	(−0.73)	(−0.89)	(1.93)	
Canada	SPTSX	−0.40	0.79	−0.11	−0.02	0.01	0.09
		(−2.07)	(2.46)	(−0.38)	(−0.64)	(0.09)	
Italy	FTSEMIB	0.14	1.07	−1.57	0.07	0.39	0.50
		(0.62)	(2.06)	(−5.98)	(1.08)	(3.11)	

we view our time-series analysis as our main contribution, in this subsection we provide further evidence by exploring the implications of our proposed measures on the cross-section of expected stock returns, especially on the momentum strategy and the value investing strategy. George and Hwang (2004) find that nearness to the 52-week high dominates and improves upon the forecasting power of past returns for future returns. In this section, we want to highlight the role of the historical high anchor in the cross-section of returns.

As we argued in Section 2, for firms with one anchor (i.e., the same 52-week high and historical high), nearness to the 52-week high is a clearer proxy for underreaction, and hence, we expect that nearness to the 52-week high predicts future returns more strongly among this category of stocks. Similarly, among the firms with different 52-week and historical highs, we conjecture a higher value premium since book-to-market may be better at capturing information on overreaction in this category of firms. To test these effects in the cross-section, for each month we separate the full sample into two subsamples, one with equal 52-week and historical highs, and the other with different 52-week and historical highs. We then investigate the momentum and value premium effects in each subsample.

In the tests that follow, we examine the impact of 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 nearness to the 52-week high on the value investment strategy of Fama and French (1996). To exclude the potential effects of small stocks, we use all the common shares from NYSE/Amex from 1963 to 2008. For the momentum strategies, we adopt the same approach as JT and GH to calculate monthly returns. Both JT and GH focus on strategies that hold the portfolio for six months. Specifically, each month investors form a portfolio based on past 6-month returns (or nearness to the 52-week high), and hold the position for six months.

Specifically, we consider a momentum strategy conditional on the case where the 52-week high equals the historical high. We construct this 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 $t-1$. We rank the selected stocks in ascending order according to their past 6-month returns, or their nearness to the 52-week high, $x_{52,i,t-1} = p_{i,t-1}/p_{i,52,t-1}$, 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 this ranking, five portfolios are formed. Stocks ranked in the top 20% form the winner portfolio, and stocks in the bottom 20% form the loser portfolio. Following the momentum literature, we form equally weighted

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) (1993) quintile portfolios are formed based on past 6-month returns, and George and Hwang (GH) (2004) quintile portfolios are based on the ratio of current price to the past 52-week high price. All portfolios are held for six months. Panel A reports results for the sample where the 52-week high price is less than the historical high price, that is, there are two reference points (anchors). Panel B reports results for the sample where the 52-week high price is equal to the historical high price, that is, there is only one reference point (anchor). Returns are equally weighted, and the Newey–West t-stats given in parentheses control for heteroskedasticity and autocorrelation. α^{FF3F} is the abnormal return of the Winner-Loser portfolio in the Fama and French (1993) three-factor model test. Our sample includes all common stocks listed in NYSE/Amex from CRSP, and the sample data are monthly from 1963.01 to 2009.12.

Return	Loser	2	3	4	Winner	Winner-Loser	α^{FF3F}
Panel A: Two-anchor sample: 52-week high < historical high							
JT strategy	1.14	1.20	1.23	1.25	1.40	0.27	0.60
	(2.79)	(4.06)	(4.90)	(5.17)	(5.08)	(1.11)	(3.31)
GH strategy	1.15	1.20	1.28	1.32	1.28	0.13	0.76
	(2.54)	(3.70)	(4.74)	(5.73)	(6.35)	(0.41)	(3.66)
Panel B: One-anchor sample: 52-week high = historical high							
JT strategy	0.64	1.05	1.19	1.29	1.53	0.89	1.06
	(2.04)	(4.12)	(5.15)	(5.31)	(5.22)	(4.64)	(6.06)
GH strategy	0.55	1.11	1.29	1.35	1.35	0.80	1.17
	(1.59)	(3.98)	(4.99)	(5.66)	(6.14)	(3.90)	(7.70)

portfolios.[12] The strategy is to hold a self-financing portfolio that is long the top quintile portfolio (the winners) and short the bottom quintile portfolio (the losers) for six months. 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 six 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 further consider a momentum strategy conditional on the case in which the 52-week high is less than the historical high. The strategy is the same as before except that we form portfolios based on the subset of stocks for which, at the beginning of month t, their 52-week high is less than their historical high. We also form quintile portfolios by ranking on the nearness to the historical high using a similar procedure. Finally, in addition to momentum portfolios, we form quintile portfolios based on book-to-market following Fama and French (1996).

Table 9 shows that the average return from momentum strategy conditional on the firms having the same 52-week and historical highs is about three times larger than the return from the momentum strategy conditional on firms having different 52-week and historical highs. Not surprisingly, the Fama-French three-factor model yields a large alpha for the 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 nearness to the 52-week high (GH strategy) as the past performance measure. In contrast, Table 10 shows that the return spread from the value strategy conditional on the case in which the 52-week high is less than the historical high is much larger than the return spread from the value strategy conditional on the case in which the 52-week high equals the historical high. The effect is strong for both equal-weighted and value-weighted returns. These results indicate that psychological anchoring is part of the force behind momentum and the value premium.

Table 9 also indicates that the average return to the JT strategy conditional on stocks having different 52-week and historical highs is not significantly different from zero. However, at the beginning of each month t, we select the same set of stocks and rank this set of stocks by nearness to the historical high first. Based on this ranking, we obtain five subgroups of stocks. In each subgroup, we further form five portfolios based on nearness to the 52-week high as before. This leads to the formation of 25 portfolios each month, which are held for six months. We then calculate the momentum spread for each of the five subgroups sorted by nearness to the historical high, and then average the spreads across the five subgroups. This gives us the spread for nearness to the 52-week high by controlling for nearness to the historical high. Comparing Table 11 to Table 9, it can be seen that this double-sort momentum strategy can generate a significantly larger spread compared to the simple one-way sorting on past performance. This evidence further indicates that nearness to the historical high works against the momentum strategy and hence, that it is important to control for this effect.

A similar result obtains when we sort on the historical high. Table 12 shows that conditional on the set of stocks with different 52-week and historical highs, a simple one-way sort strategy based on the historical high generates an insignificant spread of -0.48 per month. However, in a double-sorting, after controlling for the nearness to the 52-week high, the portfolio longing the bottom 20% nearness to the historical high and shorting the top 20% nearness to the historical high results in a return spread of 0.75 per month, which is also statistically significant with t-value of 4.24.

[12] For value-weighted portfolios, the results are weaker. However, this is consistent with our story since smaller stocks are more subject to mispricing due to anchoring.

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 on Fama and French (1996). Panel A reports results for the 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 the 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 (EW) and value-weighted (VW) returns are presented, and the Newey–West t-stats given in parentheses control for heteroskedasticity and autocorrelation. α^{FF3F} is the abnormal return of the Value-Growth portfolio in the Fama and French (1993) three-factor model test. Our sample includes all common stocks listed in NYSE/Amex from CRSP, and the sample data are monthly from 1963.01 to 2009.12.

Return	Growth	2	3	4	Value	Value-Growth	α^{FF3F}
Panel A: Two-anchor sample: 52-week high < historical high							
EW	0.73	0.96	1.15	1.39	1.65	0.92	0.54
	(2.37)	(3.73)	(4.47)	(5.11)	(4.86)	(5.90)	(4.78)
VW	0.59	0.85	0.88	1.11	1.18	0.59	0.03
	(2.92)	(4.31)	(4.33)	(5.13)	(4.67)	(3.65)	(0.23)
				High			
Panel B: One-anchor sample: 52-week high = historical high							
EW	0.94	1.15	1.19	1.31	1.41	0.47	0.15
	(3.35)	(4.44)	(4.69)	(5.46)	(5.51)	(3.28)	(1.50)
VW	1.01	0.98	0.97	1.11	1.23	0.22	−0.22
	(4.39)	(4.59)	(4.37)	(5.20)	(5.31)	(1.27)	(−1.61)

Table 11
Double-sorted portfolios on historical high and momentum (or 52-week high) on two-anchor sample.

This table reports equal-weighted returns of portfolios on the 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 quintiles and then, among each quintile, sorted into quintiles either by the past 6-month return following Jegadeesh and Titman (JT) (1993) in Panel A, or by the ratio of current price to 52-week high price following George and Hwang (GH) (2004) in Panel B . Our sample includes all common stocks listed in NYSE/Amex from CRSP, and the sample data are monthly from 1963.01 to 2009.12. The Newey–West t-stats in parentheses control for heteroskedasticity and autocorrelation.

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	1.80	1.54	1.67	1.56	1.63	−0.17	
	(3.02)	(3.27)	(4.06)	(4.09)	(4.32	(−0.48)	
2	0.60	1.13	1.31	1.43	1.46	0.86	
	(1.47)	(3.22)	(4.04)	(4.61)	(4.54)	(4.29)	
Hist high	0.75	1.07	1.12	1.21	1.45	0.70	
	(2.35)	(3.73)	(4.18)	(4.64)	(5.00)	(4.60)	
4	0.93	1.05	1.14	1.12	1.30	0.37	
	(3.55)	(4.51)	(5.08)	(4.92)	(5.20)	(2.87)	
High	1.10	1.11	1.10	1.14	1.35	0.25	0.40
	(5.25)	(5.84)	(5.93)	(5.73)	(5.65)	(2.08)	(2.55)

Panel B: First sorted by historical high, then sorted by 52-Week high(GH)

Return	Loser	2	52-Week	4	Winner	Winner-Loser	Ave.(winner-loser)
Low	1.86	1.54	1.60	1.66	1.63	−0.23	
	(2.87)	(3.10)	(3.67)	(4.42)	(5.37)	(−0.51)	
2	0.50	1.07	1.30	1.50	1.54	1.04	
	(1.17)	(2.89)	(3.82)	(4.86)	(5.62)	(4.30)	
Hist high	0.57)	1.14	1.23	1.26	1.38	0.81	
	(1.64)	(3.77)	(4.40)	(4.89)	(5.91)	(4.79)	
4	0.80	1.05	1.17	1.24	1.26	0.46	
	(2.82)	(4.09)	(5.02)	(5.74)	(6.39)	(3.50)	
High	1.09	1.14	1.22	1.16	1.15	0.06	0.43
	(4.62)	(5.57)	(6.35)	(6.25)	(6.27)	(0.69)	(2.28)

Taken together, the results in this section point to the importance of separating the roles of the 52-week high and the historical high, confirming the findings from the time-series regressions in the previous subsections.

4. Conclusion

In this paper, motivated by limited investor attention and anchoring, we propose two predictors for aggregate market

Table 12
Historical high portfolios for sample with two anchors.
Panel A of this table reports the equal-weighted returns of one-way sorted quintile portfolios based on the ratio of current price to historical high price. Panel B reports the equal-weighted returns 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. Our sample includes all common stocks listed in NYSE/Amex from CRSP, and the sample data are monthly from 1963.01 to 2009.12. The Newey–West t-stats in parentheses control for heteroskedasticity and autocorrelation.

Panel A: One-way sorting by historical high

	Low	2	3	4	High	High-Low
Return	1.65	1.18	1.12	1.12	1.17	−0.48
	(3.82)	(3.52)	(4.01)	(4.76)	(5.85)	(−1.57)

Panel B: Two-way sorting first by 52-week high and then by historical high

Return	Low	2	Hist high	4	High	High-Low	Ave.(high-low)
Low	2.42	1.38	0.85	0.64	0.56	−1.85	
	(3.94)	(2.70)	(1.85)	(1.58)	(1.53)	(−4.69)	
2	1.66	1.26	1.14	0.97	0.95	−0.71	
	(4.21)	(3.52)	(3.54)	(3.26)	(3.35)	(−3.62)	
52-Week	1.60	1.37	1.21	1.13	1.08	−0.52	
	(4.84)	(4.76)	(4.57)	(4.50)	(4.46)	(−3.39)	
4	1.54	1.37	1.24	1.22	1.20	−0.34	
	(5.38)	(5.57)	(5.52)	(5.72)	(5.93)	(−2.40)	
High	1.45	1.32	1.21	1.19	1.13	−0.31	−0.75
	(5.87)	(6.23)	(6.16)	(6.52)	(6.10)	(−2.58)	(−4.24)

excess returns. In time-series regression analysis, we show that nearness to the 52-week high positively predicts future returns, while the nearness to the historical high negatively predicts future market returns. In general, the predictive power of these two variables is stronger than that of traditional macro variables, and they capture information about future aggregate market returns that is not captured by other macroeconomic variables. Our evidence suggests that behavioral biases can not only affect individual stock prices, but also the aggregate market as a whole. Our findings also highlight the importance to consider both the 52-week high anchor and the historical high anchor.

On the cross-sectional side, for stocks for which overreaction was less likely in the past, we show that the momentum effect is three to six times stronger. On the other hand, for stocks for which underreaction was less likely, the momentum effect is no longer significant in a simple one-way sorting based on nearness to the 52-week high. However, after controlling for the second anchor, namely, the historical high, the momentum effect re-emerges significantly. Our findings suggest that models (e.g., Peng and Xiong, 2006; Grinblatt and Han, 2005) in which agents' attention is limited and agent's valuations depend on anchors/reference points are likely to be successful in explaining price movements.

References

Aggarwal, R., Lucey, B., 2007. Psychological barriers in gold prices? Review of Financial Economics 16, 217–230.
Ang, A., Bekaert, G., 2007. Stock return predictability: is it there? Review of Financial Studies 20, 651–707.
Baker, M., Pan, X., Wurgler, J., 2009. The Effect of Reference Point Prices on Mergers and Acquisitions. Unpublished Working Paper. Harvard Business School and New York University.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.
Burke, S., 2001. Barriers in US benchmark bonds. Unpublished working paper. University of British Columbia.
Campbell, J., 1991. A variance decomposition for stock returns. Economic Journal 101, 157–179.
Campbell, J., Cochrane, J., 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. Journal of Political Economy 107, 205–251.
Campbell, J., Shiller, R., 1988. Stock prices, earnings, and expected dividends. Journal of Finance 43, 661–676.
Campbell, J., Thompson, S., 2008. Predicting excess stock returns out of sample: can anything beat the historical average? Review of Financial Studies 21, 1509–1531.
Campbell, J., Yogo, M., 2006. Efficient tests of stock return predictability. Journal of Financial Economics 81, 27–60.
Chen, N., Roll, R., Ross, R., 1986. Economic forces and the stock market. Journal of Business 59, 383–403.
Cochrane, J., 2008. The dog that did not bark: a defense of return predictability. Review of Financial Studies 21, 1533–1575.
Cutler, D., Poterba, J., Summers, L., 1991. Speculative dynamics. Review of Economic Studies 58, 529–546.
Cyree, K., Domian, D., Louton, D., Yobaccio, E., 1999. Evidence of psychological barriers in the conditional moments of major world stock indices. Review of Financial Economics 8, 73–91.
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investors, psychology and security market under- and overreactions. Journal of Finance 53, 1839–1885.
De Bondt, W., Thaler, R., 1985. Does the stock market overreact? Journal of Finance 40, 793–805.
De Ceuster, M., Dhaene, G., Schatteman, T., 1998. On the hypothesis of psychological barriers in stock markets and Benford's law. Journal of Empirical Finance 5, 263–279.
De Grauwe, P., Decupere, D., 1992. Psychological barriers in the foreign exchange markets. Journal of International and Comparative Economics 9, 87–101.
Donaldson, G., 1990a. International Evidence on Psychological Barriers in Asset Prices and the Efficient Market Hypothesis. Princeton Financial Research Center Memorandum 116.
Donaldson, G., 1990b. Psychological Barriers in Asset Prices, Rationality and the Efficient Market Hypothesis. Princeton Financial Research Center Memorandum 114.
Donaldson, G., Kim, H., 1993. Price barriers in the Dow–Jones industrial average. Journal of Financial and Quantitative Analysis 28, 313–330.

Edwards, W., 1968. Conservatism in human information processing. In: Kleinmutz, B. (Ed.), Formal Representation of Human Judgment, John Wiley and Sons, New York, pp. 17–52.
Engle, R., Ng, V., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48, 1749–1778.
Fama, E., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49, 283–306.
Fama, E., French, K., 1988. Dividend yields and expected stock returns. Journal of Financial Economics 22, 3–25.
Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.
Fama, E., French, K., 1996. Multifactor explanation of asset pricing anomalies. Journal of Finance 51, 55–84.
Ferson, W., Harvey, C., 1991. The variation of economic risk premiums. Journal of Political Economy 99, 385–415.
Gallant, R., Rossi, P., Tauchen, G., 1992. Stock prices and volume. Review of Financial Studies 5, 199–242.
George, T., Hwang, C., 2004. The 52-week high and momentum investing. Journal of Finance 59, 2145–2176.
Goyal, A., Welch, I., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.
Griffin, D., Tversky, A., 1992. The weighing of evidence and the determinants of confidence. Cognitive Psychology 24, 411–435.
Grinblatt, M., Han, B., 2005. The disposition effect and momentum. Journal of Financial Economics 78, 311–339.
Grinblatt, M., Keloharju, M., 2001. What makes investors trade? Journal of Finance 56, 589–616.
Hart, O., Moore, J., 2008. Contracts as reference points. Quarterly Journal of Economics 123, 1–48.
Inoue, A., Kilian, L., 2004. In-sample or out-of-sample tests of predictability: which one should we use? Econometric Reviews 23, 371–402
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for market efficiency. Journal of Finance 48, 65–91.
Kahneman, D., Slovic, P., Tversky, A., 1982. In: Judgment Under Uncertainty: Heuristics and Biases Cambridge University Press, New York.
Keim, D., Stambaugh, R., 1986. Predicting returns in the stock and bond markets. Journal of Financial Economics 17, 357–390.
Koedijk, K., Stork, P., 1994. Should we care? Psychological barriers in stock markets. Economics Letters 44, 427–432.
Kroner, K., Ng, V., 1998. Modeling asymmetric comovements of asset returns. Review of Financial Studies 11, 817–844.
Kutner, M., Nachtsheim, C., Neter, J., 2004. In: Applied Linear Regression Modelsfourth ed. McGraw-Hill Irwin, New York.
Lakonishok, J., Shleifer, A., Vishny, R., 1994. Contrarian investment, extrapolation, and risk. Journal of Finance 49, 1541–1578.
Lettau, M., Ludvigson, S., 2001a. Consumption, aggregate wealth, and expected stock returns. Journal of Finance 56, 815–849.
Lettau, M., Ludvigson, S., 2001b. Resurrecting the (C)CAPM: a cross-sectional test when risk premia are time-varying. Journal of Political Economy 109, 1238–1287.
Lettau, M., 2008. Van Nieuwerburgh, 2008. Reconciling the return predictability evidence. Review of Financial Studies 21, 1607–1652.
Ley, E., Varian, H., 1994. Are there psychological barriers in the Dow–Jones index? Applied Financial Economics 4, 217–224.
Li, Y., 2001. Expected returns and habit persistence. Review of Financial Studies 14, 861–899.
Ljungqvist, A., Wilhelm, W., 2005. Does prospect theory explain IPO market behavior? Journal of Finance 60, 1759–1790.
Newey, W., West, K., 1987. A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708.
Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775–1798.
Pagan, A., Schwert, W., 1990. Alternative models for conditional stock volatility. Journal of Econometrics 45, 267–290.
Peng, L., Xiong, W., 2006. Investor attention, overconfidence, and category learning. Journal of Financial Economics 80, 563–602.
Pontiff, J., Schall, L., 1998. Book-to-market ratios as predictors of market returns. Journal of Financial Economics 49, 141–160.
Stambaugh, R., 1986. Bias in Regressions with Lagged Stochastic Regressors. Unpublished Working Paper. University of Chicago.
Stambaugh, R., 1999. Predictive regressions. Journal of Financial Economics 54, 375–421.
Tversky, A., Kahneman, D., 1974. Judgment under uncertainty: heuristics and biases. Science 185, 1124–1131.
Valkanov, R., 2003. Long-horizon regressions: theoretical results and applications. Journal of Financial Economics 68, 201–232.
Wachter, J., 2006. A consumption-based model of the term structure of interest rates. Journal of Financial Economics 79, 365–399.
Wang, J., Yu, J., Yuan, Y., 2010. Underreaction, Overreaction, and Foreign Exchange Predictability. Unpublished Working Paper. University of Minnesota.
Westerhoff, F., 2003. Anchoring and psychological barriers in foreign exchange markets. Journal of Behavioral Finance 4, 65–70.
Yuan, Y., 2008. Attention and Trading. Unpublished Working Paper. University of Pennsylvania.
Zarowin, P., 1989. Does the stock market overreact to corporate earnings information? Journal of Finance 44, 1385–1400.