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Anchor Reversion: The Case of the 52-Week High and Asset Prices

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ABSTRACT
This study attempts to jointly identify the effects of anchoring and mean reversion on asset prices. In particular, we define "anchor reversion" as the tendency for stock prices to revert back toward an anchor, for example, the 52-week high. Our results show that the further a stock moves away from its 52-week high, the more likely it is to revert back toward that 52-week high in the following month. Conversely, if a stock moves toward its 52-week high in a given month, it is less likely to experience a large movement toward that 52-week high in the following month. Portfolios constructed according to a long-short anchor reversion strategy result in future returns that range from 1.40% to 1.62% per month. These results are robust to controls for various risk factors as well as several cross-sectional stock characteristics, such as the monthly reversal phenomena.

KEYWORDS
Anchoring; asset pricing; behavioral finance; mean reversion

JEL CODES
G10; G19; G40; G41

Introduction

In this study, we attempt to bridge the ideas of anchoring and mean reversion in the setting of financial markets. Kahneman, Slovic, and Tversky (1982) describe anchors as initial values from which individuals have difficulty adjusting or deviating. Even though anchors are often just common reference points used as benchmarks or rules of thumb, prior research suggests that anchoring bias often plays an important role in the economic decision-making process of individuals (see, e.g., Tversky and Kahneman 1974 and Kristensen and Gärling 1997). For instance, Tversky and Kahneman (1974) demonstrate that anchoring bias causes individuals to assess subjective probability distributions too tightly.[1] Anchoring bias can be so strong that even arbitrary numbers can be influential. For example, Ariely, Loewenstein, and Prelec (2003) find that when participants are asked to write down the last two digits of their social security numbers before answering a question, those numbers, even though arbitrary, have an anchoring effect on their responses.

In a statistical sense, mean reversion is the idea that the greater the deviation of a random variate from its mean, the greater the probability that the next measured variate will be closer to its mean. In a financial setting, mean reversion commonly refers to the tendency for asset prices to return toward a trend path, such as a historical average. There is considerable evidence that stock returns exhibit mean reversion over longer horizons (see, e.g., Fama and French 1988; Poterba and Summers 1988; Cecchetti, Lam, and Mark 1988; Balvers, Wu, and Gilliland 2000; Campbell et al. 2001; Bali, Demirtas, and Levy 2008), but momentum over shorter horizons (see, e.g., Jegadeesh and Titman 1993; Moskowitz and Grinblatt 1999). The theoretical model of Barberis, Shleifer, and Vishny (1998) explains the coexistence of momentum and mean reversion as integrated responses by the market to news—an underreaction to news in the short run creates momentum, while an overreaction to news in the long run invokes mean reversion.[2]

Given that anchors can heavily influence the decision-making of individuals, and that mean reversion is evident in a variety of settings, we develop and test the idea that asset prices could experience what we denote as *anchor reversion*. Specifically, we hypothesize that anchoring bias is strong enough to move the prices of assets that have deviated away from a particular anchor back toward that anchor, similar to how mean reversion pushes returns back toward the mean. The 52-week high has been proposed as a possible anchor in financial markets, as it has long been a standard metric used in stock valuation. Given the prevalence of the 52-week high, and how often it is used as a reference point in financial news, some

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investors might adjust their decisions based on, or nearness to, that anchor. We predict that large movements away from the 52-week high are more likely to be followed by movements back toward that anchor, while movements toward the 52-week high are less likely to be followed by large additional movements toward the anchor. To the extent that anchor reversion is strong enough, we predict that movements away from the 52-week high will generate positive future returns while movements toward the 52-week high will not.

Perhaps the most plausible theoretical explanation for anchor reversion around the 52-week high is related to the disposition effect, as described in Shefrin and Statman (1985). In this setting, investors tend to sell winners too early and hold on to losers too long. This is arguably driven by both prospect theory (Kahneman and Tversky 1979) and mental accounting (Thaler 1980). According to prospect theory, investors place more weight on perceived gains than they do on perceived losses. Mental accounting explains how investors set reference points for determining these gains and losses. Therefore, as stocks approach the 52-week high, they might induce selling as investors attempt to realize capital gains at or near the reference point. Consistent with this conjecture, Della Vedova, Grant, and Westerholm (2022) empirically show that household investors substantially increase their limit order selling when prices are near the 52-week high. We contend that this sell-side overreaction to the 52-week high reference point might trigger a price drawdown with a subsequent buy-side reversal to the anchor. This would be consistent with the investor sentiment model of Barberis, Shleifer, and Vishny (1998) in which investors overact to certain news. This, however, would run contrary to George and Hwang (2004) who argue that investors are slow to react to the good news associated with stock prices that are near their 52-week high, which induces short-term momentum gains with no long-run reversals.

Because George and Hwang (2004) suggest that nearness to the 52-week high explains, at least in part, the momentum premium, then the nearness ratio, which is the ratio of the current share price to the 52-week high, should be associated with a positive return premium generally. During our sample period, we find some evidence consistent with this notion, particularly when we examine equal-weighted portfolios and estimate alphas using the a capital asset pricing model (CAPM) and the Fama and French (1996) three-factor models. In cross-sectional tests, however, the return premium associated with the nearness ratio is not robust to the inclusion of various controls in different model specifications or in different sample periods.

To test our anchor reversion hypothesis, we focus on how changes relative to the 52-week high influence future stock price movements. We calculate the month-over-month percentage change in the nearness ratio (%Δ*Nearness*). We then conduct a series of traditional asset pricing tests to determine whether movements away from the 52-week high are associated with positive expected returns. After sorting stocks into portfolios based on %Δ*Nearness,* we find that mean portfolio returns are decreasing monotonically across increasing portfolios. The difference in mean returns between extreme portfolios is -0.0162 ($t=-8.72$), or -1.62% per month. Thus, the further a stock moves away from its 52-week high, the more likely it is to move back toward that 52-week high in the following month. Conversely, if a stock moves toward its 52-week high in a given month, it is less likely to experience a large move toward that 52-week high in the following month. These results contrast the findings in George and Hwang (2004), as they do not show an underreaction to the good news associated with a 52-week high and a slow momentum price run-up. Instead, this pattern shows an overreaction selloff to the 52-week high reference point with a subsequent reversal back to the anchor. Thus, we see these results as strong support for the idea that anchor reversion influences asset prices and returns. It is also worth noting that qualitatively similar results are found when we examine alphas from various multifactor models.

Although our initial results are encouraging, we also want to examine the idea of anchor reversion in a cross-sectional setting. It is important to employ cross-sectional analysis so that we can control for more general mean reversion in asset prices, which has been shown to be highly explanatory of future returns (see, e.g., Jegadeesh 1990; Lehman, 1990). It could be the case that %Δ*Nearness* is simply another measure of mean reversion like the monthly reversal phenomena. We, therefore, control for price reversals in our cross-sectional regression analysis. We run a series of Fama and MacBeth (1973) regressions to examine the monthly return predictability of various stock characteristics and find the coefficient on %Δ*Nearness* to be negative and significant. This finding again suggests that, after controlling for other stock characteristics such as the reversal phenomena, movements away from the 52-week high predict positive next-month returns. In economic terms, the results from the Fama and MacBeth (1973) regressions suggest that a one–standard deviation decrease in %Δ*Nearness* is associated with an increase in next-month returns of more than 1% per month. Our results are robust to the inclusion of a variety of control variables across different sample periods. These findings support our hypothesis that anchor reversion can influence asset prices as movements away from anchors, such as the 52-week high, are likely to predict positive stock price movements in an economically meaningful way.

Taken together, our findings highlight the effect of cognitive biases and behavioral finance on asset prices (Barberis and Thaler 2003; Shiller 2003; Thaler 2005; Barberis, Huang, and Thaler 2006; Barberis and Huang 2008; Shiller 2016). Our study also contributes to the debate on market efficiency, as outlined in Fama (1970). The results indicate a violation of at least the semi-strong form efficient market hypothesis, as abnormal profits can be generated using publicly available information: the 52-week high. As in De Long et al. (1990), Shleifer and Vishny (1997), and Barberis, Shleifer, and Vishny (1998), we assume that deviations from efficient prices can persist as arbitrageurs fail to eliminate mispricing due to uncertainty about investor sentiment. Our study also contributes to the broad psychology literature regarding anchoring and reference dependence (see e.g., Tversky and Kahneman1974; Kahneman, Slovic, and Tversky 1982; Kristensen and Gärling 1997; Camerer 1998; Thaler 2000; Ariely, Loewenstein, and Prelec 2003; Stracca 2004). These results also extend the growing body of research that examines anchoring and reference points around the 52-week high price (George and Hwang 2004; Marshall and Cahan 2005; Huddart, Lang, and Yetman 2009; Gupta, Locke, and Scrimgeour 2013; Liu, Liu, and Ma 2011; Baker, Pan, and Wurgler 2012; Bhootra and Hur 2013). Beyond the academic contribution, the results from our study have important practical implications and suggest that a simple trading strategy of buying stocks that have moved away from their 52-week high can lead to profitable returns.

In the next section, we describe the data used throughout the analysis. Then, we discuss our empirical tests and highlight the results from these tests. Finally, we offer some concluding statements.

Data description

The data used throughout the analysis come from a variety of sources. From the Center for Research in Security Prices (CRSP), we obtain daily and monthly returns, prices, market capitalizations, and volumes. We also gather annual balance sheets from Compustat. From Wharton Research Data Services, we obtain value-weighted market returns, one-month U.S. T-bill yields (risk-free rate), and several risk factors that are discussed in Fama and French (1996) and Carhart (1997). To be included in our sample, a stock must have existing data on both CRSP and Compustat. We also require that the balance sheet equity account is positive in a given stock-year. Our sample period extends from 1980 to 2019. Our final sample consists of more than 2.28 million stock-month observations and more than 19,300 unique stocks.

Table 1 reports some statistics that describe our sample. Panel A reports the summary statistics for the entire sample period. Panel B shows a correlation matrix, along with corresponding *p* value (in brackets), of the variables used in the analysis. *Beta* is obtained by estimating a CAPM each month using daily data where the dependent variable is the excess return (raw return less the yield on the U.S. T-bill) for a particular stock and the independent variable is the market risk premium (value-weighted CRSP market return less the risk-free rate). *Size* is the market capitalization, or price times shares outstanding, on the last day of each month. *B/M* is the book-to-market ratio, where the market value and book value are obtained from CRSP and Compustat, respectively. *Momentum* is the cumulative return from month t-12 to t-2 calculated on a rolling basis. *Illiquidity* is the Amihud (2002) measure of illiquidity, obtained by calculating the ratio of the absolute value of returns scaled by dollar volume (in $100,000s). *IdioVolt* is the idiosyncratic volatility obtained by calculating the standard deviation of the daily residual returns from estimating a four-factor model (Fama and French 1993; Carhart 1997). Following George and Hwang (2004), we define *Nearness* as the ratio of the current price scaled by the 52-week high. We then calculate the change in *Nearness*, which is the month-over-month percentage change in the nearness ratio (%Δ*Nearness*).

Panel A shows that the average stock has *Beta* of .7069, a *Size* of $2.3 billion, and a *B/M* ratio of 3.9125. We also report that the average stock has *Momentum* of approximately 14.5%, *Illiquidity* of 9.67, and *IdioVolt* of 2.76%. Furthermore, the average *Nearness* is 0.7390 and the average %Δ*Nearness* is −0.0175. This negative average is likely explained by the notion that monthly movements away from the 52-week high tend to be much larger (in absolute value) than movements toward the 52-week high.

Table 1. Summary statistics.

Panel A. Summary Statistics

	Beta [1]	*Size* [2]	*B/M* [3]	*Momentum* [4]	*Illiquidity* [5]	*IdioVolt* [6]	*Nearness* [7]	*%ΔNearness* [8]
Mean	0.7069	2,269,606,846	3.9125	0.1447	9.6654	0.0276	0.7390	−0.0175
Std. Dev.	2.3139	13,859,543,059	92.9399	0.5502	621.3713	0.0270	0.2245	0.3656
25th Perc.	0.0680	30,400,000	0.3677	−0.1219	0.0046	0.0124	0.5921	−0.0678
Median	0.6557	139,181,250	0.6534	0.1219	0.0711	0.0202	0.7907	0.0000
75th Perc.	1.3126	745,314,203	1.0840	0.3683	1.0073	0.0337	0.9272	0.0606
Panel B. Correlation Matrix								
Beta	1.0000	0.0209	−0.0009	0.0507	−0.0042	−0.0072	−0.0148	−0.0091
		[<.0001]	[0.1998]	[<.0001]	[<.0001]	[<.0001]	[<.0001]	[<.0001]
Size		1.0000	−0.0058	0.0097	−0.0025	−0.0926	0.0808	0.0045
			[<.0001]	[<.0001]	[0.0002]	[<.0001]	[<.0001]	[<.0001]
B/M			1.0000	−0.0131	0.0011	−0.0008	−0.0058	−0.0014
				[<.0001]	[0.1045]	[0.2564]	[<.0001]	[0.0410]
Momentum				1.0000	−0.0111	−0.1092	0.3419	−0.0734
					[<.0001]	[<.0001]	[<.0001]	[<.0001]
Illiquidity					1.0000	0.0664	−0.0179	−0.0021
						[<.0001]	[<.0001]	[0.0019]
IdioVolt						1.0000	−0.4069	−0.0379
							[<.0001]	[<.0001]
Nearness							1.0000	0.1509
								[<.0001]
%ΔNearness								1.0000

Notes: The table reports statistics that describe the sample. Panel A reports the summary statistics for the entire sample period (1980 to 2019), while Panel B shows a correlation matrix, along with corresponding *p* value. *Beta* is obtained by estimating a capital asset pricing model each month for each stock using daily data. *Size* is the market capitalization. *B/M* is the book-to-market ratio, where the market value and book value are obtained from CRSP and Compustat, respectively. *Momentum* is the cumulative return from month t-12 to t-2. *Illiquidity* is the Amihud (2002) measure of illiquidity, obtained by calculating the ratio of the absolute value of returns scaled by the dollar volume (in 1,000,000s). *IdioVolt* is the idiosyncratic volatility obtained by calculating the standard deviation of the daily residual returns, which are obtained by estimating a four-factor model (Fama and French (1993) and Carhart (1997)) for each stock in each month. *Nearness* is the ratio of the closing monthly price scaled by the 52-week high price. %Δ*Nearness* is the percentage change in the nearness ratio.

Panel B reports the correlation matrix for the variables used throughout the analysis. A few results are noteworthy. First, we find that *Nearness* is negatively related to *Beta*, *B/M*, *Illiquidity*, and *IdioVolt*. We also find that *Nearness* is positively related to *Size* and *Momentum*. This last finding is important given that George and Hwang (2004) use *Nearness* as an approximation of momentum. The cross-correlations reported in Panel B are mostly significant and highlight the need to carefully control for these variables in our asset-pricing tests that follow.

Empirical results

In this section, we report the results of our empirical analysis. We begin by conducting a series of tests using a portfolio approach. In particular, we sort stocks into portfolios based on *Nearness* and analyze returns and alphas from various risk-factor models across the portfolios. We then examine the cross-sectional association between *Nearness* and expected returns using a Fama and MacBeth (1973) approach. In our third and fourth set of tests, we replicate our initial analyses but use %Δ*Nearness* as the variable of interest.

Nearness return premium: portfolio tests

In this subsection, we begin by attempting to document a return premium in stocks that are nearest to their 52-week high. We begin by creating both equal-weighted and value-weighted portfolios based on last month's *Nearness*. We then examine returns across the *Nearness* portfolios with the expectation that returns in stocks with the highest *Nearness* will have the highest returns given the momentum findings in George and Hwang (2004). Table 2 reports the results for mean returns and various measures of alphas from single and multifactor models, such as the CAPM, the Fama and French (1996) three-factor (FF3F) model, and the Carhart (1997) four-factor (FF4F) model. The estimates for these alphas are obtained using variations of the following equation:

$$Excess\ Return_{p,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{p,t}. \tag{1}$$

The dependent variable is the excess return or the difference between the raw return and the risk-free rate (or the yield on one-month U.S. T-bills) for each portfolio in month *t*. The independent variables

Table 2. Nearness return premium: portfolio tests.

Panel A. Equal-Weighted Portfolio Returns (Equal-Weighted Market Index)	Q I [1]	Q II [2]	Q III [3]	Q IV [4]	Q V [5]	Q V − Q I [6]
Mean Returns	0.0168***	0.0085***	0.0098***	0.0119***	0.0140***	−0.0028
	(4.16)	(3.07)	(4.33)	(6.06)	(6.84)	(-0.89)
CAPM Alphas	0.0001	−0.0047***	−0.0016***	0.0018***	0.0043***	0.0042*
	(0.08)	(-10.72)	(-3.55)	(2.78)	(4.39)	(1.79)
FF3F Alphas	0.0004	−0.0048***	−0.0019***	0.0014**	0.0049***	0.0045*
	(0.26)	(-10.46)	(-4.50)	(2.27)	(4.45)	(1.83)
FF4F Alphas	0.0050***	−0.0037***	−0.0024***	−0.0002	0.0013*	−0.0037*
	(3.41)	(-9.31)	(-4.89)	(-0.37)	(1.67)	(-1.74)
Panel B. Value-Weighted Portfolio Returns (Value-Weighted Market Index)						
Mean Returns	0.0248***	0.0183***	0.0164***	0.0156***	0.0153***	−0.0095***
	(7.31)	(6.74)	(7.42)	(8.23)	(8.15)	(-3.59)
CAPM Alphas	0.0017	−0.0018	−0.0008	0.0001	0.0010	−0.0007
	(1.11)	(-1.61)	(-1.08)	(0.27)	(1.14)	(-0.32)
FF3F Alphas	0.0023	−0.0016	−0.0014*	−0.0005	0.0012	−0.0011
	(1.42)	(-1.44)	(-1.79)	(-0.95)	(1.19)	(-0.47)
FF4F Alphas	0.0070***	0.0013	0.0004	−0.0009*	−0.0018***	−0.0088***
	(4.76)	(1.27)	(0.60)	(-1.81)	(-2.62)	(-4.66)

Notes: The table reports the monthly mean returns and alphas from estimating the capital asset pricing model as well as three-factor (Fama and French 1993) and four-factor (Carhart 1997) models. Panel A reports the results for equally-weighted portfolios sorted into quintiles based on the variable Nearness. Q1 represents the portfolio of stocks furthest away from their 52-week high, while Q5 represents the portfolio of stocks closest to their 52-week high. The final column reports the difference between the Q5 and Q1 portfolios with a corresponding *t* statistic. Panel B reports results from a portfolio analysis similar to that of Panel A but where stocks are sorted into portfolios where stocks are value-weighted instead of equal-weighted. Portfolios are obtained by sorting stocks based on last month's nearness ratio. The estimates are obtained using variations of the following equation:

$$Excess\ Return_{p,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{p,t}.$$

The dependent variable is the monthly excess return of the portfolio over the T-Bill yield in period *t*. The independent variables include the following in time t: MRP, which is the market risk premium or the difference between market return and the risk-free rate; SMB, which is the small-minus-big return factor; the high-minus-low return factor, HML; and the up-minus-down factor, UMD. Reported *t* statistics were obtained using White (1980) robust standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

include the following: *MRP* is the market risk premium, *SMB* is the size premium from a portfolio of small-minus-big stocks, *HML* is the value premium from a portfolio of high-minus-low book-to-market stocks, and *UMD* is the momentum premium from the up-minus-down portfolio. These independent variables are measured in month *t*.

Panel A in Table 2 reports the results for equal-weighted portfolios sorted into quintiles based on *Nearness*. QI represents the portfolio of stocks farthest away from their 52-week high (low *Nearness*), while Q5 represents the portfolio of stocks closest to their 52-week high (high *Nearness*). In the first row of panel A, we find that mean returns are neither increasing nor decreasing across increasing portfolios. The difference in means (column [6]) is −0.0028 ($t = -0.89$). At first glance, it does not appear that there is a return premium associated with *Nearness*, at least when looking at raw returns. In the second and third rows, we report CAPM alphas and FF3F alphas across increasing equal-weighted portfolios on *Nearness*. While we do not find evidence that alphas are increasing monotonically, we do find that the differences in excess returns between extreme portfolios are both positive (alphas = 0.0042 and 0.0045) and marginally significant ($t = 1.79$ and 1.83). In the fourth row, we find that the alphas from the four-factor model are neither increasing nor decreasing. However, we do find that the alphas from the difference between extreme portfolios in column [6] is negative and marginally significant (difference = −0.0037, $t = -1.74$). These results suggest that when estimating the full specification in equation (1), we do not find a significant return premium associated with *Nearness*. Together, the positive return premium associated with *Nearness* appears to be weak at best, which is inconsistent with the momentum results reported by George and Hwang (2004).

Perhaps the lack of evidence of a positive return premium associated with nearness to the 52-week high in Panel A is that we are only focused on equal-weighted portfolios. In panel B of Table 2, we replicate the analysis in panel A but for value-weighted portfolios. When looking at mean raw returns in the first row, we find that returns are decreasing monotonically across increasing portfolios. The difference in means between extreme returns in column [6] is negative and significant (difference = −0.0095, $t = -3.59$). These results indicate that there is a negative return premium associated with *Nearness*. We note that these results do not hold when we examine alphas from the CAPM or the FF3F model. Similar results, however, are found when we estimate the four-factor model. That is, the fourth row shows that alphas are decreasing monotonically across increasing *Nearness* portfolios and the alpha from differences in excess returns between extreme portfolios (column [6]) is negative and significant (alpha $= -0.0088$, $t = -4.66$). These results run contrary to the momentum hypothesis proposed in George and Hwang (2004).

Nearness return premium: cross-sectional tests

Our analysis in Table 2 suggests that the positive return premium associated with *Nearness* is not robust to controls for various risk factors in a four-factor model. However, given the many factors that have been shown to influence future stock returns, it might be important to control for other stock-specific factors that might influence our results more directly. To do this, we estimate Fama and MacBeth (1973) cross-sectional regressions using pooled stock-month observations. Specifically, we estimate variations of the following equation:

$$\begin{aligned} Return_{i,t+1} = \beta_0 &+ \beta_1 Nearness_{i,t} + \beta_2 Beta_{i,t} \\ &+ \beta_3 Ln(Size_{i,t}) + \beta_4 Ln(B/M_{i,t}) \\ &+ \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} \\ &+ \beta_7 IdioVolt_{i,t} + \beta_8 Reversal_{i,t} + \varepsilon_{i,t+1}. \end{aligned} \tag{2}$$

The dependent variable, $Return_{i,t+1}$, is the return for stock i in month $t+1$. The independent variable of interest is *Nearness*. As mentioned above, *Nearness* is the ratio of the current monthly closing price scaled by the 52-week high. With the exception of *Reversal*, which is the monthly stock return for each stock i in month t, the control variables have previously been defined. We report t statistics obtained from the time-series mean of standard errors that have been corrected using the Newey and West (1987) correction using three lags.

Table 3 reports the results from estimating variations of equation (2). We note that in column [1], we estimate a simple regression only including *Nearness* as the independent variable of interest. In the remaining columns, we add each of the control variables to the specification. The purpose of doing so is to determine the robustness of the results. To the extent that a positive return premium exists in stocks that are near their 52-week high, we expect the coefficient on *Nearness* to be positive and significant. Focusing on the coefficient on *Nearness*, we find that in columns [1] through [7], *Nearness* produces coefficients that are negative but only significant in columns [5] through [7]. In the full model specification, in column [8], we find that the coefficient on *Nearness* is positive but not reliably different from zero (coefficient $=$ 0.0047, $t = 1.16$). These results suggest that the positive return premium associated with the level nearness to the 52-week high does not hold particularly well in a Fama and MacBeth (1973) framework.

Regarding the control variables, a few results are noteworthy. First, we find some evidence of a size premium as the coefficient on *Ln*(*Size*) is negative across columns and significant columns [3], [4], [5], and [7]. We also find evidence of a value premium as the coefficient on *Ln*(*B/M*) is uniformly positive and significant across columns. Similar results are found when focusing on the *Momentum* coefficient and the *Illiquidity* coefficient, respectively. We also find some evidence for a negative return premium on idiosyncratic volatility as the coefficient on *IdioVolt* is negative and significant in column [7] (coefficient $= -0.0838$, $t = -2.81$). However, that result does not hold when we control for *Reversal* in column [8], which does produce a negative and reliable coefficient (coefficient $= -0.0461$, $t = -13.33$). Regardless, our findings question the notion that nearness to the 52-week high produces any significant return premium, either positive or negative.

Perhaps the positive return premium associated with nearness to the 52-week high is a function of the sample period. In Table 4, we replicate our analysis in Table 3 but estimate equation (2) for different periods. For simplicity, we estimate the Fama and MacBeth regressions for the 1980s, the 1990s, the 2000s, and the 2010s. Results from the full specification are reported in the table. For brevity, we only discuss the coefficients on *Nearness*. We find that in columns [1] through [3], *Nearness* does not produce a reliably significant coefficient. However, in column [4], during the 2010s, the coefficient on *Nearness* is positive and significant (coefficient $=$ 0.0140, $t = 2.44$). In economic terms, a one–standard deviation increase in the nearness ratio is associated with a 31-basis point increase in next-month returns. This is true after controlling for several stock characteristics that have been shown to predict future stock returns. Despite the finding in column [4] of Table 4, the combined analyses in Tables 2 through 4 do not provide consistent evidence of a robust return premium associated with nearness to the 52-week high.

Table 3. Nearness return premium: cross-sectional regressions.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.0167***	0.0175***	0.0382***	0.0313***	0.0337***	0.0292***	0.0340***	0.0171**
	(2.85)	(3.08)	(3.91)	(3.06)	(3.28)	(2.85)	(4.01)	(2.01)
Nearness	−0.0081	−0.0085	−0.0043	−0.0066	−0.0116**	−0.0105**	−0.0115***	0.0047
	(-1.55)	(-1.65)	(-0.90)	(-1.44)	(-2.56)	(-2.31)	(-2.73)	(1.16)
Beta		−0.0008	−0.0005	−0.0003	−0.0006	−0.0005	−0.0003	−0.0002
		(-1.41)	(-0.90)	(-0.62)	(-1.15)	(-0.96)	(-0.60)	(-0.33)
Ln(Size)			−0.0013***	−0.0007*	−0.0007*	−0.0005	−0.0006**	−0.0005
			(-3.75)	(-1.91)	(-1.79)	(-1.35)	(-2.03)	(-1.57)
Ln(B/M)				0.0053***	0.0058***	0.0057***	0.0056***	0.0051***
				(8.54)	(10.25)	(10.24)	(10.88)	(10.26)
Momentum					0.0062***	0.0064***	0.0064***	0.0045***
					(6.00)	(5.99)	(6.20)	(4.25)
Illiquidity						0.0001***	0.0001***	0.0001***
						(4.01)	(4.63)	(4.28)
IdioVolt							−0.0838***	0.0085
							(-2.81)	(0.28)
Reversal								−0.0461***
								(-13.33)

Notes: The table reports the results from estimating variations of the following equation using pooled stock-month observations:

$$Return_{i,t+1} = \beta_0 + \beta_1 Nearness_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Ln(Size_{i,t}) + \beta_4 Ln(B/M_{i,t}) + \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} + \beta_7 IdioVolt_{i,t} + \beta_8 Reversal_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable, $Return_{i,t+1}$, is the return for stock *i* in month $t+1$. The independent variable of interest is $Nearness_{i,t}$, which is the ratio of the closing monthly price in month *t* scaled by the 52-week high. With the exception of *Reversal*, which is the monthly stock return for each stock *i* in month *t*, the control variables have previously been defined. We report *t* statistics in parentheses obtained using Newey and West (1987) correction with three lags. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

%ΔNearness return premium: portfolio tests

In this subsection, we replicate the analyses in Tables 2 through 4, but instead of examining *Nearness*, we focus on the percentage change in *Nearness* (%Δ*Nearness*). This allows us to measure whether or not anchor reversion occurs around the 52-week high and how big an impact it has on stock prices and returns. Table 5 reports the results from sorting stocks into portfolios based on the month-over-month percentage change in nearness to the 52-week high (%Δ*Nearness*). Stocks in the lowest quintile portfolio are those stocks that experienced the largest movement away from the 52-week high in percentage terms, while stocks in the highest quintile portfolio represent stocks that have moved closest to the 52-week high.

Panel A of Table 5 reports the results for equal-weighted portfolios. Focusing on the first row in Panel A, we find that mean raw portfolio returns are decreasing monotonically across increasing %Δ*Nearness* portfolios. The difference in mean returns between extreme portfolios in column [6] is −0.0162 ($t = -8.72$). Qualitatively similar results are found when we obtain alphas from estimating equation (1). We note that while alphas are not decreasing monotonically (alphas in QIII are slightly larger than alphas in QII), the differences between the extreme portfolios are negative and significant and robust to the different types of multifactor models we estimate. In economic terms, the alphas in column [6] are extremely negative and suggest that a long-short portfolio can produce alphas that are between 1.4% to 1.52% per month. In annual terms, these alphas suggest that a strategy that buys stocks that move farthest away from the 52-week high and sells stocks that move closest to their 52-week high can outperform the market by 16.8% to 18.2%, respectively.

These unusually significant alphas are likely affected by the weighting scheme in panel A. Perhaps a more robust approach is to value-weight the returns of the stocks in the portfolio. Panel B of Table 5 reports these results. The findings are qualitatively similar across each of the rows. Focusing on the last row in panel B, we find that alphas from the four-factor model are decreasing (monotonically) across increasing %Δ*Nearness* portfolios. The alphas from the hedge portfolio in column [6] is −0.0049 ($t = -2.28$). These results suggest that buying a portfolio of stocks that have moved farther away from their 52-week high and selling a portfolio of stocks that have moved closer to their 52-week high produces alphas of about 49 basis points per month. In annual terms, this strategy seems to generate about a 6% abnormal return. These results are robust to the findings in panel A and suggest that while the nearness ratio does not produce a consistent and significant return premium, changes in the nearness ratio do. We believe that these results provide strong evidence in favor of our anchor reversion hypothesis. Anchors appear to be so

Table 4. Nearness return premium: sample period partitions.

	1980s [1]	1990s [2]	2000s [3]	2010s [4]
Intercept	0.0251	0.0200	0.0166	0.0067
	(1.31)	(1.14)	(0.88)	(0.61)
Nearness	0.0006	−0.0009	0.0050	0.0140**
	(0.13)	(-0.13)	(0.40)	(2.44)
Beta	−0.0004	0.0007	−0.0013	0.0003
	(-0.54)	(0.99)	(-1.04)	(0.23)
Ln(Size)	−0.0005	−0.0005	−0.0006	−0.0004
	(-0.63)	(-0.75)	(-1.11)	(-0.90)
Ln(B/M)	0.0079***	0.0059***	0.0051***	0.0015**
	(8.04)	(5.17)	(7.58)	(2.41)
Momentum	0.0101***	0.0083***	−0.0005	0.0000
	(4.89)	(5.37)	(-0.25)	(0.01)
Illiquidity	0.0001**	0.0001***	0.0001**	0.0001**
	(2.21)	(4.42)	(2.34)	(2.19)
IdioVolt	−0.0966*	0.1731***	0.0425	−0.0857
	(-1.73)	(3.82)	(0.69)	(-1.40)
Reversal	−0.0610***	−0.0537***	−0.0437***	−0.0258***
	(-10.49)	(-9.44)	(-5.45)	(-4.19)

Notes: The table reports the results from estimating variations of the following equation using pooled stock-month observations for different decades in our sample period (Column [1] 1980s, Column [2] 1990s, Column [3] 2000s, and Column [4] 2010s):

$$\begin{aligned} Return_{i,t+1} = \beta_0 + \beta_1 Nearness_{i,t} + \beta_2 Beta_{i,t} \\ + \beta_3 Ln(Size_{i,t}) + \beta_4 Ln(B/M_{i,t}) + \beta_5 Momentum_{i,t} \\ + \beta_6 Illiquidity_{i,t} + \beta_7 IdioVolt_{i,t} + \beta_8 Reversal_{i,t} + \varepsilon_{i,t+1}. \end{aligned}$$

The dependent variable, $Return_{i,t+1}$, is the return for stock i in month $t+1$. The independent variable of interest is $Nearness_{i,t}$, which is the ratio of the closing monthly price in month t scaled by the 52-week high. The remaining control variables have previously been defined. We report t statistics in parentheses obtained using Newey and West (1987) correction with three lags. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

strong that a regression to the anchor occurs when stocks move away from that anchor.

%Δ*Nearness* return premium: cross-sectional tests

In our first set of tests in this subsection, we estimate specifications of the following cross-sectional regression equation:

$$\begin{aligned} Return_{i,t+1} = \beta_0 + \beta_1 \%\Delta Nearness_{i,t} + \beta_2 Beta_{i,t} \\ + \beta_3 Ln(Size_{i,t}) + \beta_4 Ln(B/M_{i,t}) \\ + \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} \\ + \beta_7 IdioVolt_{i,t} + \beta_8 Reversal_{i,t} + \varepsilon_{i,t+1}. \end{aligned} \quad (3)$$

The only difference between equations (2) and (3) is the independent variable of interest, which is now %Δ*Nearness* as opposed to level *Nearness*. Given our findings in Table 5, we expect that, in these Fama and MacBeth (1973) regressions, the coefficient on %Δ*Nearness* to be negative and significant. This would be consistent with our anchor reversion hypothesis. Such a coefficient suggests that, after controlling for other stock characteristics, movements away from the 52-week high predict positive next-month returns. The results of this analysis are reported in Table 6, with t statistics in parentheses obtained from Newey and West (1987) standard errors that use three lags.

In the simple regression in column [1], which only includes the independent variable of interest, the coefficient on %Δ*Nearness* is −0.0360 ($t = -11.29$). In economic terms, this result suggests that a one–standard deviation increase in %Δ*Nearness* is associated with a reduction in next-month returns of 1.3%. These findings suggest that the coefficient on %Δ*Nearness* is both statistically and economically significant. We draw similar inferences in the remaining columns in Table 6 as the coefficient on %Δ*Nearness* ranges between −0.0343 and −0.0366 when including different combinations of control variables. These results again support the findings in the previous subsection and suggest that movements away from the 52-week high generate positive return premia. The results thus far, however, could be simply capturing the short-term reversals described in the previous empirical asset pricing literature (see, e.g., Jegadeesh 1990). In the full model specification in column [8], we include the *Reversal* control which, as expected, is negatively related to next-month returns. However, despite controlling for short-term reversals, %Δ*Nearness* still produces a negative and significant estimate (coefficient = −0.0264, $t = -8.18$) that is both highly statistically reliable and economically meaningful. In economic terms, a one–standard deviation decrease in %Δ*Nearness* is associated with a 130–basis point increase in next-month returns. These findings support the premise that anchor reversion impacts asset prices.

Table 7 presents the results from estimating equation (3) for the different decades in our sample period. Columns [1] through [4] show the results from the 1980s, 1990s, 2000s, and 2010s, respectively. Again, for brevity, we focus our discussion on the independent variable of interest, %Δ*Nearness*. As can be seen, the coefficient on %Δ*Nearness* is negative and significant across each of the periods. The coefficients range from −0.0195 (in the 1980s) to −0.0430 (in the 1990s). The coefficient on %Δ*Nearness* for the most recent period is −0.0212 ($t = -2.55$). These findings suggest that the negative return premium associated with %Δ*Nearness* is robust across time and robust to controls for various stock characteristics. Combined, our findings suggest that movements away from the 52-week high are associated with positive and significant return premia.

Table 5. %ΔNearness return premium: portfolio tests.

Panel A. Equal-Weighted Portfolio Returns (Equal-Weighted Market Index)						
	Q I [1]	Q II [2]	Q III [3]	Q IV [4]	Q V [5]	Q V – Q I [6]
Mean Returns	0.0211***	0.0124***	0.0122***	0.0103***	0.0049*	−0.0162***
	(6.17)	(5.24)	(5.80)	(4.79)	(1.78)	(-8.72)
CAPM Alphas	0.0062***	0.0007	0.0015***	−0.0006	−0.0078***	−0.0140***
	(6.09)	(1.51)	(3.19)	(-1.11)	(-9.96)	(-8.98)
FF3F Alphas	0.0066***	0.0005	0.0014***	−0.0009*	−0.0075***	−0.0141***
	(6.17)	(0.94)	(2.90)	(-1.77)	(-9.15)	(-8.45)
FF4F Alphas	0.0080***	0.0001	0.0004	−0.0014**	−0.0071***	−0.0152***
	(5.82)	(0.23)	(0.70)	(-2.25)	(-7.83)	(-7.12)
Panel B. Value-Weighted Portfolio Returns (Value-Weighted Market Index)						
Mean Returns	0.0213***	0.0185***	0.0160***	0.0145***	0.0152***	−0.0061***
	(7.47)	(8.64)	(8.32)	(7.23)	(6.23)	(-3.26)
CAPM Alphas	0.0010	0.0018**	0.0004	−0.0015**	−0.0028***	−0.0038**
	(0.74)	(2.48)	(0.78)	(-2.00)	(-2.94)	(-1.98)
FF3F Alphas	0.0013	0.0018**	0.0005	−0.0017**	−0.0027***	−0.0040**
	(0.96)	(2.33)	(0.86)	(-2.38)	(-2.71)	(-2.04)
FF4F Alphas	0.0030**	0.0019**	−0.0001	−0.0016**	−0.0019*	−0.0049**
	(2.05)	(2.20)	(-0.24)	(-2.07)	(-1.88)	(-2.28)

Notes: The table reports the monthly mean returns and alphas from estimating the capital asset pricing model as well as three-factor (Fama and French 1993) and four-factor (Carhart 1997) models. Panel A reports the results for equally weighted portfolios sorted into quintiles based on the variable %Δ*Nearness*. Q1 represents the portfolio of stocks furthest away from their 52-week high, while Q5 represents the portfolio of stocks closest to their 52-week high. The final column reports the difference between the Q5 and Q1 portfolios with a corresponding *t* statistic. Panel B reports results from a portfolio analysis similar to that of Panel A but where stocks are sorted into portfolios where stocks are value-weighted instead of equally weighted. Portfolios are obtained by sorting stocks based on last month's change in the nearness ratio. The estimates are obtained using variations of the following equation.

$$Excess\ Return_{p,t} = \alpha + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{p,t}.$$

The dependent variable is the monthly excess return of the portfolio over the T-Bill yield in period *t*. The independent variables include the following in time *t*: *MRP*, which is the market risk premium or the difference between market return and the risk-free rate; *SMB*, which is the small-minus-big return factor; the high-minus-low return factor, *HML*; and the up-minus-down factor, *UMD*. Reported *t* statistics were obtained using White (1980) robust standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 6. %ΔNearness return premium: cross-sectional regressions.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Intercept	0.0114***	0.0118***	0.0357***	0.0275***	0.0270***	0.0233**	0.0282***	0.0245***
	(4.00)	(4.39)	(3.57)	(2.66)	(2.71)	(2.35)	(3.71)	(3.33)
%Δ*Nearness*	−0.0360***	−0.0362***	−0.0361***	−0.0366***	−0.0352***	−0.0343***	−0.0347***	−0.0264***
	(-11.29)	(-11.64)	(-12.05)	(-12.38)	(-12.04)	(-11.72)	(-12.34)	(-8.18)
Beta		−0.0006	−0.0003	−0.0001	−0.0004	−0.0003	−0.0000	−0.0001
		(-1.03)	(-0.48)	(-0.21)	(-0.59)	(-0.45)	(-0.05)	(-0.17)
Ln(Size)			−0.0013***	−0.0008	−0.0008*	−0.0006	−0.0008**	−0.0006*
			(-2.99)	(-1.64)	(-1.73)	(-1.35)	(-2.24)	(-1.80)
Ln(B/M)				0.0055***	0.0056***	0.0054***	0.0053***	0.0053***
				(8.44)	(9.55)	(9.57)	(10.29)	(10.22)
Momentum					0.0026*	0.0030**	0.0030**	0.0035***
					(1.91)	(2.15)	(2.27)	(2.70)
Illiquidity						0.0001***	0.0001***	0.0001***
						(3.95)	(4.58)	(4.47)
IdioVolt							−0.0910***	−0.0572
							(-2.63)	(-1.53)
Reversal								−0.0180***
								(-4.19)

Notes: The table reports the results from estimating variations of the following equation using pooled stock-month observations:

$$Return_{i,t+1} = \beta_0 + \beta_1 \%\Delta Nearness_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Ln(Size_{i,t}) + \beta_4 Ln(B/M_{i,t}) + \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} + \beta_7 IdioVolt_{i,t} + \beta_8 Reversal_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable, $Return_{i,t+1}$, is the return for stock *i* in month $t+1$. The independent variable of interest is $\%\Delta Nearness_{i,t}$, which is the month-over-month percentage change in the ratio of the closing monthly price in month *t* scaled by the 52-week high. The remaining control variables have previously been defined. We report *t* statistics in parentheses obtained using Newey and West (1987) correction with three lags. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. %ΔNearness return premium: sample period partitions.

	1980s [1]	1990s [2]	2000s [3]	2010s [4]
Intercept	0.0273	0.0269*	0.0278*	0.0162
	(1.52)	(1.75)	(1.94)	(1.63)
%Δnearness	−0.0195***	−0.0430***	−0.0220***	−0.0212**
	(-6.96)	(-9.84)	(-2.84)	(-2.55)
Beta	−0.0005	0.0008	−0.0009	−0.0002
	(-0.58)	(0.97)	(-0.57)	(-0.48)
Ln(Size)	−0.0006	−0.0008	−0.0008	0.0016***
	(-0.69)	(-1.13)	(-1.31)	(2.58)
Ln(B/M)	0.0080***	0.0060***	0.0054***	0.0016***
	(7.77)	(5.10)	(7.33)	(2.58)
Momentum	0.0096***	0.0057***	−0.0027	0.0014
	(4.51)	(3.75)	(-0.78)	(0.66)
Illiquidity	0.0001**	0.0001***	0.0001**	0.0001**
	(2.23)	(4.45)	(2.46)	(2.44)
IdioVolt	−0.1244**	0.1230**	−0.0545	−0.1739**
	(-1.99)	(2.20)	(-0.61)	(-2.38)
Reversal	−0.0429***	−0.0169***	−0.0128	0.0008
	(-6.56)	(-2.89)	(-1.31)	(0.09)

Notes: The table reports the results from estimating variations of the following equation using pooled stock-month observations for different decades in our sample period (Column [1] 1980s, Column [2] 1990s, Column [3] 2000s, and Column [4] 2010s):

$$Return_{i,t+1} = \beta_0 + \beta_1\%\Delta Nearness_{i,t} + \beta_2 Beta_{i,t} + \beta_3 Ln(Size_{i,t}) + \beta_4 Ln(B/M_{i,t}) + \beta_5 Momentum_{i,t} + \beta_6 Illiquidity_{i,t} + \beta_7 IdioVolt_{i,t} + \beta_8 Reversal_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable, $Return_{i,t+1}$, is the return for stock i in month $t+1$. The independent variable of interest is $\%\Delta Nearness_{i,t}$, which is the month-over-month percentage change in the ratio of the closing monthly price in month t scaled by the 52-week high. The remaining control variables have previously been defined. We report t statistics in parentheses obtained using Newey and West (1987) correction with three lags. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In our final set of tests, we attempt to disentangle whether movements away from or movements toward the 52-week high are driving the results. To do so, we estimate the following equation using our pooled sample of stock-month observations:

$$Return_{i,t+1} = \beta_0 + \beta_1 Away_{i,t} + \beta_2 Closer_{i,t} + \beta_3 Beta_{i,t} + \beta_4 Ln(Size_{i,t}) + \beta_5 Ln(B/M_{i,t}) + \beta_6 Momentum_{i,t} + \beta_7 Illiquidity_{i,t} + \beta_8 IdioVolt_{i,t} + \beta_9 Reversal_{i,t} + \varepsilon_{i,t+1}. \quad (4)$$

The dependent variable is the next-month return for each stock i in month t. The control variables have previously been defined. The independent variables of interest are *Away* and *Closer*. *Away* is defined as *%ΔNearness* if the change in *Nearness* is negative and zero otherwise. Likewise, *Closer* is the *%ΔNearness* if the change is positive and zero otherwise. If movements away from the 52-week high generate positive return premia, then we expect a significant negative coefficient on *Away*. If movements toward the 52-week high generate negative return premia, then we expect to observe a significant, negative estimate for *Closer*. Table 8 presents the results of the analysis. Again, we note that t statistics are obtained from Newey and West (1987) standard errors that use three lags.

In columns [1] and [2], we report different specifications that focus primarily on the independent variable of interest *Away*. We do so by excluding the variable *Closer* in this portion of the analysis. We find in both the simple regression in column [1] and the regression including all of the control variables in column [2], *Away* produces a negative and significant coefficient. These findings suggest that as the truncated variable *Away* decreases, next-month returns increase significantly. Columns [3] and [4] show the results focusing on the variable *Closer* while excluding *Away*. In the simple regression in column [3], *Closer* produces a negative estimate suggesting that as *Closer* becomes more positive, next-month returns become more negative. However, this result does not hold when including all of the control variables in column [4] as the estimate on *Closer* is −0.0059 ($t = -1.13$).

Columns [5] and [6] present the analysis including both *Away* and *Closer* in the same specifications. Focusing on the full model specification in column [6], we find that *Away* produces a negative and significant coefficient of −0.0293 ($t = -8.26$). Closer also produces a negative estimate (coefficient = −0.0133, $t = -2.52$). We note that the coefficient on *Away* is 2.2 times more negative than the coefficient on *Closer*. A t statistic that tests the significance of the difference between the two estimates is −2.51, suggesting that the estimate on *Away* is statistically more negative than the estimate on *Closer*.[3] Combined with our earlier results that show that changes in the nearness ratio produce a significant return premium, we find that results are stronger for movements away from the 52-week high than for movements toward the 52-week high. These findings support the idea of anchor reversion described previously. It appears that movements away from and toward the anchor are informative for future returns but that movements away from the anchor drive the return premium associated with *%ΔNearness*.

Robustness

It might be that the price reversal observed around the 52-week high is unrelated to anchoring. In an

Table 8. %ΔNearness return premium: *Away* vs. *Closer*.

	[1]	[2]	[3]	[4]	[5]	[6]
Intercept	0.0094***	0.0232***	0.0145***	0.0219***	0.0114***	0.0238***
	(3.42)	(3.14)	(5.27)	(2.96)	(4.34)	(3.27)
Away	−0.0419***	−0.0289***			−0.0375***	−0.0293***
	(-9.96)	(-8.24)			(8.42)	(-8.26)
Closer			−0.0609***	−0.0059	−0.0454***	−0.0133**
			(-8.94)	(-1.13)	(-6.70)	(-2.52)
Beta		−0.0002		−0.0001		−0.0001
		(-0.29)		(-0.25)		(-0.24)
Ln(Size)		−0.0006*		−0.0005		−0.0006*
		(-1.69)		(-1.46)		(-1.75)
Ln(B/M)		0.0053***		0.0053***		0.0053***
		(10.30)		(10.31)		(10.32)
Momentum		0.0042***		0.0046***		0.0038***
		(3.29)		(3.59)		(3.00)
Illiquidity		0.0001***		0.0001***		0.0001***
		(4.52)		(4.30)		(4.49)
IdioVolt		−0.0781**		−0.0170		−0.0713**
		(-2.08)		(-0.48)		(-1.96)
Reversal		−0.0252***		−0.0391***		−0.0204***
		(-6.47)		(-8.56)		(-4.33)

Notes: The table reports the results from estimating variations of the following equation using pooled stock-month observations:

$$Return_{i,t+1} = \beta_0 + \beta_1 Away_{i,t} + \beta_2 Closer_{i,t} + \beta_3 Beta_{i,t} + \beta_4 Ln(Size_{i,t}) + \beta_5 Ln(B/M_{i,t}) + \beta_6 Momentum_{i,t} + \beta_7 Illiquidity_{i,t} + \beta_8 IdioVolt_{i,t} + \beta_9 Reversal_{i,t} + \varepsilon_{i,t+1}.$$

The dependent variable, $Return_{i,t+1}$, is the return for stock i in month $t+1$. The independent variables of interest consist of two variables. *Away* is equal to the $\%\Delta Nearness_{i,t}$ if the change in the nearness ratio is negative and zero otherwise. *Closer* is equal to the $\%\Delta Nearness_{i,t}$ if the change in the nearness ratio is positive and zero otherwise. We note that $\%\Delta Nearness_{i,t}$ is the month-over-month change in the ratio of the closing monthly price in month *t* scaled by the 52-week high. The remaining control variables have previously been defined. We report *t* statistics in parentheses obtained using Newey and West (1987) correction with three lags. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

attempt to provide evidence that anchoring bias is an economic mechanism driving the results, we examine an alternative historical price reference point that is not widely established as an anchor. More specifically, we use the previous calendar year's closing price as the anchor. We then reestimate our main cross-sectional regressions using nearness and percentage change in nearness to that reference point. Although unreported, after controlling for other factors, it does not appear that movements away from the previous year's closing price are predictive of future returns.[4] This provides further evidence that the results reported in the paper are a function of anchoring bias to the widely reported 52-week high.

Conclusion

In this study, we examine a novel idea of anchor reversion, which states that large movements away from an anchor are more likely to be followed by movements back toward the same anchor. To explore this hypothesis, we test for a return premium based on movements toward and movements away from the 52-week high, a well-recognized and highly publicized reference point. To the extent that the 52-week high acts as an anchor, then month-over-month movements away from the 52-week high should predict positive future returns. Empirically, we find that movements toward the 52-week high are associated with negative next-month returns and that movements away from the 52-week high are associated with positive next-month returns. These results hold in a portfolio setting with equal- and value-weighted market returns, in cross-sectional Fama and MacBeth (1973) regressions that control for various stock characteristics, and in various sample periods. These findings provide strong empirical support for the notion that the 52-week high can be an anchor that stock prices revert to in the short to intermediate term.

As a possible explanation for these findings, we contend that investors attempting to realize capital gains might overreact around the 52-week high reference point, which could trigger a temporary price decline that subsequently reverses back to the anchor once buying resumes. We believe that the results are consistent with the disposition effect as described in Shefrin and Statman (1985) and the empirical findings of Della Vedova, Grant, and Westerholm (2022). We fail to find consistent evidence that nearness to the 52-week high is associated with a positive momentum return premium, as outlined in George and Hwang (2004). Therefore, moving toward the 52-week high does not result in consistent underreaction by investors. Perhaps a fruitful area for future research might be to identify other reference points that investors anchor to and examine whether prices display a reversal behavior around those anchors.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. Baker, Pan, and Wurgler (2012) find that prior stock-price peaks act as reference points and affect several aspects of mergers and acquisitions. In particular, the authors find that M&A offer prices are biased toward recent price peaks and that the probability of a targets' acceptance of an acquirers' offer is higher if the offer price is above the price peak.
2. Much of the volatility forecasting literature is based on the notion of mean reversion (see, e.g., Engle, 1982; Bollerslev, Engle, and Wooldridge 1988; Bollerslev 1990; Bollerslev, Chou, and Kroner 1992; Bollerslev and Engle 1993; Engle 2002b).
3. In column [5], without including controls, both the coefficients on *Away* and *Closer* are negative and significant. The difference between the two coefficients is 0.0079, but the t statistic, testing the significance of that difference, is only 0.79, suggesting that the two estimates are statistically similar.
4. These results are available from the authors upon request.

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