Momentum crashes and an investor's anchoring bias[*]

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Abstract

Despite their strong performance of momentum strategies, they suffer from occasional large drawdowns referred as momentum crashes. We find that during the momentum crash periods, nearness to the 52-week high subsumes the predictive power of past 12-month return. It suggests that momentum crashes are due to an investor's anchoring bias. Furthermore, we provide a revised momentum strategy that is neutral on nearness to the 52-week high. The strategy is free of crashes and exhibits normal-like distribution without sacrificing its profitability.

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Keywords: momentum, momentum crash, 52-week high, anchoring bias, investor sentiment, market state

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1. Introduction

Since the seminal work of Jegadeesh and Titman (1993), momentum has been one of the most robust and pervasive anomalies. A conventional momentum strategy that longs the top decile of past 12-month winners and shorts the bottom decile of past 12-month losers earns highly positive profits over various time periods and asset classes[1]. In US market, for example, the momentum strategy generates monthly profits of 1.45% with monthly Sharpe ratio of 0.17 while the market rises up by 0.61% per month with Sharpe ratio of 0.11. Therefore, it is not a big surprise that the momentum strategy caught vast attention from both academics and practitioners.

Despite of its strong performance, the momentum strategy suffers from occasional large drawdowns referred as momentum "crashes" (Daniel and Moskowitz (2014)). In our sample, there were two noteworthy crash incidents among many: July to August of 1932 and March to April of 2009. The momentum strategy had severe losses of -88.14% and -67.43% during the crash periods of 1932 and 2009, respectively. These infrequent but persistent and strong crashes are documented in international markets, commodity market, and currency market. Chabot, Ghysels, and Jagannathan (2014) document momentum crashes even in the Victorian-era London.

An examination on the momentum crashes is worthwhile to both practitioners and academicians. In practice, the crashes contribute significantly to the negative skewness and the excessive kurtosis of the momentum strategy returns, which in turn makes the momentum strategy undesirable as a long-term trading strategy. If an investor had invested his wealth on the momentum strategy at the beginning of July 1932, for example, it would have taken nearly 30 years for him to recover his loss from the crash period of 1932. At the same time, the crashes also implies that a precise prediction of the crashes can significantly improve the profitability

[1] The profitability of momentum strategy is documented in international stock markets (Rouwenhortst, 1998), equity indices, currencies, commodity futures markets (Asness, Moskowitz, and Pedersen, 2013), and it dates back to 1800s (Geczy, and Samonov, 2013).

of the momentum strategy [2]. Academically, momentum crashes can be a key to the understanding of the continued profitability of the momentum strategy. After it became well known in the early 1990s and attracted vast investors, it seemed to have disappeared in the early 2000s (Chordia, Subrahmanyam, and Tong, 2013). However, it reappeared in recent years. If the crash risk is hard-wired into the momentum strategy and the crash risk is not captured by traditional factor models, it can explain why the momentum strategy continuously earns high profits.[3]

Therefore the literature had focus extensively on timing of the momentum strategy. The most commonly documented regularity in momentum crashes is that their occurrence are concentrated on the market rebound. For example, Asem and Tian (2010) finds that momentum earns significantly negative profits when the past 12 months market return is negative and the concurrent market return is positive. Daniel and Moskowitz (2014) also find that 14 of the 15 worst momentum returns had occurred when the lagged two-year market return was negative and the market rose contemporaneously.

As to why momentum crashes, the particular timing of the momentum crashes has attracted the risk-based explanation. Since the momentum strategy is constructed based on the stocks' past returns, the risk loading of the strategy depends on the past market return (Kothari and Shanken (1992)). If the momentum portfolios are formed after the market decline, the momentum strategy that longs past winners and shorts past losers is likely to load negatively on the market. Hence when the market rebound, this negative risk loadings on the market drives momentum

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[2] Many researches had identified the determinants of momentum profits such as business conditions (Chordia and Shivakumar, 2002), the past market return (Cooper, Gutiereez, and Hameed, 2004; Asem and Tian, 2010), past market volatility (Wang and Xu, 2010), past market liquidity (Avaramov, Cheng, and Hameed, 2014), the market's recent cross-sectional dispersion in stock returns (Stivers and Sun, 2010) and others. Building on these research, Daniel and Moskowitz (2014), Barroso and Santa-Clara (2015), Heidari(2015), and Daniel, Jagannathan and Kim (2012) provides their own version of momentum strategy that is free of crashes and exhibit near-zero skewness and low volatility.

[3] Chabot, Ghysels, and Jagannathan (2014) takes this route and argue that "the periodic crashes are what keep momentum alive." They argue that the high profitability of the momentum strategy attracts the blind capital which makes the strategy more likely to crash. When crashes occur, the capital move away from the momentum strategy which in turn revives the profitability of the momentum strategy.

to crash. Grundy and Martin (2001) shows that hedging this dynamic risk exposure reduces return volatility and improve the poor performance of momentum strategy.

However, Daniel and Moskowitz (2014) find that the result of Grundy and Martin (2001) is biased and hence the risk only partly explains the momentum crashes. They argue that Grundy and Martin's (2001) ex-post estimate of the market beta is overestimated due to optionality of the momentum losers. They document that an ex-ante market hedged momentum strategy still experiences severe losses. Hence, they argue that the momentum crashes because the optionality of the losers are not reflected in the market price[4]. Asem and Tian (2010) provide another behavioral explanation based on the model of Daniel, Hirshleifer, and Subrahmanyam (1998)[5]. They argue that when the market rebound, overconfidence of the short-sellers attenuate, and hence the overreaction is muted. Therefore the momentum strategy, which stems from the continuing overreaction of investors, does not earn profits.

In this paper, we address the question why momentum crashes. We hypothesize that momentum crashes are due to investor's anchoring bias and document empirical results that are consistent with our hypothesis.

We argue that the large demand on stocks far from their 52-week highs during the market rebound drives momentum to crash. As the market dramatically rebounds from its long-lasting downturn and as the market-wide sentiment recovers from its trough, investors become more prone to behavioral bias (or investors prone to behavioral bias flow into the market). Since these bias-prone investors anchor on the 52-week highs, demand on stocks that are far from their 52-week highs increases, which results in their price run-up. Then, the conventional momentum strategy that longs winners and shorts losers "crashes" because past 12-month losers are likely to be stocks that are far from their 52-week highs. In other words, as the market

[4] Daniel and Moskowitz (2014) employ Merton (1974)-style theory to support the optionality of the losers. However, they acknowledge that the theory does not apply to other types of securities such as currencies. Furthermore, they does not explicitly explain why the optionality is not priced.

[5] Cooper, Gutiereez, and Hameed (2004), and Avaramov, Cheng, and Hameed (2014) also employ the model of Daniel, Hirshleifer, and Subrahmanyam (1998) to explain the dependence of the momentum profits on the past market return and illiquidity.

index run up, investors seek stocks that will rebound the most and their natural choice is the stocks that have enough room to run. To anchoring-susceptible investors, stocks that are far from their previous price peaks would be the first that comes to mind. Hence, the momentum strategy crashes because stocks with high anchoring price outperform stocks with low anchoring price and a momentum measure is just a mirror image of nearness to the 52-week high.

Next, we test the empirical implication of our hypothesis: the dominant role of nearness to the 52-week highs during the momentum crash periods. For the richer economical interpretation and statistical reliability, we do not restrain our empirical investigation on just few momentum crash months, but focus extensively on the market rebound periods. Specifically, we define momentum crash periods as months when the contemporaneous market return is positive and the past 1-year cumulative market return is negative. We test several empirical predictions based on our hypothesis. We first predict that, during the momentum crash periods, stocks far from their 52-week highs (anchoring losers) will outperform stocks near their 52-week highs (anchoring winners). Second, anchoring losers will still outperform anchoring winners when their momentum measure is set to be similar. Third, holding nearness to the 52-week highs constant, the past 12-month losers (momentum losers) will no longer outperform the past 12-month winners (momentum winners) during the crash periods.

In our 1927 to 2013 US market data, we find that the top 10% of stocks that are near their 52-week highs earns a monthly return of 3.36% while the bottom 10% earns 11.99% per month during the crash periods. The anchoring losers outperform the anchoring winners by a large margin (8.63%) which is both statistically and economically significant. Interestingly, the momentum losers outperform momentum winners by 5.07% during the same period. This smaller return dispersion is suggestive of the dominant role of nearness to the 52-week highs during the crash periods. Moreover, when the nearness to 52-week highs are accounted for, the momentum winners and losers show return patterns that are distinct from previous studies. Among the momentum losers, the anchoring losers rebound by 10.37% during the crash periods while the anchoring winners fall by 2.33%. Similarly among the momentum winners, the anchoring losers shows dramatic rebound of 12.62%. Furthermore, when the nearness to the

52-week highs are set to be similar, the momentum losers no longer outperform the momentum winners. Among bottom 20% of stocks far from their 52-week highs, for example, momentum winners earn 12.62% while momentum losers earn 10.73%.

Having established that the anchoring bias is the main driver of momentum crashes, we revise the conventional momentum strategy to become anchoring-neutral. We find that the anchoring-neutral momentum strategy is free of crashes and exhibits more normal-like distribution, which makes it more desirable as a long-term investment strategy. In our sample, revising the momentum strategy increases the minimum monthly return from -70.63% to -25.41%, skewness from -1.82 to 0.02, and monthly Sharpe ratio from 0.17 to 0.31. Moreover, we find that the anchoring-neutral momentum strategy vary much less with the market condition, business cycle, and investor sentiment. Most importantly, the anchoring-neutral momentum strategy does not sacrifice its profitability to attain aforementioned desirable attributes.

We contribute to the literature in three aspects. First, we find that in cross-section, not all the momentum losers (winners) outperform (underperform) the market. We find that the momentum losers (winners) that are near (far from) their 52-week highs underperform (outperform) the market during the crash periods. To our knowledge, this is a unique finding that has never been documented and poses challenges to the existing explanations on the momentum crashes. Our results still hold after the risk-adjustment, and there is no ex-ante apparent reason why momentum losers that are near and far from their stocks have different optionality or the degree of investors' overconfidence.

Second, we provide a concise and consistent behavioral explanation on momentum crashes. Our explanation that anchoring bias is the driving force behind momentum crashes can explain when and why crashes occur, and is qualitatively different from previous explanations. Previous studies such as Daniel and Moskowitz (2014) and Asem and Tian (2010) suggest an explanation that applies to momentum winners and losers as a whole. Hence, though their model can successfully address the timing of the momentum crashes, they cannot explain aforementioned cross-sectional return pattern within winners and losers. In contrast, since our explanation relies on individual stock characteristics, it can explain not only the timing of momentum crashes but also the cross-sectional pattern within the momentum winners and losers.

Third, we suggest a revised momentum strategy that generates positive profit without crash. Our strategy, without sacrificing its profitability, significantly improves over the conventional momentum strategy in that its moments are much desirable to investors. Our revision on the momentum strategy also differs from other studies. Other studies also present their own version of momentum strategy in a spirit to avoid momentum crashes. For example, Barroso and Santa-Clara (2015) suggest that the momentum strategy is improved if it is scaled by its trailing volatility. They report that their version of momentum strategy has a minimum return of -28.40%, and a skewness of -0.42. Daniel, Jagannathan, and Kim (2012) also shows that moving to the risk-free asset during their definition of "turbulent state" can significantly improve the traditional momentum strategy. Likewise, previous studies mostly focus on the dynamic weighting scheme of the momentum strategy based on their prediction of the momentum crashes.[6] Our improvement, however, is restricted to the stock-selection technique hence is less prone to short-sale constraint, leverage constraint and trading costs.[7]

The rest of the paper is organized as follows. The next section describes data and measures employed in our empirical research. Section 3 tests our hypothesis that anchoring bias drives momentum crashes. Section 4 introduces the anchoring-neutral momentum strategy that is free from crashes. Section 5 concludes our paper.

2. Data and Variables

In this section, we describe our data and variables employed in our empirical research. We use data of all NYSE/NYSE MKT/NASDAQ listed securities on the Center for Research in Security Prices (CRSP) daily and monthly tape. We only include ordinary common shares (ADRs, REITs, closed-end funds were excluded). Book equity data, monthly risk-free rates and

[6] Yan (2013) is a notable exception.

[7] Heidari (2015) find that the dynamic weighting scheme suffers from a high turnover because the weight is based on the volatile variables

Fama and French (1993) three factors are from Ken French's website.[8] Firm fundamentals are from COMPUSTAT database. Our sample period covers from January 1926 to December 2013.

Our two main variables are momentum and anchoring measures. Following, Daniel and Moskowitz (2014), we define a momentum measure of a stock *i* at month *t-1* as its cumulative returns from the beginning of month *t-12* to the end of month *t-2*. Our anchoring measure is a nearness to the 52-week high that is first proposed by George and Hwang (2004). Nearness to the 52-week high at each month is the ratio of the price at the end of month *t-1* to the highest price during the past 12 months. A definition on the other firm-specific variables is provided in the appendix. At month *t*, a stock *i* is included in our sample if and only if $r_{i,t}$, $Momentum_{i,t-1}$, $Anchroing_{i,t-1}$, $Srev_{i,t-1}$, $Beta_{i,t-1}$, $ME_{i,t-1}$, $BM_{i,t-1}$, $Price_{i,t-1}$ measures are valid[9]. This data trimming rule results in total of 2,215,669 firm-months.

Since our study focuses on the role of anchoring when momentum crashes, it is necessary to define the "crash period". Table 1 summarizes the 15 largest momentum crashes. Consistent with extant literature, the momentum crashes when the market rebound from its large drawdown. On August 1932, for example, when the momentum strategy earned -70.63%, the market rose by 37.14% after the market crash of 1929. Therefore, for the richer economical interpretation and statistical reliability, we do not restrain our empirical investigation on the 15 largest momentum crash months but focus extensively on the market rebound periods. Specifically, we define crash periods as months that the contemporaneous market return is positive and the past 1-year cumulative market return is negative. Market return is defined as the CRSP value-weighted index return. Of 15 months in table 1, 14 months matches our definition of the crash periods. The definition is also consistent with previous studies including Asem and Tian (2010) and Daniel and Moskowitz (2014). Our definition of market state recognizes 148 out of 1044 months as the "crash periods".

[Table 1 about here]

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[8] Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

[9] Every variable is time-indexed *t* if it is observable at the end of the month *t*. See Appendix for the details.

3. Dominance of anchoring during crash periods

3.1 Univariate analysis

In this section, we examine how momentum and anchoring measure is related to the cross-section of stock returns. At the beginning of each month, stocks are ranked based on their momentum and anchoring measures. Based on these rankings, value-weighted decile portfolios are formed, and stocks are held until the end of the next month. To mitigate microstructure effects associated with low price stocks, stocks are excluded if their prices at the end of the formation period is below $1. We also form a hedge portfolio that longs the top decile and shorts the bottom decile.

We control for risk by calculating risk-adjusted return,

$$r_{p,t}^{risk-adjusted} = r_{p,t}^{raw} - \sum_{i=1}^{n} \widehat{\beta_{i,p}} f_{i,t} \tag{1}$$

where $r_{p,t}$ is the return on portfolio p at month t, n is the number of factors, $f_{i,t}$ is the realization of the i-th factor at month t. $\widehat{\beta_{i,p}}$ is calculated by estimating equation (2) using the full-sample regression.

$$r_{p,t}^{raw} - r_f = \sum_{i=1}^{n} \beta_{i,p} f_{i,t} \tag{2}$$

We use CAPM and Fama and French (1996) three factor model (FF) as our risk-return model.

[Table 2 about here]

Table 2 reports raw and risk-adjusted returns of the decile portfolios formed based on momentum and anchoring measure. Panel A of Table 2 restates the profitability of momentum strategy and its crashes. During the crash periods (panel A1), the monthly return monotonically decreases from the bottom decile to the top decile. The momentum losers earn monthly return of 10.00%, while the momentum winners earn 4.93%. Therefore, the momentum strategy earns −5.07% per month when the market rebound. CAPM and FF-adjusted return is −2.22% and

−2.00%, respectively. Significantly negative risk-adjusted returns of the momentum strategy during the crash periods is consistent with Daniel and Moskowitz (2014) and others who report that the risk only partly explains momentum crashes. Outside the crash periods (panel A2), the momentum strategy earns statistically and economically large monthly profit of 2.56%. Controlling for risk reduces the profitability only by a small margin consistent with Jegadeesh and Titman (1993) and numerous other studies.

Panel B of Table 2 reports monthly raw and risk-adjusted return of the decile portfolios formed based on the nearness to the 52-week highs. During the crash periods (panel B1), the anchoring losers outperform anchoring winners by 8.63% per month. It is noteworthy that the outperformance of the anchoring losers over the anchoring winners is more distinct than the result of panel A1. Irrespective of the risk-return models, a hedge portfolio that longs the anchoring winners and shorts the anchoring losers earns negative returns roughly 50% bigger than the momentum strategy. CAPM and FF adjusted monthly return of the anchoring winner minus loser portfolio is −3.18% and −2.85% while the return of the momentum winner minus loser portfolio is −2.22% and −2.00%, respectively. The dominance comes mostly from the short side of the portfolio. In other words, stocks that are far from their 52-week highs outperform the market during crash periods more than stocks that has fallen in prices for the past 12-months do. Outside the crash periods (panel B2), the anchoring winners outperform the anchoring losers as documented in George and Hwang (2004). However, the profitability of the anchoring winner minus loser portfolio is smaller in magnitude than the momentum strategy.

The results of the table 2 shows empirical pattern consistent with our hypothesis that increased demand on anchoring losers during the market rebound pushes their prices up. Furthermore, it is suggestive of the dominance of the anchoring measure over the momentum measure during the crash periods. During the crash periods, anchoring winners underperform anchoring losers by far more than momentum winners underperform momentum losers. Hence it is plausible that during the times of the momentum crashes, it is stocks that are far from the 52-week highs that rebounds, and momentum losers are just a resembling collection of such stocks. On the contrary, outside the crash periods, we find that the anchoring winner minus loser strategy does not dominates the momentum winner minus loser strategy. It suggests that the dominance is unique to the market rebound period and hence the dominance should be considered alongside the market condition.

3.2 Bivariate analysis

We take a closer look at the interaction between momentum and anchoring measure during the crash periods using the double-sort analysis. Table 3 reports monthly raw and risk-adjusted returns of portfolios independently double sorted by momentum and anchoring measure during crash periods. At each month *t*, firms are divided into quintiles based on their momentum and anchoring measure, which results in 25(5×5) portfolios. We report the value-weighted return of each portfolio during the crash periods. The bottommost row, and the rightmost column reports the monthly average value-weighted return of the long-short portfolio. Due to high cross-sectional correlation between momentum and anchoring measure, cells are not evenly balanced and sometimes empty. Hence, for the long-short portfolio, both long and short side of the portfolio should be nonempty to be included in the analysis of table 3.

We find remarkably consistent result that the anchoring measure dominates the momentum measure. First, the anchoring losers outperform the anchoring winners even when their momentum measures are set to be similar. Among stocks in the top momentum quintile, for example, top 20% stocks that are near their 52-week highs underperform the bottom 20% by 9.23% per month. Accounting for risk does not reduces the large returns dispersion. The same pattern is consistently observed in the other momentum quintiles. In every momentum quintiles, anchoring losers outperform anchoring winners by more than -7%. Second, when stocks have similar level of the anchoring measure, the momentum measure no longer predicts returns. Within bottom 20% of stocks that are far from their 52-week highs, for example, the top momentum quintile portfolio and the bottom quintile portfolio shows small return differential, which is statistically insignificant. In some anchoring quintiles, the momentum winners even outperform losers as opposed to the previous literature. Irrespective of the risk-return models, the momentum losers never significantly outperform the momentum winners when their anchoring measure is set to be similar. Third, among 25 portfolios we examined, the five portfolios that rebounded the most during the crash periods are not the momentum losers but the anchoring losers exclusively. Again, the five portfolios that fell the most are anchoring winners, not the momentum winners.

[Table 3 about here]

To mitigate the negative effect of empty or sparse cells on the statistical reliability, we also do conditional double-sorts. At the beginning of each month, we group stocks into quintiles based on their anchoring measure. Within each anchoring quintile, we group stocks into deciles based on their momentum measure, which results in 50 value-weighted evenly-spaced portfolios. We hold the stocks until the end of the month. Then we form ten cohorts by equal-weighting five portfolios from the same momentum decile. As a result, we construct ten portfolios with equal number of stocks, similar level of the anchoring measure (anchoring-neutral) and different level of the momentum measure. For future reference, we call these portfolios an anchoring-neutral momentum winners and losers.

Table 4 reports raw and risk-adjusted return of the anchoring-neutral momentum portfolios and the winner minus loser portfolio (WML*) during the crash periods. Panel A reports average anchoring and momentum measure of each portfolio. The ten portfolios have similar level of anchoring measure. The anchoring-neutral momentum winners are on average only 6.09% closer to their 52-week highs than the losers. In contrast, the momentum measure of the winners is 73.12% higher than the losers. Panel B shows that despite the huge dispersion of the momentum measure among ten portfolios, their raw and risk-adjusted returns are almost the same. The raw returns of ten portfolios fall within the narrow range of 6.57% to 8.12%. Therefore, WML* earns statistically insignificant returns. The raw, CAPM and FF adjusted return of WML* is 1.55%, 0.59% and 0.67%, respectively. Given that the raw return of WML is -5.07%, the improvement from setting the anchoring measure constant is large.[10]

[Table 4 about here]

Bivariate analysis provides a clear picture that the anchoring measure dominates the

[10] Description and further investigation on the anchoring-neutral momentum portfolios and WML* will appear again in section 4

momentum measure during the momentum crash periods. Although momentum winners were known to underperform momentum losers, when their nearness to the 52-week highs is set to be similar, momentum winners no longer underperform losers. Moreover, it is anchoring losers not momentum losers that rebound during the crash periods. The results so far indicates that momentum crashes, not because momentum losers outperform momentum winners, but because anchoring losers outperform anchoring winners and the momentum measure is just a noisy proxy of the anchoring measure. This finding is consistent with our explanation that investors' anchoring biases drives momentum to crash.

3.3 Robustness check: alternative test setups

We test whether the dominance of the anchoring measure robustly holds for other test setups. For brevity, we compare raw and risk-adjusted return of the conventional momentum winner minus loser portfolio (WML) and the anchoring-neutral momentum winner minus loser portfolio (WML*) under different test setups. Specifically, panel A of table 5 compares WML and WML* returns during the crash periods when our samples are restricted: stocks whose price exceed $5, stocks listed in NYSE, NYSE MKT, and NASDAQ. In every cases, WML earns significantly negative returns while WML* earns positive returns. In panel B, we employ alternative definition of the crash periods. When we define the crash periods as months that the past 2-year or 3-year return is negative and contemporaneous return is positive, WML earns significantly negative returns while WML* earns positive returns. We also define the momentum crash periods as the 100 largest months when the momentum crashed the most. In these months, WML earns -15.84% on average. However, the return of WML* dramatically increases to -3.09%. In panel C, we define the momentum measure in alternative ways: the past 12-month return without skipping 1-month, recent 6-month return, and intermediate 6-month return. In all cases, WML* is much higher than WML. In panel D, we employ alternative definitions of the anchoring measure: nearness to the 52-week low, nearness to the 26-week high and unrealized capital gains as proposed by Grinblatt and Han (2005). WML* again earns insignificant returns while WML earns less than 2%.

[Table 5 about here]

3.4 Robustness check: cross-sectional regression analysis

To further test the robustness of our results, we run Fama and Macbeth (1973) regression. By running cross-sectional regression at each crash months, we are able to distinguish marginal effect of the anchoring and momentum measure on subsequent stock returns in the presence of other variables. Table 6 reports time-series average and t-statistics of the coefficients from the 148[11] cross-sectional regressions.

[Table 6 about here]

In Model 3 of table 6, the average coefficient on momentum is significantly negative, which is consistent with extant literature that momentum losers earn higher returns than winners during the crash periods. However, when nearness to the 52-week high is included as an independent variable (model 4), the average coefficient on momentum turns positive and no longer has predictive power on future returns. Anchoring measure, however, is negative and statistically significant with p-value less than 1%. Including additional control variables (model 5 and model 6) does not change our result. When the anchoring measure is excluded, the coefficient on the momentum measure is -0.0279 and is statistically significant at 1% level. However, when the anchoring measure is included, the coefficient becomes insignificantly positive. In addition, a comparison between model 2, 4 and 6 further reveals that other firm-specific characteristics cannot account for the dominance of anchoring measure.

Although table 6 supports that anchoring measure subsumes the predictive power of momentum measure during crash periods, we need to zero in on extreme months when momentum crashed the most. Since the crash periods consist of more than 100 months, it is possible that positive signs on the momentum measure (see model 4 of table 6) are driven by modest crash months while the coefficient on momentum remains significantly negative during extreme crash months. Therefore, we focus on months with the largest crash. In Table 7, we report cross-sectional regression coefficients of model 4 in table 6 at each 15 largest crash month. To readily compare economic significance, we standardize independent variables using

[11] 148 is the number of momentum crash months.

their cross-sectional mean and standard deviation. We reported coefficient on anchoring and momentum measures exclusively for brevity.

Table 7 shows that even in the extreme months when the momentum crashed the most, momentum has no predictive power when anchoring measure is included as an independent variable. For example, on August 1932, increase in one standard deviation of momentum measure decreases subsequent returns by 1.72% while one standard deviation increase in anchoring measure reduces the returns by 20.60%. In 13 out of 15 months, the coefficient of the anchoring measure is larger than the coefficient on the momentum measure. Moreover, the coefficient of the momentum measure is negative and statistically significant at 5% level only in 2 months, while the coefficient on the anchoring measure is negative and significant in 12 out of 15 months.

[Table 7 about here]

3.5 Discussion

We find hard evidence that stocks far from their 52-week highs significantly outperform stocks near their 52-week highs during the crash periods, and momentum crashes because the past-12 month return is just a noisy proxy of nearness to the 52-week high. Our finding poses challenge to existing explanations on the momentum crashes. First, risk-based explanation cannot explain our result because it holds even after various risk-controls. Second, the optionality-based explanation cannot address why the anchoring-neutral momentum winners outperform the anchoring-neutral losers during the crash periods. According to their explanations, the anchoring-neutral momentum losers are likely to be distressed stocks which behaves like written call option. Hence they are likely to significantly outperform the anchoring-neutral momentum winners when the market rebound. Our data suggest the opposite pattern. Overconfidence-based story also cannot explain why stocks near their 52-week highs do not rebound even though they are losers or why momentum winners far from their 52-week highs rebound. There is no ex-ante apparent reason why nearness to the 52-week high is conditionally related with the degree of investors' overconfidence.

Our findings are consistent with our hypothesis that the momentum crashes are due to an investor's anchoring bias. Our explanation builds on two premises: investors become more prone to bias when the market rebound and bias-prone investors anchor on the 52-week high. As the market-wide sentiment recovers from its slump, investors become more prone to behavioral bias (or investors prone to behavioral bias flow into the market). Since these bias-prone investors anchor on the 52-week highs, demand on stocks that are far from their 52-week high increases, which results in price run-up. Hence the momentum losers which is the resembling collection of stocks far from the 52-week highs will rebound by a large margin and result in momentum crashes.

Dependence of aggregate investor's susceptibility to behavioral bias on the market states and investor sentiment has been widely documented.[12]

Investors' tendency to anchor on the previous price peaks has also been widely documented. George and Hwang (2004) are the first to rigorously document the role of an anchoring bias in the field of finance[13]. They argue that investors' estimates on stocks' fundamental value are anchored on the 52-week highs. Therefore, the investors irrationally prefer stocks that the current price is far from their 52-week high because there is enough "room to run". As true information reveals, stocks that are near their 52-week high outperform those that are far from their 52-week high. Other studies document similar findings in international markets. (Marshall and Cahan (2005), Du (2008) Liu, Liu, Ma (2011)). Moreover, the anchoring effect measured by nearness to price peaks was documented in various aspects of the market. Birru (2014) and George, Hwang, and Li (2014) find that the post-earnings announcement drift can be explained using investors' anchoring bias. Baker, Pan, and Wurgler (2012) find that the 52-week highs and prior price peaks are used as anchors in merger decisions. Heath, Huddart, and Lang (1999) report that stock options are exercised massively when the stock prices exceed the previous

[12] See footnote 3 of Stambaugh, Yu, and Yuan (2012) for the detailed list of papers addressing market-wide sentiment.

[13] Anchoring bias was first proposed by Tversky and Kahneman (1974) as "one of the most reliable and robust results of experimental psychology". According to their explanation, when people estimate a probability or a number, they start from a first approximation (anchor) and then make an adjustment from their initial anchor. Most of the time, the adjustment is insufficient. Therefore the estimate is biased.

year's highs. Li and Yu (2012) find that the 52-week high of a market index also serves as an anchor that influence investors' decision. Hao, Chou, and Ko (2014) finds that investors' anchoring bias are attenuated when the investor sentiment is low.

4. Anchoring-neutral momentum strategy

In this section, we explore more on the anchoring-neutral momentum strategy. The conventional momentum strategy exhibits high volatility, negative skewness and large drawdowns due to its crashes. Since we identified anchoring bias as a major source of the momentum crashes, we expect the anchoring-neutral momentum strategy to be free of these attributes. Moreover, since the momentum crashes contribute significantly to the time-variation of momentum profits, we predict that our anchoring-neutral momentum strategy will vary less with various measures of market conditions such as market returns, business cycles, and investor sentiments.

4.1 WML versus WML*

We focus our investigation on the comparison of WML and WML* strategies.[14] WML and WML* strategies are similar in that they long momentum winners and losers. However, while WML picks momentum winners and losers from the entire universe of stocks, WML* picks momentum winners and losers evenly from the five subsets with different nearness to the 52-week highs. Therefore, WML* winners and losers consist of stocks with similar level of the anchoring measure, while WML does not.

In section 3, we have documented that WML* earns positive returns during the momentum crash periods. However, this does not necessarily guarantees the dominance of WML* over WML as a trading strategy. First, WML* may still earn largely negative returns during periods that were not examined in our analysis. Second, even if WML* does not crashes during the

[14] Explanation on WML* and WML can be found in section 3.2.

entire periods, this could have been achieved by sacrificing its profitability compared to WML.

[Table 8 about here]

In table 8, we report descriptive statistics of the conventional momentum strategy (WML) and the anchoring-neutral momentum strategy (WML*). The investment period covers from January 1927 to December 2013. In line with Table 1 of Barroso and Santa-Clara (2015), WML exhibits excessive kurtosis (12.02), highly negative skewness (−1.82), and large negative minimum returns (−70.63%), which all points to the fat-tailed distribution of WML on the negative side. However, such pattern is muted when we revise the momentum strategy to be anchoring-neutral. Skewness is almost zero (0.02) and kurtosis decreases to 3.37. Minimum return dramatically increases to −25.41%. Moreover, the monthly Sharpe ratio of WML* doubles that of WML. In overall, distribution of WML* returns shows normal-like behavior and earns positive returns without crashes. The dominance of WML* over WML is more pronounced in case of an equal-weighted strategy.

[Table 9 about here]

Furthermore, in the pronounced momentum crash months, WML* manages to survive. Table 9 compares WML and WML* returns on the 15 largest crash months. Although WML* portfolio still earns negative returns, the magnitude is much smaller. During the catastrophic crash of July to August 1932, WML earns −88.14% while WML* earns −32.01%. During the recent financial crisis (March to April 2009), WML earns −67.43% while WML* earns −28.64%.

[Figure 1 about here]

[Figure 2 about here]

Surprisingly, the improvement of WML* strategy is achieved without sacrificing the profitability of WML. Figure 1 plots cumulative raw return of WML and WML* from July 1927 to December 2013. Solid line and dotted line corresponds to WML* and WML, respectively. The figure shows that WML* earns higher cumulative return than WML. Moreover, in line with Table 8, the cumulative return of WML* increases smoothly without sudden drawdowns while WML plotted in the dotted line shows several rapid and large declines. In figure 2, We have a similar result when we plot ex-ante market hedged return[15] as Daniel and Moskowitz (2014).

The results show a clear reason why WML* dominates WML. WML* earns steady profits without crashes and exhibits more normal-like distribution. More importantly, investors do not need to sacrifice the profitability of the momentum strategy to extract desirable properties such as near-zero skewness and low volatility. Therefore, WML* can serve as a desirable long-term investment strategy.

4.2 Time-variation of WML*

We now turn our attention to the time-variation of our anchoring-neutral momentum strategy. The conventional momentum strategy is known to vary with market states, macroeconomic condition, and investor sentiment.[16] Since the large negative profits during the crash periods contribute significantly to the time-variation, we predict that WML* will vary much less than WML. Heidari (2015) finds that most of the power of the momentum predictors comes from crash periods. Hence resolving crashes can resolve the time-variation of momentum strategy. To test our hypothesis, we regress time-series of WML* monthly returns on variables that are known to predict or co-move with momentum profits.

In model 1 of table 10, we regress WML and WML* on the past 12-month cumulative market return (MKTRET) and its square (MKTRETSQ) following Cooper, Gutierrez, and Hameed (2004). Panel A shows that the conventional momentum strategy earns higher return following bull market, while WML* strategy does not vary with past market condition. In model 2, we regress WML and WML* on past market illiquidity, MKTILLIQ. In line with Avramov, Cheng,

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[15] We compute ex-ante market hedged returns following Daniel and Moskowitz (2014). $r_{p,t}^{hedged} = r_{p,t}^{raw} - \widehat{\beta_{p,t}} r_{m,t}$ where the market-beta is estimated at the beginning of each month using the past 126-days daily returns. The market beta is the sum of the elven betas from the time-series regression $r_{p,d} = \alpha + \beta_1 r_{M,d} + \cdots + \beta_{11} r_{M,d-10} + \varepsilon$

[16] See Chordia and Shivakumar (2002), Cooper, Gutierrez, and Hameed (2004), Wang and Xu (2010), Antoniou, Doukas, and Subrahmanyam (2013) and Avramov, Cheng, and Hameed (2014).

and Hameed (2014), we define MKTILLIQ as the value-weighted average of each stock's Amihud (2002) illiquidity measure at the last month. While WML depends on the past market illiquidity significantly (t-statistics = –5.87), WML* does not depend on market illiquidity (t-statistics = 1.70). We also regress momentum profits on the past market volatility, MKTVOL, which is the variance of the past 126-day market returns. Consistent with Daniel and Moskowitz (2014) and Wang and Xu (2010), we find significantly negative relation between the conventional momentum profits and the past market volatility. However, when we regress WML* on MKTVOL, the coefficient is insignificant. Model 4, 5, and 6 also confirms our hypothesis that WML* does not vary with the determinants of WML. Specifically, January effect is not pronounced in WML* and Baker and Wurgler (2006) investor sentiment variable and Chordia and Shivakumar (2002) macroeconomic variables do not influence WML* profits.

[Table 10 about here]

The results so far confirms that our revision on momentum strategy is successful. Without damaging the profitability, the anchoring-neutral momentum strategy earns steady and normal-like profits regardless of the market conditions. Our revision on the momentum strategy is qualitatively different from previous attempts. Daniel and Moskowitz (2014), Barroso and Santa-Clara (2015), Daniel, Jagannathan and Kim (2012) and Heidari (2015) have designed a way that focuses on the timing of the momentum crashes. When investor's expect momentum to crash, they move away from or underweight momentum portfolio. In contrast, our strategy focus exclusively on the stock selection. Hence it is less prone to leverage or short-sale constraint and is implementable with lower trading costs.

5. Conclusion

The momentum is the powerful anomaly and trading strategy in normal environments. However, when the market rebound from its trough, the strategy crashes in large magnitude. Despite the vast attention drawn to it, there was no complete and consistent explanation on the reason why.

In this paper, we provide a concise explanation on the subject. As the market rebound, investors become more susceptible to behavioral biases. Hence, demand on stocks that are far from their 52-week highs increases as investors start to anchor on the 52-week high. Therefore, nearness to the 52-week high is in negative relation with subsequent returns. Since momentum measure is positively correlated with nearness to the 52-week high, the momentum strategy crashes.

We present several empirical findings that are consistent with our hypothesis. First, during the crash periods, stocks far from their 52-week highs outperform stocks near their 52-week highs. Second, anchoring losers still outperform anchoring winners when their momentum measure is set to be similar. Third, momentum losers no longer outperform momentum winners when their anchoring measure is set to be similar.

Furthermore, in a spirit that anchoring drives momentum to crash, we devise anchoring-neutral momentum strategy. The strategy is free from the disadvantages of the conventional momentum strategy such as high volatility, negative skewness, and largely negative minimum return. The strategy does not vary with market condition, business cycle, and investor sentiment. Most importantly, the strategy does not sacrifice its profitability compared to the conventional momentum strategy.

Appendix

In the appendix, we describe variables employed in our research. Table A1 describes the definition of each variable.

[Table A1 about here]

References

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Antoniou, Constantinos, John A. Doukas, and Avanidhar Subrahmanyam, 2013, Cognitive dissonance, sentiment, and momentum, *Journal of Financial and Quantitative Analysis* 48, 245-275.

Asem, Ebenezer, and Gloria Y. Tian, 2010, Market dynamics and momentum profits, *Journal of Financial and Quantitative Analysis* 45, 1549-1562.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013, Value and momentum everywhere, *Journal of Finance* 68, 929-985.

Avramov, Doron, Si Cheng, and Allaudeen Hameed, 2014, Time-varying momentum payoffs and illiquidity, *Working paper*.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, Xin Pan, and Jeffrey Wurgler, 2012, The effect of reference point prices on mergers and acquisitions, *Journal of Financial Economics* 106, 49-71.

Barroso, Pedro, and Pedro Santa-Clara, 2015, Momentum has its moments, *Journal of Financial Economics* 116, 111-120.

Birru, Justin, 2015, Psychological barriers, expectational errors, and underreaction to news, *Working paper*.

Chabot, Benjamin, Eric Ghysels, and Ravi Jagannathan. 2014, Momentum trading, return chasing, and predictable crashes, *Working paper*.

Chordia, Tarun, and Lakshmanan Shivakumar, 2002, Momentum, business cycle, and time-varying expected returns, *Journal of Finance* 57, 985-1019.

Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2013, Trends in the cross-section of expected stock returns, *Working paper*.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609-642.

Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345-1365.

Daniel, Kent D., and Tobias J. Moskowitz, 2014, Momentum crashes, *Working paper.*

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under-and overreactions, *Journal of Finance* 53, 1839-1885.

Daniel, Kent, Ravi Jagannathan, and Soohun Kim, 2012, Tail risk in momentum strategy returns, *Working paper*.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389-406.

Du, Ding, 2008, The 52-week high and momentum investing in international stock indexes, *The Quarterly Review of Economics and Finance* 48, 61-77.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Geczy, Christopher, and Mikhail Samonov, 2013, 212 Years of Price Momentum (The World's Longest Backtest: 1801-2012), *Working paper*.

George, Thomas J., and Chuan-Yang Hwang, 2004, The 52-week high and momentum investing, *Journal of Finance* 59, 2145-2176.

George, Thomas J., Chuan-Yang Hwang, and Yuan Li, 2014, Anchoring, the 52-week high and post earnings announcement drift, *Working paper.*

Grinblatt, Mark, and Bing Han, 2005, Prospect theory, mental accounting, and momentum, *Journal of Financial Economics* 78, 311-339.

Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29-78.

Hao, Ying, Robin K. Chou, and Kuan-Cheng Ko, 2014, The 52-week high, momentum, and investor sentiment, *Working paper*.

Heath, Chip, Steven Huddart, and Mark Lang, 1999, Psychological factors and stock option exercise, *Quarterly Journal of Economics* 114, 601-627.

Heidari, Mahdi, 2015, Momentum crash management, *Working paper*

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Kothari, Shanker P., and Jay Shanken, 1992, Stock return variation and expected dividends: A time-series and cross-sectional analysis, *Journal of Financial Economics* 31, 177-210.

Li, Jun, and Jianfeng Yu, 2012, Investor attention, psychological anchors, and stock return predictability, *Journal of Financial Economics* 104, 401-419.

Liu, Ming, Qianqiu Liu, and Tongshu Ma, 2011, The 52-week high momentum strategy in international stock markets, *Journal of International Money and Finance* 30, 180-204.

Marshall, Ben R., and Rachael M. Cahan, 2005, Is the 52-week high momentum strategy profitable outside the US? *Applied Financial Economics* 15, 1259-1267.

Merton, Robert C, 1974, On the pricing of corporate debt: The risk structure of interest rates, *The Journal of Finance* 29, 449-470.

Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance*, 267-284.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stivers, Chris, and Licheng Sun, 2010, Cross-sectional return dispersion and time variation in value and momentum premiums, *Journal of Financial and Quantitative Analysis* 45, 987-1014.

Tversky, Amos, and Daniel Kahneman, 1974, Judgment under uncertainty: Heuristics and biases, *Science* 185, 1124-1131.

Wang, Kevin Q., and Jianguo Xu, 2010, Time-varying momentum profitability, *Working paper.*

Yan, Philip, 2013, Crowded trades, short covering, and momentum crashes, *Working paper*.

Table 1. Top 15 momentum crashes.

Table 1 describes the 15 largest momentum crashes. Column labeled W, L, and WML reports raw returns of the momentum winners, losers and their difference, respectively. The last two columns report the past 1-year cumulative market return and the contemporaneous market return. Market return is the CRSP value-weighted index return. Every number is in percent.

Rank	Date	W	L	WML	$Mkt_{[t-12,t-1]}$	Mkt_t
1	1932-08	17.57	88.20	−70.63	−50.96	37.14
2	1932-07	17.23	76.87	−59.63	−65.85	34.06
3	2001-01	−6.52	45.08	−51.60	−11.16	3.96
4	2009-04	0.05	45.41	−45.35	−38.61	10.94
5	1939-09	7.71	51.98	−44.27	−1.13	16.18
6	2009-03	4.60	45.02	−40.42	−44.09	8.67
7	1933-04	30.28	68.60	−38.32	−12.63	39.41
8	2002-11	3.47	37.80	−34.33	−13.49	6.13
9	1938-06	11.04	43.93	−32.89	−39.04	23.79
10	1931-06	7.03	39.49	−32.47	−45.73	14.03
11	1933-05	20.70	47.20	−26.50	−48.44	21.33
12	2001-11	4.68	30.84	−26.16	−25.98	7.88
13	1970-09	3.88	27.82	−23.94	−14.51	4.75
14	2001-10	1.71	25.26	−23.55	−29.75	2.78
15	2002-10	3.83	27.29	−23.46	−17.28	7.49

Table 2. Univariate sort on momentum and anchoring.

Table 2 reports raw and risk-adjusted returns of momentum and anchoring decile portfolios. At the beginning of each month, stocks are ranked based on their momentum (anchoring) measures. Based on these rankings, value-weighted decile portfolios are formed and stocks are held until the end of the month. We also form a hedge portfolio that longs the top decile and shorts the bottom decile. Panel A (B) of table 2 reports raw and risk adjusted returns to these portfolios. Specifically, panel A1 (B1) reports returns during the crash periods and panel A2 (B2) reports returns outside the crash periods. Column labeled "WML" reports raw and risk-adjusted return of the hedge portfolio. Our risk-return model is CAPM and Fama and French (1996) three factor model (FF). Every number is in percent. Numbers in parenthesis are t-statistics.

	1(L)	2	3	4	5	6	7	8	9	10(W)	WML
Panel A : Momentum Decile Portfolio											
Panel A1 : Crash periods											
Raw	10.00	8.85	7.80	7.25	6.41	5.87	5.11	4.57	4.71	4.93	−5.07
	(7.93)	(8.53)	(8.92)	(9.49)	(9.41)	(10.07)	(10.09)	(10.92)	(11.72)	(11.96)	(−4.34)
CAPM	1.68	1.76	1.53	1.47	0.94	0.60	0.07	−0.29	−0.41	−0.55	−2.22
	(2.21)	(3.22)	(3.73)	(4.47)	(3.71)	(3.13)	(0.38)	(−1.63)	(−1.75)	(−1.49)	(−2.19)
FF	1.49	1.63	1.44	1.41	0.89	0.57	0.07	−0.28	−0.40	−0.51	−2.00
	(2.19)	(3.31)	(3.82)	(4.53)	(3.80)	(3.00)	(0.40)	(−1.60)	(−1.76)	(−1.51)	(−2.17)
Panel A2 : Non-Crash Periods											
Raw	−1.43	−0.82	−0.54	−0.19	0.00	0.07	0.3	0.62	0.61	1.08	2.56
	(−5.12)	(−3.63)	(−2.75)	(−1.06)	(0.02)	(0.42)	(2.13)	(3.48)	(3.11)	(4.53)	(11.41)
CAPM	−1.28	−0.69	−0.43	−0.08	0.10	0.17	0.46	0.71	0.71	1.18	2.47
	(−8.08)	(−5.91)	(−4.39)	(−1.04)	(1.51)	(2.99	(8.11)	(11.04)	(8.81)	(9.17)	(10.86)
FF	−1.42	−0.80	−0.51	−0.14	0.05	0.13	0.46	0.72	0.73	1.27	2.69
	(−9.50)	(−7.00)	(−5.34)	(−1.82)	(0.76)	(2.50)	(8.18)	(11.18)	(9.32)	(11.07)	(12.17)
Panel B : Anchoring Decile Portfolio											
Panel B1 : Crash Periods											
Raw	11.99	10.37	8.99	8.35	7.54	6.44	5.75	5.10	4.28	3.36	−8.63
	(8.52)	(9.32)	(9.55)	(10.30)	(9.61)	(10.37)	(10.17)	(11.20)	(11.35)	(10.17)	(−6.64)
CAPM	2.51	1.98	1.49	1.55	1.26	0.73	0.46	0.15	−0.06	−0.67	−3.18
	(2.96)	(3.52)	(3.62)	(4.46)	(4.04)	(3.27)	(2.84)	(1.10)	(−0.36)	(−2.88)	(−3.12)
FF	2.22	1.81	1.39	1.47	1.19	0.68	0.43	0.17	−0.03	−0.63	−2.85
	(3.09)	(3.78)	(3.68)	(4.70)	(4.17)	(3.12)	(2.69)	(1.19)	(−0.18)	(−2.88)	(−3.27)
Panel B2 : Non-Crash Periods											
Raw	−0.86	−0.65	−0.38	−0.13	−0.09	0.03	0.17	0.28	0.54	0.49	1.36
	(−2.59)	(−2.35)	(−1.57)	(−0.59)	(−0.47)	(0.18)	(0.99)	(1.69)	(3.43)	(3.04)	(5.30)
CAPM	−0.68	−0.49	−0.24	−0.00	0.02	0.13	0.27	0.38	0.62	0.56	1.26
	(−3.45)	(−3.70)	(−2.24)	(−0.05)	(0.31)	(2.27)	(4.98)	(7.95)	(11.70)	(8.15)	(5.47)
FF	−0.89	−0.61	−0.32	−0.05	−0.03	0.09	0.24	0.39	0.65	0.59	1.50
	(−5.23)	(−5.03)	(−3.08)	(−0.66)	(−0.51)	(1.59)	(4.54)	(8.14)	(12.41)	(8.65)	(7.27)

Table 3. Double sort analysis: Crash periods

Table 3 reports monthly raw and risk-adjusted returns of portfolios independently double-sorted by momentum and anchoring measure during crash periods. At each month *t*, firms are divided into quintiles based on their momentum and anchoring measure, which results in 25(5×5) portfolios. We report the average value-weighted return of each portfolio at month *t* during the crash periods. The row or column labeled “5−1” reports the return of the long-short portfolio that longs the top quintile and shorts the bottom quintile. Due to high cross-sectional correlation between momentum and anchoring measure, cells are not evenly balanced and sometimes empty. For long-short portfolio, both long and short side of the portfolio should be nonempty to be included in the analysis. Every number is in percent. Numbers in parenthesis are t-statistics.

Panel A : Raw Return

		Anchoring					
		1(Far)	2	3	4	5(Near)	5−1
Momentum	1(Loser)	10.73	7.68	4.00	3.97	−2.33	−9.23
		(8.58)	(7.50)	(3.75)	(1.91)	(−0.98)	(−4.08)
	2	11.28	8.74	6.61	4.78	2.22	−8.09
		(10.58)	(10.33)	(9.04)	(5.89)	(1.85)	(−6.23)
	3	13.24	8.89	6.89	5.33	4.80	−7.56
		(6.88)	(9.84)	(9.86)	(8.31)	(7.43)	(−4.88)
	4	12.06	8.59	7.14	5.46	3.83	−8.23
		(7.21)	(9.10)	(9.84)	(11.66)	(9.62)	(−5.33)
	5(Winner)	12.62	8.99	6.98	6.23	4.17	−8.49
		(5.82)	(8.26)	(9.29)	(11.88)	(11.60)	(−4.05)
	5−1	2.16	1.97	3.06	2.59	5.77	
		(1.26)	(1.68)	(3.06)	(1.44)	(2.41)	

Panel B : CAPM-adjusted Returns

		Anchoring					
		1(Far)	2	3	4	5(Near)	5−1
Momentum	1(Loser)	2.11	0.65	−1.64	−1.49	−5.23	−6.16
		(3.03)	(1.22)	(−1.83)	(−0.83)	(−2.25)	(−2.75)
	2	2.92	1.94	0.93	−0.14	−1.53	−4.48
		(4.77)	(5.04)	(2.84)	(−0.28)	(−1.35)	(−3.64)
	3	3.08	1.74	0.98	0.22	0.54	−2.54
		(2.37)	(3.89)	(3.46)	(0.81)	(1.14)	(−1.98)
	4	3.21	1.49	0.78	0.30	−0.53	−3.81
		(2.49)	(1.95)	(2.38)	(1.71)	(−2.43)	(−2.73)
	5(Winner)	3.37	1.79	0.47	0.18	−0.63	−3.88
		(1.84)	(1.71)	(0.89)	(0.59)	(−2.31)	(−2.01)
	5−1	1.23	1.27	2.05	1.71	5.34	
		(0.72)	(1.07)	(2.04)	(0.93)	(2.22)	

Panel C :FF-adjusted Returns

		Anchoring					
		1(Far)	2	3	4	5(Near)	5−1

Momentum	1(Loser)	1.89	0.50	−1.75	−1.70	−5.29	−6.34
		(3.19)	(1.03)	(−2.01)	(−0.98)	(−2.24)	(−2.80)
	2	2.74	1.85	0.85	−2.07	−1.56	−4.31
		(5.11)	(5.23)	(2.75)	(−0.41)	(−1.40)	(−3.53)
	3	2.69	1.63	0.91	1.76	0.52	−2.19
		(2.33)	(4.01)	(3.52)	(0.68)	(1.14)	(−1.96)
	4	2.81	1.43	0.72	3.05	−0.51	−3.37
		(2.27)	(2.08)	(2.27)	(1.65)	(−2.37)	(−2.53)
	5(Winner)	2.97	1.65	0.41	1.53	−0.59	−3.50
		(1.71)	(1.75)	(0.88)	(0.52)	(−2.31)	(−1.94)
	5−1	1.11	1.23	2.09	1.92	5.29	
		(0.65)	(1.12)	(2.12)	(1.09)	(2.17)	

Table 4. The anchoring-neutral momentum portfolio: Crash periods.

Table 4 reports raw and risk-adjusted returns of the anchoring-neutral momentum portfolios and winner minus loser portfolio (WML*) during crash periods. At each month, we group stocks into quintile based on their anchoring measure. Within each anchoring quintile, we group stocks into decile based on their momentum measure, which results in 50 portfolios. Then, we hold the stocks until the end of the month. Lastly, we form equal-weighted cohorts with five portfolios from the same momentum decile. Therefore, we construct ten cohorts with equal number of stocks, similar level of the anchoring measure and different level of the momentum measure. Panel A reports time-series average of the anchoring and momentum measure for each portfolios. Panel B reports the raw and risk-adjusted return of the anchoring-neutral portfolios and WML*.

	1(L*)	2	3	4	5	6	7	8	9	10(W*)	WML*
Panel A : Average measure											
Anchoring	59.97	61.82	63.03	63.96	64.55	65.19	65.52	65.90	66.06	66.06	6.09
Momentum	−41.02	−33.45	−29.20	−25.63	−22.15	−18.39	−13.95	−8.03	1.59	32.10	73.12
Panel B : Average return											
Raw	6.57	6.91	7.07	7.17	7.17	7.05	7.49	7.46	7.64	8.12	1.55
	(7.63)	(8.49)	(9.24)	(9.90)	(9.77)	(10.55)	(10.65)	(10.87)	(11.46)	(11.83)	(2.91)
CAPM	0.35	0.78	1.04	1.00	0.94	0.91	1.09	0.87	8.96	9.50	0.59
	(0.76)	(2.12)	(3.43)	(3.79)	(3.67)	(3.52)	(4.33)	(3.42)	(3.12)	(2.77)	(1.06)
FF	0.19	0.67	0.94	0.92	0.83	0.82	1.00	0.78	0.80	0.86	0.67
	(0.50)	(2.11)	(3.45)	(3.78)	(4.06)	(3.82)	(4.64)	(3.78)	(3.39)	(3.03)	(1.28)

Table 5. Robustness test on alternative setups: Crash periods

We report raw and risk-adjusted return of the conventional momentum strategy (WML) and the anchoring-neutral momentum strategy (WML*) during the crash periods under alternative test setups. In panel A, we restrict our samples: stocks whose prices exceed $5, NYSE-listed stocks, NYSE MKT-listed stocks, and NASDAQ-listed stocks. In panel B, we use alternative definition of the crash periods. The row labeled "2-(3-)year" defines the crash periods as the months when the past 2-(3-)year market return is negative and the contemporaneous market return is positive. The row labeled "100 Negative" consider the 100 largest momentum crash months as the crash periods. In panel C, we define the momentum measure in alternative ways: the past 12-month return without skipping 1-month, recent 6-month return, and intermediate 6-month return. In panel D, we employ alternative definitions of the anchoring measure. We define the anchoring measure as nearness to the 52-week low, nearness to the 26-week high and unrealized capital gains as described by Grinblatt and Han (2005). Every number is in percent. Numbers in parenthesis are t-statistics.

	Raw		CAPM		FF	
	WML	WML*	WML	WML*	WML	WML*
Panel A : Robustness to sub-samples						
Prc>$5	−4.14	1.55	−2.08	0.59	−1.89	0.67
	(−4.34)	(2.91)	(−2.52)	(1.06)	(−2.58)	(1.28)
NYSE	−4.67	1.10	−2.22	0.45	−1.98	0.50
	(4.39)	(2.09)	(−2.41)	(0.83)	(−2.46)	(0.97)
AMEX	−6.44	0.63	−4.61	−0.66	−4.20	−0.68
	(−3.13)	(0.78)	(−2.27)	(−0.82)	(−2.13)	(−0.84)
NASDAQ	−5.07	1.59	−3.78	−0.19	−3.17	0.06
	(−2.36)	(1.44)	(−1.79)	(−0.17)	(−1.53)	(0.06)
Panel B : Robustness to alternative definitions of "crash period"						
2-year	−6.80	1.68	−3.30	0.50	−2.34	0.87
	(−4.41)	(2.56)	(−2.47)	(0.72)	(−1.96)	(1.39)
3-year	−5.18	1.90	−1.89	0.79	−0.85	1.20
	(−3.50)	(2.86)	(−1.48)	(1.13)	(−0.76)	(1.93)
100 Negative	−15.84	−3.09	−13.62	−3.84	−11.92	−3.17
	(−13.73)	(−4.55)	(−14.95)	(−5.68)	(−13.72)	(−5.15)
Panel C : Robustness to alternative definitions of momentum measure						
$r_{[t-12,t-1]}$	−6.68	−0.65	−3.54	−1.42	−3.31	−1.34
	(−5.56)	(−1.20)	(−3.42)	(−2.49)	(−3.49)	(−2.52)
$r_{[t-6,t-2]}$	−4.58	0.30	−1.94	−0.28	−1.78	−0.28
	(−4.42)	(0.55)	(−2.22)	(−0.50)	(−2.19)	(−0.49)
$r_{[t-12,t-7]}$	−2.38	1.28	−0.99	0.67	−0.80	0.74
	(−2.46)	(2.71)	(−1.09)	(1.41)	(−0.98)	(1.60)
Panel D : Robustness to alternative definitions of anchoring measure						
52-week low	−5.07	−5.09	−2.23	−1.30	−2.00	−1.01
	(−4.34)	(−4.45)	(−2.19)	(−1.38)	(−2.17)	(−1.27)
26-week high	−5.07	−0.52	−2.23	−0.20	−2.00	−0.07
	(−4.34)	(−0.69)	(−2.19)	(−0.27)	(−2.17)	(−0.11)

UCG	−5.07 (−4.34)	−1.80 (−2.27)	−2.23 (−2.19)	−1.07 (−1.42)	−2.00 (−2.17)	−1.05 (−1.46)

Table 6. Fama-Macbeth Regression analysis : Crash periods

Table 6 reports the result of Fama and Macbeth regression during the crash periods. Every month, we regress each firm's raw return on various firm characteristics including momentum and anchoring measure. Table 6 reports time-series average and t-statistics of the coefficient on each variables. Description of each variable can be found in the appendix. Numbers in parenthesis are t-statistics.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Momentum	−0.0518	0.0489	−0.0287	0.0061	−0.0279	0.0051
	(−3.88)	(7.34)	(−2.97)	(1.05)	(−2.90)	(0.89)
Anchoring		−0.1919		−0.0781		−0.0748
		(−7.82)		(−4.97)		(−5.50)
Srev			−0.1652	−0.1362	−0.1721	−0.1425
			(−12.48)	(−9.56)	(−13.30)	(−11.60)
Beta			0.0098	0.0079	0.0091	0.0076
			(5.81)	(5.18)	(5.62)	(5.04)
Log(ME)			0.0025	0.0029	0.0006	0.0009
			(3.19)	(3.67)	(0.89)	(1.43)
Log(BM)			0.0026	0.0032	0.0030	0.0033
			(1.68)	(2.11)	(2.09)	(2.32)
Log(price)			−0.0100	−0.0065	−0.0076	−0.0051
			(−3.37)	(−2.54)	(−3.35)	(−2.44)
Lrev					−0.0041	−0.0040
					(−1.50)	(−1.53)
Ivol					0.0508	−0.0205
					(0.89)	(−0.40)
Retskew					0.0015	0.0019
					(2.77)	(2.39)
Retkurt					−0.0015	−0.0014
					(−5.27)	(−5.35)
Amihud					−0.0002	−0.0002
					(−3.89)	(−3.48)

Table 7. Coefficient of cross-sectional regression at the 15 largest crash months.

Table 7 reports coefficient on momentum and anchoring measure from a cross-sectional regression of model 4 in table 6 at the 15 largest momentum crashes. Independent variables are standardized using their cross-sectional mean and standard deviation.

Rank	Date	WML	Momentum	t	Anchoring	t
1	1932-08	−70.63	0.0172	0.46	−0.2060	−6.04
2	1932-07	−59.63	−0.1035	−2.72	−0.0322	−0.82
3	2001-01	−51.60	−0.0190	−2.01	−0.0676	−5.33
4	2009-04	−45.35	−0.0206	−1.62	−0.0862	−6.75
5	1939-09	−44.27	−0.0047	−0.19	−0.1950	−5.38
6	2009-03	−40.42	−0.0243	−1.78	0.0107	0.70
7	1933-04	−38.32	0.0158	0.84	−0.0724	−2.52
8	2002-11	−34.33	−0.0010	−0.16	−0.1059	−12.60
9	1938-06	−32.89	−0.0233	−1.41	−0.0798	−4.40
10	1931-06	−32.47	−0.0085	−0.37	−0.0191	−0.70
11	1933-05	−26.50	0.0364	1.65	−0.0753	−2.36
12	2001-11	−26.16	0.0117	2.16	−0.0580	−8.72
13	1970-09	−23.94	0.0165	2.03	−0.0730	−8.52
14	2001-10	−23.55	0.0201	2.91	−0.0534	−5.86
15	2002-10	−23.46	0.0123	2.32	−0.0205	−2.54

Table 8. Moments of momentum strategies.

Table 8 reports the moments of the conventional momentum strategy (WML) and the anchoring-neutral momentum strategy (WML*) returns from 1927:01 to 2013:12. Panel A and B reports average, standard deviation, skewness, kurtosis, minimum, maximum, and monthly Sharpe ratio of the value-weighted and equal-weighted raw returns.

	Average	St.dev	Skew	Kurt	Min	Max	Sharpe
Panel A : Value-weighted Portfolio							
WML	0.0145	0.0856	−1.8228	12.0246	−0.7063	0.4240	0.1711
WML*	0.0167	0.0522	0.0258	3.3732	−0.2541	0.2986	0.3195
Panel B : Equal-weighted Portfolio							
WML	0.0071	0.0820	−3.9504	33.7443	−0.8352	0.2588	0.0865
WML*	0.0158	0.0457	0.2245	5.1227	−0.1967	0.2766	0.3456

Table 9. WML versus WML* during the 15 largest crash months.

Table 9 reports raw returns of the conventional momentum strategy (WML) and the anchoring-neutral momentum strategy (WML*) during the 15 largest crash months. Columns labeled W (W*) and L (L*) reports the returns of the long and short side of the strategy, respectively. Each portfolios are value-weighted. Every number is in percent

Rank	Date	W	L	WML	W*	L*	WML*
1	1932-08	17.57	88.20	−70.63	49.74	71.88	−22.14
2	1932-07	17.23	76.87	−59.63	37.28	49.96	−12.68
3	2001-01	−6.52	45.08	−51.60	9.51	23.02	−13.51
4	2009-04	0.05	45.41	−45.35	16.31	36.51	−20.20
5	1939-09	7.71	51.98	−44.27	32.95	48.33	−15.39
6	2009-03	4.60	45.02	−40.42	9.92	20.50	−10.58
7	1933-04	30.28	68.60	−38.32	45.62	45.93	−0.31
8	2002-11	3.47	37.80	−34.33	11.16	19.96	−8.80
9	1938-06	11.04	43.93	−32.89	30.44	32.44	−2.00
10	1931-06	7.03	39.49	−32.47	22.20	17.61	4.60
11	1933-05	20.70	47.20	−26.50	51.88	37.64	14.24
12	2001-11	4.68	30.84	−26.16	8.76	14.91	−6.15
13	1970-09	3.88	27.82	−23.94	15.19	11.41	3.78
14	2001-10	1.71	25.26	−23.55	10.28	6.61	3.67
15	2002-10	3.83	27.29	−23.46	8.69	9.15	−0.46

Table 10. Time-variation of WML and WML*.

Table 10 reports coefficient and t-statistics of time-series regressions. In panel A and B, we regress WML and WML* return on variables that are known predict or explain momentum profits. MKTRET is the past 1-year cumulative market return. MKTRETSQ is the square of MKTRET. MKTILLIQ is a value-weighted average of Amihud (2002) illiquidity measure of each firm in NYSE and NYSE MKT at month t-1. MKTVOL is the variance of past 126-days market return (approximately from month t-6 to month t-1). $I_{January}$ is an indicator variable that takes 1 if January and zero otherwise. $I_{Sentiment}$ is an indicator variable that takes 1 if the Baker and Wurgler (2006) investor sentiment is positive, and zero otherwise. We also include macroeconomic variable of Chordia and Shivakumar (2002). DIV is the dividend yield on the CRSP value-weighted index at month t-1. YLD is the yield on Treasury bills with three months to maturity at month t-1. TERM is the yield spread between ten-year Treasury bonds and three-month Treasury bills at month t-1. DEF is the yield spread between Baa-rated bonds and Aaa-rated bonds at month t-1. Numbers in parenthesis are t-statistics.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A : Time-variation of WML						
Intercept	0.0130 (4.27)	0.0189 (6.97)	0.0230 (7.25)	0.0188 (6.91)	0.0111 (3.59)	0.0241 (2.27)
Mktret	0.0671 (4.81)					
Mktretsq	−0.1085 (−4.42)					
Mktilliq		−0.0046 (−5.87)				
Mktvol			−0.3022 (−4.76)			
$I_{January}$				−0.0523 (−5.54)		
$I_{Sentiment}$					0.0124 (2.09)	
Div						−0.3038 (−1.47)
Yld						0.1784 (1.91)
Term						0.2499 (1.02)
Def						−0.6079 (−1.17)
Panel B : Time-variation of WML*						
Intercept	0.0175 (9.25)	0.0158 (9.46)	0.0158 (8.07)	0.0168 (9.98)	0.0177 (9.36)	0.0227 (2.96)
Mktret	−0.0044 (−0.51)					
Mktretsq	−0.0050 (−0.33)					
Mktilliq		0.0008 (1.70)				

Mktvlol			0.0309 (0.79)			
$I_{January}$				−0.0019 (−0.33)		
$I_{Sentiment}$					−0.0038 (−1.05)	
Div						−0.2588 (−1.73)
Yld						−0.0025 (−0.04)
Term						0.0248 (0.14)
Def						0.4183 (1.11)

Figure 1. Cumulative raw return of WML and WML*

Figure 1 plots cumulative raw return of WML and WML* from 1927:07 to 2013:12. Solid line and dotted line corresponds to WML* and WML, respectively. Portfolios are value-weighted.

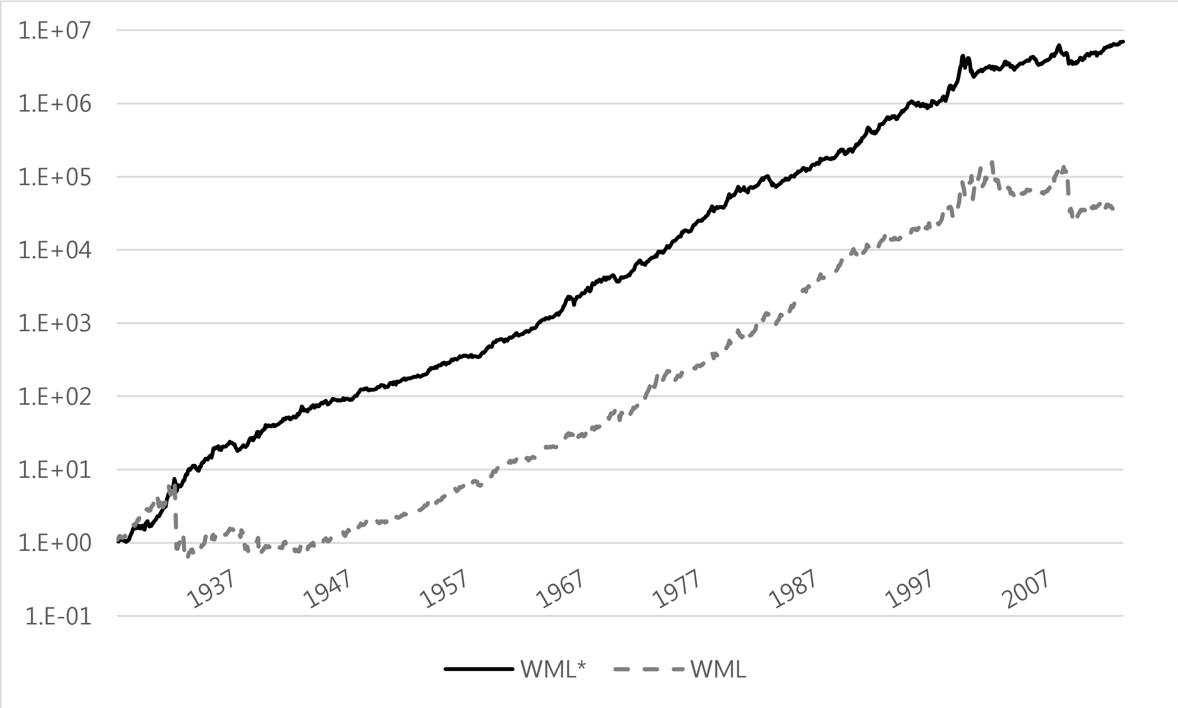

Figure 2. Cumulative ex-ante market hedged return of WML and WML*

Figure 1 plots cumulative ex-ante market hedged return of WML and WML* from 1927:07 to 2013:12. We compute ex-ante market hedged returns following Daniel and Moskowitz (2014). $r_{p,t}^{hedged} = r_{p,t}^{raw} - \widehat{\beta_{p,t}} r_{m,t}$ where the market-beta is estimated at the beginning of each month using the past 126-days daily returns. The market beta is the sum of the elven betas from the time-series regression $r_{p,d} = \alpha + \beta_1 r_{M,d} + \cdots + \beta_{11} r_{M,d-10} + \varepsilon$. Solid line and dotted line corresponds to WML* and WML, respectively. Portfolios are value-weighted.

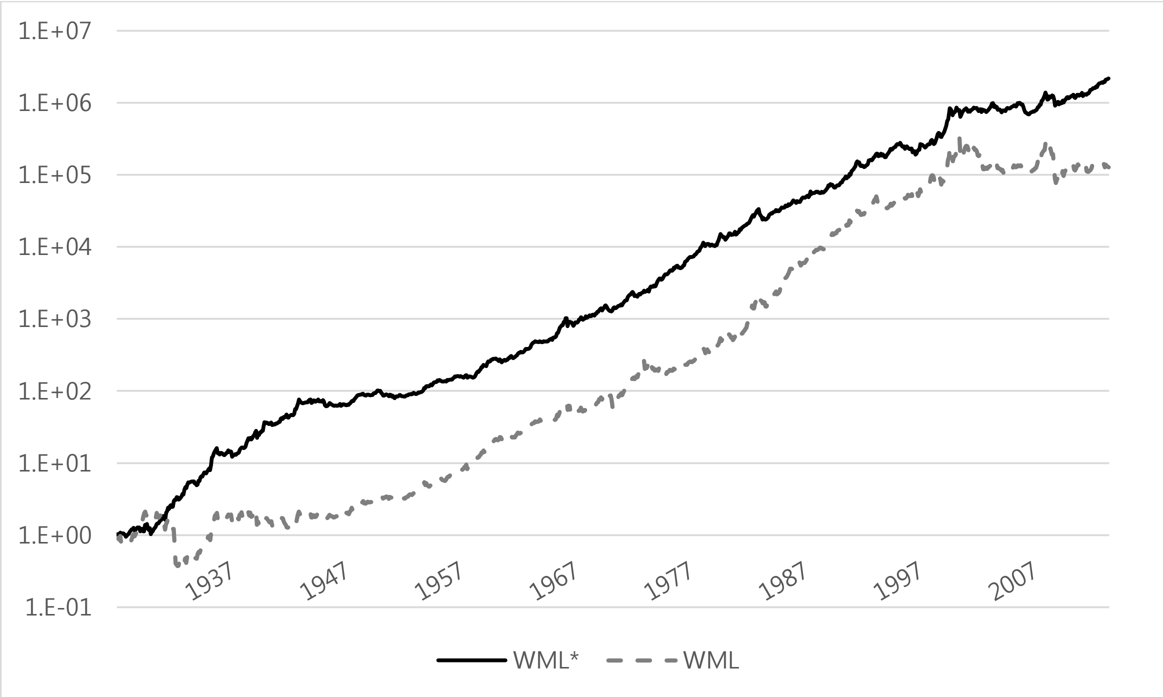

Table A1. Variable Description

Table A1 describes variables employed in our empirical research. Every variable is winsorized at the top and bottom 1% each month.

Name	Symbol	Description
Return	$r_{i,t}$	Raw return of a stock *i* over the month *t*
Momentum	$Momentum_{i,t-1}$	Cumulative raw return of a stock over the month $t-12$ to the month $t-2$. We require at least 8 months of return data to be valid.
Anchoring	$Anchoring_{i,t-1}$	Stock price at the end of the month $t-1$ over the highest daily closing price from month $t-12$ to month $t-1$.
Short-run reversal	$Srev_{i,t-1}$	Raw return of the month $t-1$
Long-run reversal	$Lrev_{i,t-1}$	Cumulative raw return of a stock over the month $t-36$ to $t-11$
Beta	$Beta_{i,t-1}$	Sum of three betas estimated using daily individual/market return data at the month *t* from the following equation: $r_{i,d} = \alpha + \beta_1 r_{M,d} + \beta_2 r_{M,d-1} + \beta_3 r_{M,d-2} + \varepsilon$.
Market equity	$ME_{i,t-1}$	The logarithm of share price times the number of shares outstanding at the end of month $t-1$
Book-to-market ratio	$BM_{i,t-1}$	The ratio of the book equity at the end of month $t-1$ to the ME_{t-1}. We first use Moody's book equity information collected by Davis, Fama, and French (2000). If not available, we compute the book equity using the COMPUSTAT annual fundamental files and the methodology outlined by Cohen, Polk, and Vuolteenaho (2003). The book equity data of fiscal year *y* is assumed to be available from the June of year $y+1$.
Price	$Price_{i,t-1}$	Closing price at the end of month $t-1$
Idiosyncratic volatility	$Ivol_{i,t-1}$	Standard-deviation of residuals from the regression during the month $t-1$ from the following equation: $r_{i,d} = \alpha + \beta_1 r_{M,d} + \beta_2 r_{M,d-1} + \beta_3 r_{M,d-2} + \varepsilon$.
Skewness	$Skew_{i,t-1}$	Skewness of daily returns at the month $t-1$
Kurtosis	$Kurt_{i,t-1}$	Kurtosis of daily returns at the month $t-1$
Illiquidity	$Illiq_{i,t-1}$	Amihud (2002) illiquidity measure.