Momentum crashes and investors' anchoring bias [*]

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Abstract

Despite their strong performance, momentum strategies suffer from occasional large drawdowns referred to as momentum crashes. In this paper, we argue that momentum crashes are due to increase in anchoring-motivated demand on stocks far from their previous price peaks during the market rebounds. Consistent with our hypothesis, we find that nearness to 52-week high subsumes the predictive power of momentum measure during momentum crash periods. Furthermore, we provide a revised momentum strategy that is neutral on nearness to 52-week high. The strategy is free of crashes and exhibits a normal-like distribution without sacrificing its profitability.

JEL Classification: G12, G14

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 past 12-month winners and shorts the past 12-month losers earns highly positive profits over various time periods and asset classes.[1] However, despite its strong performance, the momentum strategy suffers from occasional large drawdowns. For example, the momentum strategy experienced severe losses of –88.48% and –45.60% during the two month periods of 1932 and 2009, respectively. Daniel and Moskowitz (2013) name these incidents "momentum crashes" and find that they are prevalent in other markets as well: currency, bonds, commodity futures, and equity index. Furthermore, they find that momentum crashes are concentrated on the market rebound: 14 of the 15 worst momentum returns occurred during the market rebound and momentum strategy earns large negative returns when the market rebounds.

Momentum crash has attracted considerable interest due to its practical and academic importance. There were several attempts to answer why momentum crashes motivated from their particular timing. Risk-based explanation by Grundy and Martin (2001) suggest that since the momentum strategy loads negatively on the market after the market decline, it earns large negative profits when the market rebounds. Daniel and Moskowitz (2013) argue that momentum losers are underpriced because their optionality is not reflected in their prices. However, both of these explanations are not perfect. Daniel and Moskowitz (2013) find that the result of Grundy and Martin (2001) is biased, and the risk only partly explains momentum crashes. For the optionality based explanation, the authors themselves admit that they are not explicit as to why the optionality is mispriced. Furthermore, they acknowledge that their story does not apply to other types of securities such as currencies.

In this paper, we provide concise and consistent explanation on why momentum crashes using investors' anchoring bias. We argue that the large increase in demand on stocks far from their

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

previous price peaks during the market rebound drives momentum to crash. As the market dramatically rebounds from its long-lasting downturn, the market-wide sentiment recovers from its trough and speculative demand flow into the market (Brown and Cliff 2004) Moreover, these investors anchor on the price peaks: they prefer stocks whose current prices are far from their peaks (George and Hwang 2004). Hence demand for stocks that are far from their peaks increases, which results in their price run-up. Since these stocks are likely to be the past 12-month losers, the conventional momentum strategy that longs winners and shorts losers earns negative profits. In practical terms, as the market index runs up, investors seek stocks that will rebound the most, and their natural choice is the stocks that have enough room to run. Stocks far from their previous price peaks would be the first that come to their mind. Hence, stocks far from peaks outperform stocks near peaks and momentum crashes are just a manifestation of the outperformance.

We document that during the market rebounds, stocks far from their 52-week highs outperform stocks near their 52-week highs and momentum crashes are just another replication of the outperformance. We first find that momentum losers no longer outperform momentum winners when their nearness to 52-week high is similar. Specifically, among the bottom 20% of stocks far from their 52-week highs, momentum winners earn 9.31% while momentum losers earn a similar return of 9.31%. In all the other groups of stocks with the similar level of nearhigh measure, the momentum losers no longer outperform the momentum winners. We still find consistent result after accounting for various firm characteristics using Fama and MacBeth (1973) regression. The negative coefficient on the momentum measure disappears once the nearhigh measure is included as an independent variable. The results are robust to alternative specification of sample stocks, sample periods, crash periods, momentum measure and nearhigh measure. Therefore, our empirical results suggest hard evidence that is consistent with our anchoring hypothesis.

We next consider alternative explanations on why stocks far from peaks outperform stocks near peaks during the market rebound. We first find that risk only partly explains our results. Even after accounting for possibly missing risk factor, stocks far from peaks outperform stocks near peaks by a large margin. We next consider underpricing story. Stocks far from peaks may outperform not because they become overpriced as anchoring-induced demand increases, but because their previous underpricing is resolved. However, we find that the outperformance reverses in the long-run, which is inconsistent with underpricing explanation. Lastly, we investigate alternative sources of overpricing. We consider firm characteristics that attract speculative demand such as age, profitability, distress and lottery-like payoff. We find that the relation between the momentum measure and the nearhigh measure is unchanged after accounting for these characteristics. Hence, we find that other potential explanations are inconsistent with empirical results.

Having established the source of momentum crashes, we revise the conventional momentum strategy to become nearhigh-neutral.[2] We find that the nearhigh-neutral momentum strategy is free of crashes and exhibits a more normal-like distribution: skewness is closer to zero, kurtosis is smaller, and minimum return increases. Moreover, the nearhigh-neutral momentum strategy is free from the pro-cyclical behavior of the conventional momentum strategy. The nearhigh-neutral momentum strategy does not vary with the past market return, the past market volatility, the past market illiquidity, and business cycle. Most importantly, our improvement on the conventional momentum strategy is achieved without sacrificing its profitability. The Sharpe ratio of the nearhigh-neutral momentum strategy is about 50% larger than that of the conventional momentum strategy. Therefore, we provide another form of momentum strategy that is much more desirable to investors.

We contribute to the literature in several aspects. First of all, we identify the nearness to 52-week high as the cross-sectional determinant of momentum crashes. We find hard evidence that the stocks far from peaks outperform stocks near peaks and momentum crashes are just a manifestation of the outperformance. To our knowledge, this is a unique and as yet undocumented finding. Previous literatures have mostly focused on the timing of momentum crashes and provide explanations based on it.[3] Apart from this strand of research, we provide

[2] The strategy is "nearhigh-neutral" in that the stocks on the long and short sides of the strategy have the similar level of the nearhigh measure.

[3] Other studies identify various determinants of momentum profits: market state (Cooper, Gutierrez, and Hameed 2004), investor sentiment (Antoniou, Doukas, and Subrahmanyam 2013), past market volatility (Wang and Xu

explanation motivated from the cross-sectional relations. This provides new perspective on momentum crashes and poses challenges to the existing explanations. Our anchoring-based explanation, on the contrary, can explain both the timing and cross-sectional pattern of momentum crashes.

Second of all, our study provide two important insight on the momentum profitability. First, we find that crash risk is not the source of momentum strategy's continued profitability. Some research argue that if the crash risk is hard-wired into the momentum strategy and is not captured by traditional factor models, it can explain why the momentum strategy continuously earns high profits.[4] However, we find that crashes are not random or spontaneous and that they can be avoided, which implies that the crash risk is not what keeps momentum alive. Secondly, our results imply that of many factors that determine momentum profits (e.g. risk, overconfidence, diffusion of news, etc.), anchoring bias contribute substantially to the time-variation of momentum profits. We find that momentum strategy consistently earns positive profits after neutralizing the effect of anchoring bias. Therefore, our results provide useful insight on the momentum itself, and makes its profitability even more puzzling.

Lastly, we suggest a revised momentum strategy that generates positive profit without crashing. Our strategy, without sacrificing its profitability, is a significant improvement over the conventional momentum strategy in that its moments are much more desirable to investors. Our revision on the momentum strategy differs from that of previous research. Though other studies present their own version of the momentum strategy in a bid to avoid momentum crashes, they focus on the dynamic weighting scheme based on their prediction of the crashes.[5]

2010), business cycle (Chordia and Shivakumar 2002), cross-sectional return dispersion (Stivers and Sun 2010), and past market illiquidity (Avramov, Cheng, and Hameed 2015).

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

[5] 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 the momentum strategy has a minimum return of −28.40% and a

Our improvement is qualitatively different from them in that our revision is restricted to the stock selection technique.

The rest of the paper is organized as follows. The next section describes the data and variables employed in our empirical research. Section 3 tests if the nearness to 52-week high subsumes the predictive power of the momentum measure. Section 4 examines several alternative explanations on why stocks far from their peaks outperform stocks near their peaks. Section 5 introduces the nearhigh-neutral momentum strategy and compare it with the conventional momentum strategy. Section 6 concludes our paper.

2. Data and Variables

In this section, we describe the data and variables employed in our empirical research. We use the data of all NYSE/NYSE MKT/NASDAQ-listed securities on the Center for Research in Security Prices (CRSP). We only include ordinary common shares (ADRs, REITs, closed-end funds were excluded). Data on monthly risk-free rates (one-month Treasury bill rates) and the Fama and French (1993) three factors are sourced from Ken French's website.[6] Book equity data are from the COMPUSTAT database. Since the COMPUSTAT data starts from the 1960s, we complement the book equity data in the early era using Moody's manual (available from Ken French's website). Our sample period spans from January 1926 to December 2015. Actual investment period of examined portfolios start from July 1927. The first year is used for construction of measures and the next six months is used to estimate factor loadings.

Our two main variables are momentum measure and nearness to 52-week high (nearhigh measure). Following Daniel and Moskowitz (2013), we define a momentum measure of stock i at the end of month t as its cumulative returns from the end of month t–12 to the end of month t–1. Nearness to the 52-week high for each month t is the ratio of the price at the end of month

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skewness of –0.42. Daniel, Jagannathan, and Kim (2012) also show that moving to the risk-free asset during their definition of "turbulent state" can significantly improve the traditional momentum strategy.

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

t to the highest closing price during the past 12 months. Definitions on the other stock-specific variables are provided in the appendix. In month t+1, stock i is included in our sample if and only if the measures of $r_{i,t+1}$, $Momentum_{i,t}$, $Nearhigh_{,t}$, $Srev_{i,t}$, $Beta_{i,t}$, $Me_{i,t}$, $Bm_{i,t}$, and $Prc_{i,t}$ are valid. To mitigate microstructure effects associated with low price stocks, stocks are excluded if their prices are below $5. This data trimming rule results in a total of 1,896,129 stock-months.

Since our study focuses on momentum crashes, it is necessary to define the "crash period." Daniel and Moskowitz (2013) find that 14 of 15 largest crashes occurs during the market rebound. Asem and Tian (2010) also document that momentum earns negative returns when the market rebound. Therefore, for a richer economical interpretation and improved statistical reliability, we do not restrain our empirical investigation to just a few momentum crash month but focus extensively on the market rebound periods. Specifically, we define momentum crash periods as months in which 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. Our definition of the market state recognizes 149 of 1062 months as the crash periods.

3. Momentum crashes and anchoring bias

3.1 Predictability of the momentum and nearhigh measure

In this section, we first examine how the momentum and nearhigh measures interact with individual stock returns. At the end of each month t, stocks are ranked based on their momentum or nearhigh measures. Based on these rankings, value-weighted decile portfolios are formed, and stocks are held until the end of month t+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,

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

where $r_{p,t+1}$ is the return on portfolio p at month t+1, n is the number of factors, and $f_{i,t+1}$ is the realization of the *i*-th factor at month *t*+1. The factor loading $\widehat{\beta_{i,p,t}}$ is the sum of three betas estimated by running a time-series regression (2) at the end of month *t* using the past 6-month daily return data.

$$r_{p,d}^{raw} - r_f = \sum_{i=1}^{n} \beta_{i,p}^{1} f_{i,d} + \beta_{i,p}^{2} f_{i,d-1} + \beta_{i,p}^{3} f_{i,d-2} \tag{2}$$

We use the capital asset pricing model (CAPM) and Fama and French (1993) three-factor model (FF) as our risk-return model.

[Table 1 about here]

Table 1 reports raw and risk-adjusted returns of the decile portfolios based on the momentum and nearhigh measures. Panel A of table 1 restates the profitability of the momentum strategy and its crashes. During the crash periods (panel A1), the monthly return monotonically decreases from the bottom loser decile to the top winner decile. The momentum losers earn a monthly return of 8.88%, while the momentum winners earn 4.73%. Therefore, the momentum strategy earns −4.15% per month when the market rebounds. The CAPM- and FF-adjusted returns are −1.58% and −1.69%, respectively. The significantly negative risk-adjusted returns of the momentum strategy during the crash periods are 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 a statistically and economically large monthly profit of 2.11%. Controlling for risk reduces the profitability only by a small margin, consistent with Jegadeesh and Titman (1993).

Panel B of table 1 reports monthly raw and risk-adjusted returns of the decile portfolios based on the nearhigh measure. During the crash periods (panel B1), the monthly return monotonically decreases from the bottom decile to the top decile. The stocks far from peaks earn a monthly return of 10.41% while the stocks near peaks earn 3.29%. Therefore, the stocks far from peaks outperform the stocks near peaks by 7.12% per month, and the outperformance comes mostly from the short side of the portfolio. CAPM- and FF-adjusted monthly returns of near minus far portfolio (NMF) that longs the top decile of stocks near peak and shorts the bottom decile of stocks far from peak are −2.11% and −1.76%, respectively. Outside the crash periods (panel B2), the stocks near peaks outperform the stocks far from peaks, as documented by George and Hwang (2004).

The results of table 1 show an empirical pattern that both the momentum and the nearhigh measure is in negative relation with subsequent stock returns. Interestingly, the simple result shown here is suggestive of the dominance of the nearhigh measure over the momentum measure during the crash periods. During the crash periods, stocks far from peaks outperform stocks near peaks by more than losers outperform winners. Hence, it is plausible that during the momentum crash periods, stocks far from peaks rebound, and momentum losers just resemble the collection of such stocks.

3.2 Interaction between momentum and nearhigh measure

We take a closer look at the interaction between the momentum and nearhigh measures during the crash periods using the double-sort analysis. Table 2 reports monthly raw returns of portfolios that are independently double-sorted by the momentum and nearhigh measures during the crash periods. At the end of each month *t*, stocks are divided into quintiles based on their momentum and nearhigh measures, which results in 25 (5×5) portfolios. We report the value-weighted monthly return of each portfolio during the crash periods. The bottom-most row and the right-most column report the monthly average value-weighted return of the long–short portfolio. Owing to high cross-sectional correlation between the momentum and nearhigh measures, cells are not evenly balanced and are sometimes empty.[7] Hence, for the long–short portfolio, both the long and short sides of the portfolio should be nonempty to be included in the analysis of table 2.

We find a remarkably consistent result, namely, that the nearhigh measure subsumes the predictive power of the momentum measure. First, the stocks far from peaks outperform the stocks near peaks even when their momentum measures are set to be similar. Among stocks in the top momentum quintile, for example, the bottom 20% stocks far from their 52-week highs

[7] For this reason, return time-series of each portfolio is not continuous. Hence, we do not report their CAPM- and FF-adjusted returns. However, in conditional 5×5 sort, we find qualitatively same results in terms of both raw and risk-adjusted return.

outperform the top 20% by 5.43% per month. The same pattern is consistently observed in the other momentum quintiles. In every momentum quintile, stocks far from peaks outperform stocks near peaks by more than 4%. Second, when stocks have a similar nearhigh measure, the momentum measure no longer predicts returns. Within the bottom 20% of stocks that are far from their 52-week highs, for example, the top momentum quintile portfolio and the bottom quintile portfolio show small return differential, which is statistically insignificant. In some nearhigh quintiles, the momentum losers even underperform the winners as opposed to the previous momentum crash literature. Third, among the 25 portfolios we examined, the 5 portfolios that rebounded the most during the crash periods are not the losers but the stocks far from peaks exclusively. Again, the five portfolios that fell the most are mostly the stocks near peaks.

[Table 2 about here]

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

Table 3 reports the raw and risk-adjusted returns of the nearhigh-neutral momentum portfolios and the winner minus loser portfolio (WML*) during the crash periods. Panel A reports the average nearhigh and momentum measures of each portfolio. The ten portfolios have a similar level of nearhigh measure. The nearhigh-neutral momentum winners are, on average, only 5.40% closer to their 52-week highs than the nearhigh-neutral momentum losers. In contrast, the momentum measure of the winners is 77.02% higher than that of the losers. Panel B shows that despite the huge dispersion of the momentum measure among the ten portfolios, their raw and risk-adjusted returns are almost the same. The raw returns of the ten portfolios fall within the narrow range of 5.76% to 7.16%. Therefore, WML* earns statistically insignificant positive returns. The raw, CAPM- and FF-adjusted return of WML* is 1.39%, 0.66%, and 0.46%, respectively. Given that the raw return of WML is –4.15%, the disappearance of such large negative returns owing to the neutralization of the nearhigh measure is impressive.[8]

[Table 3 about here]

3.3 Robustness check: cross-sectional regression analysis

To account for the effect of other firm characteristics, we run the Fama and MacBeth (1973) regression. By running a cross-sectional regression at each crash month, we are able to distinguish the marginal effect of the nearhigh and momentum measures on subsequent stock returns in the presence of other stock-specific variables. Table 4 reports time-series average and *t*-statistics of the coefficients from the 149 cross-sectional regressions.

[Table 4 about here]

In Model 1 of table 4, the average coefficient on the momentum measure is significantly negative, which is consistent with extant literature that losers earn higher returns than winners during the crash periods. However, when the nearhigh measure is included as an independent variable (model 2), the average coefficient on the momentum measure turns positive and no longer has negative predictive power on future returns. The nearhigh measure, however, is negative and statistically significant with a *p*-value of less than 1%. Including additional control variables (models 3, 4, 5, and 6) does not alter our result. In model 3, for example, when the nearhigh measure is not included, the coefficient on the momentum measure is –0.0174 and is statistically significant at the 5% level. However, when the nearhigh measure is included (model 4), the coefficient on the momentum measure becomes insignificantly positive. In addition, a comparison between models 2, 4, and 6 further reveals that other stock-specific characteristics cannot account for the dominance of the nearhigh measure.

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[8] The descriptions and further investigation regarding the nearhigh-neutral momentum portfolios and WML* will appear again in section 5.

Although table 4 supports the notion that the nearhigh measure subsumes the predictive power of the momentum measure during the crash periods, we need to zero in on extreme months, namely, when the momentum crashed the most. Since the crash periods consist of more than 100 months, it is possible that the positive signs on the momentum measure (see model 4 of table 4) are driven by modest crash months while the coefficient on momentum remains significantly negative during the extreme crash months. Therefore, we focus on the 15 largest crash months among the 149 crash periods. In table 5, we report the cross-sectional regression coefficients of model 4 in table 4 for each of the 15 largest crash months.[9] To readily compare the economic significance, we standardize independent variables using their cross-sectional means and standard deviations. For brevity, we only report the coefficients on the nearhigh and momentum measures.

Table 5 shows that even in the extreme months when the momentum crashed the most, momentum has no predictive power when the nearhigh measure is included as an independent variable. For example, for August 1932, an increase in one standard deviation of the momentum measure decreases subsequent returns by 0.71% while a one-standard deviation increase in the nearhigh measure reduces the returns by 13.71%. In 13 of the 15 months, the coefficient on the nearhigh measure is more negative than that on the momentum measure. Moreover, the coefficient on the momentum measure is negative and statistically significant at the 5% level for two months only, while that on the nearhigh measure is negative and significant in 12 of the 15 months.

[Table 5 about here]

3.3 Robustness check: alternative test setups

We test robustness of our results that nearness to previous price peak drives the momentum to crash. We replicate Fama and MacBeth (1973) regression (model 4 of table 4) under various alternations. For brevity, in table 6, we only report coefficient on the momentum and nearhigh

[9] We choose model 4 because it does not reduce the number of observations used in the analysis compared to the portfolio analyses in the previous subsections.

measure. Specifically, panel A of table 6 compares the momentum and nearhigh measure during the crash periods when our sample stocks are extended to stocks whose prices exceed $1 and restricted to stocks listed on the NYSE, NYSE MKT, and NASDAQ and to non-financial stocks. In every case except when the sample is restricted to stocks listed on the NYSE MKT, the coefficient on the nearhigh measure is significantly negative while the coefficient on the momentum measure is positive. In panel B, we do sub-period analysis. We divide our sample periods into 5 periods. We find that our results robustly holds in various sub-periods. In panel C, we define the momentum measure in alternative ways: the past 12-month return without skipping the 1-month, recent 6-month, and intermediate 6-month returns. In all cases, the coefficient on the nearhigh measure is significantly negative while the coefficient on the momentum measure is insignificant. In panel D, we employ alternative definitions of the nearhigh measure: nearness to the 13-, 26-, and 104-week high. We again find that our results are robust to such variations. In panel E, we alter our definition of the crash periods. We substitute value-weighted market return with equal-weighted market return or past 1-year market return with past 2- and 3-year market return. Our result still holds in all three settings.

[Table 6 about here]

3.4 Investors' anchoring bias

We find consistent pattern that stocks far from peaks outperform stocks near peaks when the market rebounds and momentum crashes are just a manifestation of such outperformance. Therefore, the right question researchers should ask is why stocks far from peaks outperform stocks near peaks. We argue that stocks far from peaks become overpriced as anchoring-susceptible demand increases. As the market rebounds, market-wide sentiment recovers and speculative demand flow into the market. Moreover, these investors anchor on the 52-week highs: they prefer stocks whose current prices are far from their 52-week highs. Hence demand for stocks that are far from their 52-week highs increases, which results in their overpricing. The evidence that investors anchor on previous price peaks and prefer stocks far from peaks can be easily found from the extant literature. Grinblatt and Keloharju (2001) find that individual investors buy stocks whose prices are distant from previous price peaks and sell stocks near their peaks. George and Hwang (2004) document cross-sectional return pattern that is consistent with such anchoring-motivated preference. They find that nearness to 52-week high is in positive relation with subsequent stock returns. Marshall and Cahan (2005), Du (2008), and Liu, Liu, and Ma (2011) document similar findings in the international markets. Moreover, the anchoring effect was documented for various aspects of the market. Birru (2015) and George, Hwang, and Li (2015) find that the post-earnings announcement drift can be explained using investors' anchoring bias. They argue that investors underreact to positive earnings news if stock price is near peak because investors think that the news has already been incorporated into price. Baker, Pan, and Wurgler (2012) note that the 52-week highs and prior price peaks are used as anchors in merger decisions. They find that target shareholders are more likely to accept an offer if offer price is above 52-week high. Heath, Huddart, and Lang (1999) report that stock options are exercised massively when the stock prices exceed the previous year's highs. Li and Yu (2012) observe that the 52-week high of a market index also serves as an anchor that influences investors' decisions. Therefore the anchoring-based explanation seems to be parsimonious with many consistent evidences.

For clarity, it is worthwhile to reconcile our results to that of George and Hwang (2004). They find that, in full sample, stocks near peaks outperform stocks far from peaks, which is the exact opposite of our results. They argue that at the time of portfolio formation, stocks far from peaks are already overpriced. Hence, during holding period, they underperform as the information reveals. In the full sample, speculative demand is almost always exist in the market because the market is bullish in general. Therefore, at the time of the portfolio formation, stocks near peaks are already mispriced. On the other hand, our investigation is focused on the market rebound period. Hence, at the time of the portfolio formation, speculative demand is almost extinct because the market had suffered from a long-lasting decline. As the market rebounds, speculative demand flows in, which results in the overpricing of stocks far from peaks. In other words, our market-rebound-focused research times the mispricing stage, while the unconditional research by George and Hwang (2004) is likely to capture the revelation stage.

In this regard, we examine the performance of NMF in different market states. We consider four market states based on the sign of past 1-year market return and the sign of contemporaneous market return. UU is a market state where the past 1-year market return is positive and contemporaneous market return is positive. UD, DD and DU is defined analogously and DU refers to the crash periods we examined. At the portfolio formation, if the past market return was positive (UU and UD), stocks far from peaks are overpriced. Hence, as information reveals, NMF earns positive returns. In addition, if the contemporaneous market return is negative (UD), the portfolio will earn even higher positive return since there is an outflow of speculative demands. When the market continues to go down (DD), there is neither previous overpricing nor contemporaneous overpricing. Hence, NMF will earn zero return. To sum up, we predict near minus far portfolio to earn positive return, higher positive return, negative return, and zero return in UU, UD, DU, and DD states respectively.

Table 7 confirms our prediction. We find that in UU and UD, NMF earns 0.49% and 1.48% respectively. In DD, the portfolio earns near zero and statistically insignificant return of 0.26%. The pattern is unchanged after controlling for three factors.[10] Therefore, our hypothesis that combines the anchoring bias and the market states is consistent not only during the market rebounds, but also throughout the whole sample periods.

[Table 7 about here]

4. Alternative explanations

In this section, we consider several potential alternative explanations for the outperformance of the stocks far from peaks over the stocks near peaks.

4.1 Risk-based explanation

We first investigate whether the risk can explain the outperformance of the stocks far from peaks. Similar to momentum strategy, NMF loads negatively on the market after the market decline. Hence, their expected return is negative when the market rebounds. However in the previous section, we have shown that the stocks far from peaks outperform the stocks near

[10] Raw returns show very different pattern from CAPM- and FF-adjusted returns. Since we are focused on a very specific market state, market loadings play crucial role in determining raw return. Hence, looking solely at the raw return blurs the true abnormal performance of near minus far portfolio. Therefore, we focus on risk-adjusted returns.

peaks even after accounting for such time-variation in risk loadings. The outperformance was economically large (more than 1.7% per month) and statistically significant with t-statistics of roughly 3.5. Therefore risk only partly explains the outperformance.

It is possible, however, that the outperformance is driven by some risk factor that is not captured by traditional CAPM or Fama and French (1993) three-factor model. To address this possibility, we form a factor mimicking portfolio based on the nearhigh measure and compute each stock's loading on the portfolio. Then we compare the predictive power of the loading and the nearhigh measure itself analogues to Daniel and Titman (1997). Specifically, at each month, we estimate each stock's risk loading by running a time-series regression of equation (2) where it has four factors (FF three factors + NMF).[11] Then, we run a Fama and MacBeth (1973) regression to compare the predictive power of the risk-loading on NMF factor and the nearhigh characteristic itself. Table 8 reports average regression coefficient during the crash periods. Table 8 reports that the predictive power of the nearhigh is not subsumed by the risk loadings. In model 3, for example, the average coefficient on the nearhigh measure is –0.0576 and is significant at 1% level. When the three factor and NMF factor loadings are included (model 4), the coefficient changes little (–0.0555) and is still statistically significant at 1% level.

[Table 8 about here]

Therefore, outperformance of the stocks far from peaks cannot be fully explained by risk alone.

4.2 Underpricing explanation

In our anchoring hypothesis, we argue that the stocks far from peaks rebound as they become overpriced. However, the stocks far from peaks may earn positive profits because their previous underpricing is resolved as the information reveals over time. To test whether the outperformance is due to previous underpricing, we first examine long-run performance of

[11] To maintain consistency with other factors, we employ alternative definition of NMF here. At the end of each month, we divide stocks into small and large stocks based on NYSE median market equity. Then within each group, we divide stocks into terciles based on their nearhigh measure. NMF is a portfolio that longs the top nearhigh tercile and shorts the bottom nearhigh tercile.

NMF during the momentum crash periods. In panel A of table 9, we report series of cumulative raw and risk-adjusted returns of the near minus far portfolio that was held during the crash month *t*+1. We find an evidence of long-run reversal. At the first two month, NMF earns largely negative CAPM- and FF-adjusted returns of −3.15% and −2.16%. However, it subsequently earns positive returns and hence the cumulative return from month *t*+1 to month *t*+12 is indistinguishable from zero. The CAPM- and FF- adjusted 5-year cumulative return ($ret_{[t+1,t+60]}$) of the near minus far portfolio is also nonnegative.[12] Next, we step further and examine the long-run reversal when the momentum crashed the most. Since our definition of crash periods includes some months when momentum did not earn negative returns, it could have affected our results on the long-run reversal. Hence, we focus on the 100 largest crashes (panel B). As expected, during the first two months, the stocks far from peaks outperform the stocks near peaks by a large margin. However, it reverses in the long run. The 1-year cumulative return of NMF is indistinguishable from zero and the 3-, 4- and 5-year cumulative return is also non-negative.

[Table 9 about here]

In table 10, we provide another piece of evidence that supports overpricing story of stocks far from peaks. We look at daily return of near minus far portfolio during the crash periods. We divide these roughly 3,300 daily observation into deciles based on the day's market return. We find that the outperformance is mostly severe on the days that the market earns negative returns. On the top 10% days that market rebounded the most (2.78%) CAPM- and FF-adjusted returns of stocks near peaks minus loser portfolio earns −0.47% and −0.58% just in one day. On the contrary, on the bottom 10% days that market fell the most (−1.92%), CAPM- and FF-adjusted returns of stocks near peaks minus loser portfolio earns small return that is indistinguishable from zero. This pattern is hard to reconcile with underpricing story. If underpricing is resolved as the information diffuses into the market, there should be no discernable difference on the

[12] In case of raw return, we find no evidence of long-run reversal. However, since we are focusing on a very specific market state, which is the market rebound period, raw return is severely influenced from the market loading. Therefore, raw return provides little information on the long-run performance.

days that market went up and down.

[Table 10 about here]

4.3 Alternative sources of overpricing

Having established the overpricing story, we consider other possible sources of overpricing. Baker and Wurgler (2006) posit that speculators are attracted to young, small, unprofitable, and distressed stocks. Hence, we consider if these characteristics can explain the performance of stocks far from peaks. In table 11, we run Fama and MacBeth (1973) regression with additional control variables that proxy for age, profitability, distress, and lottery-like payoff.[13] We find that including the control variables does not alter the economic and statistical significant of the momentum and nearhigh measure. In model 7, for example, the coefficient on the momentum measure is insignificant while the coefficient on the nearhigh measure is still significantly positive. Therefore, investors' anchoring bias that is captured by nearness to 52-week high is the most consistent explanation.

[Table 11 about here]

5. Nearhigh-neutral momentum strategy

In this section, we further explore the nearhigh-neutral momentum strategy and compare with the conventional momentum strategy. The conventional momentum strategy exhibits undesirable attributes such as high volatility, negative skewness, and largely negative minimum return due to its crashes. Since we identify nearness to 52-week high as a major source of momentum crashes, we expect the nearhigh-neutral momentum strategy to be free of these attributes. Moreover, since momentum crashes contribute significantly to the pro-cyclicality of momentum profits, we predict that our nearhigh-neutral momentum strategy will not vary with various measures of market conditions such as market returns, and business cycles.

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[13] We use samples after 1978 since every variables become available after 1978.

5.1 Moments

We focus our investigation on the comparison of the WML and WML* strategies.[14] These strategies are similar in that they long winners and short losers. However, while WML picks momentum winners and losers from the entire universe of stocks, WML* picks momentum winners and losers evenly from the 5 subsets with different nearness to the 52-week highs. Therefore, WML* winners and losers consist of stocks with similar levels of the nearhigh measure, while WML does not.

In section 3, we document that WML* earns positive returns during the momentum crash periods. However, this does not necessarily guarantee 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 crash during the entire period, this could have been achieved by sacrificing its profitability compared to WML. Therefore we examine the properties of WML and WML* in the full sample period.

[Table 12 about here]

In table 12, we report descriptive statistics of the conventional momentum strategy (WML) and the nearhigh-neutral momentum strategy (WML*). The investment period spans from July 1927 to December 2015. In line with table 1 of Barroso and Santa-Clara (2015), WML exhibits excessive kurtosis (16.77), highly negative skewness (−1.73), and large negative minimum returns (−69.30%), all of which point to the fat-tailed distribution of WML return on the negative side. However, this pattern is muted when we revise the momentum strategy to be nearhigh-neutral. Skewness is almost zero (0.48), and kurtosis decreases to 6.07. Minimum return dramatically increases to −26.87%. Overall, the distribution of WML* returns shows normal-like behavior and earns positive returns without crashes. Controlling for market and three-factor risk does not change our result. In an unreported result, we find that the dominance of WML* over WML is pronounced in case of an equal-weighted strategy. Importantly, the improvement is made without sacrificing profitability. Raw and risk-adjusted return of

[14] The explanations for WML* and WML can be found in section 3.2.

nearhigh-neutral momentum strategy is higher and it has much higher Sharpe ratio. For example, monthly Sharpe ratio of the conventional momentum strategy is 16.68% while that of the nearhigh-neutral momentum strategy is 29.30%.

Figure 1 plots the cumulative raw and risk-adjusted return of WML and WML* from July 1927 to December 2015. The solid line and dotted lines correspond to WML* and WML, respectively. The figure shows that, in line with table 12, the cumulative return of WML* increases smoothly without sudden drawdowns while WML shows several rapid and large declines. Again, the improvement in WML* is achieved without sacrificing the profitability of WML, regardless of the risk-return model.

[Figure 1 about here]

5.2 Time-variation

We now turn our attention to the time-variation of the nearhigh-neutral momentum strategy. The conventional momentum strategy is known to vary with market states and macroeconomic condition..[15] Heidari (2015) finds that most of the momentum predictors' power comes from momentum crash periods. Therefore, we predict that WML* can resolve the pro-cyclicality of WML as it resolves the crashes.

In table 13, we regress the time-series of WML and WML* monthly returns on variables that are known to predict momentum profits. In model 1 of table 13, we regress WML and WML* on the past 12-month cumulative market return (Mktret) and its square (Mktretsq), following Cooper et al. (2004). Panel A shows that the conventional momentum strategy earns higher return following a bull market, while the WML* strategy does not vary with the past condition of the market (panel B). In model 2, we regress WML and WML* on past market illiquidity, Mktilliq. In line with Avramov et al. (2015), we define Mktilliq as the value-weighted average of each stock's Amihud (2002) illiquidity measure in the last month. While WML depends on

[15] Many studies identify the determinants of momentum profits, such as business conditions (Chordia and Shivakumar 2002), past market return (Cooper et al. 2004; Asem and Tian 2010), past market volatility (Wang and Xu 2010), past market liquidity (Avramov et al. 2015), the market's recent cross-sectional dispersion in stock returns (Stivers and Sun 2010), and others.

the past market illiquidity significantly (*t*-statistics=–2.89), WML* does not (*t*-statistics=0.72). We also regress momentum profits on past market volatility, Mktvol, which is the variance of the past 126-day market returns. Consistent with Wang and Xu (2010) and Daniel and Moskowitz (2013), we find a significantly negative relationship between conventional momentum profits and past market volatility. However, when we regress WML* on Mktvol, the coefficient is insignificant. Models 4, and 5 also confirm our hypothesis that WML* does not vary with the determinants of WML. Specifically, the January effect and Chordia and Shivakumar (2002) macroeconomic variables do not influence WML* profits.

[Table 13 about here]

From the traditional asset pricing perspective, investors lean towards high return and away from high volatility, negative skewness, and pro-cyclicality. Therefore the nearhigh-neutral momentum strategy certainly provides investors with much desirable strategy.

It is noteworthy that our revision on the momentum strategy is qualitatively different from previous attempts. Daniel et al. (2012), Daniel and Moskowitz (2013), Barroso and Santa-Clara (2015), and Heidari (2015) propose ways that focus on the timing of momentum crashes. When investors expect the momentum to crash, they move away from or underweight the momentum portfolio. In contrast, our strategy focuses exclusively on stock selection. Hence, it is less prone to leverage and short-sale constraint

6. Conclusion

Momentum is both a powerful anomaly and a trading strategy in normal environments. However, when the market rebounds from its trough, the magnitude of the strategy crash is large. Despite the vast attention given to this issue, there was no complete and consistent explanation about why it occurs.

In this paper, we provide a concise explanation on the subject. As the market rebounds, speculative demands increases. Since investors are prone to anchoring bias, demand on stocks that are far from their 52-week highs increases, which results in price run-ups. Therefore, nearness to the 52-week high is negatively related with subsequent returns. Since the momentum measure is positively correlated with nearness to the 52-week high, the momentum strategy crashes.

Consistent with our hypothesis, we find that the nearness to 52-week highs subsumes the negative predictability of the momentum measure. We consider alternative explanations and find that they are inconsistent with various empirical pattern we documented.

Furthermore, given that the nearness to 52-week high drives momentum to crash, we devise a nearhigh-neutral momentum strategy. The strategy is free from the disadvantages of the conventional momentum strategy such as high volatility, negative skewness, a large negative minimum return and pro-cyclicality. Most importantly, the strategy does not sacrifice its profitability compared to the conventional momentum strategy.

Appendix

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

[Table A1 about here]

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Table 1. Portfolios sorted by momentum and nearhigh measure

Table 1 reports raw and risk-adjusted returns of the momentum and nearhigh decile portfolios. At the end of each month, stocks are ranked in ascending order based on their momentum (nearhigh) measures. Based on these rankings, value-weighted decile portfolios are formed, and stocks are held until the end of the next month. We also form a hedge portfolio that longs the top decile and shorts the bottom decile. Panel A (B) of table 1 reports the raw and risk-adjusted returns of these portfolios. Specifically, panel A1 (B1) reports returns during the crash periods, and panel A2 (B2) reports returns outside the crash periods. The column labeled "10−1" reports the raw and risk-adjusted return of the long-short portfolio. Our risk-return models are the CAPM and the Fama and French (1993) three-factor model (FF). Every number is in percent. Numbers in parentheses are Newey and West (1987) *t*-statistics (lag=12).

	1	2	3	4	5	6	7	8	9	10	10−1
Panel A: Momentum Decile Portfolio											
Panel A1: Crash Periods											
Raw	8.88	7.85	6.83	6.36	5.78	4.96	4.93	4.37	4.73	4.73	–4.15
	(7.32)	(7.50)	(8.14)	(7.65)	(8.33)	(8.37)	(9.31)	(8.46)	(8.92)	(12.63)	(–3.72)
CAPM	1.13	1.16	0.79	0.88	0.52	–0.01	0.19	–0.27	–0.02	–0.45	–1.58
	(3.08)	(3.41)	(3.50)	(3.90)	(2.96)	(–0.08)	(1.05)	(–1.57)	(–0.11)	(–1.52)	(–2.81)
FF	1.04	1.11	0.70	0.94	0.54	0.04	0.10	–0.33	–0.23	–0.65	–1.69
	(3.19)	(3.30)	(2.82)	(3.96)	(3.45)	(0.25)	(0.59)	(–1.95)	(–0.89)	(–2.09)	(–2.98)
Panel A2: Non-crash Periods											
Raw	–1.11	–0.69	–0.28	–0.07	0.11	0.16	0.44	0.61	0.65	1.00	2.11
	(–2.73)	(–2.00)	(–0.91)	(–0.26)	(0.42)	(0.68)	(1.77)	(2.47)	(2.41)	(3.28)	(9.18)
CAPM	–0.63	–0.36	–0.02	0.12	0.25	0.25	0.47	0.57	0.56	0.90	1.54
	(–4.62)	(–3.62)	(–0.31)	(1.70)	(4.17)	(4.72)	(8.44)	(8.11)	(5.99)	(6.07)	(7.14)
FF	–0.61	–0.32	–0.03	0.09	0.25	0.25	0.47	0.58	0.57	0.98	1.59
	(–4.77)	(–3.46)	(–0.40)	(1.45)	(4.15)	(4.31)	(7.84)	(7.59)	(5.90)	(6.97)	(7.23)
Panel B : Nearhigh Decile Portfolio											
Panel B1: Crash Periods											
Raw	10.41	8.88	8.02	7.20	6.29	5.61	5.06	4.68	3.96	3.29	–7.12
	(7.92)	(8.22)	(8.63)	(8.28)	(9.16)	(8.66)	(9.14)	(9.45)	(8.69)	(8.50)	(–6.10)
CAPM	1.72	1.37	1.26	0.85	0.54	0.19	–0.02	0.05	–0.24	–0.38	–2.11
	(3.84)	(4.33)	(4.72)	(3.34)	(2.66)	(0.89)	(–0.16)	(0.30)	(–1.15)	(–1.76)	(–3.64)
FF	1.22	1.19	1.06	0.72	0.47	0.29	0.23	0.18	–0.34	–0.54	–1.76
	(3.51)	(3.78)	(3.95)	(2.88)	(2.25)	(1.54)	(1.21)	(1.02)	(–1.57)	(–2.13)	(–3.49)
Panel B2: Non-crash Periods											
Raw	–0.88	–0.47	–0.16	–0.12	0.01	0.12	0.16	0.41	0.47	0.43	1.31
	(–1.98)	(–1.22)	(–0.47)	(–0.39)	(0.03)	(0.42)	(0.63)	(1.69)	(1.98)	(1.98)	(4.64)
CAPM	–0.38	–0.09	0.09	0.09	0.19	0.22	0.25	0.45	0.53	0.38	0.76
	(–2.41)	(–0.76)	(1.08)	(1.31)	(2.66)	(3.23)	(4.38)	(7.44)	(7.50)	(4.94)	(3.82)
FF	–0.31	0.00	0.20	0.10	0.21	0.25	0.27	0.46	0.49	0.36	0.67
	(–2.21)	(0.01)	(2.10)	(1.32)	(3.05)	(3.50)	(4.49)	(7.09)	(6.80)	(4.44)	(3.73)

Table 2. Independently sorted portfolio

Table 2 reports monthly raw returns of portfolios independently double-sorted by momentum and nearhigh measure during the crash periods. At the end of month *t*, firms are divided into quintiles based on their momentum and nearhigh measure, which results in 25(5×5) portfolios. We report the average value-weighted return of each portfolio at month *t*+1 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 nearhigh 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 Newey and West (1987) *t*-statistics (lag=12).

		Nearhigh					
		1(Far)	2	3	4	5(Near)	5−1
Momentum	1(Loser)	9.34	7.16	4.39	2.44	3.76	–4.34
		(7.26)	(6.86)	(5.50)	(1.48)	(1.14)	(–1.44)
	2	9.75	7.78	5.72	3.78	3.12	–5.46
		(9.45)	(8.89)	(6.40)	(6.45)	(3.34)	(–5.02)
	3	10.21	7.58	6.03	4.52	3.04	–7.00
		(8.77)	(8.46)	(9.76)	(7.79)	(6.34)	(–7.05)
	4	9.22	8.62	6.17	5.03	3.44	–5.95
		(7.36)	(7.71)	(9.73)	(10.76)	(7.59)	(–5.31)
	5(Winner)	9.27	6.88	6.53	5.99	4.04	–5.43
		(7.81)	(9.35)	(7.64)	(9.71)	(8.40)	(–4.80)
	5−1	0.88	0.68	1.75	3.59	–0.16	
		(0.74)	(0.95)	(1.95)	(2.30)	(–0.05)	

Table 3. The nearhigh-neutral momentum portfolio

Table 3 reports raw and risk-adjusted returns of the nearhigh-neutral momentum portfolios and winner minus loser portfolio (WML*) during the crash periods. At each month, we group stocks into quintile based on their nearhigh measure. Within each nearhigh quintile, we group stocks into deciles based on their momentum measure, which results in value-weighted and evenly-spaced 50 portfolios. Then, we hold the stocks until the end of the next month. Lastly, we form equal-weighted cohorts with five portfolios from the same momentum decile. Therefore, we construct ten portfolios with equal number of stocks, similar level of the nearhigh measure and different level of the momentum measure. Panel A reports time-series average of the nearhigh and momentum measure for each portfolios. Panel B reports the raw and risk-adjusted return of the nearhigh-neutral momentum portfolios and WML*. Every number is in percent. Numbers in parenthesis are Newey and West (1987) *t*-statistics (lag=12).

	1(L*)	2	3	4	5	6	7	8	9	10(W*)	WML*
Panel A : Average measure											
Nearhigh	65.21	66.91	68.01	68.71	69.31	69.71	70.11	70.41	70.61	70.61	5.4
Momentum	–35.31	–27.81	–23.71	–20.31	–16.91	–13.21	–8.81	–3.01	6.61	41.71	77.02
Panel B : Average return											
Raw	5.76	6.04	6.27	6.28	6.32	6.41	6.71	6.47	7.06	7.16	1.39
	(7.29)	(7.55)	(8.24)	(8.63)	(8.28)	(9.00)	(9.64)	(10.11)	(9.19)	(10.33)	(3.15)
CAPM	0.00	0.41	0.70	0.75	0.66	0.67	0.85	0.49	0.89	0.66	0.66
	(0.00)	(1.92)	(4.10)	(3.87)	(3.27)	(3.78)	(4.79)	(1.78)	(3.43)	(2.25)	(1.62)
FF	–0.11	0.33	0.53	0.61	0.54	0.48	0.55	0.23	0.67	0.35	0.46
	(–0.48)	(1.53)	(3.66)	(3.06)	(2.86)	(2.84)	(3.24)	(1.11)	(2.71)	(1.21)	(1.09)

Table 4. Cross-sectional predictability of momentum and nearhigh measure

Table 4 reports the result of the Fama and MacBeth (1973) regression during the crash periods. For every month, we regress individual stock's raw return on various stock characteristics, including momentum and nearhigh measures. Table 4 reports the time-series average and *t*-statistics of the coefficient on each variable. The description of each variable can be found in the appendix. Numbers in parentheses are Newey and West (1987) *t*-statistics (lag=12).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Momentum	–0.0384 (–2.94)	0.0393 (4.85)	–0.0174 (–2.05)	0.0071 (1.35)	–0.0194 (–2.19)	0.0073 (1.46)
Nearhigh		–0.1601 (–7.40)		–0.0576 (–4.39)		–0.0617 (–4.43)
Srev			–0.131 (–8.81)	–0.1039 (–6.12)	–0.1323 (–9.38)	–0.1017 (–6.49)
Beta			0.0257 (6.71)	0.0217 (6.17)	0.0210 (7.50)	0.0178 (7.15)
Log(Me)			0.0006 (1.13)	0.0010 (1.71)	–0.0015 (–2.94)	–0.0012 (–2.32)
Log(Bm)			0.0014 (0.94)	0.0020 (1.28)	0.0015 (0.99)	0.0017 (1.14)
Log(Prc)			–0.0054 (–3.13)	–0.0033 (–2.17)	–0.0048 (–3.48)	–0.0031 (–2.47)
Lrev					–0.0061 (–1.89)	–0.0065 (–1.99)
Ivol					–0.1107 (–1.09)	–0.1920 (–2.04)
Skew					–0.0008 (–0.83)	–0.0002 (–0.25)
Kurt					–0.0011 (–4.64)	–0.0010 (–4.09)
Illiq					–0.0017 (–4.05)	–0.0016 (–4.10)
Max					0.0606 (1.79)	0.0428 (1.23)

Table 5. Cross-sectional predictability of momentum and nearhigh measure (15 largest crash months)
Table 5 reports the coefficients on the momentum and nearhigh measures from a cross-sectional regression of model 4 in table 4 for the 15 largest momentum crashes. Independent variables are standardized using their cross-sectional means and standard deviations. Column labeled WML reports raw return of the momentum winner minus loser strategy. The next two column report the past 1-year cumulative market return and the contemporaneous market return. Market return is the CRSP value-weighted return. The last two columns report coefficient on the momentum and nearhigh measure. Coefficients on the other firm characteristics are omitted for brevity. Numbers in parentheses are standard *t*-statistics.

Rank	Date	WML	$Mkt_{[t-11,t]}$	Mkt_{t+1}	Momentum	Nearhigh
1	1932-07	–69.29	–65.86	34.06	–2.91 (–0.60)	–3.31 (–0.67)
2	1932-08	–62.46	–50.97	37.13	–0.71 (–0.15)	–13.71 (–3.51)
3	2001-01	–40.02	–11.17	3.95	–0.51 (–1.00)	–7.01 (–9.74)
4	2009-04	–35.77	–38.61	10.93	–2.01 (–2.45)	–5.31 (–6.11)
5	1938-06	–34.21	–39.05	23.79	–2.91 (–1.91)	–3.91 (–2.26)
6	1931-06	–32.31	–45.73	14.03	–4.11 (–2.00)	3.21 (1.28)
7	1939-09	–31.62	–1.14	16.18	2.61 (1.79)	–17.41 (–8.09)
8	1933-04	–26.93	–12.63	39.41	–1.81 (–0.95)	–1.71 (–0.64)
9	1970-09	–19.87	–14.52	4.75	1.01 (1.49)	–5.61 (–7.67)
10	1973-07	–19.16	–7.32	5.69	0.31 (0.50)	–2.81 (–3.48)
11	1975-01	–17.06	–27.95	14.16	0.71 (1.27)	–5.41 (–8.38)
12	1931-01	–16.48	–28.91	6.37	0.91 (0.94)	–4.51 (–3.06)
13	1931-02	–16.14	–28.54	10.96	0.51 (0.35)	–4.51 (–2.82)
14	2009-05	–15.30	–35.21	6.77	–0.11 (–0.19)	–4.61 (–7.28)
15	2002-11	–14.83	–13.49	6.12	0.11 (0.18)	–6.01 (–12.03)

Table 6. Robustness test

Table 6 reports the Fama and MacBeth (1973) regression coefficients on the momentum and nearhigh measure under various alternations. We run a cross-sectional regression of model 4 in table 4 each month. In panel A, we extend our samples to stocks whose prices exceed $1 and restrict to NYSE-, NYSE MKT-, and NASDAQ-listed stocks, and non-financial stocks. In panel B, we divide our sample into five sub-periods. In panel C, we define the momentum measure in alternative ways: the past 12-month return without skipping the 1-month, recent 6-month returns, and intermediate 6-month returns. In panel D, we employ alternative definitions of the nearhigh measure: the nearness to 13-, 26-, and 104-week highs. In panel E, we use alternative definitions of the crash periods. We substitute the past 1-year market return with the past 2- or 3-year market return or value-weighted market return with equal-weighted market return. Numbers in parentheses are Newey and West (1987) *t*-statistics (lag=12).

	Momentum	Nearhigh		Momentum	Nearhigh
Panel A: Sub-samples			*Panel B: Sub-periods*		
Prc>$1	0.0038	−0.0605	1927-1946	−0.0031	−0.0780
	(0.66)	(–4.44)		(–0.26)	(–2.24)
Non-financial	0.0066	−0.0567	1947-1966	0.0135	−0.0213
	(1.25)	(–4.26)		(2.40)	(–1.88)
NYSE	0.0056	−0.0612	1967-1986	0.0148	−0.0434
	(0.92)	(–4.52)		(1.05)	(–1.88)
NYSE MKT	0.0089	−0.0351	1987-2006	0.0143	−0.0638
	(0.95)	(–1.39)		(5.02)	(–2.98)
NASDAQ	0.0132	−0.0567	2007-2015	−0.0054	−0.0931
	(2.68)	(–3.51)		(–0.72)	(–3.92)
Panel C: Definitions of momentum measure			*Panel D: Definitions of nearhigh measure*		
$r_{[t-12,t-1]}$	0.0103	−0.0615	13-week	−0.0105	−0.0718
	(1.86)	(–4.76)		(–1.40)	(–5.85)
$r_{[t-6,t-2]}$	−0.0071	−0.0365	26-week	−0.0044	−0.0591
	(–0.86)	(–2.89)		(–0.66)	(–4.25)
$r_{[t-12,t-7]}$	0.0033	−0.0470	104-week	−0.0177	−0.0391
	(0.68)	(–3.56)		(–0.22)	(–3.76)
Panel E: Definitions of crash periods					
EW	0.0132	−0.0693			
	(2.34)	(–4.84)			
2-year	0.0068	−0.0728			
	(0.99)	(–4.00)			
3-year	0.0096	−0.0550			
	(2.18)	(–2.98)			

Table 7. Near minus far portfolio return for each market states

Table 7 reports raw and risk-adjusted returns of near minus far portfolio that longs the top 10% of stocks near peaks and shorts the bottom 10% of stocks far from peaks for each market states. Market states is divided into four depending on their past 1-year market return and the contemporaneous market return. UU, for example, refers to months when the past 1-year market return is positive and the contemporaneous market return is positive. Every number is in percent. Numbers in parentheses are Newey and West (1987) t-statistics (lag=12).

	UU	UD	DU	DD
Raw	−0.76	2.70	−7.12	6.56
	(−2.98)	(7.67)	(−6.10)	(9.50)
CAPM	0.49	1.48	−2.11	0.26
	(2.10)	(4.91)	(−3.64)	(0.35)
FF	0.62	0.98	−1.76	0.19
	(2.62)	(4.10)	(−3.49)	(0.29)

Table 8. Comparison between risk loading and characteristics

Table 8 reports the result of the Fama and MacBeth (1973) regression during the crash periods. For each month, we regress individual stock's raw return on various stock characteristics and risk-loading on FF three factors and NMF. Table 8 reports the time-series average and *t*-statistics of the coefficient on each variable. Numbers in parentheses are Newey and West (1987) t-statistics (lag=12)..

	Model 1	Model 2	Model 3	Model 4
Momentum	0.0393 (4.85)	0.0357 (5.58)	0.0071 (1.35)	0.0060 (1.11)
Nearhigh	–0.1601 (–7.40)	–0.1241 (–6.97)	–0.0576 (–4.39)	–0.0555 (–4.41)
Srev			–0.1039 (–6.12)	–0.1044 (–6.43)
Log(Me)			0.0010 (1.71)	0.0011 (1.89)
Log(Bm)			0.0020 (1.28)	0.0018 (1.37)
Log(Prc)			–0.0033 (–2.17)	–0.0031 (–2.30)
β_{MKT}		0.0204 (5.42)		0.02146 (5.97)
β_{HML}		–0.0000 (–0.00)		0.0010 (0.75)
β_{SMB}		0.0025 (1.04)		0.0016 (0.64)
β_{NMF}		–0.0218 (–3.70)		–0.0237 (–4.21)

Table 9. Long-run performance of near minus far portfolio

Table 9 reports cumulative raw and risk-adjusted returns of near minus far portfolio after portfolio formation at the end of month *t*. Cumulative raw and risk-adjusted return is the sum of each month's raw and risk-adjusted return. In panel A, we report long-run return of the near minus far portfolio during the crash periods. In panel B, we report cumulative returns during the largest 100 momentum crash months. Every number is in percent. Numbers in parentheses are Newey and West (1987) t-statistics (lag=60).

	Panel A: Crash periods			Panel B: Top 100		
	Raw	CAPM	FF	Raw	CAPM	FF
$Ret_{[t+1,t+2]}$	−8.76	−3.15	−2.16	−11.90	−7.59	−4.68
	(−5.94)	(–3.69)	(–2.75)	(–4.62)	(–7.80)	(–5.58)
$Ret_{[t+1,t+12]}$	−8.48	1.41	2.77	−9.34	−2.47	−0.25
	(–2.20)	(0.35)	(0.71)	(–2.50)	(–0.66)	(–0.07)
$Ret_{[t+1,t+24]}$	−15.68	2.68	5.24	−16.99	−1.43	0.48
	(–3.04)	(0.38)	(0.92)	(–2.75)	(–0.22)	(0.10)
$Ret_{[t+1,t+36]}$	−17.69	11.98	13.72	−23.51	2.74	6.17
	(–2.64)	(1.48)	(2.00)	(–2.92)	(0.32)	(1.32)
$Ret_{[t+1,t+48]}$	−22.81	14.80	16.58	−25.25	6.47	7.42
	(–2.78)	(1.58)	(2.14)	(–3.08)	(0.63)	(1.18)
$Ret_{[t+1,t+60]}$	−33.04	17.52	20.99	−35.57	6.77	10.61
	(–3.73)	(1.69)	(2.51)	(–3.75)	(0.51)	(1.24)

Table 10. Daily market return and near minus far portfolio

Table 10 reports average daily raw and risk-adjusted returns of near minus far portfolio during the crash periods. We divide each daily observations into deciles based on daily market return. Then we report average daily raw and risk-adjusted returns of near minus far portfolio. Every number is in percent. Numbers in parentheses are standard *t*-statistics.

Rank	Market	Raw	CAPM	FF
1	-1.92	2.14	-0.05	0.09
		(18.33)	(-0.57)	(0.93)
2	-0.75	0.72	0.01	0.10
		(10.64)	(0.17)	(1.61)
3	-0.36	0.43	0.09	0.14
		(7.31)	(1.63)	(2.53)
4	-0.12	0.15	0.04	0.11
		(2.65)	(0.71)	(2.11)
5	0.05	-0.04	0.01	0.02
		(-0.71)	(0.20)	(0.45)
6	0.24	-0.31	-0.10	-0.11
		(-5.55)	(-1.90)	(-2.27)
7	0.45	-0.43	-0.03	-0.07
		(-6.30)	(-0.47)	(-1.07)
8	0.73	-0.66	-0.04	-0.07
		(-10.01)	(-0.63)	(-1.09)
9	1.19	-1.49	-0.27	-0.33
		(-17.09)	(-3.35)	(-4.35)
10	2.78	-3.55	-0.47	-0.58
		(-21.86)	(-3.99)	(-4.80)
10-1	4.70	-5.68	-0.41	-0.67
		(28.44)	(2.72)	(4.34)

Table 11. Alternative sources of overpricing

Table 11 reports the result of the Fama and MacBeth (1973) regression during the crash periods after 1978. For each month, we regress individual stock's raw return on various stock characteristics, including momentum and nearhigh measures. Table 11 reports the time-series average and *t*-statistics of the coefficient on each variable. The description of each variable can be found in the appendix. Numbers in parentheses are Newey and West (1987) t-statistics (lag=12).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Momentum	0.0069	0.0050	0.0070	0.0065	0.0064	0.0072	0.0041
	(1.70)	(1.41)	(1.80)	(1.60)	(1.37)	(1.86)	(1.10)
Nearhigh	−0.0583	−0.0734	−0.0588	−0.0581	−0.0602	−0.0607	−0.0712
	(−3.43)	(−4.63)	(−3.47)	(−3.46)	(−3.40)	(−3.70)	(−4.68)
Srev	−0.0498	−0.0473	−0.0501	−0.0506	−0.0483	−0.0444	−0.0483
	(−4.23)	(−4.04)	(−4.31)	(−4.36)	(−4.18)	(−3.96)	(−4.47)
Beta	0.0212	0.0210	0.0214	0.0209	0.0206	0.0215	0.0198
	(6.95)	(7.36)	(6.95)	(6.97)	(6.80)	(6.99)	(6.78)
Log(Me)	0.0016	0.0011	0.0019	0.0017	0.0012	0.0014	0.0016
	(2.04)	(1.38)	(2.58)	(2.26)	(1.78)	(1.93)	(2.16)
Log(Bm)	0.0005	0.0011	0.0024	0.0007	0.0006	0.0004	0.0039
	(0.33)	(0.73)	(1.29)	(0.47)	(0.38)	(0.32)	(2.13)
Log(Prc)	−0.0041	−0.0047	−0.0043	−0.0038	−0.0056	−0.0044	−0.0058
	(−1.96)	(−2.37)	(−2.18)	(−1.85)	(−2.63)	(−2.24)	(−3.20)
Sue		0.0043					0.0039
		(6.78)					(4.62)
Gp			0.0207				0.0156
			(3.92)				(3.04)
Log(Age)				−0.0012			−0.0026
				(−1.53)			(−2.39)
Oscore					−0.0011		−0.0005
					(−2.82)		(−1.39)
Max						−0.0320	−0.0084
						(−1.21)	(−0.30)

Table 12. Moments of momentum strategies

Table 12 reports the moments of the conventional momentum strategy (WML) and the nearhigh-neutral momentum strategy (WML*) returns from July 1927 to December 2015. Panels A, B and C report the average, standard deviation, skewness, kurtosis, minimum, maximum, and monthly Sharpe ratio of the value-weighted raw, CAPM-, and FF-adjusted returns.

	Average	St.dev	Skew	Kurt	Min	Max	Sharpe
Panel A: Raw return							
WML	0.0123	0.0740	–1.7323	16.7711	–0.6930	0.4989	0.1668
WML*	0.0149	0.0508	0.4845	6.0784	–0.2687	0.4015	0.2930
Panel B: CAPM-adjusted return							
WML	0.0110	0.0639	–0.5861	6.6858	–0.4308	0.4689	0.1726
WML*	0.0121	0.0473	0.5286	4.7957	–0.1696	0.3705	0.2556
Panel C: FF-adjusted return							
WML	0.0113	0.0605	–0.8426	5.7828	–0.4100	0.2775	0.1873
WML*	0.0130	0.0447	0.2240	3.1491	–0.2540	0.2374	0.2900

Table 13. Time-variations of WML and WML*

Table 13 reports the coefficients and *t*-statistics of time-series regressions. In panels A and B, we regress WML and WML* returns on variables that are known to 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 for each stock listed on the NYSE and NYSE MKT in the last month. Mktvol is the variance of the past 126-day market return. $I_{January}$ is an indicator variable that takes 1 for January and zero otherwise. We also include the macroeconomic variable of Chordia and Shivakumar (2002): Div is the dividend yield on the CRSP value-weighted index, Yld is the yield on Treasury bills with three months to maturity, Term is the yield spread between ten-year Treasury bonds and three-month Treasury bills, and Def is the yield spread between Baa-rated bonds and Aaa-rated bonds in the last month. Numbers in parentheses are Newey and West (1987) *t*-statistics (lag=12).

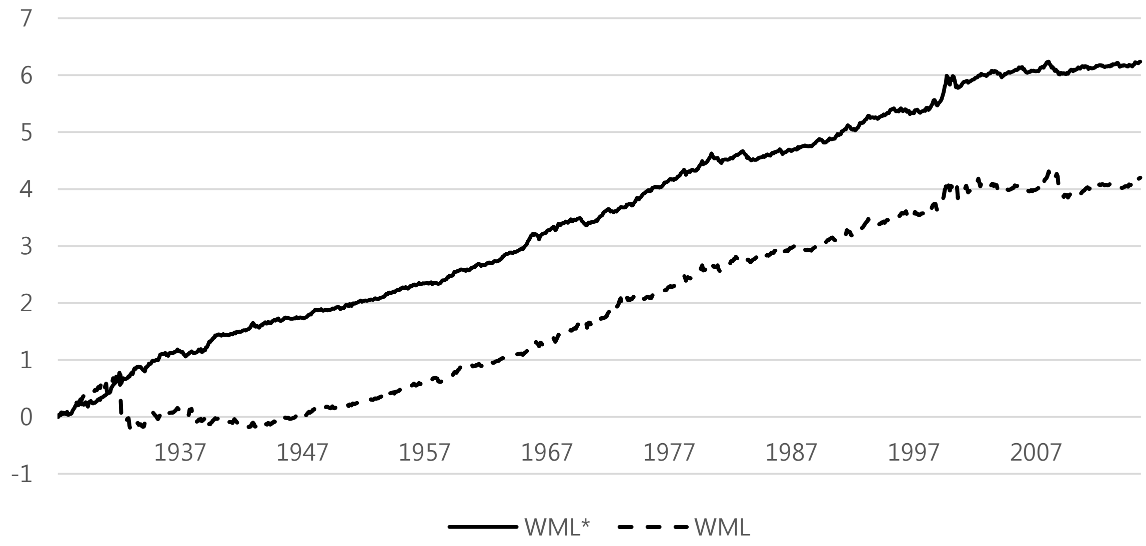
	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A : Time-variation of WML					
Intercept	0.0114 (3.70)	0.0166 (7.32)	0.0184 (7.63)	0.0152 (6.45)	0.0326 (3.23)
Mktret	0.0522 (2.27)				
Mktretsq	−0.0889 (–2.42)				
Mktilliq		−0.0047 (–2.89)			
Mktvol			−0.2172 (–2.51)		
$I_{January}$				−0.0347 (–3.98)	
Div					−0.3981 (–2.13)
Yld					0.0610 (0.81)
Term					0.0323 (0.13)
Def					−0.5778 (–1.31)
Panel B : Time-variation of WML*					
Intercept	0.0160 (8.12)	0.0143 (8.09)	0.0140 (6.86)	0.0150 (8.69)	0.0250 (2.68)
Mktret	−0.0047 (–0.36)				
Mktretsq	−0.0094 (–0.54)				
Mktilliq		0.0005			

	(0.72)			
Mktvlol		0.0279 (0.43)		
$I_{January}$			−0.0015 (–0.30)	
Div				−0.2515 (–1.36)
Yld				−0.0540 (–0.79)
Term				–0.0086 (–0.04)
Def				0.2710 (0.74)

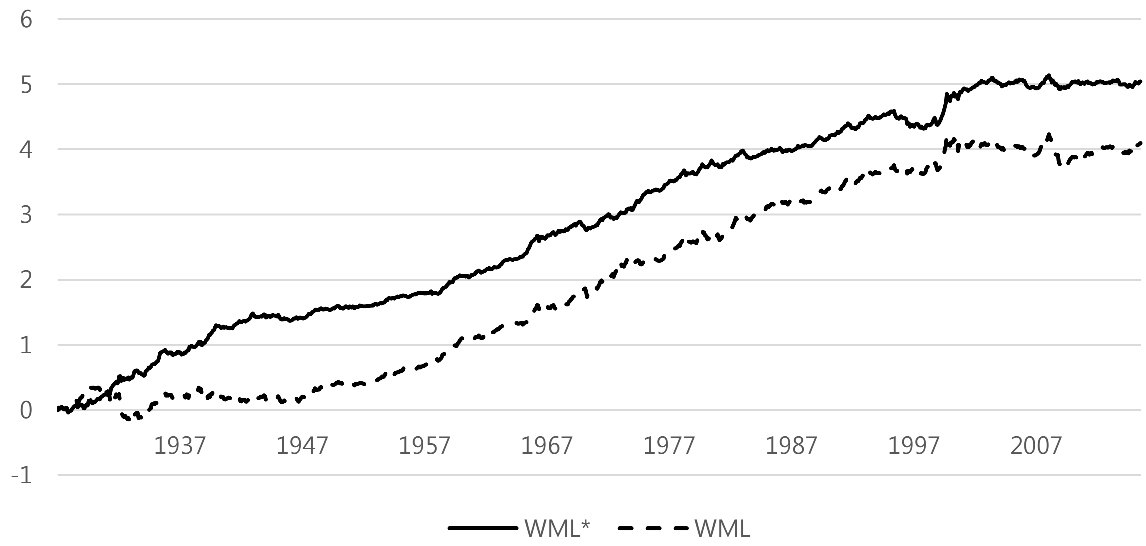
Figure 1. Cumulative return of WML and WML*

Figure 1 plots the cumulative return of WML and WML* from July 1927 to December 2015. The solid line and dotted line correspond to WML* and WML, respectively. Portfolios are value-weighted. Panel A, B and C depicts the cumulative raw, CAPM-, and FF-adjusted returns, respectively.

Panel A: Raw return



Panel B: CAPM-adjusted return



Pacnel C: FF-adjusted return

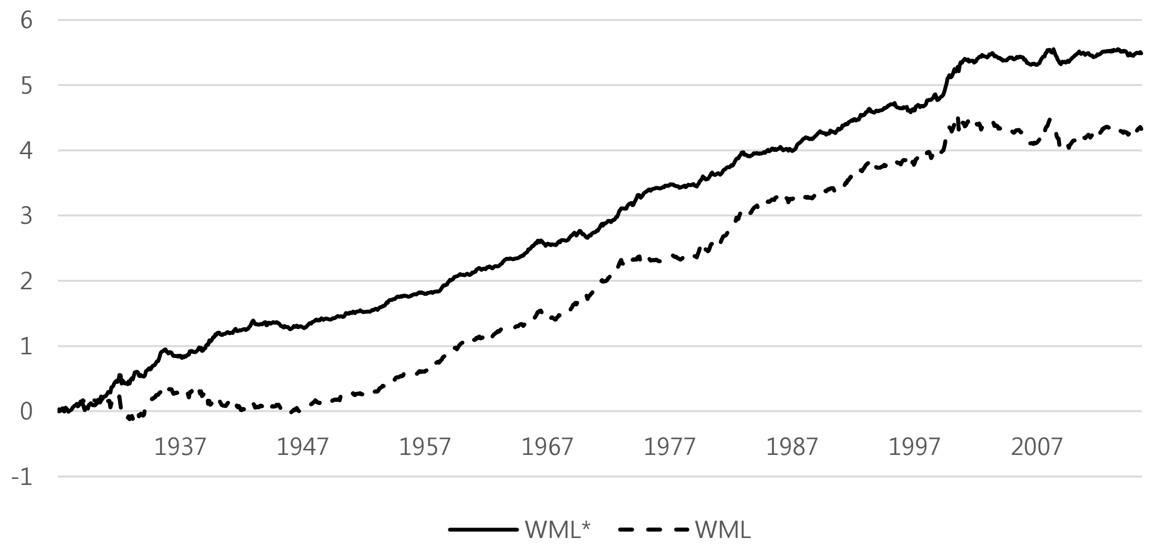

6
5
4
3
2
1
0
-1
1937
1947
1957
1967
1977
1987
1997
2007
WML*
WML

Table A1. Variable description

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

Name	Symbol	Description
Return	$r_{i,t+1}$	Raw return of stock *i* over month *t*+1
Momentum	$Momentum_{i,t}$	Cumulative raw return of a stock from the end of month $t-12$ to the end of month $t-1$. We require at least eight months of return data to be valid.
Nearness to 52-week high	$Nearhigh_{i,t}$	Stock price at the end of month *t* over the highest daily closing price from the end of month $t-12$ to the end of month *t*
Short-run reversal	$Srev_{i,t}$	$r_{i,t}$
Long-run reversal	$Lrev_{i,t}$	Cumulative raw return of a stock from the end of month $t-36$ to the end of month $t-12$
Beta	$Beta_{i,t}$	Sum of three betas estimated from the equation below using the past 6 month daily individual/market return data. $r_{i,d} = \alpha + \beta_1 r_{M,d} + \beta_2 r_{M,d-1} + \beta_3 r_{M,d-2} + \varepsilon$ At least 50 valid daily observations are required
Market equity	$Me_{i,t}$	Share price times the number of shares outstanding at the end of month *t*
Book-to-market ratio	$Bm_{i,t}$	The ratio of book equity at the end of month *t* to the market equity. We follow the methodology outlined by Fama and French (1993) to compute value of book equity. We complement book equity data at the early years using Moody's book equity information collected by Davis, Fama, and French (2000). We assume that the book equity data for all fiscal yearends in calendar year $t-1$ is available from the July of year *t*.
Price	$Prc_{i,t}$	Closing price at the end of month *t*
Idiosyncratic volatility	$Ivol_{i,t}$	Standard deviation of residuals from the daily return regression during month *t* of 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	$Skew_{i,t}$	Skewness of daily raw returns at month *t*
Kurtosis	$Kurt_{i,t}$	Kurtosis of daily raw returns at month *t*
Illiquidity	$Illiq_{i,t}$	Amihud (2002) illiquidity measure
Maximum return	$Max_{i,t}$	Maximum daily raw return at month *t*
Standardized unexpected earnings	$Sue_{i,t}$	Following Foster, Olsen, and Shevlin (1984), we calculate Sue as the change in the most recent quarterly eps from its value 4 quarters ago, divided by the standard deviation of this change in quarterly earnings over the prior 8 quarters (6 quarters minimum). We assume that the quarterly eps is public after its announcement date.

		We discard information from an earnings announcement that was made more than 6 months ago.
Gross profitability	$Gp_{i,t}$	Revenue minus cost of goods sold divided by total asset. We assume that the fundamental data for all fiscal yearends in calendar year $t-1$ is available from the July of year t.
Ohlson's score	$Oscore_{i,t}$	We follow Ohlson (1980) to construct Oscore.
Age	$Age_{i,t}$	Number of months that the stock i appeared in CRSP universe.