Momentum Crashes and the 52-week High*

Suk-Joon Byun** and Byoung-Hyun Jeon***

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Abstract

Momentum strategies suffer from occasional large drawdowns referred to as momentum crashes when the market rebounds. This paper documents that contemporaneous with the market rebound, stocks far from 52-week highs outperform stocks near 52-week highs. More importantly, such outperformance explains most part of momentum crashes. Furthermore, this contributes substantially to time-variation and fat tailed distribution of unconditional momentum profits. Our empirical evidence is consistent with Baker and Wurgler (2007) who document outperformance of speculative stocks contemporaneous with surge in investor sentiment. Our finding extends to Japan, the United Kingdom, and continental Europe.

JEL Classification: G10, G12, G14, G15

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

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** KAIST College of Business, Seoul, Republic of Korea, Tel: (82)29583552; E-mail: sjbyun@kaist.ac.kr

*** (Corresponding author) KAIST College of Business, Seoul, Republic of Korea, Tel: (82)29583968; E-mail: bh.jeon@kaist.ac.kr

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 across asset classes.[1] However, despite its strong performance, the momentum strategy suffers from occasional large drawdowns. For example, it experienced severe losses of −88.48% from July to August of 1932 and −45.60% from March to April of 2009. Interestingly, these "momentum crashes" are not just random events. They date back to the Victorian-era (Chabot, Ghysels and Jagannathan, 2014) and are also found in international equity markets and other asset classes (Daniel and Moskowitz, 2016). Most importantly, there is a notable regularity in their occurrence: crashes mostly happen contemporaneous with the market rebounds (Asem and Tian, 2010; Daniel and Moskowitz, 2016).[2] Therefore, momentum crashes have received substantial attention from both practitioners and academics. Investigating why momentum crashes can shed light on the source of momentum profits and pro-cyclic behavior of momentum profits.[3] However, a complete explanation for why they happen remains elusive.

One plausible approach to solving this puzzle is to examine a determinant of momentum profits. Of particular interest to this study is the nearness to the 52-week highs. George and Hwang (2004) document that stocks near their 52-week highs outperform stocks far from their 52-week highs and that such outperformance explains large part of positive momentum profits, noting the positive correlation between nearness to 52-week high and past 12-month return They explain their findings

[1] The profitability of the momentum strategy is documented in international stock markets (Rouwenhorst (1998)), equity indices, currencies, government bonds, and commodity futures markets (Asness, Moskowitz and Pedersen (2013)), and it dates back to the 1800s (Geczy and Samonov (2016)).

[2] Daniel and Moskowitz (2016) find that 14 of the 15 worst momentum returns had occurred when the past two-year market return was negative and the contemporaneous market return was positive. Asem and Tian (2010) also find that momentum strategy earns significantly negative profits when the past one-year market return is negative and the contemporaneous market return is positive.

[3] Chabot, Ghysels and Jagannathan (2014) argue that the periodic crashes are what keep momentum alive. Heidari (2015) finds that most of the momentum predictors' power comes from momentum crash periods.

with anchoring bias.[4] Since speculative investors' estimates on firm value are anchored on the 52-week highs, they prefer stocks whose prices are far from their 52-week highs in a belief that those stocks are underpriced, and that they have enough "room to run." Consequently, stocks far from (near) peaks are overpriced (underpriced) at portfolio formation, which results in subsequent negative (positive) return during the holding period.

In this paper, we investigate whether the nearness to 52-week high can explain momentum crashes. We provide robust finding that contemporaneous with the market rebounds, stocks far from peaks outperform stocks near peaks by a large margin, and the outperformance explains most part of negative momentum profits.[5] First, in a bivariate portfolio sort, momentum losers no longer outperform momentum winners when their nearness to the 52-week highs are set to be similar. For example, within the bottom 20% of stocks far from their 52-week highs, both momentum losers and winners earn a similar excess return (in excess of market) of 4.12% and 4.73%, respectively. Momentum winners "outperform" momentum losers in the other quintiles as well, contrary to momentum crash. In contrast, stocks far from peaks outperform stocks near peaks by more than 3.41% per month, in every momentum quintile. The results hold for the most extreme momentum crash months and are robust to alternative specification of sample stocks, sample periods, market rebound, momentum measure, and nearness to price peaks. Furthermore, the return dynamics related to nearness to 52-week high largely contributes to time-variation in momentum profits. Therefore, stocks far from peaks outperforming stocks near peaks during the market rebounds are the key to understanding the economic channel behind momentum crashes and momentum profits' time-variation.

Why does stocks far from peaks outperform stocks near peaks when the market rebounds

[4] Anchoring bias was first documented by Tversky and Kahneman (1974). 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. Ever since, numerous studies have documented evidence that is consistent with investors' anchoring bias in the financial context (see section 4.1 for a list of papers).

[5] Following Asem and Tian (2010) and Daniel and Moskowitz (2016), the market rebound periods is defined as months when the past one-year market return is negative and the contemporaneous market return is positive.

during the holding period? The potential explanation can be found from a strand of research that document time-variation of anomaly profits with respect to investor sentiment (Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012). In particular, Baker and Wurgler (2007) links change in investor sentiment with contemporaneous returns to speculative stocks. To be specific, Baker and Wurgler (2007) hypothesize as follows:

> "…sentiment almost by definition is a higher demand for more speculative securities. So when sentiment increases, we expect such "speculative" stocks to have contemporaneously higher returns..."

In other words, if investor sentiment increases during the portfolio holding periods, stocks that are prone to speculative demands generate higher returns. Consistent with the hypothesis, they document a positive contemporaneous relation between change in investor sentiment and returns to highly volatile stocks. Building on Baker and Wurgler (2007), we hypothesize that increase in investor sentiment, triggered by the market rebounds, results in high contemporaneous returns of stocks far from peaks, as they are prone to speculative demands (George and Hwang, 2004). Therefore, stocks far from peaks outperform stocks near peaks contemporaneous with the market rebounds.[6]

In support of the explanation, we provide three sets of evidence: investor sentiment increases with the market rebound, speculative demands concentrates on stocks far from peaks, and high returns to stocks far from peaks reverses in the long-run. First, every 14 proxies investigated indicates increase in investor sentiment during the market rebounds, and the increment is statistically significant for 12 proxies. On the contrary, for all proxy, investor sentiment remains unchanged or decreases outside the market rebounds.[7] Second, during the market rebounds, stocks far from peaks experience a large

[6] In a related study Hao, Chou and Ko (2014) also document the effect of investor sentiment on the return predictability of nearness to 52-week high. Consistent with Baker and Wurgler (2006), return predictability of nearness to 52-week highs heightens following the high investor sentiment. Our study complement theirs by investigating contemporaneous relation between change in investor sentiment and the return predictability of nearness to 52-week high.

[7] This is consistent with Brown and Cliff (2004) and Baker and Wurgler (2007), which documents a positive relation between contemporaneous market return and increase in investor sentiment. Baker and Wurgler (2007),

increase in the amount of speculative trading, proxied by proportion of small trades (Han and Kumar, 2013). One standard deviation decrease in nearness to the 52-week highs results in 24.74% more small trading compared to the past 12-month average. The past 12-month return, however, is not related to cross-sectional variation in the proportion of small trades. Moreover, such trades are identified as buyer-initiated using Lee and Ready (1991) algorithm. Lastly, the outperformance of stocks far from peaks over stocks near peaks reverses in the long run. The cumulative return of a long-short strategy based on nearness to 52-week highs is no longer negative, one year after the portfolio formation and onwards. This is consistent with the price increment by speculative demands being corrected in the long run. In sum, we provide various evidence that are consistent with our sentiment-driven mispricing hypothesis. We consider alternative explanations and find no empirical support.

We step further and extent our finding to the momentum profits in full sample. First, we investigate how nearness to 52-week high contribute to time -variation in momentum profits. To do so, we revise the conventional momentum strategy to be neutral on nearness to the 52-week high. That is, we long the past 12-month winners and short the past 12-month losers, but select them in a way that the long and short sides of the portfolio have similar nearness to the 52-week highs.[8] We document that the nearhigh-neutural momentum strategy earns stable profits and does not exhibit pro-cyclicality. Following up and down market, the strategy earns similar return of 1.50% and 1.46% while the conventional momentum strategy earns 1.57% and 0.30%, respectively. Furthermore, the past market return, past market volatility, past market illiquidity, and proxies for business cycle do not predict profits of nearhigh-neutral momentum strategy, as opposed to the conventional momentum strategy.

Furthermore, the nearhigh-neutral momentum strategy is free of crashes and exhibits normal-like distribution; skewness is closer to zero, kurtosis is smaller, and minimum return attenuates. In particular, minimum return increases from −69.3% to −26.87%, and skewness from −1.73 to 0.48. Most

for example, report that the time-series correlation between the market return and investor sentiment exceeds 0.3 and is highly significant.

[8] This revised momentum strategy is called the "nearhigh-neutral momentum strategy."

importantly, we achieve such improvement without sacrificing its profitability. After neutralizing the effect of nearness to 52-week high, average return increases from 1.23% to 1.49%, and standard deviation decreases from 7.40% to 5.08%, which generate 50% increase in Sharpe ratio. The improvement is robust to an alternative choice of sample stocks and sample periods. Therefore, we provide another form of momentum strategy, which is more desirable to investors.

The empirical findings of this paper can be generalized to non-U.S. markets also. Analogous to Daniel and Moskowitz (2016), we find negative momentum profits in Japan (−2.65%), United Kingdom (−2.98%), and continental Europe (−2.86%) during the market rebound. However, the nearhigh-neutral momentum strategy earns positive returns in all three markets. Furthermore, in the full sample, the nearhigh-neutral momentum strategy generates a higher Sharpe ratio, less extreme minimum return, and near-zero skewness than the conventional momentum strategy. It also revives momentum profits in Japan.

We contribute to the literature in several aspects. First, our study provides explanation on why momentum crashes and further insights on unconditional momentum profitability. The hypothesis is based on a behavioral theory and hence different from Daniel and Moskowitz (2016) who focus on the optionality of momentum losers. They acknowledge that optionality does not extend to other asset classes, and that they cannot explain why optionality is not priced in stock prices. Ours, however, have potential to be applied in other markets and context. Furthermore, our result implies that of the many factors that determine momentum profits (e.g., risk, overconfidence, conservatism, diffusion of news, etc.), anchoring bias combined with investor sentiment contributes substantially to the time-variation of momentum profits. This poses challenge to previous explanations on why momentum generate profits. Several papers including Cooper, Gutierrez and Hameed (2004), Chabot, Ghysels and Jagannathan (2014) attribute momentum profits to investors' overconfidence and crash risk based on time-variation of momentum profits. However, there is no time-variation to base on, when the effect of nearness to 52-week high is accounted for. Moreover, in relation to Antoniou, Doukas and Subrahmanyam (2012) who examines the relation between past investor sentiment and momentum

profits, our study provides a clearer link on how (change in) investor sentiment impacts momentum returns. Therefore, our results provide useful insight on momentum itself, and makes its profitability even more puzzling.

Second, we complement Baker and Wurgler (2007) by examining the under-explored relation between change in investor sentiment and contemporaneous stock returns. We document a positive relation between the degree of (52-week high related) mispricing and contemporaneous change in investor sentiment using various sets of test including stock returns and proportion of small trades. Our results can be generalized to other types of mispricing, and could shed light on the source of time-variation in anomaly profits.

Lastly, we provide a revised momentum strategy that generates similar or even higher profit without crashing in both the US and international equity markets. Previous attempts to improve momentum profitability focus on the dynamic weighting schemes based on their prediction of the crashes.[9] Our improvement is qualitatively different from theirs as our revision is restricted to the stock selection technique, which makes it particularly attractive for leverage-constrained investors.

The rest of the paper is organized as follows. Section 2 describes the data sources and variables employed in our empirical research. Section 3 investigates if nearness to the 52-week highs contributes to momentum crashes. Section 4 examines the potential explanations for why stocks far from their peaks outperform stocks near their peaks during the market rebound. Section 5 extends our finding to the full sample and investigates the impact of nearness to 52-week high on time-variation and moments of momentum profits. Section 6 generalizes our empirical results to non-US markets, including Japan, the United Kingdom, and continental Europe. Section 7 concludes the paper.

[9] Barroso and Santa-Clara (2015) suggest that the momentum strategy improves if it is scaled by its trailing volatility. Daniel, Jagannathan and Kim (2012) also show that moving to a risk-free asset during their definition of the "turbulent state," can significantly improve the traditional momentum strategy.

2. Data Sources and Variables

In this section, we describe the data sources and variables employed in our empirical research. Data on the stock market are from the Center for Research in Security Prices (CRSP). Accounting numbers, including book equity, are from COMPUSTAT. We complement book equity data before 1963 with data from Moody's manual, which is available from Ken French's website. Data on mutual fund flow are from CRSP Survivorship-Bias-Free Mutual Fund Database. Data on intraday trades and quotes are extracted from ISSM and TAQ. International equity data are extracted from Datastream. 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. Lastly, we downloaded proxies for investor sentiment from Bloomberg and Jeffery Wurgler's website.[10]

The two main variables of interest in this study are past 12-month returns (*Momentum*) and nearness to 52-week high (*Nearhigh*). Following Daniel and Moskowitz (2016), we define *Momentum* of stock i at the end of month t as its cumulative returns from t–11 to month t–1. *Nearhigh* is the ratio of the price at the end of month t to the highest closing price during the past 12 months (George and Hwang, 2004). Hence, *Nearhigh* ranges from zero to one. Other firm-specific variables are described in detail in Appendix A.

Our sample is every common stock listed on the NYSE, AMEX, and NASDAQ. A stock is included in our sample if *Momentum*, *Nearhigh*, *Srev*, *Beta*, *ME*, *BM*, and *PRC* 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 1,755 stocks per month. Our sample period spans from January 1926 to December 2015.

As our study focuses on the cross-sectional return pattern when the momentum strategy crashes, it is necessary to define the "crash period." Following Asem and Tian (2010) and Daniel and

[10] Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french. Jeffery Wurgler's website: http://people.stern.nyu.edu/jwurgler/

Moskowitz (2016), we focus on months when the market rebounds. The market rebound periods are months in which the contemporaneous market return is positive and the past 1-year cumulative market return is negative. Market return is the CRSP value-weighted index return. Our definition of the market state recognizes 149 of 1062 months as the market rebounds, and it matches all the 10 largest crash incidents. Our results are qualitatively unchanged when we investigate extreme months in which the momentum strategy crashed the most. Therefore, we use the term "crash period" and "market rebound period" interchangeably.

3. Momentum Crashes and Nearness to 52-week Highs

3.1 Individual Predictability of *Momentum* and *Nearhigh*

We first examine the individual predictability of *Momentum* and *Nearhigh*. At the end of each month *t*, stocks are grouped into deciles based on their *Momentum* and *Nearhigh*. Stocks in each portfolio are value-weighted and held until the end of the next month. We also investigate the return of a long-short portfolio that longs the top decile and shorts the bottom decile. The risk-adjusted return of a portfolio is calculated following Daniel and Moskowitz (2016). They find bias in beta calculated based on future realized returns, and hence suggest ex-ante measure of beta. Our results are qualitatively unchanged when we control for risk using ex-post beta.

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

$r_{p,t+1}^{risk-adjusted}$, $r_{p,t+1}^{raw}$ is the risk-adjusted and raw return on portfolio *p* at month *t*+1, $r_{f,t+1}$ is the risk-free rate, *N* is the number of factors, $f_{i,t+1}$ is the factor realization and $\widehat{\beta_{i,p,t+1}}$ is the factor loading. To properly account for time-variation in factor loading, the factor loading $\widehat{\beta_{i,p,t+1}}$ is the sum of three betas estimated every month by running a time-series regression (2), using the past six-month daily return data.

$$r_{p,d}^{raw} - r_f = \sum_{i=1}^{N} \beta_{i,p}^{1} f_{i,d} + \beta_{i,p}^{2} f_{i,d-1} + \beta_{i,p}^{3} f_{i,d-2} + \varepsilon_{p,d} \quad (2)$$

The capital asset pricing model (CAPM) and the Fama and French (1993) three-factor model (FF) are used as the main factor models. To compute average and standard errors of returns during the crash periods, we regress raw or risk-adjusted returns on a dummy that takes 1 if month t+1 is the crash month as equation (3)

$$r_{p,t+1}^{risk-adjusted} = \beta_1 I_{t+1}^{Crash} + \beta_2\left(1 - I_{t+1}^{Crash}\right) + \varepsilon_{p,t+1} \quad (3)$$

We employ White (1980) heteroscedasticity-consistent estimator to account for different variance in errors depending on the market states. Newey and West (1987) adjustment yields quantitatively similar results.

[Table 1]

Table 1 reports the excess (in excess of market) and risk-adjusted returns of decile portfolios based on *Momentum* and *Nearhigh*. 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 (3.48%) to the top winner decile (−0.67%). Therefore, the momentum strategy that longs the winners and shorts the losers earns –4.16% per month when the market rebounds. Corresponding CAPM- and FF-adjusted returns are –1.58% and –1.73%, respectively, which indicates that risk only partly explains momentum crashes. Outside the crash periods (Panel A2), the momentum strategy earns a significantly positive profits of 2.11%.

Panel B of Table 1 reports the monthly excess and risk-adjusted returns of the decile portfolios based on *Nearhigh*. During the crash periods (Panel B1), the monthly return monotonically decreases from the bottom to top decile from 5.01% to −2.11%, which results in large return spread of −7.12% per month. Ananlogously, CAPM- and FF-adjusted returns of near minus far portfolio (NMF) are −2.11% and −1.84%, respectively. Outside the crash periods (Panel B2), we find the opposite pattern. The stocks near peaks outperform stocks far from peaks by 1.32% per month, in line with the empirical results of George and Hwang (2004).

In sum, both *Momentum* and *Nearhigh* are in a negative relationship with subsequent stock returns when the market rebounds. On the contrary, they are in a positive relationship with subsequent stock returns outside the crash periods. In this simple investigation, *Nearhigh* produces much larger cross-sectional variation in returns compared to *Momentum*, which is suggestive of *Nearhigh* being the dominant driver of momentum crashes.

3.2 Interaction between *Momentum* and *Nearhigh*

We take a closer look at the interaction between *Momentum* and *Nearhigh* during the crash periods using the double-sort analysis. Table 2 reports the monthly excess returns of portfolios sequentially double-sorted by *Momentum* and *Nearhigh* during the crash periods. In Panel A, stocks are first divided into quintiles based on their *Nearhigh*, then within each quintile, stocks are further classified into five groups based on *Momentum*, which results in 25 (5×5) portfolios. In Panel B, stocks are sorted firstly on *Momentum* and then on *Nearhigh*. We report the value-weighted monthly returns of each portfolio during the crash periods and the return spreads between the top and bottom quintiles.

[Table 2]

We find a consistent result, primarily, that *Nearhigh* subsumes the negative predictive power of *Momentum*. First, when stocks have a similar level of *Nearhigh*, the negative return predictability of *Momentum* disappears. From Panel A, for stocks in the bottom *Nearhigh* quintile, the winners "outperform" the losers by 0.61%, contrary to the previous finding of negative momentum profits. Moreover, within every *Nearhigh* quintile, the return spread between the winners and losers ranges from positive 0.61% to 1.60%, with three of them being statistically significant. On the contrary, from Panel B, the stocks far from peaks outperform the stocks near peaks even when their *Momentum* is set to be similar. Within every *Momentum* quintile, the return spread between the top and bottom *Nearhigh* quintile ranges from −5.04% to −3.41%.

In order to readily compare with conventional momentum strategy that longs the top 10% winners and the bottom 10% losers, we devise neahigh-netural momentum strategy. At the end of each

month, stocks are divided into quintiles based on *Nearhigh*. Within each *Nearhigh* quintile, stocks are divided into deciles based on *Momentum*, which results in 50 value-weighted and evenly spaced portfolios. Then, we form 10 cohorts by equal-weighting five portfolios in the same *Momentum* decile. Consequently, we construct 10 portfolios with an equal number of stocks, similar level of *Nearhigh* (nearhigh-neutral), and dispersed level of *Momentum*. For future reference, we call these portfolios "nearhigh-neutral" momentum winners and losers.

[Table 3]

Table 3 reports the excess and risk-adjusted returns of the nearhigh-neutral momentum portfolios and the return spread between the top and bottom decile (WML*) during the crash periods. Panel A reports the average value of *Nearhigh* and *Momentum* for each portfolio. As expected, the 10 portfolios have a similar level of *Nearhigh*. On average, the stocks in the top decile are only 5.45% closer to their 52-week highs than those in the bottom decile are. In contrast, the average value of *Momentum* for stocks in the top decile is 77.06% higher than that for stocks in the bottom decile.

What happens to momentum strategy when the effect of the nearness to the 52-week high is neutralized? Panel B shows that despite the huge dispersion of the momentum measure across the 10 portfolios, their excess and risk-adjusted returns are almost the same. The excess returns of the 10 portfolios fall within the narrow range of 0.36% to 1.39%, and the WML* earns positive returns. The excess, CAPM- and FF-adjusted return of the WML* is 1.39%, 0.67%, and 0.47%, respectively. Therefore, there is no momentum crash once the effect of nearness to the 52-week high is neutralized.[11]

For robustness, and to account for possible misspecification of the crash periods, we examine the return of WML* in months with the most negative WML returns. Appendix Table A1 reports the raw and risk-adjusted returns of WML* for each of the 10 largest momentum crash months. Even in the extreme momentum crash months, WML* returns are relatively modest. In July 1932, for instance,

[11] The descriptions and further investigation of the nearhigh-neutral momentum portfolios and WML* will appear again in Section 5.

WML earns a profit of −69.30% while WML* earns −6.31%. The risk-adjusted returns of WML* are also near zero while WML earns largely negative risk-adjusted returns up to −30%. In general, the returns of WML* are less extreme and become less "black-swan like" (Daniel, Jagannathan and Kim, 2012).

3.3 Robustness Check

To account for the effect of other firm characteristics, we run the Fama and MacBeth (1973) regression during the crash months. To compare economic significance and account for the effect of outliers, every independent variable is winsorized at the top and bottom 1% and scaled by its cross-sectional standard deviation.

[Table 4]

In a univariate regression of future returns on momentum measure (Table 4 Model 1), the coefficient on *Momentum* is significantly negative, consistent with momentum crash. One standard-deviation increase in *Momentum* results in 0.94% lower returns in the following month. However, when *Nearhigh* is included as an independent variable (Model 2), the coefficient on *Momentum* turns positive (0.0102). In contrast, the coefficient on *Nearhigh* is negative (−0.0268) and statistically significant (*t*-statistics=−7.30). Including additional control variables (Models 3, 4, 5, and 6) does not alter our result. For example, in Model 3, when *Nearhigh* is not included, the coefficient on *Momentum* is −0.0039 and significant at the 5% level. However, after including *Nearhigh* (Model 4), the coefficient on *Momentum* turns insignificant while the coefficient on *Nearhigh* (−0.01) is significant.

In Appendix Table A2, we zero in on the extreme months. We report the cross-sectional regression coefficients of Model 4 in Table 4 for each of the 10 largest crash months. In 7 of the 10 months, the coefficient on *Nearhigh* is negative and larger in magnitude than that on *Momentum*. Moreover, the coefficient on *Momentum* is negative and statistically significant at the 5% level for only one month, while that on *Nearhigh* is negative and significant for seven months.

In Appendix Table A3, we replicate Fama-Macbeth regression of Model 4 in Table 4 under

various alternations. We find qualitatively similar results in every alternative test setups.

4. Potential Explanations

Stocks far from peaks outperform stocks near peaks when the market rebounds, and momentum crashes are attributable to such outperformance. Therefore, the question is why stocks far from peaks outperform stocks near peaks when the market rebounds. In this section, we examine several potential explanations for our empirical findings.

4.1 Sentiment-driven Mispricing Explanation

Notably, the outperformance documented in the previous section is in sharp contrast to the results in George and Hwang (2004). They find that in a full sample, stocks far from their 52-week highs "underperform" stocks near their 52-week highs, which we also confirm outside the market rebounds. They explain their finding with anchoring bias. Because speculative investors' estimates of firm value are anchored on the 52-week highs, they prefer stocks whose prices are far from their 52-week highs believing them to be underpriced, and that they have enough "room to run." Hence, at portfolio formation, stocks far from (near) their 52-week highs are overpriced (underpriced). Subsequently, as information is revealed, negative (positive) return is realized during the holding period. Many studies have since supported the notion that various market participants perceive stocks that are far from peaks as cheap, and hence, they provide perfect venue for speculation.[12]

Then how does the market rebound reverse the relationship between nearness to the 52-week highs and subsequent returns? The potential explanation can be found from a strand of research that document time-variation of anomaly profits with respect to investor sentiment (Baker and Wurgler, 2006; Stambaugh, Yu and Yuan, 2012). In particular, Baker and Wurgler (2007) links change in investor

[12] See Heath, Huddart and Lang (1999), Marshall and Cahan (2005), Du (2008), Liu, Liu and Ma (2011), Baker, Pan and Wurgler (2012), Birru (2015), George, Hwang and Li (2015), Yuan (2015), Li, Lin and Lin (2016).

sentiment with contemporaneous returns to speculative stocks. To be specific, Baker and Wurgler (2007) hypothesize as follows:

> "…sentiment almost by definition is a higher demand for more speculative securities. So when sentiment increases, we expect such "speculative" stocks to have contemporaneously higher returns..."

In other words, if investor sentiment increases during the portfolio holding periods, stocks that are prone to speculative demands generate higher returns. Consistent with the hypothesis, they document a positive contemporaneous relation between change in investor sentiment and returns to highly volatile stocks. Building on Baker and Wurgler (2007), we hypothesize that increase in investor sentiment, triggered by the market rebounds, results in high contemporaneous returns of stocks far from peaks, as they are prone to speculative demands (George and Hwang, 2004). Therefore, stocks far from peaks outperform stocks near peaks if the market rebound during the holding period.

In the rest of this subsection, we present three sets of evidence that are consistent with the sentiment-driven mispricing hypothesis. First, investor sentiment increases substantially when the market rebounds. Second, speculative demands concentrates on stocks far from peaks. Third, high returns for stocks far from peaks reverses in the long-run.

4.1.1 Investor Sentiment and the Market Rebound

We first document that investor sentiment increases when the market rebounds. As our investor sentiment proxy, we consider an extensive list of both direct and indirect measures introduced by Brown and Cliff (2004) and Baker and Wurgler (2006). As a direct measure of investor sentiment, we employ two survey-based measures: bull-bear spread of survey conducted by the American Association of Individual Investors (AAII) and Investor Intelligence (II). We also employ several measures that are positively correlated to investor sentiment: NYSE advance to decline ratio (ADV/DEC), number of new highs to lows ratio (HI/LO), aggregate mutual fund flow (FLOW), small minus big portfolio return (SMB), average first-day returns after IPO (RIPO) and the Baker and Wurgler (2006) sentiment index

(BW). For proxies that are negatively related to investor sentiment, we examine the ARMS ratio (ARMS), aggregate market illiquidity (ILLIQ), dividend premium (PDND), CBOE put to call volume ratio (PCRATIO), S&P100 volatility index (VIX), and expected volatility to realized volatility ratio (VIX/SIG). Appendix A contains detailed descriptions and data. To filter out the common business condition component from each sentiment proxy (Baker and Wurgler, 2006), we first orthogonalize each proxy on the macroeconomic variables: growth in the industrial production index, growth in consumer durables, nondurables, and services, and a dummy variable for NBER recessions. We then report monthly changes in the orthogonalized value of proxies during crash and non-crash periods.

[Table 5]

From Table 5, all 14 macro-adjusted sentiment proxies imply increment in investor sentiment during the market rebounds with significant difference for 12 proxies.[13] On the contrary, during the non-crash periods, every proxy implies decrease or negligible change in investor sentiment. The difference between the market states is statistically significant in 12 proxies. For example, the American Association of Individual Investors bull-bear spread increases by 7.15% when the market rebounds while it decreases by 1.01% outside the market rebounds. The difference of 8.16% is large and statistically significant at the 1% level. Another example is the put to call ratio, which is negatively associated with investor sentiment. It decreases by 6.55% when the market rebounds and increases by 1.10% in the other months. The result is qualitatively unchanged when we examine the raw values of investor sentiment proxies.

4.1.2 Speculative Demands and Nearness to 52-week Highs

Next, we investigate if speculative trades concentrate on stocks far from peaks. Han and Kumar (2013) document that the proportion of small trades serves as a proxy for speculative trading. Following

[13] The synthetic sentiment index of Baker and Wurgler (2006) shows insignificant increase in investor sentiment during the market rebound. Note that the sentiment index includes firm-supply related variables, such as share issuance and number of IPOs. These variables tend to be sluggish, and cannot properly capture change in investor sentiment in monthly frequency.

their study, we investigate the relation between the proportion of small trades and nearness to the 52-week high. As the measure properly proxies for speculative trading before decimalization, the sample period examined here is from January 1983 to January 2001. Using ISSM and TAQ data, we classify trades less than $5,000 as small trades, and compute their proportion to total trades during the month.

[Table 6]

Panel A of Table 6 reports the result of Fama-Macbeth regression during crash periods, where we regress the percentage change in small trade to the past 12-month average on various firm characteristics. The result suggests that stocks far from their 52-week highs experience large increases in speculative trading. In Model 3, for example, stocks that are one standard-deviation more away from their 52-week highs experience 24.74% more increase in small trades (*t*-statistics = 3.49). On the contrary, the relationship between *Momentum* and increase in small trades is insignificant. The coefficient on *Momentum* is 0.0127 with small *t*-statistics of 0.20.

Furthermore, such increased speculative trading is mostly buyer-driven. In Panel B, we examine the buy and sell order imbalance of small trades, where orders are classified following Lee and Ready (1991). The result of the Fama-Macbeth regression shows a negative relationship between *Nearhigh* and buy-sell order imbalance. In Model 6, for example, when stocks are one standard deviation more away from their 52-week highs, the buy-sell order imbalance increases by 2.99%. On the contrary, *Momentum* has a positive relationship with buy-sell order imbalance. In sum, when stocks are far from their peaks, they experience "inflow" of speculative "demands," consistent with the sentiment-driven mispricing hypothesis.

4.1.3 Long-run Performance of Near minus Far Portfolio

Lastly, we examine if high returns to stocks far from peaks during the market rebound reverses in the long-run. If the price increment of stocks far from peaks are by speculative demands, the increment during the holding period will reverses in long-run. Furthermore, this allows us to reject potential group of alternative hypothesis which argues that the outperformance is due to the

underpricing at the portfolio formation date. Table 7 Panel A reports a series of average monthly cumulative excess and risk-adjusted returns of the near minus far portfolio after the market rebounds. We find evidence of long-run reversal. In the first two months, NMF earns largely negative CAPM- and FF-adjusted returns of −1.56% and −1.07% per month. However, it subsequently earns positive returns, and hence, the future one-year cumulative return is non-negative and indistinguishable from zero. CAPM- and FF- adjusted average monthly cumulative return are 0.19% and 0.28%, respectively. The same holds for the longer holding periods also.[14] Next, for robustness, we examine post-formation returns after the 100 months that the momentum strategy crashed the most (Panel B). As expected, during the first two months, the stocks far from peaks outperform the stocks near peaks by −3.80% (CAPM) and −2.34% (FF) per month. However, the 5-year CAPM- and FF-adjusted average monthly cumulative return of NMF is 0.06% and 0.13%, respectively, and is indistinguishable from zero. Therefore, it confirms the sentiment-driven mispricing hypothesis.

[Table 7]

4.2 Risk-based Explanation

Does risk explain our finding? Though our result is robust after adjusting for factor exposure, it is possible that there is some risk factor not captured by traditional CAPM or the Fama and French (1993) three-factor model. To address this possibility, we first form a factor-mimicking portfolio based on the *Nearhigh* and compute the loading of each stock on the portfolio. We then compare the predictive power of the loading and *Nearhigh* itself analogous to Daniel and Titman (1997).

[Table 8]

Table 8 reports that the risk loadings do not subsume the predictive power of *Nearhigh*. Comparing Model 5 and Model 6, for example, shows that including risk loadings decreases the

[14] In case of raw return, we find no evidence of long-run reversal. However, as we are focusing on a very specific market state, market rebound, raw return is severely influenced by the market loading (Note the large difference between raw and risk-adjusted returns.) Therefore, raw return provides little information on long-run performance.

coefficient on *Nearhigh* only by a small margin: –0.0139 to −0.0101. Therefore, risk cannot fully explain the outperformance of stocks far from peaks.

4.3 Alternative Sources of Overpricing

Furthermore, we consider alternative firm-characteristics that can attract speculative demands, such as age, profitability, distress, and lottery-likeness following Baker and Wurgler (2006). Fama-Macbeth regression in Table 9 reports that the significance on *Nearhigh* is not affected after controlling for aforementioned variables. Throughout Model 1 to Model 6, the coefficient on *Nearhigh* ranges between −0.0112 to −0.0135, while that on *Momentum* ranges from 0.0013 to 0.0025.

[Table 9]

5. Time-variation and Moments of Nearhigh-neutral Momentum Strategy

So far, we investigated how nearness to 52-week highs influence momentum profits when the market rebounds. In this section, we further extend our finding to full sample, and examine the contribution of nearness to 52-week high on time-variation and moments of the conventional momentum strategy. To do so, we compare returns to the conventional momentum strategy (WML) and the nearhigh-neutral momentum strategy (WML^*). These strategies are similar in that they long past 12-month winners and short past 12-month losers. However, while the WML picks momentum winners and losers from the entire universe of stocks, WML* does so evenly from each *Nearhigh* quintile. Therefore, the long and short side of the WML* consist of stocks with similar levels of *Nearhigh*, while those of WML do not.

5.1 Time-variation of WML and WML*

As a preliminary analysis, we simply compare WML and WML^* profits following up and down market, depending on the sign of past 12-month market return. Consistent with Cooper, Gutierrez and Hameed (2004), WML earns monthly excess returns of 1.56% and 0.30% following up and down

markets. On the contrary, WML* generate similar profits of 1.50% and 1.46% in each case. For former statistical test, we investigate previously documented predictors of momentum profits: cumulative market return and its square (Cooper, Gutierrez and Hameed, 2004), past market illiquidity (Avramov, Cheng and Hameed, 2016), past market volatility (Wang and Xu, 2010), dummy for January, and proxies for macroeconomic variables as in Chordia and Shivakumar (2002).

[Table 10]

In Table 10, the time-series of WML and WML* returns are regressed on aforementioned predictors. Table 10 reports strong regularity that WML* is unpredictable as opposed to WML. Seven of nine predictors significantly predict WML returns while none of them predicts WML*. For example, while WML return decreases substantially following increased market illiquidity (t-statistics=−2.89), returns of WML* is independent from past market illiquidity (t-statistics=0.72). Appendix Table A4 investigates risk-adjusted returns of WML and WML*, and reports similar results. In sum, WML* generate profits that is stable across market states, and do not exhibit pro-cyclicality.

5.2 Moments of WML and WML*

We now focus our investigation on the moments of the WML and WML* strategies. Table 11 reports the descriptive statistics of the returns to WML and WML* during the full sample period from July 1927 to December 2015. In line with Barroso and Santa-Clara (2015), WML exhibits excessive kurtosis (16.77), highly negative skewness (−1.73), and large negative minimum return (−69.30%), all of which point to the fat-tailed distribution of WML return on the negative side. However, this pattern substantially attenuates for WML*. Skewness is almost zero (0.48), and kurtosis decreases to 6.07. Minimum return increases to −26.87%. Overall, the distribution of WML* returns shows normal-like behavior and earns positive returns without crashes. Most importantly, the improvement is achieved without sacrificing profitability. The returns of WML* are higher and it offers higher Sharpe ratio. For example, the average return increases from 1.23% to 1.49% and Sharpe ratio from 16.62% to 29.33%. Controlling for market and three-factor risk show similar results.

[Table 11]

To mitigate concerns that our results are driven by early sample periods, or by small and illiquid stocks, we do sub-period and sub-sample analysis in Appendix Table A5. Panel A, for example, restricts sample period to new millennium. After 2000, consistent with Bhattacharya, Kumar and Sonaer (2012), WML generates much lower returns (0.67%) with high volatility (8.98%). In contrast, WML* earns better returns (0.70%) with much lower volatility (6.23%). Results are similar for risk-adjusted returns and the remaining panels.

From the perspective of traditional asset pricing, investors lean towards high returns and away from high volatility, negative skewness, and pro-cyclicality. Therefore, the nearhigh-neutral momentum strategy provides a desirable strategy to investors. Furthermore, our revised momentum strategy is confined to stock-selection technique. This is qualitatively different from previous attempts such as Daniel, Jagannathan and Kim (2012), Barroso and Santa-Clara (2015), Heidari (2015), and Daniel and Moskowitz (2016). Their focus is on the timing of momentum crashes and propose dynamic weighting of momentum strategy. Hence, our strategy is potentially beneficial for leverage constrained investors.

6. Generalization to International Equity Markets

In this section, we generalize our results to international equity markets. Momentum crashes exist not only in the US market but also in Japan, the United Kingdom, and continental Europe. Therefore, it would be interesting to examine if nearness to the 52-week highs explains momentum crashes in these markets, and if the nearhigh-neutral momentum strategy outperforms the conventional momentum strategy. Furthermore, as this section was not included in an earlier draft of this paper, it serves as an out of sample test, which can mitigate data mining concerns.

6.1 Sample Construction

Analogous to Asness, Moskowitz and Pedersen (2013) and Daniel and Moskowitz (2016), we

investigate three international equity markets: the United Kingdom, Japan, and continental Europe. The sample period starts from January 1972 for the U.K., and January 1974 for Japan, and continental Europe.[15] To ensure the quality of data regarding Datastream (Ince and Porter, 2006), we apply several filters to the imported data analogous to Chui, Titman and Wei (2010). We include all common stocks listed on the major stock exchange in each country. We only include primary class and local firms. Since data errors in Datastream are mainly concentrated in small stocks (Ince and Porter, 2006), we exclude the bottom 20% of stocks with small market capitalization for each country every month. Furthermore, returns larger (less) than 100% (−95%) are set to 100% (−95%). Market return is defined as the value-weighted average of returns to securities in each market.

6.2 Interaction between *Momentum* and *Nearhigh* during the market rebound

We first investigate how nearness to the 52-week high influence momentum profits during the market rebound. Analogous to Table 3, we compare returns to conventional momentum portfolios and nearhigh-neutral momentum portfolios during the crash periods. In each month, we group stocks into quintiles, based on their *Nearhigh*. Within each *Nearhigh* quintile, we group stocks into quintiles based on their *Momentum*, which results in 25 value-weighted and evenly spaced portfolios. We then form five cohorts by equal-weighting five portfolios in the same *Momentum* quintile. We compare returns to these portfolios with the *Momentum* quintile portfolios.[16]

[Table 12]

Table 12 Panel A reports the excess returns for each portfolio in Japan. When the market rebounds, the portfolio return monotonically decreases from losers to winners, which results in WML return of −2.65% (t-statistics=−3.36). On the contrary, the nearhigh-neutral momentum strategy earns a significantly positive return of 0.77% (t-statistics=2.05). Both Panel B and C, which investigate the

[15] List of countries that are included in our analysis is similar to that of Chui, Titman and Wei (2010). For countries in continental Europe, we start including the country when there are more than 30 stocks listed after filtering. See Table A6 in Appendix A for details.

[16] Our results are qualitatively the same for tercile and decile portfolios as well.

U.K. and continental Europe markets, report a similar pattern. Table 12 suggests a robust finding that when the market rebounds, stocks far from peaks outperform stocks near peaks, which mostly explains the momentum crash.

6.3 Moments of WML and WML*

We next investigate the profitability of nearhigh-neutral momentum strategy in the full sample. We compare moments of conventional momentum strategy (WML) and nearhigh-neutral momentum strategy (WML*), analogous to Table 11.

[Table 13]

Panel A of Table 13 compares the momentum of WML and WML* in Japan. WML earns small returns of 0.45% with large standard deviation of 6.62%, which results in a monthly Sharpe ratio of 6.78%. Its minimum return is −34.99%. However, WML* in Japan earns a significant return of 0.73% with lower standard deviation of 4.43%, which results in large a Sharpe ratio of 16.52%. The minimum return and skewness increases compared to WML. It is also noteworthy that neutralizing the effect of *Nearhigh* revives momentum in Japan with *t*-statistics of 3.72.

Panel B compares WML and WML* in the U.K. market. Neutralizing the effect of *Nearhigh* increases skewness from −1.4293 to −0.7285 and minimum return from −54.14% to −22.19%. Despite such improvement, the average return stays similar and standard deviation significantly decreases. As a result, the monthly Sharpe ratio increases from 15.98% to 27.61%. Stocks in the continental Europe market (Model 3) show qualitatively the same pattern. Therefore, the empirical results suggest that our finding can be generalized to the international equity market.

7. Conclusion

Momentum is a strong and robust trading strategy in normal environments. However, when the market rebounds from its trough, momentum strategy crashes in large in magnitude. Despite the

vast attention given to this issue, there was no complete and consistent explanation about why it occurs.

In this paper, we document the negative relationship between the nearness to the 52-week highs and subsequent returns, and find that momentum crashes are attributable to such relationship. This relationship is robust for various risk-controls, sample periods, and sample stocks. Furthermore, such relationship contribute substantially to time-variation of momentum profits.

Among several potential explanations, the empirical results are mostly consistent with the sentiment-driven mispricing hypothesis of Baker and Wurgler (2007). Market rebounds triggers increase in investor sentiment, or equivalently, inflow of speculative demands. Since speculators are prone to anchoring bias, these demands concentrate on stocks far from their 52-week highs, which results in their price run-ups. Consistent with the hypothesis, we find that proxies for investment sentiment increase during the market rebound, and small trades increase among stocks far from peaks. Furthermore, the outperformance of stocks far from peaks reverses in the long run.

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

Our findings can be generalized to the international equity market. In Japan, the U.K., and continental Europe, the conventional momentum strategy uniformly earns negative returns when the market rebounds. However, when the effect of nearness to the 52-week high is neutralized, the momentum strategy no longer earns negative returns. The nearhigh-neutral momentum strategy outperforms the conventional momentum strategy in all three markets, and it even revives momentum profits in Japan.

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Table 1. One-way sort on *Momentum* and *Nearhigh*.

Table 1 reports excessand 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. Panel A (B) reports the excess (in excess of market) 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 return spread between the top and the bottom decile. 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 *t*-statistics computed from White robust standard error.

	1	2	3	4	5	6	7	8	9	10	10−1
Panel A: Momentum Decile Portfolio											
Panel A1: Crash Periods											
Excess	3.48	2.45	1.43	0.96	0.38	−0.44	−0.47	−1.03	−0.68	−0.67	−4.16
	(5.53)	(5.71)	(4.60)	(3.71)	(1.91)	(−2.14)	(−2.51)	(−5.08)	(−2.65)	(−1.70)	(−4.38)
CAPM	0.88	0.92	0.55	0.64	0.28	−0.26	−0.05	−0.52	−0.27	−0.70	−1.58
	(1.89)	(2.78)	(2.16)	(2.89)	(1.66)	(−1.40)	(−0.30)	(−2.93)	(−1.20)	(−2.18)	(−2.31)
FF	0.83	0.88	0.46	0.72	0.30	−0.20	−0.15	−0.58	−0.47	−0.90	−1.73
	(1.93)	(2.64)	(1.76)	(2.81)	(1.58)	(−1.11)	(−0.90)	(−3.43)	(−1.80)	(−2.53)	(−2.46)
Panel A2: Non-crash Periods											
Excess	−1.30	−0.89	−0.48	−0.26	−0.07	−0.02	0.26	0.42	0.46	0.82	2.11
	(−10.07)	(−9.36)	(−6.00)	(−4.04)	(−1.27)	(−0.42)	(4.55)	(6.55)	(5.43)	(6.21)	(10.60)
CAPM	−0.93	−0.65	−0.31	−0.17	−0.04	−0.03	0.19	0.29	0.27	0.62	1.54
	(−7.62)	(−7.10)	(−4.11)	(−2.57)	(−0.63)	(−0.54)	(3.45)	(4.54)	(3.43)	(4.96)	(7.90)
FF	−0.90	−0.61	−0.32	−0.19	−0.03	−0.03	0.18	0.29	0.29	0.71	1.61
	(−7.98)	(−6.98)	(−4.40)	(−2.99)	(−0.52)	(−0.59)	(3.38)	(4.73)	(3.88)	(6.70)	(8.98)
Panel B: Nearhigh Decile Portfolio											
Panel B1: Crash Periods											
Excess	5.01	3.48	2.62	1.80	0.89	0.21	−0.34	−0.72	−1.44	−2.11	−7.12
	(7.04)	(7.36)	(7.42)	(5.39)	(3.33)	(1.02)	(−2.09)	(−3.46)	(−6.06)	(−5.87)	(−6.97)
CAPM	1.48	1.13	1.02	0.61	0.30	−0.05	−0.28	−0.19	−0.49	−0.64	−2.11
	(2.88)	(3.23)	(3.85)	(2.21)	(1.30)	(−0.24)	(−1.74)	(−1.12)	(−2.66)	(−2.74)	(−3.14)
FF	1.04	0.99	0.84	0.48	0.24	0.04	0.00	−0.07	−0.60	−0.80	−1.84
	(2.49)	(2.82)	(2.92)	(1.64)	(0.98)	(0.21)	(0.02)	(−0.41)	(−3.03)	(−2.93)	(−3.02)
Panel B2: Noncrash Periods											
Excess	−1.07	−0.66	−0.35	−0.31	−0.18	−0.07	−0.02	0.23	0.34	0.25	1.32
	(−6.63)	(−5.63)	(−3.81)	(−4.33)	(−2.82)	(−1.26)	(−0.48)	(4.72)	(6.11)	(3.53)	(6.39)
CAPM	−0.67	−0.38	−0.19	−0.19	−0.09	−0.06	−0.03	0.17	0.24	0.10	0.76
	(−4.74)	(−3.52)	(−2.20)	(−2.79)	(−1.49)	(−1.15)	(−0.62)	(3.58)	(4.41)	(1.48)	(4.33)
FF	−0.59	−0.28	−0.09	−0.18	−0.07	−0.03	−0.02	0.18	0.20	0.08	0.66
	(−4.56)	(−2.88)	(−0.98)	(−2.46)	(−1.02)	(−0.59)	(−0.32)	(3.52)	(3.66)	(1.17)	(4.06)

Table 2. Two-way sort on *Momentum* and *Nearhigh*: crash period

Table 2 reports monthly excess returns of portfolios double-sorted by *Momentum* and *Nearhigh* during the crash periods. At the end of each month, stocks are sequentially divided into quintiles based on their *Momentum* and *Nearhigh*, which results in 25 (5×5) portfolios. In Panel A (B), we first sort on *Nearhigh* (*Momentum*), and then on *Momentum* (*Nearhigh*).We report the average value-weighted excess return of each portfolio during the crash periods. The column labeled 5−1 reports the return spread between the top and the bottom quintile. Every number is in percent. Numbers in parentheses are *t*-statistics computed from White robust standard error.

Panel A: Sort on Nearhigh-Momentum

		Momentum					
		1(Loser)	2	3	4	5(Winner)	5−1
Nearhigh	1(Far)	4.12	4.26	3.38	4.28	4.73	0.61
		(5.29)	(6.14)	(5.78)	(7.55)	(7.75)	(0.94)
	2	1.88	1.91	2.03	2.66	2.55	0.67
		(3.97)	(5.60)	(5.36)	(6.19)	(5.96)	(1.26)
	3	−0.20	0.45	0.84	0.84	1.10	1.31
		(−0.58)	(1.46)	(3.14)	(2.95)	(3.16)	(2.51)
	4	−0.96	−0.78	−0.45	−0.35	0.64	1.60
		(−4.00)	(−3.83)	(−1.97)	(−1.41)	(2.00)	(3.64)
	5(Near)	−2.09	−1.88	−1.59	−1.74	−1.03	1.06
		(−7.46)	(−6.19)	(−5.53)	(−4.34)	(−2.50)	(3.02)

Panel B: Sort on Momentum−Nearhigh

		Nearhigh					
		1(Far)	2	3	4	5(Near)	5−1
Momentum	1(Loser)	5.59	4.55	3.38	2.89	0.72	−4.86
		(6.42)	(6.73)	(5.27)	(6.14)	(1.66)	(−6.48)
	2	4.19	2.69	2.07	0.64	−0.86	−5.04
		(8.07)	(7.14)	(4.97)	(1.84)	(−2.85)	(−8.25)
	3	3.22	1.38	0.21	−0.60	−1.48	−4.70
		(5.55)	(4.08)	(0.89)	(−2.98)	(−5.61)	(−6.55)
	4	2.02	0.55	−0.26	−1.41	−1.94	−3.96
		(5.28)	(2.19)	(−1.27)	(−4.62)	(−6.98)	(−6.62)
	5(Winner)	1.37	0.41	−0.46	−1.04	−2.03	−3.41
		(2.97)	(1.19)	(−1.37)	(−2.46)	(−5.09)	(−5.87)

Table 3. The nearhigh-neutral momentum portfolio: crash period

Table 3 reports excess and risk-adjusted returns of the nearhigh-neutral momentum portfolios during the crash periods. At each month, we group stocks into quintile based on their *Nearhigh*. Within each *Nearhigh* quintile, we group stocks into deciles based on their *Momentum*, which results in value-weighted and evenly-spaced 50 portfolios. Then, stocks are held until the end of the next month. Lastly, we form ten cohorts by equal-weighting five portfolios in the same *Momentum* decile. Panel A reports average level of *Nearhigh* and *Momentum* for each decile portfolios. Panel B reports the excess and risk-adjusted return of the nearhigh-neutral momentum portfolios. Column labeled "WML*" reports the difference between the top and bottom decile. We refer to this portfolio as nearhigh-neutral momentum portfolio. Every number is in percent. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	1(L*)	2	3	4	5	6	7	8	9	10(W*)	WML*
Panel A: Average Measure											
Nearhigh	65.15	66.89	67.95	68.75	69.30	69.71	70.08	70.35	70.58	70.60	5.45
Momentum	−35.31	−27.81	−23.72	−20.29	−16.90	−13.21	−8.79	−2.95	6.61	41.75	77.06
Panel B: Average Return											
Excess	0.36	0.64	0.86	0.87	0.91	1.01	1.32	1.07	1.64	1.75	1.39
	(1.14)	(2.51)	(4.41)	(4.35)	(4.58)	(5.30)	(6.68)	(4.37)	(6.99)	(5.83)	(3.10)
CAPM	−0.25	0.17	0.45	0.51	0.41	0.44	0.61	0.25	0.63	0.43	0.67
	(−0.83)	(0.76)	(2.54)	(2.78)	(2.36)	(2.50)	(3.28)	(1.00)	(2.61)	(1.47)	(1.56)
FF	−0.36	0.09	0.29	0.38	0.30	0.25	0.31	0.01	0.43	0.13	0.49
	(−1.22)	(0.38)	(1.70)	(1.99)	(1.68)	(1.38)	(1.67)	(0.04)	(1.86)	(0.48)	(1.11)

Table 4. Return predictability of *Momentum* and *Nearhigh*: crash period

Table 4 reports the result of the Fama-Macbeth regression during the crash periods. The description of each variable can be found in the Appendix A. Every independent variable is winsorized at the top and bottom 1%, and scaled with its cross-sectional standard-deviation. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Momentum	−0.0094	0.0102	−0.0039	0.0025	−0.0045	0.0024
	(−3.90)	(6.36)	(−2.35)	(2.36)	(−2.68)	(2.19)
Nearhigh		−0.0268		−0.0100		−0.0105
		(−9.00)		(−4.77)		(−4.87)
Srev			−0.0138	−0.0108	−0.0137	−0.0103
			(−10.70)	(−8.00)	(−10.87)	(−8.19)
Beta			0.0146	0.0123	0.0120	0.0101
			(7.96)	(7.62)	(7.74)	(7.31)
Log(*ME*)			0.0012	0.0018	−0.0023	−0.0019
			(1.30)	(1.93)	(−2.48)	(−2.08)
Log(*BM*)			0.0014	0.0019	0.0015	0.0017
			(1.12)	(1.52)	(1.24)	(1.44)
Log(*PRC*)			−0.0040	−0.0024	−0.0037	−0.0024
			(−3.26)	(−2.04)	(−3.37)	(−2.26)
Lrev					−0.0014	−0.0017
					(−1.56)	(−1.87)
Ivol					−0.0020	−0.0032
					(−1.20)	(−1.92)
Skew					−0.0008	−0.0003
					(−0.97)	(−0.41)
Kurt					−0.0029	−0.0026
					(−3.95)	(−3.60)
Illiq					−0.0055	−0.0052
					(−6.31)	(−6.06)
Max					0.0034	0.0027
					(1.60)	(1.30)

Table 5. Market states and change in investor sentiment

Table 5 reports average change in various proxies for investor sentiment at each market states. List of proxies for investor sentiment is described in detail in Appendix A. Panel A (B) include proxies that are positively (negatively) related to investor sentiment. We report change in both macro-adjusted value and raw value. Columns labeled "Diff" report difference in change in these proxies between market states. Every number except BW is in percent. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	Macro-adjusted			Unadjusted		
Measure	Non-Crash	Crash	Diff	Non-Crash	Crash	Diff
Panel A: Positively associated proxies						
AAII	−1.01	7.15	8.16	−1.09	7.71	8.80
	(−1.33)	(3.77)	(3.99)	(−1.43)	(4.03)	(4.27)
II	−0.32	3.89	4.20	−0.33	4.12	4.45
	(−0.40)	(1.55)	(1.60)	(−0.41)	(1.98)	(1.99)
ADV/DEC	−2.84	19.26	22.11	−3.08	18.85	21.93
	(−2.90)	(5.86)	(6.45)	(−3.82)	(8.09)	(8.90)
HI/LO	−57.66	362.93	420.60	−44.69	271.69	316.39
	(−0.79)	(2.82)	(2.84)	(−0.86)	(3.54)	(3.41)
FLOW	−0.03	0.25	0.28	−0.03	0.28	0.31
	(−1.04)	(2.29)	(2.48)	(−1.22)	(3.05)	(3.27)
SMB	−0.19	1.28	1.47	−0.24	1.52	1.76
	(−1.19)	(2.49)	(2.73)	(−1.73)	(3.41)	(3.77)
RIPO	−0.50	3.83	4.34	−0.49	3.71	4.19
	(−0.73)	(2.00)	(2.12)	(−0.70)	(1.95)	(2.07)
BW	−0.03	0.19	0.22	−0.02	0.13	0.15
	(−0.62)	(1.73)	(1.83)	(−0.44)	(1.20)	(1.27)
Panel B: Negatively associated proxies						
ARMS	0.71	−4.67	−5.38	1.57	−9.19	−10.76
	(1.69)	(−3.97)	(−4.31)	(3.26)	(−6.33)	(−7.03)
ILLIQ	0.00	−0.01	−0.01	0.02	−0.13	−0.15
	(0.84)	(−1.90)	(−2.06)	(0.44)	(−0.62)	(−0.70)
PDND	0.10	−0.97	−1.07	0.08	−0.87	−0.95
	(0.60)	(−2.27)	(−2.33)	(0.60)	(−2.78)	(−2.80)
PCRATIO	1.10	−6.55	−7.65	1.25	−7.27	−8.52
	(1.96)	(−4.00)	(−4.42)	(2.53)	(−6.93)	(−7.35)
VIX	0.40	−3.46	−3.86	0.47	−3.94	−4.41
	(1.51)	(−3.36)	(−3.63)	(1.93)	(−5.58)	(−5.90)
VIX/SIG	0.51	−5.71	−6.22	0.40	−4.66	−5.05
	(0.46)	(−2.31)	(−2.30)	(0.41)	(−2.93)	(−2.72)

Table 6. *Nearhigh* and speculative demands: crash period

Table 6 reports the result of Fama-Macbeth regression during the crash periods. In Panel A, dependent variable is percentage in the proportion of small trades compared to its past 12-month average. The proportion of small trades is the ratio of small trade volume (with trades less than $5,000) to total trade volume. In Panel B, dependent variable is order imbalance of small trades, where trades are classified following Lee and Ready (1991). Every independent variable is winsorized at the top and bottom 1%, and scaled with its cross-sectional standard-deviation. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	Panel A: Small trades			*Panel B: Order Imbalance*		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Momentum	−0.0371	−0.0680	0.0127	0.0343	0.0232	0.0206
	(−2.77)	(−4.16)	(0.20)	(7.72)	(4.91)	(5.06)
Nearhigh	−0.2369	−0.2279	−0.2474	−0.0354	−0.0299	−0.0254
	(−3.55)	(−4.22)	(−3.49)	(−4.70)	(−4.05)	(−3.84)
Srev		−0.0960	−0.1100		−0.0151	−0.0188
		(−2.16)	(−1.61)		(−5.43)	(−3.86)
Beta		−0.0219	−0.0850		0.0051	0.0017
		(−0.74)	(−1.87)		(0.87)	(0.27)
Log(*ME*)		0.1226	0.1580		−0.0052	−0.0076
		(1.06)	(1.13)		(−0.65)	(−1.24)
Log(*BM*)		0.0342	0.1275		−0.0239	−0.0158
		(1.35)	(1.07)		(−5.27)	(−4.68)
Log(*PRC*)		0.0564	0.0172		0.0267	0.0277
		(2.18)	(0.69)		(5.06)	(6.65)
Lrev			0.2695			0.0134
			(0.98)			(4.40)
Ivol			−0.2259			0.0006
			(−0.95)			(0.11)
Skew			−0.0327			−0.0048
			(−1.05)			(−2.89)
Kurt			−0.0027			−0.0076
			(−0.16)			(−3.02)
Illiq			0.1370			−0.0079
			(1.74)			(−1.19)
Max			0.1877			0.0104
			(0.87)			(1.38)

Table 7. Long-run performance of near minus far portfolio

Table 7 reports average monthly cumulative returns of near minus far portfolio after portfolio formation. 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 after the largest 100 momentum crash months. Every number is in percent. Since returns can overlap, we compute *t*-statistics with Newey-West correction of lag 60.

	Panel A: Crash periods			*Panel B: Top 100*		
	Raw	CAPM	FF	Raw	CAPM	FF
$Ret_{[t+1,t+2]}$	–4.62	–1.56	–1.07	–6.39	–3.80	–2.34
	(–3.76)	(–2.35)	(–1.86)	(–4.04)	(–7.72)	(–5.59)
$Ret_{[t+1,t+12]}$	–0.66	0.04	0.12	–0.79	–0.26	–0.11
	(–1.69)	(0.08)	(0.27)	(–2.34)	(–0.67)	(–0.29)
$Ret_{[t+1,t+24]}$	–0.38	0.00	0.14	–0.43	–0.17	–0.04
	(–1.45)	(0.00)	(0.46)	(–2.12)	(–0.48)	(–0.16)
$Ret_{[t+1,t+36]}$	–0.22	0.23	0.32	–0.35	0.02	0.19
	(–0.76)	(0.71)	(1.38)	(–1.92)	(0.09)	(1.48)
$Ret_{[t+1,t+48]}$	–0.34	0.18	0.27	–0.41	0.11	0.17
	(–1.02)	(0.58)	(1.38)	(–2.07)	(0.52)	(1.28)
$Ret_{[t+1,t+60]}$	–0.50	0.19	0.28	–0.55	0.06	0.13
	(–1.53)	(0.79)	(1.79)	(–2.86)	(0.33)	(0.93)

Table 8. Comparison between risk loading and characteristics: crash period

Table 8 reports the result of the Fama-Macbeth regression during the crash periods. We include each stock's risk-loading on Fama-French three factors and NMF. Every independent variable is winsorized at the top and bottom 1%, and scaled with its cross-sectional standard-deviation. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Momentum	0.0102 (6.36)	0.0089 (6.86)	0.0045 (3.62)	0.0024 (2.23)	0.0032 (2.82)	0.0023 (2.12)
Nearhigh	−0.0268 (−9.00)	−0.0206 (−8.60)	−0.0164 (−6.23)	−0.0094 (−4.72)	−0.0139 (−5.75)	−0.0101 (−4.87)
β_{MKT}		0.0136 (6.97)		0.0144 (7.89)		0.0121 (7.46)
β_{HML}		0.0001 (0.12)		0.0012 (1.12)		0.0012 (1.24)
β_{SMB}		0.0003 (0.18)		−0.0009 (−0.66)		−0.0011 (−0.87)
β_{NMF}		−0.0102 (−5.41)		−0.0110 (−5.91)		−0.0090 (−5.46)
Srev			−0.0086 (−6.07)	−0.0109 (−8.02)	−0.0102 (−7.97)	−0.0104 (−8.00)
Log(*ME*)			0.0046 (4.04)	0.0020 (2.15)	−0.0010 (−1.10)	−0.0017 (−1.88)
Log(*BM*)			0.0018 (1.33)	0.0018 (1.52)	0.0016 (1.35)	0.0018 (1.60)
Log(*PRC*)			−0.0035 (−3.01)	−0.0023 (−2.06)	−0.0029 (−2.71)	−0.0023 (−2.25)
Lrev					−0.0014 (−1.46)	−0.0015 (−1.73)
Ivol					−0.0059 (−3.47)	−0.0033 (−2.04)
Skew					−0.0018 (−2.37)	−0.0004 (−0.58)
Kurt					−0.0048 (−6.63)	−0.0026 (−3.65)
Illiq					−0.0068 (−7.32)	−0.0051 (−6.21)
Max					0.0090 (3.99)	0.0029 (1.43)

Table 9. Alternative sources of overpricing: crash period

Table 9 reports the result of the Fama-Macbeth regression during the crash periods. We include firm characteristics that are potentially associated with speculative demands: Standard unexpected earnings (Foster, Olsen and Shevlin, 1984), gross profitability (Novy-Marx, 2013), log of age, and Ohlson (1980) O-score. The description of each variable can be found in the Appendix A. Every independent variable is winsorized at the top and bottom 1%, and scaled with its cross-sectional standard-deviation. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Momentum	0.0024	0.0015	0.0025	0.0023	0.0024	0.0013
	(1.93)	(1.17)	(2.11)	(1.84)	(1.81)	(1.09)
Nearhigh	−0.0116	−0.0135	−0.0117	−0.0117	−0.0112	−0.0128
	(−4.51)	(−5.04)	(−4.57)	(−4.53)	(−4.28)	(−4.68)
Srev	−0.0058	−0.0057	−0.0058	−0.0058	−0.0064	−0.0066
	(−4.06)	(−4.06)	(−4.22)	(−4.12)	(−4.43)	(−4.65)
Beta	0.0120	0.0119	0.0120	0.0117	0.0110	0.0106
	(5.78)	(5.93)	(5.70)	(5.65)	(5.08)	(4.85)
Log(*ME*)	−0.0001	−0.0005	0.0006	0.0006	0.0001	0.0012
	(−0.09)	(−0.37)	(0.47)	(0.43)	(0.09)	(0.85)
Log(*BM*)	0.0002	0.0009	0.0017	0.0007	0.0000	0.0028
	(0.15)	(0.69)	(1.21)	(0.50)	(0.03)	(1.98)
Log(*PRC*)	−0.0034	−0.0039	−0.0035	−0.0033	−0.0039	−0.0041
	(−2.24)	(−2.58)	(−2.33)	(−2.11)	(−2.53)	(−2.86)
Lrev	−0.0005	−0.0009	−0.0004	−0.0006	−0.0012	−0.0013
	(−0.39)	(−0.68)	(−0.29)	(−0.47)	(−0.99)	(−1.09)
Ivol	0.0008	0.0009	0.0010	0.0005	0.0018	0.0019
	(0.43)	(0.54)	(0.53)	(0.27)	(0.91)	(1.04)
Skew	0.0018	0.0019	0.0019	0.0018	0.0019	0.0018
	(2.22)	(2.17)	(2.26)	(2.24)	(2.28)	(2.11)
Kurt	−0.0017	−0.0016	−0.0019	−0.0017	−0.0022	−0.0022
	(−2.08)	(−1.93)	(−2.28)	(−2.07)	(−2.52)	(−2.65)
Illiq	−0.0058	−0.0061	−0.0056	−0.0057	−0.0060	−0.0063
	(−6.43)	(−6.65)	(−6.32)	(−6.42)	(−5.16)	(−5.58)
Max	−0.0014	−0.0016	−0.0014	−0.0014	−0.0012	−0.0013
	(−0.59)	(−0.63)	(−0.59)	(−0.58)	(−0.49)	(−0.50)
SUE		0.0059				0.0059
		(7.63)				(6.78)
Profitability			0.0046			0.0037
			(3.72)			(2.58)
Log(*Age*)				−0.0025		−0.0025
				(−3.08)		(−2.67)
Oscore					−0.0026	−0.0015
					(−3.08)	(−1.61)

Table 10. Time-variations of WML and WML*

Table 10 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 AMEX 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 White *t*-statistics.

	Panel A: WML					*Panel B: WML**				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Intercept	0.0114	0.0164	0.0185	0.0152	0.02288	0.0160	0.0144	0.0141	0.0150	0.0146
	(3.70)	(7.32)	(7.63)	(6.45)	(2.01)	(8.14)	(8.21)	(6.90)	(8.69)	(1.46)
Mktret	0.0522					–0.0047				
	(2.27)					(–0.36)				
Mktretsq	–0.0890					–0.0095				
	(–2.42)					(–0.54)				
Mktilliq		–0.0047					0.0006			
		(–2.89)					(0.69)			
Mktvol			–0.2179					0.0275		
			(–2.51)					(0.42)		
$I_{January}$				–0.0348					–0.0015	
				(–3.98)					(–0.30)	
Div					–0.0989					0.1518
					(–0.32)					(0.51)
Yld					0.2354					0.0495
					(1.84)					(0.45)
Term					0.1874					0.0924
					(0.61)					(0.36)
Def					–1.8807					-0.8421
					(–2.12)					(-1.34)

Table 11. Moments of momentum strategies

Table 11 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 excess, CAPM-, and FF-adjusted returns.

	Average	St.dev	Skew	Kurt	Min	Max	Sharpe
Panel A: Excess return							
WML	0.0123	0.0740	−1.7323	16.7711	−0.6930	0.4989	0.1662
WML*	0.0149	0.0508	0.4842	6.0766	−0.2687	0.4015	0.2933
Panel B: CAPM-adjusted return							
WML	0.0110	0.0639	−0.5861	6.6858	−0.4308	0.4689	0.1721
WML*	0.0121	0.0473	0.5236	4.7948	−0.1698	0.3705	0.2558
Panel C: FF-adjusted return							
WML	0.0113	0.0605	−0.8426	5.7828	−0.4100	0.2775	0.1868
WML*	0.0130	0.0447	0.2168	3.1600	−0.2540	0.2374	0.2908

Table 12. The nearhigh-neutral momentum portfolio during crash period (international)

Table 12 reports excess returns of the conventional momentum portfolios and nearhigh-neutral momentum portfolios during the crash periods. The first row of each panel reports excess returns of each *Momentum* quintile portfolios, and the return spread between the top and bottom quintile. The second row of each panel reports excess returns of each nearhigh-neutral momentum portfolios. At each month, we group stocks into quintile based on their *Nearhigh*. Within each *Nearhigh* quintile, we group stocks into quintile based on their *Momentum*, which results in value-weighted and evenly-spaced 25 portfolios. Then, we form five cohorts by equal-weighting five portfolios in the same *Momentum* quintile. Panel A, B, and C corresponds to Japan, United Kingdom, and continental Europe market, respectively. Every number is in percent. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	1	2	3	4	5	5−1
Panel A: Japan						
Conventional	2.08	0.62	0.00	−0.49	−0.57	−2.65
	(3.82)	(2.06)	(0.02)	(−2.41)	(−1.86)	(−3.36)
Nearhigh-neutral	0.18	0.22	0.54	0.47	0.95	0.77
	(0.58)	(0.99)	(2.38)	(2.19)	(3.28)	(2.05)
Panel B: United Kingdom						
Conventional	2.17	0.96	0.41	−0.49	−0.81	−2.98
	(2.41)	(2.52)	(1.58)	(−2.56)	(−1.94)	(−2.55)
Nearhigh-neutral	0.47	0.27	0.73	0.93	1.61	1.14
	(0.88)	(0.81)	(2.95)	(2.98)	(4.82)	(2.16)
Panel C: Continental Europe						
Conventional	2.10	0.90	0.01	−0.59	−0.76	−2.86
	(3.08)	(3.02)	(0.05)	(−2.79)	(−2.31)	(−3.02)
Nearhigh-neutral	0.02	0.57	0.37	0.47	0.39	0.37
	(0.06)	(2.38)	(2.24)	(3.09)	(1.52)	(0.82)

Table 13. Moments of momentum strategies (International)

Table 13 reports the moments of the conventional momentum strategy (WML) and the nearhigh-neutral momentum strategy (WML*) returns for non-US markets. It reports the average, standard deviation, skewness, kurtosis, minimum, maximum, and monthly Sharpe ratio. It also reports White t-statistics on the average return. Panel A, B, and C corresponds to Japan, United Kingdom, and continental Europe market, respectively.

	Average	St.dev	Skew	Kurt	Min	Max	Sharpe	*t*-stat
Panel A: Japan								
WML	0.0045	0.0662	−0.5828	3.7331	−0.3499	0.2536	0.0678	1.50
WML*	0.0073	0.0443	−0.3352	4.3662	−0.2441	0.1928	0.1652	3.66
Panel B: United Kingdom								
WML	0.0110	0.0689	−1.4293	9.0732	−0.5414	0.2154	0.1598	3.63
WML*	0.0112	0.0405	−0.7285	4.0561	−0.2219	0.1472	0.2761	6.27
Panel C: Continental Europe								
WML	0.0134	0.0628	−0.8869	4.7044	−0.3461	0.2353	0.2135	4.74
WML*	0.0130	0.0383	−0.1648	1.5966	−0.1469	0.1585	0.3392	7.52

Appendix A

A.1. Description on Firm Characteristics

We define firm characteristics at the end of month *t*, which is used to predict subsequent stock returns during month *t*+1.

Momentum (*Momentum*): Cumulative raw return of a stock from month the end of month *t*−12 to *t*−1. We require at least eight months of return data to be valid.

Nearness to 52-week high (*Nearhigh*): Stock price at the end of month *t* divided by the highest daily closing price from month *t*−11 to month *t*.

Short-run reversal (*Srev*): Return during month *t*.

Long-run reversal (*Lrev*): Cumulative raw return of a stock from the end of the month *t*−36 to *t*−12.

Market beta (*Beta*): 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

Size (*ME*): Share price times the number of shares outstanding at the end of month *t*

Book-to-market ratio (*BM*): 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 year-ends in calendar year *t* is available from the July of year *t*+1.

Price (*PRC*): Closing price at the end of month *t*.

Idiosyncratic volatility (*Ivol*): 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*): Skewness of daily raw returns at month t.

Kurtosis (*Kurt*): Kurtosis of daily raw returns at month t.

Illiquidity (*Illiq*): Following Amihud (2002), we divide absolute value of daily return by daily dollar trading volume, and then take average during month t. We multiply by 1,000,000 to make the numbers reasonably large.

Maximum return (*Max*): Maximum of daily raw returns during month t.

Standardized unexpected earnings (*SUE*): 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 (*Profitability*): Revenue minus cost of goods sold divided by total asset. We assume that the fundamental data for all fiscal yearends in calendar year t is available from the July of year t+1.

Ohlson score (*Oscore*): We follow Ohlson (1980) to construct O-score. Symbols below are COMPUSTAT code. O-score is defined as:

$$O = -1.32 - 0.407\log(AT_t) + 6.03(DLC_t+DLTT_t)/AT_t - 1..43(ACT_t-LCT_t)/AT_t + 0.076LCT_t/ACT_t$$
$$- 1.72X_t - 2.37NI_t/AT_t - 1.83(PI_t/LT_t) + 0.285Y_t - (NI_t-NI_{t-1})/(|NI_t|+|NI_{t-1}|)$$

where X_t is 1 if LT>AT, and 0 otherwise, Y_t is 1 if NI_{t-1} and NI_{t-2} is both negative, and 0 otherwise. We assume that the fundamental data for all fiscal year ending in calendar year t is available from the July of year t+1.

Age (*Age*): Number of months that the stock appeared in CRSP universe

Proportion of small trades to total trades (*Small trades*): Using ISSM and TAQ data, we classify trades as small trades if the trade size is less than $5,000, following Han and Kumar (2013). We divide sum of small trading volume during month *t* with total trading volume during month *t*.

Order imbalance in small trades (*Imbalance*): Trades are classified into buy- and sell-initiated orders following Lee and Ready (1991). Order imbalance in small trades is small-buy volume minus small sell-volume divided by total small trading volume during month *t*.

A.2. Proxies of Investor Sentiment[17]

Survey by the American Association of Individual Investors (*AAII*): Every week, the association asks each participant where they think the stock market will be in 6 months: up, down, or the same. AAII the label these responses as bullish, bearish, or neutral, respectively. We use bull-bear spread as a proxy for level of investor sentiment. We convert weekly series to monthly series by averaging out bull-bear spread based on the calendar month of the each week-end. It is available from July 1987, and is downloaded from Bloomberg.

Investor Intelligence (*II*): II compiles weekly bull-bear spread by categorizing approximately 150 market newsletters. We use bull-bear spread from II as a proxy. We convert weekly series to monthly series by averaging out bull-bear spread based on the calendar month of the each week-end. It is available from February 1989 to December 2002, and is downloaded from Bloomberg.

Advance to decline ratio (*ADV/DEC*): Each month, using NYSE stocks, we divide the number of observations with positive daily return by the number of observations with negative daily return. The data is available throughout the full sample period.

Number of new highs to new lows (*HI/LO*): Each month, using NYSE stocks, we divide the number of 52-week high breaking event by the number of 52-week low breaking event.

[17] See Brown and Cliff (2004) and Baker and Wurgler (2006) for further description.

Aggregate flow to mutual funds (*FLOW*): Total net asset-weighted average of inflow to mutual funds. Inflow to the fund is measured as monthly growth rate of total net assets minus monthly investment return. We consider all domestic equity mutual funds in CRSP SBF Mutual Fund Database. The data is available from January 1991.

Small stock returns (*SMB*): SMB is provided through Ken French's website. The data is available throughout the full sample period.

Average first day returns of IPO (*RIPO*): First day returns after IPO is provided through Wurgler's website and is available from January 1960 to November 2015.

Baker-Wurgler sentiment index (*BW*): Baker and Wurgler (2006) sentiment index provided through Wurgler's website, which is available from July 1965 to September 2015.

ARMS ratio (*ARMS*): Advance to decline ratio divided by trading volume of advancing stocks over the trading volume of declining stocks.

Market illiquidity (*ILLIQ*): Value-weighted average of individual stocks' Amihud (2002) illiquidity measure.

Dividend premium (*PDND*): The log difference of the average market-to-book ratios of payers and nonpayers. Data is from Wurgler's website and is available from January 1961 to December 2014.

Put to call ratio (*PCRATIO*): Total trading volume of CBOE equity put options divided by total trading volume of CBOE equity call options. The series is available from January 1997.

Volatility index (*VIX*): S&P500 VIX index, which is available from January 1990.

Expected volatility to current volatility (*VIX/SIG*): Log of VIX to realized volatility, where realized volatility is standard-deviation of daily value-weighted CRSP return during the past 126 days.

Table A1. The nearhigh-neutral momentum portfolio: 10 largest crash months

Table A1 reports returns of the conventional momentum strategy (WML) and the nearhigh-neutral momentum strategy (WML*) during the 10 largest crash months. Every number is in percent

		Excess		CAPM		FF	
Rank	Date	WML	WML*	WML	WML*	WML	WML*
1	1932-07	−69.30	−6.31	−34.44	1.11	−29.41	−1.29
2	1932-08	−62.47	−26.88	−21.72	−15.48	−20.98	−25.40
3	2001-01	−40.02	−9.16	−43.08	−14.02	−41.75	−15.33
4	2009-04	−35.77	−9.93	−24.45	−10.41	−26.02	−7.94
5	1938-06	−34.21	−5.20	−9.24	−2.80	−13.50	−3.65
6	1931-06	−32.31	2.14	−14.86	5.39	−12.26	5.40
7	1939-09	−31.62	8.26	−28.61	2.64	−37.40	−0.39
8	1933-04	−26.93	−0.29	−6.10	−8.16	−9.88	−8.04
9	1970-09	−19.87	2.02	−17.66	0.52	−10.69	−1.77
10	1973-07	−19.17	−0.08	−18.55	−1.75	−11.54	−0.14

Table A2. Return predictability of M*omentum* and *Nearhigh*: 10 largest crash months

Table A2 reports the coefficients on *Momentum* and *Nearhigh* from a cross-sectional regression of Model 4 in Table 4 for the 10 largest momentum crashes. 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 *Momentum* and *Nearhigh*. Numbers in parentheses are *t*-statistics computed from White robust standard error.

Rank	Date	WML	$\text{Mkt}_{[t-11,t]}$	Mkt_{t+1}	Momentum	Nearhigh
1	1932-07	−69.30	−65.85	34.06	−0.0292 (−0.60)	−0.0331 (−0.67)
2	1932-08	−62.47	−50.96	37.14	−0.0071 (−0.16)	−0.1374 (−3.53)
3	2001-01	−40.02	−11.16	3.96	−0.0051 (−1.02)	−0.0688 (−9.51)
4	2009-04	−35.77	−38.61	10.94	−0.0202 (−2.49)	−0.0528 (−6.03)
5	1938-06	−34.21	−39.04	23.79	−0.0287 (−1.91)	−0.0389 (−2.27)
6	1931-06	−32.31	−45.73	14.03	−0.0405 (−1.98)	0.0315 (1.26)
7	1939-09	−31.62	−1.13	16.18	0.0262 (1.78)	−0.1735 (−8.09)
8	1933-04	−26.93	−12.63	39.41	−0.0181 (−0.98)	−0.0158 (−0.60)
9	1970-09	−19.87	−14.51	4.75	0.0102 (1.49)	−0.0561 (−7.65)
10	1973-07	−19.17	−7.32	5.70	0.0035 (0.52)	−0.0280 (−3.50)

Table A3. Return predictability of *Momentum* and *Nearhigh*: Robustness test

Table A3 reports the Fama-Macbeth regression coefficients on *Momentum* and *Nearhigh*, where we replicate Model 4 of Table 4 under alternative setups. In Panel A, we restrict our sample to NYSE-, AMEX-, 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. Every independent variable is winsorized at the top and bottom 1%, and scaled with its cross-sectional standard-deviation. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	Momentum	*Nearhigh*		*Momentum*	*Nearhigh*
Panel A: Sub-samples			*Panel B: Sub-periods*		
Non−financial	0.0025	−0.0099	1927−1946	0.0005	−0.0123
	(2.28)	(−4.69)		(0.20)	(−2.20)
NYSE	0.0020	−0.0102	1947−1966	0.0025	−0.0032
	(1.62)	(−4.83)		(1.54)	(−1.47)
AMEX	0.0029	−0.0077	1967−1986	0.0045	−0.0075
	(1.04)	(−1.97)		(1.61)	(−2.00)
NASDAQ	0.0036	−0.0093	1987−2006	0.0058	−0.0131
	(1.62)	(−2.71)		(4.34)	(−3.57)
			2007−2015	−0.0016	−0.0168
				(−0.67)	(−3.49)
Panel C: Definitions of Momentum			*Panel D: Definitions of Nearhigh*		
$r_{[t-12,t-1]}$	0.0035	−0.0107	13−week	−0.0021	−0.0079
	(2.94)	(−5.35)		(−1.33)	(−6.98)
$r_{[t-6,t-2]}$	−0.0012	−0.0069	26−week	−0.0004	−0.0085
	(−0.91)	(−3.56)		(−0.31)	(−5.16)
$r_{[t-12,t-7]}$	0.0013	−0.0085	104−week	0.0003	−0.0077
	(1.64)	(−4.08)		(0.19)	(−4.04)
Panel E: Definitions of crash periods					
EW	0.0042	−0.0116			
	(3.57)	(−5.60)			
2−year	0.0035	−0.0116			
	(3.88)	(−5.02)			
3−year	0.0040	−0.0088			
	(3.53)	(−3.61)			

Table A4. Time-variations of risk-adjusted WML and WML* returns

Table A4 regress CAPM and FF-adjusted returns of WML and WML* portfolio on various time-series determinants of momentum profits. Numbers in parentheses are *t*-statistics computed from White robust standard error.

	WML					WML*				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Panel A: CAPM-adjusted return										
Intercept	0.0101	0.0134	0.0163	0.0142	0.0122	0.0134	0.0116	0.0117	0.0125	0.0112
	(4.07)	(6.53)	(7.12)	(6.43)	(1.01)	(7.04)	(6.60)	(5.57)	(7.10)	(1.15)
Mktret	0.0437					−0.0105				
	(3.45)					(−0.90)				
Mktretsq	−0.0718					−0.0014				
	(−3.23)					(−0.09)				
Mktilliq		−0.0027					0.0006			
		(−4.18)					(0.98)			
Mktvol			−0.1883					0.0149		
			(−3.21)					(0.26)		
$I_{January}$				−0.0377					−0.0048	
				(−4.33)					(−0.87)	
Div					0.1106					0.0904
					(0.36)					(0.32)
Yld					0.2358					0.0912
					(2.01)					(0.94)
Term					0.3104					0.0477
					(1.06)					(0.20)
Def					−1.6604					−0.6996
					(−1.90)					(−1.15)
Panel B: FF-adjusted returns										
Intercept	0.0101	0.0131	0.0168	0.0140	0.0140	0.0137	0.0127	0.0131	0.0134	0.0164
	(3.95)	(6.01)	(5.96)	(6.20)	(1.05)	(6.76)	(7.25)	(5.72)	(7.50)	(1.68)
Mktret	0.0449					−0.0017				
	(3.23)					(−0.12)				
Mktretsq	−0.0680					−0.0082				
	(−3.23)					(−0.47)				
Mktilliq		−0.0020					0.0003			
		(−3.02)					(0.36)			
Mktvol			−0.1949					−0.0053		
			(−2.26)					(−0.07)		
$I_{January}$				−0.0325					−0.0052	
				(−3.61)					(−0.96)	
Div					−0.0234					−0.1400
					(−0.07)					(−0.50)
Yld					0.3569					0.1994
					(2.25)					(1.94)
Term					0.4315					0.1276
					(1.19)					(0.53)
Def					−1.9967					−0.9438
					(−1.59)					(−1.23)

Table A5. Moments of momentum strategies

Table A5 reports the moments of WML and WML* for sub-samples and sub-periods. In Panels A and B, we restrict sample periods to post-2000 period and the later-half of the full sample. In Panel C and D, we restrict sample stocks to the most big and liquid stocks using NYSE median breakpoint of *ME* and *Illiq*.

	Average	St.dev	Skew	Kurt	Min	Max	Sharpe
Panel A: Post-2000							
WML							
Excess	0.0067	0.0898	−0.0118	6.9293	−0.4002	0.4989	0.0746
CAPM	0.0047	0.0838	−0.1355	8.5144	−0.4308	0.4689	0.0561
FF	0.0051	0.0770	−0.5827	5.3465	−0.4100	0.2775	0.0662
WML*							
Excess	0.0070	0.0623	1.2129	10.1803	−0.2087	0.4015	0.1124
CAPM	0.0061	0.0570	1.4169	8.6620	−0.1402	0.3705	0.1070
FF	0.0075	0.0516	0.5679	2.3584	−0.1538	0.2346	0.1453
Panel B: Later-half of the sample periods							
WML							
Excess	0.0138	0.0734	−0.1699	6.5130	−0.4002	0.4989	0.1880
CAPM	0.0120	0.0698	−0.3514	6.9779	−0.4308	0.4689	0.1719
FF	0.0126	0.0644	−0.5781	5.0055	−0.4100	0.2775	0.1957
WML*							
Excess	0.0135	0.0551	0.6657	6.5000	−0.2087	0.4015	0.2450
CAPM	0.0107	0.0503	0.5515	5.3542	−0.1636	0.3705	0.2127
FF	0.0128	0.0454	0.2723	1.7966	−0.1538	0.2346	0.2819
Panel C: Large stocks only							
WML							
Excess	0.0154	0.0689	−2.0085	23.3682	−0.7763	0.4204	0.2232
CAPM	0.0143	0.0622	−0.9140	9.4768	−0.5102	0.3699	0.2292
FF	0.0149	0.0597	−1.3551	10.5356	−0.4955	0.2558	0.2500
WML*							
Excess	0.0169	0.0486	0.3830	5.0641	−0.2575	0.3335	0.3478
CAPM	0.0141	0.0468	0.3581	4.0008	−0.1895	0.2639	0.3025
FF	0.0141	0.0457	0.1400	3.5394	−0.1967	0.2554	0.3088
Panel D: Liquid stocks only							
WML							
Excess	0.0109	0.0754	−1.1968	15.8023	−0.7094	0.5493	0.1452
CAPM	0.0096	0.0665	−0.1327	7.4937	−0.3925	0.5159	0.1447
FF	0.0104	0.0629	−0.2945	5.1834	−0.3808	0.4275	0.1657
WML*							
Excess	0.0124	0.0558	0.5680	11.9777	−0.3833	0.5399	0.2225
CAPM	0.0096	0.0513	0.6709	10.6411	−0.2613	0.5054	0.1874
FF	0.0107	0.0464	0.4091	2.7233	−0.1894	0.2694	0.2309

Table A6. List of non-U.S. countries

Table A6 reports list of non-U.S. countries included in our analysis. Sample period and number of stocks at the beginning and at the end of the sample period is reported. Average number of stocks per month during the sample period is reported as well.

Country	Exchange	Sample Period	No. of Stocks (Start)	No. of Stocks (End)	No. of Stocks (Average)
Japan	Tokyo & Osaka	197401-201512	618	2,785	1,836
United Kingdom	London	197201-201512	1,337	1,027	1,324
Continental Europe		197401-201512	504	3,696	2,483
Austria	Vienna	197401-201512	36	54	63
Belgium	Brussels	197401-201512	37	112	102
Denmark	Copenhagen	197406-201512	30	108	115
Finland	Helsinki	198804-201512	30	107	88
France	Paris	197401-201512	66	566	400
Germany	Frankfurt	197401-201512	107	856	607
Greece	Athens	198802-201512	45	114	175
Ireland	Dublin	198105-201512	30	27	39
Italy	Milan	197401-201512	64	184	159
Netherland	Amsterdam	197401-201512	137	82	132
Norway	Oslo	198002-201512	36	156	120
Poland	Warsaw	199507-201512	30	623	277
Portugal	Lisbon	198802-201512	49	37	71
Spain	Madrid	198704-201512	56	120	123
Sweden	Stockholm	198202-201512	48	358	221
Switzerland	Zurich	197401-201512	57	192	154