What explains price momentum and 52-week high momentum when they really work?*

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Abstract

After long being one of the main puzzles in asset pricing, momentum has ironically became a case of observational equivalence. It can now be explained both by factors proxying for mispricing and by the risk-based q-factor theory. On top of this, q-factor theory also explains the related 52-week-high anomaly. We note that all these recent tests are unconditional exercises while the bulk of momentum profits are predictable and occur after periods of low-volatility. Comparing asset pricing models *conditionally*, when the strategies actually work, we find the unconditional fit is misleading. The models fit well most of the time but not when the profits are produced. Noticeably, q-theory implies time-varying loadings that are generally inconsistent with the data. We proxy underreaction more directly with earnings announcement returns and analyst forecast errors and find that it markedly decreases with volatility. This supports an underreaction channel as closer to the heart of both anomalies.

Keywords: Conditional Asset Pricing; Momentum; 52-week high; Investor Underreaction; Investment CAPM; Momentum Risk; Market States
JEL Classification: G11; G12

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1 Introduction

> "Effort should be focused on ruling out alternative explanations for momentum and trying to hone in on the"true" explanation(s) rather than allowing the finding to get "over-identified" via multiple stories for the same phenomenon."
>
> Avanidhar Subrahmanyam

Momentum is one of the most robust and central asset pricing anomalies. Investor underreaction is an often proposed behavioral explanation for the phenomenon (Jegadeesh and Titman, 1993; Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999). Consistent with this explanation, multiple studies find that improving firm fundamentals explain or even subsume price momentum (Daniel, Hirshleifer, and Sun, 2020; Novy-Marx, 2015a; DeMiguel, Martin-Utrera, Nogales, and Uppal, 2020).[1] But recent work argues that momentum can also be perfectly explained as an equilibrium result with rational investors, a substantially different explanation. In an influential study, Hou, Xue, and Zhang (2015) show that the investment CAPM explains an impressive broad range of anomalies. Arguably, the major success of the model is explaining price momentum – a long-standing puzzle before that. Furthermore, George, Hwang, and Li (2018) show that an also strong relative strength strategy, 52-week high momentum, is also priced by the investment CAPM. This is remarkable since the original economic explanation proposed for the strategy is explicitly its ability to exploit a behavioral bias, "adjustment and anchoring bias", that would drive investor underreaction (George and Hwang, 2004). So the momentum puzzle in the literature shifted. It now seems compatible with two perspectives that are hard to reconcile and that is what is most intriguing about it.

The starting motivation of our paper is the realization that momentum is an unusual anomaly due to its pronounced predictability using market states (Cooper, Gutierrez, and Hameed, 2004) and its own lagged volatility (Daniel and Moskowitz, 2016; Barroso and Santa-Clara, 2015) among other predictors. In this study, we establish this also applies to 52-week high and argue that as a result the two anomalies should be studied conditionally. Models aiming to explain price momentum and 52-week high should address the fact that these have no premiums at all in months following bear markets or high volatility – hence no puzzle to explain in the first place. In fact, we find that for most of the sample,

[1] Lim, Sotes-Paladino, Wang, and Yao (2020) and Huang, Zhang, Zhou, and Zhu (2019) also find evidence consistent with underreaction of stock prices to changes or trends in firm fundamentals. Gebhardt, Hvidkjaer, and Swaminathan (2005) find supportive evidence for underreaction in the corporate bond market.

price momentum and 52-week high momentum are merely dismal investment strategies with high volatility, extreme crash risk, and no statistically significant profitability. By contrast, more than 70% of the profits of the momentum strategy and more than 80% of the profits of the 52-week high strategies are realized in less than a *third* of the sample periods, those after safe months (and with lower risk on top of that).It is only then that the premiums are truly produced. We use this predictable time-variation in profits of the two strategies to discern between the two explanations of the anomalies.

Prior studies that assess whether a model can explain price momentum or 52-week high momentum focus on standard unconditional performance. Indeed in asset pricing conditional models are often used when unconditional models fail (e.g. Avramov and Chordia (2006)). That is the converse of what we do in this study. Unconditional testing typically assumes constant risk premiums for both factors and test assets and this fails to incorporate the observed predictablity in the strategies. In this study, we impose an additional criterion on the assessment that is whether a model can also match the time-varying profitability of the two anomalies. We hypothesize that if a factor model can capture the premiums both unconditionally and conditionally, the rationale behind the factor model comes out reinforced. Otherwise, the unconditional fit of the model is of challenging interpretation.

The primary factor models we consider in our time-series tests include the Daniel, Hirshleifer, and Sun (2020) behavioral factor model (BF3), the Novy-Marx (2015a) fundamental-momentum model (NM5), the Hou, Xue, and Zhang (2015) q-factor model (HXZ4), and the Hou, Mo, Xue, and Zhang (2020) augmented q-factor model (HXZ5), all of which can explain price momentum and 52-week high momentum unconditionally. The first two models explain the anomalies through earnings-surprise factors, which are designed to capture investor underreaction to quarterly earnings announcements. The other two models build on the neo-classical theory of investment and price the same anomalies through factors that proxy for the marginal profitability of investment – which is, in turn, a function of expectations of future firm growth and profitability.[2]

Our main set of results splits the time series of momentum returns according to lagged 6-month realized volatility in the momentum strategy, computed from daily returns, into three bins: 'safe'(bottom 30%), middle 40%, and 'risky' (top 30%). We use a holding period of one month to define momentum returns as in the portfolios available in Kenneth French data library portfolios and is standard in most asset pricing tests, including recent studies on momentum papers (e.g. Daniel and Moskowitz (2016)).[3] We then run

[2]We focus on these models for two reasons: i) they are successful explaining momentum unconditionally as opposed to other plausible candidates such as Fama and French (1993) or Fama and French (2015); and ii) they do not include momentum per se such as Carhart (1997) which would result in a tautology given our research topic.

[3]Predictability at different horizons could conceivably be a different economic question. But in unreported results we generally find that using holding periods between one and six months did not materially change the results.

spanning repressions in sub-samples and test for differences in alphas. If the true model is unconditional, this empirical setting bias the tests in favor of all models, as alphas are less likely to be significant in subsamples due to power.

The results of our conditional time-series regressions show that the good unconditional performance of the four primary factor models is driven by their strong performance only following high and medium levels of momentum risk. This is non-trivial as those periods comprise 70% of the overall sample. So models fit anomalies *most of the time*. However, most profits of the two strategies are realized in the other 30% of the sample that is subsequent to safe months. The best performing model in capturing the two anomalies is Novy-Marx (2015a)'s fundamental-momentum model. This model has in common with BF3 a factor built with cumulative abnormal returns around earnings announcements. But, on top of it, it includes a earnings surprise factor. This factor turns out to help explaining the anomaly returns after safe months.[4] Nevertheless, these models are not able to fully account for the profitability of momentum and 52-week-high in safe months.

The models based on the investment CAPM also fail to explain momentum and 52-week high when they are profitable. This poses a challenge for that explanation but does not necessarily dismiss the economic rationale of the theory. Expected profitability and expected investment growth, the drivers of expected returns it proposes, are unobservable. Earnings-surprise factors could proxy for more than underreaction alone. They may as well capture the very same economic fundamentals investment CAPM posits as true drivers of expected returns. Supporting this interpretation, Liu, Whited, and Zhang (2009) show that innovations in earnings are positively correlated with future investment growth. If this positive relation is stronger after safe months, then the pattern of predictability would be as expected according to the investment CAPM.

To assess that possibility, we follow George, Hwang, and Li (2018) and directly examine how past returns and nearness to 52-week high are linked with future profitability and investment growth using Fama and MacBeth (1973) predictive regressions. Strikingly, we find that the relation between the two anomaly variables and the marginal benefits of investment does not change much with momentum's risk regimes. Price momentum and price-to-the-52-week-high ratio are always (strong) predictors of firm profitability and investment growth. They convey roughly the same information on the firm's investment opportunity set in safe and low months. But their correlation with expected returns increases significantly after safe months. As a result, firm expected investment growth and profitability do not speak to the observed conditionality of price momentum and 52-week high anomalies. Furthermore, we find the 52-week high signal is *less* related to future profitability after safe months. This has the opposite sign of what the investment CAPM

[4]On the other hand, NM5 is a model specifically designed to explain momentum while BF3 is an asset pricing factor model able to explain a wider set of anomalies. Regardless, NM5 best fits the returns of the two anomalies in our study when it matters.

theory would imply.

Given the relative success of Novy-Marx (2015a) in the conditional setting, we examine if more direct proxies for underreaction match the observed time-variation in expected profitability of the two strategies. Several studies use quarterly announcement returns to proxy for possible corrections in investor expectations (Jegadeesh and Titman, 1993; La Porta, 1996; Porta, Lakonishok, Shleifer, and Vishny, 1997). We follow these and find that when volatility in momentum is low strong (poor) past price performance or high (low) price-to-the-52-week-high ratio signals predict better high (low) returns surrounding the forthcoming earnings announcement date. This is consistent with underreaction being stronger (weaker) after safe (risky) months. We also directly observe the magnitude of analyst forecast errors close to earnings announcements. We find analysts tend to be overly optimistic on average. Their excessive optimism is concentrated on losers and low price-to-the-52-week-high stocks. Furthermore, the excessive optimism is much stronger after low-volatility months.

Finally, we re-examine the relation between the two anomalies. George and Hwang (2004)'s study uses a sample between 1963 and 2001. Its empirical setting implicitly overweights micro- and small-cap stocks as their portfolios are equally-weighted. We replicate their results for a longer sample with value-weighted portfolios and find that the 52-week high strategy performs less well than conventional price momentum strategy over the period of January 1927 through December 2019. The results of spanning tests and cross-sectional Fama and MacBeth (1973) regressions suggest that price momentum, in fact, fully subsumes 52-week high momentum unconditionally. This suggests that 52-week high is only a weak form of price momentum. However, nearness to 52-week high is not subsumed *conditionally*. After safe months, when the anomaly is truly there, price momentum does not explain it. For this reason we see the 52-week high anomaly of George and Hwang (2004) as a genuine different phenomenon than conventional momentum. This underscores the importance of studying the conditionality of the two anomalies.

For robustness, we use the DOWN-market state variable first proposed by Cooper, Gutierrez, and Hameed (2004) instead of the realized volatility of momentum. We find this variable predicts a change in profitability not only for price momentum, as originally shown, as also for 52-week high – which does not feature in the original study and therefore offers out-of-sample evidence of robustness for Cooper, Gutierrez, and Hameed (2004)'s seminal study.

In sum, the evidence on earnings announcement returns, analyst forecast errors, and conditional spanning regressions is more supportive of volatility capturing time-variation in underreaction. Our results thus generally support the underreaction economic channel in Daniel, Hirshleifer, and Subrahmanyam (1998) and Daniel, Hirshleifer, and Sun (2020) for momentum while documenting volatility as a robust predictor of its intensity.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes data sources and methodology. Section 4 shows conditional performance of the recently proposed factor models. Section 5 explains whether the investment CAPM predicts the time-variation in payoffs of price momentum and 52-week high momentum. Section 6 checks whether time-varying underreaction to news related to short-term prospects of firms explains the two anomalies's time-varying behaviors. Section 7 re-examines the relation between price momentum and 52-week high momentum. In Section 8, we replace the risk of momentum with market states and repeat the analyses in Section 4. In addition, we check the optionality of 52-week high momentum. Section 9 concludes the paper.

2 Related Literature

Our paper is related to the literature on explanations of momentum. Jegadeesh and Titman (1993) show that stocks with high returns over past three to twelve months outperform in the following 6 months. Early explanations of momentum are mostly behavioral. Jegadeesh and Titman (1993) find that winners have higher returns in the following earnings announcements suggesting investor underreaction to news in prices (and subsequent corrections in expectations) as an explanation. Barberis, Shleifer, and Vishny (1998) (BSV) propose investor conservatism and Hong and Stein (1999) (HS) propose gradual information diffusion of information as explanations of underreaction. Daniel, Hirshleifer, and Subrahmanyam (1998) propose initial underreaction coupled with delayed overreaction as explanations.

Price momentum is not the only relative strength strategy of interest. George and Hwang (2004) find that stocks whose prices are close to or at their 52-week highs earn higher returns than stocks whose prices are far from their 52-week highs. They further show that nearness to the 52-week high, the common past price-level information, can subsume the predictive power of past price changes for expected returns. Prior returns and nearness to the 52-week high appear to be closely related, and a stock with strong (poor) past performance seems to be more likely to have a price close to (far from) its 52-week high. However, a stock whose price is close to (far from) the 52-week high is not necessarily a stock with strong (poor) performance in the past year, and vice versa.[5]

Similar to the conventional momentum strategy, the profits of the 52-week high strategy have been attributed to delayed price reaction to firm-specific information due to

[5] To understand the differences, we can consider two simple examples. 1) A stock can start with the 52-week high price one year ago, perform poorly over months, and then experience a positive shock pushing its price near or above its previous 52-week high just at the formation date of the relative strength portfolio. Conversely, a stock can persistently perform well at the beginning of the ranking period but experience a severe negative shock pushing the price back to the starting price which is, in turn, far from its 52-week high. Another example is that a stock can fluctuate around the 52-week high price over the entire ranking period.

conservatism of investors (Li and Yu, 2012). In addition, George and Hwang (2004) justify the relation between nearness to the 52-week high and market underreaction using "adjustment and anchoring bias" of investors. Based upon the experimental evidence of Kahneman, Slovic, Slovic, and Tversky (1982) and Ginsburgh and Van Ours (2003), they hypothesize that traders tend to use the 52-week high as an anchor against which they assess the potential impacts of new firm-specific information on prices.

Recently, the behavioral factor model of Daniel, Hirshleifer, and Sun (2020) (BF3) supplements the market factor with two behavioral factors, which are designed to capture the long and short horizon mispricing due to investors' psychological bias. We find this model explains in unconditional spanning regressions the two relative strength anomalies in our study. This is mostly through the short-run underreaction (earnings-surprise) factor computed from cumulative abnormal return (CAR) around earnings announcements. Novy-Marx (2015a) (NM5) proposes a fundamental momentum model to explain momentum. This adds to the Fama and French (1993) three factors two earnings-surprise factors. One uses CAR as BF3 while the other is based on the most recent standardized unexpected earnings. The earnings-surprise factors in both models are primarily designed to account for the post-earnings announcement drift (Ball and Brown, 1968).

An alternative explanation is that price momentum and nearness to the 52-week high proxy for risk-based risk premiums. Hou, Xue, and Zhang (2015) document that the q-factor model based on the investment CAPM, which is first proposed by Cochrane (1991), can capture a broad range of anomalies including momentum. Built on the neoclassical q-theory of investment, the investment CAPM posits that expected stock returns are positively correlated with expectations of firm profitability and investment growth (Cochrane, 1991; Liu, Whited, and Zhang, 2009; Liu and Zhang, 2014; Hou, Xue, and Zhang, 2015; Hou et al., 2020).

Hou, Xue, and Zhang (2015) (HXZ4) show that the q-factor model captures momentum through a profitability factor sorted on firms Return on Equity. This builds on Liu and Zhang (2014) who estimate the investment model structurally and document that past stock performance proxy firms expected profitability and expected investment growth. Intuitively, a firm with strong (poor) past performance is more likely to have experienced positive (negative) productivity shocks and is also expected to be more (less) profitable in the future. Managers of the firm have incentives to invest in more (fewer) projects, as marginal benefits are higher (lower). Assuming an upward sloping marginal cost of capital for the firm, this raises (reduces) its equilibrium cost of capital on incremental projects.

HXZ4 outperforms the popular Fama and French (1993) 3-factor model and the Fama and French (2015) 5-factor model in explaining momentum-like anomalies. On top of this, George, Hwang, and Li (2018) find that the q-factor model of Hou, Xue, and Zhang (2015) is robust to explaining the 52-week high anomaly. Furthermore, they find that the profitability of this strategy comes from the positive relation between nearness to the 52 week high and the marginal benefit of investment, which is, in turn, determined by expected profitability and expected investment growth.

But ROE is perhaps a weak proxy for expected investment growth. Recently, Hou et al. (2020) argue the empirical q-model can be further improved using three predictors of future investment growth, which are Tobin's q, operating cash flows and change in return on equity. With these they recover firm growth expectations and augment the original q-factor model with a new factor sorted on these.

We contribute to the literature on factor model explanations of momentum adopting a conditional setting. There is compelling evidence of predictability for the returns and risk of price momentum. Cooper, Gutierrez, and Hameed (2004)'s seminal study finds that momentum strategies are profitable only in the "UP" market state, which is defined as non-negative average market returns over the past three years. Stivers and Sun (2010) demonstrate that momentum profits are negatively related to the cross-sectional return dispersion. Wang and Xu (2015) show that the performance of momentum strategies is significantly attenuated following high market volatility states. Antoniou, Doukas, and Subrahmanyam (2013) posit that momentum profits exists only in times of high sentiment. Avramov, Cheng, and Hameed (2016) find that momentum strategies are more profitable in liquid market states. Huang (2019) find that momentum profits are negatively correlated with the momentum gap, which is defined as the formation period return difference between past winners and losers. Barroso and Santa-Clara (2015) find that the risk of price momentum, defined as the realized variance of daily momentum returns, is strongly autocorrelated. Therefore, volatility of momentum predicts itself positively. Furthermore, it predicts the returns of the strategy negatively. On top of this, Barroso, Edelen, and Karehnke (2019) recently show that price momentum volatility predicts the skewness and excess kurtosis of the strategy. This strong predictive relation with *all* four first moments of the factor make it a particular strong predictor of the strategy performance. Barroso and Santa-Clara (2015) propose a volatility-scaling risk management strategy exploiting this predictability. It scales the self-financing portfolio to a constant target volatility level, investing more after periods of low risk. This strategy almost doubles the Sharpe ratio of the unmanaged strategy. Similar volatility-scaling momentum strategies have since featured in multiple studies (Daniel and Moskowitz, 2016; Novy-Marx, 2015a; Grobys, Ruotsalainen, and Äijö, 2018; Hanauer and Windmüller, 2020). In this study, we take realized volatility of momentum and, instead of trying to improve the Sharpe ratio of the strategy, or manage its tail risk, study its implications for the conditional fit of asset pricing models purporting to explain the anomaly unconditionally. The purpose is to understand what contributes to the difference in profits in high- versus low-risk months, and whether this difference is useful for distinguishing between different explanations for the anomaly.

We contribute to a growing literature on the 52-week high strategy. We are unaware of any study conducting a systematic examination of the conditionality of its profits. We find that the 52-week high strategy shares a common set of predictors with the price momentum strategy. In particular, payoffs of the 52-week high strategy depend on lagged realized volatility of momentum and market states. Also, the strategy in "DOWN" markets is effectively a call option written on the market, just as (Daniel and Moskowitz, 2016) first show for price momentum.

3 Data and Methodology

3.1 Data

We obtain stock market data from the Centre for Research in Security Prices (CRSP) and accounting information from the Compustat Annual and Quarterly Fundamental Files. Our sample includes all common stocks with CRSP share code of 10 or 11 traded on the NYSE, AMEX and NASDAQ (CRSP exchange codes 1, 2 and 3). We adjust CRSP returns for delisting events using the procedure of Beaver, McNichols, and Price (2007). Following Fama and French (2006), Hou, Xue, and Zhang (2015), George, Hwang, and Li (2018) and Hou, Xue, and Zhang (2020), we exclude financial firms with Standard Industrial Classification (SIC) codes between 6000 and 6999. The main sample period is from July 1972 to December 2019. The starting date is restricted by the availability of quarterly earnings announcement dates, as well as the behavioral factors, while the ending date is restricted by the availability of the behavioral factors.

3.2 Variable and Portfolio construction

The two primary variables we consider are the cumulative prior 11-month return from month $t-12$ to $t-2$ ($r_{2,12}$) and the ratio of the closing price in month $t-2$ of a stock to its 52-week high price, adjusted by stock splits and stock dividends, over month $t-13$ to $t-2$ (pth). At the end of each month $t-1$, all common stocks[6] traded on NYSE, AMEX and NASDAQ are sorted into deciles based on their $r_{2,12}$ (pth) using NYSE breakpoints. The purpose of using NYSE breakpoints is to prevent the extreme deciles from being dominated by microcaps (Hou, Xue, and Zhang, 2020). We follow Hou, Xue, and Zhang (2015) in using pth smaller than one to form the NYSE breakpoints as there are a disproportionally large number of stocks approaching the 52-week high at the same time with pth equal to one. Following George, Hwang, and Li (2018) and Daniel and Moskowitz (2016), we skip month $t-1$ for both anomalies to avoid the effects of short-term reversal (Jegadeesh, 1990). We calculate monthly value-weighted returns of each

[6] We exclude the stocks of financial firms and the stocks with fewer than 11 (12) months of return (price) history.

decile in month t using the market equity at the end of month $t-1$ as weights. Similarly, we calculate daily value-weighted returns of each decile on each trading day of month t using the beginning-of-day market equity as weights.[7] The decile portfolios are held for one month and rebalanced at the end of each month. The holding period of six months is also commonly used in the momentum and the 52-week high literature. We choose one-month holding period to better identify the state of the holding month because of the one-to-one relationship between a formation period and a holding period under this method.

The main two zero-cost portfolios of interest are high-minus-low deciles on $r_{2,12}$ and pth, denoted by WML and PTH, respectively. The main predictor of the two strategies we consider is the realized volatility of WML. Following Barroso and Santa-Clara (2015), at the beginning of each month t, we compute the realized volatility, $\hat{\sigma}_{\mathrm{WML,t}}$, using daily returns in the previous 126 trading days. Specifically,

$$\hat{\sigma}_{\mathrm{WML,t}} = \left(21 \sum_{j=0}^{125} \mathrm{r}^2_{\mathrm{WML,d_{t-1}-j}} / 126\right)^{0.5}, \tag{1}$$

where $\{r_{wml,d}\}_{d=1}^{D}$ and $\{d_t\}_{t=1}^{T}$ are the daily returns and the time series of the dates of the dates of the last trading days of each month.

Except for the lag-ROE, ΔROE, SUE and CAR4 factors, all other monthly factor returns are either obtained from Kenneth French's Web site or provided by the relevant authors[8]. We construct the lag-ROE and ΔROE factors following the methodology of Novy-Marx (2015b). First, we decompose return-on-equity (roe[9]) into lagged earnings-to-market equity and earnings-innovations-to-book equity:

$$roe = \frac{IBQ_t}{BEQ_{t-1}} = \frac{IBQ_{t-4}}{BEQ_{t-1}} + \frac{IBQ_t - IBQ_{t-4}}{BEQ_{t-1}} = lagged - E/B + \Delta E/B \tag{2}$$

Following Hou, Xue, and Zhang (2015), roe for quarter t is the quarterly income before extraordinary items(IBQ_t) divided by 1-quarter-lagged book equity (BEQ_{t-1}). IBQ_{t-4} is the quarterly income before extraordinary items for quarter $t-4$. At the end of each month $t-1$, we construct the lag-ROE and ΔROE factors on the basis of the latest lagged-E/B and Δ E/B, respectively. Analogous to the construction methodology of the

[7] We employ the daily and monthly WML returns from Lu Zhang's data library for the period 1967-2019. For the months before 1967, we use our own WML return series. The correlation between our monthly (daily) WML returns and the series from Lu Zhang's data library over 1967-2019 is 99.6% (99.3%). Different from Hou, Xue, and Zhang (2020), we do not exclude the firms with negative equity to avoid potential errors associated to the merging between CRSP and Compustat databases.The correlation between our PTH portfolio and the corresponding portfolio used in George, Hwang, and Li (2018) over 1972-2014 is 99.9%.

[8] We are grateful to all these authors for making their data available.

[9] We use lowercase letters in italics to represent a stock characteristic and capital letters to denote factor portfolios and high-minus-low decile on the characteristic.

value (HML) and momentum factors (UMD), we use six value-weighted portfolios, which are the intersections of 2 portfolios formed on size and 3 portfolios formed on lagged-E/B (ΔE/B), to construct the lag-ROE (ΔROE) factor. The monthly size breakpoint is the median NYSE market equity, while the monthly lagged-E/B (ΔE/B) breakpoints are the 30th and 70th NYSE percentiles. The lag-ROE (ΔROE) factor return is the equal-weighted return on the two high lagged-E/B portfolios minus the equal-weighted return on the two low lagged-E/B portfolios.

Te construction of two fundamental-momentum factors, SUE and CAR4, are very similar to the methodology used in Novy-Marx (2015a). Following Foster, Olsen, and Shevlin (1984) and Hou, Xue, and Zhang (2020), we calculate the standardized unexpected earnings (sue) as:

$$sue = \frac{EPSPXQ_t^{adj} - E(EPSPXQ_t^{adj})}{std(EPSPXQ_t^{adj} - E(EPSPXQ_t^{adj}))}. \tag{3}$$

We assume $EPSPXQ_t^{adj}$, the split-adjusted earnings per share for quarter t, following a seasonal random walk, which is

$$E(EPSPXQ_t^{adj}) = EPSPXQ_{t-4}^{adj}. \tag{4}$$

$EPSPXQ_{t-4}^{adj}$ is the split-adjusted earnings per share for quarter $t-4$. We use the quarterly earnings innovation over the past eight (at least six) announcements to compute the standard deviation of the quarterly innovations, denoted by $std(EPSPXQ_t^{adj} - E(EPSPXQ_t^{adj}))$. Following Chan, Jegadeesh, and Lakonishok (1996),Daniel, Hirshleifer, and Sun (2020) and Hou, Xue, and Zhang (2020), we calculate cumulative abnormal return surrounding the quarterly earnings announcement date from the two trading days preceding the announcement to the one trading day after that ($car4$):

$$car4 = \sum_{d=-2}^{+1} r_{id} - r_{md}, \tag{5}$$

where r_{id} is stock i's return on day d, r_{md} is the CRSP value-weighted market index return on day d, and $d = 0$ refers to the earnings announcement date. When an earnings announcement day is a non-trading day, we regard the first trading day subsequent to the earnings announcement as day 0. We require full return history over the 4-day event window, and the 4-day cumulative abnormal return of a stock is assumed to be available at the end of $d = 1$. At the end of each month $t-1$, we construct the SUE and CAR4 factors on the basis of the most recent sue and $car4$, respectively. We use six value-weighted portfolios, which are the intersections of 2 portfolios formed on size and 3 portfolios formed on sue ($car4$) , to construct the SUE (CAR4) factor. The monthly size breakpoint is the median NYSE market equity, while the monthly sue (car4) breakpoints are the 30th and 70th NYSE percentiles. The SUE (CAR4) factor return is the equal-weighted return on the two high *sue* (*car*4) portfolios minus the equal-weighted return on the two low *sue* (*car*4) portfolios.

All factor portfolios are rebalanced monthly. The quarterly earnings data are assumed to be publicly available on the last trading day of the month during which they are announced.

4 Time-Series Analysis

4.1 Descriptive Statistics

Table 1 reports descriptive statistics of WML, PTH and the market risk factor. Panel A shows the performance of each factor from 1927:01 to 2019:12. The high-minus-low price momentum decile earns on average 13.84% per year with a (annualized) Sharpe ratio higher than the market and PTH portfolios. However, its high excess kurtosis of 19.49 with a large negative skew of -2.49 suggests an extremely fat left tail, leading to occasional crashes of the strategy as shown by Daniel and Moskowitz (2016) and Barroso and Santa-Clara (2015). PTH performs worse. It not only yields the lower average returns and Sharpe ratio but also has a very fat left tail like WML. Panel B reports the statistics over a shorter sample period 1972:07 to 2019:12. In the short sample, the performance of PTH improves dramatically with the mean returns increasing to 8.05% per year and the Sharpe ratio almost doubling.

[Insert Table 1 near here]

4.2 Factor-adjusted Returns and Volatility States

4.2.1 Unconditional and Conditional Performance of Conventional Factor Models

Table 2 reports unconditional raw and factor-adjusted returns of WML and PTH (shown in the last column), and the values conditional on the lagged realized volatility of WML. We split each sample period into three volatility states. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods, and the remaining periods are the Medium-RV periods. The factor models considered here include: the market model (CAPM) proposed by Sharpe (1964), Lintner (1965) and Black (1972), the Fama and French (1993) three-factor model (FF3), the Carhart (1997) 4-factor model (Carhart4) consisting of the FF3 factors plus the Momentum factor (UMD), and the

Fama and French (2015) five-factor model (FF5). The FF3 factors include the market excess return (MKT), the return of small firms in excess of big firms (SMB) and the return of value firms in excess of growth firms (HML). FF5 combines the operating profitability and investment factors with the FF3 factors. These two new factors incorporate stock return predictors previously documented by Titman, Wei, and Xie (2003) and Novy-Marx (2013).

The last column of Table 2 shows that WML earns statistically positive returns on average in both long and short samples. In contrast, the raw return of PTH is not significantly different from zero over the period 1927:01 to 2019:12, though it becomes significant at the 5% level in the short sample. The CAPM, FF3 and FF5 factor models fail to explain the WML and PTH portfolios, and their returns are even higher after adjusting for the risk factors of any of the three models. Not surprisingly, FF3 and FF5 have limited explanatory power for those short-term momentum-like anomalies as the two models are designed to capture the long-term stock anomalies (Daniel, Hirshleifer, and Sun, 2020). Consistent with George, Hwang, and Li (2018)[10], we find that Carhart4 can capture the 52-week high anomaly unconditionally with insignificant alphas equal to 0.22 (t=1.76) and 0.20 (t=1.24) in the 1927-2019 and 1972-2019 samples, respectively, if the significance level is set to 5%.

The first four columns of Table 2 show the time-varying performance of WML and PTH. The general pattern is that WML and PTH tend to be stronger following safe months and weaker subsequent to risky months. This is patent immediately for raw average returns. Over the most recent sample, 73% of the profits of WML occur in less than a third of the sample, only after safe months (30% $\times$ 2.62/1.08). For PTH a similar computation yields an even more impressive 85%. So, most of the profits occur in a relatively small subsample. The natural converse of this statement is that in most of the sample the anomalies have little profitability. Except for the FF3-alpha of PTH in the 1927-2019 sample, all raw and risk-adjusted returns are statistically indistinguishable from zero for the portfolios formed in High-RV months, and both the factor models available in the full sample (CAPM, FF3 and Carhart 4) and FF5 can capture the two anomalies in after risky months. In contrast, all factor-adjusted returns in safe states and some factor-adjusted returns in normal states are positively significant. Hence, the unconditional significant positive alphas of WML and PTH are mainly driven by the strong performance of the two anomalies in the safe subsample. In addition to the regression results for each volatility state, we test the difference in alphas between the Low- and High-RV subsamples (i.e. "Low − High"). Except for the Carhart4-alpha, all alphas are highly significant suggesting that the associated factor models fail to capture the time-varying behaviors of WML and PTH. Another important takeaway from this

[10] The holding period matters for the performance of PTH relative to Carhart4. For instance, if the high-minus-low decile on pth is held for 6 months, the Carhart4-alpha will become positively significant.

table is that the realized volatility of WML, as one of predictors of WML payoffs, plays an important role in the profitability of PTH. Additionally, we find some other predictors of momentum payoffs such as market states, market volatility, cross-sectional return dispersion, momentum gap and investors' sentiment, can also predict PTH profits. The corresponding results are reported in Section 8 and in the Appendix.

[Insert Table 2 near here]

4.2.2 Unconditional Performance of New Factor Models

In this section, we report the unconditional performance of new factor models in explaining PTH and WML. As prior studies have sufficiently discussed the unconditional factor-adjusted returns of WML, we focus our discussions on PTH and briefly report the results of WML. George, Hwang, and Li (2018) document that the q-factor model (HXZ4) proposed by Hou, Xue, and Zhang (2015) outperforms all other factor models they consider in capturing the 52-week high anomaly. HXZ4 includes factors of market (MKT), size (ME), investment (IA) and profitability (ROE). Besides the factor models considered in their study, we examine other factor models recently proposed in the literature. Specifically, we consider the Hou et al. (2020) q-factor model (HXZ5) augmented with the expected growth factor (EG), the Daniel, Hirshleifer, and Sun (2020) behavioral factor model (BF3) and the Fama and French (2018) 6-factor model. BF3 consists of the market factor (MKT) and the two behavioral factors including the financing factor (FIN) and the post-earnings announcement drift factor (PEAD), which are designed to capture the long-term persistent mispricing of stocks and the short-term market underreaction, respectively. FF6 supplements the FF5 factors with the momentum factor. The remaining two models we examine are not factor models known to explain a broad range of anomalies. Instead, they are closely related to the momentum-like anomalies. As shown above, to examine the sources of the profitability factor (ROE)'s pricing power for momentum, Novy-Marx (2015b) decomposes the profitability factor (ROE) of HXZ4 into a low frequency earnings profitability factor (lag-ROE) and a post-earnings announcement drift factor (ΔROE), and shows that HXZ4 prices the momentum strategy through the earnings-surprise channel. This alternative HXZ4 model is denoted by HXZ4^a. Novy-Marx (2015a) further introduces a fundamental-momentum factor model on the basis of the FF3 factors and two earnings-surprise factors (SUE and CAR4[11]) and demonstrates

[11] Novy-Marx (2015a) uses CAR3, the cumulative abnormal return over the 3-day window starting from the day preceding the earnings announcement and ending at the day following the announcement. To keep consistent with the recent literate such as (Hou, Xue, and Zhang, 2015; Hou et al., 2020; Hou, Xue, and Zhang, 2020; Daniel, Hirshleifer, and Sun, 2020), we replace CAR3 with CAR4. Unlike Daniel, Hirshleifer, and Sun (2020) using 20% and 80% breakpoints for NYSE firms to sort the stocks, we use standard 30% and 70% breakpoints for NYSE firms to construct CAR4 factor, as well as SUE factor.

that price momentum is fully captured by momentum in firm fundamentals. Each time-series regression in Table 2 fits an unconditional factor model to one of the portfolios we consider. Specifically, time-series regressions are of the form:

$$R_{i,t} = \alpha + \boldsymbol{\beta}'\boldsymbol{X_t} + \epsilon_t, \tag{6}$$

where $R_{i,t}$ is the monthly excess returns on a portfolio i, and $\boldsymbol{X_t}$ is a column vector containing monthly excess returns to factors of a model.

[Insert Table 3 near here]

In contrast to Table 2, Table 3 shows the factor models that capture or dominate the two anomalies unconditionally. Except for BF3-alpha of PTH, all alphas are indistinguishable from zero. With this model the 52-week high anomaly is mispriced unconditionally with a *negative* alpha. Interestingly, the anomaly has significant positive loadings on the financing factor (FIN). Given that FIN is designed to capture the long-horizon mispricing of stocks (Daniel, Hirshleifer, and Sun, 2020), this suggests *pth* also reflects long-run mispricing to some extent. In the next three specifications, we examine the unconditional performance of HXZ4 and its variants in explaining PTH. Overall, q-factor models succeed in capturing PTH unconditionally. Moreover, similar to the finding of Novy-Marx (2015b) with regard to WML, we find that HXZ4 captures PTH unconditionally only through the earnings-surprise component of the ROE factor. With a t-stat of 0.88, lag ROE is irrelevant to explain the profitability of PTH. Among these candidate models, as shown in the next column, FF6 is the best performer in explaining the 52-week high anomaly with the lowest alpha (0.07) in absolute terms and highest adjusted R-squared (78%). Not surprisingly, PTH has a highly significant positive exposure to the momentum factor as the correlation between the high-minus-low deciles on the two anomalies is approximately 80%.

The regression results of WML are generally consistent with the literature. All alphas are insignificant. HXZ4^a has the lowest alpha in absolute value. HXZ4^a and NM5 have the highest adjusted R-squared, suggesting that the inclusion of earnings-surprise factors can dramatically improve the ability to fit time variation in the strategy returns. Another fact worth mentioning is that after controlling for earnings surprises, the well-known negative exposure of WML to the value factor disappears.

4.2.3 Conditional performance of the factor models that subsume WML and PTH unconditionally

As we do in Table 2, we split the 1972-2019 sample into three volatility states in Table 4. In panel A, for each volatility state, we use Equation 6 to fit the factor models that are able to explain unconditionally at least one of the two anomalies. Splitting the sample biases against finding statistically significant mispricing as the number of observations in each subsample tends to be smaller. In Panel B, we employ the following specification[12] to test the equality of alphas and factor loadings across Low- and High-RV states:

$$R_{i,t} = \alpha_0 + \alpha_{low} I_{low,t-1} + \alpha_{medium} I_{medium,t-1} + \sum_j \beta_{j,0} F_{j,t} + \sum_j (\beta_{j,low} F_{j,t} I_{low,t-1} + \beta_{j,medium} F_{j,t} I_{medium,t-1}) + \epsilon_t, \quad (7)$$

where $I_{low,t-1}$ ($I_{medium,t-1}$) is an ex-ante Low-RV (Medium-RV) indicator that equals one if the realized volatility of WML in month $t-1$ is in the bottom 30% (middle 40%), and $F_{j,t}$ is the excess returns of factor j in month t.

We find that all factor models, subsume the returns of PTH following High-RV and even Medium-RV months. For BF3, the intercept of PTH is even marginally significantly negative after risk months. The adjusted R-squared following risky months for all models is always higher than its counterpart subsequent to safe months. On the other hand, in the Low-RV subsample, PTH earns significant positive factor-adjusted returns of 0.99%, 1.09%, 0.89%, 0.72%, 0.48%, 0.56 under BF3, HXZ4, HXZ4^a, HXZ5, FF6, and NM5 models, respectively.

Table 4 shows that the significant negative unconditional BF3-alpha of PTH observed in Table 3 can be misleading. The factor-adjusted returns of PTH are (marginally) negatively significant following risky and normal months. In contrast, PTH earns a highly significant positive BF3-alpha of 0.99% per month with a t-statistic of 3.20 in the Low-RV subsample. As shown in Panel B of Table 4, BF3-alpha of the PTH portfolio following Low-RV months is 2.07% higher than the alpha following High-RV months, with a t-statistic of 2.90 on the difference. Furthermore, with the decrease in momentum risk, the 52-week high strategy has less exposure to the short-term behavioral factor. The changes in loadings on the PEAD factor across High- and Low-RV states are significant at 1% level (Panel B of Table 4). Next, we evaluate the conditional performance of q-theory-related models. Following safe months, these models lose their pricing power for PTH. The anomaly also shows less exposure to the profitability and size factors than in risky months. Panel B of Table 4 further shows that these changes are statistically significant. Hence, both the success of q-factor models in capturing PTH unconditionally and the co-movement of PTH with the ROE factor are driven by the risky subsample where PTH cannot generate any premium. This shows that the returns of the strategy and its loadings with respect to the q-factor models basically come from two separate samples.[13]

[12]It is also used in the equality tests of Table 2

[13]Barroso, Detzel, and Maio (2017) find similar results for low-risk anomalies with the Fama and French (2018) 6-factor model.

As a best performer in explaining PTH unconditionally, FF6 produces a significantly positive alpha for PTH subsequent to Low-RV months; however, FF6-alphas of PTH in Low- and High-RV states are not statistically different from zero (0.19% difference with t-statistic of 0.45). Besides, the loadings of PTH on the momentum and value factors are smaller after safe months. The momentum loading of PTH is 0.85 with a very large t-statistic of 12.78 after safe months, but it is 0.48 lower than the loading following risky months with a t-statistics of 3.89 on the difference. The value loading of PTH exhibits a similar pattern to the loading on momentum. The only difference is that the strategy does not co-move with the value factor after safe months, suggesting that the positive exposure of PTH to the value factor comes from only after risky months.

Finally, we examine the performance of NM5 conditioning on risk. This is the best performing model to explain the anomaly with the lowest t-statistic of 2.00. After safe months, SUE seems important to explain the returns of PTH, with a t-statistic on the loading of 5.23. The importance of SUE is highlighted when comparing with BF3 which also uses a PEAD factor but built only with CAR. It could be argued that the economic intuition of the PEAD factor is very similar to SUE as both result from earnings announcements. But, empirically, PEAD misses the SUE information considered in NM5. This suggests that fundamental momentum is important to explain PTH, and CAR alone does not capture all the information in changing firm fundamentals.

[Insert Table 4 near here]

In Table 5, we examine the conditional performance of WML. Similar to what we observe in Table 4, all factor models that can capture WML unconditionally can explain it in the High- and Medium-RV states as well; however, following Low-RV months, all models fail to capture the momentum strategy, and NM5 is the best performer with the lowest factor-adjusted return (0.81%) and t-statistic. Following non-Low-RV months, BF3 captures momentum through the PEAD factor. In the Low-RV subsample, in addition to the positive exposure to the PEAD factor, WML is positively exposed to the financing factor, which is designed to reflect the correction of overconfidence-driven mispricing.

The three q-theory-related models capture WML poorly in the Low-RV subsample, and the loading of WML on the ROE and lag-ROE factors are monotonically decreasing with the reduction of the realized volatility. The inclusion of the expected growth factor (EG) does attenuate the magnitude and significance of the alpha compared to HXZ4 but the alpha is still strongly significant after safe months with a t-stat of 3.45.

Panel B of Table 5 confirms the time-varying feature of the factor-adjusted returns of WML. For all models, the alphas of WML increase significantly after safe months relative to risky months. The differences are economically important, from 1.80% to 2.49% per months, and are all statistically significant at the 1% level except for the one in NM5, which is statistically significant at the 5% level. Notably, NM5, which is the best performing model in explaining the WML portfolio conditionally, still fails to explain why the NM5-alpha of WML in the Low-RV subsample is significantly higher than in the High-RV subsample. So price momentum is a much stronger phenomenon after low volatility months and none of the models in our study seems able to explain that.[14] Next, we look more closely to whether a time varying relation between stock price signals and the marginal benefit of firm investment can account for excessive predictability in WML and PTH.

[Insert Table 5 near here]

5 Does q-theory account for time variation in WML and PTH profits?

Liu and Zhang (2014) use a structural estimation procedure to examine the relations between momentum formation returns and the two components of the marginal benefit of investment: expected investment growth and expected profitability, while George, Hwang, and Li (2018) use Fama and MacBeth (1973) regressions combined with time-series regressions to investigate the relations. The two studies show that past returns and nearness to the 52-week high are indicators of future investment growth and future profitability. According to the results of the conditional time-series regressions in Section 4, the time-varying behaviors of the price momentum and 52-week high strategies cannot be fully captured by the q-factor models derived from the investment CAPM. As expected investment growth and expected profitability of a firm are unobservable, we have to use proxies for the two variables (EG and ROE). This raises the issue of a potential bias due to inefficient proxies. In this section, we use Fama and MacBeth (1973) predictive regressions to directly examine whether the relations between the two anomalies and expected profitability or expected investment growth change with the risk of momentum. If the investment CAPM can explain the two anomalies conditionally, we should expect stronger (weaker) positive relations between the two anomalies price signals and the marginal benefit of investment following safe (risky) months.

According to Hou et al. (2020) and Liu and Zhang (2014), in a multi-period world

[14] On top of this, the risk of momentum has similar predictive power for WML in the long sample from 1927 to 1972, before the main sample in our study, and when none of the factors related to earnings announcements or the q-factor models are available.

without leverage and tax costs, expected stock returns, $E_t[r^S_{it}]$, can be expressed as

$$E_t[r^S_{it}] = \frac{\kappa E_t[\frac{Y_{it+1}}{K_{it+1}}] + \frac{a}{2}E_t[(\frac{I_{it+1}}{K_{it+1}})^2]}{1+a(\frac{I_{it}}{K_{it}})} + \frac{(1-\delta_{it+1})[1+aE_t[\frac{I_{it+1}}{K_{it+1}}]}{1+a(\frac{I_{it}}{K_{it}})}$$
$$= \text{Expected dividend yield} + \text{Expected capital gain} \tag{8}$$

where κ and δ are capital's share of output and the depreciation rate, respectively. $E_t[\frac{Y_{it+1}}{K_{it+1}}]$ is the expected marginal profits of capital (i.e. expected profitability), $\frac{a}{2}E_t[(\frac{I_{it+1}}{K_{it+1}})^2]$ is the expected marginal reduction in adjustment costs, and $1 + a(\frac{I_{it}}{K_{it}})$ is the marginal costs of current investment (i.e. current investment-to-assets).

The three terms constitute the "dividend yield" component of the expected stock return, which is also the two-period (static) investment CAPM derived in Hou, Xue, and Zhang (2015). In a multi-period framework, we need an additional component of "capital gain" expressed by $\frac{(1-\delta_{it+1})[1+aE_t[\frac{I_{it+1}}{K_{it+1}}]]}{1+a(\frac{I_{it}}{K_{it}})}$ in the equation. As shown in Cochrane (1991), the term is proportional to the expected investment-to-assets growth, i.e.

$$\frac{(1-\delta_{it+1})[1+aE_t[\frac{I_{it+1}}{K_{it+1}}]]}{1+a(\frac{I_{it}}{K_{it}})} \propto \frac{E_t[\frac{I_{it+1}}{K_{it+1}}]}{\frac{I_{it}}{K_{it}}}. \tag{9}$$

We measure the expected profitability using the forthcoming annual ROE (FROE), which is the ratio of income before extraordinary items over one-year-lagged book equity. Following Liu and Zhang (2014) and George, Hwang, and Li (2018)[15], we measure the expected investment growth as forthcoming annual growth in the annual investment-to-capital ratio (FIG), which is

$$FIG_{i,t+1} = log\left(\frac{1+\frac{I_{i,t+1}}{K_{i,t+1}}}{1+\frac{I_{i,t}}{K_{i,t}}}\right), \tag{10}$$

where $I_{i,t}$ ($I_{i,t+1}$) is capital expenditures (Compustat item CAPX) minus sales of property, plant, and equipment (Compustat item SPPE, set to zero if missing) over the course of fiscal year t ($t+1$) for firm i, and $K_{i,t}$ ($K_{i,t+1}$) is net property, plant and equipment (Compustat item PPENT) at the beginning of fiscal year t ($t+1$). As a firm's annual investment can be negative and annual investment-to-capital (I/K) is bounded between -1 and 1, we add 1 to both the numerator and denominator to avoid the situation that an increase in investment is assigned a negative number. We use the natural logarithm to allow the measure to vary from negative to positive. We follow the methodology of Liu and Zhang (2014) and George, Hwang, and Li (2018) to map the two annual measures, FROE and FIG, to the monthly measure, stock return (FRET), in time. Specifically, we

[15] Hou et al. (2020) measure the expected investment growth using the forthcoming investment-to-assets in excess of current investment-to-assets. Our results are robust to this alternative measure.

match the two annual measures of fiscal year ending in month t with the monthly stock returns from $t-17$ to $t-6$. For instance, for a firm with a fiscal year ending in December, its monthly stock returns from July of year t to June of $t+1$ are matched with FROE and FIG of December of year $t+1$. We implement Fama and MacBeth (1973) predictive regression in the form of:

$$y_{i,t} = \alpha + \beta_1 r_{2,12} + \beta_c' X_{i,t-1} + \epsilon_{i,t} \tag{11}$$

$$y_{i,t} = \alpha + \beta_1 (pth_{t-2}) + \beta_c' X_{i,t-1} + \epsilon_{i,t} \tag{12}$$

where $y_{i,t}$ is a dependent variable of stock i in month t, $X_{i,t-1}$ is a vector of control variables in month $t-1$, $r_{2,12}$ is the cumulative return between $t-12$ and $t-2$, and pth_{t-2} is the ratio of monthly closing price in month $t-2$ to its 52-week (until $t-13$) high price. Following George, Hwang, and Li (2018), Harvey and Liu (2019) and Hou, Xue, and Zhang (2020), we estimate the cross-sectional regression models via weighted least squares with market equity in month $t-1$ as weights to mitigate the effects of microcaps. Independent variables at an annual frequency with fiscal year ending in year $t-1$ are assumed to be available at the end of June of year t. The quarterly earnings data are assumed to be available at the end of the month during which they are announced. Except for FRET, all variables are winsorized at the 1-99% level. The sample period runs from July 1972 to December 2019, which are the same as the sample period used in time-series regressions. All t-statistics are adjusted for Heteroskedasticity and autocorrelation (Newey and West, 1987) where the number of lags is automatically selected following the procedure specified in Newey and West (1994).

In Table 6, we reproduce the results documented in Liu and Zhang (2014) and George, Hwang, and Li (2018). The first four specifications provide results of Fama and MacBeth (1973) regressions of future stock returns onto $r_{2,12}$ or pth. Following Hou, Xue, and Zhang (2020), we use univariate regressions in specifications (1) and (2). To account for the size, value and short-term reversal effects, we add three control variables: the log of market equity(Ln(ME)), the log of book-to-market ratio (Ln(B/M)) and prior month's returns ($r_{0,1}$) in specifications three and four. The first two specifications show that the expected stock returns are positively correlated with momentum's formation returns and nearness of price to 52-week high. As shown in the next two specifications, the inclusion of three control variables does not subsume the explanatory power of $r_{2,12}$ and pth for cross-sectional variation in expected stock returns. The specifications (5)-(8) present the coefficient estimates of expected investment growth, one of the components of marginal benefit of investment, on prior performance or pth. Univariate regression results show that both past performance and pth are strong indicators of future investment growth. Results of specification (7) and (8) further suggest that $r_{2,12}$ and pth contain information about future investment growth beyond the information contained in the current investment level (IA) and current profitability (ROE). The last specifications report the coefficient estimates of expected profitability, the other component of marginal benefit of investment, on prior performance or *pth*. The results from univariate regressions show that $r_{2,12}$ and *pth* are also strong predictors of future profitability. Furthermore they can provide some unique information about future profitability that is not contained in the current profitability (ROE).

[Insert Table 6 near here]

Table 7 provides results of changes in coefficient estimates on past performance and *pth* between Low- and High-RV subsamples. We find that the positive relations between past performance and expected investment growth as well as expected profitability are time-invariant. Similarly, the relation between *pth* and expected profitability is constant across different volatility states, and the relation between *pth* and expected profitability is even weaker following safe months. The difference is statistically significant at the 5% level with a t-stat of -2.06 and it has the opposite sign of what would be needed to reconcile q-theory with the pattern of predictability. Moreover, in unreported tests, the coefficient estimates of expected stock returns on either $r_{2,12}$ or *pth* are statistically indistinguishable from zero following High-RV months; however, the relations between both anomaly variables and the marginal profit of investment are still significantly positive in this subsample. These results contradict the implications of the investment CAPM, and suggest that the time-varying behavior of WML and PTH portfolios cannot be attributed to manager's optimal alignment of investment policies with the cost of capital.

[Insert Table 7 near here]

6 Quarterly earnings announcement returns, Analyst forecast errors and Time-varying performance of WML and PTH

6.1 Upcoming quarterly earnings announcements

In this section, we examine more directly whether past returns and nearness to the 52-week high are proxies for investors' underreaction to information about future earnings. Past winners (losers) or high (low)-*pth* stocks are more likely to have favourable (unfavourable) news about forthcoming earnings in the recent past. Due to psychological bias of investors such as conservatism and "adjustment and anchoring bias," the information might not be fully incorporated into the price before the earnings are actually announced. Hence, past winners (losers) or high (low)-*pth* stocks should realise positive (negative) returns surrounding the forthcoming quarterly earnings announcement. Jegadeesh and Titman (1993) document that about 25% of the returns of the zero-cost momentum portfolio over a 6-month holding period are realized surrounding quarterly earnings announcements. We perform a similar assessment.

The two measures we consider are the 4-day cumulative abnormal return (FCAR4) and the 4-day cumulative raw return (FCR4) around the forthcoming quarterly earnings announcement date. Different from Jegadeesh and Titman (1993) who report the announcement returns of past winners in excess of the announcement returns of past losers unconditionally, we conduct univariate monthly Fama and MacBeth (1973) predictive regressions of FCAR4 or FCR4 on four different explanatory variables conditional on lagged volatility of WML. Apart from the two main variables of interest, $r_{2,12}$ and pth, we include two earnings surprise measures which are the most recent standardized unexpected earnings (sue) and the 4-day cumulative abnormal return around the most recent earnings announcement date ($car4$). These two measures are also employed to construct earnings-surprise factors under Novy-Marx (2015a) fundamental-momentum model. Adding them results in a higher bar for price signals than in Jegadeesh and Titman (1993) original setting as we control for direct proxies of lagged innovations in fundamentals.

The results from Table 8 show that prior returns and nearness to the 52-week high are more strongly related to forthcoming quarterly earnings announcements returns following safe (i.e. Low-RV) months than after other months, and they lose their predictive power for future announcement returns following High-RV months. In fact, after risky months, none of the variables, including the SUE and CAR controls, predicts reactions to earnings announcements. Evidence for predictability seems generally more compelling after safe months. More importantly, the time-variation in predictive power of the two anomaly variables for announcement returns across volatility states mirrors the time-varying relations between the two anomaly variables and future stock returns. This suggests that the profitability of the price momentum and 52-week high strategies depends on how well the two associated stock characteristics can proxy for investor underreaction to information about short-term prospects of a firm.

[Insert Table 8 near here]

6.2 Analyst forecast errors

Antoniou, Doukas, and Subrahmanyam (2016) propose using analyst forecast errors (FE) as a relatively direct measure of sentiment and noise trading activity. Ex post, forecast errors also provide a more direct proxy for analyst underreaction - that is if firms actual results meet prior expectations. For underreaction to explain our results, we should observe that analysts produce more optimistic (pessimistic) forecasts for stocks with poor (strong) past performance and low (high) *pth* after low-volatility months. In other words, when the momentum strategy is less volatile, analysts would underreact to public and / or private signals of past losers and winners, and investors would correct this bias in the next quarterly earnings announcement. To examine this possibility, at the end of each formation period, we sort all stocks into deciles by $r_{2,12}$ or *pth* using NYSE breakpoints, and then within each decile, we compute FE of upcoming quarterly earnings for the stocks covered by analysts. This is defined as (mean estimate$_{t-1}$ − actual)/abs(actual), using the data from the IBES summary files. FE is winsorized at the 5th and 95th percentile each month.

[Insert Table 9 near here]

Table 9 and Table 10 show that average analyst forecast errors are all either positive or insignificant, both for momentum and pth portfolios. So, analyst forecasts have a systematic optimistic bias. This does not necessarily reflect a biased perception for the part of analysts. Hong and Kubik (2003) document that, due to career concerns, analysts, especially sell-side analysts, are more likely to produce optimistic forecasts. But regardless of the origin of the bias in forecasts, it is striking that excessive optimism is much more prevalent for losers than winners (same for low-pth versus high-pth). There is little to no bias in winners / high-pth stocks, the bias is all in the losers. So, only winners / high-pth stocks are able to meet the high expectations of analysts on average, all others disappoint. For momentum (pth) VW portfolios, the t-statistic for the difference in FE between deciles is -13.36 (-13.16). Therefore underreaction seems stronger in the short legs of the strategies.

[Insert Table 10 near here]

Closer to the main point of the exercise, we find that the difference in FE across deciles is more than double after low-RV months when compared to other months, both for momentum and pth. All of these differences between volatility states are statistically significant with t-stats between -5.67 (for VM momentum portfolios) and -7.46 (for EW pth portfolios).

Table 11 reports the factor-adjusted returns of the long and short legs of PTH and WML separately. Consistent with the pattern of analyst forecast errors, the short and long legs of the two strategies work only in the safe months, and the short legs contribute more to their overall profits. Strikingly, the raw returns earned by the short leg of PTH are 8 times higher than the ones earned by the long leg following safe months, and the profits produced by the short leg of WML are twice as high as its counter-party. Besides, all factor models including both conventional and newly proposed models fail to capture the short legs of the two strategies, and the short legs exhibit a similar time variations in profits as the long-short portfolios.

[Insert Table 11 near here]

Based on these results, we can conclude that the predictability and profitability of the two strategies comes mostly from the short legs, and the time-varying performance and profitability of their short legs can be attributable to analysts' time-varying optimism - especially excessive optimism relative to past losers and stocks far away from their 52-week high which both tend to disappoint.

7 Does 52-week high momentum drive price momentum or vice versa?

One of the important findings of George and Hwang (2004) is that nearness to the 52-week high subsume the predictive power of past returns for expected returns using a sample from 1963 to 2001. In this section, we re-examine the relation between the two variables using a sample covering 1927 through 2019.

7.0.1 Spanning tests

Table 12 presents the results of spanning tests between price momentum and 52-week high momentum using a sample period from 1927 to 2019. In the first six specifications, we conduct spanning tests using factor portfolios. For the factor portfolio of price momentum, we use the up-minus-down(UMD) factor obtained from Ken French's data library. The construction method of the 52-week high factor ($\mathrm{PTH^f}$) portfolio is analogue to the method of UMD. Specifically, the factor portfolio is constructed from six monthly rebalanced value-weighted portfolios which are the interactions of two portfolios formed on size and three portfolios formed on the ratio of price in month $t-2$ to its 52-week high price. We use the median NYSE market equity to put stocks into large- and small-cap groups. We use the 30th and 70th NYSE percentiles[16] of *pth* to divide stocks into three portfolios. $\mathrm{PTH^f}$ is the average return on the two high *pth* portfolios minus the average return on the two low *pth* portfolios.

Specifications one and four show that the 52-week high and momentum factors earned a significant 42 basis points per month, with a t-statistic of 2.6, and 65 basis points per month, with a t-statistic of 4.59, respectively. Specifications (2) and (4) conduct the factor spanning tests by running a simple time-series regression of one factor on the other.

[16] We use only *pth* smaller than one to form the portfolio breakpoints.

Specification (2) shows that $\mathrm{PTH^f}$ has a marginally significant negative alpha relative to price momentum, while specification (4) shows that UMD earns a significant abnormal return of 35bps/month relative to $\mathrm{PTH^f}$. This suggests that price momentum subsumes $\mathrm{PTH^f}$. However, after controlling for Fama and French (1993) three factors, as shown in specification (3), $\mathrm{PTH^f}$ earns a highly significant factor-adjusted return of 0.26% per month, with a t-statistic of 4.14, and UMD has an insignificant alpha in specification (6). Moreover, after controlling for the 52-week high factor, the momentum factor positively co-varies with the market and size factors. As a result, the evidence from the first six specifications is mixed and inconclusive. In terms of raw returns, $\mathrm{PTH^f}$ is fully captured by price momentum, and in terms of factor-adjusted returns, $\mathrm{PTH^f}$ instead completely subsumes price momentum.

In our view, a possible drawback of factor spanning tests often used in the literature is that micro- and small-cap stocks are effectively overweighted in the calculation of factor returns when these are built with double sorts on size and some characteristic. This applies to UMD and $\mathrm{PTH^f}$ that use 30th and 70th NYSE percentiles as breakpoints and, therefore, put as much weight on the bottom 30% of stocks as the top 30%. For that reason, in the following six specifications, we replace the two factor portfolios with two straightforward high-minus-low decile portfolios. Specifications seven and ten show that without the double sorting on market capitalisation, the performance of the 52-week high strategy is weaker and the performance of price momentum improves. The results from the remaining specifications exhibit a consistent pattern that the high-minus-low 52-week high decile is fully subsumed by the winner-minus-loser decile. We hence conclude that, unconditionally, except for small caps, price momentum is a stronger anomaly than 52-week high.

[Insert Table 12 near here]

7.0.2 Fama-Macbeth regressions

To further investigate the relation between the two anomalies, Panel A of Table 13 reports results of Fama and MacBeth (1973) predictive regressions, with weighted least squares, of individual monthly returns in monthly t onto the past performance ($r_{2,12}$) and the ratio of price in month $t-2$ (pth) to its 52-week high. To mitigate the impacts of small- and micro-cap stocks, We use stocks' market equity in month $t-1$ as weights. We include the log of market equity (Ln(ME)), the log of book-to-market ratio (Ln(B/M)), and prior month's return ($r_{0,1}$) as controls to account for the size, value and short-term reversal effects. Independent variables are winsorised at the 1 and 99% levels. The sample covers July 1927 through December 2019. The first two specifications show the coefficient estimates on past performance and nearness to the 52-week high from univariate regressions, respectively. Unsurprisingly, specification one suggests a significant positive cross-sectional correlation between past performance and expected returns, and specification two also shows a significant positive correlation between *pth* and expected returns. Specification three includes both past performance and nearness to the 52-week high. It shows that the *pth* is subsumed by past performance in predicting future returns, and the predictive power of past performance for returns is enhanced after controlling for nearness to the 52-week high. The results are robust to the specification where we control for the size, value and short-term reversal effects. This suggests that the unconditional forecasting power of nearness to the 52-week high for cross-section of expected returns comes from its correlation with past performance.

In Panel B of Table 13, we examine whether the conclusion holds conditionally. Again, we split the sample into three volatility states using the lagged realized volatility of WML. Specifications one, two, five and six show significant time variation in correlations between the two anomalies and expected returns. Surprisingly, specification three shows that after controlling for *pth*, the price momentum strategy actually becomes profitable even following risky months. Recently, Byun and Jeon (2018) propose a 52-week-high-neutral momentum strategy and show that it is free of crashes and significantly outperforms the conventional strategy. Our results for risky months confirm that. On the other hand, specification seven, following safe months, show that *pth* has a marginally independent predictive power for cross-sectional variation in returns after controlling for past performance though the predictive power of *pth* disappears when controlling for the size, value and short-term reversal effects. So conditionally, price momentum does not completely subsume *pth*. Hence, although both unconditional spanning tests and Fama and MacBeth (1973) regressions suggest that price momentum drives the 52-week high anomaly, 52-week high tends to be an independent anomaly after safe months during which it works.

8 Market states and payoffs of WML and PTH

Following Cooper, Gutierrez, and Hameed (2004), we identify the state of the stock market for month t using the cumulative past one-year return on the CRSP value-weighted index (dividends included). If the return is non-negative (negative), the holding month is defined as "UP" ("DOWN"). This is an ex-ante indicator. Cooper, Gutierrez, and Hameed (2004) offer three definitions of market states and primarily present their results using prior three-year market returns. Daniel and Moskowitz (2016) use the two-year definition of the market state. The trade-off in the selection of a horizon is between the strength and the frequency of changes in the state of the market. Our results are generally robust to different definitions of market states. Table 14 shows the mean excess returns (raw, CAPM-adjusted, FF3-adjusted, Carhart4-adjusted, FF5-adjusted) of two high-minus-low deciles formed in "UP" and "DOWN" markets, and changes in alphas across "UP" and "DOWN" states.

During 1927:01 to 2019:12, the price momentum and the 52-week high strategies are significantly profitable following "UP" markets yielding 158 and 79 basis points per month, respectively. Moreover, both strategies have statistically positive CAPM- and FF3- alphas in up markets, and PTH earns a significant Carhart4-alpha following "UP" states. However, there is no premium of the 52-week high and price momentum strategies following "DOWN" markets in which either raw returns or factor-adjusted returns are statistically insignificant. This shows that, similar to price momentum, the profitability of 52-week high momentum is conditional on the state of the market.

[Insert Table 14 near here]

Next, we examine whether the newly proposed factor models can capture the conditionality of both strategies. Panel A of Table 15 shows that, in "DOWN" markets, only FF6 can capture PTH, and PTH loads heavily on the momentum factor. Other models dominate PTH in the sense that the anomaly earns significant negative alphas. These negative alphas are economically large, ranging between -1.40% and -2.24% per month.

[Insert Table 15 near here]

In "UP" markets, PTH instead yields significant positive HXZ4- and HXZ4^a-alphas as well as marginally significant positive FF6-alpha. This suggests that PTH's unconditional insignificant HXZ4-alpha is misleading. It is essentially an average between two significant effects of opposite signs occurring in two different *predictable* subsample. The best performing model in "UP" market is BF3 with the smallest insignificant alpha in absolute term (0.05). NM5 successfully captures PTH as well and has the highest adjusted R-squared (0.44).

The pattern for WML is similar. Panel A of Table 16 shows that, in "DOWN" markets, WML earns either insignificant or negative alphas. In "UP" markets, price momentum loads heavily on earnings-surprise factors, and NM5 is the best performing model in explaining momentum. Panel B confirms the increases of alphas for all models after "UP" markets.

[Insert Table 16 near here]

A striking pattern in panel A of both tables Table 15 and Table 16 is that the R-squared of all spanning regressions increases with "DOWN" markets. This confirms that the linear association of the anomalies with the factors explaining them comes mostly from this subsample which is not when their puzzling average returns are produced.

8.0.1 Option-like behavior of the WML and PTH portfolios

Daniel and Moskowitz (2016) document the option-like behavior of WML. They find that in "DOWN" markets, the momentum portfolio is effectively a short-call option on the market, and the optionality effect is driven by past losers. This is likely the best explanation for the strong predictability of WML returns. As we find that *pth* has similar predictability, it is natural to ask if the same optionality permeates this anomaly. Following their setting, we examine the existence of the optionality effect for the 52-week high strategy using three specifications of monthly time-series regressions whose results are shown in Table 17.

[Insert Table 17 near here]

In specification (1), we estimate an unconditional market model (CAPM):

$$R_{_{PTH,t}} = \alpha + \beta_m R^e_{m,t} + \epsilon_t, \tag{13}$$

where $R_{_{PTH,t}}$ is the return to the high-minus-low decile on *pth* in month t, and $R^e_{m,t}$ is the excess return on the CRSP value-weighted index in month t. Similar to WML, PTH yields a positive significant CAPM-alpha of 1.08% per month with a t-statistic of 5.61. In specification (2), we estimate an conditional market model which allows for the change in the alpha and the market beta with the state of the market in the form of

$$R_{_{PTH,t}} = \alpha + \alpha_B I_{B,t-1} + (\beta_m + \beta_B I_{B,t-1}) R^e_{m,t} + \epsilon_t \tag{14}$$

where $I_{B,t-1}$ is an ex-ante DOWN-market indicator. Consistent with the findings of Grundy and Martin (2001) and Daniel and Moskowitz (2016) on momentum, PTH shows more negative exposure to the market risk in "DOWN" markets, and the risk-adjusted return in down markets is -0.26% ($\alpha + \alpha_B$) per month. Specifically, the CAPM-alpha and market beta of PTH in "DOWN" markets shrink by 1.50 and 0.78 with t-statics of -2.66 and -5.67 on differences, respectively. Following Henriksson and Merton (1981) and Daniel and Moskowitz (2016), we add the contemporaneous UP-market indicator, $I_{U,t}$, of specification two into specification three, which is

$$R_{_{PTH,t}} = \alpha + \alpha_B I_{B,t-1} + [\beta_m + I_{B,t-1}(\beta_B + I_{U,t}\beta_{B,U})] R^e_{m,t} + \epsilon_t \tag{15}$$

The model is designed to test the existence of option-like behavior of PTH relative to the market. The estimate of $\beta_{B,U}$ is significantly negative, suggesting that, holding a PTH portfolio in "DOWN" markets is effectively a call option written on the market. Specifically, in holding months with a negative contemporaneous market return, the market beta of PTH is -0.8, while in holding months with a negative contemporaneous market return, the beta decreases to -1.77.[17]

9 Conclusion

Prior studies document that both investor underreaction and the investment CAPM can explain the premiums of momentum and 52-week high momentum. It is puzzling that the two polar explanations can account for the same effect. Following the suggestions of Subrahmanyam (2018), we attempt to discern the real driver by examining what drives the two effects when the two strategies yields substantial premiums. Our tests are based on the fact that the two anomalies do not persistently generate profits. Instead their profitability strongly depends on several state variables, especially the realized volatility of momentum and market states. We expect that a true driver of the two effects should be able to match this time-varying nature of the anomalies.

Our evidence is more supportive of the behavioral explanations for the two anomalies. Specifically, fundamental-momentum model is the best performing model in capturing price momentum both unconditionally and conditionally, which is consistent with the finding of Novy-Marx (2015a) that price momentum is a weak expression of fundamental momentum.

Earnings announcement returns confirm that winners (losers) have higher (lower) returns after safe months, a pattern coherent with underreaction and subsequent correction in expectations. Concurrently, analyst forecasts are excessively optimistic on average, especially with loser stocks and in times of low volatility. This is also consistent with underreaction being more prevalent in low-volatility environments.

We further show that price momentum can subsume 52-week high momentum unconditionally. However, it does not mean that the 52-week high strategy is irrelevant. Controlling for nearness to 52-week high can even make price momentum profitable when the risk of momentum is high, and nearness to 52-week high has marginally independent forecasting power for expected returns after controlling for price momentum in safe months.

[17] We note that in this last specification α is no longer a risk-adjusted return as $I_{U,t}\beta_{B,U}R^e_{m,t}$ is not the excess return of an implementable portfolio.

Table 1

Descriptive statistics

This table reports the performance of the high-minus-low deciles on the past performance (WML) and the ratio of current price to 52-week high price (PTH) compared with the market factor (RMRF). The holding period of the three zero-cost portfolios is one month. Specifically, the table reports the maximum and minimum one-month returns observed in the long and short samples, the (annualized) mean excess return, the (annualized) standard deviation of each portfolio, excess kurtosis, skewness, and (annualized) Sharpe ratio. The sample period in Panel A runs from January 1927 to December 2019, while the sample period in Panel B runs from July 1972 to December 2019, the sample period used in our main tests.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Skewness	Kurtosis	Sharpe ratio
Panel A: Jan 1927 - Dec 2019							
WML	26.26	-76.81	13.84	27.01	-2.49	19.49	0.51
PTH	29.56	-78.58	5.30	29.84	-2.78	19.68	0.18
RMRF	38.85	-29.13	7.96	18.47	0.18	7.84	0.43
Panel B: July 1972 - Dec 2019							
WML	26.18	-61.89	12.97	24.89	-1.69	12.56	0.52
PTH	27.24	-63.49	8.05	25.59	-1.84	12.78	0.31
RMRF	16.10	-23.24	6.84	15.57	-0.57	2.08	0.44

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Table 2

Alphas and Volatility States.

This table presents the raw or factor-adjusted returns of the high-minus-low deciles on the price momentum (WML) and the ratio of current price to 52-week high (PTH) across three volatility states. At the end of each month $t-1$, all common stocks traded on NYSE, AMEX and NASDAQ are sorted into deciles based on their prior 11-month returns from $t-12$ to $t-2$ (the ratio of current price to 52-week high price of $t-2$) using NYSE breakpoints. We skip month $t-1$ and calculate monthly value-weighted returns for each decile for month t. The deciles are held for one month and rebalanced at the end of month t. We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for month t. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods, and the remaining periods are the Medium-RV periods. "CAPM" denotes the market model proposed by (Sharpe, 1964; Lintner, 1965; Black, 1972). "FF3" denotes the Fama and French (1993) three-factor model. "Carhart4" denotes the Carhart (1997) 4-factor model consisting of the FF3 factors plus the Momentum factor. "FF5" denotes the Fama and French (2015) five-factor model. The sample period in Panel A runs from July 1927 to December 2019, while the sample period in Panel B runs from July 1972 to December 2019, the sample period used in our main tests. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	WML RV				Unconditional
	High	Medium	Low	Low-High	Full
Panel A: Jan 1927 - Dec 2019					
r_{WML}	0.35	1.01***	2.10***	1.75**	1.14***
	(0.53)	(3.90)	(9.72)	(2.51)	(4.86)
r_{PTH}	−0.58	0.37	1.49***	2.08***	0.42
	(−0.78)	(1.36)	(7.34)	(2.66)	(1.63)
α_{WML}^{CAPM}	0.89*	1.02***	2.09***	1.20**	1.48***
	(1.67)	(3.99)	(9.60)	(2.09)	(7.27)
α_{PTH}^{CAPM}	0.18	0.84***	1.71***	1.53***	1.05***
	(0.34)	(3.55)	(9.28)	(2.76)	(5.47)
α_{WML}^{FF3}	0.99**	1.04***	2.16***	1.17**	1.68***
	(2.02)	(3.94)	(10.38)	(2.20)	(8.38)
α_{PTH}^{FF3}	0.61	0.78***	1.70***	1.09**	1.27***
	(1.34)	(3.75)	(10.27)	(2.25)	(7.35)
$\alpha_{PTH}^{\text{Carhart4}}$	0.01	0.26	0.66***	0.65**	0.22*
	(0.03)	(1.59)	(5.10)	(2.01)	(1.76)
Panel B: July 1972 - Dec 2019					
r_{WML}	0.19	0.59	2.62***	2.43**	1.08***
	(0.24)	(1.53)	(8.52)	(2.86)	(3.59)
r_{PTH}	−0.15	0.37	1.90***	2.05**	0.67**
	(−0.19)	(0.94)	(6.22)	(2.33)	(2.17)
α_{WML}^{CAPM}	0.70	0.62	2.60***	1.90**	1.23***
	(1.01)	(1.61)	(8.44)	(2.49)	(4.29)
α_{PTH}^{CAPM}	0.74	0.73**	2.03***	1.29*	1.11***
	(1.15)	(2.12)	(7.50)	(1.84)	(4.23)
α_{WML}^{FF3}	0.73	0.80*	2.69***	1.96***	1.46***
	(1.12)	(1.93)	(9.09)	(2.72)	(5.00)
α_{PTH}^{FF3}	1.12*	0.67**	1.79***	0.67	1.23***
	(1.84)	(2.11)	(7.21)	(1.02)	(4.87)
$\alpha_{PTH}^{\text{Carhart4}}$	0.41	0.22	0.55***	0.14	0.20
	(1.21)	(0.97)	(2.62)	(0.34)	(1.24)
$\alpha_{WML}^{\text{FF5}}$	0.14	0.87**	2.54***	2.40***	1.25***
	(0.18)	(1.96)	(7.26)	(2.80)	(3.67)
$\alpha_{PTH}^{\text{FF5}}$	0.38	0.57*	1.61***	1.23	0.90***
	(0.53)	(1.72)	(6.12)	(1.62)	(3.07)

Table 3
Unconditional time-series regressions of WML and PTH

This table reports the alphas and factor loadings from time-series regressions of the winner-minus-loser decile (WML) and the high-minus-low 52-week high decile (PTH) on the well-documented sets of asset-pricing factors. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "FF6" adds the momentum factor (UMD) into the Fama-French 5-factor model (Fama and French, 2018). "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML), conservative-minus-aggressive (CMA), robust-minus-weak (RMW), momentum (UMD), and earnings surprise (SUE and CAR4). Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	PTH						WML				
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	−0.66**	0.18	0.12	−0.23	0.07	−0.39	−0.14	0.35	0.08	−0.17	−0.40
	(−2.04)	(0.62)	(0.41)	(−0.79)	(0.43)	(−1.28)	(−0.36)	(1.02)	(0.25)	(−0.49)	(−1.20)
β_{MKT}	−0.40***	−0.52***	−0.68***	−0.45***	−0.37***	−0.57***	−0.10	−0.17**	−0.42***	−0.09	−0.25***
	(−5.62)	(−7.27)	(−8.14)	(−5.95)	(−9.60)	(−9.59)	(−1.21)	(−2.13)	(−5.23)	(−1.05)	(−3.79)
β_{PEAD}	1.69***						1.85***				
	(6.55)						(6.50)				
β_{FIN}	0.70***						0.18				
	(7.48)						(1.47)				
β_{ME}		−0.35**	−0.55***	−0.30**				0.34**	0.04	0.41**	
		(−2.38)	(−4.30)	(−2.04)				(2.08)	(0.30)	(2.45)	
β_{IA}		0.29	0.29	0.18				−0.12	−0.10	−0.26	
		(1.26)	(1.33)	(0.83)				(−0.45)	(−0.43)	(−1.00)	
β_{ROE}		1.41***		1.21***				1.47***		1.22***	
		(7.20)		(5.30)				(6.61)		(4.66)	
$\beta_{lag-ROE}$			0.20						−0.35*		
			(0.88)						(−1.68)		
$\beta_{\Delta ROE}$			1.47***						2.05***		
			(6.34)						(10.03)		
β_{EG}				0.61***						0.78***	
				(3.35)						(3.27)	
β_{SMB}					−0.73***	−0.57***					0.23*
					(−10.40)	(−5.54)					(1.78)
β_{HML}					0.24***	0.20*					0.01
					(3.05)	(1.80)					(0.10)
β_{CMA}					0.11						
					(0.98)						
β_{RMW}					0.34***						
					(2.88)						
β_{UMD}					1.16***						
					(15.50)						
β_{SUE}						1.29***					1.74***
						(5.62)					(7.04)
β_{CAR4}						1.31***					1.16***
						(5.05)					(3.87)
R^2_{adj}	0.47	0.50	0.51	0.52	0.78	0.57	0.25	0.26	0.41	0.28	0.41

Table 4

Panel A: Pricing of PTH and Volatility States

This panel presents the alphas and factor loadings from time-series regressions of the high-minus-low 52-week high decile (PTH) on the well-documented sets of asset-pricing factors in each volatility state. We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for month t. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods, and the remaining periods are the Medium-RV periods. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "FF6" adds the momentum factor (UMD) into the Fama-French 5-factor model (Fama and French, 2018). "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML), conservative-minus-aggressive (CMA), robust-minus-weak (RMW), momentum (UMD), and earnings surprise (SUE and CAR4). The sample is 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High RV						Medium RV						Low RV					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	-1.08^{*}	-0.34	-0.30	-0.56	0.29	-0.45	-0.75^{**}	0.04	0.04	-0.44	0.09	-0.51^{*}	0.99^{***}	1.09^{***}	0.89^{***}	0.72^{**}	0.48^{**}	0.56^{**}
	(-1.67)	(-0.57)	(-0.46)	(-0.94)	(0.80)	(-0.74)	(-2.04)	(0.12)	(0.13)	(-1.26)	(0.41)	(-1.68)	(3.20)	(4.07)	(3.22)	(2.34)	(2.32)	(2.00)
β_{MKT}	-0.65^{***}	-0.58^{***}	-0.88^{***}	-0.54^{***}	-0.37^{***}	-0.81^{***}	-0.19^{*}	-0.34^{***}	-0.46^{***}	-0.25^{***}	-0.33^{***}	-0.37^{***}	-0.32^{***}	-0.31^{***}	-0.35^{***}	-0.28^{***}	-0.35^{***}	-0.33^{***}
	(-4.94)	(-4.38)	(-6.50)	(-3.85)	(-4.95)	(-7.18)	(-1.66)	(-4.25)	(-5.86)	(-2.96)	(-5.61)	(-5.73)	(-3.79)	(-3.48)	(-4.31)	(-3.17)	(-6.81)	(-3.81)
β_{PEAD}	2.23^{***}						1.23^{***}						0.69^{***}					
	(5.56)						(5.07)						(2.98)					
β_{FIN}	0.73^{***}						0.74^{***}						0.45^{***}					
	(5.47)						(5.55)						(3.51)					
β_{ME}		0.20	-0.11	0.22				-0.83^{***}	-0.92^{***}	-0.75^{***}				-0.57^{***}	-0.68^{***}	-0.55^{***}		
		(0.88)	(-0.55)	(0.97)				(-7.49)	(-8.81)	(-6.47)				(-4.30)	(-5.02)	(-4.22)		
β_{IA}		-0.29	-0.17	-0.35				0.57^{***}	0.51^{**}	0.51^{***}				0.52^{***}	0.61^{***}	0.39^{**}		
		(-0.70)	(-0.43)	(-0.87)				(2.66)	(2.33)	(2.62)				(3.24)	(3.52)	(2.28)		
β_{ROE}		1.94^{***}		1.82^{***}				0.94^{***}		0.75^{***}				0.70^{***}		0.58^{***}		
		(6.31)		(4.80)				(7.08)		(5.25)				(5.17)		(3.85)		
$\beta_{lag-ROE}$			0.26						0.27^{*}						0.20			
			(0.76)						(1.87)						(1.05)			
$\beta_{\Delta ROE}$			1.98^{***}						1.04^{***}						0.76^{***}			
			(5.24)						(7.66)						(5.71)			
β_{EG}				0.36						0.72^{***}						0.46^{**}		
				(1.03)						(3.37)						(2.28)		
β_{SMB}					-0.73^{***}	-0.31^{*}					-0.84^{***}	-0.94^{***}					-0.77^{***}	-0.70^{***}
					(-5.28)	(-1.86)					(-9.55)	(-9.35)					(-8.97)	(-5.24)
β_{HML}					0.47^{***}	0.14					0.28^{**}	0.33^{***}					-0.03	0.32^{**}
					(3.85)	(0.80)					(2.17)	(2.65)					(-0.21)	(2.33)
β_{CMA}					0.02						0.02						0.22^{*}	
					(0.09)						(0.08)						(1.87)	
β_{RMW}					0.20						0.37^{**}						0.15	
					(1.24)						(2.56)						(1.08)	
β_{UMD}					1.33^{***}						0.95^{***}						0.85^{***}	
					(12.77)						(14.79)						(12.78)	
β_{SUE}						1.60^{***}						1.07^{***}						0.91^{***}
						(4.83)						(6.14)						(5.23)
β_{CAR4}						1.69^{***}						0.79^{***}						0.39
						(4.88)						(3.11)						(1.47)
R^2_{adj}	0.57	0.59	0.56	0.59	0.82	0.62	0.41	0.51	0.54	0.54	0.72	0.60	0.32	0.45	0.48	0.46	0.69	0.50

Table 4 (*continued*)

Panel B: Changes in alphas and factor loadings for PTH across volatility states

This panel presents the changes in alphas and factor loadings from the conditional time-series regressions of the high-minus-low 52-week high decile (PTH) on the well-documented sets of asset-pricing factors. The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Low − High						Medium − High						Low − Medium					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	2.07***	1.43**	1.19*	1.28*	0.19	1.01	0.32	0.38	0.34	0.12	−0.20	−0.06	1.75***	1.05**	0.85**	1.17**	0.39	1.08***
	(2.90)	(2.19)	(1.68)	(1.92)	(0.45)	(1.51)	(0.43)	(0.56)	(0.47)	(0.17)	(−0.46)	(−0.09)	(3.62)	(2.51)	(2.06)	(2.50)	(1.27)	(2.60)
β_{MKT}	0.33**	0.27*	0.53***	0.26	0.02	0.48***	0.46***	0.24	0.42***	0.29*	0.04	0.43***	−0.13	0.03	0.11	−0.03	−0.01	0.05
	(2.11)	(1.69)	(3.38)	(1.55)	(0.25)	(3.39)	(2.68)	(1.54)	(2.70)	(1.78)	(0.39)	(3.34)	(−0.95)	(0.26)	(0.98)	(−0.27)	(−0.19)	(0.42)
β_{PEAD}	−1.53***						−1.00**						−0.54					
	(−3.31)						(−2.13)						(−1.60)					
β_{FIN}	−0.28						0.01						−0.29					
	(−1.50)						(0.03)						(−1.54)					
β_{ME}		−0.77***	−0.56**	−0.77***				−1.03***	−0.81***	−0.97***					0.26	0.25	0.19	
		(−2.93)	(−2.29)	(−2.93)				(−4.09)	(−3.51)	(−3.78)					(1.52)	(1.45)	(1.12)	
β_{IA}		0.81*	0.78*	0.74*				0.85*	0.68	0.85*				−0.05	0.11	−0.11		
		(1.82)	(1.83)	(1.70)				(1.84)	(1.51)	(1.92)				(−0.17)	(0.38)	(−0.43)		
β_{ROE}		−1.24***		−1.24***				−1.00***		−1.07***				−0.25		−0.17		
		(−3.70)		(−3.03)				(−2.98)		(−2.64)				(−1.29)		(−0.80)		
$\beta_{lag-ROE}$			−0.06						0.01						−0.07			
			(−0.16)						(0.02)						(−0.28)			
$\beta_{\Delta ROE}$			−1.21***						−0.94**						−0.28			
			(−3.03)						(−2.34)						(−1.45)			
β_{EG}				0.11						0.36						−0.25		
				(0.27)						(0.89)						(−0.86)		
β_{SMB}					−0.04	−0.38*					−0.11	−0.63***					0.07	0.24
					(−0.27)	(−1.79)					(−0.69)	(−3.21)					(0.56)	(1.47)
β_{HML}					−0.49***	0.18					−0.18	0.19					−0.31*	−0.01
					(−2.81)	(0.83)					(−1.01)	(0.90)					(−1.71)	(−0.04)
β_{CMA}					0.21						0.00						0.20	
					(0.97)						(0.00)						(0.82)	
β_{RMW}					−0.06						0.16						−0.22	
					(−0.27)						(0.75)						(−1.13)	
β_{UMD}					−0.48***						−0.38***						−0.10	
					(−3.89)						(−3.08)						(−1.12)	
β_{SUE}						−0.69*						−0.53						−0.17
						(−1.85)						(−1.41)						(−0.67)
β_{CAR4}						−1.30***						−0.90**						−0.40
						(−2.98)						(−2.10)						(−1.08)

Table 5

Panel A: Pricing of WML and Volatility States

This panel presents the alphas and factor loadings from time-series regressions of the high-minus-low price momentum decile (WML) on the well-documented sets of asset-pricing factors in three volatility states. We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for month t. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods, and the remaining periods are the Medium-RV periods. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML) and earnings surprise (SUE and CAR4). The sample is 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High RV					Medium RV					Low RV				
	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	−0.48	−0.57	−0.47	−0.80	−0.99	−0.50	−0.20	−0.35	-0.86^{*}	−0.62	1.56^{***}	1.92^{***}	1.42^{***}	1.28^{***}	0.81^{**}
	(−0.63)	(−0.83)	(−0.72)	(−1.15)	(−1.57)	(−1.13)	(−0.45)	(−0.93)	(−1.89)	(−1.52)	(3.73)	(5.27)	(4.28)	(3.45)	(2.31)
β_{MKT}	-0.50^{***}	-0.24^{*}	-0.63^{***}	−0.20	-0.44^{***}	0.14	0.07	−0.14	0.20	−0.06	0.11	−0.05	-0.16^{*}	−0.01	−0.05
	(−3.20)	(−1.66)	(−5.07)	(−1.29)	(−3.71)	(1.10)	(0.65)	(−1.36)	(1.58)	(−0.58)	(1.19)	(−0.56)	(−1.74)	(−0.08)	(−0.62)
β_{PEAD}	2.31^{***}					1.30^{***}					0.98^{***}				
	(5.47)					(4.23)					(3.30)				
β_{FIN}	0.08					0.25					0.27^{**}				
	(0.44)					(1.48)					(1.96)				
β_{ME}		0.91^{***}	0.45^{**}	0.93^{***}			−0.16	-0.34^{**}	−0.04			0.32^{*}	0.14	0.35^{*}	
		(3.86)	(2.33)	(3.87)			(−0.93)	(−2.18)	(−0.24)			(1.70)	(0.74)	(1.91)	
β_{IA}		-0.96^{**}	−0.61	-1.02^{**}			0.49^{*}	0.26	0.40			0.30	0.37^{*}	0.08	
		(−2.03)	(−1.51)	(−2.26)			(1.65)	(0.89)	(1.51)			(1.44)	(1.82)	(0.36)	
β_{ROE}		1.99^{***}		1.86^{***}			1.20^{***}		0.93^{***}			0.81^{***}		0.61^{***}	
		(5.69)		(4.39)			(6.34)		(4.43)			(4.22)		(2.85)	
$\beta_{lag-ROE}$			−0.34					−0.14					−0.08		
			(−1.07)					(−0.77)					(−0.35)		
$\beta_{\Delta ROE}$			2.51^{***}					1.71^{***}					1.24^{***}		
			(7.90)					(9.66)					(7.05)		
β_{EG}				0.37					0.98^{***}					0.80^{***}	
				(0.88)					(3.05)					(3.06)	
β_{SMB}					0.54^{***}					−0.22					0.20
					(2.74)					(−1.47)					(1.19)
β_{HML}					−0.19					0.21					0.46^{***}
					(−0.92)					(1.12)					(3.13)
β_{SUE}					2.08^{***}					1.72^{***}					1.39^{***}
					(5.95)					(7.38)					(6.08)
β_{CAR4}					1.39^{***}					0.43					0.60^{*}
					(3.61)					(1.24)					(1.66)
R^2_{adj}	0.38	0.43	0.53	0.43	0.53	0.16	0.18	0.38	0.23	0.35	0.10	0.10	0.24	0.14	0.24

Table 5 (*continued*)

Panel B: Changes in alphas and factor loadings for WML across volatility states

This table presents the changes in alphas and factor loadings from the conditional time-series regressions of the high-minus-low price momentum decile (WML) on the well-documented sets of asset-pricing factors. The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Low − High					Medium − High					Low − Medium				
	BF3	HXZ4	HXZ4^{a}	HXZ5	NM5	BF3	HXZ4	HXZ4^{a}	HXZ5	NM5	BF3	HXZ4	HXZ4^{a}	HXZ5	NM5
α	2.04**	2.49***	1.89***	2.08***	1.80**	−0.02	0.37	0.12	−0.06	0.37	2.06***	2.12***	1.77***	2.14***	1.43***
	(2.34)	(3.19)	(2.58)	(2.64)	(2.49)	(−0.02)	(0.45)	(0.16)	(−0.07)	(0.49)	(3.37)	(3.68)	(3.53)	(3.65)	(2.65)
β_{MKT}	0.61***	0.19	0.48***	0.19	0.39***	0.64***	0.31*	0.49***	0.40**	0.38**	−0.03	−0.13	−0.02	−0.21	0.01
	(3.36)	(1.06)	(3.07)	(1.07)	(2.69)	(3.17)	(1.71)	(3.02)	(2.00)	(2.43)	(−0.21)	(−0.86)	(−0.12)	(−1.32)	(0.06)
β_{PEAD}	−1.33***					−1.01*					−0.32				
	(−2.59)					(−1.94)					(−0.76)				
β_{FIN}	0.19					0.17					0.02				
	(0.83)					(0.69)					(0.08)				
β_{ME}		−0.59**	−0.30	−0.58*			−1.07***	−0.79***	−0.97***			0.47*	0.48*	0.39	
		(−1.97)	(−1.13)	(−1.93)			(−3.68)	(−3.19)	(−3.35)			(1.88)	(1.95)	(1.59)	
β_{IA}		1.26**	0.98**	1.11**			1.45***	0.87*	1.43***			−0.18	0.11	−0.32	
		(2.44)	(2.16)	(2.18)			(2.60)	(1.74)	(2.71)			(−0.51)	(0.30)	(−0.90)	
β_{ROE}		−1.18***		−1.25***			−0.79**		−0.93**			−0.39		−0.32	
		(−2.96)		(−2.63)			(−1.99)		(−1.96)			(−1.44)		(−1.07)	
$\beta_{lag-ROE}$			0.26					0.20					0.06		
			(0.65)					(0.53)					(0.21)		
$\beta_{\Delta ROE}$			−1.27***					−0.80**					−0.47*		
			(−3.49)					(−2.20)					(−1.87)		
β_{EG}				0.43					0.61					−0.17	
				(0.88)					(1.16)					(−0.42)	
β_{SMB}				−0.34				−0.76***					0.43*		
				(−1.30)				(−3.07)					(1.87)		
β_{HML}					0.65***					0.40					0.25
					(2.58)					(1.44)					(1.04)
β_{SUE}					−0.68					−0.36					−0.33
					(−1.64)					(−0.85)					(−1.00)
β_{CAR4}					−0.79					−0.96*					0.17
					(−1.51)					(−1.86)					(0.34)

Table 6

Unconditional Fama-MacBeth regressions (WLS) of FRET, FIG and FROE on $r_{2,12}$ and pth

The table reports results of Fama and MacBeth (1973) predictive regressions of future stock returns (FRET), profitability (FROE) and investment growth (FIG) in month t, onto formation returns of momentum stategies ($r_{2,12}$) or the ratio of stock price in month $t-2$ to its 52-week high (pth). The control variables include stocks' prior month returns ($r_{0,1}$), the log of firms' book-to-market ratio (ln(B/M)), firms' current investment growth (IA measured as total assets divided by one-year-prior total assets minus one), current profitability (ROE measured as quarterly income before extraordinary items divided by one-quarter-prior book equity), and the log of firm's market capitalization (ln(ME)). FROE is the ratio of income before extraordinary items over one-year-lagged book equity, and $FIG = log\left(\frac{1+\frac{I_{i,t+1}}{K_{i,t+1}}}{1+\frac{I_{i,t}}{K_{i,t}}}\right)$ where $I_{i,t}$ ($I_{i,t+1}$) is capital expenditures (Compustat item CAPX) minus sales of property, plant, and equipment (Compustat item SPPE, set to zero if missing) over the course of fiscal year t ($t+1$) for firm i, and $K_{i,t}$ ($K_{i,t+1}$) is net property, plant and equipment (Compustat item PPENT) at the beginning of fiscal year t ($t+1$). We follow the methodology of Liu and Zhang (2014) and George, Hwang, and Li (2018) to align the annual measures: FROE and FIG with the monthly measure: stock return (FRET) in time. Specifically, we match the two annual measures of fiscal year ending in month t with the monthly stock returns from $t-17$ to $t-6$. The cross-sectional regressions are estimated by weighted least squares with firms' market capitalization at the end of month $t-1$ as weights. We exclude financial firms. Independent variables with an annual frequency of firms with fiscal year ending in year $t-1$ are assumed to be publicly available at the end of June of year t. The quarterly earnings data are assumed to be publicly available at the end of the month during which they are announced. Except for FRET, all variables are winsorized at the 1-99% level. The sample period runs from July 1972 to December 2019, which are the same as the sample period used in time-series regressions. Heteroskedasticity-and-autocorrelation-adjusted t-statistics (Newey and West, 1987) are shown in parentheses where the number of lags is automatically selected following the procedure specified in Newey and West (1994).

	FRET				FIG				FROE			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$r_{2,12}$	0.74***		0.62***		0.05***		0.05***		0.10***		0.06***	
	(3.19)		(2.63)		(12.58)		(16.54)		(8.63)		(9.11)	
pth		1.60***		1.37***		0.17***		0.14***		0.51***		0.25***
		(3.04)		(2.60)		(13.96)		(15.93)		(13.84)		(13.35)
$r_{0,1}$			−2.56***	−2.34***								
			(−4.97)	(−4.24)								
ln(B/M)			0.12	0.09								
			(1.61)	(1.04)								
ln(ME)			−0.02	−0.04								
			(−0.46)	(−1.15)								
IA							−0.07***	−0.06***			−0.02***	−0.01*
							(−8.42)	(−7.56)			(−3.06)	(−1.72)
ROE							0.09***	0.08***			2.35***	2.31***
							(4.63)	(3.83)			(46.46)	(46.39)

Table 7

Fama-MacBeth regressions (WLS) conditional on risk of momentum

The table reports the difference of coefficient estimates between Low-RV and High-RV subsamples from conditional Fama and MacBeth (1973) predictive regressions of future stock returns (FRET), profitability (FROE) and investment growth (FIG) in month t, onto formation returns of momentum strategies ($r_{2,12}$) or the ratio of stock price in month $t-2$ to its 52-week high (pth). We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for month t. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods, and the remaining periods are the Medium-RV periods. The control variables include stocks' prior month returns ($r_{0,1}$), the log of firms' book-to-market ratio (ln(B/M)), firms' current investment growth (IA measured as total assets divided by one-year-prior total assets minus one), and firms' current profitability (ROE measured as quarterly income before extraordinary items divided by one-quarter-prior book equity). FROE is the ratio of income before extraordinary items over one-year-lagged book equity, and $FIG = log\left(\frac{1+\frac{I_{i,t+1}}{K_{i,t+1}}}{1+\frac{I_{i,t}}{K_{i,t}}}\right)$ where $I_{i,t}$ ($I_{i,t+1}$) is capital expenditures (Compustat item CAPX) minus sales of property, plant, and equipment (Compustat item SPPE, set to zero if missing) over the course of fiscal year t ($t+1$) for firm i, and $K_{i,t}$ ($K_{i,t+1}$) is net property, plant and equipment (Compustat item PPENT) at the beginning of fiscal year t ($t+1$). We follow the methodology of Liu and Zhang (2014) and George, Hwang, and Li (2018) to align the annual measures: FROE and FIG with the monthly measure: stock return (FRET) in time. Specifically, we match the two annual measures of fiscal year ending in month t with the monthly stock returns from $t-17$ to $t-6$. The cross-sectional regressions are estimated by weighted least squares with firms' market capitalization at the end of month $t-1$ as weights. We exclude financial firms. Independent variables with an annual frequency of firms with fiscal year ending in year $t-1$ are assumed to be publicly available at the end of June of year t. The quarterly earnings data are assumed to be publicly available at the end of the month during which they are announced. Except for FRET, all variables are winsorized at the 1-99% level. The sample period runs from July 1972 to December 2019, which are the same as the sample period used in time-series regressions. Heteroskedasticity-and-autocorrelation-adjusted t-statistics (Newey and West, 1987) is shown in parentheses where the number of lags is automatically selected following the procedure specified in Newey and West (1994).

	FRET		FIG		FROE	
	(1)	(2)	(3)	(4)	(5)	(6)
			Univariate Regressions			
$r_{2,12}$	1.75*** (2.58)		−0.01 (−1.14)		0.00 (0.11)	
pth		4.18*** (2.96)		0.00 (0.08)		−0.14** (−2.06)
			Multi-variate Regressions			
$r_{2,12}$	1.43** (2.07)		−0.01 (−1.45)		−0.00 (−0.03)	
pth		3.12** (2.16)		−0.00 (−0.13)		−0.07 (−1.64)
$r_{0,1}$	1.18 (0.90)	1.04 (0.72)				
ln(B/M)	0.30 (1.49)	0.35 (1.55)				
ln(ME)	0.37*** (4.00)	0.29*** (2.90)				
IA			−0.04*** (−3.43)	−0.04*** (−3.21)	0.03** (2.37)	0.04** (2.50)
ROE			0.01 (0.25)	0.02 (0.43)	−0.01 (−0.06)	0.02 (0.14)

Table 8

Conditional univariate Fama-MacBeth regressions (WLS) of returns surrounding forthcoming quarterly earnings announcements

This table reports the differences of coefficient estimates between Low-RV and High-RV subsamples from univariate conditional Fama and MacBeth (1973) predictive regressions of returns surrounding forthcoming quarterly earnings announcements, onto formation returns of momentum strategies ($r_{2,12}$) or the ratio of stock price in month $t-2$ to its 52-week high (pth). We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for month t. The sample period runs from July 1972 to December 2019, which are the same as the sample period used in time-series regressions. Heteroskedasticity-and-autocorrelation-adjusted t-statistics (Newey and West, 1987) is shown in parentheses where the number of lags is automatically selected following the procedure specified in Newey and West (1994).

	High		Medium		Low		Low − High	
	FCR4	FCAR4	FCR4	FCAR4	FCR4	FCAR4	FCR4	FCAR4
pth	0.69	0.69	0.60**	0.37	1.61***	1.73***	0.92	1.04*
	(1.53)	(1.43)	(2.25)	(1.44)	(4.83)	(5.75)	(1.56)	(1.77)
$r_{2,12}$	0.05	0.06	0.37***	0.29**	0.67***	0.64***	0.63***	0.57***
	(0.28)	(0.35)	(2.73)	(2.23)	(5.41)	(5.22)	(3.11)	(2.75)
sue	0.01	0.01	0.05**	0.04**	0.06***	0.05***	0.05	0.04
	(0.30)	(0.24)	(2.17)	(1.98)	(3.85)	(3.41)	(1.36)	(1.31)
car4	−0.29	−0.40	0.11	−0.10	2.26**	1.91*	2.56*	2.32*
	(−0.37)	(−0.53)	(0.17)	(−0.16)	(2.06)	(1.88)	(1.83)	(1.77)

Table 9

PTH, Momentum Risk and Analyst Forecast Errors

The table reports average equal- and value-weighted analyst forecast error (FE) of the decile portfolios ranked by *pth*, which is the ratio of monthly closing price to its 52-week high, (un)conditional on the risk of momentum. At the end of each month $t-1$, all stocks are sorted into deciles by *pth* of month $t-2$ using NYSE breakpoints, and then within each decile, we compute FE of **upcoming quarterly earnings** for the stocks covered by analysts, defined as (mean estimate$_{t-1}$ − actual)/abs(actual), using the data form the IBES summary files. FE is winsorized at the 5th and 95th percentile each month. The risk of momentum is defined by the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days). The sample is from 1984:07 to 2019:12. t-statistics adjusted for heteroskedasticity and autocorrelations are in parentheses.

Decile	L	2	3	4	5	6	7	8	9	H	H-L
					Panel A: EW Forecast Errors						
Full Sample	0.36	0.31	0.24	0.19	0.15	0.11	0.08	0.06	0.04	0.03	−0.33
	(12.12)	(12.78)	(12.16)	(11.84)	(11.46)	(9.86)	(8.84)	(7.77)	(6.09)	(4.09)	(−13.44)
Non-Low RV	0.26	0.23	0.18	0.14	0.11	0.08	0.06	0.04	0.02	0.01	−0.26
	(9.27)	(10.71)	(9.89)	(9.41)	(8.87)	(7.30)	(6.13)	(5.00)	(3.33)	(1.20)	(−10.49)
Low RV	0.66	0.55	0.42	0.33	0.27	0.21	0.18	0.14	0.11	0.09	−0.57
	(14.14)	(11.84)	(11.25)	(11.27)	(11.64)	(10.26)	(10.20)	(9.42)	(8.25)	(6.80)	(−14.70)
Low − Non-Low RV	0.40	0.32	0.24	0.19	0.16	0.13	0.12	0.10	0.09	0.09	−0.31
	(7.90)	(6.59)	(6.34)	(6.28)	(6.60)	(6.10)	(6.60)	(6.12)	(6.14)	(5.89)	(−7.46)
					Panel B: VW Forecast Errors						
Full Sample	0.31	0.21	0.16	0.10	0.09	0.06	0.04	0.02	0.01	0.00	−0.31
	(11.33)	(9.63)	(7.60)	(7.30)	(6.72)	(6.06)	(4.44)	(3.34)	(1.42)	(0.38)	(−13.16)
Non-Low RV	0.23	0.15	0.11	0.07	0.06	0.04	0.01	0.01	−0.01	−0.01	−0.24
	(8.67)	(7.68)	(5.82)	(5.15)	(4.37)	(3.97)	(1.88)	(1.10)	(−1.05)	(−1.91)	(−10.60)
Low RV	0.59	0.41	0.32	0.20	0.18	0.13	0.10	0.07	0.06	0.05	−0.54
	(12.27)	(8.42)	(6.35)	(6.79)	(7.07)	(6.01)	(6.05)	(4.86)	(4.33)	(3.53)	(−13.03)
Low − Non-Low RV	0.37	0.25	0.22	0.13	0.12	0.09	0.09	0.07	0.06	0.06	−0.30
	(7.20)	(5.10)	(4.28)	(4.33)	(4.67)	(4.09)	(4.86)	(4.21)	(4.58)	(4.35)	(−6.92)

Table 10

WML, Momentum Risk and Analyst Forecast Errors

The table reports average equal- and value-weighted analyst forecast error (FE) of the decile portfolios ranked by $r_{2,12}$, which is the formation returns from month $t-12$ to $t-2$, (un)conditional on the risk of momentum. At the end of each month $t-1$, all stocks are sorted into deciles by $r_{2,12}$ using NYSE breakpoints, and then within each decile, we compute FE of **upcoming quarterly earnings** for the stocks covered by analysts, defined as (mean estimate$_{t-1}$ − actual)/abs(actual), using the data from the IBES summary files. FE is winsorized at the 5th and 95th percentile each month. The risk of momentum is defined by the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days). The sample is from 1984:07 to 2019:12. t-statistics adjusted for heteroskedasticity and autocorrelations are in parentheses.

Decile	L	2	3	4	5	6	7	8	9	H	H-L
					Panel A: EW Forecast Errors						
Full Sample	0.36	0.30	0.24	0.19	0.15	0.13	0.10	0.09	0.07	0.04	−0.32
	(12.40)	(12.79)	(12.55)	(12.36)	(12.27)	(11.49)	(10.23)	(9.76)	(8.37)	(4.76)	(−13.85)
Non-Low RV	0.27	0.23	0.19	0.15	0.12	0.10	0.07	0.06	0.04	0.01	−0.26
	(9.53)	(10.35)	(9.91)	(9.75)	(9.29)	(8.73)	(7.57)	(7.13)	(5.52)	(1.83)	(−10.87)
Low RV	0.65	0.51	0.41	0.33	0.25	0.22	0.20	0.17	0.15	0.12	−0.54
	(14.34)	(11.70)	(12.04)	(11.69)	(12.86)	(11.69)	(10.87)	(10.85)	(10.39)	(7.79)	(−14.53)
Low − Non-Low RV	0.38	0.28	0.22	0.18	0.13	0.13	0.12	0.12	0.10	0.10	−0.28
	(7.85)	(6.09)	(6.21)	(5.98)	(5.95)	(6.10)	(6.44)	(6.78)	(6.64)	(6.44)	(−7.14)
					Panel B: VW Forecast Errors						
Full Sample	0.30	0.19	0.13	0.09	0.07	0.05	0.03	0.02	0.00	−0.03	−0.33
	(10.58)	(8.33)	(8.24)	(6.88)	(6.70)	(5.55)	(4.54)	(3.01)	(0.65)	(−3.78)	(−13.36)
Non-Low RV	0.22	0.13	0.09	0.07	0.05	0.03	0.01	−0.00	−0.01	−0.04	−0.26
	(8.18)	(6.57)	(6.04)	(4.81)	(4.60)	(3.23)	(2.03)	(−0.02)	(−1.45)	(−6.27)	(−11.26)
Low RV	0.58	0.36	0.24	0.17	0.12	0.12	0.10	0.08	0.05	0.03	−0.55
	(10.48)	(6.63)	(7.14)	(6.55)	(6.50)	(6.35)	(6.54)	(5.36)	(3.28)	(2.02)	(−11.04)
Low − Non-Low RV	0.36	0.23	0.14	0.10	0.07	0.09	0.08	0.08	0.06	0.07	−0.29
	(6.37)	(4.13)	(4.24)	(3.57)	(3.19)	(4.50)	(5.35)	(5.29)	(3.92)	(4.64)	(−5.67)

Table 11

Conditional alphas of long and short legs of PTH and WML

The table reports factor-adjusted returns of long and short legs of PTH and WML. The returns on the long (short) leg of a zero-cost portfolio are returns on the winner (market) portfolio in excess of returns on the market (loser) portfolio. We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for a holding month. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods, and the remaining periods are the Medium-RV periods. 'Dif' denotes the difference in alphas between Low-RV and Non-Low-RV months. "CAPM" denotes the market model proposed by (Sharpe, 1964; Lintner, 1965; Black, 1972). "FF3" denotes the Fama and French (1993) three-factor model. "Carhart4" denotes the Carhart (1997) 4-factor model consisting of the FF3 factors plus the Momentum factor. "FF5" denotes the Fama and French (2015) five-factor model. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "FF6" adds the momentum factor (UMD) into the Fama-French 5-factor model (Fama and French, 2018). "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The sample is from 1972:07 to 2019:12. t-statistics adjusted for heteroskedasticity are in parentheses.

	PTH						WML					
	long − market			market − short			long − market			market − short		
	Low	H+M	Dif	Low	H+M	Dif	Low	H+M	Dif	Low	H+M	Dif
Factor-adjusted returns (i.e. alphas)												
raw	0.21**	−0.01	0.22	1.69***	0.16	1.53***	0.88***	0.32*	0.56**	1.74***	0.10	1.64***
	(2.05)	(−0.09)	(1.41)	(6.83)	(0.47)	(3.69)	(4.42)	(1.69)	(2.04)	(8.19)	(0.32)	(4.35)
market	0.24**	0.14	0.10	1.79***	0.61**	1.17***	0.82***	0.21	0.60**	1.79***	0.46*	1.32***
	(2.45)	(1.28)	(0.71)	(8.06)	(2.20)	(3.29)	(4.32)	(1.13)	(2.25)	(8.60)	(1.69)	(3.86)
FF3	0.26**	0.21**	0.05	1.53***	0.81***	0.71**	1.09***	0.32*	0.77***	1.60***	0.63**	0.96***
	(2.47)	(1.96)	(0.36)	(8.27)	(3.16)	(2.25)	(6.82)	(1.94)	(3.37)	(8.41)	(2.37)	(2.94)
Carhart	−0.15	0.00	−0.15	0.70***	0.25	0.45*	0.18	−0.02	0.20	0.48***	−0.01	0.49**
	(−1.50)	(0.01)	(−1.19)	(4.24)	(1.36)	(1.85)	(1.26)	(−0.15)	(1.09)	(3.57)	(−0.05)	(2.38)
FF5	0.19*	0.11	0.08	1.42***	0.54*	0.89**	1.03***	0.35*	0.68***	1.51***	0.34	1.16***
	(1.69)	(0.90)	(0.47)	(7.32)	(1.89)	(2.57)	(5.60)	(1.91)	(2.60)	(6.94)	(1.15)	(3.16)
BF3	−0.07	−0.24**	0.18	1.06***	−0.78**	1.83***	0.52*	0.09	0.42	1.04***	−0.70**	1.74***
	(−0.52)	(−2.10)	(1.03)	(4.25)	(−2.48)	(4.58)	(1.89)	(0.51)	(1.28)	(4.31)	(−2.09)	(4.22)
HXZ4^a	0.06	−0.03	0.09	1.03***	−0.05	1.08***	0.71***	0.07	0.64**	1.21***	−0.28	1.49***
	(0.50)	(−0.25)	(0.53)	(5.34)	(−0.17)	(3.28)	(3.54)	(0.36)	(2.31)	(5.48)	(−1.02)	(4.19)
HXZ4	−0.04	−0.05	0.01	0.93***	−0.00	0.93***	0.38**	−0.02	0.40*	1.04***	−0.30	1.34***
	(−0.30)	(−0.44)	(0.08)	(4.61)	(−0.00)	(2.76)	(2.17)	(−0.14)	(1.71)	(4.66)	(−1.13)	(3.86)
HXZ5	−0.04	−0.16	0.12	0.76***	−0.29	1.05***	0.43**	−0.11	0.54*	0.86***	−0.55**	1.41***
	(−0.30)	(−1.31)	(0.65)	(3.42)	(−1.10)	(3.06)	(2.01)	(−0.53)	(1.82)	(3.61)	(−2.02)	(3.90)
FF6	−0.19*	−0.03	−0.15	0.67***	0.14	0.52**	0.20	0.11	0.08	0.48***	−0.10	0.58***
	(−1.95)	(−0.43)	(−1.24)	(4.03)	(0.80)	(2.13)	(1.39)	(1.04)	(0.48)	(3.19)	(−0.66)	(2.73)
NM5	−0.05	−0.21**	0.15	0.62***	−0.30	0.91**	0.29	−0.23	0.52**	0.52**	−0.49*	1.01***
	(−0.41)	(−1.99)	(0.92)	(2.87)	(−1.02)	(2.54)	(1.38)	(−1.49)	(2.00)	(2.40)	(−1.67)	(2.77)

Table 12

PTH vs WML: Spanning Test

This table presents results of time-series regression of the form:

$$y_t = \alpha + \boldsymbol{\beta' X_t} + \epsilon_t$$

where the y_t are the monthly excess returns to the 52-week high factor (PTH^f), the price momentum factor (UMD), high-minus-low 52-week high decile (PTH), or winner-minus-loser decile (WML), and main explanatory variable is the other factor portfolio or the other high-minus-low decile. Control variables are the returns to the Fama-French three factors (MKT, SMB, and HML). The sample covers July 1927 through December 2019. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	y = $\mathrm{PTH^f}$			y = UMD			y = PTH			y = WML		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	0.42***	−0.18*	0.26***	0.65***	0.35***	0.08	0.42	−0.57***	0.13	1.14***	0.84***	0.54***
	(2.60)	(−1.69)	(4.14)	(4.59)	(3.73)	(0.99)	(1.63)	(−3.29)	(1.07)	(4.86)	(5.60)	(3.84)
β_{MKT}			−0.32***			0.22***			−0.43***			0.24***
			(−11.40)			(9.14)			(−14.28)			(6.18)
β_{SMB}			−0.42***			0.37***			−0.81***			0.64***
			(−10.16)			(8.11)			(−10.69)			(8.94)
β_{HML}			−0.07*			−0.09*			−0.09			−0.20***
			(−1.70)			(−1.94)			(−1.50)			(−2.78)
β_{UMD}		0.92***	0.74***									
		(23.57)	(28.77)									
β_{PTH^f}					0.70***	0.91***						
					(13.86)	(22.28)						
β_{WML}								0.87***	0.68***			
								(22.42)	(23.54)			
β_{PTH}											0.72***	0.90***
											(18.87)	(25.03)

Table 13

Panel A: Past Performance vs Nearness to the 52-week High: unconditional Fama and MacBeth (1973) regression

This panel presents results of Fama and MacBeth (1973) regressions, with weighted least squares, of individual monthly stock returns in month t onto past performance, measured over the preceding year skipping the most recent month ($r_{2,12}$), and/or the ratio of stock price in month $t-2$ to its 52-week high (pth). We use market equity of stocks in month $t-1$ as weights. Controls are variables known to predict cross sectional variation in expected returns including the log of stocks' market capitalisation (Ln(ME)), the log of firms' book-to-market ratios (Ln(B/M)), and stocks' prior month returns ($r_{0,1}$). Independent variables are winsorised at the 1% and 99% levels. The sample covers July 1927 through December 2019. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	(1)	(2)	(3)	(4)
$r_{2,12}$	0.88***		1.23***	1.23***
	(3.91)		(5.41)	(5.63)
pth		1.71***	−0.10	−0.37
		(3.16)	(−0.16)	(−0.63)
Ln(ME)				−0.02
				(−0.80)
Ln(B/M)				0.14**
				(2.11)
$r_{0,1}$				−0.04***
				(−8.09)

Table 13 (*continued*)

Panel B: Past Performance vs Nearness to the 52-week High: conditional Fama and MacBeth (1973) regressions

This panel presents results of conditional Fama and MacBeth (1973) regressions, with weighted least squares, of individual monthly stock returns in month t onto past performance, measured over the preceding year skipping the most recent month ($r_{2,12}$), and/or the ratio of stock price in month $t-2$ to its 52-week high (pth). We employ the realized volatility of WML, calculated from daily returns in the previous 6 months (126 trading days), to define the volatility state for month t. The top (bottom) 30% observations of the realized volatility series are the High-RV (Low-RV) periods. We use market equity of stocks in month $t-1$ as weights. Controls are variables known to predict cross sectional variation in expected returns including the log of stocks' market capitalisation (Ln(ME)), the log of firms' book-to-market ratios (Ln(B/M)), and stocks' prior month returns ($r_{0,1}$). Independent variables are winsorised at the 1% and 99% levels. The sample covers July 1927 through December 2019. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High-RV				Low-RV				Low − High			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$r_{2,12}$	0.02		1.03**	0.73*	1.95***		1.49***	1.56***	1.92***		0.46	0.82
	(0.05)		(2.10)	(1.74)	(6.02)		(4.14)	(4.51)	(3.14)		(0.75)	(1.51)
pth		0.60	−0.98	−0.71		4.08***	1.50*	0.96		3.47**	2.47	1.67
		(0.50)	(−0.68)	(−0.57)		(5.76)	(1.77)	(1.17)		(2.49)	(1.48)	(1.12)
Ln(ME)				−0.16**				0.01				0.17**
				(−2.50)				(0.17)				(2.16)
Ln(B/M)				0.09				0.03				−0.06
				(0.76)				(0.29)				(−0.35)
$r_{0,1}$				−0.03***				−0.05***				−0.02
				(−2.99)				(−5.98)				(−1.34)

Table 14

Alphas and Market States

This table presents the raw or factor-adjusted returns of the high-minus-low deciles on past performance (WML) and the ratio of current price to 52-week high price (PTH) across market states, defined by the cumulative past one-year return on the market. At the end of each month $t-1$, all common stocks traded on NYSE, AMEX and NASDAQ are sorted into deciles based on their prior 11-month returns from $t-12$ to $t-2$ (the ratio of current price to 52-week high price of $t-2$) using NYSE breakpoints. We skip month $t-1$ and calculate monthly value-weighted returns for each decile for month t. The deciles are rebalanced at the end of month t.To identify the state of market for month t, we calculate the cumulative past one-year market return. If the return is non-negative (negative), the holding month is defined as "Up" ("DOWN"). "CAPM" denotes the market model proposed by (Sharpe, 1964; Lintner, 1965; Black, 1972). "FF3" denotes the Fama and French (1993) three-factor model. "Carhart4" denotes the Carhart (1997) 4-factor model consisting of the FF3 factors plus the Momentum factor. "FF5" denotes the Fama and French (2015) five-factor model. The sample period in Panel A runs from January 1927 to December 2019, while the sample period in Panel B runs from July 1972 to December 2019, the sample period used in our tests. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Market States		
	DOWN	Up	Up − DOWN
Panel A: Jan 1927 - Dec 2019			
r_{WML}	0.00 (0.01)	1.55*** (8.27)	1.54** (2.04)
r_{PTH}	−0.58 (−0.71)	0.79*** (3.85)	1.37 (1.63)
α^{CAPM}_{WML}	0.28 (0.56)	1.44*** (7.92)	1.16** (2.15)
α^{CAPM}_{PTH}	−0.26 (−0.48)	1.24*** (7.23)	1.50*** (2.66)
α^{FF3}_{WML}	0.68 (1.50)	1.58*** (8.67)	0.90* (1.84)
α^{FF3}_{PTH}	0.21 (0.49)	1.36*** (8.48)	1.15** (2.46)
$\alpha^{\text{Carhart4}}_{PTH}$	−0.33 (−1.34)	0.54*** (4.10)	0.87*** (3.11)
Panel B: July 1972 - Dec 2019			
r_{WML}	−0.12 (−0.13)	1.42*** (5.31)	1.55 (1.53)
r_{PTH}	−0.51 (−0.48)	1.01*** (3.99)	1.52 (1.38)
α^{CAPM}_{WML}	−0.01 (−0.01)	1.29*** (4.83)	1.30 (1.54)
α^{CAPM}_{PTH}	−0.36 (−0.45)	1.31*** (5.46)	1.67** (2.00)
α^{FF3}_{WML}	0.43 (0.60)	1.55*** (5.68)	1.12 (1.46)
α^{FF3}_{PTH}	0.18 (0.26)	1.36*** (5.68)	1.18* (1.68)
$\alpha^{\text{Carhart4}}_{PTH}$	−0.29 (−0.88)	0.42** (2.49)	0.71* (1.90)
$\alpha^{\text{FF5}}_{WML}$	−0.47 (−0.66)	1.59*** (5.58)	2.06*** (2.68)
$\alpha^{\text{FF5}}_{PTH}$	−0.87 (−1.40)	1.28*** (5.03)	2.15*** (3.20)

Table 15

Panel A: Pricing of PTH and Market States

This table presents the alphas and factor loadings from time-series regressions of the high-minus-low 52-week high decile (PTH) on the well-documented sets of asset-pricing factors in the two market states. To identify the state of market for month t, we calculate the cumulative past one-year market return. If the return is non-negative (negative), the holding month is defined as "Up" ("DOWN"). "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "FF6" adds the momentum factor (UMD) into the Fama-French 5-factor model (Fama and French, 2018). "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML), conservative-minus-aggressive (CMA), robust-minus-weak (RMW), momentum (UMD), and earnings surprise (SUE and CAR4). The sample is 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	UP Market						DOWN Market					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	−0.05	0.82***	0.64***	0.42	0.33*	0.11	−2.24***	−1.40***	−1.58***	−1.52***	−0.47	−1.60**
	(−0.18)	(3.02)	(2.65)	(1.55)	(1.91)	(0.48)	(−2.78)	(−2.58)	(−2.62)	(−2.73)	(−1.46)	(−2.30)
β_{MKT}	−0.30***	−0.35***	−0.48***	−0.30***	−0.41***	−0.40***	−0.45**	−0.64***	−0.81***	−0.61***	−0.18**	−0.84***
	(−4.81)	(−5.11)	(−6.58)	(−4.47)	(−8.71)	(−7.01)	(−2.54)	(−5.95)	(−5.65)	(−4.63)	(−2.16)	(−8.10)
β_{PEAD}	1.37***						1.86***					
	(8.14)						(2.97)					
β_{FIN}	0.47***						1.14***					
	(8.14)						(2.97)					
β_{ME}		−0.38**	−0.62***	−0.33**				−0.54***	−0.51***	−0.51***		
		(−2.47)	(−4.75)	(−2.20)				(−3.11)	(−2.86)	(−2.73)		
β_{IA}		0.01	0.08	−0.05				0.96***	0.75*	0.91***		
		(0.05)	(0.42)	(−0.28)				(2.98)	(1.93)	(3.26)		
β_{ROE}		0.84***		0.63***				1.80***		1.75***		
		(5.04)		(3.49)				(6.98)		(5.43)		
$\beta_{lag-ROE}$			−0.14						1.03***			
			(−0.74)						(3.29)			
$\beta_{\Delta ROE}$			1.09***						1.64***			
			(7.20)						(3.94)			
β_{EG}				0.61***						0.18		
				(3.87)						(0.49)		
β_{SMB}					−0.77***	−0.61***					−0.46***	−0.63***
					(−10.18)	(−6.41)					(−3.89)	(−3.03)
β_{HML}					0.18*	−0.03					0.20	0.81***
					(1.86)	(−0.32)					(1.61)	(4.25)
β_{CMA}					0.15						0.07	
					(0.97)						(0.42)	
β_{RMW}					0.25*						0.31*	
					(1.68)						(1.69)	
β_{UMD}					1.05***						1.41***	
					(13.53)						(10.24)	
β_{SUE}						0.73***						2.25***
						(4.63)						(6.07)
β_{CAR4}						1.41***						0.13
						(6.17)						(0.31)
R^2_{adj}	0.34	0.28	0.32	0.31	0.23	0.44	0.62	0.77	0.75	0.77	0.64	0.75

Table 15 (*continued*)

Panel B: Changes in alphas and factor loadings for PTH across market states

This table presents the changes in alphas and factor loadings from time-series regressions of the high-minus-low 52-week high decile (PTH) conditional on past market returns. The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	UP − DOWN					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	2.19*** (2.60)	2.21*** (3.66)	2.22*** (3.42)	1.94*** (3.13)	0.80** (2.19)	1.71** (2.34)
β_{MKT}	0.16 (0.83)	0.29** (2.24)	0.33** (2.05)	0.31** (2.10)	−0.23** (−2.38)	0.45*** (3.77)
β_{PEAD}	−0.49 (−0.76)					
β_{FIN}	−0.67*** (−2.87)					
β_{ME}		0.16 (0.68)	−0.11 (−0.52)	0.18 (0.74)		
β_{IA}		−0.95** (−2.51)	−0.67 (−1.57)	−0.96*** (−2.83)		
β_{ROE}		−0.96*** (−3.14)		−1.12*** (−3.03)		
$\beta_{lag-ROE}$			−1.17*** (−3.20)			
$\beta_{\Delta ROE}$			−0.55 (−1.24)			
β_{EG}				0.43 (1.08)		
β_{SMB}					−0.31** (−2.19)	0.02 (0.07)
β_{HML}					−0.02 (−0.15)	−0.84*** (−3.92)
β_{CMA}					0.07 (0.31)	
β_{RMW}					−0.06 (−0.27)	
β_{UMD}					−0.35** (−2.24)	
β_{SUE}						−1.53*** (−3.79)
β_{CAR4}						1.28*** (2.64)

Table 16

Panel A: Pricing of WML and Market States

This table presents the alphas and factor loadings from time-series regressions of the high-minus-low price momentum decile (WML) on the well-documented sets of asset-pricing factors in the two market states. To identify the state of market for month t, we calculate the cumulative past one-year market return. If the return is non-negative (negative), the holding month is defined as "UP" ("DOWN"). "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML), momentum (UMD), and earnings surprise (SUE and CAR4). The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	UP Market					DOWN Market				
	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	0.55*	1.00***	0.46*	0.52	0.21	−1.69**	−1.09*	−1.30**	−1.20*	−1.56**
	(1.84)	(3.14)	(1.85)	(1.63)	(0.74)	(−2.04)	(−1.76)	(−1.99)	(−1.91)	(−2.20)
β_{MKT}	0.09	0.07	−0.18**	0.13	−0.03	−0.24	−0.40***	−0.61***	−0.38**	−0.56***
	(1.15)	(0.87)	(−2.47)	(1.64)	(−0.43)	(−1.41)	(−3.62)	(−4.34)	(−2.57)	(−5.33)
β_{PEAD}	1.35***					2.09***				
	(6.31)					(3.34)				
β_{FIN}	−0.19*					0.87***				
	(−1.90)					(3.94)				
β_{ME}		0.41***	−0.02	0.47***			−0.24	−0.14	−0.21	
		(2.76)	(−0.18)	(3.17)			(−1.08)	(−0.57)	(−0.94)	
β_{IA}		−0.46**	−0.35**	−0.54**			0.75**	0.48	0.70**	
		(−2.14)	(−2.10)	(−2.49)			(2.08)	(1.16)	(2.22)	
β_{ROE}		0.82***		0.57***			1.78***		1.73***	
		(4.65)		(2.79)			(6.33)		(4.85)	
$\beta_{lag-ROE}$			−0.79***					0.65**		
			(−5.28)					(2.33)		
$\beta_{\Delta ROE}$			1.77***					1.94***		
			(12.39)					(4.89)		
β_{EG}				0.74***					0.16	
				(3.42)					(0.37)	
β_{SMB}					0.27**					−0.15
					(2.29)					(−0.66)
β_{HML}					−0.29**					0.76***
					(−2.38)					(3.76)
β_{SUE}					1.21***					2.42***
					(6.82)					(6.61)
β_{CAR4}					1.01***					0.34
					(3.51)					(0.83)
R^2_{adj}	0.20	0.12	0.35	0.16	0.31	0.52	0.65	0.67	0.65	0.69

Table 16 (*continued*)

Panel B: Changes in alphas and factor loadings for WML across market states

This panel presents the changes in alphas and factor loadings from the time-series regressions of the high-minus-low price momentum decile (WML) conditional on the past market returns. The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistic is shown in parentheses.

	UP − DOWN				
	BF3	HXZ4	HXZ4^{a}	HXZ5	NM5
α	2.25**	2.09***	1.76**	1.72**	1.77**
	(2.55)	(3.00)	(2.51)	(2.44)	(2.32)
β_{MKT}	0.34*	0.47***	0.43***	0.51***	0.53***
	(1.77)	(3.45)	(2.70)	(3.04)	(4.23)
β_{PEAD}	−0.74				
	(−1.12)				
β_{FIN}	−1.06***				
	(−4.37)				
β_{ME}		0.65**	0.11	0.68**	
		(2.44)	(0.42)	(2.51)	
β_{IA}		−1.21***	−0.83*	−1.24***	
		(−2.88)	(−1.86)	(−3.24)	
β_{ROE}		−0.96***		−1.16***	
		(−2.89)		(−2.82)	
$\beta_{lag-ROE}$			−1.44***		
			(−4.56)		
$\beta_{\Delta ROE}$			−0.17		
			(−0.40)		
β_{EG}				0.58	
				(1.19)	
β_{SMB}					0.42
					(1.64)
β_{HML}					−1.05***
					(−4.45)
β_{SUE}					−1.21***
					(−2.97)
β_{CAR4}					0.67
					(1.33)

Table 17

Market Timing Regression Results

This table reports the results of estimating six specifications of a monthly time-series regressions from January 1927 to December 2019. The dependent variable in the first (last) three specifications is the return on the WML (PTH) portfolio. Similar to Daniel and Moskowitz (2016), the independent variables are a constant, the DOWN-marker indicator, $I_{B,t-1}$, which equals one if the cumulative past one-year market return is negative, the excess market return, $R^e_{m,r}$, and a contemporaneous market return, $I_{U,t}$, which equals one if $R^e_{m,r}$ is positive.Heteroskedasticity-adjusted t-statistics are shown in parentheses.

Coefficient	Variable	PTH			WML		
		Estimates (t-statistics)			Estimates (t-statistics)		
		(1)	(2)	(3)	(4)	(5)	(6)
α	1	1.08*** (5.61)	1.24*** (7.23)	1.24*** (7.23)	1.50*** (7.39)	1.44*** (7.92)	1.44*** (7.92)
α_B	$\mathrm{I_{B,t-1}}$		−1.50*** (−2.66)	1.08 (1.47)		−1.16** (−2.15)	1.10 (1.45)
β_m	$\mathrm{R^e_{m,t}}$	−0.96*** (−11.41)	−0.56*** (−7.48)	−0.56*** (−7.48)	−0.52*** (−5.06)	0.13** (2.01)	0.13** (2.01)
β_B	$\mathrm{I_{B,t-1}R^e_{m,t}}$		−0.78*** (−5.67)	−0.24* (−1.68)		−1.29*** (−9.62)	−0.82*** (−6.51)
$\beta_{B,U}$	$\mathrm{I_{B,t-1}I_{U,t}R^e_{m,t}}$			−0.97*** (−3.77)			−0.85*** (−3.27)

Appendix

We reports the conditional performance of the factor models using several alternative state variables known to predict momentum payoffs.

Table A1, Table A2, and Table A3 use market volatility to define the state of a holding month. Following Wang and Xu (2015), a month is defined as high (low) volatility if the past 12-month market volatility is higher (lower) than the lagged 36-month market volatility.

Table A4, Table A5, and Table A6 use cross-sectional return dispersion of Stivers and Sun (2010) to define the state of a holding month. A month's RD is the cross-sectional standard deviation of the monthly returns of 100 BM&SZ portfolios:

$$RD_t = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(R_{i,t} - R_{\mu,t})^2}, \tag{16}$$

where n is the number of disaggregate portfolios, $R_{i,t}$ is the return of portfolio i in month t, and $R_{\mu,t}$ is the equal-weighted returns of the 100 portfolios for month t.

Table A1

Alphas and Market Volatility.

This table presents the raw and factor-adjusted returns of the high-minus-low deciles on past performance (WML) and the ratio of current price to 52-week high price (PTH) across market volatility states. At the end of each month $t-1$, all common stocks traded on NYSE, AMEX and NASDAQ are sorted into deciles based on their prior 11-month returns from $t-12$ to $t-2$ (the ratio of current price to 52-week high price of $t-2$) using NYSE breakpoints. We skip month $t-1$ and calculate monthly value-weighted returns for each decile for month t. A month is defined as high (low) volatility if the past 12-month market volatility is higher (lower) than the lagged 36-month market volatility."CAPM" denotes the market model proposed by (Sharpe, 1964; Lintner, 1965; Black, 1972). "FF3" denotes the Fama and French (1993) three-factor model. "Carhart4" denotes the Carhart (1997) 4-factor model consisting of the FF3 factors plus the Momentum factor. "FF5" denotes the Fama and French (2015) five-factor model. The sample period in Panel A runs from January 1927 to December 2019, while the sample period in Panel B runs from July 1972 to December 2019, the sample period used in our tests. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Market Volatility		
	High	Low	Low − High
Panel A: Jan 1927 - Dec 2019			
r_{WML}	0.46 (1.06)	1.60*** (6.52)	1.14** (2.40)
r_{PTH}	−0.06 (−0.13)	0.83*** (2.97)	0.89* (1.69)
α_{WML}^{CAPM}	0.88** (2.43)	1.76*** (7.64)	0.88** (2.04)
α_{PTH}^{CAPM}	0.56 (1.60)	1.38*** (6.59)	0.82** (2.03)
α_{WML}^{FF3}	1.20*** (3.51)	1.91*** (8.47)	0.71* (1.73)
α_{PTH}^{FF3}	0.87*** (2.95)	1.57*** (7.91)	0.70** (1.98)
$\alpha_{PTH}^{\text{Carhart4}}$	0.12 (0.61)	0.29* (1.68)	0.17 (0.67)
Panel B: July 1972 - Dec 2019			
r_{WML}	0.40 (0.76)	1.72*** (5.61)	1.32** (2.20)
r_{PTH}	0.03 (0.06)	1.27*** (4.30)	1.24** (2.01)
α_{WML}^{CAPM}	0.58 (1.17)	1.76*** (5.90)	1.18** (2.03)
α_{PTH}^{CAPM}	0.44 (0.93)	1.69*** (6.69)	1.26** (2.36)
α_{WML}^{FF3}	0.98** (2.06)	1.82*** (5.84)	0.84 (1.47)
α_{PTH}^{FF3}	0.70* (1.67)	1.74*** (6.40)	1.04** (2.09)
$\alpha_{PTH}^{\text{Carhart4}}$	0.08 (0.34)	0.42* (1.92)	0.34 (1.08)
$\alpha_{WML}^{\text{FF5}}$	0.51 (0.90)	1.86*** (5.41)	1.35** (2.05)
$\alpha_{PTH}^{\text{FF5}}$	0.12 (0.26)	1.66*** (5.42)	1.55*** (2.80)

Table A2

Panel A: Pricing of PTH and Market Volatility states

This panel presents the alphas and factor loadings from time-series regressions of the high-minus-low 52-week high decile (PTH) on the well-documented sets of asset-pricing factors in the two market volatility states. A month is defined as high (low) volatility if the past 12-month market volatility is higher (lower) than the lagged 36-month market volatility. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "FF6" adds the momentum factor (UMD) into the Fama-French 5-factor model (Fama and French, 2018). "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML), conservative-minus-aggressive (CMA), robust-minus-weak (RMW), momentum (UMD), and earnings surprise (SUE and CAR4). The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High MVOL						Low MVOL					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	−1.38***	−0.66*	−0.69	−0.81*	−0.07	−1.03**	0.30	1.27***	1.13***	0.60*	0.33	0.46
	(−2.69)	(−1.72)	(−1.61)	(−1.94)	(−0.31)	(−2.23)	(1.18)	(3.71)	(3.88)	(1.79)	(1.50)	(1.63)
β_{MKT}	−0.38***	−0.40***	−0.59***	−0.38***	−0.28***	−0.54***	−0.40***	−0.60***	−0.71***	−0.50***	−0.48***	−0.56***
	(−3.73)	(−4.51)	(−5.66)	(−3.87)	(−6.07)	(−6.91)	(−5.13)	(−7.27)	(−8.33)	(−5.83)	(−8.01)	(−7.22)
β_{PEAD}	1.94***						1.25***					
	(5.01)						(6.94)					
β_{FIN}	0.84***						0.45***					
	(5.01)						(6.94)					
β_{ME}		−0.55***	−0.70***	−0.54***				−0.14	−0.33**	−0.05		
		(−4.91)	(−5.69)	(−4.61)				(−0.79)	(−2.08)	(−0.27)		
β_{IA}		0.44	0.34	0.38				0.16	0.20	0.10		
		(1.55)	(1.14)	(1.47)				(0.58)	(0.73)	(0.37)		
β_{ROE}		1.74***		1.66***				0.63***		0.42*		
		(7.47)		(5.80)				(3.01)		(1.94)		
$\beta_{lag-ROE}$			0.42						−0.04			
			(1.60)						(−0.12)			
$\beta_{\Delta ROE}$			1.63***						0.92***			
			(5.72)						(5.20)			
β_{EG}				0.22						0.96***		
				(0.88)						(5.36)		
β_{SMB}					−0.84***	−0.71***					−0.67***	−0.41***
					(−8.84)	(−5.76)					(−7.61)	(−3.72)
β_{HML}					0.47***	0.25*					−0.09	0.13
					(4.95)	(1.74)					(−0.71)	(1.01)
β_{CMA}					0.03						0.16	
					(0.24)						(0.83)	
β_{RMW}					0.41***						0.23	
					(2.59)						(1.62)	
β_{UMD}					1.17***						1.14***	
					(11.95)						(13.60)	
β_{SUE}						1.70***						0.66***
						(5.79)						(3.45)
β_{CAR4}						0.88***						1.47***
						(2.91)						(5.61)
R^2_{adj}	0.50	0.63	0.60	0.63	0.44	0.63	0.41	0.29	0.32	0.34	0.25	0.43

Table A2 (*continued*)
Panel B: Changes in alphas and factor loadings for PTH across market volatility states
This panels presents the changes in alphas and factor loadings from the time-series regressions of the high-minus-low decile on the ratio of current price to 52-week high price (PTH) conditional on the level of market volatility.The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Low − High					
	BF3	HXZ4	HXZ4^{a}	HXZ5	FF6	NM5
α	1.68***	1.93***	1.82***	1.41***	0.40	1.49***
	(2.93)	(3.74)	(3.51)	(2.64)	(1.26)	(2.75)
β_{MKT}	−0.02	−0.20	−0.12	−0.12	−0.20***	−0.02
	(−0.16)	(−1.61)	(−0.86)	(−0.88)	(−2.62)	(−0.18)
β_{PEAD}	−0.69					
	(−1.63)					
β_{FIN}	−0.39**					
	(−2.39)					
β_{ME}		0.42**	0.37*	0.49**		
		(2.01)	(1.86)	(2.38)		
β_{IA}		−0.28	−0.14	−0.29		
		(−0.71)	(−0.35)	(−0.78)		
β_{ROE}		−1.11***		−1.24***		
		(−3.53)		(−3.44)		
$\beta_{lag-ROE}$			−0.46			
			(−1.13)			
$\beta_{\Delta ROE}$			−0.70**			
			(−2.10)			
β_{EG}				0.74**		
				(2.40)		
β_{SMB}					0.17	0.29*
					(1.32)	(1.78)
β_{HML}					−0.55***	−0.13
					(−3.63)	(−0.66)
β_{CMA}					0.13	
					(0.53)	
β_{RMW}					−0.18	
					(−0.83)	
β_{UMD}					−0.03	
					(−0.26)	
β_{SUE}						−1.04***
						(−2.97)
β_{CAR4}						0.59
						(1.47)

Table A3

Panel A: Pricing of WML and Market Volatility

This panel presents the alphas and factor loadings from time-series regressions of the high-minus-low price momentum decile (WML) on the well-documented sets of asset-pricing factors in the two market volatility states. A month is defined as high (low) volatility if the past 12-month market volatility is higher (lower) than the lagged 36-month market volatility. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML) and earnings surprise (SUE and CAR4). The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High MVOL					Low MVOL				
	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	−0.83	−0.37	−0.59	−0.63	−0.93*	0.75**	1.37***	0.92***	0.55	0.33
	(−1.39)	(−0.74)	(−1.22)	(−1.20)	(−1.88)	(2.23)	(3.52)	(3.19)	(1.55)	(1.03)
β_{MKT}	−0.16	−0.13	−0.39***	−0.09	−0.28***	0.02	−0.16*	−0.37***	−0.03	−0.13
	(−1.34)	(−1.23)	(−3.75)	(−0.80)	(−3.23)	(0.18)	(−1.65)	(−3.98)	(−0.36)	(−1.54)
β_{PEAD}	2.10***					1.40***				
	(5.30)					(4.93)				
β_{FIN}	0.29					−0.02				
	(1.54)					(−0.14)				
β_{ME}		−0.02	−0.18	0.01			0.74***	0.38**	0.86***	
		(−0.09)	(−1.06)	(0.07)			(4.68)	(2.40)	(5.62)	
β_{IA}		−0.23	−0.28	−0.33			0.10	0.13	0.02	
		(−0.65)	(−0.78)	(−0.99)			(0.34)	(0.53)	(0.07)	
β_{ROE}		1.83***		1.69***			0.56**		0.30	
		(6.92)		(5.26)			(2.45)		(1.21)	
$\beta_{lag-ROE}$			−0.12					−0.51*		
			(−0.45)					(−1.93)		
$\beta_{\Delta ROE}$			2.14***					1.55***		
			(8.41)					(8.66)		
β_{EG}				0.39					1.17***	
				(1.17)					(5.25)	
β_{SMB}					−0.02					0.56***
					(−0.14)					(3.98)
β_{HML}					−0.15					0.31**
					(−0.85)					(2.05)
β_{SUE}					2.02***					1.18***
					(6.37)					(5.36)
β_{CAR4}					0.77**					1.27***
					(2.37)					(3.86)
R^2_{adj}	0.30	0.42	0.49	0.43	0.50	0.19	0.15	0.32	0.22	0.31

Table A3 (*continued*)

Panel B: Changes in alphas and factor loadings for WML across market volatility states

This table presents the changes in alphas and factor loadings from the time-series regressions of the high-minus-low price momentum decile (WML) conditional on the level of market volatility. The sample is 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Low − High				
	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	1.58**	1.73***	1.51***	1.18*	1.26**
	(2.30)	(2.76)	(2.68)	(1.86)	(2.14)
β_{MKT}	0.18	−0.03	0.02	0.06	0.15
	(1.16)	(−0.20)	(0.15)	(0.39)	(1.21)
β_{PEAD}	−0.70				
	(−1.43)				
β_{FIN}	−0.30				
	(−1.31)				
β_{ME}		0.76***	0.56**	0.84***	
		(3.20)	(2.41)	(3.57)	
β_{IA}		0.33	0.40	0.35	
		(0.72)	(0.94)	(0.81)	
β_{ROE}		−1.28***		−1.39***	
		(−3.66)		(−3.44)	
$\beta_{lag-ROE}$			−0.39		
			(−1.04)		
$\beta_{\Delta ROE}$			−0.59*		
			(−1.91)		
β_{EG}				0.78**	
				(1.97)	
β_{SMB}					0.58***
					(2.65)
β_{HML}					0.46**
					(1.96)
β_{SUE}					−0.85**
					(−2.19)
β_{CAR4}					0.50
					(1.08)

Table A4

Alphas and Cross-Sectional Return Dispersion

This table presents the raw and factor-adjusted returns of the high-minus-low deciles on past performance (WML) and the ratio of current price to 52-week high price (PTH) across different levels of cross-sectional return dispersion. At the end of each month $t-1$, all common stocks traded on NYSE, AMEX and NASDAQ are sorted into deciles based on their prior 11-month returns from $t-12$ to $t-2$ (the ratio of current price to 52-week high price of $t-2$) using NYSE breakpoints. We skip month $t-1$ and calculate monthly value-weighted returns for each decile for month t. The deciles are held for one month and rebalanced at the end of month t. We employ the past 3-month moving average of the market's monthly RD to define the level of return dispersion for month t. A month's RD is defined as the cross-sectional standard deviation of returns on 100 BM- and size-based portfolios. The top (bottom) 30% observations of the return dispersion series are the High-RD (Low-RD) periods, and the remaining periods are the Medium-RD periods. "CAPM" denotes the market model proposed by (Sharpe, 1964; Lintner, 1965; Black, 1972). "FF3" denotes the Fama and French (1993) three-factor model. "Carhart4" denotes the Carhart (1997) 4-factor model consisting of the FF3 factors plus the Momentum factor. "FF5" denotes the Fama and French (2015) five-factor model. The sample period in Panel A runs from July 1927 to December 2019, while the sample period in Panel B runs from July 1972 to December 2019, the sample period used in our tests. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Return Dispersion			
	High	Medium	Low	Low-High
Panel A: Jan 1927 - Dec 2019				
r_{WML}	0.55	1.07***	1.86***	1.31**
	(0.86)	(4.06)	(7.32)	(2.17)
r_{PTH}	−0.56	0.49*	1.37***	1.93***
	(−0.75)	(1.84)	(5.42)	(2.91)
α_{WML}^{CAPM}	0.96*	1.15***	1.83***	0.88
	(1.85)	(4.37)	(6.95)	(1.51)
α_{PTH}^{CAPM}	0.04	0.95***	1.70***	1.66***
	(0.07)	(4.09)	(7.22)	(2.95)
α_{WML}^{FF3}	1.36***	1.37***	1.88***	0.52
	(2.76)	(5.17)	(7.27)	(0.94)
α_{PTH}^{FF3}	0.64	1.15***	1.57***	0.93*
	(1.43)	(5.70)	(7.01)	(1.86)
$\alpha_{PTH}^{\text{Carhart4}}$	−0.20	0.46***	0.43**	0.63*
	(−0.69)	(2.72)	(2.40)	(1.85)
Panel B: July 1972 - Dec 2019				
r_{WML}	−0.14	1.68***	1.50***	1.64**
	(−0.18)	(4.51)	(4.51)	(2.12)
r_{PTH}	−0.72	1.71***	0.67**	1.39*
	(−0.86)	(4.58)	(2.02)	(1.75)
α_{WML}^{CAPM}	0.22	1.73***	1.46***	1.24
	(0.31)	(4.66)	(4.32)	(1.55)
α_{PTH}^{CAPM}	−0.02	1.97***	0.96***	0.98
	(−0.02)	(6.12)	(3.13)	(1.33)
α_{WML}^{FF3}	0.67	1.95***	1.46***	0.79
	(0.94)	(5.29)	(4.30)	(0.99)
α_{PTH}^{FF3}	0.57	1.82***	0.99***	0.42
	(0.90)	(6.16)	(3.29)	(0.61)
$\alpha_{PTH}^{\text{Carhart4}}$	0.05	0.55**	0.18	0.13
	(0.13)	(2.41)	(0.80)	(0.31)
$\alpha_{WML}^{\text{FF5}}$	0.10	2.01***	1.42***	1.32
	(0.12)	(4.89)	(3.86)	(1.44)
$\alpha_{PTH}^{\text{FF5}}$	−0.05	1.66***	0.86***	0.91
	(−0.07)	(4.99)	(2.74)	(1.18)

Table A5

Panel A: Pricing of PTH and Cross-Sectional Return Dispersion

This panel presents the alphas and factor loadings from time-series regressions of the high-minus-low 52-week high decile (PTH) on the well-documented sets of asset-pricing factors for each return-dispersion state. We employ the past 3-month moving average of the market's monthly RD to define the level of return dispersion for month t. A month's RD is defined as the cross-sectional standard deviation of returns on 100 BM- and size-based portfolios. The top (bottom) 30% observations of the return dispersion series are the High-RD (Low-RD) periods, and the remaining periods are the Medium-RD periods. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "FF6" adds the momentum factor (UMD) into the Fama-French 5-factor model (Fama and French, 2018). "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML), conservative-minus-aggressive (CMA), robust-minus-weak (RMW), momentum (UMD), and earnings surprise (SUE and CAR4). The sample is 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High RD						Medium RD						Low RD					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	−2.25***	−0.97	−1.20*	−1.40**	−0.13	−1.45**	0.50	1.06***	1.09***	0.61*	0.43*	0.55*	0.18	0.44	0.24	0.14	0.14	−0.14
	(−3.31)	(−1.56)	(−1.88)	(−2.24)	(−0.37)	(−2.29)	(1.26)	(3.53)	(3.54)	(1.87)	(1.85)	(1.76)	(0.56)	(1.24)	(0.72)	(0.38)	(0.62)	(−0.41)
β_{MKT}	−0.52***	−0.55***	−0.77***	−0.48***	−0.34***	−0.72***	−0.39***	−0.52***	−0.63***	−0.45***	−0.43***	−0.55***	−0.24***	−0.25**	−0.37***	−0.20**	−0.33***	−0.29***
	(−3.90)	(−4.33)	(−5.54)	(−3.28)	(−4.58)	(−7.11)	(−4.62)	(−7.69)	(−9.29)	(−6.35)	(−8.62)	(−8.03)	(−2.80)	(−2.50)	(−3.85)	(−2.12)	(−5.31)	(−3.09)
β_{PEAD}	2.22***						1.30***						0.77***					
	(5.57)						(5.46)						(3.33)					
β_{FIN}	0.78***						0.46***						0.71***					
	(6.29)						(3.66)						(4.93)					
β_{ME}		0.02	−0.21	0.06				−0.67***	−0.82***	−0.59***				−0.56***	−0.75***	−0.51***		
		(0.10)	(−1.09)	(0.26)				(−5.69)	(−5.95)	(−5.06)				(−3.79)	(−5.13)	(−3.56)		
β_{IA}		0.19	0.28	0.04				0.02	−0.05	−0.03				0.85***	0.85***	0.75***		
		(0.43)	(0.72)	(0.10)				(0.12)	(−0.28)	(−0.17)				(3.57)	(3.40)	(3.25)		
β_{ROE}		1.71***		1.54***				1.16***		0.96***				0.66***		0.40		
		(6.38)		(4.62)				(8.48)		(7.32)				(2.82)		(1.64)		
$\beta_{lag-ROE}$			0.20						0.29*						−0.17			
			(0.68)						(1.71)						(−0.68)			
$\beta_{\Delta ROE}$			1.80***						1.16***						1.01***			
			(5.42)						(7.34)						(5.70)			
β_{EG}				0.59						0.63***						0.63***		
				(1.49)						(3.46)						(3.30)		
β_{SMB}					−0.69***	−0.29*					−0.82***	−0.84***					−0.78***	−0.69***
					(−5.74)	(−1.83)					(−9.02)	(−6.75)					(−8.19)	(−5.42)
β_{HML}					0.39***	0.26					0.07	−0.04					0.14	0.51***
					(3.12)	(1.59)					(0.65)	(−0.35)					(1.01)	(3.05)
β_{CMA}					0.12						−0.09						0.40**	
					(0.61)						(−0.58)						(2.04)	
β_{RMW}					0.27*						0.38***						0.09	
					(1.67)						(2.59)						(0.46)	
β_{UMD}					1.23***						0.99***						1.12***	
					(11.75)						(12.80)						(12.58)	
β_{SUE}						1.47***						1.17***						0.87***
						(4.66)						(6.17)						(4.59)
β_{CAR4}						1.60***						0.76***						1.00***
						(4.36)						(3.13)						(3.68)
R^2_{adj}	0.56	0.56	0.56	0.57	0.81	0.62	0.43	0.53	0.52	0.55	0.75	0.56	0.30	0.30	0.37	0.33	0.62	0.41

Table A5 (*continued*)

Panel B: Changes in alphas and factor loadings for PTH across across cross-sectional return dispersion levels

This panel presents the changes in alphas and factor loadings from the time-series regressions of the high-minus-low decile on the ratio of current price to 52-week high price (PTH) conditional on the lagged cross-sectional return dispersion. The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Low − High						Medium − High						Low − Medium					
	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5	BF3	HXZ4	HXZ4^a	HXZ5	FF6	NM5
α	2.43***	1.40**	1.45**	1.54**	0.27	1.32*	2.74***	2.02***	2.29***	2.01***	0.56	2.01***	−0.32	−0.62	−0.85*	−0.47	−0.29	−0.69
	(3.23)	(1.97)	(2.00)	(2.13)	(0.64)	(1.83)	(3.50)	(2.94)	(3.22)	(2.84)	(1.31)	(2.84)	(−0.62)	(−1.34)	(−1.86)	(−0.96)	(−0.90)	(−1.50)
β_{MKT}	0.28*	0.31*	0.40**	0.28	0.01	0.43***	0.13	0.04	0.14	0.03	−0.09	0.17	0.14	0.27**	0.27**	0.25**	0.10	0.25**
	(1.75)	(1.89)	(2.39)	(1.60)	(0.11)	(3.09)	(0.85)	(0.25)	(0.88)	(0.19)	(−1.02)	(1.43)	(1.20)	(2.26)	(2.28)	(2.09)	(1.28)	(2.18)
β_{PEAD}	−1.45***						−0.93**						−0.52					
	(−3.14)						(−2.00)						(−1.57)					
β_{FIN}	−0.07						−0.32*						0.25					
	(−0.35)						(−1.79)						(1.31)					
β_{ME}		−0.58**	−0.53**	−0.57**				−0.69***	−0.61**	−0.65**					0.11	0.07	0.07	
		(−2.11)	(−2.21)	(−2.09)				(−2.66)	(−2.55)	(−2.49)					(0.58)	(0.35)	(0.40)	
β_{IA}		0.66	0.57	0.71				−0.17	−0.34	−0.07				0.83***	0.90***	0.78***		
		(1.32)	(1.22)	(1.48)				(−0.36)	(−0.77)	(−0.16)				(2.88)	(2.94)	(2.76)		
β_{ROE}		−1.05***		−1.14***				−0.56*		−0.58				−0.50*		−0.56**		
		(−2.95)		(−2.75)				(−1.84)		(−1.63)				(−1.83)		(−2.00)		
$\beta_{lag-ROE}$			−0.37						0.09						−0.46			
			(−0.96)						(0.27)						(−1.53)			
$\beta_{\Delta ROE}$			−0.79**						−0.64*						−0.15			
			(−2.09)						(−1.73)						(−0.64)			
β_{EG}				0.04						0.04						−0.01		
				(0.08)						(0.10)						(−0.02)		
β_{SMB}					−0.09	−0.40**					−0.13	−0.55***					0.04	0.15
					(−0.61)	(−1.97)					(−0.87)	(−2.72)					(0.28)	(0.82)
β_{HML}					−0.25	0.25					−0.31*	−0.29					0.06	0.55***
					(−1.38)	(1.08)					(−1.86)	(−1.52)					(0.35)	(2.75)
β_{CMA}					0.28						−0.20						0.49**	
					(1.03)						(−0.84)						(1.98)	
β_{RMW}					−0.18						0.12						−0.30	
					(−0.73)						(0.53)						(−1.24)	
β_{UMD}					−0.11						−0.24*						0.13	
					(−0.80)						(−1.81)						(1.06)	
β_{SUE}						−0.60						−0.30						−0.30
						(−1.62)						(−0.81)						(−1.11)
β_{CAR4}						−0.60						−0.84*						0.24
						(−1.32)						(−1.91)						(0.66)

Table A6

Panel A: Pricing of WML and Cross-Sectional Return Dispersion

This panel presents the alphas and factor loadings from time-series regressions of the high-minus-low price momentum decile (WML) on the well-documented sets of asset-pricing factors for each return-dispersion state. We employ the past 3-month moving average of the market's monthly RD to define the level of return dispersion for month t. A month's RD is defined as the cross-sectional standard deviation of returns on 100 BM- and size-based portfolios. The top (bottom) 30% observations of the return dispersion series are the High-RD (Low-RD) periods, and the remaining periods are the Medium-RD periods. "BF3" denotes the Daniel, Hirshleifer, and Sun (2020) 3-factor model. "HXZ4" denotes the Hou, Xue, and Zhang (2015) q-factor model. "HXZ4^a" denotes the alternative q-factor model suggested by Novy-Marx (2015b) where the ROE factor is decomposed into the lag-ROE and ΔROE factors. "HXZ5" denotes the Hou et al. (2020) augmented q-factor model. "NM5" denotes the fundamental momentum factor model suggested by Novy-Marx (2015a) consisting of FF3 and the earnings-surprise factors (CAR4 and SUE). The factors are the market (MKT), post-earnings announcement drift (PEAD), financing (FIN), size (ME or SMB), investment (IA), return on equity (ROE), lagged earnings-to-book equity (lagged-ROE), earnings innovations-to-book equity (ΔROE), value (HML) and earnings surprise (SUE and CAR4). The sample is 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	High RD					Medium RD					Low RD				
	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	-1.45^{*}	-0.78	-1.24^{*}	-1.27	-1.58^{**}	0.51	0.95^{**}	0.79^{**}	0.31	0.26	0.92^{**}	0.74^{*}	0.38	0.27	-0.00
	(-1.77)	(-1.03)	(-1.75)	(-1.60)	(-2.29)	(1.11)	(2.41)	(2.26)	(0.74)	(0.66)	(2.38)	(1.73)	(1.06)	(0.72)	(-0.01)
β_{MKT}	-0.35^{**}	-0.25	-0.52^{***}	-0.17	-0.38^{***}	0.04	-0.12	-0.34^{***}	-0.03	-0.21^{**}	0.06	0.00	-0.19^{**}	0.07	-0.01
	(-2.09)	(-1.56)	(-3.53)	(-0.92)	(-3.17)	(0.38)	(-1.27)	(-3.59)	(-0.29)	(-2.16)	(0.69)	(0.03)	(-2.42)	(0.86)	(-0.15)
β_{PEAD}	2.36^{***}					1.46^{***}					0.90^{**}				
	(5.64)					(5.37)					(1.99)				
β_{FIN}	0.19					0.17					0.05				
	(1.01)					(1.19)					(0.29)				
β_{ME}		0.63^{**}	0.34^{*}	0.67^{**}			0.10	-0.23	0.23			0.25	-0.05	0.32^{*}	
		(2.31)	(1.66)	(2.47)			(0.66)	(-1.24)	(1.45)			(1.24)	(-0.29)	(1.76)	
β_{IA}		-0.47	-0.21	-0.63			0.09	-0.15	0.03			0.23	0.23	0.08	
		(-0.90)	(-0.47)	(-1.30)			(0.42)	(-0.74)	(0.12)			(0.80)	(0.81)	(0.28)	
β_{ROE}		1.72^{***}		1.52^{***}			1.28^{***}		1.00^{***}			0.96^{***}		0.55	
		(5.38)		(3.92)			(7.11)		(5.25)			(3.37)		(1.62)	
$\beta_{lag-ROE}$			-0.34					-0.32					-0.37		
			(-1.20)					(-1.55)					(-1.34)		
$\beta_{\Delta ROE}$			2.27^{***}					1.93^{***}					1.60^{***}		
			(7.41)					(10.21)					(8.16)		
β_{EG}				0.66					0.90^{***}					0.98^{***}	
				(1.30)					(3.63)					(2.98)	
β_{SMB}					0.47^{**}					-0.02					0.08
					(2.47)					(-0.11)					(0.49)
β_{HML}					-0.08					0.09					0.43^{*}
					(-0.42)					(0.54)					(1.91)
β_{SUE}					1.80^{***}					1.87^{***}					1.59^{***}
					(5.14)					(8.27)					(5.94)
β_{CAR4}					1.51^{***}					0.66^{**}					0.53
					(3.73)					(1.97)					(1.24)
R^2_{adj}	0.36	0.34	0.48	0.35	0.50	0.18	0.18	0.35	0.24	0.33	0.07	0.08	0.28	0.15	0.26

Table A6 (*continued*)

Panel B: Changes in alphas and factor loadings for WML across cross-sectional return dispersion levels

This table presents the changes in alphas and factor loadings from the time-series regressions of the high-minus-low price momentum decile (WML) conditional on the lagged cross-sectional return dispersion. The sample is from 1972:07 to 2019:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Low − High					Medium − High					Low − Medium				
	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5	BF3	HXZ4	HXZ4^a	HXZ5	NM5
α	2.37***	1.52*	1.62**	1.55*	1.57**	1.96**	1.74**	2.03**	1.58*	1.83**	0.40	−0.22	−0.41	−0.03	−0.26
	(2.61)	(1.74)	(2.04)	(1.75)	(2.02)	(2.08)	(2.03)	(2.56)	(1.76)	(2.32)	(0.67)	(−0.37)	(−0.82)	(−0.06)	(−0.49)
β_{MKT}	0.41**	0.25	0.33**	0.24	0.37**	0.39**	0.12	0.18	0.14	0.17	0.02	0.13	0.15	0.10	0.20
	(2.17)	(1.37)	(1.96)	(1.20)	(2.51)	(1.98)	(0.66)	(1.02)	(0.65)	(1.08)	(0.18)	(0.95)	(1.20)	(0.76)	(1.55)
β_{PEAD}	−1.46**					−0.91*					−0.55				
	(−2.37)					(−1.82)					(−1.05)				
β_{FIN}	−0.14					−0.01					−0.13				
	(−0.57)					(−0.06)					(−0.58)				
β_{ME}		−0.38	−0.39	−0.34			−0.52*	−0.56**	−0.44			0.14	0.17	0.10	
		(−1.12)	(−1.41)	(−1.05)			(−1.66)	(−2.07)	(−1.42)			(0.56)	(0.65)	(0.41)	
β_{IA}		0.70	0.44	0.71			0.56	0.05	0.66			0.14	0.38	0.05	
		(1.17)	(0.83)	(1.26)			(0.99)	(0.11)	(1.23)			(0.37)	(1.09)	(0.15)	
β_{ROE}		−0.76*		−0.97*			−0.43		−0.53			−0.33		−0.45	
		(−1.78)		(−1.89)			(−1.18)		(−1.21)			(−0.97)		(−1.15)	
$\beta_{lag-ROE}$			−0.03					0.02					−0.04		
			(−0.07)					(0.05)					(−0.13)		
$\beta_{\Delta ROE}$			−0.66*					−0.34					−0.33		
			(−1.82)					(−0.94)					(−1.20)		
β_{EG}				0.31					0.24					0.08	
				(0.52)					(0.42)					(0.18)	
β_{SMB}					−0.40					−0.49*					0.10
					(−1.57)					(−1.95)					(0.42)
β_{HML}					0.51*					0.17					0.34
					(1.72)					(0.67)					(1.18)
β_{SUE}					−0.21					0.07					−0.28
					(−0.47)					(0.16)					(−0.79)
β_{CAR4}					−0.99*					−0.86					−0.13
					(−1.68)					(−1.63)					(−0.24)

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