What Explains Momentum When It Really Works?*

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Abstract

Puzzlingly, the literature has shown that behavioral factors capturing mispricing, the neoclassical-inspired investment q-factors, and momentum in factors can all subsume individual stock momentum. But tests subsuming momentum are unconditional while the bulk of its profits are predictable using its own lagged volatility. We compare asset pricing models *conditionally*, when the strategy really works, and find the unconditional fit misleading. Models fit well most times but not when profits are produced. Strikingly, momentum's conditionality cannot be attributable to either q-factors or factor momentum. Yet, both earnings announcement returns and analyst forecast errors show strong conditionality consistent with an underreaction channel.

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JEL Classification: G11; G12

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"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."

—Subrahmanyam (2018).

1 Introduction

Momentum is a pervasive anomaly in US markets for more than 200 years and confirmed out of sample in at least 40 countries (Geczy and Samonov 2016; Asness, Moskowitz, and Pedersen 2013). Asness, Frazzini, Israel, and Moskowitz (2014) remarks that "[..] it has been a part of markets since their very existence". Momentum has long been seen as a puzzle.[1] But this puzzle changed. Since its discovery, many theoretical explanations for the phenomenon have been proposed.[2] A problem is that most of the work proposing theories focuses on testing isolated explanations. Subrahmanyam (2018) points out that this has gradually created a situation with too many theories to explain the same phenomenon. Furthermore, those theories do not fit well together motivating the need for new "out-of-sample" ways to test them comparatively. Goyal, Jegadeesh, and Subrahmanyam (2025) recently perform such a comparative exercise in an international setting.

In this study, we work with similar spirit to Goyal, Jegadeesh, and Subrahmanyam (2025) but take a very different path. We note that momentum is far from an "all-weather" strategy as it has strongly predictable performance and a propensity to produce large crashes which can wipe out decades of returns (Cooper, Gutierrez Jr., and Hameed 2004; Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016). Namely, the realized volatility of momentum successfully captures conditionality in mean returns, volatility, Sharpe ratios, and skewness of the strategy (Barroso and Santa-Clara 2015; Barroso, Edelen, and Karehnke 2022). We build on this literature showing that momentum's performance is strongly *negatively* predicted by

[1] For example, Fama and French (1996) dub it the 'main embarrassment' (page 81) of their original multifactor model. However, later the factor is 'somewhat reluctantly' included in the factor model of Fama and French (2018).

[2] A non-exhaustive list of notable examples of proposed explanations includes underreaction (Barberis, Shleifer, and Vishny 1998; Hong and Stein 1999), overreaction (Daniel, Hirshleifer, and Subrahmanyam 1998), business cycle risk exposures (Chordia and Shivakumar 2002), growth options of winners (Sagi and Seasholes 2007), the neoclassical q-factor model (Hou, Xue, and Zhang 2015), and momentum in factors (Ehsani and Linnainmaa 2022).

its lagged volatility, to examine leading explanations for the anomaly in a conditional setting.

The leading theories we examine are 1) underreaction (Jegadeesh and Titman 1993; Hong and Stein 1999; Daniel, Hirshleifer, and Sun 2020), 2) the capital asset pricing model based on the neoclassical q-theory of investment (Hou, Xue, and Zhang 2015, hereafter, investment CAPM), and 3) factor momentum (Ehsani and Linnainmaa 2022). We pick these as they all span momentum in standard unconditional tests while coming from very different theoretical explanations.[3]

The economic drivers of momentum in our core set of theories could hardly be more diverse. In the investment CAPM—likely the first APT-like factor model spanning momentum—winners have higher returns (mostly) due to their loading on a profitability risk factor motivated by the firm value optimization problem. The resulting q-factor model successfully spans many test assets besides momentum, granting this multifactor explanation additional relevance. The model of Daniel, Hirshleifer, and Sun (2020) includes an underreaction factor while also spanning a large set of anomalies. As underreaction is an influential explanation for momentum in the behavioral literature, this merits its inclusion in our set of leading explanations. Factor momentum is of great theoretical consequence as it posits that momentum does not exist as a standalone factor, it merely "times other factors". Ehsani and Linnainmaa (2022) show that a model combining their factor momentum portfolio with the Fama and French (2015) 5-factor model spans conventional stock momentum. Persistent factor returns would therefore create the illusion of momentum in individual stocks.

It is hard to assess if our core set of three explanations are truly incompatible between themselves. Investor behavioral biases can work their way into factor premiums if asset returns are characterized by a strong underlying factor structure (Kozak, Nagel, and Santosh 2018). Thus, for instance, the investment CAPM might be compatible with an underreaction story.[4] Also, the question of what drives momentum does not need to be binary: it is possible that several theories capture different drivers of the anomaly and they all play a role (of equal

[3] In subsection 3.7 we expand the discussion to six more leading theories of momentum or of its conditionality.

[4] Hou, Xue, and Zhang (2015) explain that "our evidence is not inconsistent with mispricing. If waves of investor sentiment affect stocks with similar investment or stocks with similar profitability simultaneously, the q-factor model would work in the data as well". Yet, Zhang (2017)'s survey on the investment CAPM characterizes it as "an inevitable response to the anomalies literature and its challenge to efficient markets [...]". In our paper, we respect this characterization of one of its authors when referring to it as a risk-based theory.

importance or not). Regardless, this current state of observational equivalence is leaving on the table an important element: the time series properties of momentum.

In our study we start by confirming that our set of core factor models all span momentum unconditionally. Then, we examine if the same ability holds conditionally using a regression specification where momentum's loadings on factors are allowed to vary across volatility states. It is important to recognize that previous evidence on the conditionality of momentum does not necessarily imply that momentum would be mispriced in a conditional setting when controlling for recent risk factors. The high Sharpe ratios of momentum after low-risk (safe) months could be due to low volatility in the factors driving the anomaly in the first place or high expected returns in those factors or some combination of these. But our conditional regression results are not supportive of this conjecture. The preview of the results is displayed in Fig. 1.

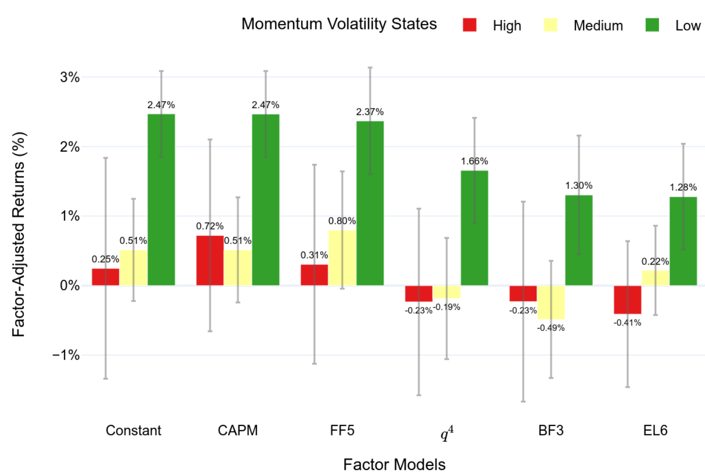

Figure 1 Conditional Performance of Momentum. This figure depicts the unadjusted and factor-adjusted performance (i.e., estimated alphas with confidence intervals) of the decile-spread momentum portfolio across three defined volatility states: High, Medium, and Low. The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), Fama-French 5-factor model (Fama and French 2015, FF5), q-factor model (Hou, Xue, and Zhang 2015, q^4), the 3-factor risk-and-behavioral model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). The sample period is 1972:07 to 2022:12. Volatility states are defined based on the lagged realized volatility of momentum, using the 30%-30% cutoff points.

Consistent with prior literature, momentum has strong conditionality. Fig. 1 shows that momentum profits concentrate in low-volatility months (2.47% vs 0.51% and 0.25% for other months), i.e., 73% of momentum profits occur in less than a third of the 1972:07–2022:12

sample.[5] In other months, momentum is a dismal strategy with insignificant returns.

More importantly, in non-low-volatility months, momentum returns can be subsumed not only by factor models that can span momentum unconditionally, including those based on q-factors, behavioral factors, and factor momentum, but also by conventional factor models such as CAPM (Sharpe 1964; Lintner 1965; Black 1972), and Fama and French (2015) 5-factor model. However, in low-volatility months, *no* models can span momentum.

An alternative test of those models' explanatory power for momentum's conditionality uses managed payoffs as recommended in Cochrane (2009, Ch. 8). We define four forms of managed momentum payoffs as functions of lagged realized volatility in momentum (i.e., investing more in the strategy when its lagged realized volatility is low). Testing the four managed momentum portfolios against three factor models results in twelve alpha estimates. Eleven of them are statistically significant at the 1% level, and the one left is still significant at the 5% level. So, consistent with conditional regression results, *none* of the factor models explains the conditionality of momentum.

Notably, both tests come to a consensus that all compared factor models fail to explain momentum returns in a conditional setting. From the conditionality tests, the specification that comes closer in terms of the magnitude of the t-statistic for regression alpha—which is proportional to information ratio of the test asset relative to the (ex-post) optimal combination of the underlying factors—is underreaction with the model of Daniel, Hirshleifer, and Sun (2020), but even this one fails to capture the returns of momentum after low-risk (safe) months and to span managed momentum payoffs. So, momentum has a conditionality beyond that of the factors.

Both forms of conditional spanning regressions are arguably only indirect tests of the economic mechanisms proposed in the literature. To account for this, we go beyond spanning tests and perform more direct tests of the explanations and their economic mechanisms. Below we briefly describe our main results for each core explanation.

Investment CAPM. According to the investment CAPM, expected profitability and expected investment growth are the relevant drivers of expected returns explaining momentum. Earnings-surprise factors in other models could capture something other than underreaction. They may capture the economic fundamentals of the investment CAPM. Supporting this interpretation, Liu, Whited, and Zhang (2009) show that innovations in earnings corre-

[5] This is computed as $\frac{2.47*0.3}{2.47*0.3+0.51*0.4+0.25*0.3} \approx 73\%$.

late positively with future investment growth. If this positive relation is stronger after safe months, then the pattern of predictability we find 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 are linked with future profitability and investment growth using Fama and MacBeth (1973, Fama-MacBeth) predictive regressions. This shows that past stock performance conveys roughly the same information about the firm's investment opportunity set in safe and risky months. But its correlation with expected returns increases significantly in safe states. As a result, firms' expected investment growth and profitability do not speak to the observed conditionality of momentum.

Factor Momentum. We first note that, unlike stock momentum, factor momentum does not exhibit conditionality on lagged volatility. Therefore, we assess if stock momentum's conditionality emanates from a time-varying association with factor momentum. But a conditional spanning regression analysis shows that stock momentum does not load more on factor momentum after low volatility periods. In fact, stock momentum tends to perform better when it is less correlated with factor momentum. On top of this, the predictive power of stock momentum volatility for returns does not disappear once controlling for factor momentum. So, factor momentum is an unlikely cause of momentum's conditionality.

Underreaction. Given the relative success of the model of Daniel, Hirshleifer, and Sun (2020) in our tests, we check if more direct proxies for underreaction match the observed time-variation in expected profitability of momentum. We build on studies using quarterly announcement returns to proxy for corrections in investor expectations (Jegadeesh and Titman 1993; La Porta 1996; La Porta, Lakonishok, Shleifer, and Vishny 1997) and find that, consistent with an underreaction channel, price signals become better predictors of subsequent earnings announcement date returns when momentum volatility is low. In an even more direct test of the underreaction hypothesis, we follow Hribar and McInnis (2012) and Antoniou, Doukas, and Subrahmanyam (2016), and study the magnitude of analyst forecast errors close to earnings announcements. This shows analysts become more optimistic than normal about loser stocks after low-volatility months, further confirming the underreaction channel.

Finally, a valid concern about conditional momentum is that is can be practically irrelevant due to excessive turnover and trading costs (Barroso and Detzel 2021). This concern is further justified as plain momentum is already costly to start with (Lesmond, Schill, and

Zhou 2004; Novy-Marx and Velikov 2016). But we show this concern can be turned on its head: momentum is costly to trade all the time while it is only (predictably) profitable in times of low volatility. So, we suggest simply not investing in the strategy when volatility is high. This, coupled with other cost mitigation approaches, saves much on costs and the resulting managed strategy overcomes reasonable transaction cost estimates by a substantial margin. The resulting best performing variant of such strategy can earn a net-of-cost Sharpe ratio of 0.80.

For robustness, we use the Down-market state variable proposed by Cooper, Gutierrez Jr., and Hameed (2004) as it was the first proposed predictor of momentum. Generally, conditionality also holds with market state variables.

Our results shed light on unresolved questions in the literature. For example, previous work on the performance of momentum conditional on its volatility relies centrally on statistical arguments such as the AR(1) nature of volatility (e.g., Barroso and Santa-Clara 2015; Moreira and Muir 2017). This does not explain though why volatility timing is much more effective for momentum than for other factors (see, for example, Moreira and Muir 2017; Cederburg, O'Doherty, Wang, and Yan 2020). All in all, our evidence on earnings announcement returns, analyst forecast errors, and conditional spanning regressions is supportive of volatility of momentum capturing time variation in underreaction in financial markets.

The starting point of our inquiry is that momentum's realized volatility is an unusually strong predictor of the anomaly and little is known before on why this holds. Our end result is that this strength is strongly linked to proxies of underreaction and not to other theories of momentum. Some explanations for underreaction would suggest this link all along. First, in the version of the model of Hong and Stein (1999) with only news watchers, a more gradual information diffusion should result in lower volatility as stocks would react less to fundamental shocks and, simultaneously, become more autocorrelated. Hirshleifer and Teoh (2003)'s model should also imply more underreaction and less volatility as limited attention increases. So, our results are broadly consistent with seminal theories of underreaction. Second, volatility can also capture time variation in the prevalence of sentiment-driven investors that are likely to underreact as argued in Antoniou, Doukas, and Subrahmanyam (2016).

Our work is particularly close to two papers contemporaneous with ours. Goyal, Jegadeesh, and Subrahmanyam (2025) test several theories of momentum in an international setting and also conclude that underreaction is the main cause. But they focus on different constructions of momentum in the cross section. By contrast, our results use time series predictors of the effectiveness of conventional momentum. Barroso, Detzel, and Maio (2025) recently adopt a similar time series approach to compare explanations for the beta anomaly conditional on volatility. Our work is on the momentum anomaly though, the one where the benefits of volatility timing most stand out and so the main mystery of volatility management strategies.

The remainder of our paper is structured as follows: Section 2 summarizes the literature related to our study, Section 3 presents the empirical results, and Section 4 concludes.

2 Related Literature

Our study is related to the literature on conditionality of momentum. Apart from low momentum risk states (Barroso and Santa-Clara 2015; Daniel and Moskowitz 2016), momentum has also been shown to be more profitable in up-market states (Cooper, Gutierrez Jr., and Hameed 2004), small-(cross-sectional)-return-dispersion states (Stivers and Sun 2010), high-sentiment states (Antoniou, Doukas, and Subrahmanyam 2013), low-market-volatility states (Wang and Xu 2015), liquid-market states (Avramov, Cheng, and Hameed 2016), and small-momentum-gap states (Huang 2022). Relative to this literature we show that recent factor models fail to capture the conditionality of momentum on its own volatility and provide a deeper examination into leading explanations for momentum.

Our work relates to the literature on explanations for momentum, such as underreaction, investment CAPM, and factor momentum. Jegadeesh and Titman (1993) discover momentum in U.S. equities and first consider investor underreaction to firm-specific information as its possible cause. Since then multiple studies argue that underreaction of stock prices to changes or trends in firm fundamentals drives momentum (Novy-Marx 2015a; Huang, Zhang, and Zhou 2019; Daniel, Hirshleifer, and Sun 2020; DeMiguel, Martín-Utrera, Nogales, and Uppal 2020; Lim, Sotes-Paladino, Wang, and Yao 2024).[6]

As for the investment CAPM literature, Hou, Xue, and Zhang (2015) show that the q-

[6] In a recent comprehensive exercise, Guo, Li, and Li (2022) compare a large number of explanations and find that underreaction to firm fundamentals is the single most promising explanation for momentum though a large portion of the anomaly is still left unexplained. Additionally, multiple theoretical models feature investors with limited attention underreacting to new information (Hirshleifer and Teoh 2003; DellaVigna and Pollet 2009; Hirshleifer, Lim, and Teoh 2011).

factor model derived from the investment CAPM captures momentum through a profitability factor sorted on firm's Return on Equity. This builds on Liu and Zhang (2014) who estimate the investment model structurally and document that past stock performance signals 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. Holding the level of investments constant, the NPV rule implies that, at the margin, high firm profitability must be offset by high cost of capital. Our study examines the compatibility of momentum's conditionality with the investment CAPM.

Our paper is also related to the recent studies on factor momentum. Ehsani and Linnainmaa (2022) document that (time-series) momentum in either 20 commonly used factors (labeled "off-the-shelf" in their paper) or high-eigenvalue principal component factors can subsume not only the conventional stock momentum of Jegadeesh and Titman (1993) but also alternative forms of stock momentum. In this study, we further investigate how time-series momentum in the off-the-shelf factors is associated with conditionality of stock momentum. Specifically, we examine whether time-varying profits of momentum stem from a similar conditionality of factor momentum or from a time-varying association with factor momentum.

Our work contributes to understanding the driver of another puzzling relative-strength anomaly: the 52-week high strategy of George and Hwang (2004). Similar to the conventional momentum strategy, the profits of the 52-week high strategy have been attributed to both underreaction-related behavioral biases (George and Hwang 2004; Li and Yu 2012) and association with q-factors including expected profitability and expected investment growth (George, Hwang, and Li 2018). We document that, in line with the patterns of analyst forecast errors sorted by the momentum signal, analysts are excessively optimistic about stocks whose prices are farthest from their 52-week highs and their excessive optimism are more pronounced when volatility is low.

Finally, by examining conditional asset pricing models, our work is also related to Avramov and Chordia (2006) who allow betas and risk premiums to vary as functions of state variables which hence characterize conditionality in the investment opportunity set. An important distinction though is that in Avramov and Chordia (2006) the predictability of characteristics for risk-adjusted returns is still assumed constant. The literature on momentum questions the validity of that assumption, and our empirical tests account for this source of conditionality.

3 Empirical Results

3.1 Data

We obtain U.S. stock market data from the Center for Research in Security Prices (CRSP) and accounting information from the Compustat Annual and Quarterly Fundamental Files. We adjust CRSP returns for delisting events following Hou, Xue, and Zhang (2020) whose procedure is adapted from that of Beaver, McNichols, and Price (2007). Analysts' forecasts for firms' quarterly earnings per share (EPS) are extracted from Institutional Brokers' Estimate System (I/B/E/S).

The sample period runs from July 1972 to December 2022.[7] Our sample selection follows standard practices in the asset pricing literature, particularly in the seminal replication study by Hou, Xue, and Zhang (2020). Specifically, our sample includes all common U.S. stocks (a CRSP share code of 10 or 11) listed on NYSE, AMEX or NASDAQ (a CRSP exchange code of 1, 2 or 3). We exclude financial firms with Standard Industrial Classification (SIC) codes between 6000 and 6999 and firms with negative book equity.[8]

The primary portfolio we examine is the decile-spread momentum portfolio (denoted as WML), whose return is calculated as the value-weighted return of the "Winners" decile minus the value-weighted return of the "Losers" decile. Daily and monthly returns of individual decile portfolios are obtained from the q-data library of Hou, Xue, and Zhang (2020).

Specifically, the momentum portfolio is formed on stocks' prior 11-month return from month $t-12$ to $t-2$ (denoted as $r_{2,12}$), which is also the primary stock-level variable in our empirical analysis. Only stocks with complete 11-month return history are considered. Note that month $t-1$ is skipped to avoid the impact of short-term reversal documented in Jegadeesh (1990).At the end of each month $t-1$, stocks are sorted into deciles based on $r_{2,12}$ using NYSE breakpoints. For each decile, a value-weighted portfolio is formed, with market

[7] The starting date is restricted by the availability of quarterly earnings announcement dates (Compustat item RDQ).

[8] These sample filters are also used in other asset pricing studies (e.g., Fama and French 2008; Hou, Xue, and Zhang 2015, 2020; Daniel, Hirshleifer, and Sun 2020; Hou, Mo, Xue, and Zhang 2021).

value at the end of month $t-1$ as weights; the portfolio is rebalanced monthly (i.e., one-month holding period). Daily value-weighted returns for each decile within month t are calculated using the market equity at the end of the previous trading day as weights. The monthly returns on portfolios for Fama and French (1993)'s 3-factor model and Fama and French (2015)'s 5-factor model are sourced from Kenneth French's Data Library, which provides the market (MKT), size (SMB), value (HML), investment (CMA), and profitability (RMW) factors. The monthly returns on portfolios for Hou, Xue, and Zhang (2015)'s q-factor model, which consists of the market (MKT), size (ME), investment (IA), and profitability (ROE) factors, are obtained from the q-data library. The monthly returns on Daniel, Hirshleifer, and Sun (2020)'s short- and long-horizon behavioral factors (PEAD and FIN factors), and Ehsani and Linnainmaa (2022)'s (off-the-shelf) factor momentum portfolio (FMOM), are obtained from the authors' respective websites. Details of other stock characteristics and portfolios used in our empirical analysis are provided in Section IA1 of the Internet Appendix.

3.2 Definition of Momentum Volatility States

The primary predictor of momentum returns we consider is the realized volatility of momentum (Barroso and Santa-Clara 2015, RV). At the end of each portfolio formation month $(t-1)$, we compute the realized volatility of WML, $\hat{\sigma}_{\mathrm{WML,t-1}}$, using daily momentum returns over the previous 126 trading days, which is given by

$$\hat{\sigma}_{\mathrm{WML,t-1}} = \left(21 \sum_{j=0}^{125} \frac{\mathrm{r}^2_{\mathrm{WML,d_{t-1}-j}}}{126} \right)^{\frac{1}{2}}, \tag{3.1}$$

where $\mathrm{r_{wml,d}}$ denotes a daily WML return and d_{t-1} denotes the last trading day of month $t-1$.

We split the sample period into three volatility states using the 30%-30% cutoff points for $\hat{\sigma}_{\mathrm{WML,t-1}}$.[9] The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML,t-1}}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. Therefore, in our study, the classification of period t as a safe or low-volatility month (or state), consistently uses a

[9] Antoniou, Doukas, and Subrahmanyam (2013) and Asness, Frazzini, and Pedersen (2019) use the same cutoff points to define states of market sentiment and market volatility.

variable known in real time (at $t-1$).

3.3 Conditional Performance of Momentum

In this section, we examine the unadjusted and factor-adjusted conditional performance of momentum. We consider five prominent factor models in the literature including the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), Fama-French 5-factor model (Fama and French 2015, FF5), q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6).

The q^4, BF3, and EL6 models have been shown to subsume momentum unconditionally by Hou, Xue, and Zhang (2015), Daniel, Hirshleifer, and Sun (2020) and Ehsani and Linnainmaa (2022), respectively.[10]

In Section 3.3.1, we employ a conditional regression specification, allowing alphas and factor loadings of momentum to vary across volatility states of momentum to investigate the conditionality of momentum. In Section 3.3.2, we examine the performance of *four* conditional momentum strategies contingent on the volatility states of momentum using an unconditional regression model, where alphas and factor loadings are time-invariant. In Section 3.3.3, we use an out-of-sample setting to demonstrate how investors can benefit from exploiting the conditionality of momentum after accounting for the transaction costs of individual stocks.

3.3.1 Conditional Regressions

[Insert Table 1 near here]

[10] Admittedly, the claim that these models subsume momentum even unconditionally is not without controversy. Novy-Marx (2015b) casts doubt on the interpretation of the q-factor result while several papers question the robustness of factor momentum (Fan, Li, Liao, and Liu 2022; Cakici, Fieberg, Metko, and Zaremba 2025). Still, these explanations are there in the literature, their economic mechanisms have not been dismissed and we confirm they span momentum in straightforward unconditional tests following the original papers. Besides, as the conditional asset pricing literature points out, dismissing a model in unconditional tests is not enough: the model can still hold conditionally (see, for example, Lewellen and Nagel 2006; Cochrane 2009).

The column labeled "Unc." in Table 1 summarizes unconditional returns and alphas of WML over the period of July 1972 to December 2022 (see Table A1 in the Appendix for full regression results). Consistent with the prior literature, WML can produce a statistically significant average monthly return of 1.02% over the sample period (t-statistic = 3.38); the CAPM and FF5 models fail to explain it with significant regression alphas at the 1% level. Not surprisingly, FF5 has limited explanatory power for momentum as the model is primarily designed to capture the long-term stock anomalies (Daniel, Hirshleifer, and Sun 2020). Additionally, WML's return is even higher after adjusting for its exposure to the market factor (CAPM-alpha = 1.21%) or the FF5 factors (FF5-alpha = 1.24%). In line with the findings shown in the corresponding papers, the q^4, BF3 and EL6 models can all subsume momentum unconditionally. Table A1 in the Appendix indicates that WML heavily loads on the three previously proposed momentum drivers: 1) the profitability (ROE) factor under the investment CAPM (t-statistic = 7.37); 2) the short-run earnings-surprise (PEAD) factor (t-statistic = 6.71), which is motivated by inattention-driven investor underreaction; and 3) the momentum in factor returns (FMOM) with a t-statistic of 12.99. The EL6 model achieves the highest R^2_{adj} of 49%. In terms of the absolute value of t-statistic associated with regression alpha ($|\hat{\alpha}|$), BF3 performs the best in capturing WML.

The following three columns of Table 1 present raw (excess) returns, alphas and Sharpe ratios earned by WML in different volatility states. We employ the following specification to estimate the alphas of WML in each volatility state:

$$\mathrm{WML_t} = \alpha_{s_0} + \alpha_{s_1} I_{s_1,t-1} + \alpha_{s_2} I_{s_2,t-1} + \sum_{k=1}^{K} (\beta_{k,s_0} + \beta_{k,s_1} I_{s_1,t-1} + \beta_{k,s_2} I_{s_2,t-1}) f_{k,t} + \epsilon_t, \quad (3.2)$$

where s_0 denotes the underlying state, s_1 and s_2 denote the remaining two states, $I_{s_1,t-1}$ ($I_{s_2,t-1}$) is an indicator for state s_1 (state s_2), and $f_{k,t}$ represents returns on factor k in month t. This specification is a standard conditional test that can be seen as a special case of Shanken (1990)'s conditional models, one in which the lagged instruments consist of dummy variables (see Barroso, Detzel, and Maio 2025, for example). Notably, the reported alphas can be conventionally interpreted as risk-adjusted returns even if volatility is not a traded factor. This is so since lagged volatility is used and therefore its interaction with any contemporaneous traded factors is still a tradeable dynamic strategy (Cochrane 2009).

"High", "Medium", and "Low" columns provide the values of the estimated alpha ($\hat{\alpha}_{s_0}$)

and Sharpe ratio when the underlying volatility state is High-RV, Medium-RV, and Low-RV, respectively. The estimated factor loadings ($\hat{\beta}_{s_0}$) in each volatility state are reported in Panel A of Table A2 in the Appendix. The general pattern is that WML tends to be stronger in safe states and weaker in risky sates. This pattern is immediately observable for raw average returns. Over the 1972–2022 period, 73% ($\frac{30\%\times 2.47}{1.02}$) of WML profits occur in less than a third of the sample, only in Low-RV months. In addition, over these safe periods, WML attains an impressive Sharpe ratio of 2.02. So, the profits of WML concentrate in a relatively small subsample. The natural converse of this statement is that in most of the sample, the anomaly has little profitability.

Notably, all factor-adjusted returns are statistically indistinguishable from zero for the WML portfolio held both in High-RV months and in Medium-RV months. The CAPM and FF5 models, which cannot capture momentum unconditionally, can even span it in the two states. In contrast, all factor-adjusted returns in Low-RV months are significantly positive, indicating that all models fail to explain the anomaly. Hence, the unconditional fit of momentum with the q^4, BF3, and EL6 models is somewhat misleading as that regression assumes time-invariant alphas and factor loadings for a test asset with significant time-varying payoffs. Notably, we should not expect factor models to explain anomalies all the time. But this test shows that a simple variable known ex ante can pick in real time subsamples when available factor models *won't* price the anomaly. On top of it, those periods correspond to a relatively small part of the sample and the one where the bulk of raw returns are produced in the first place.

Specifically, WML in the Low-RV subsample yields positive factor-adjusted returns of 2.47%, 2.37%, 1.66%, 1.30%, and 1.28% relative to the CAPM, FF5, q^4, BF3, and EL6 models, respectively, all of which are statistically significant at the 1% level. For this risk regime, BF3 outperforms other models in explaining WML in terms of t-statistic of the alpha, which is proportional to information ratio of WML relative to the (ex-post) mean-variance optimal combination of underlying factors. This highlights the importance of the earnings-surprise factor in explaining momentum. Still, no factor model seems able to fully explain momentum returns when the strategy (predictably) works. The best models—BF3 and EL6—can account for almost half of momentum's raw returns in safe periods. But the remainder is economically meaningful, about 130 basis points (bps) per month, and statistically significant.

The "L − M&H" column of Table 1 presents the differences in alphas and Sharpe ratios between the Low-RV subsample and the rest of the sample (i.e., High- and Medium-RV subsamples combined). The differences in alphas are estimated using the following specification:

$$\mathrm{WML_t} = \alpha_0 + \alpha_L I_{L,t-1} + \sum_{k=1}^{K} (\beta_{k,0} + \beta_{k,L} I_{L,t-1}) f_{k,t} + \epsilon_t, \tag{3.3}$$

where $I_{L,t-1}$ denotes an indicator for the Low-RV state, $\hat{\alpha}_L$ corresponds to the estimated difference in alphas, and $\hat{\alpha}_0$ represents the estimated alphas in non-safe states (reported in the "M&H" column). In addition, the differences in factor loadings ($\hat{\beta}_{k,L}$) are reported in Panel B of Table A2 in the Appendix.

The results in the "L − M&H" column show that returns in safe periods are significantly higher than in riskier periods with a t-statistic for the difference of 4.03. Remarkably, for all models, the factor-adjusted returns of WML increase significantly in safe months with t-statistics on the differences ranging from 2.73 to 3.62. The differences are also economically important, from 145 bps to 178 bps. The best model capturing conditionality is EL6 that explains about 30% ($\approx 1 - 1.45/2.07$) of the change in raw returns across states. Still, most conditionality in raw returns, 70% to 86%, eludes even the best models subsuming momentum in unconditional tests.

As for the difference in loadings on the three previously proposed drivers of momentum (ROE, PEAD, and FMOM) reported in Panel B of Table A2 in the Appendix, WML shows less exposure to all of them in safe states. In particular, WML is significantly less exposed in those periods to the ROE factor, suggesting that both the success of the q-factor model in capturing WML unconditionally and the co-movement of WML with the ROE factor are driven by the normal and risky subsamples where WML does not generate any premium in the fist place. So, stock momentum is a much stronger phenomenon in low volatility months and none of the models in our study seem able to explain that.

The last row shows that the Sharpe ratio of momentum increases 25 fold from High- to Low-volatility periods (0.08 versus 2.02).[11] We use 100,000 bootstrap samples to compute the associated two-sided p-value for the difference in Sharpe ratios between safe periods and the

[11] Notably, this compares with a five-fold increase in a similar test for the beta anomaly in **?**. This showcases that momentum's conditionality on lagged volatility stands out relative to other leading equity factors (of which betting-against-beta already is one of the strongest cases).

rest and find this difference is significant at the 1% level. This pronounced conditionality of the Sharpe ratio points to a possibly neglected limit of APT-like explanations for momentum as those in the tested models. If M stands for the stochastic discount factor (SDF) pricing all assets in the absence of arbitrage opportunities, then $\sigma_t(M_{t+1})/E_t(M_{t+1})$ is the maximum Sharpe ratio in the market (see, e.g., Cochrane 2009, Ch. 1). Then, the conditional Sharpe ratio of momentum should be:

$$SR_t(WML_{t+1}) := \frac{E_t(WML_{t+1})}{\sigma_t(WML_{t+1})} = \frac{\sigma_t(M_{t+1})}{E_t(M_{t+1})} \times [-\rho_t(M_{t+1}, WML_{t+1})] \tag{3.4}$$

This implies that a higher Sharpe ratio for momentum in safe months should come from either a higher Sharpe ratio for the aggregate economy or a stronger (more negative) correlation with M_{t+1}. The first channel is counterintuitive since volatility shows a very strong commonality across factors—volatile periods for momentum tend to be also volatile periods for other factors and thus for likely SDFs. As Moreira and Muir (2017) point out, rational risk-averse investors should require higher compensation for risk when risk is high, making this an implausible channel for the conditionality of momentum. The second channel is equally unlikely since momentum is generally *less* correlated with all relevant observable risk factors when risk is low (see Table A2 in the Appendix). So, the anomaly would need to significantly load on unknown factors in all tested models and also moreso when its risk is low. Furthermore, as absolute correlations cannot be larger than one, the resulting SDF would need to imply conditional Sharpe ratios in safe periods exceeding 2.02 which is the Sharpe ratio of momentum. This largely exceeds 0.5, the estimated Sharpe ratio of the market in Mehra and Prescott (1985) and considered a puzzle therein. Therefore, an hypothetical APT-like model able to span momentum in safe months should also allow for Sharpe ratios in the economy violating conventional "good deal" boundaries.[12]

3.3.2 Conditional Momentum Strategies

To further demonstrate the conditionality of momentum profits, we next examine how well the newly proposed factor models explain momentum payoffs contingent on volatility states

[12] A Sharpe ratio about twice that of the market is often considered as a rough approximation of a "good deal" boundary above which an anomaly starts to look more like an arbitrage opportunity (Ross 1976; Shanken 1992; Cochrane and Saa-Requejo 2000). MacKinlay (1995) considers a more conservative value of 0.6 already implausible for anomaly portfolios.

using unconditional regressions. We heed the advice in Cochrane (2009) and characterize conditionality through managed portfolios that change their exposure dynamically as a function of lagged instruments—which is the realized volatility of momentum in our study. We consider the following four risk-managed momentum strategies based on $\hat{\sigma}_{\mathrm{WML,t-1}}$:

- Strategy (1): holds only the risk-free asset, except in Low-RV months when it implements the momentum strategy. The excess returns in Low-RV, Medium-RV, and High-RV months are respectively the WML returns, zero, and zero;

- Strategy (2): holds the market portfolio, except in Low-RV months when it switches to the momentum strategy. The excess returns in Low-RV, Medium-RV, and High-RV months are respectively the WML returns, the market excess returns, and the market excess returns.

- Strategy (3): implements the momentum strategy in Low-RV months, holds the risk-free asset in Medium-RV months, and implements the reverse momentum strategy (i.e., losers-minus-winners) in High-RV months. The excess returns in Low-RV, Medium-RV, and High-RV months are respectively the WML returns, zero, and the WML returns multiplied by -1.

- Strategy (4): It is the risk-managed momentum strategy proposed by Barroso and Santa-Clara (2015). The monthly excess return is defined as $\frac{12\%}{\hat{\sigma}_{\mathrm{WML,t-1}} \times \sqrt{12}} \times \mathrm{WML_t}$, where the numerator corresponds to the target level of (annualized) volatility.

Table 2 presents unadjusted returns, factor-adjusted returns and Sharpe ratios of the four strategies.[13] All of them can produce statistically significant returns at the 5% level ranging from 0.67% earned by Strategy (3) to 1.24% earned by Strategy (4). After accounting for risk, Strategies (1), (2), and (4) can achieve impressive Sharpe ratios of 1.00, 0.91, and 0.88, whereas Strategy (3) delivers a more modest Sharpe ratio of 0.35 but it is designed to reflect more conditionality of momentum relative to factor models than in this metric.

For the abnormal returns relative to the three models that can subsume WML unconditionally, eleven out of the twelve alphas are statistically significant at the 1% level, and the remaining one is significant at the 5% level with a t-statistic of 2.54. In line with the

[13]The full regression results are available in Table IA1 of the Internet Appendix.

conditional regression results above, the BF3 model outperforms the q^4 and EL6 models in terms of t-statistic of alpha across all four strategies.[14] As for the two models that cannot span unmanaged momentum, both generally fail to capture the managed momentum as well.

Overall, the evidence presented in Table 1 and Table 2 jointly suggests that all models, including those capable of spanning momentum unconditionally, fail to capture the conditionality of the anomaly. The underreaction channel in BF3 generally produces the best fit, but it still leaves most conditionality of momentum unexplained.

3.3.3 Investment Implications of Momentum's Conditionality

A known problem of volatility managed strategies is that they imply too much turnover and tend to perform poorly after costs (Barroso and Detzel 2021). This leads to the question of whether investors could benefit from conditioning their exposure to momentum on its lagged realized volatility. In this section, we showcase how investors can benefit from the conditionality of momentum after transaction costs. For this we propose a minimalist dynamic strategy exploiting conditionality in momentum. More complex approaches might yield better results but this would imply shifting our focus to implementation, which is not the main research question of our study.

At the end of each formation month $(t-1)$, investors in our minimalist dynamic strategy implement the (zero-cost) momentum strategy only when the volatility state is low; otherwise they hold the risk-free asset. To ensure this investment strategy is implementable, the volatility state is defined using an expanding look-back window starting from 1927:06 to determine whether $\hat{\sigma}_{\text{WML},t-1}$ in a certain formation month is below 30% of the expanding sample.[15]

We examine the performance of this conditional momentum strategy with holding periods of 1 month, 3 months and 6 months, which are denoted as "Cond1", "Cond3", and "Cond6", respectively. The stock weights under a conditional strategy at the end of a formation month

[14] On top of this, in Section IA2.1 of the Internet Appendix, based on the specification proposed in Shanken (1990), we directly employ $\hat{\sigma}_{\text{WML},t-1}$ as a continuous variable to test the conditionality of WML. Again, BF3 performs better than q^4 and EL6 in capturing time-varying profits of momentum, with a notable t-statistic of -1.89 for the coefficient measuring the response of returns to one-standard-deviation increase in lagged $log(\hat{\sigma}_{\text{WML},t-1})$.

[15] For WML portfolios between Jan 1927 and Dec 1966, whose daily returns are not available on the q-data library, we construct them along the lines of Hou, Xue, and Zhang (2020)'s methodology (see Section IA1.1 of the Internet Appendix).

$(t-1)$ can be expressed as:

$$w_{i,t-1} = \sum_{h=1}^{H} \frac{1}{H} w_{mom,i,t-h} \times I_{L,t-h}, \tag{3.5}$$

where $H \in \{1, 3, 6\}$ denotes the holding period, $w_{mom,i,t-h}$ denotes the weights of stock i in the value-weighted decile-spread momentum portfolio formed in month $t-h$, and $I_{L,t-h}$ is an indicator for the Low-RV state for formation month $t-h$. Note that in the absence of $I_{L,t-h}$, $w_{i,t-1}$ corresponds to the weights of stock i in the (unconditional) H-month overlapping momentum strategy. Since traders are assumed to invest 100% in the risk-free asset ($w_{rf,t-1} = 1$) and the momentum portfolio is self-financed by design, the sum of asset weights (including $w_{rf,t-1}$) for a strategy at the end of month $t-1$ after rebalancing always equals one, that is, $w_{rf,t-1} + \sum_i w_{i,t-1} = 1$.

[Insert Figure 2 near here]

In Fig. 2, we compare the strategy's performance in terms of before-cost and after-cost Sharpe ratios against those of the standard unconditional momentum strategy (i.e., WML) and the unconditional momentum strategy executed with the "banding" technique, a transaction-cost-mitigation approach recommended by Novy-Marx and Velikov (2019) for common characteristic portfolios. We apply the 10%/20% rule for the "banding" strategy in which traders go long (short) stocks with past returns in the top (bottom) decile and keep them until they drop out of the top (bottom) quintile. We compute portfolio turnover (TO) as:

$$TO_{t-1} = \frac{1}{2} \sum_i |w_{i,t-1} - \tilde{w}_{i,t-1}|, \tag{3.6}$$

where $w_{i,t-1}$ denotes the weight of stock i at the end of month $t-1$ after rebalancing and $\tilde{w}_{i,t-1}$ denotes the the weight of stock i at the end of month $t-1$ just before rebalancing (i.e., inertia weight), $\tilde{w}_{i,t-1} = \frac{w_{i,t-2} r_{i,t-1}}{1 + r_{rf,t-1} + \sum_i w_{i,t-2} r_{i,t-1}}$. Note that stocks leaving the portfolio are also considered in the calculation of turnover. The net-of-cost return ($r_{net,t}$) is computed as

$$r_{net,t} = r_{rf,t} + \sum_i w_{i,t-1} r_{i,t} - \sum_i \kappa_{i,t-1} |w_{i,t-1} - \tilde{w}_{i,t-1}|, \tag{3.7}$$

where $\kappa_{i,t-1}$ denotes one-way Hasbrouck (2009) trading costs of stock i at the end of month $t-1$. We follow Novy-Marx and Velikov (2016) to impute missing values for $\kappa_{i,t-1}$. When $\kappa_{i,t-1} = 0$, Eq. (3.7) becomes the formula for gross returns. The net-of-cost Sharpe ratio (SR) is calculated as:

$$SR_{net} = \frac{mean(r_{net,t} - r_{rf,t})}{std(r_{net,t} - r_{rf,t})} \tag{3.8}$$

The turnover of WML is 72.94% per month on average, eroding gross returns by 64 bps. So, the Sharpe ratio drops from 0.47 to 0.17 after accounting for trading costs. As a result, the standard momentum portfolio is relatively expensive to trade (Lesmond, Schill, and Zhou 2004; Novy-Marx and Velikov 2016). By using the "banding" technique, the turnover and trading costs reduce by about 30 percentage points (from 72.94% to 42.17%) and 28 bps (from 64 bps to 36bps), respectively. The cost-mitigated portfolio has a net-of-cost SR of 0.30.

The gross SR of momentum can be significantly improved by implementing the momentum strategy contingent on volatility states. The before-cost SRs of the three proposed conditional strategies are 0.90, 0.96, and 0.89. As expected, the turnover of the conditional strategy is negatively correlated with the implementation period. Economically, the best-performing strategy is the 3-month conditional momentum in terms of not only before-cost SR but also after-cost SR (0.80). The 1-month and 6-month strategies deliver slightly lower net SRs of 0.62 and 0.77, respectively. All show robust improvements in after-cost profitability.

In sum, momentum is a costly strategy to implement and moreso in volatile times. But our conditional tests show this costly signal to trade on is also virtually irrelevant, even before costs, in about 70% of the sample (non-safe periods). Therefore, exploiting the conditionality of momentum does not necessarily imply more trading. In fact, conditionality can be used instead to *reduce* turnover and trading costs, canceling superfluous trades, and thus improve after-cost profitability.

3.4 Direct Tests of Three Economic Mechanisms

The core set of explanations in our study rely on considerably different economic mechanisms. These have little in common beyond motivating empirical specifications that all span momentum in unconditional tests. Here, we go beyond conditional spanning tests and take a closer look at the underlying three economic mechanisms: 1) Investment CAPM, 2) Factor Momentum, and 3) Underreaction.

Conditional tests have the merit of incorporating predictability into the setting, but it could also be argued that they are only indirect tests of the momentum drivers proposed in the literature. Indeed, the interpretation of those tests is predicated on the notion that risk factors derive their premiums from the explanations proposed for their existence, which is not necessarily true.

For instance, even in unconditional tests, there is an unsettled debate about whether the profitability factor truly captures what it is intended to measure. Novy-Marx (2015b) decomposes the ROE factor of q^4 into a low frequency earnings profitability factor and a post-earnings announcement drift factor, and posits that q^4 subsumes momentum through the earnings-surprise channel, not due to firm profitability per se. Based on this finding, Novy-Marx (2015a) further introduces an ad hoc factor model augmenting the Fama and French (1993) 3-factor model with two earnings-surprise factors and finds that momentum is fully captured by momentum in firm fundamentals. In addition to the factor based on cumulative abnormal returns around the most recent quarterly earnings announcement—the underlying variable used by Daniel, Hirshleifer, and Sun (2020) to construct the PEAD factor as well—he includes a factor formed on standardized unexpected quarterly earnings (sue). Taken together, these results suggest the ROE factor may capture the same underreaction phenomenon as PEAD in BF3. On the other hand, Liu, Whited, and Zhang (2009) show that future firm investment growth and future firm profitability are positively correlated with recent earnings surprises of firms. Hence, it could also be argued that the relative success of the BF3 model in explaining momentum conditionally can be driven through the investment CAPM channel rather than the underreaction channel. In sum, the investment CAPM profitability factor could instead proxy for underreaction while earnings surprise factors—supposed to capture underreaction—can in turn recover their explanatory power from investment CAPM fundamentals.

Given the ambiguous interpretation of the results on the earnings-surprise factor, we design a set of hopefully more incisive tests of the three mechanisms and their implications for conditionality. For the investment CAPM, we follow George, Hwang, and Li (2018) and directly examine the dynamics of the relation between past returns and both future firm profitability and investment growth using cross-sectional Fama-MacBeth regressions. For factor momentum, we first examine whether the FMOM factor itself exhibits any time variations in profits using its own lagged realized volatility. After that, we investigate whether the conditionality of stock momentum stems from its time-varying association with factor momentum. For investor underreaction, we perform two tests: i) cross-sectional Fama-MacBeth regressions to investigate how past returns are associated with cumulative returns around the upcoming quarterly earnings announcement; and ii) directly examine conditionality in earnings forecast errors of analysts.

3.4.1 Fama-MacBeth Regressions

To mitigate the biases resulting from overweighting microcaps, we follow recent studies (e.g., George, Hwang, and Li 2018; Hou, Xue, and Zhang 2020; Harvey and Liu 2021) and implement cross-sectional Fama-MacBeth regressions using weighted-least-squares (WLS) with market equity in month $t-1$ as weights and ordinary-least-squares (OLS) for non-microcap stocks (i.e., those with market capitalization exceeding the 20th percentile threshold of NYSE stocks). Specifically, for *each month* (t), we run a cross-sectional regression using the following specification

$$\sqrt{w_{i,t-1}}y_{i,t}^{k} = b_t^{0,k}\sqrt{w_{i,t-1}} + \sum_j b_t^{j,k}\sqrt{w_{i,t-1}}c_{i,t-1}^{j} + \epsilon_{i,t}^{k}, \tag{3.9}$$

where $y_{i,t}^{k}$ denotes dependent variable k in month t (e.g., future returns, future investment growth, or future profitability) for stock i, and $c_{i,t-1}^{j}$ denotes characteristic variable j such as $r_{2,12}$ computed at the end of month $t-1$ (i.e., portfolio formation month) for stock i. $w_{i,t-1}$ represents weight of stock i in a cross-sectional regression. When performing cross-sectional WLS regressions, we set $w_{i,t-1}$ proportional to market cap of stock i at the end of month $t-1$. When performing cross-sectional OLS regressions, we set $w_{i,t-1}$ to one. The main independent variable we consider is the sorting characteristic of WML (i.e., $r_{2,12}$).

In the second stage, we run a time-series regression of monthly estimated coefficients on characteristic j onto the intercept term only to get an unconditional coefficient estimate. To get the estimated coefficient on characteristic j in each volatility state, we run the following time-series regression:

$$\hat{b}_t^{j,k} = a_{s_0}^{j,k} + a_{s_1}^{j,k}I_{s_1,t-1} + a_{s_2}^{j,k}I_{s_2,t-1} + u_t^{j,k}, \tag{3.10}$$

where s_0 denotes the underlying state, s_1 and s_2 denote the remaining two states, $I_{s_1,t-1}$ ($I_{s_2,t-1}$) is an indicator for state s_1 (state s_2). For example, when the underlying state, s_0, is High-RV, $\hat{a}^{j,k}_{s_0}$ is the estimated coefficient of dependent variable k on characteristic j in the High-RV subsample. To test the difference in coefficient estimates between the Low-RV subsample and the rest of the sample, the specification of the second-stage regression becomes

$$\hat{b}^{j,k}_t = a^{j,k}_0 + a^{j,k}_L I_{L,t-1} + u^{j,k}_t, \tag{3.11}$$

where $I_{L,t-1}$ is an indicator for the Low-RV state, and $\hat{a}^{j,k}_L$ reflects the difference in coefficients of stock characteristic j on the outcome variable k between the Low-RV subsample and the rest of the sample.

To account for heteroskedasticity and autocorrelation in the error terms, standard errors of the coefficient estimates are computed using the method proposed by Newey and West (1987), with the number of lags for computing standard errors following the selection procedure introduced by Newey and West (1994).

3.4.2 Investment CAPM

Based on the q-theory of investment, Liu, Whited, and Zhang (2009) propose modeling expected stock returns as[16]:

$$\begin{aligned} E_t[r^S_{i,t+1}] = E_t[r^I_{i,t+1}] &= \frac{\kappa E_t[\frac{Y_{i,t+1}}{K_{i,t+1}}] + \frac{a}{2}E_t[(\frac{I_{i,t+1}}{K_{i,t+1}})^2]}{1 + a(\frac{I_{i,t}}{K_{i,t}})} + \frac{(1-\delta_{i,t+1})\big(1 + aE_t[\frac{I_{i,t+1}}{K_{i,t+1}}]\big)}{1 + a(\frac{I_{i,t}}{K_{i,t}})} \\ &= \text{Expected dividend yield} + \text{Expected capital gain.} \end{aligned} \tag{3.12}$$

All firms are assumed to have a Cobb-Douglas production function with constant returns to scale. In addition, we follow Hou et al. (2021) to assume that firms are in a multi-period world without taxes and have no leverage. Under constant returns to scale, the investment return ($r^I_{i,t+1}$) is equal to the stock return ($r^S_{i,t+1}$) if firm i has no leverage (Restoy and Rockinger 1994; Cochrane 1991). $E_t[\frac{Y_{i,t+1}}{K_{i,t+1}}]$ is the expectation of future profitability; $\frac{a}{2}E_t[(\frac{I_{i,t+1}}{K_{i,t+1}})^2]$ is the expected marginal reduction in adjustment costs; $1 + a(\frac{I_{i,t}}{K_{i,t}})$ is the marginal cost of current

[16] Liu, Whited, and Zhang (2009) use $I_{i,t}$, $K_{i,t}$, $Y_{i,t}$, $\delta_{i,t}$ to respectively represent investment, capital, sales and the depreciation rate of firm i at time t; κ and a represent capital's share of output and an adjustment cost parameter, respectively.

investment. $\frac{\kappa E_t[\frac{Y_{i,t+1}}{K_{i,t+1}}]+\frac{a}{2}E_t[(\frac{I_{i,t+1}}{K_{i,t+1}})^2]}{1+a(\frac{I_{i,t}}{K_{i,t}})}$ represents the expected "dividend yield" component of the expected investment return. $\frac{(1-\delta_{i,t+1})(1+aE_t[\frac{I_{i,t+1}}{K_{i,t+1}}])}{1+a(\frac{I_{i,t}}{K_{i,t}})}$ represents the expected "capital gain" component of the expected investment return. $(1-\delta_{i,t+1})(1+aE_t[\frac{I_{i,t+1}}{K_{i,t+1}}])$ is the marginal continuation value of an additional unit of capital adjusted for depreciation. Cochrane (1991) shows that this component is approximately proportional to the expected investment growth, i.e.,

$$\frac{(1-\delta_{i,t+1})[1+aE_t[\frac{I_{i,t+1}}{K_{i,t+1}}]]}{1+a(\frac{I_{i,t}}{K_{i,t}})} \propto \frac{E_t[\frac{I_{i,t+1}}{K_{i,t+1}}]}{\frac{I_{i,t}}{K_{i,t}}}. \tag{3.13}$$

Hence, the model implies that, all else equal, firms should earn higher average stock returns if they have low current investment, high expected investment growth, high expected profitability (Liu, Whited, and Zhang 2009). More importantly, the return forecasting ability of some stock characteristics can be attributable to their associations with the three determinants of stock returns.

Liu and Zhang (2014) use a structural estimation procedure to examine whether the investment CAPM can explain the WML premium. They show that past returns are informative about future investment growth and future profitability of firms.

However, as discussed in Section 3.3.1 and Section 3.3.2, the time-varying behavior of WML cannot be fully captured by the q-factor model derived from the *static* investment CAPM. Hou, Xue, and Zhang (2015) use the most recent quarterly *roe* to proxy for expected profitability and Hou et al. (2021) further use a linear combination of the most recent Tobin's q, operating cash flow, and change in quarterly *roe* as a forecast for investment growth. This raises the issue of a potential bias due to inefficient proxies. Additionally, both proxy variables contain an earnings-surprise component, i.e., the change in *roe*.

In this section, we use cross-sectional Fama-MacBeth regressions to directly examine whether the relations between the momentum signal and the expected profitability or expected investment growth change with the risk of momentum.[17] If the investment CAPM can explain the anomaly conditionally, we should expect stronger positive relations between past stock performance and future profitability and/or future investment growth in safe months.

[17]Similar exercises are implemented by Antoniou, Doukas, and Subrahmanyam (2016) who study whether the relation between beta and future returns changes with investor sentiment (see their Table 8).

Additionally, $r_{2,12}$ is expected to be unassociated with the two determinants of the expected return when momentum cannot produce any premium.

Following George, Hwang, and Li (2018), we measure future profitability using the forthcoming annual *roe* (FROE), which is the ratio of income before extraordinary items over one-year-lagged book equity. We follow prior studies (e.g., Liu, Whited, and Zhang 2009; Liu and Zhang 2014; George, Hwang, and Li 2018) to measure future investment growth as (forthcoming) growth in the annual investment-to-capital ratio (FIG), which is given by

$$FIG_{i,fy+1} = log\left(\frac{1+\frac{I_{i,fy+1}}{K_{i,fy+1}}}{1+\frac{I_{i,fy}}{K_{i,fy}}}\right), \tag{3.14}$$

where $I_{i,fy}$ is measured by 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 fy for firm i, and $K_{i,fy}$ is net property, plant and equipment (Compustat item PPENT) at the beginning of fiscal year fy.[18] The main reason why we do not directly use $(\frac{I_{i,fy+1}}{K_{i,fy+1}})/(\frac{I_{i,fy}}{K_{i,fy}})$ in Eq. (3.13) is that some firms that downsize in year fy and invest in $fy+1$ will be mistakenly assigned negative values. We follow George, Hwang, and Li (2018) to fix the issue through adding both denominator and numerator by one to compute an adjusted growth rate. We then take the natural log of the adjusted rate to make the measure vary from negative to positive since $\frac{I_{i,fy}}{K_{i,fy}}$ by definition is not smaller than -1.

We follow the methodology of Liu and Zhang (2014) and George, Hwang, and Li (2018) to align annual measures with monthly stock returns (FRET) in time. Specifically, we match the two annual measures from a fiscal year ending in month τ with the monthly stock returns from $\tau-17$ to $\tau-6$. For instance, for a firm with fiscal years ending in December, its monthly stock returns from July of calendar year cy to June of $cy+1$ are matched with FROE or FIG of fiscal year $cy+1$. Our sample includes momentum signals formed between 1972:06 and 2022:05, since for typical firms with fiscal years ending in December, the return in 2022:06 is the last to be matched with FROE and FIG of fiscal year 2022. We follow George, Hwang, and Li (2018) and winsorize all variables except for FRET at the 1% and 99% levels each

[18] Liu, Whited, and Zhang (2009) also use gross property, plant and equipment (Compustat item PPEGT) to measure capital stock of a firm and use CAPX alone to measure firm investment. Liu and Zhang (2014) and George, Hwang, and Li (2018) only use PPENT to measure capital stock of a firm and use (CAPX − SPPE) to measure firm investment.

month. In addition to the common sample selection criteria used in the formation of the WML portfolio, we require stocks to have *non-missing* FRET, $r_{2,12}$, FROE and FIG.

[Insert Table 3 near here]

Table 3 presents *univariate* Fama-MacBeth regression results regarding unconditional and conditional relations between $r_{2,12}$ and FRET, FROE, or FIG. Panel A presents results based on WLS for all stocks, while Panel B presents results using OLS for non-micro-cap stocks. We first discuss results presented in Panel A. Unsurprisingly, $r_{2,12}$ has significant positive predictive power for stock returns unconditionally with a t-statistic of 3.22. More importantly, the momentum signal significantly positively predicts future profitability and future investment growth with very large t-statistics of 9.47 and 10.47, which is consistent with the findings of Liu and Zhang (2014).

The conditional (cross-sectional) regression results with respect to FRET presented in Panel A confirm the time-varying payoffs to momentum observed at the portfolio level. That is, the estimated coefficient on $r_{2,12}$ monotonically decreases with momentum risk. The "L − M&H" row further shows that the predictive power of $r_{2,12}$ for returns is significantly higher in safe states with a t-statistic of 3.03 on the difference in coefficient estimates between the Low-RV subsample and the rest of the sample.

Yet, the conditional regression results with respect to FROE and FIG document that $r_{2,12}$ significantly positively predicts future profitability and future investment growth regardless of volatility states. More importantly, the "L − M&H" row indicates that the predictive power of $r_{2,12}$ for FIG and FROE does not decrease with momentum risk in a statistically significant way. In other words, these time-invariant relations cannot match the time-varying relations between the momentum signal and future returns. Particularly, when $r_{2,12}$ is not informative of future returns (i.e., during High-RV periods), it still significantly positively predicts FIG and FROE with t-statistics of 5.62 and 4.90.

The OLS results presented in Panel B for the subsample without micro-cap stocks are generally consistent with the WLS results: $r_{2,12}$ is consistently informative about future firm profitability and investment growth regardless of predicting stock returns or not. Besides, our findings remain robust when using an alternative profitability measure, sales-to-lagged-capital ratio, which is used by Liu, Whited, and Zhang (2009) and Liu and Zhang (2014) (see Table IA3 in the Internet Appendix).

Overall, the results shown in Table 3 contradict the implications of the investment CAPM and suggest that the time-varying behavior of the momentum portfolio cannot be attributed to manager's optimal alignment of investment policies with the cost of capital. Conversely, they also suggest possible managers deviations from optimal investment policy in times of high volatility.

3.4.3 Correlation with Factor Momentum

We next examine whether factor momentum is the underlying driver of stock momentum. We begin by investigating whether factor momentum exhibits conditionality on its own lagged volatility. The realized volatility of factor momentum is calculated in the same way as that of stock momentum, that is,

$$\hat{\sigma}_{\mathrm{FMOM,t-1}} = \left(21 \sum_{j=0}^{125} \frac{\mathrm{r}^2_{\mathrm{FMOM,d_{t-1}-j}}}{126} \right)^{\frac{1}{2}}, \tag{3.15}$$

where $\mathrm{r}_{\mathrm{FMOM,d_{t-1}-j}}$ represents daily FMOM returns. Note that whether a factor is gaining momentum is still determined at the end of each month and that we use daily returns of *each* underlying factor to compute $\mathrm{r}_{\mathrm{FMOM,d_{t-1}-j}}$.

First, we test if the risk of FMOM is predictable as that of WML. The AR(1) result of $\hat{\sigma}_{\mathrm{FMOM,t-1}}$ for 6-month, non-overlapping periods is as follows:

$$\hat{\sigma}_{\mathrm{FMOM,t-1}} = \underset{(4.09)}{0.0028} + \underset{(8.88)}{0.63} \times \hat{\sigma}_{\mathrm{FMOM,t-7}} + \epsilon_{t-1}.$$

So, factor momentum risk is quite persistent with an AR(1) coefficient of 0.63 (t-statistic = 8.88) similar to stock momentum risk that has well-known predictability (Barroso and Santa-Clara 2015).

[Insert Table 4 near here]

Panel (A) of Table 4 presents FMOM returns in three volatility states and difference in FMOM returns between the low-volatility subsample and the rest of the sample. We use the same 30%-30% cutoff points to split the sample into three volatility states. The panel shows that FMOM is profitable in a statistically significant manner regardless of volatility states and produces lower returns in low-volatility months than other months (0.29 vs 0.36) though the difference is statistically insignificant. So we can conclude that factor momentum does not feature conditionality like stock momentum.

Assuming a constant loading of WML on FMOM, its purported driver, the lack of conditionality in FMOM is hard to reconcile with the strong conditionality of conventional momentum. A possible explanation to reconcile the two results is that WML might correlate more with its driver when volatility is low. We next test if stock momentum's conditionality does emanate from a time-varying association with factor momentum. Yet, a conditional spanning regression analysis uncovers that the loading of WML on FMOM in safe months is smaller than that in other months with a difference of -0.89 and a t-statistic of -1.61 (see Panel B of Table A2 in the Appendix). This has the opposite signal to what would be needed to explain conditionality. To further examine this, we compute the lagged correlation between daily WML returns and daily FMOM returns ($\hat{\sigma}_{\text{FMOM,t-1}}$) over the same estimation window as $\hat{\sigma}_{\text{WML,t-1}}$ and $\hat{\sigma}_{\text{FMOM,t-1}}$. The AR (1) result of $\hat{\rho}_{\{\text{WML,FMOM}\},\text{t-1}}$ for 6-month, non-overlapping periods is shown below

$$\hat{\rho}_{\{\text{WML,FMOM}\},\text{t-1}} = \underset{(6.02)}{0.29} + \underset{(3.25)}{0.31} \times \hat{\rho}_{\{\text{WML,FMOM}\},\text{t-7}} + \epsilon_{t-1}.$$

$\hat{\rho}_{\{\text{WML,FMOM}\},\text{t-1}}$ is somewhat persistent with a significant AR(1) coefficient of 0.31. Panel B of Table 4 provides results on how this measure is related to momentum payoffs. Again, we use the 30%-30% cutoff points to split the sample into three correlation states. Remarkably, in the time series, profitability of stock momentum *decreases* with its correlation with FMOM. The difference in WML returns between Low-correlation months and the remaining months is 1.23% and significant at the 5% level.

In Panel C, we perform an independent double sorting of WML returns on lagged realized volatility of WML and lagged correlation between WML and FMOM. If the time-varying profits of stock momentum are indeed driven by its time-varying association with factor momentum, we should not observe a positive return spread for WML between the Low-RV subsample and the rest after accounting for its correlation with FMOM. The panel shows that the forecasting power of stock momentum volatility for WML returns tends to remain statistically significant after controlling for the correlations between the two forms of momentum. In contrast, the negative relationship between WML returns and $\hat{\rho}_{\{\text{WML,FMOM}\},\text{t-1}}$

no longer holds after accounting for stock momentum risk.

All in all, the evidence from these factor-momentum-related tests is not supportive of the mechanism that stock momentum results from momentum in factors.

3.4.4 Investor Underreaction

In this section, we examine more directly whether past stock performance is a proxy for investor underreaction to information about future earnings of firms. Table 1 and Table 2 suggest that the BF3 model, which employs an earnings-surprise factor formed on quarterly earnings announcement returns, is the best performer in capturing time-varying profits of WML but still cannot fully account for its conditionality.

We next use future announcement returns and (ex-post) analyst forecast errors as more direct proxies of the magnitude of underreaction and test if the time-series variation in momentum profits can be driven by time-varying underreaction of investors.

3.4.4.1 Future Announcement Returns

Past winners (losers) are more likely to have favorable (unfavorable) news about forthcoming earnings in the recent past. Due to investor inattention or psychological bias of investors such as conservatism, the information might not be fully incorporated into the price before the earnings are actually announced (Hong and Stein 1999). Hence, past winners (losers) should realize positive (negative) returns surrounding the upcoming quarterly earnings announcement. Using a portfolio approach, Jegadeesh and Titman (1993) document that about 25% of the returns on the zero-cost momentum portfolio for a 6-month holding period are realized surrounding quarterly earnings announcement dates. This would be consistent with corrections in expectations as new information is released, playing some role in momentum profits.

We perform a similar exercise. Yet, different from Jegadeesh and Titman (1993) who report the announcement returns of past winners in excess of the announcement returns of past losers unconditionally, in Table 5, we perform univariate unconditional and conditional cross-sectional Fama-MacBeth regressions, as described in Section 3.4.1. These examine whether $r_{2,12}$ can predict the 4-day cumulative raw and abnormal returns surrounding the upcoming quarterly earnings announcement (FCR4 and FCAR4) and whether their predictive power is conditional on volatility states.[19]

In addition to the common sample selection criteria used in the formation of the WML portfolio, we require stocks to have non-missing FRET, $r_{2,12}$, FCR4 and FCAR4.[20] Only $r_{2,12}$ is winsorized at the 1% and 99% levels each month. In line with the investment CAPM test, our sample include momentum signals formed between 1972:06 and 2022:05. Panel A of Table 5 presents WLS Fama-MacBeth regressions results for all stocks, and Panel B provides OLS Fama-MacBeth regressions results for non-micro-cap stocks.

[Insert Table 5 near here]

The "Unc." row in Panel A shows that investors seem to generally under-react to recent positive (negative) news about future earnings of past winners (losers). The next three rows show that evidence for predictability is generally more compelling when $r_{2,12}$ is formed during safe periods, that is, $r_{2,12}$ is more strongly related to forthcoming quarterly earnings announcement returns when the momentum signal is formed in Low-RV months. The last row of the panel confirms that the difference is statistically significant.

Both FCAR4 and FCR4 columns show that the momentum signal formed during risky periods is not informative about future announcement returns, which is consistent with its relation with future stock returns. More importantly, the time-variation in predictive power of $r_{2,12}$ for FCR4 across volatility states mirrors the dynamics of relations between $r_{2,12}$ and FRET. This suggests that the profitability of the momentum strategy depends on how well $r_{2,12}$ can proxy for investor underreaction to information about short-term prospects of a firm. According to Panel B, the conclusions remain unchanged when performing OLS Fama-MacBeth regressions without micro-cap stocks.[21]

[19] Suppose a firm announces quarterly earnings in month t (the previous announcement is in month $t-3$). The FCR4 and FCAR4 associated with the announcement are matched with $r_{2,12}$ computed at the end of months $t-1$, $t-2$ and $t-3$. $r_{2,12}$ and the volatility state are updated monthly, while the announcement returns are updated roughly every three months. The construction of the two announcement return variables is provided in Section IA1.2.1 of the Internet Appendix.

[20] Due to different filters applied, the regression sample used in this test is slightly different from that in the investment CAPM test.

[21] To further confirm our findings, in Table IA4 of the Internet Appendix, we restrict the sample to firms that announce quarterly earnings in the first month after the formation of the momentum signal. Both WLS and OLS results show that coefficients of $r_{2,12}$ on FCR4 monotonically decrease with momentum risk. The differences in predictive power of $r_{2,12}$ for FCAR4 and FCR4 between the Low-RV subsample and the rest of the sample are significant at the 5% level (WLS) and 10% level (OLS).

3.4.4.2 Analyst Forecast Errors

Antoniou, Doukas, and Subrahmanyam (2016) propose to use analyst forecast errors as a relatively direct measure of noise trading activity. Ex post, forecast errors also provide a more direct proxy for analyst underreaction—that is, whether 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. 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 channel, for each firm, at the end of each portfolio formation month, we summarize all analysts' forecasts for the firm's forthcoming *quarterly* earnings per share (EPS),[22] and use the consensus EPS forecast along with actual EPS to compute analyst forecast errors (FE). Specifically, we follow Antoniou, Doukas, and Subrahmanyam (2016) and compute stock-level FE at the end of each formation month ($t-1$) as

$$\mathrm{FE}_{\mathrm{i,t-1}} = \frac{(\text{Mean EPS Estimate})_{\mathrm{i,q,t-1}} - (\text{Actual EPS})_{\mathrm{i,q}}}{|(\text{Actual EPS})_{\mathrm{i,q}}|} \tag{3.16}$$

where $(\text{Mean EPS Estimate})_{\mathrm{i,q,t-1}}$ refers to the mean forecast for stock i's EPS in quarter q summarized at the end of month $t-1$ and $|(\text{Actual EPS})_{\mathrm{i,q}}|$ denotes the absolute value of stock i's actual quarterly EPS from the upcoming earnings announcement for quarter q.[23]

At the end of each formation month, we sort stocks into deciles using $r_{2,12}$. Portfolio membership matches that used for decile portfolio construction. Within each decile, we compute both equal-weighted and value-weighted average forecast errors.[24] Forecast errors

[22] "Forthcoming EPS" refers to EPS from the *forthcoming* quarterly earnings announcement. For example, at the end of January in year y, for firms with fiscal years ending in December that have already announced their Q4 earnings for year $y-1$, the next earnings to be announced are those for Q1 of year y; for firms that have not yet announced their Q4 earnings for year $y-1$, the forthcoming earnings are still those for Q4 of year $y-1$. This is akin to how the literature constructs ex ante earnings-surprise signals: *sue* and *car*4, that is, when computing the two signals, we extract earnings information or market reaction to the newly announced earnings from the most recent earnings announcement date.

[23] To avoid rounding errors on the summary files of I/B/E/S adjusted forecast data, we recreate the summary stats of EPS forecasts by joining "I/B/E/S Unadjusted Detail History" with "I/B/E/S Unadjusted Actuals" using cumulative adjustment factors provided by CRSP.

[24] Hribar and McInnis (2012) conduct similar analysis for other stock characteristics including size, profitability, volatility, age, and dividend payment. However, different from our method, they use annual forecast data to calculate monthly FE of a decile and do not use updated forecasts to calculate monthly FE.

are winsorized at the 5th and 95th percentiles in line with Antoniou, Doukas, and Subrahmanyam (2016). Restricted by the availability of analyst forecast data, momentum signals formed between 1983:12 and 2022:11 are tested.[25] Table 6 reports cross-sectional and time-series variations in value-weighted and equal-weighted forecasts errors. The t-statistics are computed based on standard errors of Newey and West (1987).

[Insert Table 6 near here]

The table shows that average analyst forecast errors of all deciles are either significantly positive or statistically insignificant at the 5% level. When weighting errors by stocks' market capitalization, we find that only the top decile has a negative and significant value-weighted average earnings forecast error of −0.03 with a t-statistic of −2.06. 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 past losers than for past winners. There is little to no bias in winners, the bias is all in the losers. So, only past winning stocks are able to meet the high expectations of analysts on average, all others disappoint. The t-statistic for the difference in equal-weighted (value-weighted) FE between the winner and loser deciles ("H − L") is −7.07 (−7.14). The magnitude of the difference is 0.29 in both settings. Therefore underreaction seems stronger in the short leg of the strategy.

Closer to the main point of the exercise, we find that across deciles, FE in Low-RV months is always larger than FE in other months, regardless of the weighting methods. All of these differences between volatility states are statistically significant with t-statistics ranging between 4.87 and 6.07 (between 3.02 and 5.11) for equal-weighted (value-weighted) forecast errors.[26] Most importantly, in the upper part of the table, the spread in forecast errors between winners and losers, patent in column "H − L", more than doubles from

[25] We restrict the sample to firms with a link quality score of 0 or 1 according to "ICLINK" file available on WRDS, which is used to link I/B/E/S and CRSP databases. In addition, we still use the 1972:07-2022:12 sample to define volatility states.

[26] Also addressing a suggested exercise, we check that the pattern remains unchanged when replacing the denominator in Eq. (3.16) with stock prices (see Table IA5 in the Internet Appendix).

−0.22 to −0.51 in safe periods relative to the rest with a t-statistic of −5.98 for the difference. Results in the lower part of the table for value-weighted forecast errors are consistent. Therefore, analysts earnings forecasts are excessively optimistic on average and even more so in safe periods. This time-variation in forecast errors fits well with the conditionality of the momentum premium if driven by an underreaction channel.

3.5 Conditional factor-adjusted returns of long and short legs

Motivated by the pattern of analyst forecast errors as well as Stambaugh, Yu, and Yuan (2012)'s finding that the short side earns higher unconditional FF3-adjusted return than the long side on average for 10 out of 11 prominent anomalies including momentum (see Panel C of their Table 1), we examine the conditional factor-adjusted returns of the long and short legs of WML in Table 7.

[Insert Table 7 near here]

Regarding unadjusted returns, the short and long legs of WML work only in Low-RV months, and momentum's short leg contributes more to its overall profit, which is consistent with asymmetric earnings forecast errors observed above. Notably, the raw returns earned by the short leg of WML on average are approximately twice as much as the returns earned by the long leg in low-volatility months. Our results for raw returns are consistent with Wang and Xu (2015) who also find more predictability in the short leg of WML.

With regard to factor models' performance in explaining the long leg, only BF3 can subsume it in Low-RV months and only FF5 fails to span it in the remaining months. Moreover, the time-varying alphas of WML can be fully captured by BF3. Generally, conditionality in the long leg is weak as for most models the differences in alphas are not significant at the 5% level.

In contrast, all models fail to explain the conditionality of the short leg during safe periods. Specifically, all alphas produced by the short leg in Low-RV states are significant at the 1% level, and the differences in alphas between the Low-RV subsample and the rest are also all significant at the 1% level.

Overall, our evidence indicates that the predictability and profitability of momentum comes mostly from the short leg, and that can be attributable to analysts' time-varying attention or optimism—especially excessive optimism relative to past losers. Moreover, our evidence suggests that underreaction and short-sale constraints jointly determine the profitability of the short leg of the anomaly. That is, consistent with Miller (1977) who argues that short-sale impediments can deter rational investors from profiting from *overpriced* stocks.[27]

3.6 Other Results

In this subsection we briefly refer to robustness results for the 52-week high anomaly, and for using market states as a conditional variable.

3.6.1 Conditionality of the 52-week High Momentum

Price momentum is not the only relative strength strategy of possible 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 argue that nearness to the 52-week high (*pth*), a common reference point, can subsume the predictive power of past price changes for expected returns.[28] The details about the construction of the stock-level *pth* variable and the corresponding decile-spread portfolio (denoted as PTH) are provided in Section IA1.5 of the Internet Appendix.

Empirically, using conditional Fama-MacBeth-WLS regressions, we find that the two anomalies have independent predicting power for return in the state of low momentum volatility, especially over the period of 1972:07 to 2022:12. (see Table IA6 of the Internet Appendix).[29] Yet, unconditionally, the predictive power of *pth* for one-month-ahead returns can be subsumed by past stock performance. This is consistent with the spanning regression

[27]Empirical studies related to this argument include Nagel (2005), Hirshleifer, Teoh, and Yu (2011), Stambaugh, Yu, and Yuan (2012), Avramov, Chordia, Jostova, and Philipov (2013), Stambaugh, Yu, and Yuan (2015), and Drechsler and Drechsler (2018).

[28]Conceptually, 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. George, Hwang, and Li (2018) argue that "momentum captures how stock prices have changed over a fixed period of time, and PTH captures how prices have changed from their recent peaks.".

[29]Table IA6 of the Internet Appendix also indicates that controlling for stocks' nearness to 52-week highs can enhance the profitability of momentum in both High-RV states and Medium-RV states and absorb the conditionality of momentum.

result of George, Hwang, and Li (2018) that the Fama and French (1993) 3-factor model augmented with a momentum factor (Carhart 1997) can span the 1-month PTH. But the same study finds it does not span both the 6-month and the 12-month PTH. Regardless, in line with the analysis for the momentum strategy, our analysis for the 52-week high anomaly is focused on the PTH portfolio with a holding period of 1 month.

Similar to the conventional momentum strategy, the profits of the 52-week high strategy have been attributed to both delayed price reaction to firm-specific information[30] and *pth*'s associations with future profitability and future investment growth of firms based on the investment CAPM.

We find the payoffs of the 52-week high strategy significantly vary with momentum volatility states. Panel A of Table IA7 in the Internet Appendix shows 75% of PTH returns are produced during Low-RV periods, and that this conditionality cannot be explained by the q^4, BF3 and EL6 models. Notably, cross-sectional Fama-MacBeth regressions testing the investment CAPM explanation for the 52-week high, which are reported in Table IA8 of the Internet Appendix, show that the associations of *pth* with future profitability and future investment growth are also not conditional on momentum's risk. So, PTH shows similar properties to momentum in our conditional tests.

[Insert Table 8 near here]

Table 8 presents time-series variation in analyst forecast errors for earnings across *pth*-sorted deciles.[31] Similar to the pattern of $r_{2,12}$-sorted deciles, average analyst forecast errors of all *pth*-sorted deciles are either significantly positive or statistically insignificant at the 5% level, irrespective of the weighting method, suggesting a systematic optimistic bias. The "L − M&H" rows of two panels show that forecast errors of stocks far from their 52-week highs are larger in safe periods. The differences in value-weighted (equal-weighted) forecast errors between safe months and other months for the bottom and high deciles are 0.43 (0.40)

[30]The underreaction can result from conservatism of investors (Li and Yu 2012) and "adjustment and anchoring bias" of investors (George and Hwang 2004), i.e., 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.

[31]Results regarding Fama and MacBeth (1973) regressions of future announcement returns on *pth* are provided in Table IA8. Similar to what we document regarding momentum, nearness to the 52-week high has stronger positive predictive power for returns surrounding upcoming earnings announcement, especially those adjusted for market returns.

and 0.11 (0.09). In other words, like past losers defined by the momentum signal, low-*pth* stocks are much more susceptible to analysts' time-varying optimism, a result consistent with time-varying underreaction.

This pattern also implies that the short leg of PTH should show more conditionality. Indeed, as shown in Panel B of Table IA7 in the Internet Appendix, the q^4, BF3 and EL6 models can all subsume the long leg of PTH regardless of the volatility level. But, despite successfully subsuming PTH when volatility is not low, all three models fail to span the short leg of PTH in safe states. Moreover, the differences in alphas between the Low-RV subsample and the rest for the three factor models are all statistically significant at the 1% level.

3.6.2 Market States

We next examine the seminal momentum predictor: market states. Following Cooper, Gutierrez Jr., and Hameed (2004), we define the market state of a formation period ending in month $t-1$ using the cumulative past one-year return on the CRSP value-weighted index (dividends included). If the return is non-negative (negative), the formation period is classified as Up (Down).[32]

The set of columns labeled y = WML in Table 9 presents unadjusted returns, factor-adjusted returns, and Sharpe ratios of WML during the full sample period, in Up-Market states, and in Down-Market states.

[Insert Table 9 near here]

Generally, the predictive power of market states for returns is somehow weaker than that of the realized volatility of momentum. Despite WML generating a significant positive return of 1.34% in Up markets, the return difference between Up and Down markets is smaller than that between the Low-RV subsample and the rest of the sample (1.41% vs 2.07%). More importantly, the difference of 1.41% is not statistically significant. But, WML's Sharpe ratio is significantly conditional on market states with a difference of 0.79 (p-value = 0.04).

[32] Cooper, Gutierrez Jr., 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 strength of a state and frequency of state changes. This state variable is an ex-ante indicator.

After accounting for WML's exposure to factors, WML is still a dismal strategy in Down markets with insignificant alphas ranging from -1.40% to 0.12%, whereas only the BF3 model can subsume momentum in Up markets at the 5% level. Furthermore, except for the CAPM model, none of the factor models captures the change in alphas of WML between the two market states. On top of this, the remaining columns present performance of three momentum strategies conditional on market sates. In strategies (1) through (3), investors are assumed to execute the momentum strategy in Up markets only and hold the risk-free asset (Strategy (1)), the market portfolio (Strategy (2)) or the reverse of momentum strategy (Strategy (3)) in Down markets. Consistent with results regarding momentum volatility, no models can span the three managed momentum portfolios. This finding is also consistent with Liu and Zhang (2014) who document that the investment CAPM fails to explain conditionality of momentum with respect to market sates using a structural model.

3.6.3 Other Factor Models

Building on two of the explanations we already examine—underreaction and the investment CAPM—there are three other factor models that can also subsume WML unconditionally. Here, for completeness, we discuss the conditional performance of WML relative to these models. The first is a modified version of the q^4 model where the ROE factor is decomposed into a low-frequency earnings profitability factor and a post-earnings announcement drift factor (Novy-Marx 2015b, q^{4a}). The second is Novy-Marx (2015a)'s ad hoc factor model, which augments the Fama and French (1993) three-factor model with two earnings-surprise factors formed on standardized unexpected quarterly earnings (SUE factor) and post-earnings announcement drift (i.e., the PEAD factor used in the BF3 model). The third is the augmented q-factor model of Hou et al. (2021), which is based on the multiperiod investment CAPM and uses *roe*, and a linear combination of Tobin's q, operating cash flow, and changes in quarterly *roe* to *proxy* for firms' expected profitability and expected investment growth, respectively.

Table A3 in the Appendix shows results for conditional tests of the three models. Overall, both conditional factor regressions and unconditional factor regressions of the four conditional momentum strategies introduced in Section 3.3.2 show that none of the three models are able to explain the conditionality of momentum. Notably, NM5, whose explanatory power for momentum comes from the two earnings-surprise factors, is the only model subsuming WML in safe months (t-statistic = 1.61) though the difference in alphas between safe and other states is still statistically significant; it also outperforms q^{4a} and q^5 in terms of the absolute value of t-statistics associated with alphas from unconditional factor regressions of the conditional momentum strategies.

3.7 Interpreting the Results

Our study focuses on a somehow comprehensive analysis of three core explanations for momentum. Given the eclectic state of the literature on momentum, this necessarily leaves out many other explanations for the phenomenon and that is a limitation of our study. Here we broaden the scope of our study discussing its possible relations with six possible explanations for momentum or its conditionality. We briefly comment on each one and the avenues of research we did not explore, also justifying these choices. We also discuss limitations and comment on possible directions for future research.

3.7.1 Other Explanations

Growth options. Momentum can be explained in a rational setting with single-firm models (Berk, Green, and Naik 1999; Johnson 2002; Sagi and Seasholes 2007). In such models, winners would have higher average returns due to their valuable growth options, not to underreaction or other investor biases. We do not test growth options explicitly as an explanation, although we test the related investment CAPM. Nevertheless, growth options should be more valuable in high-volatility periods. As momentum is much more profitable in low-volatility periods, growth options seem *a priori*, an unlikely channel for our results.

Business cycle risk. Chordia and Shivakumar (2002) find that stock momentum in the U.S. is explained by macroeconomic risk. Liu and Zhang (2008) find that industrial production is particularly effective explaining momentum profits. We do not explore whether business cycle risk is able to explain our findings for three types of reasons: i) relevance; ii) robustness concerns; and iii) plausibility. First, while business cycle risk is able to partially explain momentum in some previous studies, it typically does not subsume it as our set of core explanations does. Given limited time, it makes sense to focus first on explanations for momentum that do span it. Second, Griffin, Ji, and Martin (2003) find that macroeconomic risk shows little relation to momentum in international evidence. Additionally, Ji, Martin, and Yao (2017) show that momentum's loading on industrial production is only observed in January, which is the month of the year when momentum produces negative returns. So, industrial production looks like an unlikely candidate as an explanation. Regardless of these robustness issues, for business cycle risk to explain the conditionality of momentum on volatility, the strategy should covary more with macroeconomic risk when it becomes less volatile. While mathematically possible, this seems implausible as higher loadings on omitted macroeconomic variables should normally be associated with higher volatility of the strategy, not less. Therefore, we take this as a possible expansion path for our current research, yet one of relatively modest promise.

Frog-In-the-Pan (FIP). Intuitively, our results on underreacion may be related to those of the FIP hypothesis proposed by Da, Gurun, and Warachka (2014) according to which investors are less attentive to information being gradually incorporated into prices. Based on this, they propose a measure for information discreteness and find that for a given level of formation period returns, momentum in stocks with discrete information is much less profitable than in those with gradually released information. Also, they document that more media coverage, a proxy for attention, can narrow this cross-sectional return gap.[33] Our study differs from theirs by emphasizing the time-series variation in investor underreaction at an aggregated level. In unreported results, we find a very weak correlation of an aggregate measure of information discreteness with momentum's volatility. Therefore, FIP looks like an unlikely channel for our results. Still, we fall short of a thorough exploration of whether FIP can relate with our results in other ways and leave that for future research.

Disposition effect. Momentum can also result from investors' reluctance to sell losing stocks and eagerness to realize gains of winning stocks, i.e., disposition effect (Grinblatt and Han 2005). On top of this, Grinblatt and Moskowitz (2004) find that past winners with more consistent past returns can earn higher returns, but such pattern is not observed for past losers. We refrain from examining the disposition effect as a channel for momentum's conditionality for two reasons. First, our evidence on analyst forecast errors, does not support the implications of a disposition effect as analysts are unlikely subject to this effect as they do not necessarily own the stocks being analyzed. Second, for the disposition effect to explain

[33] Apart from momentum, Chen, He, Tao, and Yu (2023) suggest that the recently proposed factors such as RMW, CMA, ROE, and PEAD and other anomalies attributable to underreaction in the literature are more profitable among firms with low news coverage.

momentum's conditionality, we should see fewer stocks trading at prices below their investors reference points in times of high volatility. This would be surprising as high volatility periods tend to also be periods of low past market returns. The conditionality we observe, especially in the short leg, goes exactly in the other direction.

Covariance of momentum stocks. Observing negative autocorrelations and cross-serial correlations of industry, size and value portfolios, Lewellen (2002) argues that under-reaction to portfolio-specific news alone is not sufficient to explain momentum, since it cannot account for the negative serial correlation of the portfolios and, therefore, that it would be more plausible to attribute those portfolios' momentum to excess covariance among stocks. We do not explore the relation of our underreaction results with excess covariance for three reasons. First, Lewellen (2002)'s result is for momentum in diversified stock portfolios, not momentum at the individual stock level. A hypothetical absence of underreaction at the portfolio level is not necessarily inconsistent with the same bias being there for individual stocks. Second, we expect that excess co-movement of momentum stocks should be positively related to the realized volatility of the strategy. For instance, ceteris paribus, winners becoming more correlated should make the strategy riskier. From a time series perspective, it is thus unlikely that excess covariance would explain individual stock momentum as volatility predicts it negatively in the data. Finally, the literature offers explanations whereby excess covariance among momentum individual stocks can be reconciled with underreaction. For example, momentum stocks can exhibit excess co-movement due to crowding effects (Lou and Polk 2022), an accidental overlap with an underlying factor structure (Kozak, Nagel, and Santosh 2018) or noise trader risk (Shleifer 2000, Ch. 2).

Co-momentum. Focusing on individual stocks, Lou and Polk (2022) use abnormal return correlation among momentum stocks to measure arbitrage activity which can be destabilizing if the momentum crowd becomes too large. By definition, the realized volatility of momentum is positively correlated with covariance of momentum stocks. They point out that whether momentum is an underreaction phenomenon depends on the level of momentum stocks' excess covariances. The notion is that arbitrager's demand likely increases with lagged returns of individual stocks under the positive-feedback trading strategy like momentum. They rationalize their findings by leveraging the underreaction-based model of Hong and Stein (1999) as a base and assuming the number of momentum traders to change over time in a stochastic manner, that is, the spread between the numbers of observable and unobservable momentum traders (amounts of arbitrage capital) vary over time. A plausible explanation for our observed conditionality is thus that realized volatility of momentum could capture time-variation in arbitrage capital. While promising, a problem with this research path is that proxies for momentum's arbitrage capital directly obtained from institutional holdings show little relation with momentum's volatility (Barroso, Edelen, and Karehnke 2022).

A perhaps more promising path goes in another direction. Our evidence, especially results related to analyst forecast errors, is more relevant to the other trader group under the Hong and Stein (1999) model, i.e., news watchers. Instead of assuming a constant number of news watchers with time-invariant attention homogeneous to all stocks, there might be time variations in participation rates of news watchers and in their attention.

3.7.2 Limitations

One concern about the after-cost profitability of the proposed conditional momentum strategies is that price impact costs are omitted in the calculation of trading costs. These can constrain the capacity of the strategy. Still, Korajczyk and Sadka (2004) report that the 3-month (overlapping) value-weighted momentum strategy based on past 11-month returns (i.e., skipping formation month)—the best-performing variant of underlying momentum portfolios of our conditional strategies—has a zero-alpha break-even fund size of more than 2 billion dollars, which is estimated using the 1967–1999 data. As conditional momentum is much more profitable after costs than plain momentum, it seems likely that incorporating conditionality could raise this capacity limit further; how much so seems like an interesting research question for the future.

Throughout the paper, we document a clear association between the prevalence of underreaction and the occurrence of low volatility regimes, but our study remains silent on causality-related discussions. From a conventional asset pricing perspective, the causal direction is not the object of main interest since regardless of the direction, the relation is still predictive, robust, and can thus be used to expand the mean-variance frontier and evaluate the performance of fund managers in real time relative to the main factor models proposed in the literature. But we leave for future research if decreases in volatility make investors less attentive or if, instead, less attentive investors make markets less volatile. For this, possible sources of exogenous variation in attention (or in volatility) should be identified. Regardless, the two economic mechanisms are both compatible with our results.

Our analysis lacks direct calibrations of theoretical models of momentum. As mentioned above, we can potentially extend Hong and Stein (1999)'s model by allowing information to diffuse among the newswatcher population at a *time-varying* rate.[34]

Due to our in-depth focus on the U.S. market and broad examination of the core theories, we do not examine international evidence. This could be a concern since, in spite of the critical and unique economic role of the U.S. market, explanations that hold in the U.S. data do not necessarily hold internationally. For example, pronounced outperformance of the momentum portfolio formed on past returns from month $t-12$ to $t-7$ relative to that formed on past returns from month $t-6$ to $t-2$ (i.e., "echo" in returns) is not observed in international stock markets (Goyal and Wahal 2015). On the other hand, using unconditional settings with international stocks, Goyal, Jegadeesh, and Subrahmanyam (2025) uncover the leading role of investor underreaction in explaining momentum in international stocks, the same driver we identify with very different tests in the U.S.. Also, Schwarz (2021) shows that volatility-managed momentum is remarkably robust in a comprehensive sample of international markets. The two findings combined alleviate the concern from our sole focus on the U.S. stock market: neither underreaction's prominent role for momentum nor the conditionality of momentum on volatility look like U.S. singularities.

Finally, we test the conditional fit of theories of momentum using proxies for their economic mechanisms as proposed in previous studies. We do this aiming to stay close to previous literature in our setting. A consequential natural limit of our results is that those proxies might not be the best for the respective economic mechanisms. Hence, tests comparing theories might come to different conclusions with different proxies. Still, it can also be argued that it is actually better, when coming up with a new test setting, to use only proxies previously proposed in other studies and by other authors and with intuitive relations, argued independently and elsewhere, to the theories compared; this as opposed to using proxies designed having in mind the specific new test setting carried out.

[34] Although the momentum generating mechanism described in the model of Daniel, Hirshleifer, and Subrahmanyam (1998) is not based on underreaction, in unreported results, we find partial compatibility of momentum's conditionality with the model.

4 Conclusion

Prior studies document that stock momentum can be explained by investor underreaction, the investment CAPM, and momentum in factors. It is puzzling that the three explanations, which are presumably incompatible with each other can account for the same anomaly. Following the suggestion of Subrahmanyam (2018), we compare the three competing theories and try to spot the real cause by examining what drives momentum when it works. Our tests are based on the fact that the profitability of momentum strongly depends on several state variables, particularly momentum's lagged realized volatility. Specifically, momentum's payoffs strongly vary with momentum volatility in a negative direction and such conditionality is practically robust in the presence of trading costs. We posit that a true driver of the anomaly should be able to match this time variation.

Our evidence is more supportive of the underreaction explanation for the anomaly compared to the explanations based on stock momentum's associations with q-factors and factor momentum. First, we find that Daniel, Hirshleifer, and Sun (2020)'s factor model, which includes an earnings-surprise factor, not only spans price momentum unconditionally but also is the best performing model in capturing momentum when it works (i.e., during low-volatility periods). The analysis on future earnings announcement returns confirms winners (losers) earning higher (lower) returns in safe states, 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. Additionally, we document that the conditionality of momentum cannot be attributed to its time-varying associations with two return determinants implied by the investment CAPM or with momentum in factor returns.

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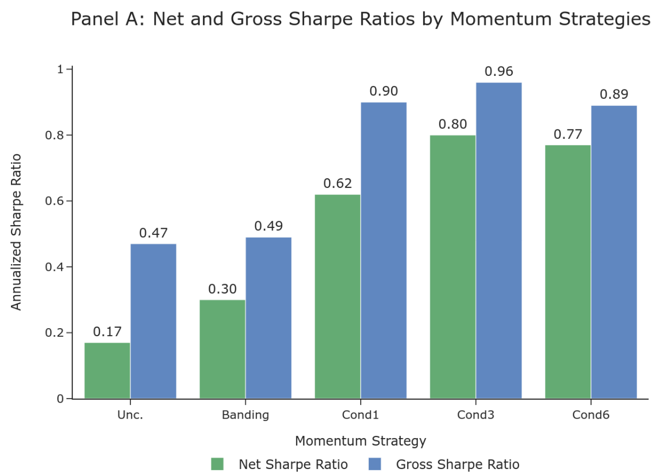
Figure 2 Before-cost and After-cost Performance of Unconditional and Conditional Momentum Strategies

The figure depicts the Sharpe ratio and net Sharpe ratio (Panel A), as well as turnover and trading costs (Panel B), for five momentum strategies: the unconditional momentum strategy (Unc.), a cost-mitigated momentum strategy using the "banding" technique introduced in Novy-Marx and Velikov (2016), and three conditional momentum strategies (Cond#) exploiting the volatility states of momentum. Trading costs of stocks are computed using the effective spread estimator of Hasbrouck (2009). We apply the 10%/20% rule for the "banding" strategy, in which traders go long (short) stocks with past returns in the top (bottom) decile and keep them until they drop out of the top (bottom) quintile. In the three conditional momentum strategies, at the end of each month, traders only implement the momentum strategy when the (ex-ante) volatility state is Low-RV, holding the portfolio for 1, 3, and 6 months, respectively (denoted as "Cond1", "Cond3", and "Cond6"). We use an expanding look-back window starting from 1927:06 to determine the percentiles of realized volatility of momentum (RV), as defined by $\hat{\sigma}_{\mathrm{WML,t-1}}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML,t-1}}$ belongs in the top 30%, middle 40%, or bottom 30%, respectively. The sample period is 1972:07 to 2022:12.



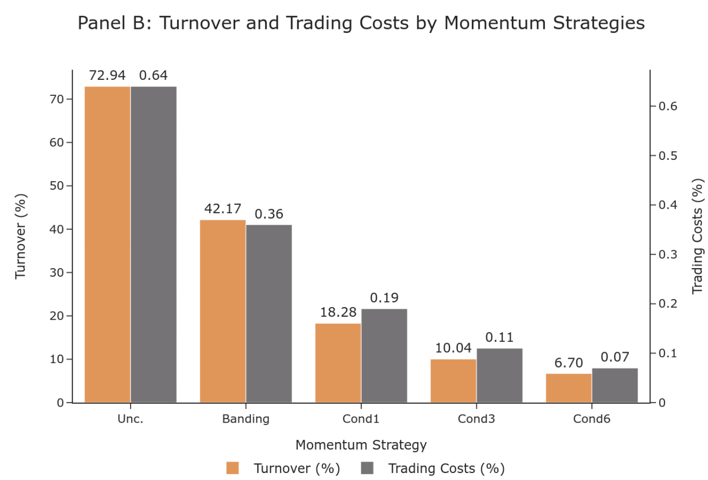


Table 1 Performance of Momentum Conditional on Volatility States

This table presents unconditional and conditional performance of the momentum (WML) strategy in terms of raw excess returns, factor-adjusted returns (a.k.a alphas) and Sharpe ratios. The sample period is 1972:07 to 2022:12. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\text{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\text{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The column labeled "Unc." reports unconditional performance of WML. The following four columns report the performance of WML conditional across different volatility states. Alphas in each volatility state are estimated using Eq. (3.2). The column labeled "L − M&H" presents differences in alphas or Sharpe ratios between the Low-RV subsample and the rest of the sample (i.e., High- and Medium-RV subsamples combined, which is denoted as M&H). The differences in alphas are estimated using Eq. (3.3). "p-value" denotes the p-value of the difference in Sharpe ratios computed from 100,000 bootstrap samples. The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), the Fama-French 5-factor model (Fama and French 2015, FF5), the q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Unc.	High	Medium	Low	M&H	L − M&H
Constant	1.02***	0.25	0.51	2.47***	0.40	2.07***
	(3.38)	(0.31)	(1.37)	(7.87)	(0.98)	(4.03)
			Factor-Adjusted Returns			
CAPM	1.21***	0.72	0.51	2.47***	0.69*	1.78***
	(4.24)	(1.03)	(1.33)	(7.85)	(1.84)	(3.62)
FF5	1.24***	0.31	0.80*	2.37***	0.72*	1.65***
	(3.87)	(0.42)	(1.86)	(6.06)	(1.75)	(2.93)
q^4	0.41	−0.23	−0.19	1.66***	−0.09	1.75***
	(1.25)	(−0.34)	(−0.42)	(4.32)	(−0.23)	(3.15)
BF3	−0.01	−0.23	−0.49	1.30***	−0.38	1.68***
	(−0.02)	(−0.32)	(−1.13)	(2.99)	(−0.87)	(2.73)
EL6	0.06	−0.41	0.22	1.28***	−0.18	1.45***
	(0.23)	(−0.77)	(0.67)	(3.30)	(−0.59)	(2.98)
			Sharpe Ratios			
SR	0.48	0.08	0.31	2.02	0.17	1.85
p-value	-	-	-	-	-	0.00

Table 2 Performance of Conditional Momentum Strategies

This table presents raw excess returns, factor-adjusted returns and Sharpe ratios for four conditional momentum strategies. The sample period is 1972:07 to 2022:12. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. Column (1) assumes investors holding only the risk-free asset (with zero excess returns), except in Low-RV months when they implement the momentum strategy. Column (2) describes a strategy where the market factor strategy is implemented consistently, except in Low-RV months when the momentum strategy is implemented. Column (3) corresponds to a strategy where investors implement the momentum strategy in Low-RV months, hold the risk-free asset in Medium-RV months, and implement the reverse momentum strategy (i.e., losers-minus-winners) in High-RV months. Column (4) explores the volatility-managed momentum strategy of Barroso and Santa-Clara (2015). The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), the Fama-French 5-factor model (Fama and French 2015, FF5), the q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	(1)	(2)	(3)	(4)
Constant	0.74***	1.22***	0.67**	1.24***
	(7.08)	(6.46)	(2.52)	(6.27)
	Factor-Adjusted Returns			
CAPM	0.75***	0.80***	0.49**	1.30***
	(7.05)	(5.63)	(2.00)	(6.63)
FF5	0.74***	0.86***	0.52*	1.35***
	(6.45)	(5.73)	(1.89)	(6.18)
q^4	0.64***	0.83***	0.92***	0.89***
	(5.71)	(5.53)	(2.93)	(4.17)
BF3	0.56***	0.73***	0.96***	0.54**
	(5.14)	(4.76)	(2.75)	(2.54)
EL6	0.60***	0.76***	1.16***	0.68***
	(5.49)	(5.06)	(4.21)	(3.77)
	Sharpe Ratios			
SR	1.00	0.91	0.35	0.88

Table 3 Testing the Investment CAPM with Cross-sectional Fama-MacBeth Regressions

This table reports coefficient estimates from *univariate* unconditional ("Unc.") and conditional Fama-MacBeth regressions of future stock returns (FRET), future profitability (FROE), or future investment growth (FIG) in month t onto the underlying variable of the momentum (WML) strategy (i.e., the cumulative return from $t-12$ to $t-2$). Panel A reports results based on cross-sectional weighted least squares (WLS) regressions for all stocks, and Panel B presents results based on cross-sectional ordinary least squares (OLS) regressions for non-micro-cap stocks. Only FRET is multiplied by 100. The first four rows of each panel report respectively unconditional coefficient estimates ("Unc.") and coefficient estimates in three volatility states ("High", "Medium", and "Low"), computed based on Eq. (3.9) and Eq. (3.10). The sample includes momentum signals formed between 1972:06 and 2022:05. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "L − M&H" row shows differences in coefficient estimates between the Low-RV subsample and the combined Medium- and High-RV subsamples (i.e., subsample M&H), as detailed in Eq. (3.11). t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

	FRET	FIG	FROE
Panel A: WLS (All Stocks)			
Unc.	0.75***	0.04***	0.11***
	(3.22)	(10.47)	(9.47)
High	0.22	0.05***	0.14***
	(0.34)	(5.62)	(4.90)
Medium	0.46**	0.03***	0.09***
	(2.00)	(6.68)	(5.88)
Low	1.68***	0.05***	0.12***
	(5.08)	(9.47)	(7.83)
M&H	0.36	0.04***	0.11***
	(1.22)	(7.75)	(7.08)
L − M&H	1.33***	0.01	0.00
	(3.03)	(1.40)	(0.23)
Panel B: OLS (Non-Micro-Cap Stocks)			
Unc.	0.68***	0.05***	0.09***
	(3.21)	(12.35)	(10.20)
High	0.16	0.05***	0.11***
	(0.26)	(6.54)	(4.49)
Medium	0.36*	0.04***	0.07***
	(1.86)	(9.93)	(7.06)
Low	1.65***	0.05***	0.11***
	(6.33)	(7.75)	(10.17)
M&H	0.27	0.04***	0.08***
	(1.03)	(10.28)	(7.27)
L − M&H	1.37***	0.00	0.02
	(3.72)	(0.47)	(1.54)

Table 4 Testing the Factor Momentum Channel

Panel A presents unconditional and conditional returns of the factor momentum (FMOM) strategy as well as difference in FMOM returns between the low-volatility subsample and the rest of the sample. Volatility states of FMOM are defined in the same way as those of stock momentum except that we use $\hat{\sigma}_{\mathrm{FMOM,t-1}}$ from Eq. (3.15) as the state variable. Panel B presents unconditional and conditional returns of the stock momentum (WML) strategy sorted on the lagged correlation between daily WML returns and daily FMOM returns ($\hat{\rho}_{\{\mathrm{WML,FMOM}\},\mathrm{t-1}}$) with the 30%-30% cutoff points. The last column reports the difference in WML returns between Low-correlation months and remaining months. Panel C presents WML returns sorted independently on the lagged realized volatility of WML ($\hat{\sigma}_{\mathrm{WML,t-1}}$) and $\hat{\rho}_{\{\mathrm{WML,FMOM}\},\mathrm{t-1}}$ and the differences in WML returns between the Low-RV (or Low-correlation) subsample and the rest of the sample. The sample period is 1972:07 to 2022:12. Heteroskedasticity-adjusted t-statistics are shown in parentheses.

Panel A: FMOM vs $\hat{\sigma}_{\mathrm{FMOM,t-1}}$

	Unc.	High	Medium	Low	M&H	L − M&H
Constant	0.34***	0.35***	0.37***	0.29***	0.36***	−0.07
	(6.64)	(2.58)	(5.65)	(5.23)	(5.23)	(−0.83)

Panel B: WML vs $\hat{\rho}_{\{\mathrm{WML,FMOM}\},\mathrm{t-1}}$

	Unc.	High	Medium	Low	M&H	L − M&H
Constant	1.02***	0.78	0.55	1.89***	0.65*	1.23**
	(3.38)	(1.23)	(1.17)	(4.05)	(1.70)	(2.05)

Panel C: Independent Double Sorting on $\hat{\sigma}_{\mathrm{WML,t-1}}$ and $\hat{\rho}_{\{\mathrm{WML,FMOM}\},\mathrm{t-1}}$ for WML

		$\hat{\rho}_{\{\mathrm{WML,FMOM}\},\mathrm{t-1}}$				
		H	M	L	M&H	L − M&H
$\hat{\sigma}_{\mathrm{WML,t-1}}$	H	0.35	−0.61	2.50	0.02	2.49
		(0.36)	(−0.40)	(0.74)	(0.02)	(0.72)
	M	0.57	−0.18	1.30**	0.05	1.25
		(0.62)	(−0.31)	(2.22)	(0.11)	(1.65)
	L	2.86***	2.38***	2.43***	2.50***	−0.07
		(3.53)	(4.59)	(5.46)	(5.72)	(−0.11)
	M&H	0.42	−0.33	1.50**	0.03	1.46*
		(0.57)	(−0.51)	(2.04)	(0.07)	(1.67)
	L − M&H	2.44**	2.70***	0.93	2.47***	
		(2.25)	(3.27)	(1.09)	(3.79)	

Table 5 Testing the Underreaction Channel: Future Announcement Returns

This table reports coefficient estimates from *univariate* unconditional ("Unc.") and conditional Fama-MacBeth regressions of returns in month t (FRET) as well as cumulative raw and abnormal returns surrounding the first quarterly earnings announcement subsequent to the formation month $t-1$ (FCR4 and FCAR4) onto the underlying variable of the momentum (WML) strategy (i.e., the cumulative return from $t-12$ to $t-2$). Panel A reports results based on cross-sectional weighted least squares (WLS) regressions for all stocks, and Panel B presents results based on cross-sectional ordinary least squares (OLS) regressions for non-micro-cap stocks. All dependent variables are multiplied by 100. The first four rows of each panel report respectively unconditional coefficient estimates ("Unc.") and coefficient estimates in three volatility states ("High", "Medium", and "Low"), computed based on Eq. (3.9) and Eq. (3.10). The sample includes momentum signals formed between 1972:06 and 2022:05. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "L − M&H" row shows differences in coefficient estimates between the Low-RV subsample and the combined Medium-RV and High-RV subsamples (i.e., subsample M&H), as detailed in Eq. (3.11). t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

	FRET	FCAR4	FCR4
Panel A: WLS (All Stocks)			
Unc.	0.77***	0.32***	0.33***
	(3.30)	(2.97)	(2.98)
High	0.23	0.21	0.12
	(0.38)	(0.98)	(0.54)
Medium	0.45*	0.20*	0.29***
	(1.89)	(1.72)	(2.89)
Low	1.72***	0.57***	0.59***
	(5.10)	(4.31)	(4.20)
M&H	0.36	0.21	0.22
	(1.24)	(1.58)	(1.63)
L − M&H	1.36***	0.36**	0.37**
	(3.12)	(2.03)	(2.01)
Panel B: OLS (Non-Micro-Cap Stocks)			
Unc.	0.68***	0.33***	0.36***
	(3.13)	(3.30)	(3.69)
High	0.14	0.18	0.20
	(0.26)	(0.95)	(1.22)
Medium	0.37*	0.19	0.24*
	(1.88)	(1.51)	(1.82)
Low	1.62***	0.66***	0.69***
	(6.10)	(6.36)	(6.56)
M&H	0.28	0.19*	0.22**
	(1.06)	(1.71)	(2.13)
L − M&H	1.34***	0.47***	0.46***
	(3.66)	(3.44)	(3.40)

Table 6 Testing the Underreaction Channel: Time-series and Cross-sectional Variation in Analyst Forecast Errors

This table presents the variation in analyst forecast errors across $r_{2,12}$-sorted deciles and different volatility states. $r_{2,12}$ represents cumulative return from month $t-12$ to $t-2$, which is the underlying variable of the momentum (WML) strategy. For each firm, at the end of each portfolio formation month $(t-1)$, we aggregate all analysts' forecasts for the firm's forthcoming quarterly earnings per share (EPS) and then calculate analyst forecast errors using the mean EPS forecast along with the actual EPS based on Eq. (3.16). At the end of each formation month $(t-1)$, we sort stocks into deciles using $r_{2,12}$. Portfolio membership mirrors that used in the construction of decile portfolios. Within each decile, we compute the *equal-weighted* and *value-weighted* average (denoted as EW and VW) forecast errors using the full sample, the three subsamples (High-RV, Medium-RV, and Low-RV) and Medium- and High-RV subsamples combined. The "L − M&H" row shows differences in EW or VW forecast errors across deciles. The sample includes momentum signals formed between 1983:12 and 2022:11. Note that subsamples (i.e., momentum volatility states) are determined using the sample period of 1972:07 to 2022:12 with the 30%-30% cutoff points. t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

Decile	L	2	3	4	5	6	7	8	9	H	H − L
					EW Forecast Errors						
Full Sample	0.31***	0.24***	0.19***	0.16***	0.12***	0.10***	0.08***	0.06***	0.05***	0.02	−0.29***
	(5.55)	(5.59)	(5.49)	(5.19)	(5.06)	(4.44)	(3.97)	(3.42)	(2.74)	(1.32)	(−7.07)
High	0.14***	0.12***	0.10***	0.08***	0.06**	0.04	0.02	0.00	−0.02	−0.04***	−0.18***
	(2.80)	(2.71)	(2.78)	(2.62)	(2.20)	(1.48)	(0.91)	(0.11)	(−0.88)	(−2.64)	(−4.70)
Medium	0.28***	0.21***	0.17***	0.13***	0.11***	0.08***	0.06***	0.05***	0.05***	0.02	−0.26***
	(4.86)	(4.82)	(4.40)	(3.89)	(3.90)	(3.62)	(3.38)	(3.17)	(2.89)	(1.46)	(−5.56)
Low	0.63***	0.48***	0.38***	0.32***	0.24***	0.22***	0.20***	0.17***	0.14***	0.12***	−0.51***
	(10.91)	(8.30)	(8.21)	(8.36)	(9.62)	(8.19)	(7.68)	(7.49)	(7.23)	(5.56)	(−12.81)
M&H	0.21***	0.17***	0.13***	0.10***	0.08***	0.06***	0.04***	0.03**	0.02	−0.01	−0.22***
	(5.06)	(5.06)	(4.90)	(4.45)	(4.31)	(3.38)	(2.85)	(2.04)	(1.18)	(−0.73)	(−6.99)
L − M&H	0.42***	0.31***	0.24***	0.21***	0.16***	0.16***	0.15***	0.14***	0.13***	0.13***	−0.29***
	(6.07)	(4.87)	(4.90)	(5.01)	(5.57)	(5.26)	(5.45)	(5.41)	(5.41)	(5.37)	(−5.98)
					VW Forecast Errors						
Full Sample	0.26***	0.16***	0.11***	0.08***	0.05***	0.04**	0.02*	0.01	−0.00	−0.03**	−0.29***
	(5.13)	(4.34)	(3.94)	(3.41)	(3.06)	(2.32)	(1.67)	(1.15)	(−0.02)	(−2.06)	(−7.14)
High	0.14***	0.08***	0.04*	0.02	0.01	−0.00	−0.02	−0.02*	−0.04***	−0.07***	−0.21***
	(2.85)	(2.94)	(1.80)	(1.30)	(0.58)	(−0.09)	(−1.23)	(−1.76)	(−2.83)	(−4.26)	(−5.24)
Medium	0.20***	0.11***	0.08***	0.07**	0.05**	0.02	0.01	0.00	0.00	−0.03**	−0.23***
	(3.87)	(3.10)	(2.99)	(2.44)	(2.25)	(1.25)	(0.77)	(0.42)	(0.12)	(−2.58)	(−5.29)
Low	0.54***	0.34***	0.24***	0.17***	0.12***	0.13***	0.11***	0.08***	0.06***	0.04**	−0.50***
	(7.97)	(5.45)	(5.18)	(4.86)	(4.61)	(5.18)	(4.71)	(4.16)	(2.86)	(2.08)	(−8.67)
M&H	0.17***	0.10***	0.06***	0.05***	0.03**	0.01	−0.00	−0.01	−0.02*	−0.05***	−0.22***
	(4.62)	(3.96)	(3.27)	(2.61)	(1.98)	(0.85)	(−0.27)	(−0.96)	(−1.84)	(−4.34)	(−7.20)
L − M&H	0.37***	0.25***	0.18***	0.13***	0.09***	0.12***	0.11***	0.09***	0.08***	0.09***	−0.28***
	(5.11)	(3.80)	(3.67)	(3.43)	(3.02)	(4.44)	(4.74)	(4.28)	(3.44)	(3.92)	(−4.61)

Table 7 Conditional Alphas of Long and Short Legs of WML

The table reports conditional unadjusted and factor-adjusted returns earned by the long and short legs of the momentum portfolio (WML). The return on the long leg is defined as the return on the top decile portfolio in excess of the market return. The return on the short leg is defined as the market returns in excess of the return on the bottom decile portfolio. The sample period is 1972:07 to 2022:12. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "Low" column provides alphas in Low-RV months, while the "M&H" column presents alphas in the subsample combining Medium-RV and and High-RV states. The column labeled "Dif" presents differences in alphas between the Low-RV subsample and the M&H subsample. The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), the Fama-French 5-factor model (Fama and French 2015, FF5), the q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	Long − Market			Market − Short		
	Low	M&H	Dif	Low	M&H	Dif
Constant	0.82***	0.35*	0.47*	1.65***	0.05	1.60***
	(4.08)	(1.89)	(1.72)	(7.65)	(0.15)	(4.15)
CAPM	0.76***	0.25	0.51*	1.71***	0.44	1.27***
	(3.93)	(1.35)	(1.90)	(8.27)	(1.62)	(3.70)
FF5	0.98***	0.36**	0.62**	1.39***	0.35	1.04***
	(4.74)	(2.12)	(2.31)	(5.99)	(1.24)	(2.83)
q^4	0.59***	0.13	0.47*	1.06***	−0.22	1.29***
	(2.86)	(0.69)	(1.68)	(4.62)	(−0.82)	(3.62)
BF3	0.44	0.16	0.28	0.86***	−0.54*	1.40***
	(1.58)	(0.94)	(0.85)	(3.48)	(−1.68)	(3.45)
EL6	0.55***	0.05	0.50*	0.73***	−0.23	0.96***
	(2.59)	(0.38)	(1.95)	(3.12)	(−1.03)	(2.98)

Table 8 52-Week-High Momentum: Time-series and Cross-sectional Variation in Analyst Forecast Errors

This table presents the variation in analyst forecast errors across *pth*-sorted deciles and different momentum volatility states. *pth* represents the ratio of current price to 52-week high price at the end of month $t-2$. For each firm, at the end of each portfolio formation month $(t-1)$, we aggregate all analysts' forecasts for the firm's forthcoming quarterly earnings per share (EPS) and then calculate analyst forecast errors using the mean EPS forecast along with the actual EPS based on Eq. (3.16). At the end of each formation month $(t-1)$, we sort stocks into deciles using *pth*. Portfolio membership mirrors that used in the construction of decile portfolios. Within each decile, we compute the *equal-weighted* and *value-weighted* average (denoted as EW and VW) forecast errors using the full sample, the three subsamples (High-RV, Medium-RV, and Low-RV) and Medium- and High-RV subsamples combined. The "L − M&H" row shows differences in EW or VW forecast errors across deciles. The sample includes 52-week high signals formed between 1983:12 and 2022:11. Note that subsamples (i.e., momentum volatility states) are determined using the sample period of 1972:07 to 2022:12 with the 30%-30% cutoff points. t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

Decile	L	2	3	4	5	6	7	8	9	H	H − L
					EW Forecast Errors						
Full Sample	0.31***	0.25***	0.19***	0.15***	0.12***	0.08***	0.06***	0.05***	0.03*	0.02	−0.30***
	(5.42)	(5.59)	(5.15)	(4.80)	(4.63)	(3.79)	(3.14)	(2.72)	(1.89)	(1.17)	(−6.64)
High	0.13***	0.12***	0.09**	0.06**	0.05*	0.02	0.00	−0.01	−0.02	−0.04***	−0.17***
	(2.81)	(2.82)	(2.54)	(2.05)	(1.80)	(0.99)	(0.15)	(−0.42)	(−1.08)	(−2.76)	(−4.45)
Medium	0.28***	0.21***	0.16***	0.12***	0.10***	0.06***	0.05***	0.04**	0.02	0.01	−0.26***
	(4.74)	(4.91)	(4.37)	(3.90)	(3.78)	(2.93)	(2.60)	(2.33)	(1.50)	(1.15)	(−5.41)
Low	0.64***	0.51***	0.40***	0.31***	0.26***	0.20***	0.17***	0.15***	0.12***	0.10***	−0.54***
	(10.61)	(8.43)	(7.85)	(7.77)	(7.91)	(7.47)	(6.90)	(6.45)	(5.76)	(5.07)	(−12.14)
M&H	0.21***	0.17***	0.13***	0.09***	0.07***	0.04***	0.03*	0.02	0.00	−0.01	−0.22***
	(4.96)	(5.19)	(4.63)	(4.01)	(3.72)	(2.71)	(1.74)	(1.22)	(0.11)	(−0.94)	(−6.58)
L − M&H	0.43***	0.34***	0.28***	0.22***	0.19***	0.16***	0.14***	0.13***	0.11***	0.11***	−0.32***
	(6.10)	(5.11)	(5.01)	(5.05)	(5.12)	(5.47)	(5.20)	(5.07)	(5.08)	(4.97)	(−6.20)
					VW Forecast Errors						
Full Sample	0.26***	0.18***	0.13***	0.08***	0.07***	0.05***	0.03*	0.02	0.00	0.00	−0.26***
	(5.22)	(4.62)	(3.81)	(3.25)	(3.20)	(2.72)	(1.79)	(1.13)	(0.32)	(0.13)	(−6.56)
High	0.12***	0.08**	0.04*	0.01	0.01	0.00	−0.02	−0.03**	−0.03***	−0.04***	−0.16***
	(2.60)	(2.52)	(1.95)	(0.35)	(0.79)	(0.18)	(−1.06)	(−2.34)	(−3.07)	(−3.20)	(−4.20)
Medium	0.21***	0.14***	0.10***	0.07***	0.06**	0.03*	0.02	0.01	0.00	−0.00	−0.22***
	(4.32)	(3.69)	(2.99)	(2.71)	(2.25)	(1.82)	(1.30)	(0.58)	(0.00)	(−0.25)	(−5.39)
Low	0.56***	0.40***	0.31***	0.21***	0.17***	0.14***	0.10***	0.10***	0.07***	0.07***	−0.50***
	(9.32)	(6.12)	(5.13)	(5.34)	(5.34)	(4.68)	(4.75)	(3.54)	(3.83)	(3.23)	(−11.04)
M&H	0.17***	0.11***	0.07***	0.04**	0.04**	0.02	0.00	−0.01	−0.02*	−0.02**	−0.19***
	(4.82)	(4.25)	(3.31)	(2.27)	(2.17)	(1.37)	(0.24)	(−0.95)	(−1.92)	(−2.02)	(−6.86)
L − M&H	0.40***	0.29***	0.24***	0.17***	0.14***	0.12***	0.10***	0.10***	0.08***	0.09***	−0.31***
	(5.97)	(4.22)	(3.91)	(4.07)	(3.96)	(3.92)	(4.30)	(3.63)	(4.54)	(3.78)	(−6.45)

Table 9 Performance of Momentum Conditional on Market States

The set of columns labeled "y = WML" presents unadjusted returns, alphas and Sharpe ratios of the momentum (WML) strategy. The first column presents unconditional performance of WML. The next two columns report the performance of the WML strategy conditional on market states, covering the sample period of 1972:07 to 2022:12. The market state for a formation period ending in month $t-1$ is determined by the cumulative market return over the past year. The market is classified as "Up" if the past year's return is non-negative, and "Down" if it is negative. The column labeled "Up − Down" presents differences in alphas or Sharpe ratios between Up markets and Down markets. "p-value" denotes the p-value of the difference in Sharpe ratios computed from 100,000 bootstrap samples. The set of columns labeled "y = Con. WML" presents raw excess returns, factor-adjusted returns and Sharpe ratios for three conditional momentum strategies. In Column (1), investors are assumed to hold only the risk-free asset (with zero excess return) except in Up-Market months when the momentum strategy is executed. Column (2) corresponds to a strategy where the market factor portfolio is held at all times except in Up-Market months when the momentum strategy is implemented. Column (3) corresponds to a strategy where investors hold WML in Up-Market months and the reverse of the momentum strategy (i.e., losers-minus-winners) in Down-Market months. The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), the Fama-French 5-factor model (Fama and French 2015, FF5), the q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). Heteroskedasticity-adjusted t-statistics are shown in parentheses.

	y = WML				y = Con. WML		
	Unc.	Up	Down	Up − Down	(1)	(2)	(3)
Constant	1.02***	1.34***	−0.07	1.41	1.04***	1.08***	1.05***
	(3.38)	(4.79)	(−0.08)	(1.44)	(4.77)	(4.40)	(3.49)
Factor-Adjusted Returns							
CAPM	1.21***	1.28***	0.12	1.16	1.01***	0.83***	0.81***
	(4.24)	(4.64)	(0.16)	(1.42)	(4.70)	(3.58)	(2.87)
FF5	1.24***	1.60***	−0.34	1.93***	1.24***	1.10***	1.25***
	(3.87)	(5.64)	(−0.49)	(2.60)	(5.44)	(4.55)	(4.43)
q^4	0.41	1.00***	−0.95	1.94***	0.84***	0.77***	1.26***
	(1.25)	(3.04)	(−1.54)	(2.78)	(3.37)	(2.83)	(3.51)
BF3	−0.01	0.59*	−1.40*	2.00**	0.60**	0.66**	1.20***
	(−0.02)	(1.91)	(−1.82)	(2.40)	(2.57)	(2.56)	(3.04)
EL6	0.06	0.50**	−0.95	1.45**	0.60***	0.63***	1.14***
	(0.23)	(2.06)	(−1.55)	(2.20)	(3.03)	(2.71)	(3.37)
Sharpe Ratios							
SR	0.48	0.77	-0.02	0.79	0.67	0.62	0.49
p-value	-	-	-	0.04	-	-	-

Appendix

A Supplementary Tables

Table A1 Detailed Regression Results: Unconditional Performance of WML

This table provides unconditional regression results supplementary to those reported in Table 1.

	RAW	CAPM	FF5	q^4	BF3	EL6
α	1.02*** (3.38)	1.21*** (4.24)	1.24*** (3.87)	0.41 (1.25)	−0.01 (−0.02)	0.06 (0.23)
β_{MKT}		−0.32*** (−3.36)	−0.30*** (−3.10)	−0.23*** (−2.97)	−0.18** (−2.13)	−0.13* (−1.93)
β_{SMB}			−0.14 (−0.86)			−0.45*** (−3.66)
β_{HML}			−0.82*** (−4.91)			−0.71*** (−5.45)
β_{CMA}			0.59** (2.20)			−0.07 (−0.40)
β_{RMW}			0.20 (0.92)			0.16 (1.33)
β_{ME}				0.30* (1.83)		
β_{IA}				−0.25 (−1.14)		
β_{ROE}				1.46*** (7.37)		
β_{PEAD}					1.78*** (6.71)	
β_{FIN}					0.14 (1.16)	
β_{FMOM}						3.93*** (12.99)
R^2_{adj}	0.00	0.04	0.10	0.27	0.24	0.49
N	606	606	606	606	606	606

Table A2 Detailed Regression Results: Conditional Performance of WML

This table provides conditional regression results supplementary to those reported in Table 1. Panel A presents estimated alphas and factor loadings in three volatility states, whereas Panel B reports differences in these estimates between the Low-RV subsample and the rest of the sample (i.e., High- and Medium-RV subsamples combined).

Panel A: Estimated alphas and factor loadings in three volatility states

	High RV					Medium RV					Low RV				
	CAPM	FF5	q^4	BF3	EL6	CAPM	FF5	q^4	BF3	EL6	CAPM	FF5	q^4	BF3	EL6
α	0.72	0.31	−0.23	−0.23	−0.41	0.51	0.80*	−0.19	−0.49	0.22	2.47***	2.37***	1.66***	1.30***	1.28***
	(1.03)	(0.42)	(−0.34)	(−0.32)	(−0.77)	(1.33)	(1.86)	(−0.42)	(−1.13)	(0.67)	(7.85)	(6.06)	(4.32)	(2.99)	(3.30)
β_{MKT}	−0.77***	−0.66***	−0.39***	−0.58***	−0.30**	−0.00	−0.03	0.09	0.16	−0.03	0.01	−0.03	−0.09	0.08	−0.08
	(−4.69)	(−3.80)	(−2.85)	(−4.22)	(−2.51)	(−0.00)	(−0.20)	(0.78)	(1.21)	(−0.27)	(0.06)	(−0.33)	(−0.97)	(0.87)	(−1.07)
β_{SMB}		0.03			−0.69***		−0.52***			−0.53***		0.22			−0.02
		(0.10)			(−2.60)		(−2.65)			(−3.23)		(1.11)			(−0.11)
β_{HML}		−1.08***			−0.59***		−0.45*			−0.78***		0.00			−0.58***
		(−4.64)			(−3.24)		(−1.88)			(−2.95)		(0.01)			(−3.28)
β_{CMA}		0.75*			−0.13		0.04			−0.10		0.01			−0.38
		(1.68)			(−0.52)		(0.10)			(−0.31)		(0.02)			(−1.44)
β_{RMW}		0.35			0.12		−0.40			−0.43**		0.50			−0.03
		(1.19)			(0.62)		(−1.48)			(−2.07)		(1.58)			(−0.10)
β_{ME}			0.74***					−0.15					0.35*		
			(2.89)					(−0.87)					(1.91)		
β_{IA}			−0.87**					0.36					0.38		
			(−2.57)					(1.25)					(1.65)		
β_{ROE}			1.77***					1.16***					0.92***		
			(6.08)					(5.88)					(4.94)		
β_{PEAD}				2.17***					1.28***					1.13***	
				(5.42)					(4.40)					(3.89)	
β_{FIN}				0.09					0.18					0.27*	
				(0.50)					(1.03)					(1.89)	
β_{FMOM}					4.24***					3.54***					3.14***
					(9.14)					(7.94)					(7.21)
R^2_{adj}	0.14	0.22	0.41	0.37	0.59	-0.00	0.07	0.16	0.15	0.38	-0.01	0.00	0.13	0.12	0.29

Panel B: Differences in alphas and factor loadings between the Low-RV subsample and the rest of the sample.

	Low − Medium&High				
	CAPM	FF5	q^4	BF3	EL6
α	1.78***	1.65***	1.75***	1.68***	1.45***
	(3.62)	(2.93)	(3.15)	(2.73)	(2.98)
β_{MKT}	0.43***	0.36**	0.15	0.35**	0.09
	(2.79)	(2.25)	(1.10)	(2.54)	(0.77)
β_{SMB}		0.41			0.55***
		(1.51)			(2.68)
β_{HML}		0.95***			0.11
		(3.23)			(0.50)
β_{CMA}		−0.68			−0.37
		(−1.50)			(−1.13)
β_{RMW}		0.32			−0.13
		(0.80)			(−0.43)
β_{ME}			0.01		
			(0.02)		
β_{IA}			0.82**		
			(2.33)		
β_{ROE}			−0.65**		
			(−2.22)		
β_{PEAD}				−0.68	
				(−1.64)	
β_{FIN}				0.18	
				(0.93)	
β_{FMOM}					−0.89
					(−1.61)

Table A3 Conditional Performance of Momentum Relative to Other Factor Models

The set of columns labeled "y = WML" in Panel A presents raw excess returns and factor-adjusted returns (a.k.a alphas) of the momentum (WML) strategy. The first three columns of this set report the performance of WML conditional on volatility states. The sample period is 1972:07 to 2022:12. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML,t-1}}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML,t-1}}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The column labeled "L − M&H" presents differences in alphas or Sharpe ratios between the Low-RV subsample and the rest of the sample (i.e., High- and Medium-RV subsamples combined). The columns under "y = Con. WML" presents raw excess returns, factor-adjusted returns and Sharpe ratios for four conditional momentum strategies introduced in Section 3.3.2. The factor models considered include: the alternative q-factor model of Novy-Marx (2015b, q^{4a}) where the ROE factor is decomposed into the lag-ROE and ΔROE factors, the Fama and French (1993) 3-factor model augmented by Standardized Unexpected Earnings (SUE) factor and the factor based on 4-day Cumulative Abnormal Returns surrounding the latest quarterly earnings announcement (CAR4) (Novy-Marx 2015a, NM5), and the augmented *q*-factor model of Hou et al. (2021, q^5). The construction of the lag-ROE, ΔROE, SUE and CAR4 factors is detailed in Section IA1 of the Internet Appendix. Heteroskedasticity-adjusted *t*-statistics are shown in parentheses.

	y = WML				y = Con. WML			
	Unc.	Low	M&H	L − M&H	(1)	(2)	(3)	(4)
Constant	1.02***	2.47***	0.40	2.07***	0.74***	1.22***	0.67**	1.24***
	(3.38)	(7.87)	(0.98)	(4.03)	(7.08)	(6.46)	(2.52)	(6.27)
	Factor-Adjusted Returns							
q^{4a}	0.08	1.19***	−0.28	1.47***	0.58***	0.77***	0.97***	0.64***
	(0.27)	(3.31)	(−0.83)	(2.99)	(5.46)	(5.23)	(3.07)	(3.46)
NM5	−0.35	0.63	−0.62*	1.25**	0.51***	0.69***	1.15***	0.38**
	(−1.10)	(1.61)	(−1.69)	(2.34)	(4.92)	(4.63)	(3.03)	(2.01)
q^5	−0.10	1.06***	−0.49	1.55***	0.54***	0.76***	1.05***	0.51**
	(−0.31)	(2.61)	(−1.21)	(2.71)	(4.69)	(5.09)	(3.27)	(2.33)

Internet Appendix for: What Explains Momentum When It Really Works?

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Abstract

This Internet Appendix provides the construction details for variables and portfolios used in the main empirical analysis, as well as additional empirical results that supplement those presented in the main text.

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IA1 Variable and Portfolio Construction

IA1.1 Before-1966 Daily WML Returns

For WML portfolios between Jan 1927 and December 1966, whose daily returns are not available on the q-data library, we construct them along the lines of Hou, Xue, and Zhang (2020)'s methodology. We supplement Compustat book equity data with historical book equity data of Davis, Fama, and French (2000). We keep firms with missing book equity so that the CRSP stocks that are not covered by the dataset of Davis, Fama, and French (2000) or Compustat are included in our sample. The correlation between our monthly (daily) WML returns and those from Lu Zhang's data library over the 1967–2022 period is 99.8% (99.7%).

IA1.2 Earnings Surprise Measures

IA1.2.1 Returns Surrounding Earnings Announcement Date

We follow prior studies (e.g., Chan, Jegadeesh, and Lakonishok 1996; Daniel, Hirshleifer, and Sun 2020; Hou, Xue, and Zhang 2020) to compute 4-day returns surrounding quarterly earnings announcement date. Specifically, We define the cumulative abnormal return surrounding an quarterly earnings announcement date from two trading days preceding that to the one trading day after that ($car4$), which is given by

$$car4 = \sum_{d=-2}^{+1} r_{id} - r_{md}, \tag{IA1.1}$$

where r_{id} denotes stock i's return on day d, r_{md} denotes return of the CRSP value-weighted market index on day d, and $d = 0$ corresponds to the earnings announcement date. When an earnings announcement date is not a trading day, we regard the first trading day subsequent to that as day 0. We remove stocks with more than two missing returns over the 4-day window; $car4$ is assumed to be observable at the end of day 1. The unadjusted 4-day announcement returns are defined as:

$$cr4 = \sum_{d=-2}^{+1} r_{id}. \tag{IA1.2}$$

IA1.2.2 Standardized Unexpected Earnings

Following Foster, Olsen, and Shevlin (1984) and Hou, Xue, and Zhang (2020), the standardized unexpected earnings (sue) is given by

$$sue = \frac{epspxq_q^{adj} - E[epspxq_q^{adj}])}{\text{std}(epspxq_q^{adj} - E[epspxq_q^{adj}])}, \tag{IA1.3}$$

where $epspxq_q^{adj}$ denotes the split-adjusted earnings per share in quarter q. Quarterly earnings per share are assumed to follow a seasonal random walk, that is,

$$E[epspxq_q^{adj}] = epspxq_{q-4}^{adj}, \tag{IA1.4}$$

where $epspxq_{q-4}^{adj}$ denotes the split-adjusted earnings per share in quarter $q-4$. We use the innovations in quarterly earnings over the past eight (at least six) quarters to compute their standard deviation ("std"). Quarterly earnings are assumed to be publicly available at the end of the month in which they are announced.

IA1.3 Decomposition of Quarterly ROE

Novy-Marx (2015b) decomposes quarterly return-on-equity (roe) into two components:

$$roe = \frac{ibq_q}{beq_{q-1}} = \frac{ibq_{q-4}}{beq_{q-1}} + \frac{ibq_q - ibq_{q-4}}{beq_{q-1}} = \text{lag-}roe + \Delta roe, \tag{IA1.5}$$

where roe denotes the ratio of quarterly income before extraordinary items (ibq_q) over 1-quarter-lagged book equity (beq_{q-1}) and ibq_{q-4} denotes quarterly income before extraordinary items in quarter $q-4$. At the end of month $t-1$, we construct the lag-ROE (ΔROE) factor on the basis of the latest lag-roe (Δroe). Quarterly earnings are assumed to be publicly available at the end of the month in which they are announced.

IA1.4 Factor Portfolio Construction

We construct four factor portfolios based on the most recent sue, $car4$, lag-roe, and Δroe, respectively (denoted as SUE, CAR4, lag-ROE, and ΔROE). The investment universe is the same as that for the WML portfolio. Our construction method is in line with Fama and

French (1996), Novy-Marx (2015b), and Novy-Marx (2015a). Specifically, at the end of each formation month (t-1), we build six value-weighted portfolios formed on *size* and one of the four characteristic variables (denoted as *cvar*). The size breakpoint is the median market equity of NYSE stocks, and the *cvar* breakpoints are the 30th and 70th NYSE percentiles. The factor return is calculated as the average return of the two high-*cvar* portfolios in excess of the average return of the two low-*cvar* portfolios. All factor portfolios are rebalanced monthly.

IA1.5 52-week High Momentum

Following George, Hwang, and Li (2018), the underlying variable of the 52-week high anomaly is the ratio of split-adjusted price at the end of month $t-2$ to the highest daily split-adjusted price over the past 12 months from the first day of month $t-13$ to the last day of month $t-2$ (denoted as *pth*). We remove stocks with incomplete price history when computing *pth*. Consistent with the momentum signal construction, we skip month $t-1$ to avoid the effect of short-term reversal (Jegadeesh 1990). We follow the literature (e.g., Hou, Xue, and Zhang 2015; George, Hwang, and Li 2018; Hou, Xue, and Zhang 2020) to use *pth* smaller than one to compute NYSE breakpoints on *pth* since a disproportionally large number of stocks approach the 52-week high at the same time (i.e., $pth = 1$). We calculate monthly value-weighted returns for each decile in month t using the market equity at the end of month $t-1$ as weights. Note that we follow George, Hwang, and Li (2018) and only remove financial firms in the construction of the PTH portfolio.

IA2 Additional Results

IA2.1 Conditionality of WML: Alternative Regression Specification

In this section, we directly use $\hat{\sigma}_{\text{WML},t-1}$ to test the conditionality of WML. Our time-series regression specification, which is based on the conditional CAPM of Shanken (1990) and allows alphas and factor loadings of WML to vary with momentum risk, is given by:

$$\mathrm{WML_t} = \alpha_0 + \alpha_z z_{t-1} + \sum_{k=1}^{K} (\beta_{k,0} + \beta_{k,z} z_{t-1}) f_{kt} + \epsilon_t, \tag{IA2.1}$$

where z_{t-1} denotes the log realized volatility of WML in month $t-1$ ($\log(\hat{\sigma}_{\mathrm{WML,t-1}})$) and f_{kt} denotes factor k's return in month t. Note that z_{t-1} is demeaned and standardized so that α_z captures the response of the factor-adjusted return of WML to a one standard deviation shock in $\log(\hat{\sigma}_{\mathrm{WML,t-1}})$, while α_0 represents the factor-adjusted return of WML when $\log(\hat{\sigma}_{\mathrm{WML,t-1}})$ is at its average level. The regression results are reported in Table IA2.

[Insert Table IA2 near here]

Each factor model is associated with two sets of estimated coefficients, with odd-numbered column providing the results of unconditional regression of WML on factor portfolios and even-numbered column providing conditional regression results based on Eq. (IA2.1).

IA2.2 Additional Tables

Table IA1 Full Regression Results for Four Volatility-managed Momentum Strategies

This table provide regression results in addition to those reported in Table 2. Panels A through D correspond to Columns (1) through (4) of Table 2, respectively.

Panel A: Column (1) of Table 2

	CAPM	FF5	q^4	BF3	EL6
α	0.75*** (7.05)	0.74*** (6.45)	0.64*** (5.71)	0.56*** (5.14)	0.60*** (5.49)
β_{MKT}	−0.01 (−0.25)	−0.01 (−0.32)	0.01 (0.23)	0.03 (0.93)	0.01 (0.37)
β_{SMB}		0.01 (0.25)			−0.03 (−0.54)
β_{HML}		−0.00 (−0.10)			0.01 (0.21)
β_{CMA}		−0.03 (−0.44)			−0.11 (−1.54)
β_{RMW}		0.04 (1.03)			0.04 (0.84)
β_{ME}			0.05 (1.09)		
β_{IA}			0.03 (0.59)		
β_{ROE}			0.15*** (3.21)		
β_{PEAD}				0.20*** (3.98)	
β_{FIN}				0.07** (2.52)	
β_{FMOM}					0.47*** (4.67)

Panel B: Column (2) of Table 2

	CAPM	FF5	q^4	BF3	EL6
α	0.80*** (5.63)	0.86*** (5.73)	0.83*** (5.53)	0.73*** (4.76)	0.76*** (5.06)
β_{MKT}	0.73*** (15.50)	0.71*** (15.20)	0.72*** (15.46)	0.73*** (14.74)	0.73*** (15.61)
β_{SMB}		−0.04 (−0.66)			−0.06 (−1.13)
β_{HML}		0.06 (1.09)			0.07 (1.21)
β_{CMA}		−0.11 (−1.20)			−0.17* (−1.73)
β_{RMW}		−0.10* (−1.83)			−0.10* (−1.79)
β_{ME}			−0.02 (−0.31)		
β_{IA}			0.00 (0.02)		
β_{ROE}			−0.06 (−1.08)		
β_{PEAD}				0.10 (1.62)	
β_{FIN}				0.00 (0.07)	
β_{FMOM}					0.34*** (3.05)

Table continues

Panel C: Column (3) of Table 2

	CAPM	FF5	q^4	BF3	EL6
α	0.49** (2.00)	0.52* (1.89)	0.92*** (2.93)	0.96*** (2.75)	1.16*** (4.21)
β_{MKT}	0.31*** (3.78)	0.30*** (3.63)	0.30*** (3.97)	0.29*** (3.73)	0.21*** (2.91)
β_{SMB}		−0.03 (−0.25)			0.13 (1.04)
β_{HML}		0.70*** (4.56)			0.64*** (5.12)
β_{CMA}		−0.61** (−2.39)			−0.25 (−1.29)
β_{RMW}		−0.17 (−0.82)			−0.15 (−1.04)
β_{ME}			−0.30** (−2.12)		
β_{IA}			0.34 (1.53)		
β_{ROE}			−0.92*** (−4.22)		
β_{PEAD}				−0.90*** (−3.28)	
β_{FIN}				0.08 (0.68)	
β_{FMOM}					−2.13*** (−6.13)

Panel D: Column (4) of Table 2

	CAPM	FF5	q^4	BF3	EL6
α	1.30*** (6.63)	1.35*** (6.18)	0.89*** (4.17)	0.54** (2.54)	0.68*** (3.77)
β_{MKT}	−0.10* (−1.81)	−0.10* (−1.75)	−0.05 (−0.90)	0.00 (0.07)	−0.01 (−0.11)
β_{SMB}		−0.09 (−0.92)			−0.27*** (−3.32)
β_{HML}		−0.32*** (−3.47)			−0.25*** (−3.00)
β_{CMA}		0.14 (1.02)			−0.23* (−1.95)
β_{RMW}		0.07 (0.62)			0.04 (0.56)
β_{ME}			0.12 (1.25)		
β_{IA}			−0.06 (−0.55)		
β_{ROE}			0.70*** (8.33)		
β_{PEAD}				1.02*** (8.84)	
β_{FIN}				0.14** (2.28)	
β_{FMOM}					2.25*** (12.23)

Table IA2 Performance of Momentum Relative to Unconditional and Conditional Factor Models

This table presents the performance of the momentum (WML) strategy in terms of both unadjusted and factor-adjusted returns, along with the loadings on respective factors under unconditional and conditional model structures. For odd-numbered columns (excluding column (1)), the factor models are considered unconditional, whereas for even-numbered columns (excluding column (2)), the abnormal returns and factor loadings are considered conditional, varying with the lagged natural logarithm of the realized volatility of momentum (denoted as z), which is demeaned and standardized. The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), the Fama-French 5-factor model (Fama and French 2015, FF5), the q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). Heteroskedasticity-adjusted t-statistics are shown in parentheses. The sample period is 1972:07 to 2022:12.

	Constant		CAPM		FF5		q^4		BF3		EL6	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α_0	1.02***	1.02***	1.21***	1.16***	1.24***	1.23***	0.41	0.48	−0.01	0.25	0.06	0.35
	(3.38)	(3.42)	(4.24)	(4.22)	(3.87)	(4.01)	(1.25)	(1.55)	(−0.02)	(0.83)	(0.23)	(1.51)
α_z		−1.14***		−0.95***		−1.13***		−0.90***		−0.72*		−0.67***
		(−2.70)		(−2.74)		(−3.39)		(−3.00)		(−1.89)		(−2.76)
β_{MKT}			−0.32***	−0.23***	−0.30***	−0.23***	−0.23***	−0.11	−0.18**	−0.10	−0.13*	−0.11*
			(−3.36)	(−3.17)	(−3.10)	(−2.84)	(−2.97)	(−1.50)	(−2.13)	(−1.57)	(−1.93)	(−1.93)
$\beta_{MKT\times z}$				−0.38***		−0.26***		−0.14**		−0.29***		−0.13**
				(−4.27)		(−2.99)		(−2.11)		(−3.94)		(−2.23)
β_{SMB}					−0.14	−0.11					−0.45***	−0.38***
					(−0.86)	(−0.80)					(−3.66)	(−3.66)
$\beta_{SMB\times z}$						−0.05						−0.31**
						(−0.27)						(−2.12)
β_{HML}					−0.82***	−0.53***					−0.71***	−0.60***
					(−4.91)	(−3.74)					(−5.45)	(−4.37)
$\beta_{HML\times z}$						−0.35**						−0.01
						(−2.37)						(−0.05)
β_{CMA}					0.59**	0.18					−0.07	−0.22
					(2.20)	(0.81)					(−0.40)	(−1.30)
$\beta_{CMA\times z}$						0.51**						0.10
						(2.19)						(0.67)
β_{RMW}					0.20	−0.06					0.16	−0.10
					(0.92)	(−0.26)					(1.33)	(−0.77)
$\beta_{RMW\times z}$						0.23						0.09
						(1.27)						(0.59)
β_{ME}							0.30*	0.25*				
							(1.83)	(1.90)				
$\beta_{ME\times z}$								0.32**				
								(2.21)				
β_{IA}							−0.25	−0.07				
							(−1.14)	(−0.35)				
$\beta_{IA\times z}$								−0.47***				
								(−2.72)				
β_{ROE}							1.46***	1.16***				
							(7.37)	(8.35)				
$\beta_{ROE\times z}$								0.46***				
								(2.84)				
β_{PEAD}									1.78***	1.42***		
									(6.71)	(7.59)		
$\beta_{PEAD\times z}$										0.40		
										(1.46)		
β_{FIN}									0.14	0.14		
									(1.16)	(1.43)		
$\beta_{FIN\times z}$										−0.04		
										(−0.35)		
β_{FMOM}											3.93***	3.61***
											(12.99)	(14.28)
$\beta_{FMOM\times z}$												0.38
												(1.27)
R^2_{adj}	0.00	0.02	0.04	0.13	0.10	0.19	0.27	0.34	0.24	0.30	0.49	0.53
N	606	606	606	606	606	606	606	606	606	606	606	606

Table IA3 Testing the Investment CAPM with Cross-sectional Fama-MacBeth Regressions: Alternative Profitability Measure

This table reports coefficient estimates from *univariate* unconditional ("Unc.") and conditional Fama-MacBeth regressions of future stock returns (FRET), future profitability (FYK), or future investment growth (FIG) in month t onto the underlying variable of the momentum (WML) strategy (i.e., the cumulative return from $t-12$ to $t-2$). FYK represents future sales-to-lagged-capital ratio, which is defined as annual sales (Compustat item SALE) divided by the one-year-lagged net property, plant and equipment (Compustat item PPENT). Panel A reports results based on cross-sectional weighted least squares (WLS) regressions for all stocks, and Panel B presents results based on cross-sectional ordinary least squares (OLS) regressions for non-micro-cap stocks. Only FRET is multiplied by 100. The first four rows of each panel report respectively unconditional coefficient estimates ("Unc.") and coefficient estimates in three volatility states ("High", "Medium", and "Low"), computed based on Eq. (3.9) and Eq. (3.10). The sample includes momentum signals formed between 1972:06 and 2022:05. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML,t-1}}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML,t-1}}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "L − M&H" row shows differences in coefficient estimates between the Low-RV subsample and the combined Medium- and High-RV subsamples (i.e., subsample M&H), as detailed in Eq. (3.11). t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

	FRET	FIG	FYK
Panel A: WLS (All Stocks)			
Unc.	0.77***	0.04***	2.60***
	(3.27)	(10.51)	(7.47)
High	0.23	0.05***	2.58***
	(0.36)	(5.65)	(4.14)
Medium	0.47**	0.03***	3.19***
	(2.03)	(6.78)	(6.85)
Low	1.70***	0.05***	1.83***
	(5.18)	(9.29)	(4.50)
M&H	0.36	0.04***	2.93***
	(1.23)	(7.83)	(7.40)
L − M&H	1.34***	0.01	−1.10**
	(3.05)	(1.37)	(−2.20)
Panel B: OLS (Non-Micro-Cap Stocks)			
Unc.	0.70***	0.05***	2.79***
	(3.27)	(12.31)	(10.45)
High	0.16	0.05***	3.12***
	(0.28)	(6.60)	(5.86)
Medium	0.37*	0.04***	2.77***
	(1.93)	(10.09)	(8.10)
Low	1.67***	0.05***	2.48***
	(6.38)	(7.39)	(6.77)
M&H	0.28	0.04***	2.92***
	(1.09)	(10.43)	(9.30)
L − M&H	1.38***	0.00	−0.44
	(3.78)	(0.41)	(−0.99)

Table IA4 Testing the Underreaction Channel: Announcement Returns in the Subsequent Month

This table reports coefficient estimates from *univariate* unconditional ("Unc.") and conditional Fama-MacBeth regressions of returns in month t (FRET) as well as cumulative raw and abnormal returns surrounding the quarterly earnings announcement in month t (FCR4 and FCAR4) onto the underlying variable of the momentum (WML) strategy (i.e., the cumulative return from $t-12$ to $t-2$). Panel A reports results based on cross-sectional weighted least squares (WLS) regressions for all stocks, and Panel B presents results based on cross-sectional ordinary least squares (OLS) regressions for non-micro-cap stocks. All dependent variables are multiplied by 100. The first four rows of each panel report respectively unconditional coefficient estimates ("Unc.") and coefficient estimates in three volatility states ("High", "Medium", and "Low"), computed based on Eq. (3.9) and Eq. (3.10). The sample includes momentum signals formed between 1972:06 and 2022:05. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "L − M&H" row shows differences in coefficient estimates between the Low-RV subsample and the combined Medium- and High-RV subsamples (i.e., subsample M&H), as detailed in Eq. (3.11). t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

	FRET	FCAR4	FCR4
Panel A: WLS (All Stocks)			
Unc.	1.00***	0.36***	0.36***
	(3.43)	(2.89)	(2.77)
High	0.20	0.33	0.17
	(0.29)	(1.21)	(0.65)
Medium	0.71*	0.12	0.22
	(1.88)	(0.63)	(1.01)
Low	2.18***	0.70***	0.73***
	(5.52)	(5.26)	(5.15)
M&H	0.49	0.21	0.20
	(1.29)	(1.26)	(1.12)
L − M&H	1.69***	0.49**	0.53**
	(3.12)	(2.28)	(2.28)
Panel B: OLS (Non-Micro-Cap Stocks)			
Unc.	0.95***	0.48***	0.51***
	(3.47)	(4.19)	(4.56)
High	−0.02	0.20	0.24
	(−0.04)	(1.06)	(1.26)
Medium	0.86***	0.50***	0.52***
	(2.61)	(2.70)	(2.85)
Low	2.04***	0.73***	0.76***
	(6.15)	(5.44)	(5.71)
M&H	0.48	0.37***	0.40***
	(1.51)	(2.86)	(3.07)
L − M&H	1.56***	0.35*	0.36*
	(3.44)	(1.87)	(1.90)

Table IA5 Testing the Underreaction Channel: Time-series and Cross-sectional Variation in Analyst Forecast Errors—Alternative measure

This table presents the variation in analyst forecast errors across $r_{2,12}$-sorted deciles and different volatility states. $r_{2,12}$ represents cumulative return from $t-12$ to $t-2$, which is the underlying variable of the momentum (WML) strategy. For each firm, at the end of each portfolio formation month, we aggregate all analysts' forecasts for the firm's forthcoming quarterly earnings per share (EPS) and then calculate analyst forecast errors using the mean EPS forecast along with the actual EPS based on Eq. (3.16) whose denominator is replaced by stock prices. At the end of each formation month, we sort stocks into deciles using $r_{2,12}$. Portfolio membership mirrors that used in the construction of decile portfolios. Within each decile, we compute the *equal-weighted* and *value-weighted* average (denoted as EW and VW) forecast errors using the full sample, the three subsamples (High-RV, Medium-RV, and Low-RV) and Medium- and High-RV subsamples combined. The "L − M&H" row shows differences in EW or VW forecast errors across deciles. The sample includes momentum signals formed between 1983:12 and 2022:11. Note that subsamples (or volatility states) are determined using the period of 1972:07 to 2022:12. t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

Decile	L	2	3	4	5	6	7	8	9	H	H − L
						EW Forecast Errors					
Full Sample	0.90***	0.42***	0.28***	0.20***	0.14***	0.10***	0.07***	0.05**	0.02	−0.01	−0.91***
	(5.32)	(5.38)	(5.04)	(4.58)	(4.25)	(3.44)	(2.86)	(2.11)	(1.04)	(−0.60)	(−5.77)
High	0.88***	0.40***	0.24***	0.15**	0.10**	0.05	0.02	−0.01	−0.04	−0.06**	−0.94***
	(2.79)	(2.82)	(2.69)	(2.33)	(2.00)	(1.15)	(0.55)	(−0.23)	(−1.25)	(−2.09)	(−3.16)
Medium	0.60***	0.29***	0.19***	0.12***	0.09***	0.06**	0.03*	0.02	0.01	−0.01	−0.61***
	(3.58)	(3.64)	(3.40)	(2.92)	(2.81)	(2.23)	(1.83)	(1.35)	(0.76)	(−0.86)	(−3.86)
Low	1.44***	0.69***	0.49***	0.39***	0.27***	0.24***	0.20***	0.17***	0.12***	0.06**	−1.38***
	(6.33)	(6.22)	(6.18)	(6.18)	(6.00)	(5.75)	(5.26)	(5.14)	(3.93)	(2.26)	(−6.62)
M&H	0.73***	0.34***	0.21***	0.14***	0.09***	0.05**	0.03	0.01	−0.01	−0.03**	−0.77***
	(4.02)	(4.10)	(3.96)	(3.45)	(3.16)	(2.12)	(1.43)	(0.49)	(−0.70)	(−2.06)	(−4.42)
L − M&H	0.71**	0.35***	0.28***	0.25***	0.18***	0.19***	0.18***	0.16***	0.14***	0.10***	−0.61**
	(2.55)	(2.65)	(3.11)	(3.47)	(3.52)	(3.97)	(4.32)	(4.33)	(3.86)	(3.05)	(−2.37)
						VW Forecast Errors					
Full Sample	0.47***	0.19***	0.10***	0.06**	0.03	0.02	−0.00	−0.01	−0.03**	−0.07***	−0.54***
	(4.59)	(3.70)	(3.04)	(2.25)	(1.51)	(0.86)	(−0.14)	(−0.74)	(−2.24)	(−5.71)	(−5.59)
High	0.37***	0.11**	0.03	−0.00	−0.01	−0.03	−0.05***	−0.05***	−0.07***	−0.10***	−0.47***
	(2.73)	(1.99)	(0.99)	(−0.02)	(−0.76)	(−1.54)	(−2.93)	(−3.09)	(−4.09)	(−5.48)	(−3.55)
Medium	0.29***	0.13**	0.06*	0.04	0.02	−0.01	−0.02	−0.03***	−0.04***	−0.07***	−0.36***
	(2.93)	(2.16)	(1.91)	(1.32)	(0.72)	(−0.30)	(−0.93)	(−2.81)	(−3.09)	(−6.87)	(−3.83)
Low	0.91***	0.39***	0.27***	0.18***	0.13***	0.12***	0.08**	0.08**	0.03	−0.02	−0.92***
	(5.25)	(4.36)	(4.20)	(3.40)	(2.74)	(3.18)	(2.26)	(2.19)	(1.04)	(−0.81)	(−5.64)
M&H	0.33***	0.12***	0.05**	0.02	0.00	−0.02	−0.03**	−0.04***	−0.06***	−0.08***	−0.41***
	(3.74)	(2.83)	(1.97)	(1.11)	(0.13)	(−1.06)	(−2.45)	(−3.89)	(−4.80)	(−7.54)	(−4.84)
L − M&H	0.58***	0.27***	0.22***	0.16***	0.13**	0.14***	0.11***	0.12***	0.09***	0.06***	−0.51***
	(3.07)	(2.79)	(3.14)	(2.83)	(2.50)	(3.33)	(3.00)	(3.15)	(2.65)	(2.67)	(−2.87)

Table IA6 52-week High vs Momentum

This table presents the estimated coefficients from unconditional and conditional Fama-MacBeth-WLS regressions of stock returns in month t onto $r_{2,12}$ and pth in month $t-1$ separately as well as both of them. t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

Panel A: 1972:07 – 2022:12

	Uncon.			High			Medium			Low			Low − Medium&High		
pth	1.59***		0.11	0.31		−1.41	0.75		−0.56	3.99***		2.51**	3.44***		3.43**
	(3.07)		(0.15)	(0.28)		(−0.89)	(0.85)		(−0.58)	(4.87)		(2.58)	(3.32)		(2.38)
$r_{2,12}$		0.77***	1.04***		0.28	1.10**		0.46**	0.98**		1.68***	1.06***		1.29***	0.03
		(3.52)	(4.08)		(0.47)	(2.03)		(2.01)	(2.54)		(5.38)	(2.74)		(3.10)	(0.05)

Panel B: 1927:07 – 2022:12

	Uncon.			High			Medium			Low			Low − Medium&High		
pth	1.42***		−0.52	0.08		−2.22	0.50		−0.94	3.98***		1.75*	3.66***		3.24**
	(2.85)		(−0.76)	(0.07)		(−1.47)	(0.78)		(−1.12)	(6.26)		(1.79)	(4.33)		(2.58)
$r_{2,12}$		0.95***	1.49***		0.25	1.88***		0.66***	1.18***		2.03***	1.53***		1.54***	0.05
		(4.26)	(5.80)		(0.39)	(2.81)		(3.30)	(3.77)		(9.03)	(4.81)		(4.36)	(0.12)

Table IA7 Performance of PTH Conditional on Momentum Volatility States

The set of columns labeled "y = PTH" in Panel A presents raw excess returns, factor-adjusted returns (a.k.a alphas) and Sharpe ratios of the 52-week-high (PTH) strategy. The first three columns of this set report the performance of PTH conditional on volatility states. The sample period is 1972:07 to 2022:12. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML,t-1}}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML,t-1}}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The column labeled "L − M&H" presents differences in alphas or Sharpe ratios between the Low-RV subsample and the rest of the sample (i.e., High- and Medium-RV subsamples combined). "p-value" denotes the p-value of the difference in Sharpe ratios computed from 100,000 bootstrap samples. The columns under "y = Con. PTH" in Panel A presents raw excess returns, factor-adjusted returns and Sharpe ratios for three PTH strategies contingent on momentum volatility states. Column (1) assumes investors hold only the risk-free asset (with zero excess returns), except in Low-RV months when they implement the PTH strategy. Column (2) describes a strategy where the market factor portfolio is held consistently, except in Low-RV months when the PTH strategy is implemented. Column (3) corresponds to a strategy where investors implement the PTH strategy in Low-RV months, hold the risk-free asset in Medium-RV months, and implement the reverse 52-week high strategy in High-RV months (−1×PTH). Panel B provides conditional alphas earned by long and short legs of PTH. The factor models considered include: the market model (Sharpe 1964; Lintner 1965; Black 1972, CAPM), the Fama-French 5-factor model (Fama and French 2015, FF5), the q-factor model (Hou, Xue, and Zhang 2015, q^4), the risk-and-behavioral 3-factor model (Daniel, Hirshleifer, and Sun 2020, BF3), and the FF5 model augmented with the (off-the-shelf) factor momentum strategy of Ehsani and Linnainmaa (2022, EL6). Heteroskedasticity-adjusted t-statistics are shown in parentheses.

Panel A: Conditional Alphas of PTH and Alphas of Conditional PTH Strategies

	y = PTH				y = Con. PTH		
	Unc.	Low	M&H	L − M&H	(1)	(2)	(3)
Constant	0.71**	1.78***	0.25	1.53***	0.54***	1.01***	0.53*
	(2.24)	(5.72)	(0.58)	(2.89)	(5.40)	(5.43)	(1.93)
			Factor-Adjusted Returns				
CAPM	1.18***	1.94***	0.89**	1.05**	0.61***	0.67***	0.32
	(4.49)	(7.16)	(2.53)	(2.38)	(6.16)	(4.06)	(1.22)
FF5	0.97***	1.43***	0.78**	0.65	0.64***	0.75***	0.63**
	(3.48)	(4.89)	(2.21)	(1.42)	(6.28)	(4.46)	(2.34)
q^4	0.29	0.91***	0.10	0.82*	0.60***	0.80***	1.15***
	(1.06)	(3.16)	(0.29)	(1.86)	(6.12)	(4.70)	(4.04)
BF3	−0.49	0.76**	−0.72*	1.47***	0.48***	0.66***	1.22***
	(−1.56)	(2.28)	(−1.88)	(2.92)	(4.81)	(3.55)	(3.39)
EL6	0.05	0.77**	0.06	0.71*	0.55***	0.70***	1.20***
	(0.21)	(2.48)	(0.21)	(1.71)	(5.58)	(4.02)	(4.15)
				Sharpe Ratios			
SR	0.32	1.47	0.10	1.37	0.76	0.76	0.27
p-value	-	-	-	0.00	-	-	-

Panel B: Conditional Alphas of Long and Short Legs of PTH

	Long − Market			Market − Short		
	Low	M&H	Dif	Low	M&H	Dif
Constant	0.17	0.03	0.14	1.61***	0.22	1.39***
	(1.63)	(0.25)	(0.90)	(6.48)	(0.63)	(3.26)
CAPM	0.21**	0.18*	0.03	1.73***	0.70**	1.02***
	(2.13)	(1.71)	(0.20)	(7.84)	(2.46)	(2.83)
FF5	0.13	0.14	−0.02	1.30***	0.64**	0.67*
	(1.06)	(1.25)	(−0.10)	(6.22)	(2.31)	(1.93)
q^4	−0.02	0.03	−0.05	0.93***	0.07	0.86***
	(−0.13)	(0.25)	(−0.27)	(4.54)	(0.26)	(2.62)
BF3	−0.14	−0.16	0.03	0.89***	−0.55*	1.45***
	(−1.01)	(−1.45)	(0.15)	(3.45)	(−1.76)	(3.56)
EL6	−0.11	−0.04	−0.07	0.88***	0.10	0.78**
	(−0.90)	(−0.41)	(−0.45)	(3.93)	(0.44)	(2.44)

Table IA8 Testing the Investment CAPM with Cross-sectional Fama-MacBeth Regressions: 52-week High

This table reports coefficient estimates from *univariate* unconditional ("Unc.") and conditional Fama-MacBeth regressions of future stock returns (FRET), future profitability (FROE), or future investment growth (FIG) in month t onto the underlying variable of the 52-week high (PTH) strategy (i.e., the ratio of current price to 52-week high price at the end of month $t-2$). Panel A reports results based on cross-sectional weighted least squares (WLS) regressions for all stocks, and Panel B presents results based on cross-sectional ordinary least squares (OLS) regressions for non-micro-cap stocks. Only FRET is multiplied by 100. The first four rows of each panel report respectively unconditional coefficient estimates ("Unc.") and coefficient estimates in three volatility states ("High", "Medium", and "Low"), computed based on Eq. (3.9) and Eq. (3.10). The sample includes 52-week high signals formed between 1972:06 and 2022:05. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML},t-1}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML},t-1}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "L − M&H" row shows differences in coefficient estimates between the Low-RV subsample and the combined Medium- and High-RV subsamples (i.e., subsample M&H), as detailed in Eq. (3.11). t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

	FRET	FIG	FROE
Panel A: WLS (All Stocks)			
Unc.	1.53***	0.15***	0.53***
	(2.88)	(14.25)	(12.19)
High	0.12	0.16***	0.66***
	(0.11)	(7.82)	(8.98)
Medium	0.80	0.14***	0.51***
	(0.88)	(8.69)	(10.02)
Low	3.91***	0.18***	0.42***
	(4.51)	(15.32)	(6.89)
M&H	0.51	0.15***	0.58***
	(0.77)	(11.23)	(11.97)
L − M&H	3.40***	0.03*	−0.16**
	(3.16)	(1.95)	(−2.19)
Panel B: OLS (Non-Micro-Cap Stocks)			
Unc.	2.23***	0.18***	0.46***
	(4.38)	(14.89)	(13.83)
High	0.72	0.18***	0.57***
	(0.59)	(6.53)	(9.40)
Medium	1.66***	0.17***	0.45***
	(2.64)	(12.17)	(12.81)
Low	4.49***	0.19***	0.35***
	(6.55)	(12.35)	(9.34)
M&H	1.25*	0.17***	0.50***
	(1.95)	(11.90)	(13.43)
L − M&H	3.23***	0.02	−0.16***
	(3.43)	(0.92)	(−3.10)

Table IA9 Testing the Underreaction Channel: Future Announcement Returns—52-week High

This table reports coefficient estimates from *univariate* unconditional ("Unc.") and conditional Fama-MacBeth regressions of returns in month t (FRET) as well as cumulative raw and abnormal returns surrounding the first quarterly earnings announcement subsequent to the formation month $t-1$ (FCR4 and FCAR4) onto the underlying variable of the 52-week high (PTH) strategy (i.e., the ratio of current price to 52-week high price at the end of month $t-2$). Panel A reports results based on cross-sectional weighted least squares (WLS) regressions for all stocks, and Panel B presents results based on cross-sectional ordinary least squares (OLS) regressions for non-micro-cap stocks. All dependent variables are multiplied by 100. The first four rows of each panel report respectively unconditional coefficient estimates ("Unc.") and coefficient estimates in three volatility states ("High", "Medium", and "Low"), computed based on Eq. (3.9) and Eq. (3.10). The sample includes 52-week high signals formed between 1972:06 and 2022:05. We split the sample period into three volatility states based on the 30%-30% cutoff points for the lagged realized volatility (RV) of momentum, as defined by $\hat{\sigma}_{\mathrm{WML,t-1}}$ from Eq. (3.1). The volatility states are determined by classifying a formation period ending in month $t-1$ as High-RV, Medium-RV, or Low-RV, according to whether $\hat{\sigma}_{\mathrm{WML,t-1}}$ belongs in the top 30%, the middle 40%, or the bottom 30%, respectively. The "L − M&H" row shows differences in coefficient estimates between the Low-RV subsample and the combined Medium- and High-RV subsamples (i.e., subsample M&H), as detailed in Eq. (3.11). t-statistics adjusted for heteroskedasticity and autocorrelation (Newey and West 1987) are shown in parentheses.

	FRET	FCAR4	FCR4
Panel A: WLS (All Stocks)			
Unc.	1.52***	0.78***	0.83***
	(2.86)	(3.32)	(3.38)
High	0.20	0.71	0.59
	(0.17)	(1.31)	(1.06)
Medium	0.71	0.22	0.48*
	(0.80)	(0.82)	(1.76)
Low	3.91***	1.59***	1.53***
	(4.54)	(5.19)	(4.36)
M&H	0.49	0.43	0.53*
	(0.74)	(1.51)	(1.80)
L − M&H	3.42***	1.16***	1.00**
	(3.19)	(2.85)	(2.22)
Panel B: OLS (Non-Micro-Cap Stocks)			
Unc.	2.08***	1.47***	1.51***
	(4.04)	(7.49)	(7.69)
High	0.60	1.04**	1.09***
	(0.48)	(2.48)	(2.64)
Medium	1.57**	1.41***	1.52***
	(2.47)	(5.22)	(5.28)
Low	4.24***	1.98***	1.91***
	(6.28)	(8.60)	(11.45)
M&H	1.15*	1.25***	1.34***
	(1.81)	(5.07)	(5.30)
L − M&H	3.09***	0.72**	0.58*
	(3.35)	(2.25)	(1.77)

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