# One Brief Shining Moment(um): Past Momentum Performance and Momentum Reversals

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**Abstract**

Motivated by behavioral theories, we test whether recent past performance of the momentum strategy (Past Momentum Performance—PMP) negatively predicts the performance of *stale* momentum portfolios. Following periods of top-quintile PMP, momentum portfolios exhibit strong reversals 2-5 years after formation, whereas, following periods of bottom-quintile PMP, stale momentum portfolios earn positive returns. The difference in cumulative five-year Fama-French alphas for momentum portfolios formed in high- and low-PMP months is 40%. A value-weighted trading strategy based on this effect generates an alpha of 0.40% per month ($t = 3.74$). These patterns are confirmed in international data. These findings present a puzzle for existing theories of momentum.

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Cross sectional equity momentum is the phenomenon that stocks that have earned the highest (lowest) returns over the preceding 3-12 months continue to outperform (underperform) the market over the coming 3-12 months. Zero investment portfolios which go long a portfolio of past winners and short a portfolio of past losers earn high Sharpe ratios and have low correlations with macroeconomic variables, posing a challenge for standard rational expectations models.

A set of studies propose behavioral hypotheses to explain the momentum anomaly. An implication of some of these models is that the momentum phenomenon is a result of delayed overreaction to certain information shocks. This implies that a sufficiently 'stale' momentum portfolio, where 'stale' refers to a momentum portfolio formed at a lag of twelve months or more, will on average earn negative abnormal returns. Jegadeesh and Titman (2001) provide evidence that stale momentum portfolios do indeed on average experience negative mean abnormal returns.

A recent literature has also examined time-series variation in profitability of momentum strategies (Cooper, Gutierrez, and Hameed 2004, Daniel and Moskowitz 2016, Barroso and Santa-Clara 2015, Stivers and Sun 2010), and found evidence that past-market returns, market volatility, and the volatility of the momentum portfolio are associated with considerable variation in the momentum premium.

However, to our knowledge, no study has yet examined the conditional variation in the performance of *stale* momentum strategies, i.e., the performance of momentum portfolios in years 2-5 post-formation. One interesting possibility, motivated by the idea that investors chase past style performance, is that strong recent past performance of the momentum style will cause investors to overvalue new momentum portfolios, resulting in poor subsequent long-run performance of these portfolios. In this paper, we explore this issue by testing whether long horizon performance of momentum portfolios is negatively related to the performance of the momentum strategy in the recent past.

In particular, we examine the relation of stale momentum returns to a measure of the recent performance of the momentum strategy, which we call *Past Momentum Performance* or PMP. PMP is simply the return of a standard (12,2) momentum strategy over the preceding 2 years (24 months). Our basic finding is that momentum portfolios formed in high PMP months (months when PMP is in the top 20% of all months in our sample) generate strongly negative returns and alphas 2-5 years after formation. Strikingly, momentum portfolios formed in low PMP months continue to (weakly) outperform in post-formation years 2-5. Thus, the momentum reversal documented by Jegadeesh and Titman (2001) is strongly state dependent.

We explore a set of behavioral hypotheses for the strong dependence of stale momentum performance on PMP. One of our hypotheses is based upon style chasing. (Since our hypotheses go somewhat beyond the style investing model of Barberis and Shleifer (2003), we refer to these hypotheses as derived from the 'style chasing approach' rather than the style investing model.)

A basic hypothesis is that the performance of the momentum style will tend to continue in the short run, so that after the momentum strategy has done well, it tends to do well again. The style chasing approach suggests that following high returns on the momentum style, owing to return extrapolation, naive investors switch into this style, meaning that they buy winners and sell losers heavily. This trading pressure reinforces the strong performance of the momentum strategy, and will temporarily cause better-than-usual momentum performance after the conditioning date if such return chasers arrive gradually.

This effect is driven by overreaction in the components of the momentum portfolio. In consequence, the returns on the momentum portfolio will eventually reverse. So after high PMP, there are on average negative returns to a *stale momentum strategy* of buying firms that were winners at least a year ago and selling firms that were losers at least a year ago.

In contrast, after low PMP, investors switch out of the momentum style. Heavy selling of winners and buying of losers induces underreaction in winner and loser returns. So after low PMP, this hypothesis implies eventual positive returns to a *stale momentum strategy.* Putting these two cases together, we expect reversal of momentum to be stronger as PMP increases.[1]

Similar predictions apply in a setting without overextrapolation, if investors update their self-confidence in their opinions about the desirability of following a momentum investing strategy in response to the return performance (PMP) that they observe. When momentum investors see high PMP they gain confidence in their belief in the strategy, and when they see

[1]A qualification to the reasoning for the case of low PMP is that there are other forces which can in general bring about reversal of momentum (i.e., negative returns to stale momentum portfolios). As modelled in settings that do not condition on PMP (Barberis, Shleifer, and Vishny 1998, Daniel, Hirshleifer, and Subrahmanyam 1998, Hong and Stein 1999), momentum is associated with overreaction to news that eventually corrects. In consequence, there is reversal of momentum. If such a setting is viewed as the unconditional baseline (i.e., not conditioning on PMP), then the prediction of strong reversal of momentum after high PMP is reinforced, but the prediction that momentum continues (i.e., that even stale momentum strategies earn positive returns) is weakened. For example, it could be that after low PMP, there is still reversal of momentum, but owing to style chasing, the reversal is weaker than usual. Regardless, we expect greater reversal of momentum returns when PMP is higher.

low PMP they update against it. Again this results in stronger momentum portfolio returns after high PMP, followed by unusually poor performance of stale momentum portfolios.[2]

Motivated by these ideas, we examine the relationship between PMP and the performance of stale momentum portfolios and find a number of novel effects. We first show that over the full CRSP sample, there is on average very little tendency of momentum to reverse after controlling for the value effect.[3] This finding is in contrast to that of Jegadeesh and Titman (2001) who find, in a shorter sample, that equal-weighted momentum portfolios exhibit strong reversals even after controlling for the value effect.

Then, turning to our main result, we find a strong relationship between PMP and long-run reversal of momentum—reversal is greater after high PMP. Specifically, we rank the months in our sample into quintiles based on PMP and examine the performance of momentum portfolios formed in each category of month (i.e., for months in each PMP quintile) during the five years after formation. Stale momentum performance declines strongly and monotonically with PMP. In Quintile 1, instead of reversal, momentum portfolios exhibit weak continuation in post-formation years 2-5. In sharp contrast, momentum portfolios formed in Quintile 5 months lose 42% of their value over the next five years. We call this strong reversal of momentum after high PMP the PMP effect.

Similar results obtain after controlling for exposure to the Fama-French factors; the difference in cumulative five-year alphas of Quintile 5 and Quintile 1 momentum portfolios is a startling 40%.[4] In particular, the average alpha of Quintile 5 momentum portfolios is negative in each of the post-formation years 2-5—significantly so in post-formation years 2 and 5. In contrast, in each of the post-formation years 2-5, almost all of the alphas of momentum portfolios formed in Quintile 1-4 months are economically modest and statistically insignificant. In addition, we show that PMP forecasts reversals for both industry and stock-specific momentum portfolios, although the results are stronger for industry momentum. We also find that PMP predicts extreme industry price run-ups that eventually crash (Greenwood,

[2]As discussed in Section 2, owing to bias in self-attribution, we expect this effect to be asymmetric with respect to high versus low PMP. This asymmetry argument has a parallel to overreaction and correction effects of attribution bias modelled by Daniel, Hirshleifer, and Subrahmanyam (1998). Here, however, attribution relates to to beliefs about the momentum investing strategy rather than beliefs about individual stocks.

[3]Several behavioral theories imply that momentum will tend to reverse in the long run (Daniel, Hirshleifer, and Subrahmanyam 1998, Barberis, Shleifer, and Vishny 1998, Hong and Stein 1999). However, these theories do not necessarily imply that there will be incremental reversal after controlling for the value effect.

[4]Our tests control for the differences in valuation ratios of momentum portfolios across the five PMP quintiles by estimating separate Fama-French loadings for each quintile.

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The finding that momentum portfolios that are formed at times of high PMP reverse strongly is consistent with a prediction of the style chasing approach. However, we also document that PMP over the same conditioning period does not positively predict short horizon performance of momentum portfolios. Indeed, the point estimate is that the relation between PMP and short horizon momentum performance is negative.[5] In other words, after high PMP, a WML portfolio does not earn higher-than-usual abnormal returns over the next 12 months. This suggests that the relationship between PMP and momentum reversals that we document is not driven by style chasers piling into momentum portfolios in the year after these portfolios are formed.[6]

Furthermore, these reversals extend too long after the conditioning date to be explained by style chasing. Style chasing implies that these reversals should be complete within a year, since stocks in a winner (loser) portfolio of the momentum strategy do not necessarily remain winners (losers) 12 months later. So a style chaser who has recently been attracted to momentum would tend to get out of any given momentum portfolio within about 12 months after formation.

Our basic tests use full sample information to rank months based on PMP, potentially introducing a look-ahead bias. Although it is not obvious why this would induce the effects that we find, we verify that similar results hold in out-of-sample tests which perform the PMP ranking of months using only information available at the time.

Our findings are also generally similar in international markets. We conduct tests in eight developed markets outside the US that have reasonably large cross-sections of large, liquid stocks. We find a strong inverse relationship between PMP and the performance of stale momentum strategies for almost all of the countries. These results help alleviate any data mining concerns.

[5]However, PMP is not useful for timing standard momentum strategies. After controlling for past market return (which strongly predicts momentum crashes), we do not find a statistically or economically significant relationship between PMP and short horizon momentum returns.

[6]This does not rule out the possibility that investors chase momentum style returns at a higher frequency. The apparent overvaluation of the momentum portfolio that is identified by high PMP must be emerging before the end of the momentum portfolio formation period (since after high PMP we do not observe high post-formation momentum returns). This could reflect investors flowing into shorter-term momentum strategies (e.g., 3-month or 6-month momentum portfolios), so that any continuation of momentum performance is complete subsequent to the end of our 12-month momentum formation period. Still, our findings do not fit well with style chasing at an annual frequency as an explanation of the PMP/momentum reversal effect that we document.

We also show that cross-sectional strategies designed to exploit the PMP effect we identify exhibit strong abnormal performance. These strategies are distinct from the standard momentum strategy, since they consist of momentum portfolios formed 13 to 60 months ago. A long-short portfolio designed to exploit the stale-momentum-reversal effect that we observe following high-PMP months—one that buys stale-loser and sells stale-winner portfolios formed only in PMP Quintile 5 months—earns an alpha of 0.37%/month ($t = 2.93$). The alphas of such strategies formed in different PMP quintile months are monotonically increasing across quintiles. Furthermore, a strategy which exploits the continuation of momentum portfolios formed in low PMP months and reversals of momentum portfolios formed in high PMP months generates still stronger performance, an alpha of 0.40%/month ($t = 3.74$). In contrast, an unconditional stale momentum strategy which pools all months generates an insignificant alpha of 0.07%/month.

Using data on institutional holdings, we test whether the behavior of institutional traders seems broadly consistent with momentum style chasing based on PMP. We find that momentum traders (institutions with a history of buying winners and selling losers) substantially increase their holdings of recent winners and decrease their holdings of recent losers following high PMP periods. On the other hand, there is no association between PMP and the subsequent trading of contrarian investors (institutions with a history of selling winners and buying losers). This suggests that the behavior of momentum-trading institutional investors may play a role in the relation between PMP and stale momentum returns documented in our tests. Also, these findings are consistent with momentum traders chasing past style returns intensely, and therefore having high sensitivity to PMP; and where contrarian investors are not heavy style chasers, and instead accommodate the trades of momentum investors. Nevertheless, as discussed earlier, our return tests suggest that style chasing alone is unlikely to fully explain our findings.

Finally, we conduct a battery of robustness tests to ensure that the PMP effect is distinct from the effects documented in previous studies that identify predictors of momentum returns. Previous studies show that negative market returns, high volatility, and high volatility of momentum strategy are followed by momentum crashes. To control for past market returns, we exclude all months for which the past two-year market return is negative. We find that the PMP effect actually become stronger once down market months are excluded from the sample. We also find that the component of PMP that is orthogonal to market and momentum portfolio volatility predicts strong momentum reversals. Furthermore, using characteristic-adjusted returns to measure abnormal performance instead of alphas does not affect the main conclusions. Finally, we show that our results are not driven by differences in momentum characteristic (formation period difference between returns of winners and losers) across the different PMP quintiles. In other words, our results are not driven by winners being bigger-than-usual conditioning-period winners, or losers being bigger-than-usual losers during high PMP periods.

We consider several possible explanations for these findings. As discussed above, style chasing provides at best incomplete explanations for the findings. We draw the same conclusion about an explanation based upon bias in investor self-attribution. We conclude that the PMP effect remains a puzzle. Our finding that momentum portfolios formed in high PMP months eventually reverse strongly, suggests that in high PMP months, WML formation period returns are at least in part overreaction. So a full explanation for the puzzle seems to require that high PMP be associated with a greater-than-usual fraction of winner-loser conditioning period returns deriving from investor overreaction. The findings on institutional trading further suggest that momentum-trading institutions may be a key source of such overreaction.

We are not the first to perform empirical tests motivated by the style chasing approach. Using Morningstar classifications along size and value dimensions and the returns of mutual funds in these styles, Teo and Woo (2004) find that stocks in styles with poorly performing funds do well in the future. Froot and Teo (2008) examine size, value/growth, and sector as styles. They find that own fund style returns and flows over the past 1-4 weeks positively forecast weekly stock returns, while opposite fund style returns and flows negatively forecast returns. We focus on return predictability at longer time horizons. Our paper also differs in studying time-variation in the performance of stale momentum portfolios. Our focus is on understanding the relationship between past momentum performance and the future performance of momentum portfolios rather than on testing the style investing model (which is just one possible motivation for such conditional effects). Our approach also differs in focusing on past strategy performance rather than past fund performance.

There is also a literature on the determinants of the strength of the momentum anomaly discussed earlier. Our paper differs in focusing on PMP, and in examining reversal of momentum, to consider hypotheses relating to style chasing and self-attribution bias.

The literature on the reversal of momentum focuses mainly on *whether* reversal occurs

(Griffin, Ji, and Martin 2003, Jegadeesh and Titman 2011), or on cross-sectional determinants of reversal (Lee and Swaminathan 2000).[7] Our paper differs in examining a time-series determinant of reversal, PMP. Also, the topic of reversal of momentum is related to the winner/loser effect (DeBondt and Thaler 1985) and the value effect (Rosenberg, Reid, and Lanstein 1985), since these effects are basically linear combinations of return serial covariances at different lags (including lags of greater than 12 months). The extensive literature on the value effect considers various interactors/conditioning variables (both cross-sectional and time series) that affect its strength. Again, our paper differs in using a different conditioning variable, PMP and in performing tests that control for the value effect.

# 1 Motivation and Hypotheses

As discussed in the introduction, the style chasing approach (building intuitively on the style investing model of Barberis and Shleifer (2003)) suggests interesting hypotheses about how past momentum performance predicts returns on momentum strategies and the returns on stale momentum strategies. The style investing theory is based on the hypothesis that investors overextrapolate past style returns in forecasting future style returns. For example, if growth stocks do well, style investors expect growth stocks to do well in the future. As Barberis and Shleifer show, this can lead to 'style chasing': overextrapolating investors buy a style when the style has provided high recent historical returns. Such trading results in continuation in style returns.

It is especially interesting to test for style effects on momentum, because it is an inherently active, high turnover strategy. The kind of investors who are potentially attracted to aggressive styles are likely to be sensation-seeking investors (Grinblatt and Keloharju 2009) who are not deeply and philosophically attached to a single style. This suggests that style effects may be especially strong for the momentum style.

The style chasing approach discussed above suggests that after high PMP, investors become enthusiastic about the momentum style, leading to buying of winners and selling of losers, and therefore to stronger-than usual performance of the momentum style. Similarly, we expect weak momentum performance after low PMP. By the same token, after high PMP,

[7] Lee and Swaminathan (2000) show that high (low) volume winners (losers) exhibit stronger reversals in raw returns but not size and book-to-market adjusted returns.

the stronger-than usual price reaction in winner and loser portfolios caused by style chasing should lead to stronger reversal as these portfolios become stale.[8]

A more subtle implication of style chasing is that for momentum portfolios formed in high-PMP months, any style-chasing reversal of momentum performance should occur within about a year after formation date. This is because past winner (loser) stocks on the long (short) side of a momentum portfolio do not necessarily remain winners (losers) 12 months later. So investors who were attracted to a 12-month winner as a result of high PMP will, on average, no longer have any special reason to be attracted to it 12 months later.[9]

The style chasing approach is based upon extrapolation of past style returns. An alternative approach would be to argue that investors believe that they receive what they regard as private informative signals about the effectiveness of different styles. For example, a group of investors might receive a 'signal,' suggesting that momentum trading is profitable, or alternatively that it is negatively profitable (so that contrarian trading is profitable). This is somewhat analogous to the approach of Daniel, Hirshleifer, and Subrahmanyam (1998), in which investors are overconfident about signals they receive about particular securities. However, the application is at a different level, to investor beliefs about the profitability of styles, not their beliefs about specific securities.

In their model, investors shift their beliefs about the quality of their signals in a self-enhancing fashion owing to *bias in self-attribution*. When their style makes money, they strongly update in favor of believing that their signal was highly accurate, and therefore become strongly reinforced in their faith in the style. In contrast, when their style loses money, they update against their signal only modestly, since they do not like admitting to themselves that they have a low-quality signal. So they only shift modestly away from their style.

[8] These predictions are not implications of the Barberis and Shleifer model; their paper does not discuss the momentum style. In their model, every stock falls into one of two 'twin' styles. For example, one could apply the model to assign winners to a winner style, and losers to a loser style. This definition of styles does not, however, seem closely aligned with how investors view momentum trading in practice. We therefore define the momentum style to be the strategy of buying winners *and* selling losers. So in what we call the style-chasing approach, we view style investors as over-extrapolating the returns of the winner-minus-loser portfolio in deciding whether to invest more heavily in the momentum style. We contrast with a 'twin' contrarian style as trading in the reverse direction. Since predictions about these styles were not made in Barberis and Shleifer (2003), we make no claim to be testing their model.

[9] The momentum effect suggests that past winners will tend to perform well going forward. However, this effect is necessarily small, since the fraction of realized returns explained by momentum is empirically small (Jegadeesh and Titman 2001).

As applied to the momentum style, this suggests that after high PMP, momentum style investors should be strongly reinforced in their enthusiasm for momentum, causing severe overvaluation of the winner-minus-loser portfolio. In consequence, eventual performance of stale momentum portfolios should be very poor.

In contrast, and asymmetrically, after low PMP, momentum style investors withdraw only modestly from the momentum style because they hate to admit to themselves that they were wrong. So there is only modest undervaluation of the winner-minus-loser portfolio. In consequence, eventual performance of stale momentum portfolios should be good, but not exceptionally good (compared to the case of no conditioning on PMP).

The basic reasoning about how high PMP should be associated with future momentum performance is reinforced by consideration of adherents to the contrarian style. Such adherents gain confidence in contrarianism after low PMP and lose confidence after high PMP. This reinforces the effect of momentum traders after high versus low PMP.

However, the reasoning for the *asymmetry* of the PMP effect is reversed for contrarian style investors. For such adherents, bias in attribution causes them to gain confidence in contrarianism especially strongly after low PMP. This asymmetrically causes weakening in any typical overreaction of the winner-minus-loser portfolio (or even causes underreaction in it). So if contrarian style investors predominate, we expect that the effect of high versus low PMP on momentum style returns and on stale momentum returns will be especially strong after *low* PMP.

Overall, the predicted direction of effect for asymmetry depends on how many investors are engaged by the momentum style versus the contrarian style.[10] Momentum investing (with a conditioning period of about 12 months) has a very high profile among professional and even individual investors. For example, many 'smart beta' funds state that they trade based upon momentum. We are not aware of any statements by investors saying that they intentionally trade against 12-month momentum. So we view the prediction for asymmetry as clear—that

[10]The answer to this question does *not* automatically follow from market clearing considerations. It is true that for every investor who follows a momentum strategy there must be other investors trading in the opposite direction. However, such opposite-trading investors are not necessarily adherents of contrarianism as an investment philosophy, and do not necessarily identify themselves as contrarians. For example, suppose there is a set of rational investors who do not over- or under-extrapolate the style returns. Instead, as in standard models of portfolio optimization, their demand for any given security is a decreasing function of its price (for a given probability distribution of its fundamentals). Then if high PMP drives up style chasing demand for the winner-minus-loser portfolio, this reduces demand for that portfolio by rational investors. This incremental 'contrarian' demand is not driven by any change in adherence to the contrarian philosophy, it is simply a rational response to price variation.

the effects of momentum traders dominate. In other words, the effect of PMP on momentum and stale momentum performance should be especially strong after high PMP.

It is important to keep in mind that the arguments provided here are different from the argument in Daniel, Hirshleifer, and Subrahmanyam (1998) for why the momentum anomaly exists. The argument here is about momentum and reversal in *momentum style return performance*, not stock return performance. In other words, it involves predictions about the returns on a new winner-minus-loser portfolio in periods after previous winner-minus-loser portfolios have done well versus badly. Similarly, the style-investing approach implies what Barberis and Shleifer call "style momentum," in which there is positive autocorrelation in *style* performance—a different concept from momentum in individual stock performance. As extended to the momentum style, this is a prediction about momentum in the momentum style, not a prediction about the basic existence of return momentum.

# 2 Data

The main dataset used in this paper is the stock return data from CRSP. Our sample includes all common stocks (CRSP share codes 10 and 11) traded on NYSE, NYSE MKT, and Nasdaq from 1926:01 to 2014:12. We obtain accounting data from the CRSP/Compustat merged database, and factor returns from Ken French's website. The data for international tests is from S&P Capital IQ and institutional ownership data is from Thomson Reuters. We discuss these data in more detail later in the paper.

Following Jegadeesh and Titman (2001), we exclude stocks with price below $5 and stocks with market capitalizations below the $10^{th}$ percentile size breakpoint (using NYSE size breakpoints) at the time of portfolio formation. At the end of each month, we rank stocks into deciles based on their cumulative return over the past 12 months, skipping the most recent month. We then construct a long-short WML portfolio that is long the value-weighted portfolio of "Winners" (top decile) and short the value-weighted portfolio of "Losers" (bottom decile). Portfolios are held for one month. This procedure results in a monthly time-series of WML returns.

We calculate past momentum performance, $PMP_t$ in month $t$ as the average monthly return of WML over the past 24 months:

$$\text{PMP}_t = \frac{1}{24} \sum_{\tau=-23}^{0} \text{WML}_{t+\tau}.$$

We then rank each month $t$ of the 973 months in our sample[11] into quintiles based on $PMP_t$ and examine the performance of WML portfolios formed in different PMP quintile months over the subsequent five years.

Table 1 reports some characteristics of the PMP quintiles. PMP Quintile 5 is associated with lower market return over the past 1 and 2 years and both high and low PMP quintile months are associated with higher market volatility in the recent past. Previous studies (Daniel and Moskowitz 2016, Cooper, Gutierrez, and Hameed 2004) document that recent decline in the market portfolio forecasts momentum crashes. Our results are not related to this finding; in fact, as we show later, the reversals that we document become stronger once we exclude down market months from our tests. Our results also are not explained by the findings of previous studies that show a relationship between momentum profits and volatility of market and momentum portfolios in the recent past (see Section 3.6). Table 1 also shows a U-shaped relationship between PMP and the momentum characteristic (formation period difference in returns of winner and loser portfolios).

Figure 1 plots the time-series of PMP. While the mean PMP value is high, there is considerable variation in momentum performance over time. The highest level of PMP in our time series is 6.9%/month, achieved in February 2000, just before the market peak in March 2000. The lowest level of PMP is achieved at the end of June, 1934, and is -6.2%/month.

# 3 Results

Figure 2 illustrates our key finding: the strong negative relationship between PMP and the long horizon performance of stale momentum portfolios, defined as portfolios formed at least one year earlier. Panel A plots the average cumulative 5-year returns of the value-weighted momentum portfolios formed in different PMP quintile months as well as in all months.

[11] The PMP time series is from 1928:12 (first month for which PMP can be calculated) to 2009:12. We end in 2009 since we examine returns five years after portfolio formation.

Specifically, we plot:

$$\frac{1}{N_q}\sum_{t\in T_q}\left[\prod_{s=1}^{\tau}(1+WML_{t+s}^{t}+rf_{t+s})-\prod_{s=1}^{\tau}(1+rf_{t+s})\right],$$

where:

- $WML_{t+s}^{t}$ is the return in month $t+s$ to the momentum portfolio formed in month $t$. That is, $WML_{t}^{t}$ is the return of the "fresh" momentum portfolio that is rebalanced at the end of each month based on the past (12,2) return. $WML_{t+s}^{t}$ is the return on the "stale" momentum portfolio which was formed $s$ months ago.

- $T_q$ denotes the set of months that are in PMP quintile $q$ and $N_q$ the number of months.

The yellow line (labeled "ALL") confirms the previous finding that momentum profits (raw returns) reverse in years 2-5 after portfolio formation—the cumulative return of the portfolio becomes negative at the end of year five. Figure 2 also shows a strong monotonically declining relationship between post-formation returns and *PMP*. Momentum portfolios formed in PMP Quintile 5 months lose over 42% of their value in five years. Interestingly, momentum portfolios formed in PMP Quintile 5 months do not generate positive returns even in the first post-formation year. However, this result can be explained by previous findings. Once we control for past market return and exposure to the value factor, these portfolios generate positive alphas in the first post-formation year (see Table 7).

Panel A of Figure 2 also shows that momentum portfolios formed in Quintile 1 months do not exhibit any reversals. This is quite surprising since this portfolio loads negatively on HML, which is known to have a high mean return.

Momentum portfolios load negatively on the value factor and the spread between the valuation ratios of winners and losers is much wider in Quintile 5 months. Therefore, the results in Panel A could just reflect the long-run underperformance of growth stocks relative to value stocks. However, Panel B shows that this is not the case. Panel B plots the cumulative Fama and French (1993) three-factor alphas (we describe the calculation of alphas below) for the momentum portfolios for portfolios formed in each PMP quintile. After controlling for Fama-French factors, momentum portfolios formed in Quintile 5 months continue to exhibit strong reversals in post-formation years 2-5, while momentum portfolios formed in Quintile 1 months exhibit continuation. Although the spread between top and bottom quintile 5-year cumulative alpha is smaller than the corresponding spread in raw returns shown in Panel A, it is still economically very large—almost 40%.

Panels A and B of Figure 3 plot the cumulative alphas of the past-winner and past-loser portfolios, respectively. For PMP Quintile 5 months, the reversals in post-formation years 2-5 are about twice as strong for the Winner portfolio as for the Loser portfolio. These results are consistent with the hypothesis that the overvaluation of the Winner portfolios is harder to arbitrage owing to short-sale constraints.

An interesting question is why the effect of PMP is especially strong in Quintile 5 months. If higher PMP is associated with stronger overreaction, resulting in reversal in stale momentum portfolios, why don't we see a strong opposite effect for Quintile 1 PMP: strong continuation in stale momentum portfolios? One possibility is that for some reason the PMP effect inherently derives mainly from winners rather than losers (perhaps for reasons unrelated to short sales constraints). If so, then in high PMP months the reversal effect will be strong, owing to the fact that the Winner portfolio is predicted to have low returns, which is hard to arbitrage owing to short sale constraints. In contrast, in low PMP months, for stale momentum portfolio to earn high return-continuation returns, the winners would need to earn high returns, which could be arbitraged away without going short.

Figures 4 and 5 provide two alternative depictions of the PMP effect. Figure 4 plots, as a function of the portfolio formation date, the cumulative return (in excess of the risk free return) of the momentum portfolio from 13-60 months post-formation; Panel A for the full sample, and Panel B for the subsample beginning in 1982. Both panels show that there is a fairly strong negative correlation between PMP at the portfolio formation date and the subsequent stale momentum portfolio return. This correlation seems to be particularly strong in the post-1982 period. As we discuss in more detail in Section 3.6, this subsample is interesting as Jegadeesh and Titman (2001) find virtually no evidence of reversal of momentum (without conditioning on PMP) in the post-1982 period.

Figure 5 provides a scatterplot of outcomes for each monthly formation date $t$. The vertical axis shows the cumulative return of the stale momentum portfolio formed on date $t$, where the cumulative return is again measured from $t + 13$ to $t + 60$ months. The horizontal axis shows the PMP leading up to formation date $t$. It is evident from the plot that there is a moderately strong negative relationship between PMP and the long-horizon returns of the stale momentum portfolios. There are also some extreme observations both in terms of

PMP and in terms of the subsequent long-horizon returns. Figure 4 shows that the large stale momentum returns of greater than 100% occur for formation dates in the 1995-1996 period, where these stale momentum returns overlap with the 'tech-bubble' period. The strong negative PMP realizations (of $<$ 2%/month) occur for formation dates just before 1935, following the extreme-negative momentum realizations in June and July of 1932 (Daniel and Moskowitz 2016).

Table 2 reports the average monthly value-weighted returns and alphas of the momentum portfolios formed in different PMP quintile months for each of the five post-formation years.[12] The rows labeled "All months" show the returns and alphas without conditioning on PMP. The t-statistics are based on Newey and West (1987) standard errors to account for serial dependence. To calculate alphas, we estimate a separate set of Fama-French loadings for each event month, $t+1, t+2, \ldots, t+60$, and PMP quintile pair and calculate alpha as the intercept plus residual. Our results are stronger if we estimate unconditional loadings by pooling all PMP months together since, not surprisingly, momentum portfolios formed in Quintile 5 months load more negatively on the value factor and also since they load more negatively on the market factor compared to portfolios formed in other months.

Panel A of Table 2 shows that post-formation momentum returns are strongly negatively related to PMP. In the first post-formation year, momentum portfolios formed in Quintile 1 months generate a highly significant return and the returns decrease monotonically as quintile ranks increases to 5. In fact, momentum returns are actually negative in the first post-formation year for Quintile 5 months, though not significantly so. The difference between top and bottom quintile returns is -1.21% per month and significant at the 5% level. The same declining pattern shows up in years two through five. For Quintile 1, average returns are economically and statistically close to zero in all four years. For Quintiles 2-4, almost all average returns are statistically indistinguishable from zero except for Quintile 3 and 4 returns in year 5, which are negative and significant. In contrast, Quintile 5 returns are all economically very large, ranging from -0.53% to -1.34% per month, and all are significant—two at the 1% level and two at the 10% level. The differences between top and bottom quintile returns are also economically and statistically large in years two through five.

Panel B of Table 2 reports the average monthly alphas. The row labeled "All months"

[12] In untabulated results, we examine returns 10 years after portfolio formation, but we do not find any reversals in years 6 through 10 both unconditionally and for high PMP quintile months.

shows that over the full CRSP sample from 1928 to 2014, momentum reversals are quite weak after controlling for Fama-French factors—only the year 5 alpha is negative, -0.17% per month ($t = -2.10$). Almost all of this effect is coming from momentum portfolios formed in PMP Quintile 4 and 5 months. These findings add nuance to the usual understanding that momentum profits reverse in the long run. We find that almost all of their reversals are explained by their negative loadings on MKT and HML factors and the rest are explained by Quintile 5 months.[13]

For Quintile 1, the alphas are all positive in years two through five, although they are not statistically significant. For Quintiles 2 to 4, only one other alpha, year 3 alpha for Quintile 3, is meaningfully negative -0.32% per month ($t = -1.92$). In sharp contrast, reversals are strong for Quintile 5—the alpha in each of the four post-formation years 2-5 is negative, and is statistically significant in years 2 and 5. The differences between Quintile 5 and Quintile 1 alphas are also all negative, and are again significant at the 1% and 10% levels in year 2 and year 5, respectively. These results strongly support the hypothesis that momentum stocks in periods of high recent momentum strategy performance become overvalued and gradually exhibit reversals during post-formation years as the mispricing is corrected.

## 3.1 Industry versus Residual Momentum

Previous studies document momentum effects for both the industry and firm-specific components of stock returns (Moskowitz and Grinblatt 1999, Asness, Porter, and Stevens 2000, Grundy and Martin 2001). We next test whether the time-variation in stale momentum portfolio reversals that we observe are driven by industry or stock-specific momentum.

To form industry momentum portfolios, we assign stocks into industries based on Fama and French (1997) 49-industry classification. We exclude industries with fewer than five stocks to ensure that our results are not driven by small industries. At the end of each month, we rank industries into quintiles based on their value-weighted return over the past 12 months, skipping the most recent month. Industries with extreme returns have a smaller number of stocks. We therefore rank industries into quintiles instead of deciles to ensure that our results are not driven by a small number of stocks. We then form a value-weighted long-short industry

[13]This does not contradict models which predict overvaluation and therefore reversal of momentum performance, since HML is built based on book-to-market, which is, in several behavioral models, a proxy for misvaluation.

momentum portfolio that is long stocks in the top quintile industries and short stocks in the bottom quintile industries.

To form residual momentum portfolios, we rank stocks into deciles based on their residual (net of value-weighted industry) return over the past 12 months, skipping the most recent month. We then form a value-weighted long-short residual momentum portfolio that is long the top decile and short the bottom decile.

Table 3 reports the average alphas of industry and residual momentum portfolios during post-formation years one through five for each of the five PMP quintiles. Although both industry and residual momentum portfolios exhibit reversals during PMP Quintile 5 months, reversals are about twice as strong for industry momentum. Industry momentum portfolios generate statistically significant alphas of -0.59% and -0.34% per month in post-formation years 2 and 5, respectively. For residual momentum portfolios, the alphas are negative in post-formation years two through five, but only significantly so in year five. The differences between extreme quintile alphas are negative in all post-formation years and generally significant for both residual and industry momentum.

In a recent study, Greenwood, Shleifer, and You (2017) find that sharp industry price run-ups predict a higher probability of industry crashes, although the run-ups do not predict low future average returns. They also identify various attributes of the price run-ups, such as volatility, turnover, magnitude of the run-up, and issuance that predict eventual crashes. We find that PMP has strong power to predict such crashes; 65% of the price run-ups that eventually crash in their sample are identified in PMP Quintile 5 months and only 26% of the price run-ups that don't crash are identified in PMP Quintile 5 months. In addition, our results on industry momentum indicate that PMP has the ability to forecast low future *returns* of high momentum industries in a broader sample (not just extreme price run-ups).

## 3.2 Out-of-Sample Estimation

The results presented so far use the full sample distribution of PMP to rank months. We next rank months into PMP quintiles using only the information available at each point in time and test whether PMP is related to momentum reversals. Specifically, at the end of each month starting in 1938:12, we use an expanding window from 1928:12 onwards to calculate a historical distribution of PMP and assign each month to a PMP quintile according to this distribution.

Table 4 shows a strong inverse relationship between PMP and momentum reversals in post-formation years two through five. For PMP Quintiles 1-4, only Quintile 4 returns and alphas in year 5 are significantly negative. All other returns are alphas are not significantly negative (even at the 10% level) and some are actually *positive* and significant. For Quintile 5, all of the raw returns are negative in years 2-5 and significant in three of these years and the alphas are negative and significant in years two and five.

## 3.3 International Tests

A possible concern with findings of return predictability is that apparent effects can be meaningless artifacts of data mining. We therefore perform out-of-sample tests of whether these effects show up in markets outside the US. Our international sample consists of stocks in the S&P BMI Developed Markets Index starting in 1989:07. We exclude the smallest 10% of stocks in each country (similar to our US tests) to focus on large, liquid stocks. We only include those countries in our tests that have at least 75 stocks per month on average to ensure that the long-short momentum portfolios are reasonably diversified. The stock return and market capitalization data are from S&P Capital IQ. Country-level factor returns are from AQR's data library.

Panel A of Table 5 lists the eight countries used in our international tests along with the average, minimum, and maximum number of stocks in each country.[14] Japan has the largest cross-section of stocks with 1,208 stocks per month on average; Switzerland has the smallest with 91 stocks per month. At the end of each month from 1989:07 to 2009:12, we rank stocks in each country excluding Japan and UK into quintiles based on their cumulative return over the past 12 months, skipping the most recent month, and construct a value-weighted long-short portfolio for each country that is long the top quintile stocks and short the bottom quintile stocks. Since the cross-section of stocks is much larger in Japan and UK, we rank stocks into deciles similar to the US tests—the long-short momentum portfolio is long the top decile and short the bottom decile. We hold the portfolios for one month. This approach yields a time-series of monthly momentum factor returns for each country. For each country and each month, we calculate PMP as the average momentum factor return over the past 24 months. We then rank the 222 months in each country (from 1991:07 to 2009:12) into quintiles

[14]Canada also has at least 75 stocks per month, but the market capitalization data for Canada starts in 1998 so we do not include Canada in our tests.

based on PMP and examine the performance of momentum portfolios in post-formation years 1-5. To calculate 3-factor alphas, we estimate conditional loadings for each PMP Quintile and event month pair. Panel B of Table 5 reports the results of this analysis; for brevity, we only report alphas in Table 5.

For most of the countries, there is a strong inverse relationship between PMP and post-formation alphas. For example, in Japan, average alphas are significantly negative in years 1 and 2 for Quintile 5 and the differences between Quintile 5 and Quintile 1 alphas are extremely large -1.66% and -1.13% per month (both significant at the 1% level) in years 1 and 2, respectively. The difference is also negative and significant at the 10% level in year 5. In the UK, Quintile 5 alphas are -1.03% and -0.87% per month in years 4 and 5 (both significant at the 5% level) and Quintile 5 minus Quintile 1 alphas are significantly negative -1.41%, -1.01%, -0.94% per month in years 1, 4, and 5, respectively. Similar patterns show up in other countries except for Australia. Overall, these results alleviate the potential concern that the PMP effect is a mere consequence of data mining.

One difference between the results in other countries and the US results is that reversal often seems to start earlier. In contrast with the US results, for some countries year one returns are statistically negative. In other words, PMP allows us to identify time periods in which the (conditional) momentum premium is negative—past-winners underperform past-losers over the next year. We are not aware of any other studies in which ex-ante conditioning results in a negative momentum premium.

## 3.4 Implications for style chasing and investor self-attribution

Our tests were motivated by the style chasing hypothesis that investors overextrapolate past momentum performance. This should result in relatively overpriced momentum portfolios after high PMP, and relatively underpriced momentum portfolios after low PMP. A similar implication follows from an account based on shifting confidence of momentum investors who attribute success or failure of their momentum trades to their abilities, and shift in or out of this strategy accordingly.

Style chasing further implies that after high PMP momentum returns will be higher in the near term, and after low PMP they will be lower. But as mispricing is corrected, the prediction is that eventually, after high PMP, we expect to see strong reversal of overpriced momentum portfolios (low returns on stale momentum portfolios), and after low PMP continuation in the returns of underpriced momentum portfolios (high returns on stale momentum portfolios).

Empirically, we find that PMP does not positively predict short horizon performance of momentum portfolios. After high *PMP*, a WML portfolio does not earn higher-than-usual abnormal returns over the next 12 months. This suggests either that style chasers are not buying further based on PMP, or that there is little delay in style chasing, so that any price pressure they place on the WML portfolio has already mostly occurred during the PMP conditioning period. Also, consistent with the style chasing and self-attribution approaches, momentum portfolios that are formed at times of high PMP reverse strongly.

However, the timing of the reversals seems to present a fatal challenge to the style chasing and investor attribution interpretations. Stocks in a winner (loser) portfolio of the momentum strategy do not necessarily remain winners (losers) 12 months later. So a style chaser or self-attributing investor who has recently been attracted to momentum would tend to get out of any given momentum portfolio within about 12 months after formation. It follows that under these hypotheses, reversals should be complete within a year. This implication is sharply contradicted by the finding that strong reversals continue over a period of five years.

Our findings also present a challenge to existing behavioral theories that model momentum as pure underreaction. In such models (Grinblatt and Han 2005) momentum does not reverse. Our finding of very strong reversals conditional on high PMP suggests that pure underreaction is not the sole explanation. Overall, the PMP reversal effect that we document presents a new puzzle for asset pricing and theories of momentum.

## 3.5 Portfolio strategy

All of the analysis done so far involves overlapping portfolios. Although our statistical tests appropriately take this into account, it is interesting to verify whether PMP predicts reversal of momentum using a trading strategy approach. Our first set of strategies consist of portfolios of stale momentum portfolios formed 13 to 60 months ago. We consider one trading strategy for each PMP quintile and, for comparison an unconditional trading strategy that buys all stale-momentum portfolios in each and every month. For each PMP quintile and each month $t$, the trading strategy is 'active' if any of the months from $t - 60$ to $t - 13$ belong to that particular PMP quintile; the portfolio in month $t$ consists of an equal-weighted average of the value-weighted stale momentum portfolios formed in months belonging to that particular PMP quintile from $t - 60$ to $t - 13$. The unconditional trading strategy is just an equal-weighted portfolio of all stale momentum portfolios formed in months $t-60$ to $t-13$.

Panel A of Table 6 reports the average returns, the 3-factor alphas, and the number of months that each strategy is active. The unconditional trading strategy generates a highly significant return of -0.27% per month ($t=-3.19$), but consistent with the results in Table 2, the alpha is insignificant and close to zero. Therefore, our results suggest that unconditionally, over the full CRSP sample, momentum profits do not reverse after controlling for Fama-French factors.

There is a strong monotonic relationship between PMP quintile rank and portfolio returns and alphas. The portfolio return is positive 0.23% per month (though not significant) for Quintile 1 and it decreases monotonically to -0.74% per month as the quintile rank increases to 5, and the return is highly significant for Quintiles 4 and 5. Quintile 1 alpha is actually positive 0.35% per month and significant ($t = 2.59$) so after poor recent momentum performance, momentum portfolios continue to generate abnormal returns in post-formation years 2 to 5. The alphas also decrease monotonically as quintile rank increases, and only Quintile 5 alpha is economically and statistically negative, -0.37% per month ($t=-2.93$).

We also consider a combined Quintile 5 and Quintile 1 strategy to exploit the reversals and continuation observed in these quintiles. This strategy is active in any given month if either Quintile 1 or Quintile 5 strategy is active, or both are active. The portfolio is long Quintile 5 portfolio during months in which only Quintile 5 strategy is active, short Quintile 1 portfolio during months in which only Quintile 1 strategy is active, and long 50% Quintile 5 portfolio and short 50% Quintile 1 portfolio during months in which both are active. Since all the portfolios are long-short portfolios, this portfolio is always \$1 long and \$1 short. This strategy generates as highly significant alpha of -0.40% per month ($t=-3.74$). These results alleviate concerns about the possibility that the significance of our main results (Table 2) might derive from bias in the computation of standard errors with overlapping observations.

We also consider similar strategies for each of the four years individually in Panel B of Table 6. For example, the year 2 strategy for Quintile 5 is active in month $t$ if any of the months from $t-13$ to $t-24$ are Quintile 5 months and the portfolio in month $t$ is an equal-weighted average of the stale momentum portfolios formed in Quintile 5 months from $t-13$ to $t-24$. These results for year by year strategies are consistent with those presented in Table 2; Quintile 5 returns and alphas are negative in all years and most are significant while Quintile 1 returns and alphas are generally positive and some significantly so. The Quintile 5 and Quintile 1 combined strategy generates significantly negative alphas in three of the four years.

### 3.6 Robustness checks

We next verify whether these findings are robust to measuring abnormal performance using characteristic-adjusted returns instead of alphas, and whether these findings are distinct from previous studies which try to predict momentum returns. While these papers try to forecast momentum returns in the month after portfolio formation unlike the long-horizon returns that we examine, it is still possible the variables studied predict long-horizon returns as well and that the results that we document arise because PMP is correlated with these variables. We believe that this is unlikely since Table 1 shows that the correlations between PMP and these variables are fairly low suggesting that our results are unique. Nonetheless, we directly control for these variables in this section.

Perhaps the most widely studied variable to forecast momentum performance is past market return. Cooper, Gutierrez, and Hameed (2004) and Daniel and Moskowitz (2016), among others, show that momentum strategies experience crashes after market declines. To rule out the possibility that our results are being driven by momentum crashes following down market months, in Panel A of Table 7, we exclude all portfolio formation months for which the cumulative market return over the past two years is negative. For brevity, we only report the alphas in Table 7.[15] In post-formation year 1, momentum portfolios formed in Quintile 5 months generate a statistically significant abnormal return of 0.76% per month, and the difference between top and bottom quintile alphas is not significant. Years 2-5 reversals are quite strong for Quintile 5, ranging from -0.45% to -0.68% per month, and three of them are significant at the 5% level. In fact, all of the Quintile 5 alphas in years 2-5 are more negative than the corresponding numbers in Panel B of Table 2. This analysis clearly indicates that our results are not being driven by past market performance.

Another possible explanation of our results is that during Quintile 5 months, the formation period difference between returns of winners and losers (the momentum characteristic spread) is extremely large and, therefore, the subsequent reversals are extremely strong compared to other months. To address this possibility, we regress PMP on the formation period difference

[15] The ability of PMP to predict momentum reversal is much stronger for raw returns; results available on request.

between mean return of winner and loser portfolios and use the residual from the regression to rank months into quintiles. Panel B of Table 7 shows that this procedure results in a U-shaped relationship between PMP and the momentum characteristic spread. Although bottom and top quintile months have a similar characteristic spread, there is a stark difference in post-formation momentum returns. For Quintile 1, the alphas in years 2-5 are all positive, though none are significant, but for Quintile 5, the alphas are all negative and significant in years 2 and 5. The difference in alphas between the two extremes is negative in each year and significant at the 5% level in years 2 and 5 and at the 10% level in year 4.

In our third test, we orthogonalize PMP with respect to momentum variance—variance of daily momentum returns over the past 6 months. Barroso and Santa-Clara (2015) show that momentum variance forecasts low momentum profits. The results in Panel C show that PMP Quintile 1 and 5 months have almost identical past momentum variance but there is a sharp difference in post-formation alphas in years 2-5—momentum portfolios formed in Quintile 1 months exhibit weak continuation, while those formed in Quintile 5 months exhibit strong reversals.

Panel D shows that our results are also robust to controlling for recent market volatility.[16] In summary, the results in Table 7 clearly show that PMP's predictability is distinct from that of other variables.

Our results are robust to measuring abnormal performance using characteristic-adjusted returns (Daniel, Grinblatt, Titman, and Wermers 1997) instead of Fama-French alphas. Specifically, in June of each year, we rank stocks into size quintiles using NYSE size breakpoints and within each quintile, we rank stocks into five book-to-market quintiles.[17] We then calculate the size and book-to-market adjusted return of each stock as the raw return minus the value-weighted return of the same size and book-to-market quintile portfolio. The sample period for this test starts in 1951:06 due to unavailability of Compustat data in prior years. Panel E of Table 7 shows that the results are actually somewhat stronger using characteristic-adjusted returns. Reversals are quite strong for Quintile 5 months. In contrast, momentum portfolios formed in Quintile 1 months exhibit return continuation—year 4 return is positive and significant. The differences between top and bottom quintile returns are all negative, economically

[16]We have also run tests in which we regress PMP on all three variables—momentum characteristic spread, momentum variance, and market variance—together and use the residual to rank months. The results are very similar and reversals are strong in Quintile 5 months.

[17]Our results are robust to using independent size and book-to-market sorts.

very large, and four are significant at the 5% or lower level, and one at 10% level.

In Panels F and G of Table 7, we sub-divide the sample into two equal periods and show that our results hold in both periods. In particular, the magnitude of the effect appears similar in the two subsamples and the overall sample. The statistical significance is lower in the two subsamples, as would be expected given the smaller sample size. In Panels H and I, we divide our sample into formation dates pre-1982 and post-1982, respectively. As noted earlier, Jegadeesh and Titman (2001) divide their sample into pre-and post-1982 subsamples, and find no evidence of reversal in the post-1982 subsample. Our tests differ from theirs in that we condition on PMP. It is interesting that this conditioning identifies reversal even in the post-1982 subsample. In this subsample, for momentum portfolios formed in PMP Quintile 5 months, stale momentum alphas are strongly negative, and statistically significant in years 2 and 5 post-formation. Momentum portfolios formed in Quintile 5 months on average lose about a third of their value in post-formation years 2-5.[18]

## 3.7 PMP and Institutional Trading

We next test whether the behavior of institutional investors seems broadly consistent with momentum style chasing based on PMP. Our institutional holdings data is from Thomson Reuters. Following previous literature (Grinblatt, Titman, and Wermers 1995), we calculate the momentum trading measure $\mathrm{L0M}_{iq}$ for fund $i$ in quarter $q$ as the vector product of quarterly portfolio weight changes and past returns:

$$\mathrm{L0M}_{iq} = \sum_{m=1}^{3} \sum_{j=1}^{N(q)} \left(w_{i,j,q} - w_{i,j,q-1}\right) R_{j,q-1,m}$$

where $R_{j,q-1,m}$ is stock $j$'s return in the $m^{th}$ month of quarter $q-1$, $w_{i,j,q}$ is fund $i$'s weight on stock $j$ at the end of quarter-$q$, and $N(q)$ is the number of stocks in quarter $q$, and where

$$(w_{i,j,q} - w_{i,j,q-1}) = \frac{\mathrm{SharesHeld}_{i,j,q} \times p_{j,q-1}}{\sum_{j=1}^{N} \mathrm{SharesHeld}_{i,j,q} \times p_{j,q-1}} - \frac{\mathrm{SharesHeld}_{i,j,q-1} \times p_{j,q-1}}{\sum_{j=1}^{N} \mathrm{SharesHeld}_{i,j,q-1} \times p_{j,q-1}}.$$

[18] In contrast, consistent with Jegadeesh and Titman (2001), without conditioning on PMP we find very weak reversals in the 1982-1998 period (even for raw returns).

Here, $\text{SharesHeld}_{i,j,q}$ is the number of shares of stock $j$ held by fund $i$ at the end of quarter $q$, and $p_{j,q-1}$ is the price of stock $j$ at the end of quarter $q-1$.[19]

At the end of each quarter from 1985:06 to 2010:03, we rank all institutional investors with at least five years of historical data available into deciles based on their average past momentum trading measure. We call the top decile institutions 'momentum traders' and the bottom decile institutions 'contrarian traders.' Thus momentum traders have a history of buying winners and selling losers while contrarian traders have a history of doing the opposite. We then calculate the time-series of mean quarterly momentum trading measures for momentum and contrarian traders. We then regress these trading measures on last quarter's PMP quintile rank to test how momentum and contrarian traders respond to PMP. To control for any mechanical relationship between momentum trading and PMP that might arise because of high cross-sectional volatility during periods with high PMP, we include past quarter's cross-sectional standard deviation of returns as a control in the regressions.

Table 8 shows that there is a highly significant relationship between PMP and future momentum trading for momentum traders; increasing PMP quintile rank from one to five increases mean momentum trading of momentum traders by 0.61, an increase of 62% relative to the unconditional mean of the dependent variable. On the other hand, there is no relationship between momentum trading and PMP for contrarian traders.[20] These results suggest that the behavior of momentum-trading institutional investors may play a role in the relation between PMP and stale momentum returns documented in our tests.

# 4 Conclusion

Motivated by behavioral theories, we examine the relationship between recent past momentum performance, PMP, and long horizon performance of momentum portfolios. Momentum portfolios exhibit strong reversals in post-formation years 2-5 after periods of top-quintile PMP,

[19]We use prior quarter prices to calculate changes in portfolio weights so that the measure does not pick up changes in weights resulting directly from changes in prices.

[20]A possible interpretation is that momentum traders pay heavy attention to past momentum performance in deciding how aggressively to follow a momentum strategy—a kind of positive feedback at the strategy rather than at the stock level; whereas contrarian investors are less active in adjusting their strategy in response to past momentum performance. Of course, equilibrium considerations imply that if the aggressiveness of the trading of momentum traders changes, there must be a corresponding shift in the trading of some counterparties. However, the trading of contrarians here is not the simple complement of the trading of momentum investors here, since most investors fall into neither category.

and weak continuation following periods of bottom-quintile PMP. The difference in cumulative five-year Fama-French alphas of momentum portfolios formed in top and bottom PMP quintile momentum portfolios is 40%. We find similar results for both industry and residual momentum and in several international markets. Our results also obtain after controlling for previously known predictors of the momentum premium.

We also show that PMP does not forecast short horizon momentum profits and that the reversals last too long to be explained by style chasing and bias in self-attribution hypotheses. These findings offer a challenge to existing theories of asset pricing and momentum.

# References


Asness, Clifford S., R. Burt Porter, and Ross L. Stevens, 2000, Predicting stock returns using industry-relative firm characteristics, Working paper, AQR Capital Management.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style investing, *Journal of Financial Economics* 68, 161–199.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

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

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

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

Daniel, Kent D., Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.

Daniel, Kent D., and Tobias J. Moskowitz, 2016, Momentum crashes, *Journal of Financial Economics* 122, 221–247.

DeBondt, Werner F. M., and Richard H. Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 40, 793–808.

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

Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Froot, Kenneth A., and Melvyn Teo, 2008, Style investing and institutional investors, *Journal of Financial and Quantitative Analysis* 43, 883–906.

Greenwood, Robin, Andrei Shleifer, and Yang You, 2017, Bubbles for Fama, NBER working paper No.23191, Harvard Business School.

Griffin, John M., Susan Ji, and J. Spencer Martin, 2003, Momentum investing and business cycle risk: Evidence from pole to pole, *Journal of Finance* 58, 2515–2547.

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

Grinblatt, Mark, and Matti Keloharju, 2009, Sensation seeking, overconfidence, and trading activity, *Journal of Finance* 64, 549–578.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *American Economic Review* 85, 1088–1105.

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

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143–2184.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699–720.

Jegadeesh, Narasimhan, and Sheridan Titman, 2011, Momentum, *Annual Review of Financial Economics* 3, 493–509.

Lee, Charles M.C., and Bhaskaran Swaminathan, 2000, Price momentum and trading volume, *Journal of Finance* 55, 2017–2069.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.

Newey, Whitney K., and Kenneth D. West, 1987, Hypothesis testing with efficient method of moments estimation, *International Economic Review* 28, 777–787.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–16.

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

Teo, Melvyn, and Sung-Jun Woo, 2004, Style effects in the cross-section of stock returns, *Journal of Financial Economics* 74, 367–398.

# Figures and Tables

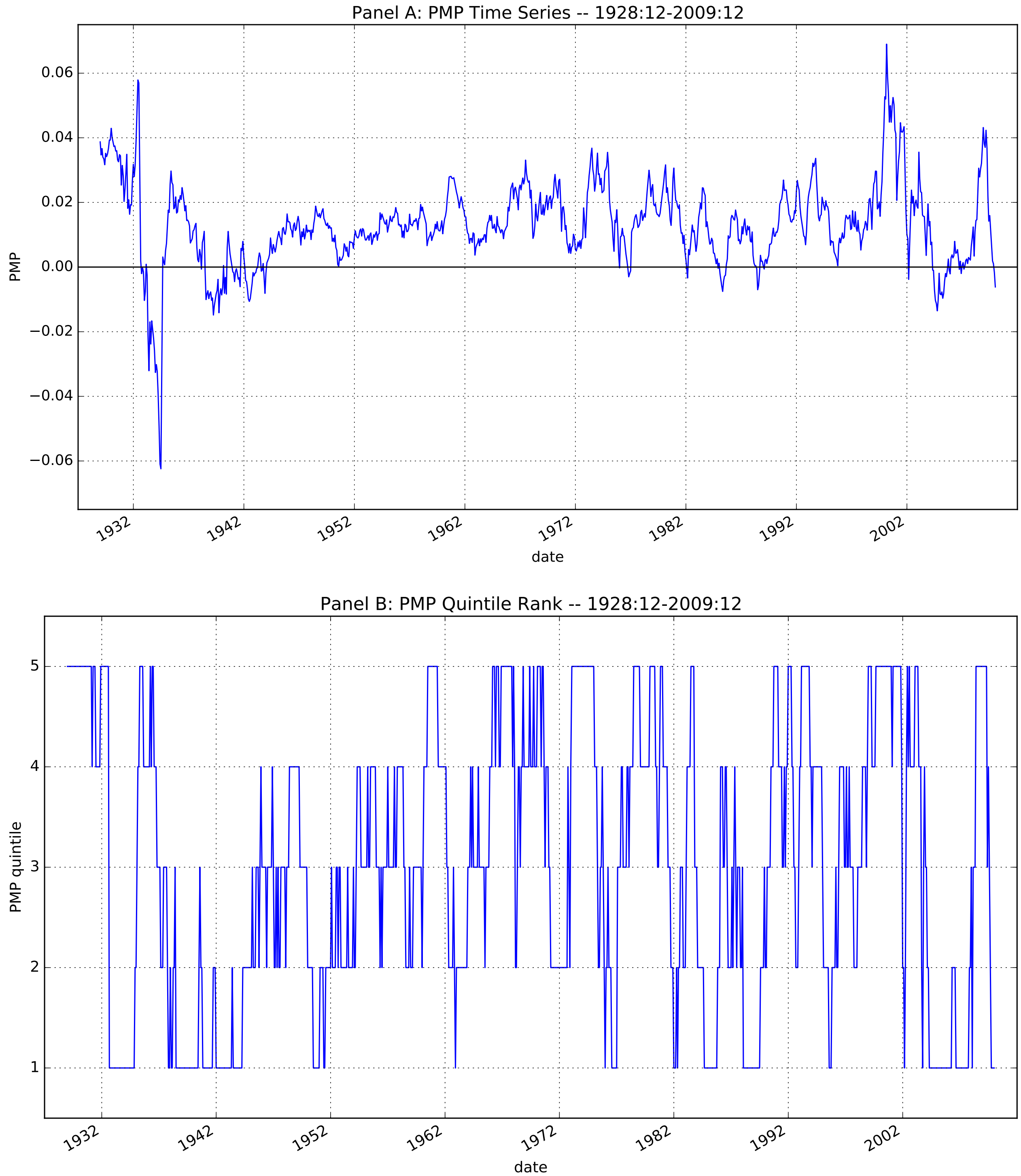


**Figure 1: PMP Time-Series**
Panel A plots the time-series of PMP from 1928:12-2009:12. Panel B plots the corresponding PMP quintile. The calculation of PMP is described in the caption of Table 1.

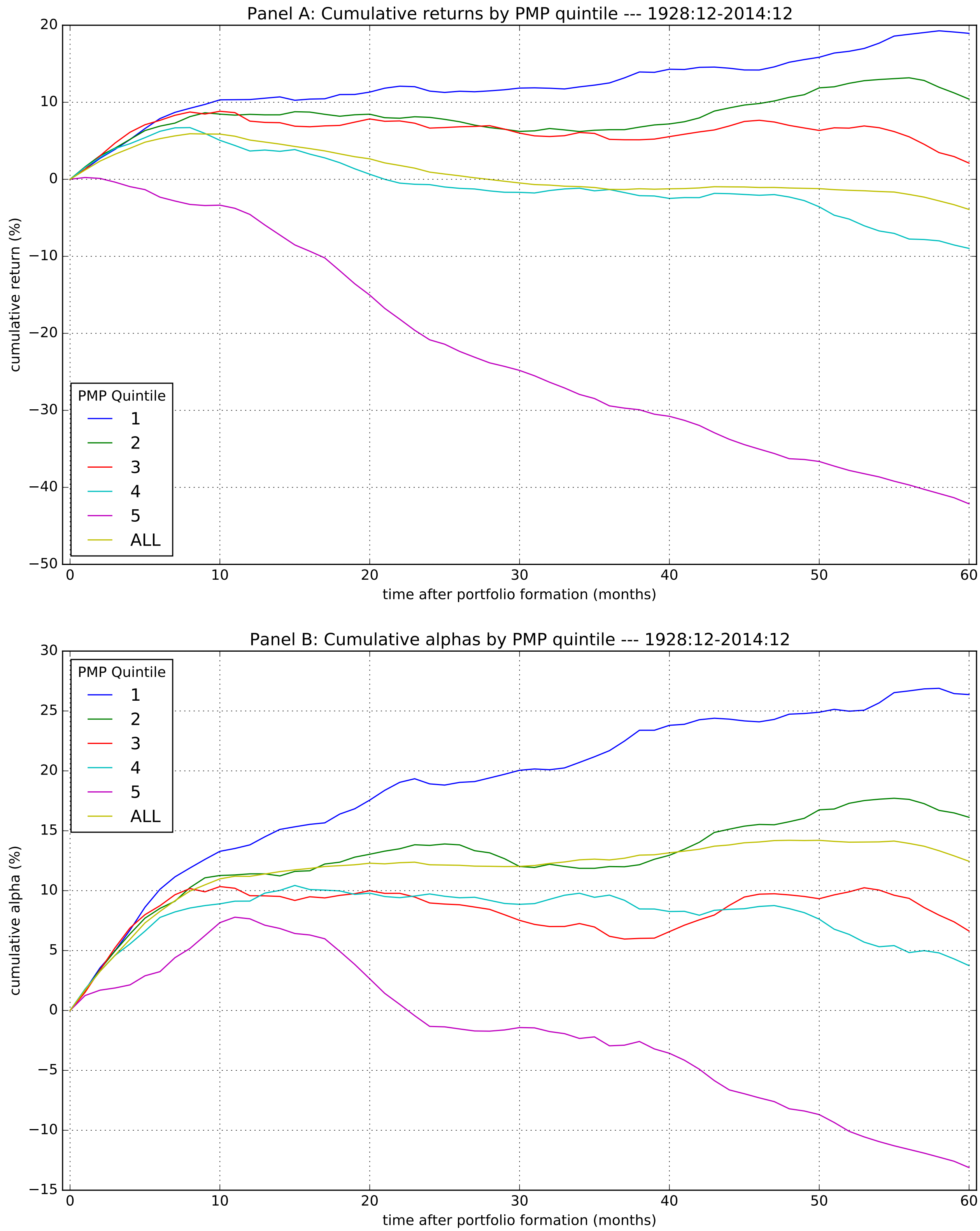


**Figure 2: Cumulative Returns and Alphas, by PMP Quintile**
These figures plot the average cumulative 5-year returns (excess of the cumulative risk-free rate) and Fama-French three-factor alphas of the value-weighted momentum portfolios formed in each of the five PMP Quintile months as well as for the momentum portfolios formed in all months.

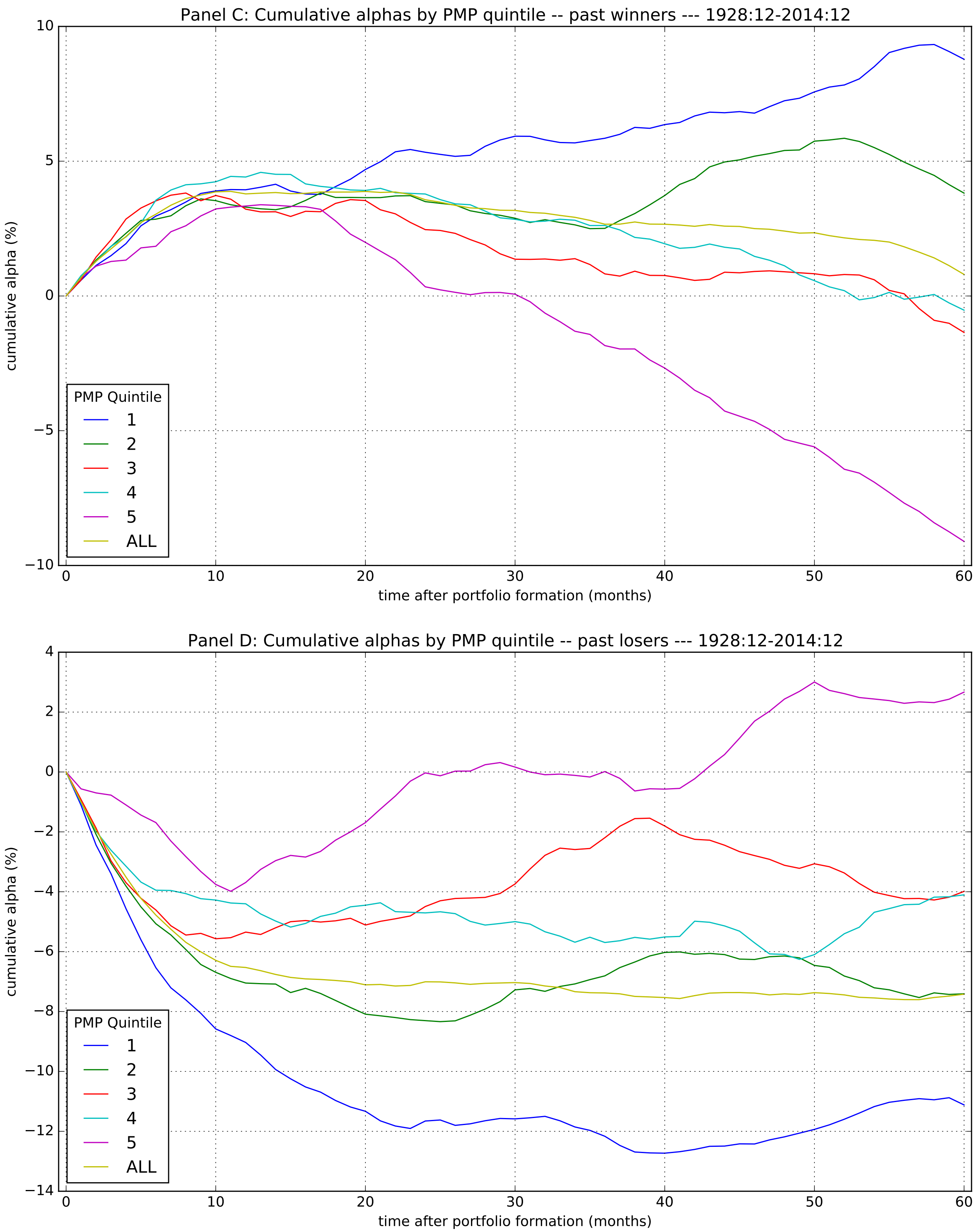


**Figure 3: Cumulative Alphas, by PMP Quintile, for past-Winner and past-Loser Portfolios** Panels A and B plot the cumulative alphas of the past-winner and past-loser portfolios, respectively. The calculation of the alphas is described in the caption of Table 2.

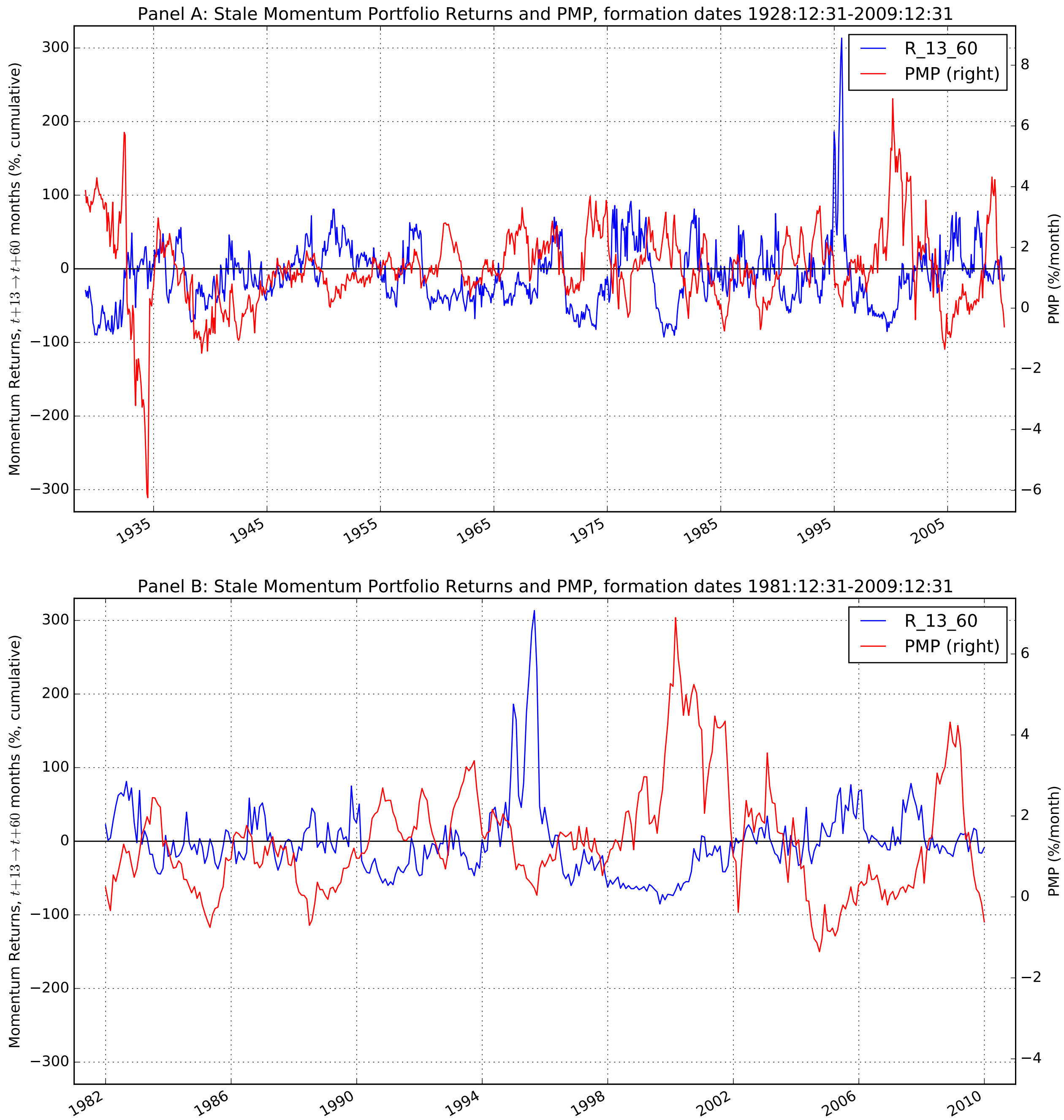


**Figure 4: Stale Momentum returns and PMP**
This figure plots, on the left axis, the stale momentum portfolio returns from $t+13$ months to $t+60$ months as a function of the (monthly) formation dates (cumulative, in %). The right axis plots the PMP measure, that is the average zero-investment momentum portfolio over the 24 months (in %/month) preceding the formation date

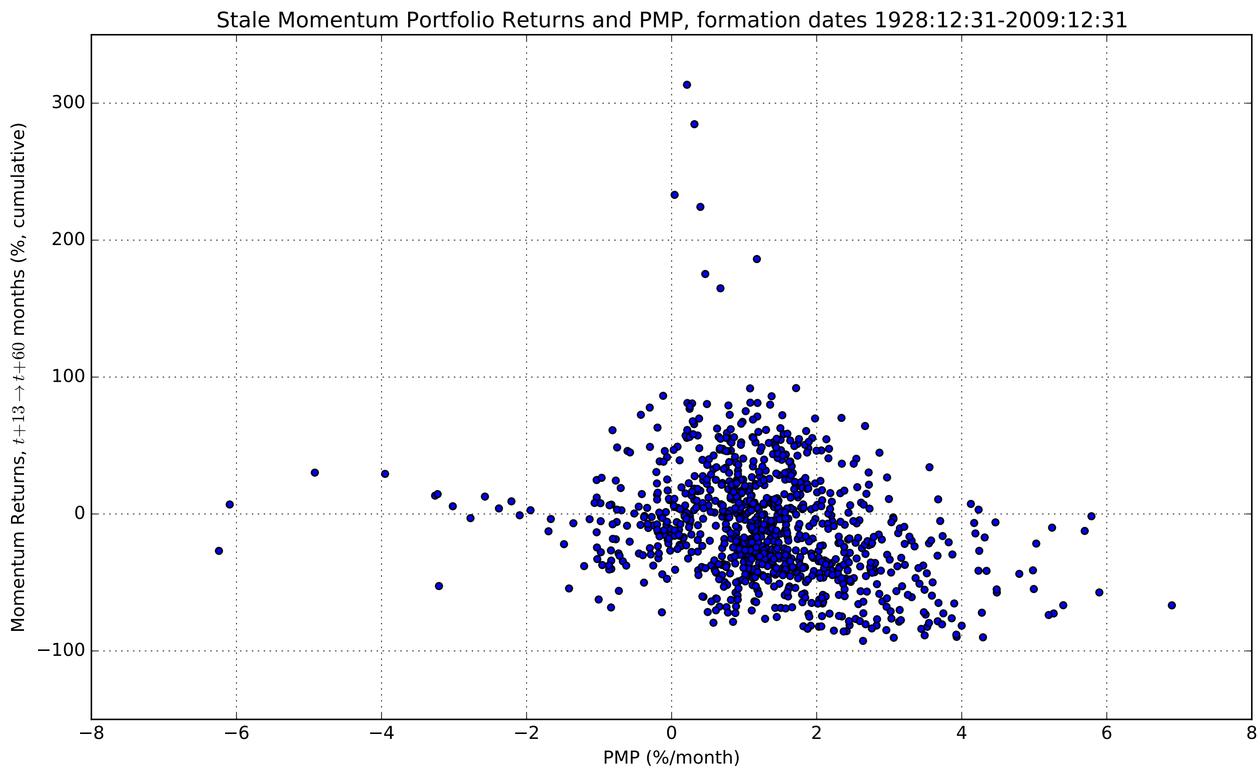


**Figure 5: Stale Momentum returns and PMP**
For each monthly momentum portfolio formation date in our sample period (from 1928:12:31 through 2009:12:31), this scatterplot shows the stale momentum portfolio returns from $t+13$ months to $t+60$ months (cumulative, in %), plotted against the PMP measure, that is the average zero-investment momentum portfolio return (in %/month) over the 24 months preceding the formation date.

**Table 1:** Table 1: PMP Characteristics

This table reports the main characteristics of PMP. The sample period is from 1928:12 to 2009:12. At the end of each month, starting in 1926:12, stocks are ranked into deciles based on their cumulative return over the past 12 months, skipping the most recent month. Stocks with price below \$5 and stocks with market capitalization below the 10th percentile size breakpoint (using NYSE size breakpoints) at the time of portfolio formation are excluded from the analysis. A value-weighted long-short WML portfolio which is long the top decile and short the bottom decile is then formed at the end of each month. Portfolios are rebalanced each month. At the end of each month, starting in 1928:12, PMP is calculated as the average return of the WML portfolio over the previous 24 months. All 973 months in the sample are then ranked into quintiles based on PMP. Panel A reports the average values of PMP ($\overline{\text{PMP}}$), the past one-year excess return of the CRSP value-weighted market index ($r^e_M(1y)$), past two-year excess market return ($r^e_M(1y)$) and its absolute value, standard deviation of monthly market return over the past 2 years ($\sigma_{r^e_M}(m{-}2y)$, standard deviation of daily market returns over the past 6 months ($\sigma_{r^e_M}(d{-}6m)$), and average formation period returns of the past-loser, past-winner, and WML portfolios. Panel B reports the correlation matrix of these variables.

Panel A: Descriptive Statistics

| Rank | No. mos. | $\overline{\text{PMP}}$ | $r^e_M(1y)$ | $r^e_M(2y)$ | $\|r^e_M(2y)\|$ | $\sigma_{r^e_M}(m{-}2y)$ | $\sigma_{r^e_M}(d{-}6m)$ | $\bar{r}_{loser}$ | $\bar{r}_{win}$ | $\bar{r}_{WML}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 194 | -0.4% | 10.9% | 11.9% | 24.6% | 6.7% | 1.1% | -27.8% | 119.2% | 147.0% |
| 2 | 195 | 0.8% | 10.6% | 23.0% | 27.5% | 4.3% | 0.7% | -25.5% | 96.8% | 122.4% |
| 3 | 195 | 1.3% | 12.8% | 29.3% | 33.3% | 3.9% | 0.7% | -24.6% | 99.8% | 124.4% |
| 4 | 195 | 1.8% | 7.9% | 15.4% | 27.3% | 4.3% | 0.8% | -31.3% | 115.5% | 146.8% |
| 5 | 194 | 3.1% | -4.4% | 2.8% | 27.2% | 5.0% | 1.2% | -45.3% | 128.0% | 173.3% |

Panel B: Correlation matrix

| | $\overline{\text{PMP}}$ | $r^e_M(1y)$ | $r^e_M(2y)$ | $\|r^e_M(2y)\|$ | $\sigma_{r^e_M}(m{-}2y)$ | $\sigma_{r^e_M}(d{-}6m)$ |
|---|---|---|---|---|---|---|
| $\overline{\text{PMP}}$ | 1 | | | | | |
| $r^e_M(1y)$ | -0.29 | 1 | | | | |
| $r^e_M(2y)$ | -0.15 | 0.63 | 1 | | | |
| $\|r^e_M(2y)\|$ | -0.01 | 0.22 | 0.54 | 1 | | |
| $\sigma_{r^e_M}(m-2y)$ | -0.30 | -0.07 | -0.31 | 0.12 | 1 | |
| $\sigma_{r^e_M}(d-6m)$ | 0.07 | -0.36 | -0.44 | 0.13 | 0.70 | 1 |

**Table 2: PMP and Long Horizon Performance of Momentum Portfolios**

This table reports the average monthly returns and alphas of the value-weighted momentum portfolios formed in each of the five PMP quintile months in post-formation years one through five. The bottom rows in the tables report the average returns and alphas of momentum portfolios formed in all months. The sample period is 1928:12 to 2014:12. At the end of each month, a WML momentum portfolio is formed and all months in the sample are ranked into PMP quintiles, as described in Table 1. Panel A (Panel B) reports the average monthly returns (Fama-French alphas) in each year. To calculate alphas, a separate set of Fama-French loadings for each event month, $t+1, t+2, \ldots t+60$, and PMP quintile pair are calculated. Alpha is then calculated as the intercept plus the residual. For the row labeled "All months", alpha is calculated using unconditional loadings for each event month. T-statistics, shown below coefficient estimates, are based on Newey and West (1987) standard errors calculated using 11 lags.

Panel A: Average monthly L/S Raw Return

| | Year | | | | |
|---|---|---|---|---|---|
| Rank | 1 | 2 | 3 | 4 | 5 |
| 1 | 0.87 | 0.09 | -0.03 | 0.07 | 0.09 |
| | (5.89) | (0.53) | (-0.14) | (0.33) | (0.60) |
| 2 | 0.66 | -0.04 | -0.14 | 0.17 | -0.12 |
| | (4.20) | (-0.19) | (-0.87) | (0.74) | (-0.73) |
| 3 | 0.58 | -0.08 | -0.18 | 0.01 | -0.23 |
| | (2.76) | (-0.52) | (-1.04) | (0.07) | (-1.96) |
| 4 | 0.33 | -0.33 | -0.07 | -0.09 | -0.52 |
| | (1.80) | (-1.46) | (-0.31) | (-0.74) | (-3.32) |
| 5 | -0.34 | -1.34 | -0.61 | -0.64 | -0.53 |
| | (-0.74) | (-4.25) | (-1.68) | (-1.76) | (-3.09) |
| 5-1 | -1.21 | -1.44 | -0.59 | -0.71 | -0.63 |
| | (-2.56) | (-3.96) | (-1.42) | (-1.71) | (-2.66) |
| All months | 0.42 | -0.34 | -0.21 | -0.10 | -0.26 |
| | (3.09) | (-2.45) | (-1.58) | (-0.77) | (-2.88) |

Panel B: Average monthly L/S Alpha

| | Year | | | | |
|---|---|---|---|---|---|
| Rank | 1 | 2 | 3 | 4 | 5 |
| 1 | 1.11 | 0.32 | 0.11 | 0.16 | 0.01 |
| | (7.35) | (1.58) | (0.57) | (0.89) | (0.09) |
| 2 | 0.87 | 0.14 | -0.17 | 0.17 | -0.03 |
| | (5.18) | (0.76) | (-1.34) | (0.93) | (-0.24) |
| 3 | 0.72 | -0.11 | -0.32 | 0.10 | -0.12 |
| | (3.61) | (-0.65) | (-1.92) | (0.75) | (-1.14) |
| 4 | 0.73 | 0.02 | -0.02 | -0.09 | -0.34 |
| | (4.04) | (0.09) | (-0.11) | (-0.75) | (-2.67) |
| 5 | 0.58 | -0.61 | -0.12 | -0.33 | -0.36 |
| | (1.65) | (-2.31) | (-0.52) | (-1.06) | (-2.57) |
| 5-1 | -0.53 | -0.93 | -0.22 | -0.48 | -0.37 |
| | (-1.39) | (-2.79) | (-0.76) | (-1.36) | (-1.92) |
| All months | 0.86 | 0.02 | -0.02 | 0.02 | -0.17 |
| | (6.62) | (0.18) | (-0.16) | (0.15) | (-2.10) |

**Table 3: Industry and Residual Momentum**

This table reports the average monthly alphas of the value-weighted industry momentum (Panel A) and residual momentum (Panel B) portfolios formed in each of the five PMP quintile months in post-formation years one through five. All months in the sample are ranked into quintiles based on PMP, as described in Table 2. At the end of each month, stocks are classified into industries based on Fama and French (1995) 49-industry classification using their CRSP SIC code at the end of that month. Stocks with price below \$5, stocks with market capitalization below the 10th percentile size breakpoint (using NYSE size breakpoints), and stocks in Fama and French residual industry 'other' at the time of portfolio formation are excluded from the analysis. Industries with fewer than 5 such stocks at the time of portfolio formation are also excluded from the analysis. For each industry, industry momentum is calculated as the value-weighted average of past 12 month return (skipping the most recent month) of stocks in that industry. In Panel A, industries are ranked into quintiles based on industry momentum. A value-weighted long-short portfolio that is long stocks in the top quintile and short stocks in the bottom quintile is then formed at the end of each month. Panel A reports the average alphas of these portfolios in post-formation years one through five for each of the five PMP quintile months. In Panel B, at the end of each month, stocks are ranked into deciles based on their residual (net of value-weighted industry) return and a long-short portfolio that is long the top decile stocks and short the bottom decile stocks is formed. Panel B reports the average alphas of these portfolios in post-formation years one through five for each of the five PMP quintile months. To calculate alphas, a separate set of Fama-French loadings for each event month, $t+1, t+2, \ldots, t+60$, and PMP quintile pair are calculated. Alpha is then calculated as the intercept plus the residual. t-statistics, shown below coefficient estimates, are based on Newey and West (1987) standard errors calculated using 11 lags.

Panel A: Industry Momentum

| | Year | | | | |
|---|---|---|---|---|---|
| Rank | 1 | 2 | 3 | 4 | 5 |
| 1 | 0.63 | 0.18 | 0.06 | 0.18 | 0.02 |
| | (5.35) | (1.20) | (0.39) | (1.28) | (0.13) |
| 2 | 0.31 | -0.07 | -0.17 | -0.02 | 0.13 |
| | (3.09) | (-0.50) | (-1.38) | (-0.12) | (0.74) |
| 3 | 0.22 | -0.34 | -0.04 | 0.09 | -0.13 |
| | (1.41) | (-2.71) | (-0.29) | (0.81) | (-1.09) |
| 4 | 0.06 | 0.01 | -0.09 | 0.05 | -0.09 |
| | (0.47) | (0.04) | (-0.47) | (0.47) | (-0.52) |
| 5 | 0.14 | -0.59 | -0.14 | -0.37 | -0.34 |
| | (0.52) | (-3.05) | (-0.76) | (-1.49) | (-2.45) |
| 5-1 | -0.49 | -0.77 | -0.21 | -0.55 | -0.35 |
| | (-1.74) | (-3.14) | (-0.83) | (-1.96) | (-1.94) |

Panel B: Residual Momentum

| | Year | | | | |
|---|---|---|---|---|---|
| Rank | 1 | 2 | 3 | 4 | 5 |
| 1 | 0.89 | 0.24 | 0.09 | 0.19 | 0.16 |
| | (7.28) | (1.51) | (0.74) | (1.30) | (1.22) |
| 2 | 0.83 | 0.04 | -0.09 | 0.07 | -0.12 |
| | (5.78) | (0.50) | (-0.84) | (0.58) | (-1.15) |
| 3 | 0.59 | -0.10 | -0.25 | 0.04 | -0.17 |
| | (3.59) | (-0.77) | (-2.31) | (0.48) | (-1.59) |
| 4 | 0.60 | 0.11 | 0.07 | -0.08 | -0.33 |
| | (4.98) | (0.67) | (0.55) | (-0.96) | (-3.28) |
| 5 | 0.32 | -0.28 | -0.07 | -0.10 | -0.32 |
| | (1.24) | (-1.26) | (-0.44) | (-0.67) | (-3.06) |
| 5-1 | -0.57 | -0.52 | -0.16 | -0.29 | -0.48 |
| | (-2.00) | (-1.88) | (-0.81) | (-1.37) | (-2.87) |

**Table 4: Out of Sample Tests**

This table reports the average monthly returns (Panel A) and alphas (Panel B) of the value-weighted momentum portfolios formed in each of the five PMP quintile months in post-formation years one through five. The sample period is 1938:12 to 2014:12. At the end of each month starting in 1938:12, an expanding widow from 1928:12 onwards is used to calculate the historical distribution of PMP and each month is assigned to a PMP quintile according to this distribution. Alphas are calculated using conditional loadings as described in Table 2. t-statistics, shown below coefficient estimates, are based on Newey and West (1987) standard errors calculated using 11 lags.

Panel A: Average monthly L/S Raw Return

| | Year | | | | |
|---|---|---|---|---|---|
| Rank | 1 | 2 | 3 | 4 | 5 |
| 1 | 1.17 | 0.29 | 0.19 | 0.34 | 0.23 |
| | (7.08) | (1.31) | (0.82) | (1.40) | (1.04) |
| 2 | 0.87 | -0.18 | -0.30 | 0.13 | -0.29 |
| | (6.35) | (-0.72) | (-1.57) | (0.49) | (-1.47) |
| 3 | 0.87 | 0.11 | -0.16 | -0.05 | -0.20 |
| | (4.79) | (0.72) | (-1.00) | (-0.29) | (-1.46) |
| 4 | 0.31 | -0.18 | -0.23 | -0.02 | -0.30 |
| | (1.88) | (-0.95) | (-1.30) | (-0.15) | (-2.40) |
| 5 | -0.11 | -1.10 | -0.43 | -0.29 | -0.51 |
| | (-0.26) | (-3.37) | (-1.65) | (-1.45) | (-3.58) |
| 5-1 | -1.28 | -1.39 | -0.62 | -0.63 | -0.73 |
| | (-2.76) | (-3.52) | (-1.78) | (-2.00) | (-2.82) |

Panel B: Average monthly L/S Alpha

| | Year | | | | |
|---|---|---|---|---|---|
| Rank | 1 | 2 | 3 | 4 | 5 |
| 1 | 1.15 | 0.32 | 0.25 | 0.42 | 0.13 |
| | (7.27) | (1.50) | (1.13) | (2.25) | (0.72) |
| 2 | 1.15 | 0.06 | -0.19 | 0.14 | -0.22 |
| | (7.83) | (0.31) | (-1.35) | (0.70) | (-1.29) |
| 3 | 1.06 | 0.09 | -0.14 | 0.05 | -0.12 |
| | (6.14) | (0.52) | (-0.99) | (0.31) | (-0.94) |
| 4 | 0.39 | -0.01 | -0.25 | -0.03 | -0.30 |
| | (2.47) | (-0.05) | (-1.56) | (-0.21) | (-3.16) |
| 5 | 0.66 | -0.45 | 0.07 | 0.06 | -0.31 |
| | (1.90) | (-1.97) | (0.32) | (0.31) | (-2.38) |
| 5-1 | -0.49 | -0.77 | -0.18 | -0.36 | -0.44 |
| | (-1.28) | (-2.47) | (-0.56) | (-1.29) | (-1.99) |

**Table 5: International Tests**

This table reports the relationship between PMP and long horizon momentum returns in eight developed markets. The sample period is 1991:07 to 2014:12. The sample includes all developed countries excluding US in the S&P BMI Developed Markets Index that have an average of at least 75 stocks per month in the index. The smallest 10% of stocks in each country are excluded from the sample. Panel A reports the average, minimum, and maximum number of stocks in each country. The stock return and market capitalization data are from S&P Capital IQ. Country-level factor returns are obtained from AQR's data library. At the end of each month from 1989:07 to 2009:12, stocks in each country excluding Japan and UK are ranked into quintiles based on their cumulative return over the past 12 months (skipping the most recent month) and a value-weighted long-short portfolio that is long the top quintile and short the bottom quintile is constructed for each country. Since the cross-section of stocks is much larger in Japan and UK, stocks are ranked into deciles based on past return (similar to the US tests)—the long-short momentum portfolio is long the top decile and short the bottom decile. Portfolios are rebalanced each month. For each country and each month, PMP is calculated as the average return of the momentum portfolio over the past 24 months. The 222 months in each country (from 1991:07 to 2009:12) are then ranked into quintiles based on PMP. Panel B reports the 3-factor alphas of the value-weighted momentum portfolios formed in each of the five PMP quintile months in post-formation years one through five for each country. To calculate alphas, a separate set of 3-factor loadings for each event month, $t+1, t+2, \ldots, t+60$, and PMP quintile pair are calculated for each country. Alpha is then calculated as the intercept plus the residual. t-statistics, not reported for brevity, are based on Newey and West (1987) standard errors calculated using 11 lags. 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

| PMP | | Years Post-Formation | | | | |
|---|---|---|---|---|---|---|
| Rank | N | 1 | 2 | 3 | 4 | 5 |
| | | | | Japan | | |
| 1 | 44 | 0.47* | 0.68** | −0.11 | 0.31 | 0.42 |
| 2 | 45 | 0.75** | 0.48* | −0.15 | −0.45** | 0.13 |
| 3 | 44 | 1.10** | 0.64** | −0.08 | −0.27 | 0.37 |
| 4 | 45 | 0.05 | 0.21 | 0.10 | 0.15 | −0.16 |
| 5 | 44 | −1.19** | −0.45** | 0.35 | 0.42 | −0.14 |
| 5-1 | | −1.66*** | −1.13*** | 0.47 | 0.11 | −0.56* |
| | | | | United Kingdom | | |
| 1 | 44 | 1.51** | −0.18 | 0.70** | −0.01 | 0.07 |
| 2 | 45 | 0.78** | 0.35 | 0.14 | −0.01 | −0.01 |
| 3 | 44 | 0.85* | 0.65* | 0.19 | −0.17 | −0.64*** |
| 4 | 45 | 1.73*** | −0.31 | 0.68 | 0.48 | −0.50 |
| 5 | 44 | 0.10 | 0.46 | 0.32 | −1.03** | −0.87** |
| 5-1 | | −1.41** | 0.64 | −0.38 | −1.01** | −0.94** |
| | | | | France | | |
| 1 | 44 | 0.67 | 0.25 | 0.99*** | −0.08 | 0.05 |
| 2 | 45 | 0.01 | 0.04 | 0.79*** | 0.28 | −0.29 |
| 3 | 44 | 0.58* | 0.30 | 0.36 | 0.49* | −0.91*** |
| 4 | 45 | −0.34 | −0.56** | −0.19 | −0.06 | −1.07*** |
| 5 | 44 | 0.06 | −0.56* | −0.15 | 0.41 | −1.42*** |
| 5-1 | | −0.61 | −0.81 | −1.14*** | 0.48 | −1.47*** |
| | | | | Australia | | |
| 1 | 44 | −0.01 | −0.18 | −0.36 | −0.72** | 0.40 |
| 2 | 45 | 0.45 | 0.23 | 0.50** | 0.38 | 0.30 |
| 3 | 44 | 0.83** | 0.32 | 0.06 | 0.42 | 0.23 |
| 4 | 45 | 1.02*** | 0.46** | 0.03 | 0.51** | −0.21 |
| 5 | 44 | 0.79 | 0.33** | 0.26 | −0.04 | 0.11 |
| 5-1 | | 0.80 | 0.51** | 0.62 | 0.68** | −0.29 |

**Table 5: Continued from previous page**

| PMP | | Years Post-Formation | | | | |
|---|---|---|---|---|---|---|
| Rank | N | 1 | 2 | 3 | 4 | 5 |
| | | | | Germany | | |
| 1 | 44 | 0.74*** | −0.35* | 0.35 | 0.88 | 1.50*** |
| 2 | 45 | 0.22 | 0.12 | 0.33* | 0.14 | 0.42 |
| 3 | 44 | 0.80*** | −0.51 | −0.58* | 0.01 | −0.41 |
| 4 | 45 | 0.43 | −1.22*** | −0.14 | 0.52 | −0.13 |
| 5 | 44 | −1.25 | 0.11 | 0.65 | 0.19 | −0.27 |
| 5-1 | | −2.00** | 0.46 | 0.30 | −0.69 | −1.77*** |
| | | | | Hong Kong | | |
| 1 | 44 | 0.56 | −0.02 | 0.44 | 0.79*** | −0.50** |
| 2 | 45 | 0.28 | −0.09 | 0.51 | 0.50 | 0.26 |
| 3 | 44 | 0.18 | −0.31 | 0.05 | −0.40** | 0.18 |
| 4 | 45 | −0.16 | −0.70** | 0.46 | −0.39 | −0.75** |
| 5 | 44 | −2.28*** | −0.58 | −0.78* | 0.07 | −1.67*** |
| 5-1 | | −2.85*** | −0.56 | −1.22** | −0.72 | −1.18*** |
| | | | | Italy | | |
| 1 | 44 | 1.36*** | 0.36 | 0.70** | 0.68*** | 0.33 |
| 2 | 45 | 1.10*** | −0.29 | 0.26 | 0.09 | 0.27 |
| 3 | 44 | 0.30 | 0.13 | 0.72 | 0.45 | −0.13 |
| 4 | 45 | −0.25 | 0.14 | 0.76** | 0.80* | 0.16 |
| 5 | 44 | −0.97* | 0.47 | 1.13** | 0.00 | 0.15 |
| 5-1 | | −2.33*** | 0.11 | 0.43 | −0.68** | −0.18 |
| | | | | Switzerland | | |
| 1 | 44 | 0.98*** | 0.08 | 0.30 | 0.39 | −0.50 |
| 2 | 45 | 0.67* | 0.10 | 0.41 | 0.08 | 0.09 |
| 3 | 44 | −0.17 | −0.79** | 0.63* | 0.20 | −0.18 |
| 4 | 45 | 0.38 | −1.11*** | 0.35 | 0.26 | −0.71*** |
| 5 | 44 | 0.04 | 0.25 | 0.37 | −0.40 | −0.45 |
| 5-1 | | −0.94** | 0.17 | 0.07 | −0.79* | 0.05 |

**Table 6: Portfolio Strategies**

This table reports the returns and Fama-French alphas of portfolio strategies constructed from stale momentum portfolios. Panel A reports the returns and alphas of trading strategies based on all stale momentum portfolios. For each PMP quintile and each month $t$, the trading strategy is "active" if any of the months from $t-60$ to $t-13$ belong to that particular PMP quintile; the portfolio in month $t$ consists of an equal-weighted average of the stale value-weighted momentum portfolios formed in months belonging to that particular PMP quintile from $t-60$ to $t-13$. The strategy labeled as "5-1" combines PMP Quintile 1 and 5 strategies; this strategy is active in any given month if either Quintile 1 or Quintile 5 strategy is active, or both are active. This portfolio is long Quintile 5 portfolio during months in which only Quintile 5 strategy is active, short Quintile 1 portfolio during months in which only Quintile 1 strategy is active, and long 50% Quintile 5 portfolio and short 50% Quintile 1 portfolio during months in which both are active. The unconditional trading strategy (labeled as "All months") is just an equal-weighted portfolio of all stale momentum portfolios formed in months $t-60$ to $t-13$. Panel B reports the returns and alphas of similar strategies for each of the four years individually. For example, the year 2 strategy for Quintile 5 is active in month t if any of the months from $t-13$ to $t-24$ are Quintile 5 months and the portfolio in month $t$ consists of an equal-weighted average of the stale value-weighted momentum portfolios formed in Quintile 5 months from $t-13$ to $t-24$. t-statistics are shown below the coefficient estimates.

Panel A

| Rank | No. of Obs | Return | Alpha |
|---|---|---|---|
| 1 | 685 | 0.23 | 0.35 |
| | | (1.55) | (2.59) |
| 2 | 930 | -0.03 | 0.07 |
| | | (-0.33) | (0.83) |
| 3 | 923 | -0.13 | -0.04 |
| | | (-1.31) | (-0.43) |
| 4 | 894 | -0.33 | -0.04 |
| | | (-2.60) | (-0.40) |
| 5 | 699 | -0.74 | -0.37 |
| | | (-4.58) | (-2.93) |
| 5-1 | 933 | -0.54 | -0.40 |
| | | (-4.62) | (-3.74) |
| All Months | 1020 | -0.27 | -0.07 |
| | | (-3.19) | (-1.07) |

Panel B

| | | Year 2 | | Year 3 | | Year 4 | | Year 5 | |
|---|---|---|---|---|---|---|---|---|---|
| Rank | No.Obs | Return | Alpha | Return | Alpha | Return | Alpha | Return | Alpha |
| 1 | 362 | 0.27 | 0.56 | 0.04 | 0.18 | 0.23 | 0.33 | -0.06 | -0.05 |
| | | (1.12) | (2.74) | (0.23) | (1.08) | (1.27) | (1.82) | (-0.30) | (-0.28) |
| 2 | 584 | 0.16 | 0.24 | -0.11 | -0.16 | 0.02 | 0.06 | -0.06 | 0.01 |
| | | (0.90) | (1.49) | (-0.70) | (-1.02) | (0.17) | (0.46) | (-0.43) | (0.09) |
| 3 | 618 | -0.05 | 0.18 | -0.08 | 0.01 | 0.10 | 0.21 | -0.42 | -0.21 |
| | | (-0.26) | (1.04) | (-0.53) | (-0.68) | (0.69) | (1.47) | (-2.86) | (-1.53) |
| 4 | 590 | -0.29 | 0.11 | -0.28 | -0.13 | -0.09 | 0.01 | -0.44 | -0.26 |
| | | (-1.34) | (0.58) | (-1.43) | (-0.77) | (-0.62) | (0.09) | (-3.15) | (-1.98) |
| 5 | 396 | -1.08 | -0.44 | -0.36 | -0.05 | -0.47 | -0.36 | -0.68 | -0.45 |
| | | (-3.23) | (-1.72) | (-1.23) | (-0.18) | (-1.86) | (-1.66) | (-3.15) | (-2.35) |
| 5-1 | 584 | -0.73 | -0.53 | -0.23 | -0.03 | -0.35 | -0.33 | -0.35 | -0.28 |
| | | (-3.47) | (-2.95) | (-1.30) | (-0.16) | (-2.19) | (-2.18) | (-2.48) | (-1.97) |
| All Months | 984 | -0.35 | 0.00 | -0.20 | -0.02 | -0.10 | -0.02 | -0.28 | -0.21 |
| | | (-2.26) | (0.01) | (-1.51) | (-0.14) | (-0.91) | (-0.17) | (-2.75) | (-2.27) |

**Table 7: Robustness Tests**

This table reports the results of robustness tests. For brevity, only the average Fama-French alphas in each of the post-formation year one through five are reported. Panel A excludes all months for which the cumulative market return over the past 2 years is negative. In Panel B, PMP is regressed on the momentum characteristic spread (mean difference in formation period return of Winner and Loser portfolios) and the residual from the regression is used to rank months into quintiles. The last column of Panel B reports the average values of the momentum characteristic spread for each of the five PMP quintiles. In Panel C, PMP is regressed on past momentum variance (annualized variance of daily momentum factor returns over the past 6 months) and the residual from the regression is used to rank months into quintiles. The last column of Panel C reports the average values of past momentum variance for each of the five PMP quintiles. In Panel D, PMP is regressed on past market variance (annualized variance of daily market returns over the past 6 months) and the residual from the regression is used to rank months into quintiles. The last column of Panel D reports the average values of past market variance for each of the five PMP quintiles. Panel E repeats the tests in Table 2 but reports size and book-to-market adjusted returns instead for alphas. In June of each year, stocks are ranked into size quintiles using NYSE size breakpoints and within each size quintile, stocks are ranked into book-to-market quintiles. For each stock, size and book-to-market adjusted return is then calculated as the raw return minus the value-weighted return of the size and book-to-market quintile portfolio that the stock belongs to. The sample period for this test is from 1951:06 to 2014:12 (due to availability of book-to-market data), but months are ranked into PMP quintiles using the full sample distribution of PMP. Panels F and G repeat the tests of Table 2 for the first and second halves of the sample, respectively, and Panels H and I split the sample at the start of 1982, consistent with Jegadeesh and Titman (2001). t-statistics, not reported for brevity, are based on Newey and West (1987) standard errors calculated using 11 lags. 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

| PMP | | Years Post-Formation | | | | | |
|---|---|---|---|---|---|---|---|
| Rank | N | 1 | 2 | 3 | 4 | 5 | |
| | | Panel A: Excluding down market months | | | | | |
| 1 | 139 | 1.03*** | 0.30 | 0.16 | 0.19 | 0.02 | |
| 2 | 182 | 0.77*** | 0.01 | −0.22 | 0.17 | −0.09 | |
| 3 | 179 | 0.75*** | −0.23 | −0.38** | 0.03 | −0.12 | |
| 4 | 160 | 0.58*** | −0.37* | −0.35* | −0.18 | −0.30** | |
| 5 | 138 | 0.76** | −0.68** | −0.45** | −0.46 | −0.46*** | |
| 5-1 | | −0.27 | −0.98*** | −0.61* | −0.65 | −0.49** | |
| | | Panel B: PMP orthogonalized to momentum spread | | | | | Mom. Spd. |
| 1 | 194 | 1.09*** | 0.30 | 0.07 | 0.13 | 0.04 | 153% |
| 2 | 195 | 0.88*** | 0.07 | −0.21 | 0.22 | −0.05 | 126% |
| 3 | 195 | 0.67*** | −0.06 | −0.39** | 0.05 | −0.12 | 125% |
| 4 | 195 | 0.75*** | −0.08 | −0.07 | −0.07 | −0.32** | 147% |
| 5 | 194 | 0.53 | −0.51** | −0.02 | −0.36 | −0.36** | 163% |
| 5-1 | | −0.56 | −0.81** | −0.09 | −0.49* | −0.39** | |
| | | Panel C: PMP orthogonalized to momentum variance | | | | | $\sigma^2_{mom}$ |
| 1 | 194 | 1.09*** | 0.32 | 0.14 | 0.16 | −0.01 | 0.0232 |
| 2 | 195 | 0.85*** | 0.07 | −0.15 | 0.17 | −0.06 | 0.0073 |
| 3 | 195 | 0.73*** | −0.15 | −0.28 | 0.11 | −0.12 | 0.0060 |
| 4 | 195 | 0.76*** | 0.04 | −0.08 | −0.07 | −0.36*** | 0.0098 |
| 5 | 194 | 0.61* | −0.63** | −0.1 | −0.37 | −0.33** | 0.0233 |
| 5-1 | | −0.48 | −0.95*** | −0.23 | −0.53 | −0.32* | |

**Table 7: Continued from previous page**

| PMP Rank | N | Years Post-Formation 1 | 2 | 3 | 4 | 5 | $\sigma^2_{mkt}$ |
|---|---|---|---|---|---|---|---|
| | | Panel D: PMP orthogonalized to market variance | | | | | |
| 1 | 194 | 1.11*** | 0.32 | 0.11 | 0.16 | 0.01 | 0.0423 |
| 2 | 195 | 0.87*** | 0.15 | −0.18 | 0.16 | −0.03 | 0.0179 |
| 3 | 195 | 0.73*** | −0.19 | −0.31* | 0.10 | −0.13 | 0.0154 |
| 4 | 195 | 0.70*** | 0.05 | 0.00 | −0.08 | −0.34*** | 0.0217 |
| 5 | 194 | 0.62* | −0.62** | −0.13 | −0.33 | −0.36*** | 0.0462 |
| 5-1 | | −0.49 | −0.94*** | −0.24 | −0.49 | −0.37** | |
| | | Panel E: Size and BM adjusted returns | | | | | |
| 1 | 93 | 1.04*** | 0.23 | 0.26 | 0.47** | 0.20 | |
| 2 | 148 | 0.72*** | 0.07 | 0.05 | 0.32 | −0.02 | |
| 3 | 150 | 0.80*** | 0.08 | −0.07 | 0.13 | −0.29*** | |
| 4 | 163 | 0.44** | −0.09 | −0.05 | −0.09 | −0.31*** | |
| 5 | 149 | 0.02 | −0.83*** | −0.33* | −0.08 | −0.30*** | |
| 5-1 | | −1.02** | −1.06*** | −0.59* | −0.55** | −0.50** | |
| | | Panel F: First half: 1928:12-1969:05 | | | | | |
| 1 | 103 | 0.93*** | 0.29 | −0.13 | −0.03 | 0.00 | |
| 2 | 103 | 0.72*** | 0.18 | −0.33** | −0.19 | 0.04 | |
| 3 | 117 | 0.37 | −0.20 | −0.56*** | 0.05 | −0.02 | |
| 4 | 86 | 0.73** | 0.09 | 0.15 | −0.10 | −0.48* | |
| 5 | 77 | 0.77* | −0.55 | −0.36 | −1.06** | −0.33 | |
| 5-1 | | −0.16 | −0.85 | −0.23 | −1.03* | −0.33 | |
| | | Panel G: Second half: 1969:06-2009:12 | | | | | |
| 1 | 91 | 1.31*** | 0.35 | 0.38 | 0.36* | 0.03 | |
| 2 | 92 | 1.04*** | 0.09 | 0.01 | 0.57** | −0.12 | |
| 3 | 78 | 1.23*** | 0.02 | 0.04 | 0.17 | −0.28 | |
| 4 | 109 | 0.73*** | −0.03 | −0.16 | −0.07 | −0.23** | |
| 5 | 117 | 0.45 | −0.65** | 0.04 | 0.15 | −0.38** | |
| 5-1 | | −0.86 | −1.01** | −0.34 | −0.21 | −0.41* | |
| | | Panel H: 1928:12-1981:12 | | | | | |
| 1 | 111 | 0.99*** | 0.38 | −0.07 | −0.01 | 0.02 | |
| 2 | 133 | 0.85*** | 0.02 | −0.35** | −0.08 | 0.03 | |
| 3 | 140 | 0.53** | −0.01 | −0.39* | 0.12 | −0.08 | |
| 4 | 129 | 0.91*** | 0.16 | 0.10 | −0.09 | −0.44** | |
| 5 | 124 | 0.93*** | −0.44 | −0.14 | −0.76** | −0.36* | |
| 5-1 | | −0.06 | −0.82* | −0.07 | −0.74 | −0.37 | |
| | | Panel I: 1982:01-2009:12 | | | | | |
| 1 | 83 | 1.27*** | 0.25 | 0.34 | 0.38* | 0.00 | |
| 2 | 62 | 0.91*** | 0.38 | 0.23 | 0.70** | −0.17 | |
| 3 | 55 | 1.19*** | −0.37 | −0.13 | 0.06 | −0.24 | |
| 4 | 66 | 0.38 | −0.25 | −0.27 | −0.07 | −0.15 | |
| 5 | 70 | −0.05 | −0.92** | −0.08 | 0.44* | −0.37** | |
| 5-1 | | −1.32* | −1.17** | −0.42 | 0.05 | −0.38 | |

**Table 8: PMP and Institutional Trading:**

This table reports the results of resgressions that examine how institutional trading is related to PMP. At the end of each calendar quarter $q$ from 1985:06 to 2010:03, all institutional investors $j$, with at least 5 years of historical data available, are ranked into deciles based on their past momentum trading measure $\mathrm{L0M}_{iq}$ (from Grinblatt et al. 1995):

$$\mathrm{L0M}_{iq} = \sum_{m=1}^{3} \sum_{j=1}^{N(q)} (w_{i,j,q} - w_{i,j,q-1}) \, R_{j,q-1,m},$$

where:

$$(w_{j,q} - w_{j,q-1}) = \frac{\mathrm{SharesHeld}_{j,q} \times p_{j,q-1}}{\sum_{j=1}^{N} \mathrm{SharesHeld}_{j,q} \times p_{j,q-1}} - \frac{\mathrm{SharesHeld}_{j,q-1} \times p_{j,q-1}}{\sum_{j=1}^{N} \mathrm{SharesHeld}_{j,q-1} \times p_{j,q-1}}.$$

$w_{i,j,q}$ is the fund $i$'s quarter-$q$ ending weight on stock $j$, $m$ identifies the month following the end of quarter $q-1$, $N(q)$ is the number of stocks in quarter $q$, and $R_{j,q,m}$ is stock $j$'s return in the $m^{th}$ month of quarter $q$. The top decile institutions are labeled as "momentum" traders and the bottom decile institutions as labeled as "contrarian" traders. The time-series of mean quarterly momentum trading measures for momentum and contrarian traders is then calculated. This table reports the results of regressions of the mean momentum trading measures of momentum and contrarian traders on lagged PMP (last quarter's PMP) quintile rank and average monthly cross-sectional standard deviation of the returns all CRSP stocks over the quarter preceding the portfolio formation date (labeled $\sigma_{R,xs}$) . The table also reports the time-series mean of average quarterly fund AUM (in $ Millions) for the two types of institutions. t-statistics are shown below coefficient estimates and 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

| | Intercept | PMP Rank | $\sigma_{R,xs}$ | $R^2_{adj}$ | Mean AUM |
|---|---|---|---|---|---|
| Momentum Traders | 0.533*** | 0.150*** | | 0.132 | 3,462 |
| | (5.02) | (3.65) | | | |
| Momentum Traders | 0.547*** | 0.152*** | -0.110 | 0.123 | |
| | (2.31) | (3.00) | (-0.06) | | |
| Contrarian Traders | -0.510*** | -0.030 | | 0.002 | 2,267 |
| | (-5.72) | (-1.01) | | | |
| Contrarian Traders | -0.251 | 0.004 | -2.100 | 0.015 | |
| | (-0.88) | (0.10) | (-0.98) | | |