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

Usman Ali, Kent Daniel, and David Hirshleifer*

Preliminary Draft: May 15, 2017
This Draft: December 27, 2017

Abstract

Following periods when momentum strategies have experienced their highest returns, stale momentum portfolios—defined as momentum portfolios formed at least 1 month earlier—experience their worse performance. Specifically, following periods of top-quintile momentum-performance, stale momentum portfolios reverse, earning cumulative returns of -41% from in years 1-5 post-formation. In contrast, following periods of bottom-quintile momentum performance, they earn +19%. A value-weighted trading strategy based on this effect generates a monthly Fama and French (1993) three-factor and Carhart (1997) four-factor alphas of 0.24% ($t = 2.50$) and 0.30% ($t = 2.97$), respectively. These patterns are confirmed in international data. These findings can be explained in part by style chasing on the part of momentum investors, but present a puzzle for existing theories of momentum.

*MIG Capital, Columbia Business School and NBER, and Merage School of Business, University of California at Irvine and NBER. We thank Sheridan Titman for helpful comments.

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 (Jegadeesh and Titman 1993). Zero investment portfolios which take long positions in past winners and short past losers earn high Sharpe ratios and have low correlations with macroeconomic variables, posing a challenge for standard rational expectations models.

Behavioral asset pricing models generate momentum, value and reversal effects consistent with empirical findings.[1] In these models, prices show a pattern of initial underreaction and continuing overreaction and slow correction that results in short-horizon momentum and long-horizon reversal. Thus these models imply that sufficiently stale momentum portfolios—that is momentum portfolios formed at least 12 months earlier—will on average earn negative returns. Jegadeesh and Titman (2001) provide evidence that stale momentum portfolios do indeed on average experience negative returns.

A recent literature has examined time-series variation in the profitability of momentum strategies (Cooper, Gutierrez, and Hameed 2004, Daniel and Moskowitz 2016, Barroso and Santa-Clara 2015, Stivers and Sun 2010). The evidence from these studies suggests that the momentum premium is strongly dependent upon past-market returns, market volatility, and the volatility of the momentum portfolio. 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 formed between 1-month and 5-years 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 pile into momentum strategies, eventually resulting in underperformance of the strategy portfolios. In this paper, we explore this issue by testing whether the long horizon performance of momentum portfolios is negatively related to realized momentum strategy performance in the recent past.

In particular, we study the relationship between stale momentum returns and 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

[1] See, for example, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999).

PMP months (months when PMP is in the top 20% of all months in our sample) generate strong negative returns and alphas post-formation. Strikingly, momentum portfolios formed in low PMP months continue to outperform post-formation. Thus, the longer-term momentum reversal documented by Jegadeesh and Titman (2001) is strongly state dependent.

We explore a set of possible behavioral hypotheses that might explain the dependence of stale momentum performance on PMP. A baseline hypotheses based upon style chasing predicts 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 will tend to do well again. (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.) Underlying the style chasing approach is the behavioral hypothesis that, following high momentum style performance, naive investors switch into this style as a result of style return extrapolation, meaning that they buy winners and sell losers more 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.

Following higher PMP, style chasing results in a stronger overpricing of past winners and underpricing of past losers. As this mispricing is corrected, there is a longer-term reversal of the momentum effect. So after high PMP, we should on average see negative returns to a *stale momentum strategy* of buying past-winners and selling past-losers. 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 longer-term positive returns to a stale momentum strategy. Putting these two cases together, we expect reversal of momentum portfolios to be stronger when they are formed in higher PMP months.[2]

However, similar predictions can apply even in a setting without direct over-extrapolation.If

[2] 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.

investors naively update their confidence in a momentum investing strategy in response to historical momentum performance (ie., to PMP), then when realized momentum returns are strong, their confidence in the strategy increases, amplifying the immediate momentum returns, but leading to eventual poor performance of stale momentum portfolios.[3]

Motivated by these ideas, we examine the relationship between PMP and stale momentum portfolio performance. We document several 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.[4] This finding is in contrast with Jegadeesh and Titman (2001), who document that, over a shorter sample, equal-weighted momentum portfolios exhibit strong reversals even after controlling for the value effect.

Turning to our main result, we demonstrate a strong negative relationship between PMP and stale momentum portfolio returns. Again, our hypothesis is that the long-horizon performance of momentum portfolios depends on the performance of momentum leading up to the portfolio formation date. If the momentum style has recently done well (i.e., if PMP is high), we expect to see high momentum stocks become more overpriced, leading to longer term reversal of the momentum portfolio. To test this, we rank the momentum portfolio formation months in our sample into quintiles based on PMP and then examine the performance of momentum portfolios formed in that month for up to five years after the formation date. Our basic finding is that, the (stale) momentum portfolio returns are strongly negatively related to PMP as of the formation date.

Specifically, momentum portfolios formed in quintile 1 (i.e, low PMP) months exhibit weak continuation post-formation, earning a cumulative return of 19% in the five years post-formation. However, in sharp contrast, momentum portfolios formed in quintile 5 months lose 42% of their value over the five years post formation. We label this strong reversal of momentum formed in high PMP months the PMP effect.

Similar results obtain after controlling for exposure to the Fama-French factors; the difference in cumulative five-year alphas of stale momentum portfolios formed in Quintile 5 and

[3]As discussed in Section 2, owing to self-attribution bias, 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.

[4]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 papers do not examine whether there will be incremental reversal after controlling for the value effect.

Quintile 1 months is 40%.[5] In particular, the estimated alpha of momentum portfolios formed in the highest quintile PMP months is negative in each of the post-formation years 2-5. 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, Shleifer, and You (2017) examine whether past industry returns predicts industry crashes, but they do not consider PMP.

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, another possible implication of this approach is that after high PMP, style chasers will pile into momentum portfolios during the year after stocks are identified as high or low momentum, resulting in strong short-term performance of momentum portfolios. In contrast, we document that PMP over the same conditioning period does not positively predict short horizon performance of momentum portfolios. Indeed, the point estimate suggests that the relation between PMP and short horizon momentum performance is slightly negative.[6] In other words, after high PMP, a newly formed momentum portfolio 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 12 months after the portfolios are formed.

This does not rule out the possibility that investors chase momentum style returns at a higher frequency. If so, the apparent overvaluation of the momentum portfolio that is identified by high PMP must emerge 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

[5]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.

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

PMP/momentum reversal effect that we document.

Furthermore, the reversals that we identify extend much too long after the conditioning date to be explained by simple 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 exit from any given momentum portfolio within about 12 months after formation. So style chasing does not provide a full explanation for our main result.

We perform a number of robustness checks. 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. In addition, we replicate our US tests in eight developed markets outside the US that have reasonably large cross-sections of large, liquid stocks. We find that a strong inverse relationship between PMP and the performance of stale momentum strategies is present for almost all of the countries we examine..

We show that cross-sectional portfolio strategies designed to exploit the PMP effect exhibit strong abnormal performance. As with our other tests, the portfolio strategies exploit the predictability of *stale* momentum portfolios, that is portfolios formed on the basis from the 11-month cumulative return of individual firms, lagged between 2 months and 5 years, rather that just one months. 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 monthly 3- and 4-factor alphas of 0.52% ($t = 3.90$) and 0.25% ($t = 1.86$). The alphas of such strategies decline monotonically with the past-momentum-performance measured as of the formation date. Furthermore, a strategy which exploits the continuation of momentum portfolios formed in low PMP months and reversal of momentum portfolios formed in high PMP months generates still stronger performance, with a four-factor alpha of 0.30%/month ($t = 2.97$). In contrast, an unconditional stale momentum strategy which pools all months generates an insignificant 4-factor alpha of 0.04%/month ($t = 0.67$).

***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.

This literature focuses on how individual investors respond to the performance of styles such as value and growth. Our focus is on momentum, and given the importance of institutional investors for price-setting, we perform tests of whether institutional traders engage in momentum style-chasing based upon PMP.[7] We define momentum traders as institutions with a history of buying winners and selling losers, and contrarian traders as institutions with a history of the reverse behavior. We find that following high PMP periods, momentum traders substantially increase their holdings of recent winners and decrease their holdings of recent losers. In contrast, there is no association between PMP and the subsequent trading of contrarian investors (institutions with a history of selling winners and buying losers). These findings suggest that momentum traders (chasers of past returns of individual stocks) tend to be chasers of past *style*, whereas contrarian investors (anti-chasers of past stock returns) are not heavy style return chasers. This in turn suggests that the behavior of momentum-trading institutional investors may help explain the PMP effect. However, as discussed earlier, our return tests indicate that simple style chasing is unlikely to fully explain our findings.

Finally, we conduct a set tests to ensure that the PMP effect is distinct from previously identified 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 becomes 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 rever-

[7]Such behavior could reflect the traits of fund managers, or the traits of the clienteles of the funds.

sals. Furthermore, we show that 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 only a partial possible explanation for the findings. We draw the same conclusion (discussed in the next section) about an explanation based upon bias in investor self-attribution. We conclude that the PMP effect remains a puzzle. The finding that momentum portfolios formed in high PMP months eventually reverse strongly suggests that in high PMP months, momentum formation period returns are at least in part overreaction. So a full explanation for the puzzle seems to require that in periods of high PMP, a greater than usual proportion of winner-loser conditioning period returns derives from investor overreaction. Our findings on institutional trading suggest that momentum-trading institutions contribute to such overreaction.

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 should predict returns both fresh and stale momentum strategies. The style investing model is based on the hypothesis that investors overextrapolate past style returns in forecasting future style returns. For example, if growth stocks have recently done well, style investors expect growth stocks to do well in the future. As Barberis and Shleifer show, this can lead to ‘style chasing’ wherein overextrapolating investors buy into a style when that style has provided high recent historical returns, leading to at least an initial continuation in style returns.

It is especially interesting to test for style effects on momentum, because momentum 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, weak momentum performance should follow low PMP periods. By the same token, after high PMP, 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 unprofitable (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.

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

[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, defined 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, which tends to cause such stocks to be part of the momentum winner portfolio in subsequent periods. However, this effect is necessarily small, since the fraction of realized returns explained by momentum is empirically small (Jegadeesh and Titman 2001).

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.

As applied to the momentum style, this suggests that after high PMP, momentum style investors should become more confident in their enthusiasm for momentum, resulting in stronger overvaluation of the winner-minus-loser portfolio. As a consequence, eventual performance of stale momentum portfolios should be very poor. In contrast, and asymmetrically, after low PMP, momentum style investors will 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

[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.

momentum. So we view the prediction for asymmetry as clear—that 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.

The arguments provided here are very 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 individual 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 poorly. 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 (formerly AMEX), 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 Winner-Minus-Loser or *WML* portfolio that is long the value-weighted portfolio of top-decile "Winners" and short the value-weighted portfolio of (bottom decile) "Losers." Portfolios are held for one month. This procedure results in a monthly time-series of WML returns.

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

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

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 a set of characteristics of the PMP quintiles. First, note that there is considerable variation in momentum performance over time; the average PMP across the bottom quintile (rank 1) months is -0.4%/month, while the average across the rank 5 months is 3.1%/month. Interestingly, the best momentum performance is associated with lower market returns, in that the average past 1-year market excess return for PMP-rank-5 months is -4.4%. Not surprisingly, both high and low PMP quintile months are associated with higher market volatility in the recent past.

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, almost exactly two years following the start of a major momentum 'crash' (see Daniel and Moskowitz 2016) and is -6.2%/month.

3 Empirical Analysis

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 excess 5-year returns of the value-weighted momentum portfolios formed in different PMP quintile months as well as in all

[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.

months. Specifically, we plot[12]:

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

as a function of τ, where:

- WML_{t+s}^{t} is the return in month $t+s$ to the momentum portfolio formed in at the start of month t (*i.e.,* which was formed s months earlier). Note that WML_t^t is conventional "fresh" momentum portfolio.
- $r_{f,t+s}$ is the riskfree rate in month $t+s$.
- 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 finding of Jegadeesh and Titman (2001) 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.[13]Figure 2 also reveals 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.[14]

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

[12]This is the average cumulative return on an implementable strategy of, at the start of month $t+s$, putting V_{t+s-1} (the value of the portfolio at that time) into the riskfree asset. In addition, V_{t+s-1} is invested in the long-side of the zero-investment portfolio WML^t, which is financed by shorting V_{t+s-1} of the short size of WML. At the end of month $t+s$, the sizes of the long- and short-positions are rescaled to a value of V_{t+s}, so that the leverage of the portfolio remains at 1. This methodology assumes that there are no margin calls, *etc.*, except at the end of each month. These calculated returns do not incorporate transaction costs. See Daniel and Moskowitz (2016) for more details.

[13]However, as we show below, the year 2-5 decline is not statistically significant.

[14]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).

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 relative to Quintile 1 months. If higher PMP is associated with stronger overreaction, resulting in long-term reversal for the stale momentum portfolios, why don't we see the opposite effect for Quintile 1 PMP, i.e. 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 riskfree rate) of the momentum portfolio from 1-60 months post-formation—this is the line labeled R_1_60—and in addition the PMP up through that date. Panel A does this 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 as of the portfolio formation date and the subsequent stale momentum portfolio return. This correlation is particularly strong in the post-1982 period. As we discuss in more detail in Section 3.6, the 1982-1997 subsample is interesting, as Jegadeesh and Titman (2001) find virtually no evidence of reversal of momentum (without conditioning on PMP) in this period.

One more view of these data is provided in Figure 5, which is a scatterplot with PMP on the x-axis and the cumulative return on the stale momentum portfolio from 1-60 months post-formation on the y axis. Each dot represents one outcomes (or, alternatively, one monthly formation date). This scatterplot again suggests 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 (see Daniel and Moskowitz 2016).

Table 2 reports the average monthly returns (in Panel A) and three-factor alphas (in Panel B) of the stale-momentum portfolios. Each row presents the result for momentum portfolios formed in a different PMP quintile month, and each column presents the average return (alpha) for each of five post-formation years. The final column presents the the average return or alpha for the entire five year period.[15] For example, for each momentum portfolio formed in a PMP-Rank 1 month t, we calculate its average monthly return (alpha) in months t+1 through t+12 (post-formation year 1), and report this number as the Rank 1/Year 1 return (alpha). The average of all post-formation returns in months t+1 through t+60 is reported in the All column.

The row labeled All months presents the average monthly returns for the stale momentum portfolios formed in any month (ie., ranks 1-5), and the row 5-1 gives the difference between the Rank 1 and Rank returns (alphas). The t-statistics presented 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 the average 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

[15] In untabulated results, we examine returns up to 10 years after portfolio formation, and find no evidence of reversals in years 6 through 10 either unconditionally or conditioning on PMP.

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" shows that over the full CRSP sample from 1928-2014, 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.[16]

For Quintile 1 months, 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 on average gradually exhibit reversals during post-formation years as the mispricing is corrected.

[16]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.

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 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 (unconditionally) 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 (one not limited to 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

To further evaluate the robustness of our results, we next examine the extent to which the pmp-related patterns we see in US data also 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 well diversified. The stock return and market capitalization data are from S&P Capital IQ. Country-level factor returns are from AQR's data library.

Based on these data requirements, we end up with eight non-US universes for our international tests.[17] 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

[17] 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.

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 based on PMP and examine the performance of momentum portfolios in each post-formation years 1-5 and—in the All column—over the full 5 years post-formation, as was done for the US stock universe in Table 2. To calculate 3-factor alphas, we estimate conditional loadings for each PMP Quintile and event month pair. Table 5 reports the results of this analysis; for brevity, we only report alphas in Table 5.

Consistent with the US-market findings reported earlier, we see that for most of the non-US universes, there is a strong inverse relationship between PMP and post-formation alphas. Specifically, the difference between the five-year post formation alphas (ie., in the All column) for momentum portfolios formed in rank-5 and rank-1 PMP months is negative for every non-US universe except for Australia. This difference is statistically significant at at least the 5% level for 6 of the 8 regions. The only region, other than Australia, where it this difference is not statistically significant is Switzerland which, as noted earlier, has the smallest cross section with an average of only 91 stocks.

One difference between the US and non-US results is that after high PMP, reversal of momentum often seems to start earlier outside the US. Indeed, for six of the eight non-US universes, the difference between PMP-rank 5 and 1 momentum returns in post-formation year 1 are significantly negative, while in the US we see relatively little difference in year 1.

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 makes clear that the style chasing and investor attribution interpretations are at best incomplete explanations for the PMP effect. 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 between 1 and 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 $t-1$ 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 $t-1$. The unconditional trading strategy is just an equal-weighted portfolio of all stale momentum portfolios formed in months $t-60$ to $t-1$.

Panel A of Table 6 reports the average returns, the 3- and 4-factor alphas, and the number of months that each strategy is active. The unconditional trading strategy, labeled All Mths, generates a return of -0.11% per month ($t = -1.23$). The 3-factor alpha is statistically significant, but the 4-factor alpha is not. These results are consistent with a small momentum effect in the first year after portfolio formation, but no (unconditional) reversal of the momentum effect over the 2-5 years post-formation.

However, the Rank 1-5 results in the upper part of Panel A show that there is a strong monotonic relationship between PMP quintile rank and portfolio returns and alphas. The monthly portfolio return is 0.38% for quintile 1, and decreases monotonically to -0.47% for quintile 5. Consistent with our earlier results, both the three- and four-factor alphas suggest that the stale momentum portfolios do well when the portfolio is formed in a low-PMP month, and poorly when it is formed in a high-PMP month.

We also consider a combined Quintile 5-minus-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 a return of -0.43%/month, and three- and four-factor monthly alphas of -0.24 and -0.30% per month, and with t-statistics of -2.50 and -2.97, respectively.[18].

We also consider similar strategies for each of the five 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

[18]We note that a strategy that skips the first year, and forms the portfolio based on the PMP from months $t-13$ to $t-60$ generates a monthly 3-factor alpha of -0.37% ($t = -3.74$)

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 Other 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 forecaster of 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 address 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.[19] 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)

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

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 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.[20] 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.[21] 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

[20] 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.

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

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 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. Panel I shows that, in the post-1982 subsample, for momentum portfolios formed in PMP Quintile 5 months, alphas are strongly negative and statistically significant in years 2 and 5 post-formation.[22]

3.7 PMP and Institutional Trading

We next test whether institutional investors engage in momentum style chasing based upon 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

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

[22] Consistent with Jegadeesh and Titman (2001), we find very weak reversals in the 1982-1998 period (even for raw returns) without conditioning on PMP. However, momentum portfolios formed in PMP quintile 5 months lose on average 32.8% of their value in post-formation years 2-5 in this 1982-1998 sample period.

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 $q-1$.[23]

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.

To test how momentum and contrarian traders respond to PMP, we then regress these trading measures on last quarter's PMP quintile rank. 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 presents the results. The highly significant intercept for momentum traders indicates that momentum trading is a highly persistent characteristic—institutions with a history of trading on momentum continue to do so in the future. Table 8 also 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.[24] 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.

[23] 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.

[24] 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.

4 Conclusion

Motivated by behavioral theories, we examine the relationship between recent past momentum performance, PMP, and long horizon performance of *stale* momentum portfolios. Following period of strong momentum performance, we see that stale momentum portfolios exhibit strong reversals for five years post-formation. In contrast, follow poor momentum returns, stale momentum portfolios do not underperform. 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 fully explained by style chasing and bias in self-attribution hypotheses. They also conflict with theories of momentum based upon pure underreaction. Overall, 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.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

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.

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.

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.

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, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

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

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.

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

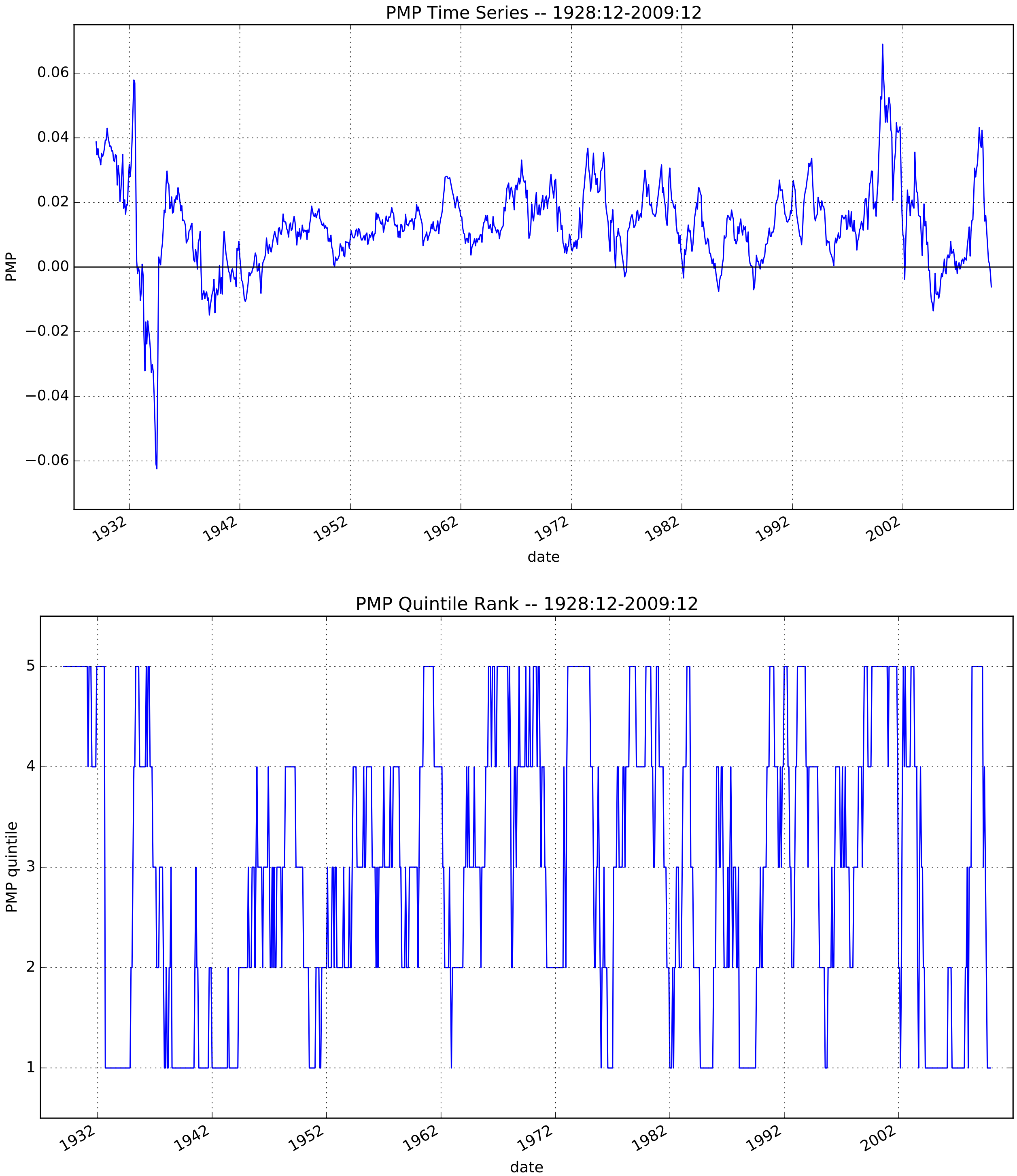
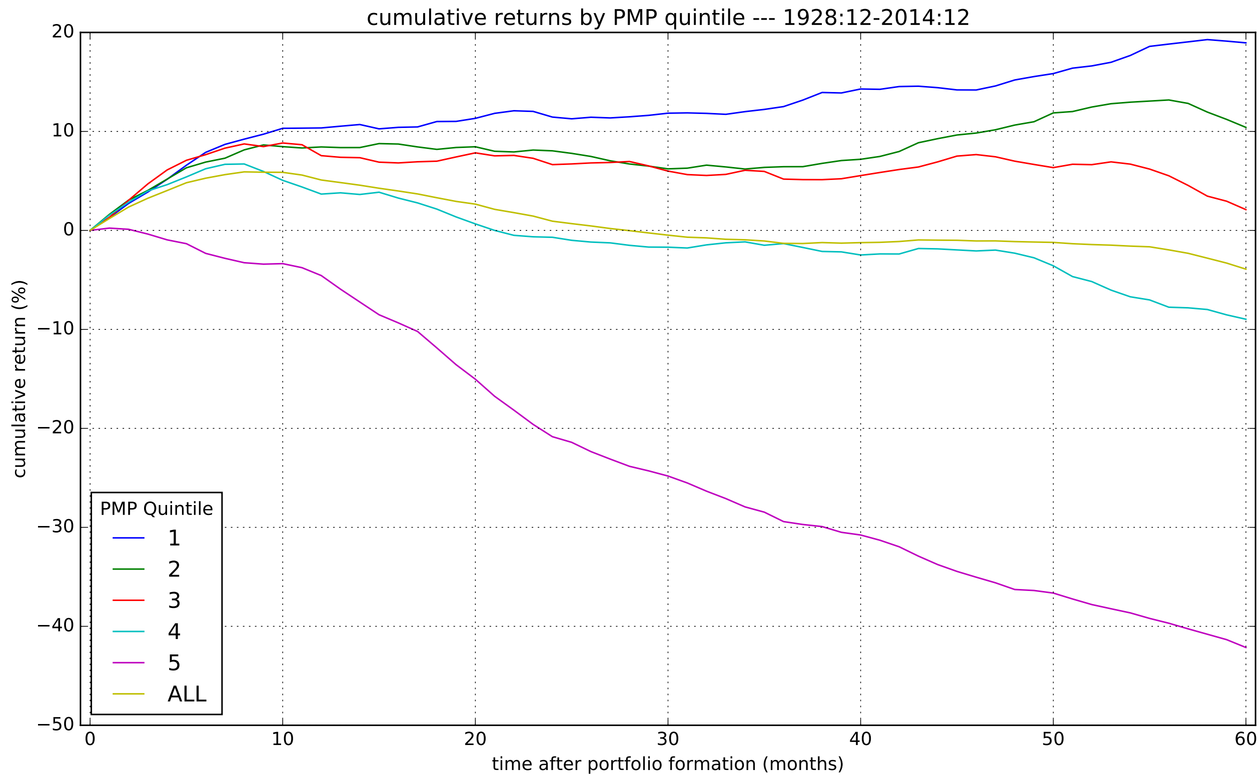


Figure 1: PMP Time-Series
Panel A plots the time-series of PMP from 1928:12-2009:12. Panel B plots the corresponding PMP quintile. The calculation of PMP is described in the caption of Table 1.



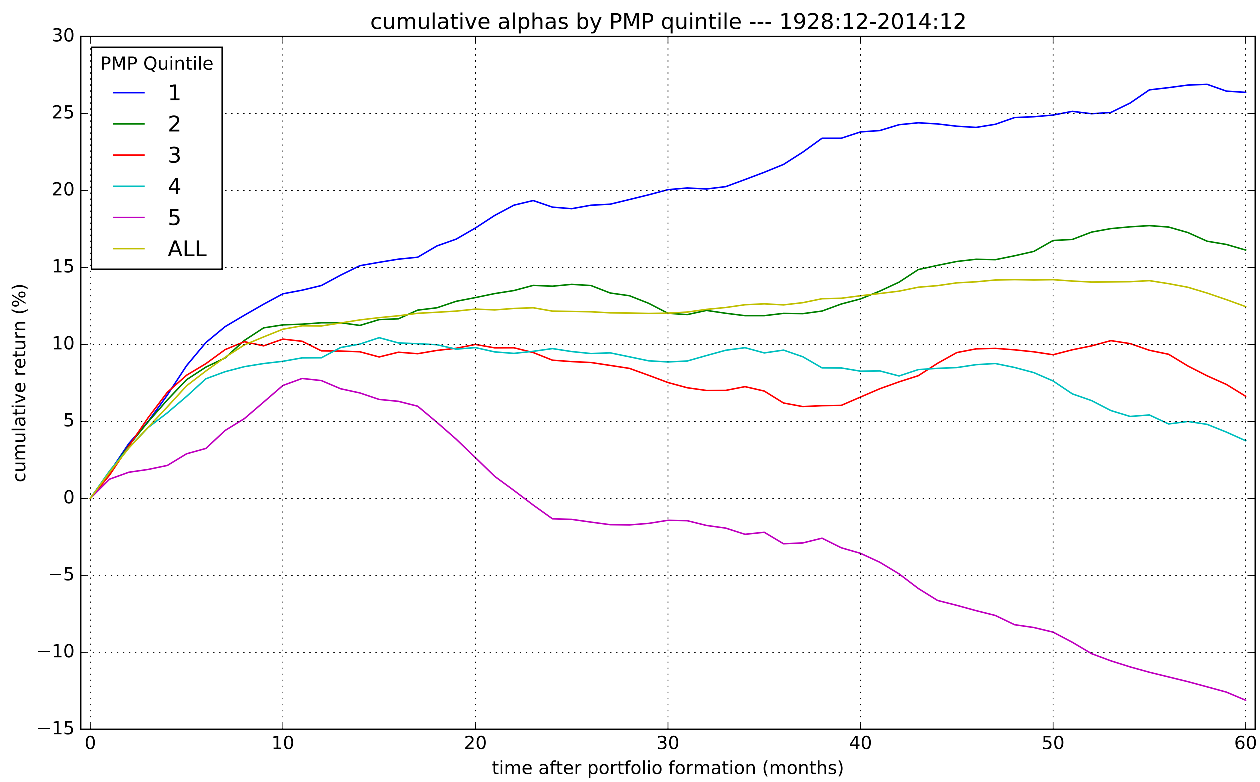


Figure 2: Cumulative Returns and Alphas, by PMP Quintile
These figures plot the average cumulative 5-year returns (excess of the cumulative risk-free rate) and Fama-French three-factor alphas of the value-weighted momentum portfolios formed in each of the five PMP Quintile months as well as for the momentum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

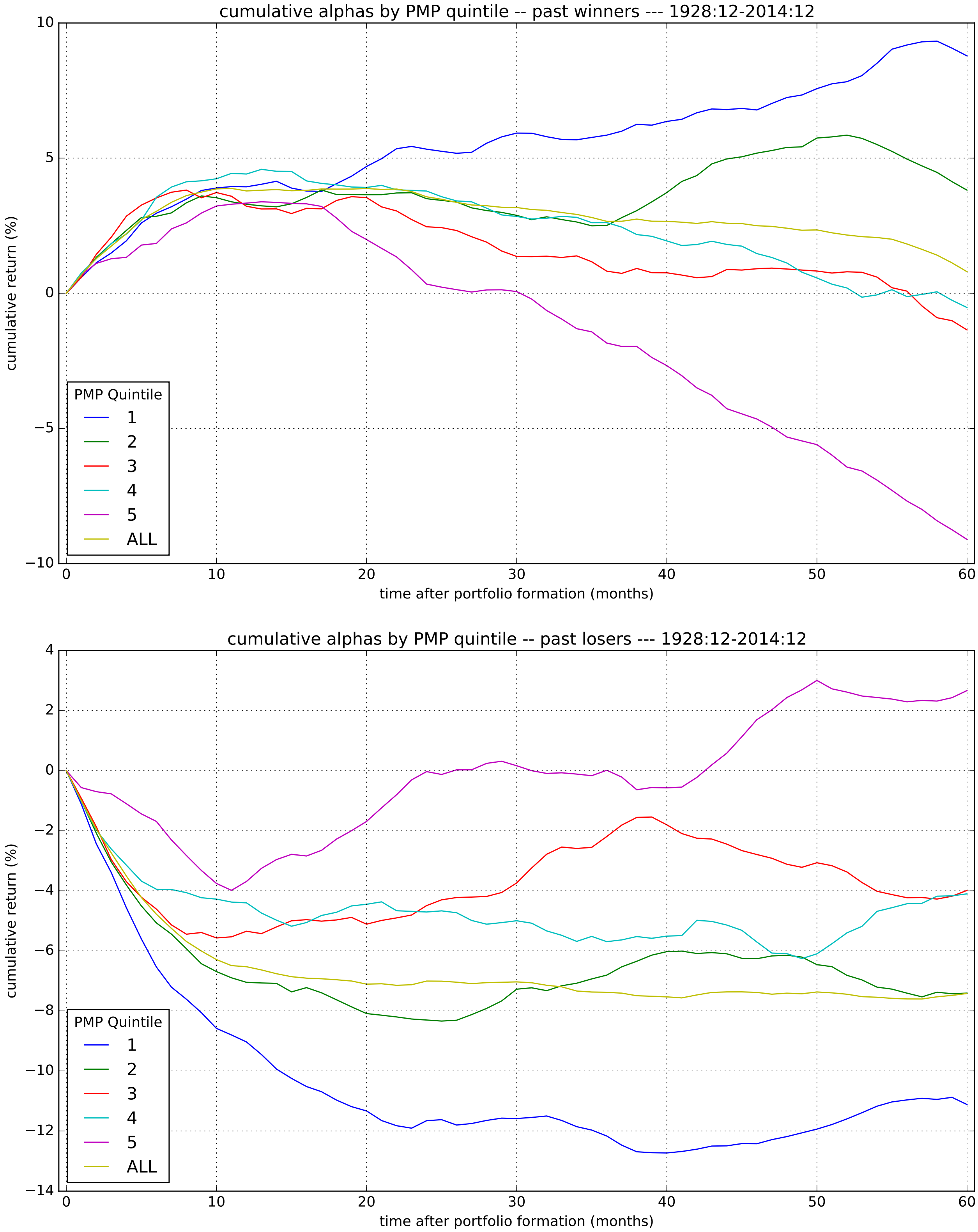


Figure 3: Cumulative Alphas, by PMP Quintile, for past-Winner and past-Loser Portfolios Panels A and B plot the cumulative alphas of the past-winner and past-loser portfolios, respectively. The calculation of the alphas is described in the caption of Table 2.

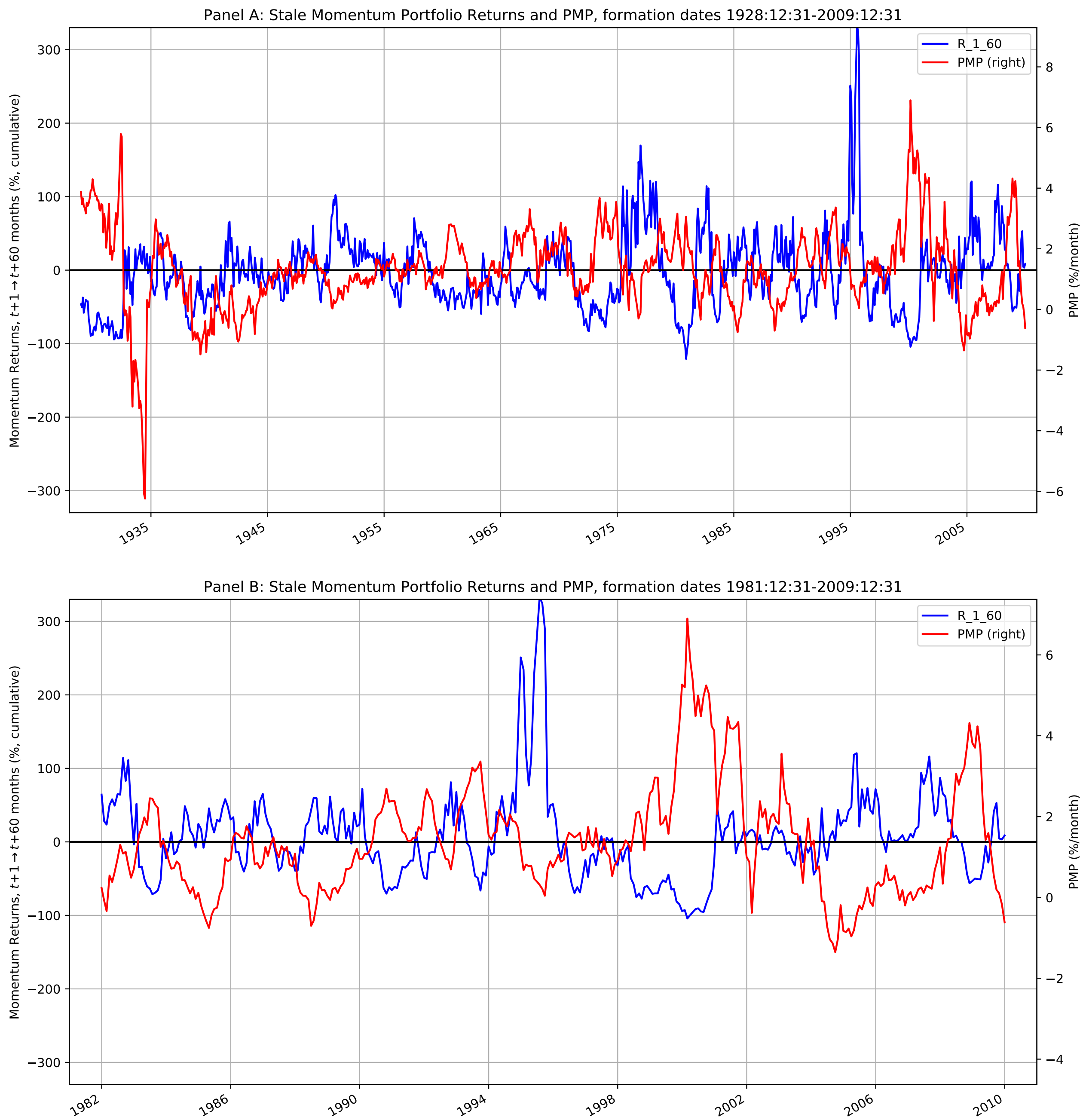


Figure 4: Stale Momentum returns and PMP
This figure plots, on the left axis, the stale momentum portfolio returns from $t+1$ to $t+60$ months (cumulative, in %) as a function of the formation date. The right axis plots the PMP measure, that is the average zero-investment momentum portfolio over the 24 months (in %/month) preceding the formation date. Panel A presents the results over the full sample (for formation dates from 1928:12:31-2009:12:31); Panel B shows only formation dates from 1981:12:31-2009:12:31.

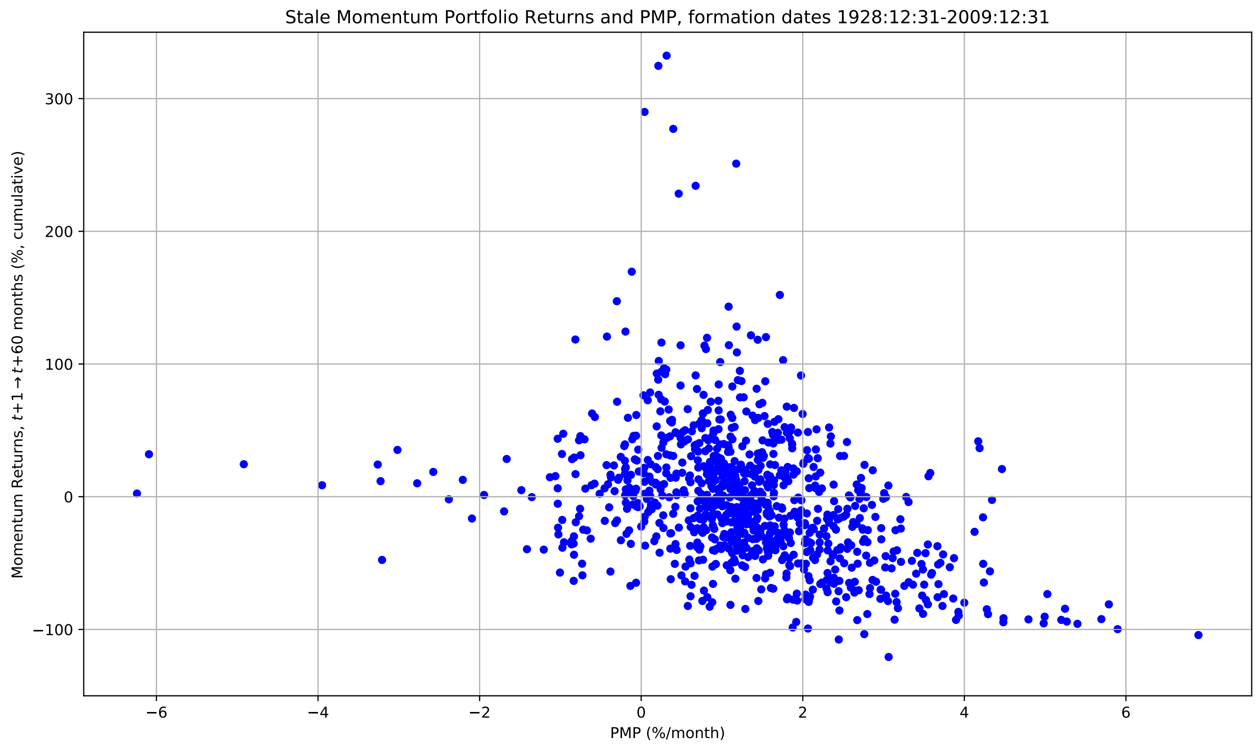


Figure 5: Stale Momentum returns and PMP
For each monthly momentum portfolio formation date in our sample period (from 1928:12:31-2009:12:31), this scatterplot shows the stale momentum portfolio returns from $t+1$ to $t+60$ months (cumulative, in %), plotted against the PMP measure, that is the average 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 ($\sigma_{r^e_M}(d\text{–}6m)$), 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.	$\overline{\text{PMP}}$	$r^e_M(1y)$	$r^e_M(2y)$	$\lvert r^e_M(2y)\rvert$	$\sigma_{r^e_M}(m{-}2y)$	$\sigma_{r^e_M}(d{-}6m)$	$\bar{r}_{loser}$	$\bar{r}_{win}$	$\bar{r}_{WML}$
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

	$\overline{\text{PMP}}$	$r^e_M(1y)$	$r^e_M(2y)$	$\lvert r^e_M(2y)\rvert$	$\sigma_{r^e_M}(m{-}2y)$	$\sigma_{r^e_M}(d{-}6m)$
$\overline{\text{PMP}}$	1					
$r^e_M(1y)$	-0.29	1				
$r^e_M(2y)$	-0.15	0.63	1			
$\lvert r^e_M(2y)\rvert$	-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 average 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 and 59 lags for one year and five year averages, respectively.

Panel A: Average monthly L/S Raw Return

	Year					
Rank	1	2	3	4	5	All
1	0.87	0.09	-0.03	0.07	0.09	0.22
	(5.89)	(0.53)	(-0.14)	(0.33)	(0.60)	(1.45)
2	0.66	-0.04	-0.14	0.17	-0.12	0.10
	(4.20)	(-0.19)	(-0.87)	(0.74)	(-0.73)	(0.83)
3	0.58	-0.08	-0.18	0.01	-0.23	0.02
	(2.76)	(-0.52)	(-1.04)	(0.07)	(-1.96)	(0.28)
4	0.33	-0.33	-0.07	-0.09	-0.52	-0.13
	(1.80)	(-1.46)	(-0.31)	(-0.74)	(-3.32)	(-1.36)
5	-0.34	-1.34	-0.61	-0.64	-0.53	-0.69
	(-0.74)	(-4.25)	(-1.68)	(-1.76)	(-3.09)	(-4.27)
5-1	-1.21	-1.44	-0.59	-0.71	-0.63	-0.91
	(-2.56)	(-3.96)	(-1.42)	(-1.71)	(-2.66)	(-4.20)
All months	0.42	-0.34	-0.21	-0.10	-0.26	-0.10
	(3.09)	(-2.45)	(-1.58)	(-0.77)	(-2.88)	(-1.15)

Panel B: Average monthly L/S Alpha

	Year					
Rank	1	2	3	4	5	All
1	1.11	0.32	0.11	0.16	0.01	0.34
	(7.35)	(1.58)	(0.57)	(0.89)	(0.09)	(3.26)
2	0.87	0.14	-0.17	0.17	-0.03	0.19
	(5.18)	(0.76)	(-1.34)	(0.93)	(-0.24)	(2.45)
3	0.72	-0.11	-0.32	0.10	-0.12	0.05
	(3.61)	(-0.65)	(-1.92)	(0.75)	(-1.14)	(0.69)
4	0.73	0.02	-0.02	-0.09	-0.34	0.06
	(4.04)	(0.09)	(-0.11)	(-0.75)	(-2.67)	(0.81)
5	0.58	-0.61	-0.12	-0.33	-0.36	-0.17
	(1.65)	(-2.31)	(-0.52)	(-1.06)	(-2.57)	(-1.25)
5-1	-0.53	-0.93	-0.22	-0.48	-0.37	-0.51
	(-1.39)	(-2.79)	(-0.76)	(-1.36)	(-1.92)	(-2.98)
All months	0.86	0.02	-0.02	0.02	-0.17	0.14
	(6.62)	(0.18)	(-0.16)	(0.15)	(-2.10)	(2.19)

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 and 59 lags for one year and five year averages, respectively.

Panel A: Industry Momentum

	Year					
Rank	1	2	3	4	5	All
1	0.63	0.18	0.06	0.18	0.02	0.21
	(5.35)	(1.20)	(0.39)	(1.28)	(0.13)	(2.83)
2	0.31	-0.07	-0.17	-0.02	0.13	0.04
	(3.09)	(-0.50)	(-1.38)	(-0.12)	(0.74)	(0.42)
3	0.22	-0.34	-0.04	0.09	-0.13	-0.04
	(1.41)	(-2.71)	(-0.29)	(0.81)	(-1.09)	(-0.66)
4	0.06	0.01	-0.09	0.05	-0.09	-0.01
	(0.47)	(0.04)	(-0.47)	(0.47)	(-0.52)	(-0.22)
5	0.14	-0.59	-0.14	-0.37	-0.34	-0.26
	(0.52)	(-3.05)	(-0.76)	(-1.49)	(-2.45)	(-2.15)
5-1	-0.49	-0.77	-0.21	-0.55	-0.35	-0.47
	(-1.74)	(-3.14)	(-0.83)	(-1.96)	(-1.94)	(-3.28)

Panel B: Residual Momentum

	Year					
Rank	1	2	3	4	5	All
1	0.89	0.24	0.09	0.19	0.16	0.31
	(7.28)	(1.51)	(0.74)	(1.30)	(1.22)	(3.80)
2	0.83	0.04	-0.09	0.07	-0.12	0.15
	(5.78)	(0.50)	(-0.84)	(0.58)	(-1.15)	(3.36)
3	0.59	-0.10	-0.25	0.04	-0.17	0.02
	(3.59)	(-0.77)	(-2.31)	(0.48)	(-1.59)	(0.44)
4	0.60	0.11	0.07	-0.08	-0.33	0.07
	(4.98)	(0.67)	(0.55)	(-0.96)	(-3.28)	(1.40)
5	0.32	-0.28	-0.07	-0.10	-0.32	-0.09
	(1.24)	(-1.26)	(-0.44)	(-0.67)	(-3.06)	(-1.14)
5-1	-0.57	-0.52	-0.16	-0.29	-0.48	-0.40
	(-2.00)	(-1.88)	(-0.81)	(-1.37)	(-2.87)	(-3.44)

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 and 59 lags for one year and five year averages, respectively.

Panel A: Average monthly L/S Raw Return

	Year					
Rank	1	2	3	4	5	All
1	1.17	0.29	0.19	0.34	0.23	0.44
	(7.08)	(1.31)	(0.82)	(1.40)	(1.04)	(3.75)
2	0.87	-0.18	-0.30	0.13	-0.29	0.04
	(6.35)	(-0.72)	(-1.57)	(0.49)	(-1.47)	(0.30)
3	0.87	0.11	-0.16	-0.05	-0.20	0.12
	(4.79)	(0.72)	(-1.00)	(-0.29)	(-1.46)	(1.54)
4	0.31	-0.18	-0.23	-0.02	-0.30	-0.08
	(1.88)	(-0.95)	(-1.30)	(-0.15)	(-2.40)	(-1.22)
5	-0.11	-1.10	-0.43	-0.29	-0.51	-0.49
	(-0.26)	(-3.37)	(-1.65)	(-1.45)	(-3.58)	(-3.45)
5-1	-1.28	-1.39	-0.62	-0.63	-0.73	-0.93
	(-2.76)	(-3.52)	(-1.78)	(-2.00)	(-2.82)	(-5.13)

Panel B: Average monthly L/S Alpha

	Year					
Rank	1	2	3	4	5	All
1	1.15	0.32	0.25	0.42	0.13	0.45
	(7.27)	(1.50)	(1.13)	(2.25)	(0.72)	(4.94)
2	1.15	0.06	-0.19	0.14	-0.22	0.19
	(7.83)	(0.31)	(-1.35)	(0.70)	(-1.29)	(2.14)
3	1.06	0.09	-0.14	0.05	-0.12	0.19
	(6.14)	(0.52)	(-0.99)	(0.31)	(-0.94)	(2.96)
4	0.39	-0.01	-0.25	-0.03	-0.30	-0.04
	(2.47)	(-0.05)	(-1.56)	(-0.21)	(-3.16)	(-0.64)
5	0.66	-0.45	0.07	0.06	-0.31	0.01
	(1.90)	(-1.97)	(0.32)	(0.31)	(-2.38)	(0.07)
5-1	-0.49	-0.77	-0.18	-0.36	-0.44	-0.45
	(-1.28)	(-2.47)	(-0.56)	(-1.29)	(-1.99)	(-3.24)

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 and 59 lags for one year and five year averages, respectively. 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

PMP		Years Post-Formation					
Rank	N	1	2	3	4	5	All
				Japan			
1	44	0.47*	0.68**	−0.11	0.31	0.42	0.35**
2	45	0.75**	0.48*	−0.15	−0.45**	0.13	0.15***
3	44	1.10**	0.64**	−0.08	−0.27	0.37	0.35***
4	45	0.05	0.21	0.10	0.15	−0.16	0.07
5	44	−1.19**	−0.45**	0.35	0.42	−0.14	−0.20**
5-1		−1.66***	−1.13***	0.47	0.11	−0.56*	−0.55***
				United Kingdom			
1	44	1.51**	−0.18	0.70**	−0.01	0.07	0.42**
2	45	0.78**	0.35	0.14	−0.01	−0.01	0.25*
3	44	0.85*	0.65*	0.19	−0.17	−0.64***	0.18
4	45	1.73***	−0.31	0.68	0.48	−0.50	0.42**
5	44	0.10	0.46	0.32	−1.03**	−0.87**	−0.20
5-1		−1.41**	0.64	−0.38	−1.01**	−0.94**	−0.62**
				France			
1	44	0.67	0.25	0.99***	−0.08	0.05	0.38***
2	45	0.01	0.04	0.79***	0.28	−0.29	0.17
3	44	0.58*	0.30	0.36	0.49*	−0.91***	0.16
4	45	−0.34	−0.56**	−0.19	−0.06	−1.07***	−0.44***
5	44	0.06	−0.56*	−0.15	0.41	−1.42***	−0.33
5-1		−0.61	−0.81	−1.14***	0.48	−1.47***	−0.71***
				Australia			
1	44	−0.01	−0.18	−0.36	−0.72**	0.40	−0.17
2	45	0.45	0.23	0.50**	0.38	0.30	0.37**
3	44	0.83**	0.32	0.06	0.42	0.23	0.37***
4	45	1.02***	0.46**	0.03	0.51**	−0.21	0.36***
5	44	0.79	0.33**	0.26	−0.04	0.11	0.29**
5-1		0.80	0.51**	0.62	0.68**	−0.29	0.46**

Table 5: Continued from previous page

PMP Rank	N	Years Post-Formation 1	2	3	4	5	All
				Germany			
1	44	0.74***	−0.35*	0.35	0.88	1.50***	0.62***
2	45	0.22	0.12	0.33*	0.14	0.42	0.25**
3	44	0.80***	−0.51	−0.58*	0.01	−0.41	−0.14
4	45	0.43	−1.22***	−0.14	0.52	−0.13	−0.11
5	44	−1.25	0.11	0.65	0.19	−0.27	−0.12
5-1		−2.00**	0.46	0.30	−0.69	−1.77***	−0.74**
				Hong Kong			
1	44	0.56	−0.02	0.44	0.79***	−0.50**	0.26*
2	45	0.28	−0.09	0.51	0.50	0.26	0.29**
3	44	0.18	−0.31	0.05	−0.40**	0.18	−0.06
4	45	−0.16	−0.70**	0.46	−0.39	−0.75**	−0.31*
5	44	−2.28***	−0.58	−0.78*	0.07	−1.67***	−1.05***
5-1		−2.85***	−0.56	−1.22**	−0.72	−1.18***	−1.31***
				Italy			
1	44	1.36***	0.36	0.70**	0.68***	0.33	0.69***
2	45	1.10***	−0.29	0.26	0.09	0.27	0.29**
3	44	0.30	0.13	0.72	0.45	−0.13	0.29***
4	45	−0.25	0.14	0.76**	0.80*	0.16	0.32**
5	44	−0.97*	0.47	1.13**	0.00	0.15	0.16
5-1		−2.33***	0.11	0.43	−0.68**	−0.18	−0.53***
				Switzerland			
1	44	0.98***	0.08	0.30	0.39	−0.50	0.25
2	45	0.67*	0.10	0.41	0.08	0.09	0.27*
3	44	−0.17	−0.79**	0.63*	0.20	−0.18	−0.06
4	45	0.38	−1.11***	0.35	0.26	−0.71***	−0.17
5	44	0.04	0.25	0.37	−0.40	−0.45	−0.04
5-1		−0.94**	0.17	0.07	−0.79*	0.05	−0.29

Table 6: Portfolio Strategies

This table reports the returns and 3-factor (Fama and French 1993) 4-factor (Carhart 1997) 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, and reports the 4-factor factor loadings and t-statistics. For each PMP quintile and each month t, the trading strategy is "active" if any of the months from $t-60$ to $t-1$ 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 $t-1$. 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. 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

	No.		3-f	4-f	4-factor loadings			
Rank	Obs.	Ret.	α	α	Mkt	SMB	HML	UMD
1	769	0.38	0.52	0.25	0.07	-0.12	-0.24	0.18
		(2.80)	(3.90)	(1.86)	(2.01)	(-2.10)	(-4.18)	(5.85)
2	954	0.09	0.22	0.13	0.09	-0.07	-0.38	0.06
		(1.01)	(2.67)	(1.44)	(3.63)	(-1.92)	(-10.19)	(3.33)
3	954	-0.03	0.09	-0.07	0.12	-0.07	-0.34	0.10
		(-0.29)	(0.89)	(-0.76)	(3.75)	(-0.89)	(-4.93)	(3.58)
4	942	-0.17	0.15	-0.10	-0.03	-0.13	-0.49	0.14
		(-1.30)	(1.38)	(-0.88)	(-0.76)	(-1.26)	(-7.17)	(4.61)
5	769	-0.47	-0.08	-0.29	0.04	-0.03	-0.71	0.13
		(-2.72)	(-0.63)	(-2.30)	(1.24)	(-0.46)	(-11.88)	(5.20)
All	1032	-0.11	0.15	-0.04	0.04	-0.13	-0.47	0.11
Mths		(-1.23)	(2.43)	(-0.67)	(2.15)	(-3.32)	(-15.61)	(7.39)
5-1	969	-0.43	-0.24	-0.30	-0.04	0.06	-0.36	0.03
		(-3.92)	(-2.50)	(-2.97)	(-1.46)	(1.17)	(-5.80)	(1.40)

Panel B

		Year 1			Year 2			Year 3			Year 4			Year 5		
	No.		3-f	4-f		3-f	4-f		3-f	4-f		3-f	4-f		3-f	4-f
Rnk	Obs.	Ret	α	α	Ret	α	α	Ret	α	α	Ret	α	α	Ret	α	α
1	362	0.83	1.13	0.31	0.27	0.56	0.35	0.04	0.18	0.12	0.23	0.33	0.26	-0.06	-0.05	-0.01
		(3.19)	(4.63)	(1.48)	(1.12)	(2.74)	(1.55)	(0.23)	(1.08)	(0.69)	(1.27)	(1.82)	(1.36)	(-0.30)	(-0.28)	(-0.07)
2	584	0.59	0.80	-0.06	0.16	0.24	0.14	-0.11	-0.16	-0.07	0.02	0.06	0.05	-0.06	0.01	0.05
		(3.18)	(4.04)	(-0.35)	(0.90)	(1.49)	(0.79)	(-0.70)	(-1.02)	(-0.42)	(0.17)	(0.46)	(0.34)	(-0.43)	(0.09)	(0.33)
3	618	0.43	0.76	0.12	-0.05	0.18	0.08	-0.08	0.011	-0.15	0.10	0.21	0.10	-0.42	-0.21	-0.24
		(2.21)	(3.97)	(0.66)	(-0.26)	(1.04)	(0.40)	(-0.53)	(-0.68)	(-0.87)	(0.69)	(1.47)	(0.68)	(-2.86)	(-1.53)	(-1.70)
4	590	0.43	0.88	-0.07	-0.29	0.11	-0.03	-0.28	-0.13	-0.07	-0.09	0.01	0.04	-0.44	-0.26	-0.23
		(1.84)	(4.11)	(-0.39)	(-1.34)	(0.58)	(-0.17)	(-1.43)	(-0.77)	(-0.34)	(-0.62)	(0.09)	(0.28)	(-3.15)	(-1.98)	(-1.61)
5	396	-0.10	0.72	0.04	-1.08	-0.44	-0.44	-0.36	-0.05	0.14	-0.47	-0.36	-0.10	-0.68	-0.45	-0.31
		(-0.24)	(2.30)	(0.17)	(-3.23)	(-1.72)	(-1.53)	(-1.23)	(-0.18)	(0.48)	(-1.86)	(-1.66)	(-0.41)	(-3.15)	(-2.35)	(-1.49)
All	984	0.43	0.87	0.01	-0.35	0.00	-0.10	-0.20	-0.02	0.04	-0.10	-0.02	0.06	-0.28	-0.21	-0.14
Mths		(2.39)	(5.83)	(0.05)	(-2.26)	(0.01)	(-0.71)	(-1.51)	(-0.14)	(0.27)	(-0.91)	(-0.17)	(0.58)	(-2.75)	(-2.27)	(-1.42)
5-1	706	-0.50	-0.17	-0.58	-0.73	-0.53	-0.46	-0.23	-0.03	0.09	-0.35	-0.33	-0.16	-0.35	-0.28	-0.23
		(-1.98)	(-0.77)	(-2.67)	(-3.47)	(-2.95)	(-2.22)	(-1.30)	(-0.16)	(0.46)	(-2.19)	(-2.18)	(-0.99)	(-2.48)	(-1.97)	(-1.52)

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 and 59 lags for one year and five year averages, respectively. 1%, 5%, and 10% statistical significance are indicated with ***, **, and *, respectively.

PMP		Years Post-Formation						
Rank	N	1	2	3	4	5	All	
		Panel A: Excluding down market months						
1	139	1.03***	0.30	0.16	0.19	0.02	0.34***	
2	182	0.77***	0.01	−0.22	0.17	−0.09	0.13*	
3	179	0.75***	−0.23	−0.38**	0.03	−0.12	0.01	
4	160	0.58***	−0.37*	−0.35*	−0.18	−0.30**	−0.12	
5	138	0.76**	−0.68**	−0.45**	−0.46	−0.46***	−0.26**	
5-1		−0.27	−0.98***	−0.61*	−0.65	−0.49**	−0.60***	
		Panel B: PMP orthogonalized to momentum spread						Mom. Spd.
1	194	1.09***	0.30	0.07	0.13	0.04	0.33***	153%
2	195	0.88***	0.07	−0.21	0.22	−0.05	0.18**	126%
3	195	0.67***	−0.06	−0.39**	0.05	−0.12	0.03	125%
4	195	0.75***	−0.08	−0.07	−0.07	−0.32**	0.04	147%
5	194	0.53	−0.51**	−0.02	−0.36	−0.36**	−0.14	163%
5-1		−0.56	−0.81**	−0.09	−0.49*	−0.39**	−0.47***	
		Panel C: PMP orthogonalized to momentum variance						σ^2_{mom}
1	194	1.09***	0.32	0.14	0.16	−0.01	0.34***	0.0232
2	195	0.85***	0.07	−0.15	0.17	−0.06	0.18**	0.0073
3	195	0.73***	−0.15	−0.28	0.11	−0.12	0.06	0.0060
4	195	0.76***	0.04	−0.08	−0.07	−0.36***	0.06	0.0098
5	194	0.61*	−0.63**	−0.1	−0.37	−0.33**	−0.16	0.0233
5-1		−0.48	−0.95***	−0.23	−0.53	−0.32*	−0.50***	

Table 7: Continued from previous page

PMP Rank	N	Years Post-Formation 1	2	3	4	5	All	
		Panel D: PMP orthogonalized to market variance						σ^2_{mkt}
1	194	1.11***	0.32	0.11	0.16	0.01	0.34***	0.0423
2	195	0.87***	0.15	−0.18	0.16	−0.03	0.19**	0.0179
3	195	0.73***	−0.19	−0.31*	0.10	−0.13	0.04	0.0154
4	195	0.70***	0.05	0.00	−0.08	−0.34***	0.06	0.0217
5	194	0.62*	−0.62**	−0.13	−0.33	−0.36***	−0.17	0.0462
5-1		−0.49	−0.94***	−0.24	−0.49	−0.37**	−0.51***	
		Panel E: Size and BM adjusted returns						
1	93	1.04***	0.23	0.26	0.47**	0.20	0.44***	
2	148	0.72***	0.07	0.05	0.32	−0.02	0.23**	
3	150	0.80***	0.08	−0.07	0.13	−0.29***	0.13**	
4	163	0.44**	−0.09	−0.05	−0.09	−0.31***	−0.02	
5	149	0.02	−0.83***	−0.33*	−0.08	−0.30***	−0.30***	
5-1		−1.02**	−1.06***	−0.59*	−0.55**	−0.50**	−0.74***	
		Panel F: First half: 1928:12-1969:05						
1	103	0.93***	0.29	−0.13	−0.03	0.00	0.21	
2	103	0.72***	0.18	−0.33**	−0.19	0.04	0.08	
3	117	0.37	−0.20	−0.56***	0.05	−0.02	−0.07	
4	86	0.73**	0.09	0.15	−0.10	−0.48*	0.08	
5	77	0.77*	−0.55	−0.36	−1.06**	−0.33	−0.31	
5-1		−0.16	−0.85	−0.23	−1.03*	−0.33	−0.52*	
		Panel G: Second half: 1969:06-2009:12						
1	91	1.31***	0.35	0.38	0.36*	0.03	0.49***	
2	92	1.04***	0.09	0.01	0.57**	−0.12	0.32**	
3	78	1.23***	0.02	0.04	0.17	−0.28	0.24*	
4	109	0.73***	−0.03	−0.16	−0.07	−0.23**	0.05	
5	117	0.45	−0.65**	0.04	0.15	−0.38**	−0.08	
5-1		−0.86	−1.01**	−0.34	−0.21	−0.41*	−0.57***	
		Panel H: 1928:12-1981:12						
1	111	0.99***	0.38	−0.07	−0.01	0.02	0.26*	
2	133	0.85***	0.02	−0.35**	−0.08	0.03	0.09	
3	140	0.53**	−0.01	−0.39*	0.12	−0.08	0.03	
4	129	0.91***	0.16	0.10	−0.09	−0.44**	0.13	
5	124	0.93***	−0.44	−0.14	−0.76**	−0.36*	−0.15	
5-1		−0.06	−0.82*	−0.07	−0.74	−0.37	−0.41*	
		Panel I: 1982:01-2009:12						
1	83	1.27***	0.25	0.34	0.38*	0.00	0.45***	
2	62	0.91***	0.38	0.23	0.70**	−0.17	0.41***	
3	55	1.19***	−0.37	−0.13	0.06	−0.24	0.10	
4	66	0.38	−0.25	−0.27	−0.07	−0.15	−0.07	
5	70	−0.05	−0.92**	−0.08	0.44*	−0.37**	−0.20	
5-1		−1.32*	−1.17**	−0.42	0.05	−0.38	−0.65***	

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):

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

where:

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

$w_{i,j,q}$ 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)		

Table 9: Average three-factor loadings The table gives the Fama and French (1993) regression loadings for stale momentum portfolios formed from 1-5 years ago, by PMP rank quintile.

Average Mkt-RF loading

	Formation Year				
Rank	1	2	3	4	5
1	-0.09	0.02	-0.02	0.11	0.29
2	-0.08	0.18	0.19	0.18	0.08
3	0.15	0.22	0.22	0.10	0.10
4	-0.10	0.11	0.12	0.10	0.05
5	-0.31	-0.05	-0.02	-0.03	0.07

Average SMB loading

	Formation Year				
Rank	1	2	3	4	5
1	-0.13	-0.18	-0.09	-0.11	-0.15
2	0.01	-0.16	-0.20	-0.26	-0.17
3	-0.10	-0.13	-0.06	-0.19	-0.08
4	-0.06	-0.41	-0.19	-0.14	-0.18
5	-0.10	-0.16	-0.30	-0.25	-0.11

Average HML loading

	Formation Year				
Rank	1	2	3	4	5
1	-0.30	-0.46	-0.15	-0.29	-0.33
2	-0.27	-0.68	-0.20	-0.33	-0.32
3	-0.67	-0.54	0.05	-0.31	-0.31
4	-0.72	-0.60	-0.29	-0.16	-0.41
5	-1.21	-0.98	-0.61	-0.23	-0.56