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Macroeconomic risk and seasonality in momentum profits

Xiuqing Ji[11], J. Spencer Martin[2*], Yaqiong Yao[32]

[1]College of Business, Governors State University, University Park, IL 60484, United States
[2]Faculty of Business and Economics, University of Melbourne, Level 12, 198 Berkeley Street, Parkville, Victoria 3010, Australia
[3]Department of Accounting and Finance, Lancaster University Management School, Lancaster LA1 4YX, United Kingdom
sji@govst.edu
martis@unimelb.edu.au
yaqiong.yao@lancaster.ac.uk
[*]Corresponding author. Tel.: +61 3 83446466.

Abstract

We contribute to the growing debate on the relation between macroeconomic risk and stock price momentum. Not only is momentum seasonal, so is its net factor exposure. We show that winners and losers only differ in macroeconomic factor loadings in January, the one month when losers overwhelmingly outperform winners. In the remainder of the year, when momentum does exist, winner and loser factor loadings offset nearly completely. Furthermore, the magnitude of macroeconomic risk premia appears to seasonally vary contra momentum. In contrast, the relatively new profitability factor does a much better job of capturing the described seasonality.

JEL Classification: G12; E44

Keywords: Momentum; Macroeconomic risk; ROE; Seasonality; January effects

1. Introduction

A momentum strategy, buying recent winners and selling recent losers, generates considerable profits (Jegadeesh and Titman, 1993). This finding has prevailed in further studies both geographically and temporally. Among others, Rouwenhorst (1998), Griffin, Ji, and Martin (2003), and Asness, Moskowitz, and Pedersen (2013) document the continuing prevalence of momentum in the United States and the United Kingdom, as well as many European and Asian equity markets.

[1] Tel.: +1 7082357642.
[2] Tel: +44 1524 510731.

Neither the capital asset pricing model nor the Fama–French three-factor model can account for momentum profits (Jegadeesh and Titman, 1993; Fama and French, 1996; Grundy and Martin, 2001). Recently, some researchers have examined the link between macroeconomic risk and the cross section of returns (Cooper and Priestley, 2011; Savor and Wilson, 2013; Bali, Brown, and Caglayan, 2014; Moller and Rangvid, 2015), and thereby the momentum effect. Chordia and Shivakumar (2002) argue that a conditional macroeconomic risk-factor model can capture the momentum phenomenon. In contrast, Griffin, Ji, and Martin (2003) suggest that neither the unconditional nor the conditional application of the five-factor model of Chen, Roll, and Ross (1986) can explain momentum profits. Similarly, Liew and Vassalou (2000) show that, although the size and value effects can be linked to macroeconomic growth, little evidence is found to support such an explanation for the momentum effect. Liu and Zhang (2008) respond with a finding that the growth rate of industrial production is particularly useful in explaining momentum profits. More recently Hou, Xue, and Zhang (2015, 2016) claim that the q-theory, which is based on a multi-factor asset pricing model consisting of a market factor, a size factor, an investment factor, and a profitability factor, can account for the momentum effects.

To get further traction on these issues, we go back to some basic empirical patterns that began the whole debate. A much neglected characteristic of price momentum is its strong seasonality: momentum strategies produce only substantial losses in January, more than triple the monthly magnitude of the overall momentum profits (Jegadeesh and Titman, 1993; Grundy and Martin, 2001; Asness, Moskowitz, and Pedersen, 2013). Grundy and Martin (2001) argue that the losses are attributable to betting against the January size effect by selling losers that tend to be extremely small firms. Grinblatt and Moskowitz (2004) add that tax minimization contributes to these patterns.

Recent studies further highlight the importance of seasonality in understanding market anomalies (Bogousslavsky, 2015, 2016; Keloharju, Linnainmaa, and Nyberg, 2016). Since so much of the mean and variance in momentum returns is seasonal, we argue that it is important to exercise greater caution in employing the usual metrics for empirical success. In this paper, we construct a sample from 1947 to 2014 for the United States and demonstrate that, although the five-factor macroeconomic model of Liu and Zhang (2008) does capture about half of momentum returns unconditionally, the explanatory power is concentrated in January, the month when there are no momentum profits to explain, only massive losses.

Factor loadings too are significant mainly in January. Outside of January, for instance, the production factor loadings for the winner and loser portfolios are almost identical. Those findings are consistent with prior studies (e.g., Kramer, 1994) that show significant seasonality in the macroeconomic risk of small stocks. Both winners and losers are small firms (Jegadeesh and Titman, 1993; Grundy and Martin, 2001). Thus, winner-minus-loser portfolios have essentially a net zero loading outside of January.

We also examine the role of January seasonality in understanding the ability of the *ROE* factor in explaining momentum effects. In a marked contrast with the *MP* factor, winners have higher loadings on *ROE* than losers do in both January and non-January months. The loading difference persists, and this difference is not consistent with the well-documented momentum reversal (Jegadeesh and Titman, 1993), which casts some doubt on its sole responsibility for driving momentum.

The remainder of the article proceeds as follows. In Section 2, we describe data and analyze the seasonal patterns of momentum trading strategies. In Section 3, we examine the exposures of momentum portfolios to macroeconomic risk, and investigate the role of macroeconomic variables in explaining momentum profits. In Section 4, we address the development of investment and profitability factor models. Concluding remarks are given in Section 5.

2. Data and definitions

2.1. Macroeconomic variables

For macroeconomic variables, the Chen, Roll, and Ross (1986) five factors (hereafter CRR5)—unexpected inflation (*UI*), change in expected inflation (*DEI*), term spread (*UTS*), default spread (*UPR*), and changes in industrial production (*MP*)—are constructed monthly in the sample period. Unexpected inflation is defined as $UI_t \equiv I_t - E[I_t | t-1]$ and change of expected inflation as $DEI_t \equiv E\left[I_{t+1} | t\right] - E\left[I_t | t-1\right]$ following Fama and Gibbons (1984). Term spread (*UTS*) is defined as the yield difference between 20- and 1-year Treasury bonds, and default spread (*UPR*) is the yield difference between BAA- and AAA-rated corporate bonds in the FRED database at the Federal Reserve Bank of St. Louis. The growth rate of industrial production for month t is defined as $MP_t \equiv \log IP_t - \log IP_{t-1}$, where IP_t is the industry production index (INDPRO series) in month t from the FRED database. Note that *MP* is led by one month since INDPRO is recorded at the beginning of a month, whereas stock returns are recorded as of the end of a month. In addition to the CRR5 specification, sometimes it is necessary to omit the default factor *UPR* and we label it CRR4.

Table 1 contains summary statistics. Panel A shows that, from March 1947 to December 2014, the mean of monthly industrial production is 0.25%; both unexpected inflation and change in expected inflation average zero. Term spread and default spread are much larger, 1.22% and 0.95%, respectively. Term spread also dominates in standard deviation, 1.36%. Panel B has the correlations among the five variables. They mostly range from -0.22 to 0.13, with the high outlier of 0.71 coming from unexpected inflation and change in expected inflation.

[Insert Table 1 here]

2.2. Other variables

Fama-French (1996) factors from the French data library are: (1) the market factor (*MKT*), the monthly return to the market portfolio in excess of the risk-free rate (i.e., one-month Treasury bills); (2) the size factor (*SMB*), the difference in returns between a portfolio of small firms and a portfolio of large firms; (3) the value factor (*HML*), the difference in returns between a portfolio of high-book-to-market firms and a portfolio of low-book-to-market firms.[3]

Hou, Xue, and Zhang's (2015) q-factors are: (1) the market factor (*MKT*), the monthly excess return to the market portfolio; (2) the size factor (*ME*), the difference in returns between small and large firms; (3) the investment factor (*I/A*), the difference in returns between a portfolio of low investment firms and a portfolio of high investment firms; (4) the profitability factor (*ROE*), the difference in returns between a portfolio of high-*ROE* firms and a portfolio of low-*ROE* firms. Restricted by the availability of accounting variables, we construct the four factors for the January 1967 to December 2014.

10 size and 10 value portfolios are one-way sorted decile portfolios based on size (market capitalization) and value (book-to-market equity), respectively. Industry portfolios are formed according to various industry definitions.[4] All these portfolios contain data from the French data library.

[3] Please refer to http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/f-f_factors.html.
[4] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.

2.3. Portfolio definitions

To construct our sample, we obtain data from the monthly files of the Center for Research in Security Prices (CRSP) for all stocks traded on the NYSE, AMEX, and NASDAQ. Closed-end funds, real estate investment trusts, American depository receipts, and foreign stocks are excluded. The sample period runs from March 1947 to December 2014 to match the data availability of macroeconomic variables.

Each month, all NYSE, AMEX, and NASDAQ stocks in the sample are ranked on the basis of cumulative returns in month $t - 7$ to month $t - 2$, and are assigned into ten deciles.[5] Stocks with the highest returns in the preceding two-to-seven months are defined as winners (P10), whereas stocks with the lowest returns during the same period are defined as losers (P1). In the momentum strategy, prior winners (P10) are purchased and prior losers (P1) are sold. Zero-investment winner–loser portfolios (P10–P1) are rebalanced each month, and held for six months from month $t + 1$ to month $t + 6$. There is a one-month gap between portfolio formation and portfolio investing in order to circumvent the mechanical bid–ask bias.[6]

2.4. Momentum profits

In Table 2, we report average monthly returns on winner–loser portfolios formed on the basis of the past two-to-seven months' returns. Between March 1947 and December 2014, the average

[5] Jegadeesh and Titman (1993) examine momentum trading strategies by analyzing a sample portfolio of NYSE and AMEX stocks; they exclude NASDAQ stocks in order to avoid the results being driven by small and illiquid stocks or the mechanical bid–ask bias. Nevertheless, both Jegadeesh and Titman (2001) and Liu and Zhang (2008) add NASDAQ stocks to the sample to construct momentum portfolios. They argue that the addition of NASDAQ stocks has very little impact on the profitability of momentum strategies, but it may increase the January losses noticeably. To demonstrate the robustness of our findings, we analyze the NYSE and AMEX stock sample in addition to the sample NYSE, AMEX, and NASDAQ stocks. The results show that our findings still hold.

[6] Strong winners are much more likely to have close prices at the ask than at the bid, and strong losers are more likely to have close prices at the bid than at the ask.

monthly return to the momentum strategy is 0.64% (t-statistic = 3.49). The average return is decreased by large losses in Januaries (see Jegadeesh and Titman, 1993; Grundy and Martin, 2001; Asness, Moskowitz, and Pedersen, 2013). Prior winners underperform prior losers by 5.67% (t-statistic = −4.91) in Januaries.

[Insert Table 2 here]

Further, neither the capital asset pricing model (CAPM) nor the Fama–French (1993) three-factor model can capture the momentum portfolio returns obtained from long–short positions in the extreme deciles.

3. Macroeconomic risk and momentum profits

Many studies have documented that momentum strategies are profitable outside of January, whereas they suffer substantial losses in January (e.g., Jegadeesh and Titman, 1993; Grundy and Martin, 2001; Yao, 2012). If the momentum phenomenon is driven by winners having different macroeconomic risk factor loadings than losers, as argued in Liu and Zhang (2008), then it is important to know whether those loadings also exhibit seasonality. It is particularly relevant to investigate in light of the strongly seasonal expected stock returns documented by Heston and Sadka (2008), Bogousslavsky (2015, 2016), and Keloharju, Linnainmaa, and Nyberg (2016).

3.1. Momentum exposure to macroeconomic risk

To examine the relation between prior performance and factor loading, we focus on the *MP* (industrial production growth) factor, the factor having the most explanatory power in the findings of Liu and Zhang (2008). As in their Table 1, Panel A of Figure 1 here shows increasing single-factor *MP* loadings as prior returns increase across the first six deciles, then a rapid increase indicating that the winner portfolio is related to macro risk. Controlling for the Fama–French or CRR4 or CRR5 factors does not change the single-factor patterns.

[Insert Figure1 here]

We distinguish January and non-January months in Panels B and C of Figure 1. Panel B displays the *MP* loadings for the ten decile momentum portfolios from time-series regressions using January observations only. Notice that the first three deciles have a sharp increase in *MP* loadings, which is followed up by a gradual increase up to the winner decile. The momentum strategy has a significant large exposure to the *MP* loadings in January when it loses substantially.

3.1.1. Are the economics of risk exposure so seasonal?

Prior studies show that momentum stocks are usually small caps (Jegadeesh and Titman, 1993; Grundy and Martin, 2001). Kramer (1994) shows that, similar to macroeconomic variables, small firms exhibit strong seasonality in January, which tends to be more sensitive to macroeconomic variables (Fama and French, 1993; Balvers and Huang, 2007).[7] There is a paucity of literature regarding the macro risk factors that impact such seasonal effects (Bogousslavsky, 2015, 2016; Keloharju, Linnainmaa, and Nyberg, 2016).

It is not difficult, however, to imagine our econometric measurements as a coincidence where momentum stocks, the smaller/volatile firms, happen to have their long-known January outperformance behavior manifest in a measured seasonality of covariance with the industrial production growth factor. *MP* could then appear to be influential despite no real economic link.

[7] Previous studies suggest that tax-loss selling (Sias and Starks, 1997; Poterba and Weisbenner, 2001; Ivkovic, Poterba, and Weisbenner, 2005) and window dressing (Sias and Starks, 1997; He, Ng, and Wang, 2004; Ng and Wang, 2004) can contribute to the January seasonality. To mitigate the potential impacts, we also use various proxies to control for tax-loss selling and window dressing when estimating the *MP* loadings, and find that the patterns of the *MP* loadings remain similar. For brevity, we do not report the results, which are available upon request.

In light of the contrary results we find with the *ROE* factor, this is perhaps the best explanation to date.

3.1.2. Explanations of other aspects of the momentum phenomenon

Panel C of Figure 1 displays the *MP* loadings from time-series regressions using non-January observations. In sharp contrast to Panels A and B, the loser portfolios load strongly on the *MP* factor. Across the model specifications, Panel C shows that winners and losers have almost identical *MP* loadings outside of January. The results suggest that there is essentially a net-zero factor loading in the 11 months of the year when momentum is present in the data. The implication is that differences measured in previous work arise due to January seasonality, particularly in the loser decile. Detailed numerical results for Figure 1 are in Table 3.

Is the measured risk exposure temporary, as momentum profits are? To the extent that momentum effects fade to nil over the year following the ranking, measured risk loadings ought to disappear as well (particularly the winner-minus-loser differences). Figure 2 displays the *MP* loadings of winners and losers estimated from pooled time-series factor regressions for each of the 12 event months after portfolio formation. In line with Liu and Zhang (2008), the one-factor MP model (top left panel) generates an enormous apparent dispersion in *MP* loadings between the winner and loser portfolios: 0.83 in month t, 0.56 in month $t + 1$, and 0.54 in month $t + 2$. The spread between winners and losers converges in the eighth month. Controlling for more factors produces similar patterns, as shown in the panels for the models of FF+MP, CRR4, and CRR5.

Once again, however, that effect and story are upset by a stubborn January effect. Using February-to-December observations instead of all observations (the right-most panels of Figure 2), only in the first three months following portfolio formation do winners have a slightly higher *MP* loading than losers, with one exception (i.e., CRR5). Subsequently, winners have lower *MP* loadings than losers. For the CRR5 model, winners and losers have similar *MP* loadings even in the first three months after portfolio formation.

3.2. Momentum profits and macroeconomic risk

3.2.1. Estimating risk premia

We estimate the macroeconomic risk premia with two-stage Fama–MacBeth (1973) cross-sectional regressions. The first-stage time-series regression involves regressing the returns of the test assets on the Fama–French three factors and/or CRR five factors in order to estimate factor loadings. We use full sample (unconditional), extended-window (existing life to date, but at least 24 months), and rolling window (60 months) methods to compute first-stage time-series betas.[8]

$$r_{P,t} = \alpha_P + \beta_{UI,P} UI_t + \beta_{DEI,P} DEI_t + \beta_{UTS,P} UTS_t + \beta_{UPS,P} UPR_t + \beta_{MP,P} MP_t + \varepsilon_{P,t}. \tag{1}$$

The second-stage cross-sectional regression fits the returns of the test assets in excess of the risk-free rate to the factor loadings obtained from the first-stage regressions:

$$r_{P,t} - r_{f,t} = \gamma_{0,t} + \gamma_{UI,t}\hat{\beta}_{UI,P} + \gamma_{DEI,t}\hat{\beta}_{DEI,P} + \gamma_{UTS,t}\hat{\beta}_{UTS,P} + \gamma_{UPR,t}\hat{\beta}_{UPR,P} + \gamma_{MP,t}\hat{\beta}_{MP,P} + \varepsilon_t. \tag{2}$$

[8] Liu and Zhang (2008, Tables 5 and 6) show that the results, from both full-sample and extended-window regressions, suggest that the *MP* premium is economically and statistically significant, and also that the growth rate of industrial production can account for momentum profits. Their results from rolling-window regressions, however, provide the opposite findings. The focus of our discussions is on the result from the full-sample and extended-window regressions, unless mentioned otherwise.

Table 4 presents risk-premium estimates using momentum, size, and value decile portfolios as the test assets. The Overall panel shows the general patterns of findings in prior work. Of the CRR5 factors, *UTS* (the term premium), *UPR* (the default premium), and *MP* (industrial production growth) are the ones having significant priced risk premium estimates. The *UTS* factor exhibits a negative risk premium, however. The positive estimate on *MP* is robust to other specifications including one-factor regression and also inclusion with the Fama-French factors. The estimates range from 0.83% to 1.04% per month.

Choice of test assets.

Is the pricing of macro risk sensitive to the choice of test assets? Interestingly, the answer is no other than for the *MP* factor. Despite marked changes to *MP* risk-premium estimates, adding industry portfolios to the existing test assets does not change other risk-premium estimates substantially.

Table 5 shows that adding 10 industry-sorted portfolios into the roster of test assets does quantitatively weaken the *MP* risk-premium estimates, although a majority of cases still produce statistically significant *MP* risk-premium estimates. Panel A presents the risk-premium estimates of the 40 test assets (10 momentum-, 10 size-, 10 value-, and 10 industry portfolios). For the one-factor *MP* model, the *MP* risk-premium estimate to be 0.46% per month (*t*-statistic=2.02) in the sample of March 1943 to December 2014. This figure is less than half of the corresponding estimate from the 30 test assets in Table 4, 1.00% per month (*t*-statistic=3.34).

Seasonality effects and implications.

Is the pricing evidence of macro risk sensitive to the January seasonality? The results in Panels C of Table 4 and 5 indicate a strong yes. While the significantly negative *UTS* and *UPR* premium estimates remain, the result for *MP* disappears in five of the six specifications.

While these estimates can show ex post conditional realized premia, they do not satisfyingly estimate ex ante conditional risk premia, a complex task as shown in Mayfield (2004). Note that the difference is important because the time when a risk is realized and the time when the risk premium is realized generally will not coincide.

The realized *MP* risk premium appears to concentrate in January. In Panel B of Table 4, the *MP* risk premiums in Januaries are significant, being −1.76% per month (*t*-statistic=−5.98) for the single-factor MP model and −2.78% per month (*t*-statistic =−2.10) for the CRR5 model specification. Interestingly, using the Fama−French three-factor model makes the *MP* risk premium insignificant. However, the size factor is priced. In Panel C of Table 4, outside of January, the *MP* risk premium ranges from −0.34% per month (*t*-statistic=−1.04) to 0.11% per month (*t*-statistic=0.33) depending on model specifications.

3.2.2. Model-based expected momentum profits

If macroeconomic factor models can capture momentum returns, then expected momentum returns implied from the models should not differ much from the observed momentum returns, and vice versa. Similarly, we conjecture that, if a particular factor can account for momentum returns, then its incremental contribution to expected return should also not differ significantly from what is observed in momentum returns.

Specifically, we estimate factor loadings of a momentum strategy on the Chen, Roll, and Ross (1986) five factors CRR5:

$$WML_t = \alpha + \beta_{UI} UI_t + \beta_{DEI} DEI_t + \beta_{UTS} UTS_t + \beta_{UPS} UPR_t + \beta_{MP} MP_t + \varepsilon_t. \quad (3)$$

The beta estimates are combined with risk premium estimates from Tables 4 and 5 to generate model-expected momentum returns, $E[WML]$. Comparing these to actual *WML* returns provides evidence on whether the factors drive momentum. These comparisons not only allow us to disentangle any contamination effect associated with the month of January from the rest of the year, but also enable us to directly address the issue of whether macroeconomic risk can rationalize momentum profits, profits that exist only outside of January.

Observed vs expected momentum profits.

Panel A of Table 6 reports the expected momentum returns implied by macroeconomic risk as well as the *t*-statistics for the difference tests between the observed *WML* returns and expected *WML* returns. In estimating risk premia for computing expected *WML* returns, we use 30 test assets—10 momentum portfolios, 10 size portfolios, and 10 value portfolios. The full sample yields some conflicting findings for different model specifications.

The single-factor MP model estimates $E[\beta_{MP}\gamma_{MP}]$ to be 0.30% per month (or 50% of the observed returns), with the other 50% being insignificant. Controlling for the three Fama–French factors does not have a material impact on the ability of the *MP* risk factor to capture momentum returns. The FF+MP model determines the *MP* incremental distribution to be 0.41% (or 68% of the observed returns), with the remaining 32% being insignificant. The findings suggest that industrial production risk can provide explanatory power for roughly half of momentum profits.

Conversely, the Chen, Roll, and Ross (1986) five-factor (CRR5) model produces an *MP* incremental contribution of 0.17% per month, or 28% of the observed returns. The remaining 72% is significant (*t*-statistic=2.41). It indicates that industrial production risk can hardly subsume the momentum effect.

As to the issue of whether macroeconomic risk factors taken together can capture the momentum effect, the full sample provides little supportive evidence. For example, we find that for the FF+MP model, the expected WML return, $E[WML]$, is 0.34% per month (or 57% of the observed WML return), which is significant from the observed average return.

Explanations are not stable to change in estimation window.

In contrast with the evidence from using a full-sample estimation, the no-look-ahead (extended window) estimation results show that neither the *MP* risk factor nor the multi-factor models can account for momentum returns.[9] For instance, the single-factor MP model predicts the expected return, $E\left[\beta_{MP}\gamma_{MP}\right]$, to be 0.15% (or 25% of the observed WML return), with the remaining 75% being significant (*t*-statistic=2.23).

The CRR5 model determines the incremental contribution of *MP*, $E\left[\beta_{MP}\gamma_{MP}\right]$, to be 0.03% or 5% of the observed *WML* return, and the difference between them is significant (*t*-statistic=3.15). What follows is our analysis of the role of macroeconomic risk factors combined together in rationalizing momentum profits. The CRR5 model generates the expected WML return to be 0.42% per month, or 70% of the observed return, with the remaining 30% being significant (*t*-statistic=3.19). Since the *MP* risk factor captures only 5% out of 70% being explained by the

[9] We replicate Table 6 Panel B of Liu and Zhang (2008) using the extended-window regressions in the same sample period of 1960–2004. We find that the growth rate of industrial production can provide explanatory power for the momentum returns in the 1960–2004 sample period. However, the results fall apart out of the sample.

combined CRR5 model, this finding reflects that the *MP* risk factor is the least important source among the CRR five factors.[10]

Our analysis of the momentum effect all year round appears to suggest that *MP* has some relation to rationalized momentum profits; however, we need to exercise caution in offering any conclusive statements, due to the complexity associated with the month of January. We next address the concerns associated with the month of January: (a) massive momentum losses in January and (b) the exclusive presence in January of the relation between momentum returns and the *MP* factor. Excluding January is the most direct way to tackle the above-mentioned concerns.

Pivotal role of January in measuring macroeconomic risk effects.

The findings in January are striking. In Panel B of Table 6, both the *MP* risk factor itself and the complete standard asset-pricing models can capture the observed loss in January (with one exception, the FF+MP model). For the full sample, the one-factor *MP* model generates expected *WML* return, $E[\beta_{MP}\gamma_{MP}]$, as −8.28% per month (or 147% of the observed *WML* return). Controlling for the three Fama and French factors significantly weakens the results. For example, with the full sample, the FF+MP model yields the incremental contribution of *MP* to be −1.23% per month or 22% of the observed *WML* losses.

Excluding the month of January leads to considerable changes compared with the counterpart overall findings. Both the *MP* risk factor itself and the complete standard asset-pricing models can barely capture the observed profits outside of January.[11] Standing in sharp contrast with the findings of averaging across the year, with the extended window, the one-factor MP model

[10] Like the extended-window findings, the rolling-window results suggest that macroeconomic risk cannot rationalize momentum returns, regardless of which model specification is used.
[11] We replicate Liu and Zhang (2008, Table 6, Panel B) using the same sample period of 1960–2004. Consistent with Liu and Zhang, we find that the growth rate of industrial production can explain momentum returns across the entire year. When concentrating purely on momentum profits outside of January, that result fades in strength. Results are available on request.

generates expected *WML* return, $E[\beta_{MP}\gamma_{MP}]$, as 0.03% per month (or 2% of the observed *WML* return), with the remaining 98% being significant (*t*-statistic=7.32). Controlling for the three Fama–French factors or the five Chen, Roll, and Ross (1986) factors does not qualitatively affect the findings. For example, with the extended window, the FF+MP model results indicate that the incremental contribution of *MP* is 0.09% per month or 7% of the observed WML profit. And the remaining 93% is significant (*t*-statistic=7.23).

Further, we find that the macroeconomic factors together cannot provide a rationalization for momentum profits outside of January. In Panel C of Table 6, with the extended window, the CRR5 model produces the expected WML return of 0.76% per month (or 65% of the observed WML profit) outside of January. Although the Chen, Roll, and Ross (1986) five-factor model can capture more than half of momentum profits, a difference test rejects the null of no difference between the observed and expected *WML* returns (*t*-statistic=6.07).

Excluding the month of January alters the results by providing further supportive evidence that macroeconomic risk is not the main driving force of momentum profits. For instance, in Panel C of Table 6, for the FF+MP model, the *MP* risk factor can capture 7% of the observed *WML* profits outside of January, which are smaller than the corresponding one (51%) from averaging across the year in Panel A of Table 6. By contrast, excluding January has no material impact on the role of macroeconomic risk in capturing momentum profits outside of January for the CRR4 and CRR5 models.

Addition of industry portfolio test assets.

In Table 7, we repeat the expected profits analyses in the presence of industry portfolios as test assets. With the full sample including all months, the one-factor MP model results in Table 7 show the expected WML return, $E[\beta_{MP}\gamma_{MP}]$, as 0.14% per month (or 23% of the observed WML return). And the remaining 77% is significant (t-statistic=2.20). The *MP* incremental contribution of 0.14% per month is smaller than the corresponding value of 0.30% per month in Table 6. More importantly, it leads to the opposite inference—the growth rate of industrial production plays a negligible role in rationalizing momentum profits.

When we control for the three Fama–French (1996) factors or the five Chen, Roll, and Ross (1986) factors in the regression, the *MP* incremental contributions range from 0.09% per month to 0.17% per month (or 15% to 29% of the observed WML returns). And the remaining differences are all significant. To sum up, our analysis of momentum returns all year round appears to suggest that *MP* (and thus the tested macro models as a whole) cannot account for momentum profits.

Should we conclude that 29 percent of observed *WML* in Panel A of Table 7 is a still a pretty good result for explaining momentum? The results in Panel C of Table 7 indicate no. Outside of January, that 29% estimate falls to 0%. The *MP*-related momentum expectation ranges between −2% and 2% of the total $E[WML]$, which is very discouraging because those are the months in which momentum is present (not massive size-related negative returns, as in January). At no point do we find the "unexplained" portion of *WML* insignificant.

Summary.

This subsection shows that the momentum effect is not a manifestation of recent winners having temporarily higher loadings than recent losers on the growth rate of industrial production. Our conclusions rest on three pieces of evidence. First, outside of January, there are no significant differences, between either the observed and expected momentum returns, or between the observed momentum return and the incremental contribution of *MP*. It is obvious that excluding January observations in a variety of our tests is the most direct way to allow for a focus on the 11 months of a year when momentum is indeed present. Second, including industry portfolios in addition to size-, value-, and momentum portfolios in the test assets also undermines Liu and Zhang's (2008) arguments. Adding industry portfolios has a diluting effect on the possible January influence on our tests, due to the fact that all of the other test assets (instead of industry portfolios) are associated with the classic January size effect. Third, the untabulated results show that the *MP* risk factor plays a negligible role in providing explanatory power for the value-weighted momentum profits relative to equal-weighted momentum profits. Using value-weighted momentum returns instead of equal-weighted returns alleviates the contamination of momentum losses in January, because winners underperform losers to a lesser degree for value-weighted than for equal-weighted momentum strategies in January. All the evidence points to the fact that momentum profits are not the reward for exposure to macroeconomic risk.

3.3. Robustness checks

For robustness, we perform several additional tests. In addition to the equal-weighted results, we also use the value-weighted approach and find qualitatively similar patterns. To examine whether the length of portfolio formation period influences our findings, we extend the six-month formation period to 11 months. The main results still emerge and are available upon request.

As there are various kinds of industry partitioning,[12] we replicate the tests by including different sets of industry-sorted portfolios and uncover the similar findings. Further, another

[12] The French website also provides data for 17 industry portfolios, 30 industry portfolios, and so forth, which are formed by different industry specifications.

potential concern has to do with the extent to which our results may be due to many tiny and illiquid stocks traded on NASDAQ. To address this concern, we exclude NASDAQ stocks and use NYSE and AMEX stocks only to construct ten decile momentum portfolios. The basic inferences remain the same as in the previous subsection. For the sake of brevity, we do not report the results, which are available upon request.

4. ROE and momentum profits

Recently, Hou, Xue, and Zhang (2015, 2016) suggest that their q-factor model, consisting of the market factor (*MKT*), a size factor (*ME*), an investment (*I/A*) factor, and a profitability (*ROE*) factor, can provide explanatory power for the momentum effects. In particular, their *ROE* factor is the main driver in capturing momentum effects. In this section, we extend our analysis to the *ROE* factor and examine whether its explanatory power is also prone to seasonality in momentum profits.

4.1. The performance of the ROE factor

Table 8 reports the raw average monthly returns on the winner–loser portfolio, as well as the alpha estimated from Hou, Xue, and Zhang's (2015) q-factor model and the one-factor *ROE* model. Between January 1967 and December 2014, the average monthly return to momentum strategy is 0.51% (*t*-statistic=2.08). The January losses are large, −6.47% (*t*-statistic=−4.13), while from February to December, the average monthly return is 1.14% (*t*-statistic=5.60).

Table 8 shows that the HXZ q-factor model seems to capture momentum profits across the year, as evident by the alpha of −0.33, which is statistically insignificant with an associated *t*-

statistic of −0.85. With control for the January impact, the alpha of 0.50% is less than half of the raw return of 1.14% over the same February-December period; the associated *t*-statistic is insignificant at the 5% level.

Table 8 also shows that the alpha estimated from the single-factor ROE model is small and insignificant, being −0.10% (*t*-statistic=−0.35). Compared to the alpha estimated from the q-factor model, the *ROE* factor is the main driving force accounting for momentum profits. The *ROE* factor captures half of momentum losses in Januaries as the alpha of −3.03% (*t*-statistic=−2.30) is far less than half of the raw losses, −6.47% (*t*-statistic=−4.13) and is also small in absolute terms relative to the HXZ alpha, −4.77% (*t*-statistic=−4.68). From February to December, the *ROE* factor alone accounts for about half of the momentum profits. To summarize, the *ROE* factor seems to perform well in subsuming the momentum effect.

4.2. Momentum loadings on ROE and their seasonality

As *ROE* is shown to be the prominent driver of momentum, we now examine momentum loadings on *ROE* and their seasonality. To that end, we plot in Figure 3 loadings of momentum portfolios on two models: one is univariate with *ROE* and the other is the full model of Hou, Xue, and Zhang (2015). Panels A-C are for overall, January alone, and February to December, respectively. All three panels of Figure 3 indicate that winners consistently have higher loadings than losers in both model specifications and loadings are lower in the univariate model.

Contrasting with Figure 3 and Figure 1 shows that *MP* loadings and *ROE* loadings exhibit different patterns for extreme momentum portfolios in the months when momentum does exist(i.e., February-December). That is, *MP* loadings are nearly identical, yet *ROE* loadings are much larger for winners. Detailed results in Table 9 show that the loading differences on *ROE* are not only large in magnitude, 0.79 for univariate and 0.86 for the full model, but also statistically significant with *t*-statistics being 10.14 and 10.72, respectively. Thus, the results cast doubt on the explanatory power of *MP* in Liu and Zhang (2008).

Figure 4 displays the evolution of *ROE* loadings over the 12 event months after portfolio formation. As before, we run pooled time-series regressions for winners and losers. Except for the slight crossover in January for the univariate model, winners consistently demonstrate higher loadings in all the other scenarios. This does not seem to capture momentum reversal, which is well documented (e.g., Griffin, Ji, and Martin, 2003; Cooper, Gutierrez, and Hameed, 2004).

5. Conclusion

Using the sample of 1947 to 2014 in the United States, we study the role of macroeconomic risk in explaining momentum profits. The CRR5 model does a poor job. What appears to be a persistent loading of momentum on the growth rate of industrial production is concentrated in January, with zero measured exposure in other months. As there is no momentum effect in January, the explanatory power of industrial production is questionable.

The seasonality of loadings on a macroeconomic factor does not seem compatible with an economic story. It could, however, be a simple coincidence where momentum stocks, which is typically smaller/volatile firms, have their long-known January outperformance manifest in measured seasonal covariance with the industrial production growth factor.

In contrast to the CRR5 factors, the q-factor specification does a much better job with the data. In particular, the *ROE* profitability factor covaries with momentum returns throughout the year and does a reasonable job of explaining the observed patterns.

In all, we conclude that macroeconomic risk is not the main driving force of momentum profits. Our empirical analysis has implications for the literature on investigating the source of momentum profits. Most of the existing studies do not concentrate on the 11 months of a year when the momentum effect is actually present. As this may lead to illusory conclusions about what drives momentum, it is best to be wary of the substantial January contamination when we investigate the cause of momentum profits.

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Figure 1. MP factor loadings of momentum portfolio returns**.** This figure presents the results from calendar-based time-series regressions on the growth rate of industrial production (*MP*) using returns of ten momentum decile portfolios, L, 2, …, 9, W, where L stands for losers and W denotes winners. The figure reports the *MP* factor loadings based on two different factor models: the one-factor MP model (*MP*), and the Chen, Roll, and Ross (1986) model (CRR5). The five Chen, Roll, and Ross (1986) factors include *MP* (the growth rate of industry production), *UI* (unexpected inflation), *DEI* (change in expected inflation), *UTS* (term premium), and *UPR* (default premium). The sample period is from March 1947 to December 2014.

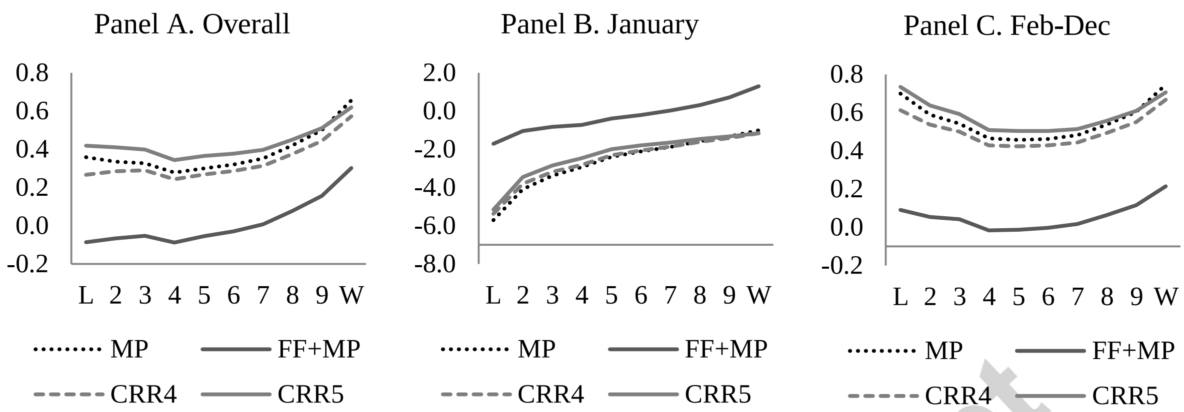
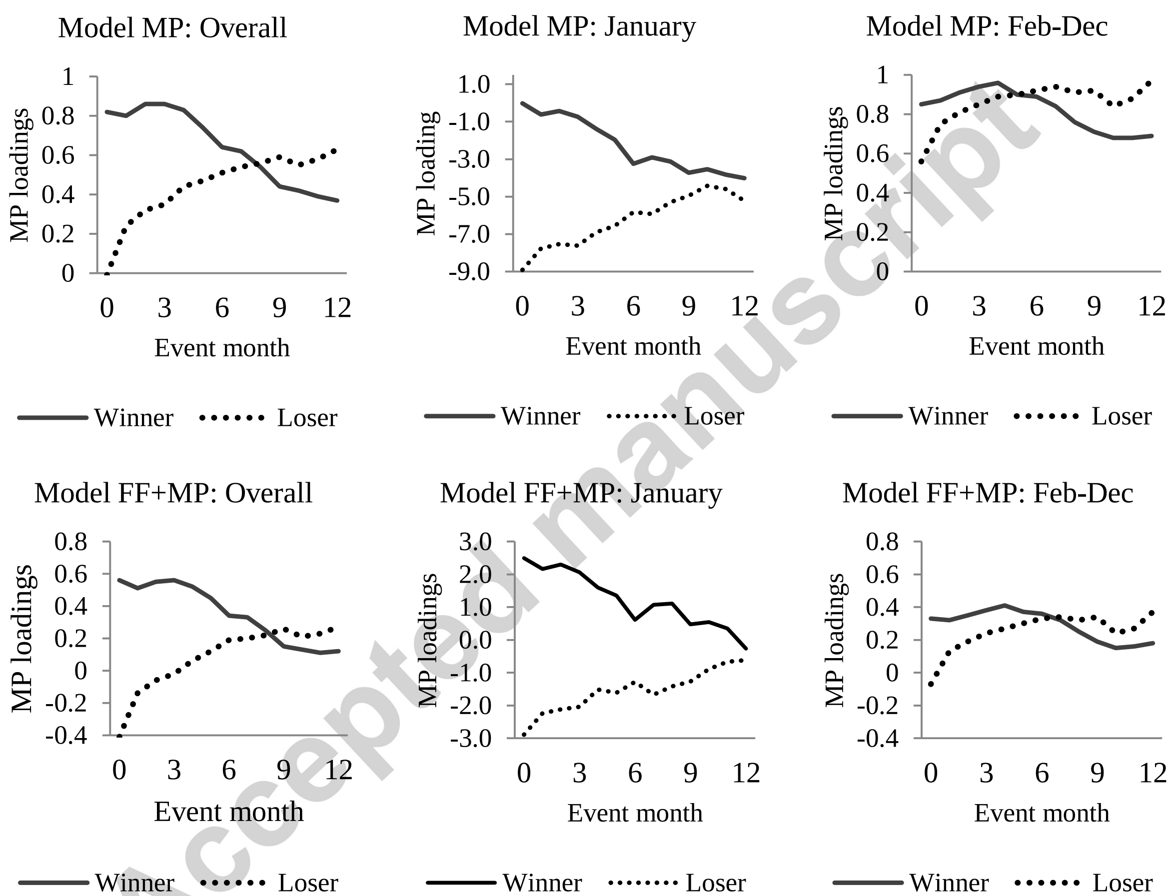

Panel A. Overall
0.8
0.6
0.4
0.2
0.0
-0.2
L 2 3 4 5 6 7 8 9 W
MP
FF+MP
CRR4
CRR5
Panel B. January
2.0
0.0
-2.0
-4.0
-6.0
-8.0
L 2 3 4 5 6 7 8 9 W
MP
FF+MP
CRR4
CRR5
Panel C. Feb-Dec
0.8
0.6
0.4
0.2
0.0
-0.2
L 2 3 4 5 6 7 8 9 W
MP
FF+MP
CRR4
CRR5

Figure 2. Event-time MP factor loadings on winners and losers**.** This figure presents the results from pooled time-series factor regressions on *MP* using returns of winners (W) and losers (L). The event month $t + m$ (where m=0, 1, …, 12) starts the month right after portfolio formation to the twelfth month. For each event month, we pool together across calendar month the observations of returns to winners and losers, the five CRR factors (the growth rate of industrial production, *MP*; unexpected inflation, *UI*; change in expected inflation, *DEI*; term premium, *UTS*; default premium, *UPR*) for each of event month $t + m$. We perform pooled time-series factor regressions to estimate *MP* factor loadings for winners (solid line) and losers (broken line). The sample period is from March 1947 to December 2014.



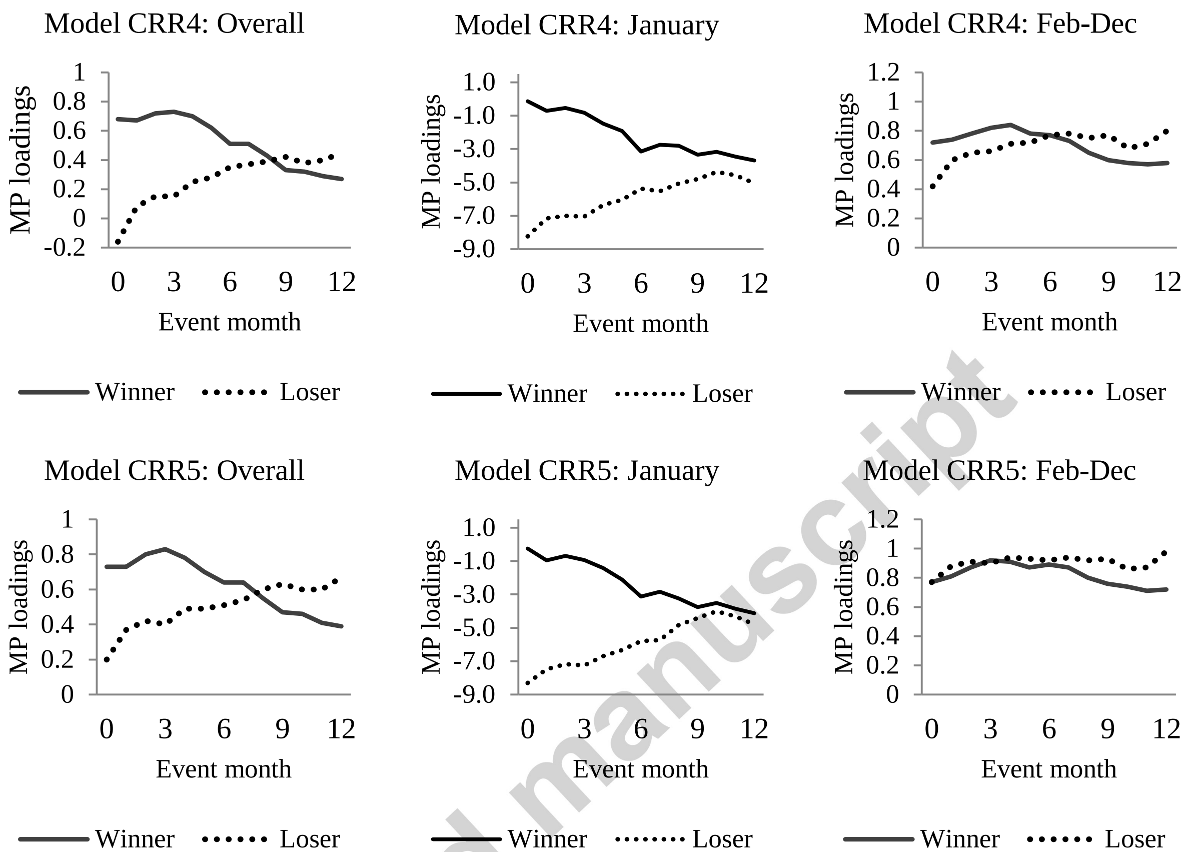

Model CRR4: Overall
MP loadings
Event momth
Winner
Loser
Model CRR4: January
MP loadings
Event month
Winner
Loser
Model CRR4: Feb-Dec
MP loadings
Event month
Winner
Loser
Model CRR5: Overall
MP loadings
Event month
Winner
Loser
Model CRR5: January
MP loadings
Event month
Winner
Loser
Model CRR5: Feb-Dec
MP loadings
Event month
Winner
Loser

Figure 3. ROE factor loadings of momentum portfolio returns. This figure presents the results from calendar-based time-series regressions on the return on equity (*ROE*) using returns of ten momentum decile portfolios, L, 2, …, 9, W, where L stands for losers and W denotes winners. EW denotes the equal-weighted momentum ten decile portfolios while VW denotes the value-weighted momentum ten decile portfolios. The figure reports the *ROE* factor loadings based on two different factor models: the one-factor ROE model (*ROE*), and the q-factor mode of Hou, Xue, and Zhang (2015) model (HXZ). The HXZ q-factor model includes *MKT* (the market excess return), *ME*(the difference between the return on a diversified portfolio of small size stocks and the return on a diversified portfolio of large size stocks), *I/A*(the difference between the return on a diversified portfolio of low investment stocks and the return on a diversified portfolio of high investment stocks), *ROE* (the difference between the return on a diversified portfolio of high return on equity and the return on a diversified portfolio of low return on equity). The sample period is from January 1967 to December 2014.

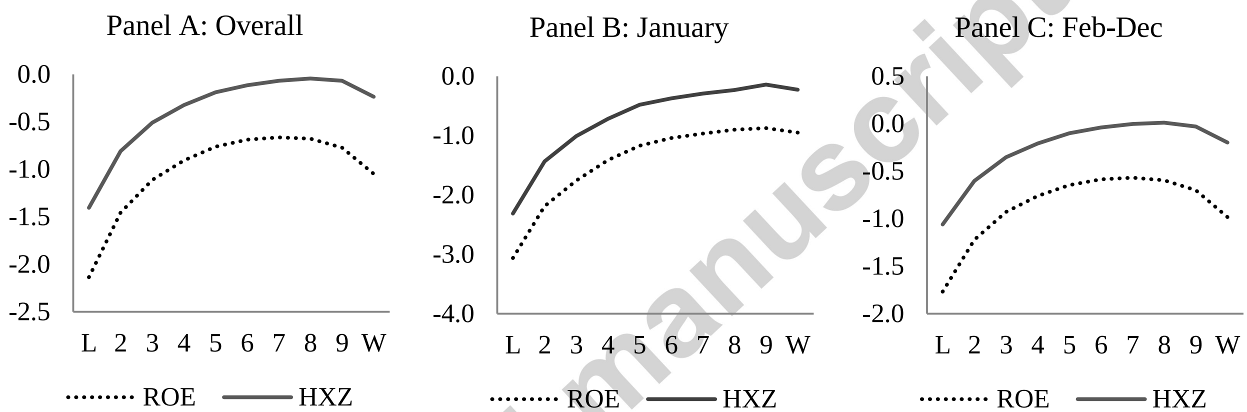


Figure 4. Event-time ROE factor loadings on winners and losers. This figure presents the results from pooled time-series factor regressions on *ROE* using returns of winners (W) and losers (L). The event month $t + m$ (where m=0, 1, …, 12) starts the month right after portfolio formation to the twelfth month. For each event month, we pool together across calendar month the observations of returns to winners and losers, the four Hou, Xue, and Zhang (2015) factors (the market excess return, *MKT*; the size factor, *ME*; the investment factor, *I/A*; and the return-to-equity factor, *ROE*), for each of event month $t + m$. We perform pooled time-series factor regressions to estimate *ROE* factor loadings for winners (solid line) and losers (broken line). The sample period is from January 1967 through December 2014.

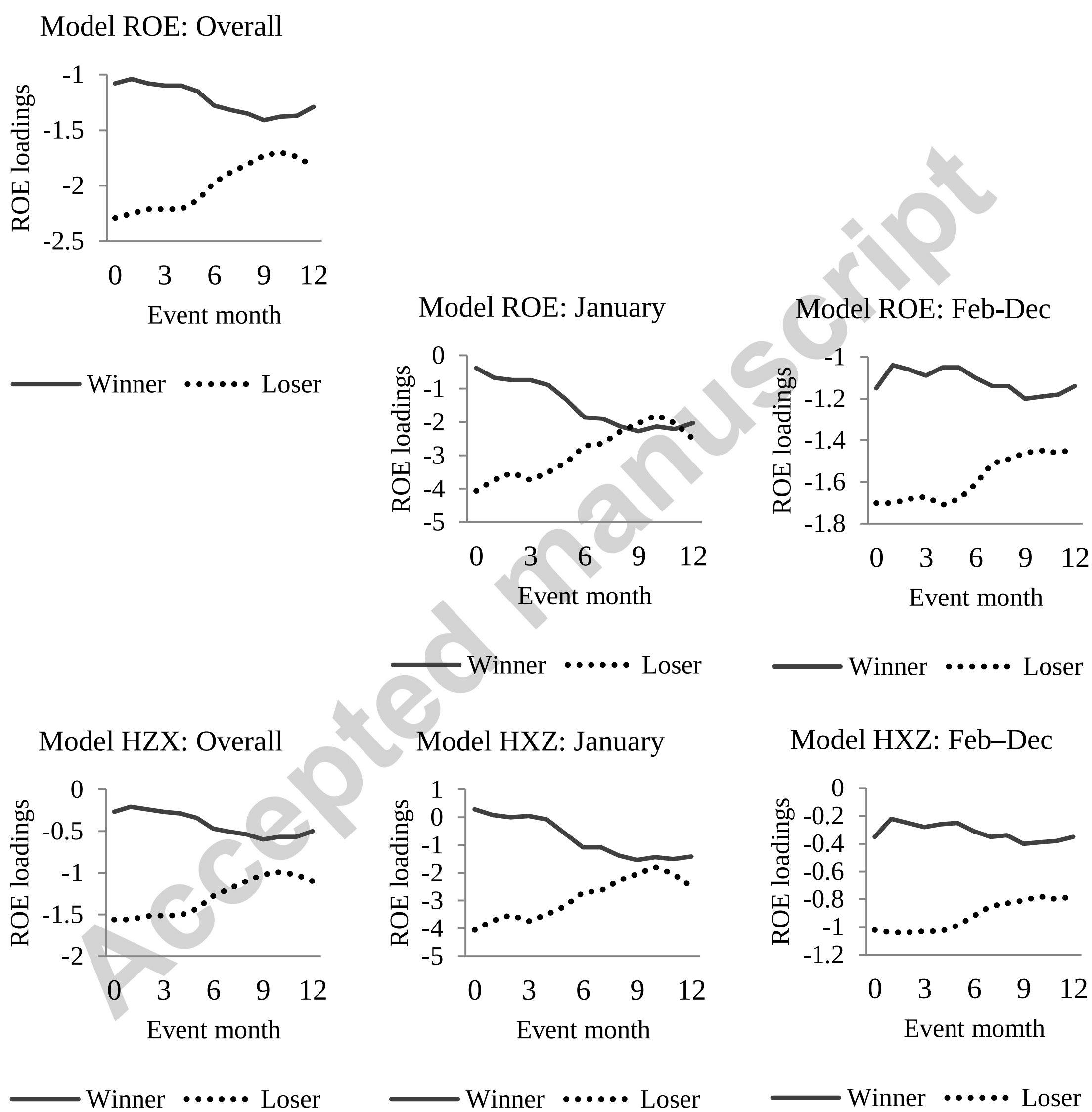


Table 1. Descriptive summary statistics of the five Chen, Roll, and Ross (1986) factors

The table reports the summary statistics and correlation coefficients of the key variables, the five Chen, Roll, and Ross (1986) factors, used in the analysis. Those five factors refer to changes in industrial production (*MP*), unexpected inflation (*UI*), change in expected inflation (*DEI*), term spread (*UTS*), and default spread (*UPR*), which are constructed monthly. The growth rate of industrial production for month t is defined as $MP_t \equiv \log IP_t - \log IP_{t-1}$, where IP_t is the industry production index (INDPRO series) in month t from the FRED database. Note that *MP* is led by one month since INDPRO is recorded at the beginning of a month, whereas stock returns are recorded as of the end of a month. Unexpected inflation is defined as $UI_t \equiv I_t - E[I_t | t-1]$ and change of expected inflation as $DEI_t \equiv E\left[I_{t+1} | t\right] - E\left[I_t | t-1\right]$ following Fama and Gibbons (1984). Term spread (*UTS*) is defined as the yield difference between 20- and 1-year Treasury bonds, and default spread (*UPR*) is the yield difference between BAA- and AAA-rated corporate bonds in the FRED database at the Federal Reserve Bank of St. Louis. All of the numbers in Panel A are in percentage. The sample period is from March 1947 to December 2014.

Panel A: Variables	Mean		Median	Standard Deviation
MP	0.25		0.30	0.97
UI	0.00		0.01	0.28
DEI	0.00		0.00	0.10
UTS	1.22		1.10	1.36
UPR	0.95		0.80	0.44
Panel B: Correlation	*MP*	*UI*	*DEI*	*UTS*
UI	0.10			
DEI	0.13	0.71		
UTS	0.04	0.05	−0.03	
UPR	−0.22	−0.03	−0.09	0.18

Table 2. Momentum strategy payoffs: 03/47-12/14

All NYSE, AMEX, and NASDAQ stocks on the monthly file of CRSP are ranked on the basis of cumulative returns in month $t-7$ to month $t-2$, and accordingly are assigned to ten deciles. Stocks with the highest returns in the preceding two to seven months are defined as winners (P10), whereas stocks with the lowest returns during the same period are defined as losers (P1). The momentum strategy buys prior winners (P10) and sells prior losers (P1). Zero-investment winner–loser portfolios (WML) are reconstructed at the start of each month, and held for six months from month $t+1$ to month $t+6$. There is a one-month gap between portfolio formation and portfolio investing in order to avoid the mechanical bid-ask bias. The table reports average monthly returns of the *WML* portfolios; the associated t-statistics are in parentheses. “CAPM alpha” refers to the *WML* alpha from the CAPM regression, whereas “Fama–French alpha” refers to the *WML* alpha from the Fama–French (1993) three-factor model. The sample period is from March 1947 to December 2014.

	Overall	January	Feb−Dec
Panel A: 3/47–12/14			
Mean profits	0.64	−5.67	1.20
	(3.49)	(−4.91)	(7.82)
CAPM alpha	0.69	−5.36	1.22
	(3.73)	(−4.57)	(7.90)
Fama–French alpha	0.80	−4.48	1.30
	(4.37)	(−3.79)	(8.42)
Panel B: 3/47–12/69			
Mean profits	1.03	−3.85	1.45
	(5.04)	(−3.74)	(7.97)
Panel C: 1/70–12/92			
Mean profits	0.24	−7.02	0.90
	(0.55)	(−2.54)	(2.47)
Panel D: 1/93–12/14			
Mean profits	0.02	-8.03	0.77
	(0.05)	(-2.54)	(1.95)

Table 3. MP factor loadings of momentum portfolio returns

The table presents the results from calendar-based time-series regressions on the growth rate of industrial production (*MP*) using returns of ten momentum decile portfolios, L, P2, …, P9, W, where L stands for losers, W denotes winners, and WML denotes the winner-minus-loser portfolio. The *MP* factor loadings are estimated from two different factor models, including the one-factor MP model (MP), and the Chen, Roll, and Ross (1986) model (CRR5). The associated *t*-statistics are in parentheses. The five Chen, Roll, and Ross (1986) factors include *MP* (the growth rate of industry production), *UI* (unexpected inflation), *DEI* (change in expected inflation), *UTS* (term premium), and *UPR* (default premium). The sample period is from March 1947 to December 2014.

	L	2	3	4	5	6	7	8	9	*W*	*WML*
Panel A: Overall											
MP	0.36	0.34	0.33	0.28	0.30	0.32	0.35	0.42	0.50	0.66	0.30
	(1.07)	(1.24)	(1.39)	(1.27)	(1.49)	(1.66)	(1.83)	(2.18)	(2.45)	(2.81)	(1.58)
FF+MP	-0.09	-0.07	-0.05	-0.09	-0.05	-0.03	0.01	0.08	0.16	0.30	0.39
	(-0.54)	(-0.62)	(-0.68)	(-1.43)	(-1.20)	(-0.84)	(0.24)	(2.12)	(2.83)	(3.43)	(2.08)
CRR4	0.27	0.29	0.29	0.24	0.27	0.29	0.31	0.38	0.44	0.57	0.30
	(0.82)	(1.08)	(1.25)	(1.13)	(1.36)	(1.50)	(1.65)	(1.96)	(2.19)	(2.45)	(1.62)
CRR5	0.42	0.41	0.40	0.34	0.37	0.38	0.40	0.45	0.51	0.62	0.20
	(1.38)	(1.69)	(1.88)	(1.74)	(1.99)	(2.11)	(2.21)	(2.47)	(2.62)	(2.74)	(1.04)

Panel B. January											
MP	-5.71	-4.08	-3.37	-2.93	-2.39	-2.11	-1.87	-1.58	-1.33	-1.01	4.70
	(-2.75)	(-2.47)	(-2.28)	(-2.10)	(-1.86)	(-1.74)	(-1.53)	(-1.38)	(-1.10)	(-0.88)	(3.69)
FF+MP	-1.70	-1.05	-0.82	-0.72	-0.39	-0.21	0.03	0.31	0.71	1.29	3.00
	(-1.87)	(-2.34)	(-2.48)	(-2.56)	(-1.71)	(-1.17)	(0.14)	(1.51)	(2.35)	(2.73)	(2.54)
CRR4	-5.37	-3.80	-3.18	-2.81	-2.31	-2.06	-1.87	-1.61	-1.41	-1.15	4.21
	(-3.03)	(-2.53)	(-2.28)	(-2.10)	(-1.86)	(-1.75)	(-1.57)	(-1.43)	(-1.19)	(-1.02)	(3.42)
CRR5	-5.16	-3.45	-2.85	-2.46	-1.99	-1.80	-1.65	-1.46	-1.33	-1.15	4.00
	(-2.83)	(-2.44)	(-2.25)	(-2.07)	(-1.78)	(-1.64)	(-1.47)	(-1.32)	(-1.13)	(-0.97)	(3.00)
C: Feb−Dec											
MP	0.70	0.59	0.54	0.47	0.46	0.46	0.48	0.54	0.61	0.75	0.05
	(2.49)	(2.54)	(2.66)	(2.43)	(2.57)	(2.67)	(2.77)	(2.98)	(3.13)	(3.26)	(0.30)
FF+MP	0.09	0.05	0.04	-0.02	-0.01	0.00	0.02	0.06	0.12	0.22	0.12
	(0.66)	(0.59)	(0.66)	(-0.32)	(-0.30)	(-0.08)	(0.56)	(1.70)	(2.07)	(2.54)	(0.79)
CRR4	0.61	0.54	0.50	0.43	0.42	0.43	0.44	0.49	0.55	0.67	0.06
	(2.18)	(2.32)	(2.46)	(2.25)	(2.39)	(2.48)	(2.56)	(2.75)	(2.87)	(2.91)	(0.36)
CRR5	0.73	0.64	0.59	0.51	0.50	0.50	0.51	0.56	0.61	0.71	−0.03
	(2.84)	(2.99)	(3.15)	(2.90)	(3.01)	(3.07)	(3.08)	(3.22)	(3.26)	(3.17)	(−0.17)

Table 4. Risk-premium estimates of the Chen, Roll, and Ross (1986) model

The table reports risk premia of the five Chen, Roll, and Ross (1986) factors and the three Fama and French (1993) factors, including the growth rate of industrial production (*MP*), unexpected inflation (*UI*), change in expected inflation (*DEI*), term premium (*UTS*), default premium (*UPR*), market premium (*MKT*), size premium (*SMB*), and value premium (*HML*) from two-stage Fama−MacBeth (1973) cross-sectional regressions. The Fama−MacBeth *t*-statistics are calculated from the Shanken (1992) method and reported in parentheses. The average cross-sectional R-squares are also reported. We use thirty test assets, including decile one-sorted portfolios formed on size (market capitalization), value (book-to-market equity) and momentum (past two-to-seven months' returns). The sample period is from March 1947 to December 2014. In the first-stage time-series regressions, for each test portfolio, we estimate factor loadings using the full samples and the extended window. In the second-stage cross-sectional regressions, we estimate risk premia by regressing test assets' excess returns on factor loadings estimated from the first-stage time-series regressions. The sample period for the second-stage cross-sectional regressions starts from March 1949 in order to ensure that there are at least two years of monthly observations in the first-stage extended-window time-series regressions. For the extended-window case, the first-stage time-series regressions start from the first month to month t and the second-stage cross-sectional regressions regress test assets' excess returns in month t + 1 on factor loadings using information up to month t. For brief, the table reports the results based on the full samples in the first-stage time-series regressions, and the extended-window regressions generate quantitatively similar results.

	$\hat{\gamma}_0$	$\hat{\gamma}_{MP}$	$\hat{\gamma}_{UI}$	$\hat{\gamma}_{DEI}$	$\hat{\gamma}_{UTS}$	$\hat{\gamma}_{UPR}$	$\hat{\gamma}_{MKT}$	$\hat{\gamma}_{SMB}$	$\hat{\gamma}_{HML}$	$\bar{R}^2$
Panel A. Overall										
MP	0.50	1.00								15%
	(3.34)	(3.34)								
FF	0.90						-0.20	0.16	0.17	44%
	(3.65)						(-0.70)	(1.39)	(1.59)	
FF+MP	0.90	1.04					-0.15	0.07	0.21	49%
	(3.65)	(3.51)					(-0.54)	(0.60)	(2.05)	
CRR5	0.77	0.83	0.15	0.07	-1.41	0.29				47%
	(4.43)	(2.71)	(0.76)	(0.47)	(-2.65)	(2.42)				
Panel B. January										
MP	-0.08	-1.76								36%
	(-0.12)	(-5.98)								
FF	0.84						0.10	3.33	0.22	59%
	(0.96)						(0.10)	(7.19)	(0.45)	
FF+MP	1.01	-0.41					-0.07	3.31	0.26	64%
	(1.29)	(-1.44)					(-0.07)	(7.36)	(0.57)	
CRR5	-2.60	-2.78	-0.34	-0.03	2.93	0.40				57%
	(-3.66)	(-2.10)	(-0.31)	(-0.04)	(2.04)	(0.53)				
Panel C. Feb−Dec										
MP	0.77	-0.34								22%
	(4.99)	(-1.04)								
FF	1.44						-0.78	-0.11	0.05	43%
	(6.08)						(-2.71)	(-0.88)	(0.40)	
FF+MP	1.46	0.11					-0.79	-0.12	0.05	46%
	(6.27)	(0.30)					(-2.77)	(-1.03)	(0.42)	
CRR5	1.29	0.11	0.32	0.08	-3.12	0.59				46%
	(7.39)	(0.33)	(1.19)	(0.27)	(-6.93)	(3.46)				

Table 5. Risk-premium estimates of the Chen, Roll, and Ross (1986): using alternative test assets

The table reports risk premia of the five Chen, Roll, and Ross (1986) factors and the three Fama and French (1993) factors, including the growth rate of industrial production (*MP*), unexpected inflation (*UI*), change in expected inflation (*DEI*), term premium (*UTS*), default premium (*UPR*), market premium (*MKT*), size premium (*SMB*), and value premium (*HML*) estimated from two-stage Fama–MacBeth (1973) cross-sectional regressions. The Fama–MacBeth *t*-statistics are calculated from the Shanken (1992) method and reported in parentheses. The average cross-sectional R-squares are also reported. We use forty test assets, including decile one-sorted portfolios formed on size, value, momentum and industry portfolios. The sample period is from March 1947 to December 2014. In the first-stage time-series regressions, for each test portfolio, we estimate factor loadings using the full samples and the extended window. In the second-stage cross-sectional regressions, we estimate risk premia by regressing test assets' excess returns on factor loadings estimated from the first-stage time-series regressions. The sample period for the second-stage cross-sectional regressions starts from

March 1949 in order to ensure that there are at least two years of monthly observations in the first-stage extended-window time-series regressions. For the extended-window case, the first-stage time-series regressions start from the first month to month *t* and the second-stage cross-sectional regressions regress test assets' excess returns in month *t* + 1 on factor loadings using information from the first month to month *t*. For brief, the table only reports the results based on the full samples in the first-stage time-series regressions, and the extended-window regressions generate quantitatively similar results.

	$\hat{\gamma}_0$	$\hat{\gamma}_{MP}$	$\hat{\gamma}_{UI}$	$\hat{\gamma}_{DEI}$	$\hat{\gamma}_{UTS}$	$\hat{\gamma}_{UPR}$	$\hat{\gamma}_{MKT}$	$\hat{\gamma}_{SMB}$	$\hat{\gamma}_{HML}$	$\bar{R}^2$
Panel A. Overall										
MP	0.67	0.46								13%
	(4.83)	(2.02)								
FF	0.72						0.00	0.17	0.08	39%
	(3.87)						-0.01	1.47	0.74	
FF+MP	1.02	0.45					-0.27	0.13	0.09	42%
	(5.11)	(2.11)					-1.10	1.13	0.80	
CRR5	0.79	0.48	0.11	0.06	-0.91	0.18				38%
	(5.97)	(2.18)	(0.57)	(0.35)	(-2.32)	(1.83)				
Panel B. January										
MP	0.09	-1.58								26%
	(0.15)	(-6.19)								
FF	1.43						-0.39	3.13	0.08	51%
	(2.11)						(-0.43)	(7.17)	(0.18)	
FF+MP	1.64	-0.08					-0.62	3.19	0.07	56%
	(2.41)	(-0.23)					(-0.67)	(7.47)	(0.15)	
CRR5	-0.62	-1.56	-0.13	-0.07	2.39	0.19				43%
	(-1.04)	(-4.31)	(-0.55)	(-0.31)	(2.63)	(0.49)				
Panel C. Feb−Dec										
MP	0.72	-0.23								16%
	(5.23)	(-1.04)								
FF	0.85						-0.17	-0.11	0	38%
	(4.53)						(-0.71)	(-0.94	(-0.04)	
FF+MP	0.83	-0.04					-0.16	-0.10)	0	41%
	(4.71)	(-0.18)					(-0.66)	(-0.91)	(-0.04)	
CRR5	0.92	0.67	0.03	0.01	-2.16	0.16				38%
	(6.66)	(2.90)	(0.14)	(0.05)	(-6.40)	(1.72)				

Table 6. Expected momentum profits versus observed momentum profits

The table reports estimated momentum profits based on four different factor models, including the one-factor MP model (*MP*), the Fama−French (1993) model augmented with *MP* (FF+MP), the Chen, Roll, and Ross (1986) models (CRR4, CRR5). We calculate expected momentum profits as the sum of the products of factor sensitivities and estimated risk premium: $E[WML] = \hat{\beta}_{MP}\hat{\gamma}_{MP} + \hat{\beta}_{UI}\hat{\gamma}_{UI} + \hat{\beta}_{DEI}\hat{\gamma}_{DEI} + \hat{\beta}_{UTS}\hat{\gamma}_{UTS} + \hat{\beta}_{UPR}\hat{\gamma}_{UPR}$. Factor sensitivities are estimated from

$WML_t = \alpha + \beta_{MP} MP_t + \beta_{UI} UI_t + \beta_{DEI} DEI_t + \beta_{UTS} UTS_t + \beta_{UPR} UPR_t + \varepsilon_t$. Risk premia are estimated from two-stage Fama−MacBeth (1973) cross-sectional regressions using 10 size-, 10 value- and 10 momentum portfolios as test assets. In the first-stage time-series regressions, for each of 30 test assets, we estimate factor sensitivities by regressing test assets' returns on factors, using the full-sample, extended windows and rolling windows: $r_{P,t} = \alpha_P + \beta_{MP,P} MP_t + \beta_{UI,P} UI_t + \beta_{DEI,P} DEI_t + \beta_{UTS,P} UTS_t + \beta_{UPR,P} UPR_t + \varepsilon_{P,t}$. In the second-stage cross-sectional regressions, we regress 30 test assets' excess returns on the estimated factor sensitivities from the first-stage time-series regressions for each month: $r_{P,t} - r_{f,t} = \gamma_{0,t} + \gamma_{MP,t}\hat{\beta}_{MP,P} + \gamma_{UI,t}\hat{\beta}_{UI,P} + \gamma_{DEI,t}\hat{\beta}_{DEI,P} + \gamma_{UTS,t}\hat{\beta}_{UTS,P} + \gamma_{UPR,t}\hat{\beta}_{UPR,P} + \varepsilon_t$. This table also presents the *t*-statistics, *t(diff1)*, testing the null that the difference between the observed momentum return and the incremental contribution of *MP*, $E(\beta_{MP}\gamma_{MP})$, is zero and the *t*-statistics, *t(diff2)*, testing the null that the difference between observed and expected momentum returns is zero.

	Model Success			*MP* Contribution			Model Success			*MP* Contribution		
	$E[WML]$	$\frac{E[WML]}{WML}$	*t(diff1)*	$E[\beta_{MP}\gamma_{MP}]$	$\frac{E[\beta_{MP}\gamma_{MP}]}{WML}$	*t(diff2)*	$E[WML]$	$\frac{E[WML]}{WML}$	*t(diff1)*	$E[\beta_{MP}\gamma_{MP}]$	$\frac{E[\beta_{MP}\gamma_{MP}]}{WML}$	*t(diff1)*
	Full-sample in the first-stage regression						Extended-window in the first-stage regression					
Panel A. Overall												
MP	0.30	50%	1.40	0.30	50%	1.40	0.15	25%	2.23	0.15	25%	2.23
FF+MP	0.34	57%	2.75	0.41	68%	1.62	0.23	38%	3.01	0.30	51%	2.00
CRR4	0.47	78%	2.80	0.29	49%	1.69	0.37	62%	3.29	0.08	13%	2.96
CRR5	0.52	87%	1.77	0.17	28%	2.41	0.42	70%	3.19	0.03	5%	3.15
Panel B. January												
MP	-8.28	147%	5.40	-8.28	147%	5.40	-7.19	122%	2.15	-7.19	122%	2.15
FF+MP	-5.28	94%	-2.61	-1.23	22%	-5.36	-5.30	90%	-2.22	-0.85	15%	-6.46
CRR4	-6.59	117%	3.60	-11.07	196%	4.01	-6.17	105%	0.81	-4.22	72%	-1.37
CRR5	-6.74	119%	3.90	-11.15	197%	4.15	-5.84	99%	-0.12	-2.93	50%	-2.91
Panel C. Feb−Dec												
MP	-0.02	-1%	7.35	-0.02	-1%	7.35	0.03	2%	7.32	0.03	2%	7.32
FF+MP	0.07	6%	7.69	0.01	1%	7.37	0.18	15%	7.07	0.09	7%	7.23
CRR4	0.85	73%	4.19	0.01	1%	7.36	0.62	54%	6.02	0.10	8%	7.17
CRR5	0.97	83%	3.20	0	0%	7.39	0.76	65%	6.07	0.09	8%	7.16

Table 7. Expected momentum profits versus observed momentum profits: using alternative test assets

The table reports estimated momentum profits based on four different factor models, including the one−factor MP model (*MP*), the Fama−French (1993) model augmented with MP (FF+MP), the Chen, Roll, and Ross (1986) model (CRR4, CRR5). We calculate expected momentum profits as the sum of the products of factor sensitivities and estimated risk premium: $E[WML]=\hat{\beta}_{MP}\hat{\gamma}_{MP}+\hat{\beta}_{UI}\hat{\gamma}_{UI}+\hat{\beta}_{DEI}\hat{\gamma}_{DEI}+\hat{\beta}_{UTS}\hat{\gamma}_{UTS}+\hat{\beta}_{UPR}\hat{\gamma}_{UPR}$. Factor sensitivities are estimated from $WML_t=\alpha+\beta_{MP}MP_t+\beta_{UI}UI_t+\beta_{DEI}DEI_t+\beta_{UTS}UTS_t+\beta_{UPR}UPR_t+\varepsilon_t$ .Risk premia are estimated from two-stage Fama-MacBeth (1973) cross-sectional regressions using 10 size-, 10 value-, 10 momentum and 10 industry portfolios as test assets. In the first-stage time-series regressions, for each of 40 test assets, we estimate factor sensitivities by regressing test assets' returns on factors, using the full-sample, extended windows and rolling windows: $r_{P,t}=\alpha_P+\beta_{MP,P}MP_t+\beta_{UI,P}UI_t+\beta_{DEI,P}DEI_t+\beta_{UTS,P}UTS_t+\beta_{UPR,P}UPR_t+\varepsilon_{P,t}$. In the second-stage cross-sectional regressions, we regress 40 test assets' excess returns on the estimated factor sensitivities from the first-stage time-series regressions for each month: $r_{P,t}-r_{f,t}=\gamma_{0,t}+\gamma_{MP,t}\hat{\beta}_{MP,P}+\gamma_{UI,t}\hat{\beta}_{UI,P}+\gamma_{DEI,t}\hat{\beta}_{DEI,P}+\gamma_{UTS,t}\hat{\beta}_{UTS,P}+\gamma_{UPR,t}\hat{\beta}_{UPR,P}+\varepsilon_t$. This table also presents the *t*-statistics, $t(diff1)$, testing the null that the difference between the observed momentum return and the incremental contribution of *MP*, $E(\beta_{MP}\gamma_{MP})$, is zero and the *t*-statistics, $t(diff2)$, testing the null that the difference between observed and expected momentum returns is zero.

	Model Success			*MP* Contribution			Model Success			*MP* Contribution		
	$E[WML]$	$\frac{E[WML]}{WML}$	*t(diff 1)*	$E[\beta_{MP}\gamma_{MP}]$	$\frac{E[\beta_{MP}\gamma_{MP}]}{WML}$	*t(diff 2)*	$E[WML]$	$\frac{E[WML]}{WML}$	*t(diff 1)*	$E[\beta_{MP}\gamma_{MP}]$	$\frac{E[\beta_{MP}\gamma_{MP}]}{WML}$	*t(diff1)*
	Full-sample in the first-stage regression									Extended-window in the first-stage regression		
Panel A. Overall												
MP	0.14	23%	2.20	0.14	23%	2.20	0.08	13%	2.62	0.08	13%	2.62
FF+MP	0.14	23%	3.29	0.17	29%	2.67	-0.04	-6%	3.79	0.04	7%	3.01
CRR4	0.31	51%	3.06	0.09	15%	2.87	0.34	56%	2.33	0.05	9%	2.98
CRR5	0.38	64%	2.63	0.10	16%	2.83	0.38	64%	2.37	0.05	9%	3.09
Panel B. January												
MP	-7.40	1.31	3.08	-7.40	1.31	3.08	-5.81	99%	-0.08	-5.81	99%	-0.08
FF+MP	-4.36	0.77	-4.75	-0.25	0.04	-5.92	-3.86	66%	-3.76	-0.04	1%	-6.10
CRR4	-6.71	1.19	2.96	-6.31	1.12	0.56	-5.27	90%	-0.96	-3.54	60%	-2.29

CRR 5	-6.93	1.23	3.94	-6.26	1.11	0.53	-4.89	83%	-1.79	-1.94	33%	-4.01
Panel C. Feb−Dec												
MP	-0.01	-1%	7.36	-0.01	-1%	7.36	0.03	2%	7.29	0.03	2%	7.29
FF+ MP	0.01	1%	7.68	0	0%	7.40	0.10	8%	7.02	0.04	3%	7.25
CRR 4	0.70	60%	3.95	0.03	2%	7.31	0.42	36%	5.76	0.05	4%	7.22
CRR 5	0.78	67%	3.57	-0.02	-2%	7.44	0.50	43%	5.77	0.04	3%	7.22

Table 8: Momentum strategy payoffs: 1/1967-12/2014

All NYSE, AMEX, and NASDAQ stocks on the monthly file of CRSP are ranked on the basis of cumulative returns in month $t-7$ to month $t-2$, and accordingly are assigned to ten deciles. Stocks with the highest returns in the preceding two to seven months are defined as winners (P10), whereas stocks with the lowest returns during the same period are defined as losers (P1). The momentum strategy buys prior winners (P10) and sells prior losers (P1). Zero-investment winner–loser portfolios (WML) are reconstructed at the start of each month, and held for six months from month $t+1$ to month $t+6$. There is a one-month gap between portfolio formation and portfolio investing in order to avoid the mechanical bid-ask bias. The table reports average monthly returns of the winner–loser portfolios (WML); the associated t statistics are presented in the parentheses. “HXZ alpha” refers to the WML alpha from the Hou, Xue, and Zhang’s (2015) q-factor model. “ROE alpha” refers to the WML alpha from the single-factor ROE model. The sample period starts from January 1967 to December 2014.

	Overall	January	Feb−Dec
		1/67–12/14	
Mean profits	0.51	−6.47	1.14
	(2.08)	(−4.13)	(5.60)
HXZ alpha	−0.33	−4.77	0.50
	(−0.85)	(−4.68)	(1.91)
ROE alpha	−0.10	−3.03	0.55
	(−0.35)	(−2.30)	(1.99)

Table 9. ROE factor loadings of momentum portfolio returns

The table presents the results from calendar-based time-series regressions on the *ROE* factor using returns of ten momentum decile portfolios, L, P2, …, P9, W, where L stands for losers and W denotes winners. The *ROE* factor loadings are estimated from two different factor models, including the single-factor ROE model (ROE), and the q-factor mode of Hou, Xue, and Zhang (2015) (HXZ). The associated t-statistics are in parentheses. The Hou, Xue, and Zhang (2015) q-factor model consists of *MKT* (the market excess return), *ME*(the difference between the return on a diversified portfolio of small size stocks and the return on a diversified portfolio of large size stocks), *I/A*(the difference between the return on a diversified portfolio of low investment stocks and the return on a diversified portfolio of high investment stocks), *ROE* (the difference between the return on a diversified portfolio of high return on equity and the return on a diversified portfolio of low return on equity). The sample period is from January 1967 to December 2014.

	L	2	3	4	5	6	7	8	9	W	WML
Panel A: Overall											
ROE	-2.14	-1.46	-1.11	-0.91	-0.76	-0.69	-0.66	-0.68	-0.77	-1.05	1.09
	(-9.12	(-8.84)	(-8.22)	(-7.48)	(-6.95)	(-6.83)	(-6.65)	(-6.82)	(-6.66)	(-7.29)	(12.90)
HXZ	-1.41	-0.81	-0.51	-0.32	-0.19	-0.11	-0.07	-0.04	-0.07	-0.24	1.17
	(-6.50)	(-6.29)	(-5.79)	(-4.89)	(-3.78)	(-2.75)	(-1.81)	(-1.16)	(-1.45)	(-2.97)	(13.06)
Panel B: January											
ROE	-3.06	-2.19	-1.75	-1.41	-1.17	-1.04	-0.96	-0.90	-0.87	-0.95	2.11
	(-3.04)	(-3.78)	(-4.10)	(-3.43)	(-3.02)	(-2.89)	(-2.63)	(-2.74)	(-2.61)	(-3.35)	(4.68)
HXZ	-2.31	-1.43	-1.01	-0.71	-0.48	-0.37	-0.29	-0.23	-0.14	-0.22	2.09
	(-3.39)	(-3.78)	(-4.90)	(-5.31)	(-4.68)	(-4.11)	(-2.87)	(-2.12)	(-1.09)	(-1.00)	(5.32)
Panel C: Feb−Dec											
ROE	-1.77	-1.22	-0.93	-0.76	-0.64	-0.58	-0.57	-0.60	-0.70	-0.98	0.79
	(-9.20)	(-8.10)	(-7.24)	(-6.62)	(-6.09)	(-6.02)	(-5.91)	(-5.87)	(-5.54)	(-5.89)	(10.14)
HXZ	-1.06	-0.60	-0.35	-0.21	-0.10	-0.04	0.00	0.01	-0.03	-0.20	0.86
	(-7.60)	(-6.71)	(-5.27)	(-3.85)	(-2.28)	(-1.06)	(-0.02)	(0.32)	(-0.56)	(-2.42)	(10.72)