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MOMENTUM PROFITS AND MACROECONOMIC RISK

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ABSTRACT

Previous work shows that the growth rate of industrial production is a common macroeconomic risk factor in the cross-section of expected returns. We demonstrate the connection between momentum profits and shifts in factor loadings on this macroeconomic variable. Winners have temporarily higher loadings on the growth rate of industrial production than losers. The loading dispersion derives mostly from the high, positive loadings of winners. Depending on model specification, this loading dispersion can explain up to 40% of momentum profits.

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1 Introduction

This paper investigates the connection between macroeconomic risk and momentum profits (e.g., Jegadeesh and Titman (1993)). We focus on the growth rate of industrial production (MP hereafter) as a macroeconomic risk factor. This focus is motivated by Chen, Roll, and Ross (1986), who show that MP is a priced macroeconomic risk variable. Our use of MP and investigation of macroeconomic risk shifts for momentum portfolios are also motivated by the theoretical work of Johnson (2002). He argues that apparent momentum profits can merely reflect temporary increases in growth-related risk for winner-minus-loser portfolios.

Our central result is that winners have temporarily higher MP loadings than losers. In univariate regressions, the winner decile has a MP-loading of 0.47, much higher than that of the loser decile, -0.44, in the month after portfolio formation. Two additional features of the loading dispersion stand out. First, like momentum, it is temporary, as the two extreme deciles both have MP loadings of about 0.20 in month six after portfolio formation. Second, the dispersion is asymmetric. The first seven momentum deciles display little dispersion over the entire holding period, and the dispersion is mainly from deciles seven through ten. A battery of robustness checks confirm the statistical significance of this asymmetry.

The MP-loading dispersion between winners and losers is economically important. MP appears to be a priced risk factor, consistent with Chen, Roll, and Ross (1986). Depending on model specification, our estimated risk premium for the MP factor estimated from the Fama-MacBeth (1973) cross-sectional regressions ranges from 0.19% to 1.04% per month, and is often highly significant. As a result, the MP-loading dispersion can explain up to 40% of the momentum profits. Because momentum profits are distributed largely symmetrically across momentum portfolios, the asymmetric MP loadings can only partially explain momentum

profits. Not surprisingly, winner returns are better captured than loser returns.

Our findings are directly connected with the literature in several ways. First, our results contrast with Griffin, Ji, and Martin (2003). Using 11 years of monthly data, they find no difference in MP loadings between winners and losers. Our analysis uses data from 1960 through 2001, and our tests for risk shifts are also more extensive.

Second, a simple economic interpretation of a temporary MP-loading dispersion between winners and losers is provided by Johnson (2002). He argues that stock returns should be more sensitive to changes in expected growth when expected growth is high. If MP is a common factor summarizing firm-level changes of expected growth, then MP loadings should be high among stocks with high expected growth and low among stocks with low expected growth. Although we do not test his model here (see Liu, Warner, and Zhang (2004) for tests), we document that winners have temporarily higher average future growth rates of dividend, investment, and sales than losers, and that the duration of the expected-growth dispersion matches roughly that of the momentum profits.

Finally, our study is connected to other work on growth-related asset pricing and risk-based explanations of momentum. Chan, Chen, and Hsieh (1985) and Chen, Roll, and Ross (1986) first show that MP is a significantly priced risk factor. Vassalou (2003) uses a closely related variable, GDP growth rate, to price the size and book-to-market portfolios. Berk, Green, and Naik (1999) and Conrad and Kaul (1998) propose risk-based explanations of momentum. Recent papers testing risk based momentum explanations include Grundy and Martin (2001), Ahn, Conrad, and Dittmar (2003), Moskowitz (2003), Vassalou and Apedjinou (2003), and Bansal, Dittmar, and Lundblad (2004). Finally, Pastor and Stambaugh (2003) show that a liquidity risk factor accounts for half of momentum profits.

Section 2 describes the data. Section 3 presents evidence on MP loadings of momentum

portfolios, and examines to what extent these loadings explain momentum profits. Section 4 examines why there are risk shifts for momentum portfolios. Section 5 concludes.

2 Data

We obtain data on stock return, stock price, and shares outstanding from the Center for Research in Security Prices (CRSP) monthly return file. We use the common stocks listed on the NYSE, AMEX, and NASDAQ from January 1960 to December 2001 but exclude closed-end funds, real estate investment trust, American depository receipts, and foreign stocks. We also ignore firms with negative book values and use firms with only December fiscal yearend. Financial statement data such as book value of equity, investment expenditure, and earnings are from the Compustat merged annual and quarterly data files.

To construct momentum portfolios, we sort all stocks at the beginning of every month on the basis of their past six-month returns and hold the resulting ten portfolios for six months. All stocks are equally-weighted within each portfolio. To avoid microstructure bias, we skip one month between the end of the ranking period and the beginning of the holding period. This momentum strategy is profitable in our sample (not reported in tables). The average winner-minus-loser (WML) return is 0.85% per month with a significant t -statistic of 3.56. Standard factor models cannot explain momentum. The alpha of WML from the CAPM regression is 0.87% with a t -statistic of 3.61. And the alpha from the Fama-French (1993) three-factor model is 1.03% with a highly significant t -statistic of 4.25. Controlling for size and book-to-market factors thus deepens the momentum puzzle.

We primarily analyze factor loadings of momentum portfolios on MP. We define MP as $MP_t = \log IP_t - \log IP_{t-1}$, where IP_t is the index of industry production in month t from Federal Reserve Bank of St. Louis. From January 1960 to December 2001, the annualized

MP is on average 3.13% and its volatility is 2.66%.

To be consistent with Chen, Roll, and Ross (1986) and Griffin, Ji, and Martin (2003), we also use other macroeconomic factors. We define unexpected inflation, UI, and change of expected inflation, DEI, as $UI_t \equiv I_t - E[I_t|t-1]$ and $DEI_t \equiv E[I_{t+1}|t] - E[I_t|t-1]$, respectively. We measure the inflation rate from time $t-1$ to t as $I_t \equiv \log CPISA_t - \log CPISA_{t-1}$ where $CPISA_t$ is the seasonally adjusted Consumer Price Index at time t , from FRED. The expected inflation is $E[I_t|t-1] = r_{ft} - E[RHO_t|t-1]$, where r_{ft} is the risk-free rate from CRSP, and $RHO_t \equiv r_{ft} - I_t$ is the ex post real return on Treasury bills in period t .

We follow Fama and Gibbons (1984) to measure the ex ante real rate, $E[RHO_t|t-1]$. The difference between RHO_t and RHO_{t-1} is modeled as $RHO_t - RHO_{t-1} = u_t + \theta u_{t-1}$. Then $E[RHO_t|t-1] = (r_{ft-1} - I_{t-1}) - \hat{u}_t - \hat{\theta}\hat{u}_{t-1}$. We define the term premium, UTS, as the yield spread between the long-term and the one-year Treasury bonds. The government bond yields are from the Ibbotson database. Finally, we measure the default premium, URP, as the yield spread between Moody's Baa and Aaa corporate bonds. Data on the corporate bond yields are available from Federal Reserve Bank of St. Louis.

3 Macroeconomic Risk in Momentum Strategies

3.1 MP Loadings

Table 1 reports the estimated MP loadings of momentum deciles. Following Chen, Roll, and Ross (1986), we lead MP by one month to align the timing of macro and financial variables. Panel A uses MP as the single factor. The losers have an MP loading of 0.03, and the winners have an MP loading of 0.37. The hypothesis that all loadings are jointly zero is rejected (p -value = 0.03). But the hypothesis that MP loadings are equal across winners and losers cannot be rejected (p -value = 0.14).

From Panel A of Table 1, the dispersion in MP loadings is driven by the top winner deciles. Decile seven has a MP loading of 0.03, and the loading then rises monotonically to 0.37 for decile ten. In contrast, there is not much dispersion in MP loadings from deciles one to seven, as both deciles have a loading of 0.03. To assess this apparent asymmetric pattern, we perform a variety of tests for statistical significance. First, the MP loading of the winner portfolio is higher than the MP loading of the equally-weighted portfolio of momentum deciles one through nine (p -value = 0.03) or one through eight (p -value = 0.03). The equally-weighted portfolio of momentum deciles nine and ten has higher MP loading than the equally-weighted portfolio of momentum deciles one through eight (p -value = 0.03).

From Panel B of Table 1, controlling for the Fama-French (1993) three factors in the regressions reinforces the results in Panel A. Losers' loading stays at 0.03, but winners' loading rises slightly to 0.41. More important, winners' loading becomes significant (p -value = 0.01 in most comparisons). The hypothesis that all ten loadings are jointly zero is strongly rejected. The asymmetric pattern in loadings also persists. The loading rises from 0.01 to 0.41 going from decile seven to ten. There is again not much dispersion among deciles one to seven. Further, all of the tests for asymmetry confirm the strong asymmetric effects in MP loadings.

Finally, as shown in Panel C, the dispersion in MP loadings between winners and losers increases dramatically if we include the other four factors from Chen, Roll, and Ross (1986). These additional factors are unexpected inflation, change in expected inflation, term premium, and default premium. The last two rows of Table 1 show that, in the multiple regressions with the other Chen-Roll-Ross factors, the MP loading of the winners becomes 1.35 and that of the loser becomes -0.14. However, these loadings are also estimated with less precision. And the tests on the winners having higher MP loadings than the losers yield significant results only at the 10% significance level.

3.2 Time-Series Evolution of MP Loadings

Because the momentum portfolios used in Table 1 have a six-month holding period, the reported loadings are effectively averages over the six months. It is informative to see how these loadings evolve month-by-month after portfolio formation, and to see if they are temporary. We thus perform an event-time factor regression for each month after portfolio formation.

For each portfolio formation month t from January 1960 to December 2001, we calculate equally-weighted returns for all the ten momentum portfolios for $t+m$, where $m=0, 1, \dots, 12$. We then pool together across calendar time the observations of momentum portfolio returns, the Fama-French three factors, and the Chen-Roll-Ross factors for event month $t+m$. We then estimate the factor loadings using the pooled time series factor regressions.

Table 2 reports the MP loadings of momentum portfolios during the 13 months including and after the month of portfolio formation. The underlying model is the one-factor MP model. The results are dramatic. The first row in Panel A shows that, at the portfolio formation month, month zero, the loading rises almost monotonically from -0.44 for the loser portfolio to 0.47 for the winner portfolio. From the tests reported in the first row of Panel B, the winner portfolio has a reliably higher loading than the loser portfolio, the equally-weighted portfolio of momentum deciles one to eight, and the equally-weighted portfolio of deciles one to nine. Further, the equally-weighted portfolio of the top two winner deciles has a reliably higher loading than the equally-weighted portfolio of deciles one to eight.

The next three rows of Panel A in Table 2 show that the negative MP loading of the loser portfolio increases rapidly from -0.44 in month zero to -0.04 in month three. But the positive loading of the winner portfolio remains at the steady level of 0.50. And the tests reported in the corresponding rows of Panel B again show that the winner portfolio has a

reliably higher MP loading than the rest of the momentum deciles.

The MP loading of the loser portfolio continues to rise from month three to month six. In the meantime, the loading of the winner portfolio starts to decline rapidly. By month six, the dispersion in the MP loading converges as both the winner and the loser portfolios have MP loadings of about 0.20. And from the remaining rows of Table 2, the loser portfolio has mostly higher MP loadings than the winner portfolio in the remaining months.

Adding the Fama-French factors or the other four Chen-Roll-Ross factors into the factor regression yields similar patterns of MP loadings. Figure 1 reports the event-time MP loadings from the one-factor MP model, the four-factor model including the Fama-French three factors and MP, and the Chen-Roll-Ross five-factor model. To avoid redundancy with Table 2, we report the MP loadings for the winner and loser quintiles, instead of deciles.

Comparing Panel A of Figure 1 with Panel A of Table 2 shows that using quintiles instead of deciles reduces somewhat the dispersion in MP loadings between the loser and the winner portfolios. But the basic pattern remains unchanged. More important, Panels B and C of Figure 1 show that using the two alternative factor structures does not change the pattern of MP loadings. The winner portfolio continues to have disproportionately higher MP loadings than the loser portfolio. And the dispersion is temporary, as it converges around month six or seven after portfolio formation.

3.3 Alternative Momentum Strategies

So far we have shown that winners have asymmetrically higher MP loadings than losers using the six-six momentum construction that sorts stocks based on their prior six-month returns and holds the resulting portfolios for six months. This central result is robust to the general $J \setminus K$ construction of momentum strategies, i.e., sorting stocks based on their prior

J -month returns and holding the resulting portfolios for K months. Further, the economic and statistical significance of the result increases with the holding period K , but is basically unaffected by the sorting period J .

Table 3 reports the results. To save space, we only display the MP loadings for the zero-cost portfolio that buys the equally-weighted portfolio of the top two winner deciles and sells that of the other eight deciles. This design of the winner-minus-loser portfolio captures the asymmetry in MP loadings. We also report the p -values of the one-sided tests that the MP loadings for these asymmetric winner-minus-loser portfolios are equal to or less than zero.

From the first two rows of Panel A in Table 3, the one-factor MP loading of the asymmetric winner-minus-loser portfolio from the 12\12 momentum construction is 0.11 and its one-sided p -value is an insignificant 26%. Reducing the holding period K raises the magnitude of the loading from 0.11 when $K = 12$ to 0.30 when $K = 3$, and further to 0.36 when $K = 1$. The pattern that the loading decreases with the holding period also applies with alternative sorting periods J . And from Panels B and C, adding the Fama-French factors or the Chen-Roll-Ross factors into the factor regressions yields quantitatively similar results.

3.4 Momentum Profits and MP Loadings

A natural question is what percentage of momentum profits the MP-loading dispersion can explain. Depending on specific factor model, the MP loadings can explain up to 40% of the momentum profits. Not surprisingly, winner returns are better captured than loser returns.

Our test design follows that of Griffin, Ji, and Martin (2003, Table III). For each month t , we sort stocks into deciles based on their performance over the six months $t-7, \dots, t-2$. The momentum strategy, WML, buys the winner decile and sells the loser decile and holds these positions for the six months $t, \dots, t+5$. To calculate what percentage of momentum

profits the one-factor MP model can explain, we first estimate the unconditional loadings of WML on the factor by fitting the following regressions:

$$\text{WML}_t = \alpha + \beta_{\text{MP}} \text{MP}_t + \epsilon_t \quad (1)$$

Estimates of expected momentum profits from the one-factor model are given by

$$\text{E}[\text{WML}_t] = \hat{\beta}_{\text{MP}} \hat{\gamma}_t^{\text{MP}} \quad (2)$$

where $\hat{\beta}_{\text{MP}}$ is the MP loading estimated from fitting regression (1), and $\hat{\gamma}_t^{\text{MP}}$ is the estimated risk premium associated with MP in month t . The percentage of momentum profits that the model can explain is then $\text{E}[\text{WML}_t] / \overline{\text{WML}}$, where $\overline{\text{WML}}$ is the average return of WML.

Before calculating $\text{E}[\text{WML}_t]$ in equation (2), we need to estimate the risk premium $\hat{\gamma}_t^{\text{MP}}$. Following Chen, Roll, and Ross (1986) and Griffin, Ji, and Martin (2003), we estimate the risk premium by using the Fama and MacBeth (1973) technique on a set of portfolios with a wide spread in expected returns. For this purpose, we use the 100 size and book-to-market portfolios available from Kenneth French's website.¹ For each portfolio p , we regress its returns onto MP using a 60-month rolling window to obtain a time series of factor loadings, $\hat{\beta}_{pt}$. We then fit the cross-sectional regressions of returns onto the factor loadings:

$$r_{pt+1} = \gamma_t^0 + \gamma_t^{\text{MP}} \hat{\beta}_{pt} + \epsilon_{pt+1} \quad (3)$$

The estimated slope $\hat{\gamma}_t^{\text{MP}}$ provides the risk premium needed in equation (2).

The first two rows of Table 4 report the results from the one-factor MP model. The MP risk premium is on average 1.04% per month with a highly significant t -statistic of 5.97

¹Griffin, Ji, and Martin (2003) use the 25 size and book-to-market portfolios for the same purpose. But the 100 size and book-to-market portfolios provide a wider cross-sectional dispersion in expected returns.

estimated from the one-factor model. Combined with a MP loading of 0.33 for WML, the one-factor MP model predicts an average momentum profit of 0.34% per month. The realized WML return is on average 0.85% per month from January 1960 to December 2001, suggesting that the risk-based one-factor model can explain about 40% of the momentum profits. But the average difference in returns between the realized and the predicted momentum profits remains significant with a t -statistic of 2.07.

From the next two rows in Table 4, using the Fama-French three factors in addition to MP does not change the results. The risk premium of MP estimated from this four-factor structure in equation (3) is on average 0.68% per month with a t -statistic of 4.08. The MP loading of WML rises slightly to 0.38 relative to that from the one-factor model. And WML has negative loadings on all the Fama-French three factors. The four-factor model predicts an average momentum profit of 0.32% per month that is about 38% of the realized momentum profits. But the difference stays significant with a t -statistic of 2.18.

The remaining rows of Table 4 show that, consistent with Griffin, Ji, and Martin (2003), using the other Chen-Roll-Ross factors besides MP cannot explain much of the momentum profits. The full-blown Chen-Roll-Ross model actually predicts a negative average momentum profit of -0.05% per month. Two reasons are behind this result. The MP risk premium estimated from using the Chen-Roll-Ross specification in equation (3) is only an insignificant 0.19% per month. Further, WML loads negatively on a number of the Chen-Roll-Ross factors that earn positive risk premiums.

Specifically, the loadings of WML on the change in expected inflation (DEI) and the term premium (UTS) are -0.38 and -0.44, respectively. But DEI earns a positive risk premium of 0.05% per month with a t -statistic of 0.78. More important, UTS earns a positive risk premium of 0.30% with a significant t -statistic of 3.43. Dropping the default premium (UPR)

from the factor model as in Griffin, Ji, and Martin (2003) improves the results somewhat.² The reason is that the average risk premium associated with MP goes back to the significant level of 0.65% per month. As a result, the factor model predicts an average momentum profit of 0.17% per month, which is about 20% of the average realized momentum profit.

Figure 2 reports more detailed evidence on the average returns of winners and losers and their counterparts predicted from various models. From Panel A, the one-factor MP model over-predicts the average return of losers by about 0.20% per month, but under-predicts that of winners by about 0.30%. From Panel B, the Fama-French model augmented with MP over-predicts the average return of losers by about 0.73%, but only over-predicts that of winners by 0.20%. Finally, Panel C shows that the Chen-Roll-Ross model over-predicts the average return of losers by 0.50% per month but under-predicts that of winners by 0.40%. Overall, the models seem to do a better job in explaining winner returns than loser returns.

As an additional test, not reported in Table 4, we examine how momentum profits (defined simply as decile ten minus decile one returns) line up with the month-by-month temporary factor loading shifts shown in Table 2. Momentum profits also display a temporary pattern, but their duration is much longer than that of the MP-loading dispersion. In the first month of the holding period, the average winner-minus-loser return is 0.73% per month. This average return remains at roughly 0.70% through month seven, then drops to 0.05% in month ten and further to -0.89% by month 12. Neither winner nor loser returns show much variability over months one through six. These results make it difficult to argue that momentum returns are entirely due to risk shifts.

²Griffin, Ji, and Martin (2003) do not include the default premium into their factor model because of data restrictions in international applications.

4 Fundamentals and MP Loadings

What are the economic forces driving the MP-loading dispersion across momentum portfolios? A complete investigation is beyond the scope of this paper. However, some guidance is provided by the theoretical model of Johnson (2002), who argues that the log price-dividend ratio is a convex function of expected growth.³ From the convexity, changes of log price-dividend ratio or stock returns are more sensitive to changes in expected growth when expected growth is high.⁴ If MP is a priced factor summarizing common changes in expected growth, and if winners have higher expected growth than losers, then our results that winner returns are more sensitive to shocks to MP than loser returns would be expected.

This section reports descriptive statistics on the cross-sectional relation between momentum portfolios and economic fundamentals, specifically expected growth. The results show that winners have temporarily higher expected growth than losers. The evidence establishes a potentially important link between growth-related risk and momentum.

4.1 Procedure

Besides dividend growth, we also use investment growth and sales growth. Shocks to aggregate and firm-level profitabilities are typically reflected in large movements of investment and sales, rather than the relatively smooth dividends. Investment growth and sales growth are therefore more likely to contain useful pricing information than dividend growth.

Stock returns are observable monthly and momentum involves monthly rebalancing. But accounting variables such as investment and dividend are available at quarterly or annual

³Sagi and Seasholes (2005) present a model with similar economic insights on the importance of convexity in understanding the sources of momentum profits. Pastor and Veronesi (2003, 2005) use the same convexity property to explain the high stock valuation levels.

⁴The intuition can be seen in the Gordon growth model, i.e., $P = D/(k - g)$ where P is stock price, D is dividend, k is discount rate, g is expected dividend growth, and $k > g$. Let $U = P/D$ be the price dividend ratio. Simple algebra yields $\partial \log U / \partial g = 1/(k - g)$, which increases with g because $\partial^2 \log U / \partial g^2 > 0$.

frequency. We obtain monthly measures of these flow variables by dividing their current year annual observations by 12 and their current quarterly observations by three. Each month after ranking all stocks on their past six-month returns, we aggregate the fundamentals for the individual stocks held in that month in each portfolio to obtain the fundamentals at the portfolio level. Although a crude adjustment, this method takes into account monthly changes in stock composition of momentum strategies.⁵

We also study how the average growth rates evolve before and after portfolio formation. For each month t from January 1965 to December 2001, we calculate the growth rates for $t+m$, where $m = -36, \dots, 36$. We then average the growth rates for $t+m$ across portfolio formation months, thus capturing average growth rates for three years before and three years after the portfolio formation. We obtain financial statement data from Compustat quarterly files. Using quarterly rather than annual data better illustrates the month-to-month evolution of growth rate measures before and after portfolio formation.⁶

Finally, to see if future growth rates of momentum portfolios are predictable, we perform Fama and MacBeth (1973) cross-sectional regressions of future growth rates onto past returns. Because some firm-year observations have zero dividend and zero or even negative capital investment, the usual definition of growth rates are not meaningful at the firm-level. Instead, we measure firm-level growth by normalizing changes of dividend, investment, and sales by beginning-of-period book value. To adjust standard errors for the resultant persistence in the slope coefficients, we follow Pontiff (1996) by regressing the time-series of slope coefficients on an intercept term and modeling the residuals as a sixth-order

⁵We have tried to measure the portfolio fundamentals at the end of a quarter or a year. All the flow and stock variables are then current quarterly or annual observations. This method avoids the ad hoc adjustment from low-frequency flow to monthly flow variables, but it ignores the monthly changes of stock composition within a quarter or a year. However, this method yields quantitatively similar results (not reported).

⁶We have also used Compustat merged annual files and obtained similar results (not reported).

autoregressive process. We then use the standard error of the intercept term as the corrected standard error in constructing the Fama-MacBeth t -statistics.

4.2 Results

Table 5 reports descriptive statistics on dividend growth, investment growth and sales growth for momentum deciles from July 1965 to December 2001. The starting period is chosen to avoid Compustat selection bias in earlier periods. Winners have much higher average growth rates than losers, and the spreads are highly significant. The dividends of winners grow at an annual rate of 18%, while the dividends of loser stocks fall at a rate of 12%. Wide spreads between winners and losers are also evident for other growth rates. Regarding the time series of growth variables and profitability, with a few exceptions, winners have higher growth rates and profitability than losers in almost every year in the sample (not reported).

Figure 3 reports average growth rates before and after portfolio formation. From Panels A to C, momentum displays temporary shifts in expected growth rates. At the month of portfolio formation, the growth-rate dispersions between winners and losers are sizable: 11% in dividend growth, 22% in investment growth, and 5% per quarter in sales growth. The dispersions converge in about ten to 20 months before and, more importantly, 15 to 20 months after the month of portfolio formation. The durations of the growth-rate dispersions thus match roughly the duration of momentum profits.

From Table 6, past six- to 12-month returns are significantly positive predictors of future one-year and two-year growth rates. The slopes on past returns are all positive and highly significant. This result also holds after we control for the lagged values of growth rates. The average R^2 ranges from 1–6.5%, depending on whether lagged growth rates are used.

Our evidence contrasts with Chan, Karceski, and Lakonishok (2003), who conclude that:

“Contrary to the conventional notion that high past returns signal high future growth, the coefficient of [past returns] is negative (p. 681).” Our results differ because Chan et al. regress future growth rates onto past six-month returns along with eight other explanatory variables. Some regressors such as earnings-to-price, book-to-market, and dividend yield are highly correlated with stock returns contemporaneously. To generate a cleaner picture, we instead focus on univariate regressions of future growth rates onto past returns.

5 Conclusion

Momentum winners have temporarily higher loadings on the growth rate of industrial production than momentum losers. The loading dispersion is mainly driven by winner deciles. Depending on model specification, the loading dispersion can account for up to 40% of the momentum profits. This evidence suggests that risk plays a role in driving momentum.

There are unresolved issues, however. Why do risk shifts occur for winners, but not for losers? Why does the duration of risk shifts for momentum portfolios not match the duration of their returns? A better understanding of these issues would provide insights into the relation between time-varying expected growth, growth-related risk, and expected returns.

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Table 1 : Factor Loadings of Ten Momentum Portfolios on the Growth Rate of Industrial Production

This table reports the results from monthly regressions using returns on ten momentum deciles. The sample is from January 1960 to December 2001. The regression equations in Panels A to C are, respectively, $r_{it+1} = a_i + b_i \text{MP}_{t+1} + \epsilon_{it+1}$, $r_{it+1} = a_i + b_i \text{MP}_{t+1} + c_i \text{MKT}_{t+1} + s_i \text{SMB}_{t+1} + h_i \text{HML}_{t+1} + \epsilon_{it+1}$, and $r_{it+1} = a_i + b_i \text{MP}_{t+1} + c_i \text{UI}_{t+1} + d_i \text{DEI}_{t+1} + e_i \text{UTS}_{t+1} + f_i \text{UPR}_{t+1} + \epsilon_{t+1}$, where MKT, SMB, and HML are Fama-French three factors. The Chen, Roll and Ross (1986) five factors are MP (growth rate of industrial production), UI (unexpected inflation), DEI (change in expected inflation), UTS (term premium), and UPR (default premium). The left panel reports the loadings, b_i , on MP and their t -statistics, and the right panel reports p -values from five hypothesis tests. The first p -value is for the Wald test on $b_L = b_2 = \dots = b_W$, where L (loser) and W (winner) denote momentum deciles one and ten, respectively. The second p -value is for the one-sided t -test of $b_W \leq b_{L \sim 9}$, where $b_{L \sim 9}$ is the factor loading on the equally-weighted portfolio of momentum deciles one to nine. The third p -value is for the one-sided t -test of $b_W \leq b_{L \sim 8}$, where $b_{L \sim 8}$ is the factor loading on the equally-weighted portfolio return of momentum deciles one to eight. The fourth p -value is for the one-sided t -test on $b_{9 \sim W} \leq b_{L \sim 8}$, where $b_{9 \sim W}$ is the factor loading on the equally-weighted portfolio return of momentum deciles nine and ten. The last column reports the p -value for the t -test $b_W \leq b_L$. Following Chen, Roll and Ross (1986), we lead the growth rate of industrial production by one period. The t -statistics are adjusted for heteroscedasticity and autocorrelations of up to 12 lags using GMM.

19

Factor loadings											p -values from hypothesis tests				
	L	2	3	4	5	6	7	8	9	W	$b_L = \dots = b_W$	$b_W \leq b_{1 \sim 9}$	$b_W \leq b_{L \sim 8}$	$b_{9 \sim W} \leq b_{L \sim 8}$	$b_W \leq b_L$
Panel A: Loadings on MP from $r_{it+1} = a_i + b_i \text{MP}_{t+1} + \epsilon_{it+1}$															
f_i	0.03	-0.01	-0.04	-0.10	-0.08	-0.03	0.03	0.12	0.21	0.37					
t_f	0.06	-0.02	-0.09	-0.28	-0.25	-0.08	0.10	0.40	0.62	0.98	0.03	0.03	0.03	0.03	0.14
Panel B: Loadings on MP from $r_{it+1} = a_i + b_i \text{MP}_{t+1} + c_i \text{MKT}_{t+1} + s_i \text{SMB}_{t+1} + h_i \text{HML}_{t+1} + \epsilon_{it+1}$															
f_i	0.03	-0.03	-0.07	-0.13	-0.11	-0.06	0.01	0.11	0.21	0.41					
t_f	0.11	-0.16	-0.48	-1.31	-1.63	-1.06	0.09	1.44	1.95	2.68	0.00	0.01	0.01	0.01	0.11
Panel C: Loadings on MP from $r_{it+1} = a_i + b_i \text{MP}_{t+1} + c_i \text{UI}_{t+1} + d_i \text{DEI}_{t+1} + e_i \text{UTS}_{t+1} + f_i \text{UPR}_{t+1} + \epsilon_{t+1}$															
f_i	-0.14	-0.01	0.00	-0.05	-0.02	0.03	0.08	0.15	0.21	1.35					
t_f	-0.26	-0.02	0.00	-0.16	-0.07	0.10	0.26	0.49	0.61	1.61	0.05	0.09	0.08	0.07	0.10

Table 2 : Factor Loadings of Ten Momentum Portfolios on the Growth Rate of Industrial Production from the One-Factor Model for Each Month After Portfolio Formation

For each portfolio formation month t from January 1960 to December 2001, we calculate the equally-weighted returns for ten momentum deciles for $t+m$, where $m=0, \dots, 12$. Month 0 denotes the month immediately following portfolio formation. The left panel reports the factors loadings, b_i , from the regression equation $r_{it+1} = a_i + b_i \text{MP}_{t+1} + \epsilon_{it+1}$. The loadings are computed from the pooled time series regressions for a given event month. The right panel reports p -values from five hypotheses tests. The first p -value is associated with the Wald test on $b_L = b_2 = \dots = b_W$, where b_L and b_W denote the loadings of momentum deciles one and ten, respectively. The second p -value is for the one-sided t -test of $b_W \leq b_{L\sim 9}$, where $b_{L\sim 9}$ is the factor loading of the equally-weighted portfolio of momentum deciles one to nine. Similarly, the third p -value is for the one-sided t -test of $b_W \leq b_{L\sim 8}$, where $b_{L\sim 8}$ is the factor loading of the equally-weighted portfolio of momentum deciles one to eight. The fourth p -value is for the one-sided t -test of $b_{9\sim W} \leq b_{L\sim 8}$, where $b_{9\sim W}$ is the factor loading of the equally-weighted portfolio of momentum deciles nine and ten. And the last column reports the p -value for the t -test of $b_W \leq b_L$.

20

Panel A: Factor loadings											Panel B: p -values from hypothesis tests				
Month	L	2	3	4	5	6	7	8	9	W	$b_L = \dots = b_W$	$b_W \leq b_{L\sim 9}$	$b_W \leq b_{L\sim 8}$	$b_{9\sim W} \leq b_{L\sim 8}$	$b_W \leq b_L$
0	-0.44	-0.18	-0.10	-0.02	-0.06	0.12	0.12	0.24	0.28	0.47	0.07	0.03	0.03	0.02	0.02
1	-0.14	-0.15	0.00	-0.04	-0.06	-0.03	0.05	0.16	0.28	0.39	0.05	0.04	0.04	0.03	0.09
2	-0.06	-0.07	-0.10	-0.05	-0.08	-0.06	0.01	0.19	0.23	0.44	0.08	0.02	0.02	0.03	0.09
3	-0.04	0.03	-0.10	-0.16	-0.13	-0.03	0.09	0.18	0.18	0.50	0.00	0.01	0.01	0.02	0.07
4	0.08	0.06	0.04	-0.18	-0.09	-0.01	-0.02	0.10	0.20	0.37	0.00	0.04	0.04	0.04	0.19
5	0.17	0.05	0.00	-0.07	-0.08	-0.07	0.02	0.06	0.17	0.33	0.70	0.06	0.06	0.07	0.29
6	0.20	0.03	-0.06	-0.10	-0.05	0.05	0.03	0.05	0.18	0.21	0.18	0.19	0.18	0.13	0.49
7	0.16	0.09	-0.10	-0.04	0.00	0.02	-0.01	0.00	0.14	0.26	0.06	0.12	0.12	0.12	0.35
8	0.19	0.11	-0.05	-0.04	-0.10	-0.01	0.11	0.11	0.00	0.18	0.01	0.24	0.26	0.39	0.51
9	0.23	0.02	-0.01	-0.04	-0.02	0.02	0.03	0.02	0.08	0.14	0.93	0.31	0.31	0.33	0.64
10	0.13	0.08	0.05	-0.17	0.01	0.02	0.02	0.01	0.13	0.14	0.00	0.29	0.29	0.25	0.49
11	0.21	0.09	-0.01	-0.09	-0.01	-0.04	0.06	-0.05	0.21	0.08	0.00	0.43	0.39	0.22	0.69
12	0.27	0.14	0.02	0.00	-0.03	-0.05	-0.01	0.08	-0.04	0.05	0.20	0.49	0.51	0.62	0.80

Table 3 : Loadings of Top Quintile Less Bottom Four Quintiles on the Growth Rate of Industrial Production

This table reports the factor loadings on the growth rate of industrial production of the momentum strategy that buys the equally-weighted portfolio of momentum deciles nine and ten and sells the equally-weighted portfolio of momentum deciles one to eight. We use three regression models including the one-factor MP model; the Fama-French three-factor model augmented with MP; and the Chen-Roll-Ross (1986) model with five factors. These factors are the growth rate of industrial production (MP), unexpected inflation (UI), change in expected inflation (DEI), and term premium (UTS), and the default premium (UPR). In constructing momentum portfolios, we vary the sorting period J and the holding period K . The J - K -strategy generates ten momentum portfolios by sorting on the prior J -month compounded returns and then holding the resulting portfolios in the future K months. The rows indicate different sorting periods and the columns indicate different holding periods. The p -values of the one-sided tests that the factor loadings are equal to or less than zero are reported in parentheses.

Panel A: The One-Factor Model						Panel B: Fama-French + MP						Panel C: The Chen-Roll-Ross Model					
$J \backslash K$	12	9	6	3	1	$J \backslash K$	12	9	6	3	1	$J \backslash K$	12	9	6	3	1
12	0.11 (0.26)	0.15 (0.19)	0.21 (0.12)	0.30 (0.06)	0.36 (0.04)	12	0.19 (0.08)	0.23 (0.06)	0.29 (0.04)	0.37 (0.02)	0.42 (0.01)	12	0.06 (0.27)	0.11 (0.28)	0.16 (0.20)	0.25 (0.11)	0.31 (0.07)
9	0.16 (0.16)	0.20 (0.12)	0.27 (0.06)	0.36 (0.03)	0.45 (0.02)	9	0.22 (0.04)	0.26 (0.03)	0.33 (0.02)	0.41 (0.01)	0.49 (0.01)	9	0.11 (0.26)	0.14 (0.21)	0.21 (0.12)	0.31 (0.06)	0.39 (0.04)
6	0.19 (0.09)	0.23 (0.06)	0.30 (0.03)	0.36 (0.02)	0.36 (0.03)	6	0.24 (0.02)	0.28 (0.02)	0.34 (0.01)	0.40 (0.01)	0.40 (0.02)	6	0.14 (0.17)	0.18 (0.12)	0.25 (0.07)	0.33 (0.04)	0.31 (0.07)
3	0.19 (0.05)	0.23 (0.03)	0.27 (0.03)	0.34 (0.02)	0.37 (0.02)	3	0.23 (0.01)	0.26 (0.01)	0.30 (0.01)	0.37 (0.01)	0.39 (0.01)	3	0.14 (0.11)	0.19 (0.07)	0.23 (0.06)	0.31 (0.03)	0.31 (0.47)

Table 4 : Explaining Momentum Profits Using Risk Exposures and the Risk Premium ($\hat{\gamma}^{\text{MP}}$) on the Growth Rate of Industrial Production

We report the factor loadings and their corresponding t -statistics (in parentheses) of WML on the growth rate of industrial production, MP, with and without controlling for the Fama-French (1993) three factors and the other Chen-Roll-Ross (1986) four factors. The other Chen-Roll-Ross factors include unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR). More important, we also report the average expected momentum profits, $E(\text{WML}_t) = \sum_i \hat{\beta}_i \hat{\gamma}_{it}$ where $\hat{\beta}_i$ is the factor loading for factor i and $\hat{\gamma}_{it}$ is its associated risk premium that we estimate using the Fama-MacBeth (1973) regressions with the Fama-French 100 size and book-to-market portfolios. Finally, we also report the average risk premium for the MP factor, denoted $\hat{\gamma}^{\text{MP}}$, the average WML return in the sample, denoted $\overline{\text{WML}}$, the average of the expected momentum profits, denoted $E(\text{WML})$, the percentage of momentum profits that the factor models can explain, $E(\text{WML})/\overline{\text{WML}}$, and the t -statistics for the difference between WML and $E(\text{WML})$. All t -statistics are adjusted for heteroscedasticity and autocorrelations of up to six lags. The sample goes from January 1960 to December 2001.

22

Factor Loadings								Pricing Results				
UI	DEI	UTS	UPR	MKT	SMB	HML	MP	$\hat{\gamma}^{\text{MP}}$	$E(\text{WML})$	$\overline{\text{WML}}$	$E(\text{WML})/\overline{\text{WML}}$	$t(\text{DIFF})$
							0.33 (1.07)	1.04% (5.97)	0.34%	0.85%	40%	2.07
				-0.03 (-0.54)	-0.38 (-4.82)	-0.28 (-3.13)	0.38 (1.22)	0.68% (4.08)	0.32%	0.85%	38%	2.18
0.14 (0.09)	-0.38 (-0.09)	-0.44 (-2.28)	-0.03 (-0.05)				0.44 (1.31)	0.19% (1.40)	-0.05%	0.85%	—	3.96
0.15 (0.09)	-0.37 (-0.09)	-0.44 (-2.30)					0.44 (1.36)	0.65% (4.51)	0.17%	0.85%	20%	2.79

Table 5 : Descriptive Statistics for Subsequent Annual Growth Rates of Momentum Portfolios

This table reports the mean m and volatility σ of dividend growth, investment growth, and sales growth for ten momentum portfolios. The mean and volatility are all annualized. The t -statistics in the last column are for testing the average spread in growth rates between the winner and loser portfolios equals zero. All the t -statistics are adjusted for heteroscedasticity and autocorrelations up to six lags. Accounting variables are from the Compustat annual files. Investment is capital expenditure from cash flow statement (item 128); dividend is common stock dividends (item 21); and sales are net sales (item 12). The sample period is from 1965 to 2001, and the starting point is chosen to avoid sample selection bias.

	Loser	2	3	4	5	6	7	8	9	Winner	Spread	t_{Spread}
Panel A: Dividend Growth												
m	-0.12	0.00	0.04	0.06	0.07	0.08	0.08	0.11	0.14	0.18	0.30	4.50
σ	0.27	0.12	0.07	0.05	0.06	0.05	0.07	0.08	0.15	0.34	0.42	
Panel B: Investment Growth												
m	-0.08	0.03	0.06	0.08	0.08	0.11	0.12	0.16	0.20	0.33	0.41	9.53
σ	0.16	0.13	0.12	0.11	0.12	0.14	0.18	0.20	0.18	0.27	0.27	
Panel C: Sales Growth												
m	0.03	0.06	0.07	0.08	0.09	0.09	0.10	0.12	0.14	0.18	0.15	10.69
σ	0.08	0.07	0.06	0.06	0.07	0.06	0.06	0.07	0.07	0.10	0.09	

Table 6 : Cross-Sectional Regressions of Growth Rates on Past Returns

This table reports the annual cross-sectional regressions of future dividend growth, investment growth, and sales growth onto past six-month return $r_{t-5,t}$ and past 12-month return $r_{t-11,t}$ with and without controlling for an autoregressive term. We consider one-year-ahead ($\tau=12$) and two-year-ahead ($\tau=24$) growth rates. The Fama-MacBeth (1973) t -statistics adjusted for serial correlations in the slope coefficients (e.g., Pontiff (1996)) are reported in parentheses. Because some firms have zero or negative dividend and investment, we measure growth rates by normalizing changes in dividend, investment, and sales (denoted $\Delta D, \Delta I$, and ΔS , respectively) by book value (denoted B). Accounting variables are from the Compustat annual files. Investment is capital expenditure from cash flow statement (item 128); dividend is common stock dividends (item 21); sales are net sales (item 12); and book value is from common equity (item 60) plus deferred taxes (item 74). The sample is from 1965 to 2000 with 36 cross-sections when $\tau=12$ and from 1965 to 1999 with 35 cross-sections when $\tau=24$. The average R^2 values are in percent.

24

Horizon	Panel A: Predicting $\Delta D_{t,t+\tau}/B_t$				Panel B: Predicting $\Delta I_{t,t+\tau}/B_t$				Panel C: Predicting $\Delta S_{t,t+\tau}/B_t$			
	$r_{t-5,t}$	$r_{t-11,t}$	$\Delta D_{t-12,t}/B_{t-12}$	$R^2(\%)$	$r_{t-5,t}$	$r_{t-11,t}$	$\Delta I_{t-12,t}/B_{t-12}$	$R^2(\%)$	$r_{t-5,t}$	$r_{t-11,t}$	$\Delta S_{t-12,t}/B_{t-12}$	$R^2(\%)$
$\tau=12$	0.044			1.27	0.620			1.67	1.825			0.90
	(3.42)				(5.80)				(4.84)			
		0.063		1.06		1.165		1.61		4.50		1.32
		(3.36)				(8.50)				(7.43)		
	0.039		-0.051	6.36	0.658		-0.041	6.53	1.645		0.098	3.25
	(2.34)		(-0.70)		(4.95)		(-0.75)		(4.42)		(3.81)	
		0.059	-0.050	6.04		1.065	-0.046	6.72		3.124	0.093	3.43
		(2.53)	(-0.69)			(7.44)	(-0.84)			(5.56)	(3.64)	
$\tau=24$	0.075			1.62	0.615			1.55	2.982			0.90
	(8.77)				(1.65)				(3.40)			
		0.088		1.50		1.444		1.46		7.964		1.40
		(6.49)				(3.67)				(6.34)		
	0.074		0.012	4.54	0.885		-0.103	4.00	2.364		0.154	3.16
	(9.87)		(0.18)		(2.75)		(-2.02)		(3.41)		(3.12)	
		0.085	0.013	4.43		1.261	-0.109	4.17		5.626	0.146	3.36
		(6.61)	(0.20)			(5.43)	(-2.08)			(6.39)	(3.00)	

Figure 1 : Event-Time Factor Loadings on the Growth Rate of Industrial Production

For each portfolio formation month t from January 1960 to December 2001, we calculate the equally-weighted returns for winner and loser quintiles for month $t+m$, where $m=0, 1, \dots, 18$. The graphs plot the factor loadings on the growth rate of industrial production (MP) from three regression models including the one-factor MP model; the Fama-French three-factor model augmented with MP; and the Chen-Roll-Ross (1986) model with MP, unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR). The loadings are calculated from the pooled time series regressions for a given event month.

25

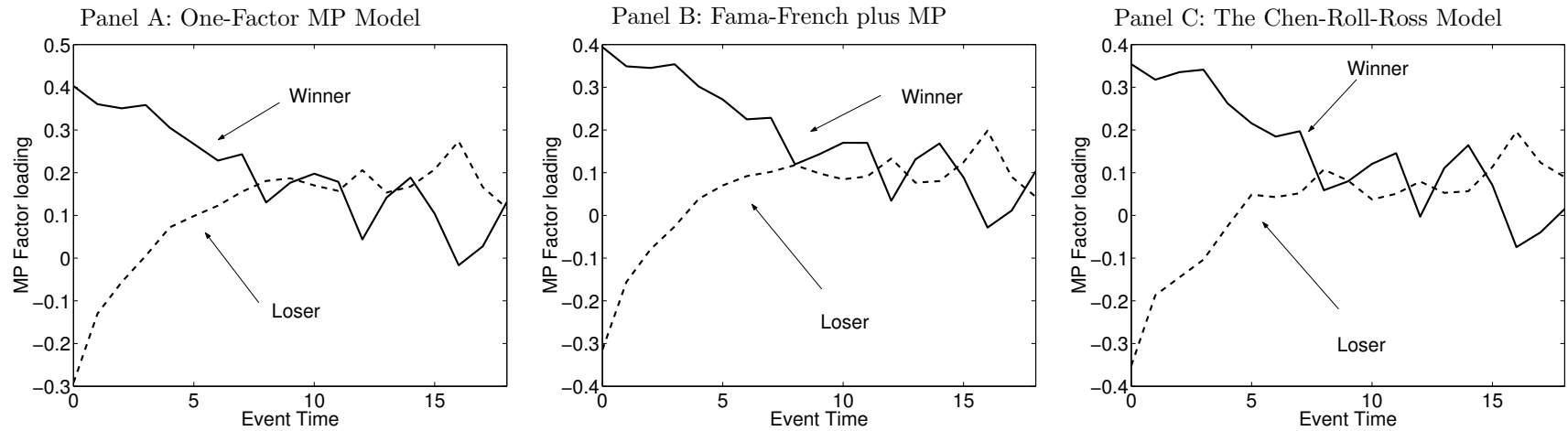


Figure 2 : Explaining Average Returns of Momentum Portfolios Using Risk Exposures on the Growth Rate of Industrial Production

We report the bar plots for the average realized returns of winners and losers (the white bars) along with their average predicted returns (the black bars) from various factor models. These models include the one-factor MP model (Panel A), the Fama-French (1993) three-factor model augmented with MP (Panel B), and the Chen-Roll-Ross five-factor model (Panel C). Besides the growth rate of industrial production (MP), the other Chen-Roll-Ross factors are unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR). We calculate the average predicted portfolio returns as $\sum_i \hat{\beta}_i \hat{\gamma}_{it}$, where $\hat{\beta}_i$ is the factor loading for factor i and $\hat{\gamma}_{it}$ is its associated risk premium that we estimate using the Fama-MacBeth (1973) cross-sectional regressions with the Fama-French 100 size and book-to-market portfolios. The average returns are in percent per month. The sample goes from January 1960 to December 2001.

26

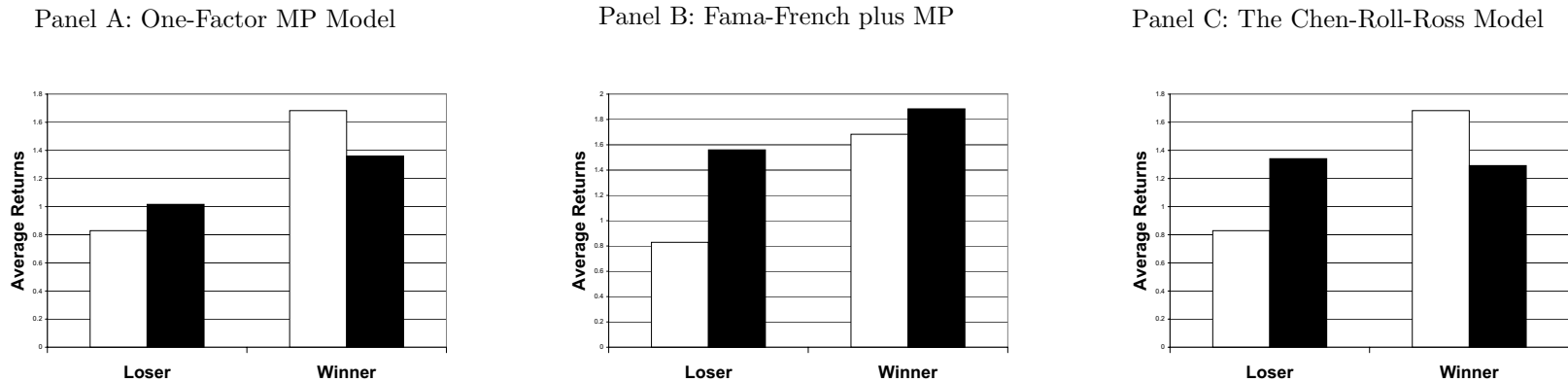


Figure 3 : Quarterly Growth Rates and Profitability of Winner and Loser Portfolio in Event Time (36 Months Before and After Portfolio Formation)

For each portfolio formation month from $t = \text{July 1965}$ to December 2001, we calculate growth rates and return on equity for $t+m, m = -36, \dots, 36$ for all the stocks in each portfolio. The measures for $t+m$ are then averaged across portfolio formation months. To construct price momentum portfolios, at the beginning of every month, we rank stocks on the basis of past six-month returns and assign the ranked stocks to one of ten decile portfolios. All stocks are equally-weighted within a given portfolio. We obtain dividend from Compustat quarterly item 20, sales from item two, and investment from item 90. For capital investment, Compustat quarterly data begin at 1984, so we use the sample from 1984 to 2001 for investment growth. To capture the effects of monthly changes in stock composition of winner and loser portfolios, we continue to dividend quarter dividend, earnings, investment, and sales data by three to obtain monthly observations. We exclude firm/month observations with negative book values.

27

