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Abstract

We study the connection between momentum portfolio returns and shifts in factor loadings on the growth rate of industrial production. Winners have temporarily higher loadings than losers. The loading spread derives mostly from the high, positive loadings of winners. Small stocks have higher loadings than big stocks, and value stocks have higher loadings than growth stocks. Using standard multifactor tests, we present evidence that the growth rate of industrial production is a priced risk factor. In most of our tests, however, the combined effect of factor pricing and risk shifts does not explain a large fraction of momentum returns.

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1 Introduction

This paper investigates the connection between macroeconomic risk, factor pricing, and momentum profits. We focus on the growth rate of industrial production (MP hereafter). This focus is motivated partially by Chen, Roll, and Ross (1986). Their early work argued that MP should be a priced factor. Their tests supported this argument, and have been replicated elsewhere (e.g., Shanken and Weinstein 2006). An additional motivation is that, as documented later, small stocks have higher MP loadings than big stocks, and value stocks have higher MP loadings than growth stocks. This raises the possibility that size and value proxy for common factor risk, and that MP could potentially help explain both the cross section of returns and momentum returns. Our use of a growth-related macroeconomic risk variable to study momentum portfolios is also motivated by the theoretical work of Johnson (2002). He argues that apparent momentum profits can reflect temporary increases in growth related risk for winner-minus-loser portfolios.

We present a number of new results. First, winners have temporarily higher MP loadings than losers. Winner loadings temporarily rise, and loser loadings temporarily fall. For example, in univariate regressions the loadings for winners and losers in the first month of the holding period following portfolio formation are, 0.63 and −0.17, respectively, but six months later the loadings are similar at about 0.38. Second, most of the high MP loadings occur in high momentum deciles. These loading patterns are predicted by Johnson (2002). Third, MP appears to be a priced risk factor. Depending on model specification, the MP risk premium estimated from Fama-Macbeth (1973) multifactor cross-sectional regressions ranges from 0.11% to 1.29% per month.

These various results suggest the potential usefulness of growth related risk variables. While these results could help point the way toward risk-based explanations for the cross section of returns, they fall short in one key area, however. In most of our tests, the combined effect of factor pricing and risk shifts does not explain a large fraction of momentum returns. We make no claim that our results have solved the momentum puzzle (e.g, Jegadeesh and Titman 1993). The role of MP remains an open question because the risk premium estimates are sensitive to test procedure.

Our findings are directly connected with the literature in several ways. 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 and no evidence of MP pricing. Our analysis uses data from 1960 through 2004, and our tests for risk shifts are also more extensive.

Our study is connected with Johnson (2002) in many ways. 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. We document that winners have temporarily higher future growth rates of dividend, investment, and sales on average than losers, and that the duration of the expected-growth spread matches roughly that of momentum. However, additional evidence on the pricing of the expected-growth risk is weak.

Our study is also connected to 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 momentum explanations. Recent papers testing these explanations include Grundy and Martin (2001), Ahn, Conrad, and Dittmar (2003), Moskowitz (2003), Vassalou and Apedjinou (2003), and Bansal, Dittmar, and Lundblad (2005). 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 risk shifts for momentum portfolios. Section 5 concludes.

2 Data

We obtain data on stock returns, stock prices, 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 2004 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 the subsequent six months. All stocks are equally-weighted within each portfolio. To avoid potential microstructure biases, 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 0.77% per month with a significant t-statistic of 4.19 (adjusted for heteroscedasticity and autocorrelations). Standard factor models cannot explain momentum. The alpha of WML from the CAPM regression is 0.81% (t-statistic = 4.73), and the alpha from the Fama-French (1993) three-factor model is 0.96% (t-statistic = 4.56). Controlling for size and book-to-market factors appears to exacerbate the momentum puzzle.

We primarily analyze factor loadings of momentum portfolios on MP. We define MP as $\mathrm{MP}_t = \log \mathrm{IP}_t - \log \mathrm{IP}_{t-1}$, where IP_t is the index of industry production in month t from Federal Reserve Bank of St. Louis. From January 1960 to December 2004, the monthly MP is on average 0.26% and its volatility is 0.75%. 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 $\mathrm{UI}_t \equiv I_t - \mathrm{E}[I_t|t-1]$ and $\mathrm{DEI}_t \equiv \mathrm{E}[I_{t+1}|t] - E[I_t|t-1]$, respectively. We measure the inflation rate from time $t-1$ to t as $I_t \equiv \log \mathrm{CPISA}_t - \log \mathrm{CPISA}_{t-1}$ where CPISA_t is the seasonally adjusted Consumer Price Index at time t, from Federal Reserve Bank of St. Louis. The expected inflation is $\mathrm{E}[I_t|t-1] = r_{ft} - \mathrm{E}[\mathrm{RHO}_t|t-1]$, where r_{ft} is the one-month Treasury bill rate from CRSP, and $\mathrm{RHO}_t \equiv r_{ft} - I_t$ 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, $\mathrm{E}[\mathrm{RHO}_t|t-1]$. The difference between RHO_t and RHO_{t-1} is modeled as $\text{RHO}_t - \text{RHO}_{t-1} = u_t + \theta u_{t-1}$, then $\text{E}[\text{RHO}_t|t-1] = (r_{ft-1} - I_{t-1}) - \hat{u}_t - \hat{\theta}\hat{u}_{t-1}$. 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 for Momentum Portfolios

Table 1 reports the MP loadings for momentum deciles. The four extreme portfolios, L_A, L_B, W_A, and W_B, split the bottom and top deciles in half (as in, for example, Fama and French 1992). Following Chen, Roll, and Ross (1986), we lead MP by one month to align the timing of macroeconomic and financial variables. Panel A uses MP as the single factor. Portfolio L_A has a MP loading of 0.04, and portfolio W_B has a MP loading of 0.60. The hypothesis that all loadings are jointly zero can be rejected (p-value = 0.02). However, the hypothesis that portfolio W_B has a MP loading lower than or equal to that of portfolio L_A can only be rejected at the 10% significance level (p-value = 0.07).

From Panel A of Table 1, the difference in MP loadings is mostly driven by the top four winner deciles. Decile six has a MP loading of 0.06, and the loading then rises monotonically to 0.60 for portfolio W_B. In contrast, there is not much difference in MP loadings from portfolio L_A to six, which have MP loadings of 0.04 and 0.06, respectively. To assess this apparent asymmetric pattern, we perform a variety of hypothesis tests to evaluate statistical significance. These tests show that, first, the MP loading of the winner decile is higher than the MP loading of the equally-weighted portfolio of momentum deciles one through nine (p-value = 0.01) and one through eight (p-value = 0.01). And the equally-weighted portfolio of momentum deciles nine and ten has a higher MP loading than the equally-weighted portfolio of momentum deciles one through eight (p-value = 0.01).

From Panel B of Table 1, controlling for the Fama-French (1993) three factors in the regressions does not affect materially the results in Panel A. The MP loadings of portfolios L_A and W_B drop slightly to -0.07 and 0.54, respectively, but the spread between the two is increased relative to that in Panel A. And the MP loadings for several winner portfolios now become individually significant. The hypothesis that the MP loadings of momentum portfolios are jointly zero is again strongly rejected. The asymmetric pattern in loadings also persists. The loading rises from 0.01 to 0.54 going from decile seven to ten, but there is not much difference among the rest of the portfolios.

Finally, from Panel C of Table 1, the MP-loading spread between winners and losers further increases if we include four other 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 all the Chen-Roll-Ross factors, the MP loading of portfolio W_B becomes 0.52 and the MP loading of portfolio L_A becomes -0.19. And the asymmetric pattern in MP loadings continues to hold.[1]

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 2004, we calculate equally-weighted returns for all the ten momentum portfolios for $t+m$, where $m = 0, 1, \ldots, 12$. We then pool together across calendar time the observations of momentum portfolio returns, the Fama-French (1993) three factors, and the Chen-Roll-Ross (1986) factors for event month $t+m$. We estimate the factor loadings using the pooled time series factor regressions.

Table 2 reports the MP loadings of momentum portfolios for every month during the 12-month holding period after portfolio formation. The underlying model is the one-factor MP model. The

[1] In untabulated results, we find that, consistent with Pastor and Stambaugh (2003), winners have higher liquidity loadings than losers. More important, our MP-loading results persist after controlling for their liquidity factor.

results are dramatic. The first row in Panel A shows that at the first holding-period month, month one, the MP loading rises almost monotonically from -0.17 for the loser portfolio L_A to 0.63 for the winner portfolio W_B. From the tests reported in the first row of Panel B, portfolio W_B has a reliably higher MP loading than portfolio L_A. And the winner decile has a reliably higher loading than the equally-weighted portfolio of momentum deciles one to eight and the equally-weighted portfolio of deciles one to nine. Moreover, 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 L_A increases from -0.17 in month one to -0.05 in month three. The positive loading of the winner portfolio W_B increases somewhat to 0.71. The tests reported in the corresponding rows of Panel B again show that the top winner decile 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 seven, the spread in the MP loading largely converges as portfolios L_A and W_B both have MP loadings of about 0.35. From the remaining rows of Table 2, portfolio L_A has mostly higher MP loadings than portfolio W_B in the remaining months.

Adding the Fama-French (1993) factors or the other four Chen-Roll-Ross (1986) factors into the regressions 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 spread in MP loadings between the extreme portfolios, but the basic pattern remains unchanged. More important, Panels B and C show that using the two alternative factor structures does not affect the pattern of MP loadings. The winner quintile continues to have disproportionately higher loadings than the loser quintile. And the spread is temporary because it converges around month 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, skips one month, and holds the resulting portfolios for the subsequent six months. This central finding is robust to the general $J\backslash K$ construction of momentum strategies by sorting stocks based on their prior J-month returns, skipping one month, and holding the resulting portfolios for the subsequent K months. Table 3 reports the details. 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 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-lower 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-lower portfolio from the $12\backslash 12$ momentum construction is 0.15 and its one-sided p-value is an insignificant 0.18. Reducing the holding period K raises the magnitude of the loading from 0.15 with $K=12$ to 0.36 with $K=3$ (p-value = 0.03), and further to 0.40 with $K=1$ (p-value = 0.02). The pattern that the MP loading decreases with the holding period also applies with alternative sorting periods J. Further, from Panels B and C, adding the Fama-French (1993) factors or the Chen-Roll-Ross (1996) factors into the regressions yields quantitatively similar results.

3.4 MP, Size, and Book-to-Market

In addition to our evidence that winners have higher MP loadings than losers, our analysis below (Table 4) shows that small stocks have higher MP loadings than big stocks, and that value stocks have higher MP loadings than growth stocks.[2] Collectively, these results suggest that MP-related

[2] In untabulated results, we also find important cross-sectional variations of MP loadings among industry portfolios (the data for ten industry portfolios are from Kenneth French's website). Cyclical industries such as consumer durables and energy have large and positive MP loadings, and health care and utility have large and negative MP loadings. The null hypothesis that the MP loadings are jointly zero across all ten industry portfolios is strongly rejected.

risk is potentially important for understanding the driving forces behind the cross section of returns.

Table 4 reports the MP loadings from monthly time series regressions for ten size, ten book-to-market, and the Fama-French (1993) 25 size and book-to-market portfolios. The testing portfolio returns from January 1960 to December 2004 are from Kenneth French's website. The overall patterns of the estimated loadings are dramatic. Panel A uses MP as the single factor. From the first two rows of the panel, the small-cap decile has an estimated MP loading of 0.44, higher than that of the big-cap decile, -0.11, but the null hypothesis that the two extreme deciles have the same MP loading cannot be rejected at conventional significance levels (p-value = 0.11). The MP loadings are individually insignificant, but the null hypothesis that all ten loadings are jointly zero is rejected (p-value = 0.03). From the next two rows, the high book-to-market decile (value) has a MP loading of 0.43, higher than that of the low book-to-market decile (growth), -0.07. The null that these two extreme book-to-market deciles have the same MP loading is rejected (p-value = 0.04). So is the null that all ten loadings are jointly zero (p-value = 0.04).

From Panel A of Table 4, two-way sorts on size and book-to-market yield similar results to the one-way sorts. Specifically, the small-value portfolio has an estimated MP loading of 0.43, higher than that of the big-growth portfolio, -0.27, and the null hypothesis that the two extreme portfolios have the same MP loading is rejected (p-value = 0.03). Across all book-to-market quintiles, small stocks have higher MP loadings than big stocks. Controlling for size, value stocks have higher MP loadings than growth stocks, but the loading spread between value and growth stocks is somewhat lower than that between small and big stocks. Liew and Vassalou (2000) report that SMB and HML are linked to future GDP growth using quarterly and annual predictive regressions. We complement their evidence by documenting that size and book-to-market portfolio returns covary contemporaneously with monthly growth rates of industrial production.

These results from the one-factor MP model are not materially affected by including the Fama-French (1993) three factors and the factors other than MP from the Chen-Roll-Ross (1986) model in the regressions. From Panel B of Table 4, using the Fama-French factors lowers somewhat the spread in MP loadings between small and big stocks and the spread between value and growth stocks. But the loadings are more precisely estimated, a pattern reflected in the often significant individual MP loadings. From Panel C, using the full Chen-Roll-Ross model does not affect much the point estimates of MP loadings, but their standard errors are higher, as shown in the higher reported p-values.

Our later tests will use MP, but it can also be motivated from the consumption-CAPM because changes in aggregate output are closely related to changes in aggregate consumption, at least conceptually. Recent applications of the consumption-CAPM have been successful in the cross section of returns.[3] In untabulated results, we use monthly consumption data from Bureau of Economic Analysis (BEA) and find that from January 1960 to December 2004 the correlations of MP with the growth rates of aggregate consumption, nondurables, and services are 0.12, 0.07, and 0.16 (p-values testing zero correlations are 0.01, 0.12, and 0.00), respectively.[4] However, momentum portfolios do not display much spread in loadings on consumption growth. One interpretation is that winners do not have higher consumption risk than losers. Another possibility is that MP can be more correlated with true consumption growth than empirically observable consumption growth due to measurement errors in consumption data (e.g., Ferson and Harvey 1992; Wilcox 1992; Heaton 1995).[5]

3.5 Momentum Profits and MP Loadings

A natural question is how much momentum profits the MP-loading spread can explain. To this end, we need to estimate the risk premium for the MP factor.

Estimating Risk Premiums

Following Chen, Roll, and Ross (1986) and Griffin, Ji, and Martin (2003), we estimate the risk premiums by using the two-stage Fama and MacBeth (1973) cross-sectional regressions on portfo-

[3]See, for example, Lettau and Ludvigson (2001), Parker and Julliard (2003), Bansal, Dittmar, and Lundblad (2005), Hansen, Heaton, and Li (2005), and Malloy, Moskowitz, and Vissing-Jorgensen (2005).

[4]Table 2.8.3 on the BEA website `http://www.bea.gov/bea/dn/nipaweb/SelectTable.asp?Selected=N` is the source where we obtain monthly consumption data. Growth rates are calculated as the differences of log consumption.

[5]Specifically, Wilcox (1992) shows that serially correlated measurement errors can be induced in aggregate consumption data by sampling error, imputation procedures, and difficulties involved in constructing measures of real aggregate consumption from monthly survey data on nominal sales. As a result, aggregate consumption data are likely to measure consumption responses with delay, even if the true consumption response is instantaneous.

lios that display wide spreads in average returns. We use two sets of testing assets. Motivated from our evidence in Tables 1 and 4, the first set of 30 portfolios includes ten size, ten book-to-market, and ten momentum portfolios, all based on one-way sorts. The same set of testing portfolios is also used by Bansal, Dittmar, and Lundblad (2005). The second set includes 125 portfolios based on a three-way $5 \times 5 \times 5$ sort on size, book-to-market, and prior six-month returns, following Daniel, Grinblatt, Titman, and Wermers (1997).[6] We have also used an alternative set of 120 portfolios including 100 size and book-to-market portfolios from a two-way 10×10 sort and 20 momentum portfolios from a one-way sort on prior six-month returns. The results are quantitatively similar to those using the 125 portfolios (not reported).

Following Ferson and Harvey (1999), we use either 60-month rolling windows or extending windows in the first-stage regressions. The extending windows always start at January 1960 and end at the current month in which the month's second-stage cross-sectional regression is run. An advantage of using the extending windows is that more sample observations are used to estimate the factor loadings. Using the full sample to estimate factor loadings (e.g., Black, Jensen, and Scholes 1972, Fama and French 1992, and Lettau and Ludvigson 2001) produces stronger pricing results (not reported).[7] In the second stage, we regress portfolio excess returns on factor loadings. The average slopes then provide the risk premiums.

The first two rows of Table 5 report the results from the one-factor MP model with the 30 size, book-to-market, and momentum portfolios as the testing assets. The MP risk premium is on average 0.31% per month (t-statistic = 2.52) when we use rolling factor loadings in the first-stage regression. Using extending windows to estimate loadings yields a much higher MP risk premium of 1.16% per month (t-statistic = 3.32). In untabulated results, we find that the first-stage factor

[6] The construction of the 125 portfolios is similar to that of Daniel et al. (1997). At the end of June of each year, we sort the universe of common stocks from NYSE, AMEX, and Nasdaq into quintiles based on each stock's market equity just prior to the formation using the NYSE breakpoints. The stocks within each size quintile are further sorted into quintiles based on book-to-market, measured as the ratio of the book equity at the end of the firm's last fiscal yearend. Finally, the stocks in each of the 25 size and book-to-market portfolios are then sorted into quintiles based on their preceding six-month returns (through the end of May), generating a total of 125 portfolios. We value-weight the stocks within each of the 125 portfolios.

[7] Shanken (1992) and Shanken and Weinstein (2006) discuss advantages and disadvantages of different approaches.

loadings are estimated much more precisely from extending-window regressions than from 60-month rolling-window regressions. The standard errors for the extending loadings range from one-fifth to one-third of the corresponding standard errors for the rolling factor loadings across the testing portfolios. This applies to all the factor models tested in Table 5. Because the attenuation bias (e.g., Green 1997) is less severe, using extending factor loadings in the second-stage regressions is expected to yield higher and less biased risk premium estimates.[8]

Rows three and four of Table 5 show that the Fama-French (1993) three-factor model does not explain well the average returns of the 30 portfolios. Some of the risk premium estimates are negative. The intercept, $\hat{\gamma}_0$, is 1.33% per month (t-statistic = 4.41) when we use rolling windows to estimate factor loadings, and is 1.65% per month (t-statistic = 3.29) when we use extending windows. Adding MP loadings into the Fama-French model improves the performance dramatically. $\hat{\gamma}_0$ with rolling windows drops from 1.33% per month to 0.83% (t-statistic = 2.99), and $\hat{\gamma}_0$ with extending windows drops from 1.65% per month to 0.34% (t-statistic = 0.42). Controlling for the Fama-French factor loadings does not materially affect the MP premium estimates. Finally, the MP premium estimates from the Chen-Roll-Ross (1986) model are quantitatively similar to our earlier estimates.

Panels C and D of Table 5 reports the cross-sectional regressions using the 125 portfolios from a triple 5×5×5 sort on size, book-to-market, and prior six-month returns. The MP premium estimates are largely significant, but generally lower than those estimated from the 30 one-way sorted portfolios. One possible reason is that the 125 portfolios display less amount of spread in average returns. For example, the intercepts are generally lower and less significant in Panels C and D, suggesting that the factor models do better in explaining the average returns of the 125 portfolios than those of the 30 portfolios. Overall, out of 16 intercept tests reported in Table 5, eight are statistically insignificant. However, the magnitudes of these insignificant intercepts, ranging from 0.18% to 0.83% per month, are economically large. Noteworthy, the intercepts from the Chen-Roll-Ross (1986) model

[8] Consistent with this point, using 120-month rolling windows we obtain risk premiums higher than those from using 60-month rolling windows but lower than those from using extending windows in the first-stage regressions (not reported).

in Panels C and D are relatively small, 0.18% and 0.46% (t-statistics 0.74 and 0.79), respectively.

Explaining Momentum Profits Using MP Loadings

Armed with the MP premium estimates in Table 5, we can now ask how much of momentum profits the MP-loading spread can explain. A quick, back-of-the-envelope calculation shows that, given the MP loadings reported in Table 1, the risk premiums for the MP factor estimated in Table 5 are too small to explain the momentum profits. For simplicity, consider the one-factor MP model. From Table 1, the MP loading of the winner portfolio (the equally-weighted average of portfolios W_A and W_B) is 0.52, and the MP loading of the loser portfolio (the equally-weighted average of portfolios L_A and L_B) is 0.08. The average return spread between the two extreme deciles is 0.77% per month. For the MP spread of 0.44 to explain this difference, the MP risk premium must be 0.77/0.44, or 1.75% per month. However, the highest MP risk premium from the one-factor MP model reported in Table 5 is only 1.16% per month.

Table 6 reports results using a more precise procedure. We follow the intuitive test design of Griffin, Ji, and Martin (2003, Table III). To calculate what percentage of momentum profits a given factor model, for example, the Fama-French (1993) model augmented with MP, can explain, we first estimate the factor loadings, $\hat{\beta}_i$, where i = MKT, SMB, HML, or MP:

$$\mathrm{WML}_t = \hat{\alpha} + \hat{\beta}_{\mathrm{MKT}}\,\mathrm{MKT}_t + \hat{\beta}_{\mathrm{SMB}}\,\mathrm{SMB}_t + \hat{\beta}_{\mathrm{HML}}\,\mathrm{HML}_t + \hat{\beta}_{\mathrm{MP}}\,\mathrm{MP}_t + \epsilon_t \tag{1}$$

Estimates of the expected momentum profits from the factor model are then given by:

$$\mathrm{E[WML]} = \hat{\beta}_{\mathrm{MKT}}\hat{\gamma}_{\mathrm{MKT}} + \hat{\beta}_{\mathrm{SMB}}\hat{\gamma}_{\mathrm{SMB}} + \hat{\beta}_{\mathrm{HML}}\hat{\gamma}_{\mathrm{HML}} + \hat{\beta}_{\mathrm{MP}}\hat{\gamma}_{\mathrm{MP}} \tag{2}$$

where $\hat{\gamma}_i$ is the estimated risk premium of factor i. The percentage of momentum profits that the model can explain is then $\mathrm{E[WML]}/\overline{\mathrm{WML}}$, where $\overline{\mathrm{WML}}$ denotes the average WML return.

In Table 6, we report the expected winner-minus-loser return, E(WML), and the ratio of E(WML) to the average WML return observed in the data. We calculate E(WML) from the one-factor MP model, the Fama-French (1993) model, the Fama-French model augmented with MP, and the Chen-Roll-Ross (1986) model. Because the risk premium estimates vary with testing portfolios and the estimation method for factor loadings (rolling or extending windows), we report four cases corresponding to four sets of risk premium estimates for each factor model reported in Table 5.

From Panel A of Table 6, the one-factor MP model can explain 9–66% of the momentum profits, depending on different risk premium estimates. From Panel B, using the Fama-French (1993) model exacerbates the momentum profits by 12–27%. Augmenting the Fama-French model with MP dramatically improves the performance, especially when risk premiums are estimated using extending-window regressions on the 30 one-way sorted portfolios (Panel C). The Chen-Roll-Ross (1986) model can explain up to 60% of momentum profits, but it also exacerbates the momentum profits by 4% when we estimate the risk premiums using the 125 portfolios and rolling windows.

In interpreting our results, an important caution is in order. The inability of our tests to explain momentum is due, in part, to the low magnitude of our risk premium estimates. Estimates of the MP risk premium reported by Shanken and Weinstein (2006, Table 1), are often higher than ours, sometimes exceeding 1.75% per month (sufficient to explain momentum returns). Their results are not strictly comparable because their time period is much shorter, and their procedures differ. That MP pricing conclusions are sensitive to estimation procedure in both their paper and ours is a troubling issue, but whether MP-related risk explains momentum returns could still be an open question.

4 What Drives the MP Loadings of Momentum Portfolios?

A full investigation of the economic forces driving the MP-loading spread is beyond the scope of this paper. However, some guidance is provided by Johnson (2002), who argues that the log price-dividend ratio is a convex function of expected growth.[9] From the convexity, changes in log price-dividend ratio or stock returns are more sensitive to changes in expected growth when

[9]Pastor and Veronesi (2003, 2005) use the same logic to explain the high stock valuation levels in the late 1990s. Sagi and Seasholes (2005) present a growth options model with similar economic insights as those in Johnson (2002) on the importance of convexity in understanding the sources of momentum profits.

expected growth is high. If MP is a common factor summarizing aggregate changes in expected growth, and if winners have higher expected growth than losers, then our evidence that winner returns are more sensitive to MP than loser returns would be expected. Moreover, because the convexity effect is more important quantitatively when expected growth is high, the simulation results of Johnson (2002, Table II) show that his model is more successful in explaining winner returns than loser returns. His results are strikingly similar to our evidence that the MP-loading spread is asymmetric across momentum portfolios.

Three necessary conditions must hold for Johnson (2002) to plausibly explain momentum. We present evidence on each. First, expected growth rates should differ monotonically across the momentum portfolios (Section 4.1). Second, the expected-growth risk as defined by Johnson should increase with expected growth (Section 4.2). Third, the expected-growth risk should be priced in the cross section of returns (Section 4.2). In general, we only find reliable evidence consistent with the first condition.

4.1 Momentum and Expected Growth

Our evidence suggests that winners have temporarily higher expected growth than losers. To measure growth, we use investment growth and sales growth in addition to dividend growth. Shocks to aggregate and firm-specific profitabilities are typically reflected in large movements of investment and sales, rather than in movements of relatively smooth dividends. Investment growth and sales growth are therefore more likely to contain useful pricing information than dividend growth.

Stock returns are monthly and momentum involves monthly rebalancing. But accounting variables such as investment and dividend are available at quarterly or annual 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.[10]

Average Growth Rates of Momentum Portfolios

Table 7 reports descriptive statistics on dividend growth, investment growth and sales growth for momentum deciles from July 1965 to December 2004. The starting period is chosen to avoid Compustat selection bias in earlier periods. The dividends of winners grow at an annual rate of 19%, 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. All the spreads are highly significant. In untabulated results, we find that winners have higher growth rates than losers in almost every year in the sample.

We also study how the average growth rates evolve before and after portfolio formation. For each month t from January 1965 to December 2004, we calculate the growth rates for $t+m$, where $m=-36,\ldots,36$. We then average the growth rates for $t+m$ across portfolio formation months to capture 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. Using Compustat merged annual files yields similar results (not reported).

From Panels A to C of Figure 2, momentum portfolios display temporary shifts in expected growth. At the portfolio formation month, the expected-growth spreads between winners and losers are sizable: 14% in dividend growth, 22% in investment growth, and 5% per quarter in sales growth. The spreads converge in about ten to 20 months before and, more important, 12 to 20 months after the month of portfolio formation. The durations of the expected-growth spreads thus match roughly the duration of momentum profits.

[10] We 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 to monthly flow variables, but it ignores the monthly changes of stock composition within a quarter or a year. This method yields quantitatively similar results (not reported).

Predicting Future Growth Rates with Past Returns

Collectively, Table 7 and Figure 2 show that average growth rates differ largely monotonically across momentum portfolios. To complement this evidence, we study directly the relation between expected growth and past returns at the firm level. Specifically, we perform Fama and MacBeth (1973) cross-sectional regressions of future growth rates on past returns and test whether the slopes are significantly positive. The answer is strongly affirmative.

Because many firm-year observations have zero dividend or investment, the usual growth-rate definition is not meaningful at the firm level. We instead measure firm-level growth rates by normalizing changes of dividend, investment, and sales by the beginning-of-period book equity. Accounting variables are from the Compustat annual files.[11] The sample is from 1965 to 2004. To adjust standard errors for the persistence in the slopes, we follow Pontiff (1996) by regressing the time-series of slope coefficients on an intercept term and modeling the residuals as a sixth-order autoregressive process. We then use the standard error of the intercept term as the corrected standard error in constructing the Fama-MacBeth (1973) t-statistics.

Table 8 reports the annual cross-sectional regressions. Past six- and 12-month returns are strong, positive predictors of future one-year and two-year growth rates. The slopes on past returns are universally positive and highly significant. This pattern also holds after we control for the lagged values of growth rates. The average cross-sectional R^2 ranges from 1.4–10.7%, depending on whether lagged growth rates are used. Our evidence suggests that contemporaneous stock returns are positively correlated with expected growth at the firm level.

This 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)." One reason why our results differ is that Chan et al. regress future growth rates on past six-month returns along with eight other variables. Some such as

[11]Specifically, we measure investment as capital expenditure from cash flow statement (item 128), dividend as common stock dividends (item 21), sales as net sales (item 12); and book value of equity as common equity (item 60) plus deferred taxes (item 74).

earnings-to-price, book-to-market, and dividend yields are highly correlated with stock returns contemporaneously. To generate a cleaner picture, we opt to use simpler regression specifications.

4.2 Momentum and Expected Growth Risk

To guide our empirical tests on risk related to expected growth in the context of momentum profits, we turn to the theoretical model developed by Johnson (2002). The basic intuition can be illustrated within the Gordon (1962) growth model, which says that $P = D/(k-g)$ where P is stock price, D is dividend, k is the market discount rate, g is the constant growth rate of dividend, and $k > g$. Let $U = P/D$ be the price-dividend ratio, then $\partial^2 \log U / \partial g^2 > 0$. Intuitively, the curvature of log price-dividend ratio with respect to expected growth is convex, and the log price-dividend ratio is more sensitive to changes in expected growth when expected growth is high. Johnson generalizes this intuition in a stochastic framework, in which expected growth is stochastic and its covariation with the pricing kernel is nonzero. The convexity in log equity price with respect to expected growth amplifies the amount of covariation between expected growth and the pricing kernel when expected growth is high, and dampens the covariation when expected growth is low.

In Johnson (2002), the expected-growth risk is defined as the covariance of expected dividend growth with the pricing kernel. In practice, both the expected growth and the pricing kernel are unobservable. We thus make auxiliary assumptions to operationalize our tests. Motivated by our new evidence in Section 3, we specify the pricing kernel as a linear function of MP, and then directly use the covariance of expected growth rates with MP as the measure of the expected-growth risk.

Because firms often pay zero dividends, making dividend growth not well-defined at the firm level, we conduct our tests at the portfolio level. Because the Johnson (2002) model is primarily developed to understand momentum profits, we use six/six momentum portfolios as our testing assets. Specifically, in each month t, there are for each of the testing portfolios six sub-portfolios formed at month $t-1$, $t-2$, $t-3$, $t-4$, $t-5$, and $t-6$, respectively. We sum up the dividends for all the firms in each one of the six sub-portfolios to obtain the dividends for a given momentum portfolio. We then calculate dividend growth as the changes of dividends in the past six months divided by the dividends six months ago.

The expected dividend growth is unobservable and must be estimated. We use the fitted component from Fama-MacBeth (1973) cross-sectional regressions of the dividend growth over the future six months on the dividend growth over the past six months and the changes in market equity over the past six months normalized by the book equity six months ago. As an alternative specification for expected growth, we also use past-six-month returns along with the past-six-month dividend growth in the regressions. The estimated expected growth is time-varying because both the regressors and the slopes are time-varying.

Because of the auxiliary assumptions on the expected growth, our estimates of the expected-growth risk and its risk premium are affected by measurement errors in expected growth. This problem is more challenging than the measurement-error problem of estimating betas from regressing stock returns on common factors in traditional asset pricing tests. The expected-growth risk is defined as the covariance of the expected growth with common factors. Stock returns are perfectly measured, but expected growth rates are not. Accordingly, the power of our tests to detect either risk shifts or a positive risk premium is reduced. However exploratory, our tests provide a first cut into the pricing of the expected-growth risk predicted by Johnson (2002).

Table 9 shows that the estimated correlations between expected growth for ten momentum portfolios and MP ranges from 7% to 28%, and are mostly significant. Using 25 six/six momentum portfolios yields similar results (not reported). This positive correlation is a necessary condition for the nonzero expected-growth risk and for the Johnson (2002) explanation of momentum. However, there is no evidence that the correlation increases with expected growth. In fact, the estimated correlations seem higher for losers than for winners. We have also experimented with an alternative measure of the expected-growth risk, namely the correlation between returns and expected growth.[12] We examine whether the MP loading increases across momentum portfolios because

[12] We thank one of the referees for suggesting this measure of expected-growth risk to us.

the correlation between stock returns and expected growth rates increases with expected growth. In untabulated results, we find that this correlation is indeed higher for winners than for losers. However, the correlation does not display the asymmetric pattern as the MP loadings documented in Table 1. In all, while MP appears to be a common factor, it is unclear whether it represents the expected-growth risk, perhaps because our expected growth proxies are weak.

We also examine whether the expected-growth risk as defined by Johnson (2002) is priced in the cross section of returns. Using the 25 six/six momentum portfolios as testing assets, we perform Fama-MacBeth (1973) cross-sectional regressions of portfolio excess returns on the covariance between realized dividend growth and MP as well as the covariance between expected dividend growth and MP. This regression specification is motivated from Johnson (p. 588). We use both 60-month rolling windows and extending windows to estimate the covariances. In untabulated results, we find that the estimated risk premiums for the expected-growth risk range from 0.11–0.31% per month but are all insignificant with the highest t-statistic slightly above one. The caution is, however, that difficulties in measuring expected growth can reduce the power of our tests.

5 Conclusion

Collectively, our results suggest that growth related risk variables are potentially useful. While these results could help point the way toward risk-based explanations for the cross section of returns, they fall short in one key area. In most of our tests, the combined effect of factor pricing and risk shifts does not explain a large fraction of momentum. We make no claim that our results have solved the momentum puzzle. However, the inability of our tests to explain momentum is due, in part, to a low estimated MP risk premium. The magnitude of the estimated premium is sensitive to test procedure. Higher estimates reported in Shanken and Weinstein (2006) appear sufficient to explain winner-minus-loser returns. Thus, the role of MP-related risk is still an open question.

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Table 1 : Factor Loadings of Momentum Portfolio Returns on the Growth Rate of Industrial Production (January 1960–December 2004)

This table reports the results from monthly regressions on the growth rate of industrial production (MP) using returns of ten momentum deciles, $L, 2, \ldots, 9, W$, where L denotes the loser portfolio and W denotes the winner portfolio. The four extreme portfolios (L_A, L_B, W_A, and W_B) split the bottom and top deciles in half. The sample is from January 1960 to December 2004. The regression equations in Panels A to C are, respectively, $r_{it+1} = a_i + b_i \mathrm{MP}_{t+1} + \epsilon_{it+1}$; $r_{it+1} = a_i + b_i\,\mathrm{MP}_{t+1} + c_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + \epsilon_{it+1}$; and $r_{it+1} = a_i + b_i \mathrm{MP}_{t+1} + c_i \mathrm{UI}_{t+1} + d_i \mathrm{DEI}_{t+1} + e_i \mathrm{UTS}_{t+1} + f_i \mathrm{UPR}_{t+1} + \epsilon_{t+1}$, where MKT, SMB, and HML are the Fama-French (1993) three factors. The Chen-Roll-Ross (1986) five factors include MP, 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 $b_L = b_2 = \cdots = b_W$. The second p-value is for the one-sided t-test of $b_W \leq b_{L\sim9}$, where $b_{L\sim9}$ 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 $b_W \leq b_{L\sim8}$, where $b_{L\sim8}$ 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 $b_{9\sim W} \leq b_{L\sim8}$, 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 $b_{W_B} \leq b_{L_A}$. Following Chen, Roll and Ross (1986), we lead the growth rate of industrial production by one period. The t-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelations of up to 12 lags using GMM.

MP loadings												Hypothesis tests (p-values)				
L_A	L_B	2	3	4	5	6	7	8	9	W_A	W_B	$b_L = \cdots = b_W$	$b_W \leq b_{L\sim9}$	$b_W \leq b_{L\sim8}$	$b_{9\sim W} \leq b_{L\sim8}$	$b_{W_B} \leq b_{L_A}$
Panel A: Loadings on MP from $r_{it+1} = a_i + b_i\,\mathrm{MP}_{t+1} + \epsilon_{it+1}$																
0.04	0.12	0.06	0.03	−0.03	−0.01	0.06	0.12	0.23	0.33	0.44	0.60					
(0.06)	(0.23)	(0.13)	(0.07)	(−0.09)	(−0.03)	(0.18)	(0.40)	(0.74)	(0.99)	(1.21)	(1.43)	0.02	0.01	0.01	0.01	0.07
Panel B: Loadings on MP from $r_{it+1} = a_i + b_i\,\mathrm{MP}_{t+1} + c_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + \epsilon_{it+1}$																
−0.07	0.01	−0.06	−0.09	−0.15	−0.13	−0.06	0.01	0.12	0.24	0.36	0.54					
(−0.21)	(0.05)	(−0.33)	(−0.68)	(−1.39)	(−1.63)	(−0.98)	(0.14)	(1.73)	(2.35)	(2.76)	(3.09)	0.00	0.00	0.00	0.00	0.05
Panel C: Loadings on MP from $r_{it+1} = a_i + b_i\,\mathrm{MP}_{t+1} + c_i\,\mathrm{UI}_{t+1} + d_i\,\mathrm{DEI}_{t+1} + e_i\,\mathrm{UTS}_{t+1} + f_i\,\mathrm{UPR}_{t+1} + \epsilon_{t+1}$																
−0.19	0.06	0.09	0.09	0.04	0.07	0.14	0.19	0.28	0.36	0.42	0.52					
(−0.31)	(0.12)	(0.20)	(0.23)	(0.12)	(0.22)	(0.44)	(0.61)	(0.88)	(1.01)	(1.10)	(1.17)	0.02	0.05	0.04	0.04	0.04

Table 2 : Factor Loadings of Momentum Portfolios on the Growth Rate of Industrial Production from the One-Factor Model for Each Month After Portfolio Formation (January 1960–December 2004)

For each portfolio formation month t from January 1960 to December 2004, we calculate the equally-weighted returns for momentum deciles for $t+m$, where $m = 1, \cdots, 12$. The momentum deciles are denoted by $L, 2, \ldots, 9, W$, where L denotes the loser portfolio and W denotes the winner portfolio. The four extreme portfolios (L_A, L_B, W_A, and W_B) split the bottom and top deciles in half. The left panel reports the factors loadings, b_i, from the regression equation $r_{it+1} = a_i + b_i \, \mathrm{MP}_{t+1} + \epsilon_{it+1}$. 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 column of p-values is associated with the Wald test on $b_L = b_2 = \cdots = b_W$, where b_L and b_W denote the loadings of momentum deciles one and ten, respectively. The second column of p-values is for the one-sided t-test of $b_W \leq b_{L\sim 9}$, where $b_{L\sim 9}$ denotes the factor loading of the equally-weighted portfolio of momentum deciles one to nine. Similarly, the third column of p-values 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 column of p-values 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. Finally, the last column reports the p-values for the t-test of $b_{W_B} \leq b_{L_A}$.

	Panel A: Factor loadings												Panel B: Hypothesis tests (p-values)				
Month	L_A	L_B	2	3	4	5	6	7	8	9	W_A	W_B	$b_L = \cdots = b_W$	$b_W \leq b_{L\sim 9}$	$b_W \leq b_{L\sim 8}$	$b_{9\sim W} \leq b_{L\sim 8}$	$b_{W_B} \leq b_{L_A}$
1	−0.17	−0.01	−0.07	0.07	0.02	0.01	0.06	0.14	0.27	0.40	0.40	0.63	0.01	0.02	0.02	0.02	0.04
2	0.03	−0.06	0.00	−0.03	0.02	0.00	0.01	0.11	0.30	0.35	0.53	0.63	0.03	0.02	0.01	0.01	0.09
3	−0.05	0.06	0.09	−0.05	−0.09	−0.06	0.05	0.19	0.30	0.31	0.58	0.71	0.00	0.01	0.01	0.00	0.04
4	0.08	0.15	0.13	0.08	−0.11	−0.02	0.08	0.08	0.21	0.32	0.37	0.66	0.00	0.01	0.01	0.02	0.08
5	0.07	0.33	0.09	0.06	0.00	−0.01	0.02	0.11	0.16	0.31	0.40	0.57	0.10	0.02	0.02	0.02	0.09
6	0.25	0.25	0.10	0.03	−0.03	0.02	0.12	0.12	0.14	0.30	0.36	0.36	0.13	0.17	0.16	0.11	0.36
7	0.33	0.15	0.18	−0.01	0.04	0.07	0.09	0.08	0.08	0.24	0.38	0.38	0.08	0.15	0.14	0.09	0.44
8	0.39	0.15	0.18	0.05	0.04	−0.03	0.07	0.18	0.21	0.11	0.29	0.33	0.03	0.23	0.22	0.20	0.58
9	0.37	0.24	0.11	0.07	0.04	0.06	0.09	0.11	0.11	0.19	0.16	0.37	0.94	0.16	0.17	0.27	0.50
10	0.19	0.22	0.16	0.12	−0.07	0.09	0.10	0.10	0.10	0.24	0.36	0.15	0.00	0.49	0.46	0.26	0.56
11	0.31	0.27	0.17	0.08	−0.01	0.07	0.04	0.15	0.05	0.31	0.21	0.18	0.00	0.45	0.44	0.40	0.67
12	0.29	0.40	0.22	0.10	0.07	0.05	0.03	0.08	0.18	0.07	0.14	0.18	0.15	0.45	0.45	0.48	0.64

Table 3 : Loadings of Top Quintile Less Bottom Four Quintiles on the Growth Rate of Industrial Production (January 1960–December 2004)

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 (1993) three-factor model augmented with MP; and the Chen-Roll-Ross (1986) model with five factors. The Chen-Roll-Ross 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 $J\backslash K$-strategy generates ten momentum portfolios by sorting on the prior J-month compounded returns, skipping one month, and then holding the resulting portfolios in the subsequent 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 MP model

$J\backslash K$	12	9	6	3	1
12	0.15	0.20	0.27	0.36	0.40
	(0.18)	(0.12)	(0.07)	(0.03)	(0.02)
9	0.20	0.25	0.33	0.42	0.50
	(0.09)	(0.06)	(0.03)	(0.01)	(0.01)
6	0.24	0.28	0.36	0.41	0.40
	(0.04)	(0.02)	(0.01)	(0.01)	(0.02)
3	0.23	0.27	0.31	0.38	0.40
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)

Panel B: Fama-French + MP

$J\backslash K$	12	9	6	3	1
12	0.22	0.27	0.33	0.41	0.45
	(0.05)	(0.03)	(0.02)	(0.01)	(0.01)
9	0.26	0.31	0.38	0.47	0.54
	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)
6	0.28	0.32	0.39	0.45	0.43
	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)
3	0.26	0.30	0.34	0.40	0.42
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)

Panel C: The Chen-Roll-Ross Model

$J\backslash K$	12	9	6	3	1
12	0.11	0.16	0.23	0.31	0.36
	(0.27)	(0.18)	(0.12)	(0.06)	(0.04)
9	0.16	0.20	0.27	0.37	0.44
	(0.16)	(0.11)	(0.06)	(0.03)	(0.02)
6	0.19	0.24	0.31	0.36	0.34
	(0.09)	(0.06)	(0.03)	(0.03)	(0.05)
3	0.19	0.23	0.27	0.33	0.33
	(0.05)	(0.03)	(0.03)	(0.02)	(0.03)

Table 4 : Factor Loadings of Size and Book-to-Market Portfolios on the Growth Rate of Industrial Production (January 1960–December 2004)

This table reports the loadings on the growth rate of industrial production, MP, for one-way sorted ten size portfolios, ten book-to-market portfolios, and the two-way sorted Fama-French (1993) 25 size and book-to-market portfolios. The sample is from January 1960 to December 2004. 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: MP, unexpected inflation (UI), change in expected inflation (DEI), and term premium (UTS), and the default premium (UPR). For all the testing portfolios, we report the MP loadings and their corresponding t-statistics (in parentheses) adjusted for heteroscedasticity and autocorrelations of up to 12 lags. We also report the p-values associated with the Wald test, denoted p_{Wald}, on the null hypothesis that the MP loadings for a given group of testing portfolios are jointly zero. The data for all the testing portfolios are from Kenneth French's website.

	Panel A: The one-factor MP model										
	Ten size portfolios										
	Small	2	3	4	5	6	7	8	9	Big	p_{Wald}
	0.44	0.08	−0.00	−0.06	−0.06	−0.12	−0.18	−0.21	−0.25	−0.11	0.03
	(1.01)	(0.18)	(−0.00)	(−0.17)	(−0.17)	(−0.36)	(−0.52)	(−0.68)	(−0.81)	(−0.37)	
	Ten book-to-market portfolios										
	Low	2	3	4	5	6	7	8	9	High	p_{Wald}
	−0.07	−0.11	−0.02	0.06	0.08	−0.01	0.10	0.09	0.22	0.43	0.04
	(−0.14)	(−0.28)	(−0.04)	(0.18)	(0.24)	(−0.04)	(0.29)	(0.27)	(0.61)	(0.97)	
	Fama-French 25 size and book-to-market portfolios										
	Low	2	3	4	High	Low	2	3	4	High	p_{Wald}
Small	0.37	0.21	0.18	0.23	0.43	(0.67)	(0.48)	(0.42)	(0.59)	(1.01)	0.09
2	−0.21	−0.16	−0.41	−0.00	−0.25	(−0.47)	(−0.41)	(−1.20)	(0.00)	(−0.69)	
3	−0.26	−0.11	−0.09	−0.08	0.01	(−0.64)	(−0.32)	(−0.30)	(−0.27)	(0.02)	
4	−0.27	−0.13	−0.15	−0.15	−0.04	(−0.73)	(−0.40)	(−0.48)	(−0.49)	(−0.11)	
Big	−0.27	−0.15	−0.19	−0.19	−0.00	(−0.79)	(−0.49)	(−0.62)	(−0.66)	(0.00)	

Table 4, Continued

Panel B: Fama-French + MP

	Ten size portfolios										
	Small	2	3	4	5	6	7	8	9	Big	p_{Wald}
	0.31	−0.03	−0.10	−0.15	−0.14	−0.20	−0.26	−0.30	−0.33	−0.16	0.02
	(1.93)	(−0.30)	(−1.24)	(−2.03)	(−1.74)	(−2.67)	(−3.20)	(−4.01)	(−4.19)	(−2.88)	
	Ten book-to-market portfolios										
	Low	2	3	4	5	6	7	8	9	High	p_{Wald}
	−0.06	−0.16	−0.10	−0.04	−0.04	−0.14	−0.04	−0.06	0.05	0.24	0.03
	(−0.45)	(−1.64)	(−1.02)	(−0.42)	(−0.44)	(−1.81)	(−0.59)	(−0.79)	(0.62)	(1.47)	
	Fama-French 25 size and book-to-market portfolios										
	Low	2	3	4	High	Low	2	3	4	High	p_{Wald}
Small	0.32	0.11	0.05	0.09	0.26	(1.33)	(0.67)	(0.30)	(0.73)	(1.70)	0.07
2	−0.23	−0.26	−0.48	−0.16	−0.38	(−1.76)	(−2.31)	(−1.75)	(−2.09)	(−1.38)	
3	−0.26	−0.20	−0.23	−0.24	−0.19	(−2.43)	(−1.98)	(−2.29)	(−2.94)	(−1.72)	
4	−0.27	−0.24	−0.28	−0.32	−0.24	(−2.67)	(−2.17)	(−2.63)	(−3.15)	(−1.94)	
Big	−0.26	−0.23	−0.30	−0.34	−0.19	(−3.43)	(−2.54)	(−2.67)	(−3.83)	(−1.73)	

Panel C: The Chen-Roll-Ross (1986) model

	Ten size portfolios										
	Small	2	3	4	5	6	7	8	9	Big	p_{Wald}
	0.39	0.14	0.09	0.06	0.06	0.01	−0.06	−0.08	−0.15	0.00	0.18
	(0.92)	(0.35)	(0.22)	(0.17)	(0.18)	(0.02)	(−0.18)	(−0.24)	(−0.46)	(0.00)	
	Ten book-to-market portfolios										
	Low	2	3	4	5	6	7	8	9	High	p_{Wald}
	−0.07	−0.03	0.05	0.15	0.15	0.07	0.18	0.16	0.26	0.39	0.14
	(−0.15)	(−0.07)	(0.14)	(0.42)	(0.46)	(0.21)	(0.55)	(0.49)	(0.74)	(0.92)	
	Fama-French 25 size and book-to-market portfolios										
	Low	2	3	4	High	Low	2	3	4	High	p_{Wald}
Small	0.34	0.23	0.21	0.27	0.39	(0.62)	(0.51)	(0.52)	(0.68)	(0.95)	0.41
2	−0.14	−0.00	−0.25	0.14	−0.13	(−0.29)	(−0.04)	(−0.79)	(0.44)	(−0.38)	
3	−0.17	0.05	0.07	0.07	0.11	(−0.38)	(0.13)	(0.24)	(0.22)	(0.30)	
4	−0.17	−0.03	−0.00	0.00	0.13	(−0.43)	(−0.08)	(−0.02)	(0.01)	(0.38)	
Big	−0.22	−0.02	−0.08	−0.03	0.15	(−0.58)	(−0.05)	(−0.24)	(−0.11)	(0.46)	

Table 5 : Risk Premiums from Two-Stage Fama-MacBeth (1973) Cross-Sectional Regressions (January 1960–December 2004)

We estimate risk premiums of the growth rate of industrial production (MP), the Fama-French (1993) factors, and the other four Chen-Roll-Ross (1986) factors including unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR). We use the two-stage Fama-MacBeth (1973) regressions. In the first stage, we estimate factor loadings using either 60-month rolling-window regressions or extending-window regressions. The extending windows always start at January 1960 and end at the month t, in which we perform the second-stage cross-sectional regressions of portfolio excess returns from t to $t+1$ on factor loadings estimated using information up to month t. We use two sets of testing assets. The first set has 30 portfolios including the ten size, ten book-to-market, and ten six/six momentum portfolios. The second set of testing assets has 125 portfolios based on a triple $5 \times 5 \times 5$ sort on size, book-to-market, and past six-month returns, following Daniel, Grinblatt, Titman, and Wermers (1997). The table reports the second-stage cross-sectional regressions including the intercepts ($\hat{\gamma}_0$), risk premiums ($\hat{\gamma}$), and average cross-sectional R^2s. The intercepts and the risk premiums are in percentage per month. The Fama-MacBeth t-statistics adjusted for the errors-in-variable problem in factor loadings with the Shanken (1992) method are reported in parentheses.

Panel A: 30 portfolios, rolling windows in the first stage

$\hat{\gamma}_0$	$\hat{\gamma}_{\text{UI}}$	$\hat{\gamma}_{\text{DEI}}$	$\hat{\gamma}_{\text{UTS}}$	$\hat{\gamma}_{\text{UPR}}$	$\hat{\gamma}_{\text{MKT}}$	$\hat{\gamma}_{\text{SMB}}$	$\hat{\gamma}_{\text{HML}}$	$\hat{\gamma}_{\text{MP}}$	R^2
0.90								0.31	20%
(3.46)								(2.52)	
1.33					−0.73	0.41	0.32		52%
(4.41)					(−2.43)	(2.03)	(1.60)		
0.83					−0.28	0.37	0.44	0.29	60%
(2.99)					(−0.89)	(1.82)	(2.52)	(2.09)	
0.51	−0.01	−0.02	0.15	−0.01				0.39	60%
(1.67)	(−0.26)	(−1.42)	(0.75)	(−0.23)				(2.93)	

Panel B: 30 portfolios, extending windows in the first stage

$\hat{\gamma}_0$	$\hat{\gamma}_{\text{UI}}$	$\hat{\gamma}_{\text{DEI}}$	$\hat{\gamma}_{\text{UTS}}$	$\hat{\gamma}_{\text{UPR}}$	$\hat{\gamma}_{\text{MKT}}$	$\hat{\gamma}_{\text{SMB}}$	$\hat{\gamma}_{\text{HML}}$	$\hat{\gamma}_{\text{MP}}$	R^2
0.77								1.16	16%
(1.68)								(3.32)	
1.65					−1.09	0.18	0.52		52%
(3.29)					(−2.18)	(0.92)	(3.32)		
0.34					0.37	0.01	0.71	1.29	62%
(0.42)					(0.43)	(0.04)	(4.18)	(3.12)	
0.83	0.14	0.01	0.45	0.04				1.10	64%
(1.16)	(0.74)	(0.36)	(0.57)	(0.16)				(2.38)	

Panel C: 125 portfolios, rolling windows in the first stage

$\hat{\gamma}_0$	$\hat{\gamma}_{\text{UI}}$	$\hat{\gamma}_{\text{DEI}}$	$\hat{\gamma}_{\text{UTS}}$	$\hat{\gamma}_{\text{UPR}}$	$\hat{\gamma}_{\text{MKT}}$	$\hat{\gamma}_{\text{SMB}}$	$\hat{\gamma}_{\text{HML}}$	$\hat{\gamma}_{\text{MP}}$	R^2
0.73								0.15	8%
(3.13)								(1.71)	
0.72					−0.22	0.47	0.23		33%
(3.47)					(−1.06)	(2.27)	(1.33)		
0.52					−0.04	0.41	0.30	0.11	36%
(2.48)					(−0.20)	(2.29)	(1.84)	(1.62)	
0.18	−0.02	−0.02	0.24	0.00				0.15	30%
(0.74)	(−1.13)	(−3.15)	(1.44)	(0.06)				(2.01)	

Panel D: 125 portfolios, extending windows in the first stage

$\hat{\gamma}_0$	$\hat{\gamma}_{\text{UI}}$	$\hat{\gamma}_{\text{DEI}}$	$\hat{\gamma}_{\text{UTS}}$	$\hat{\gamma}_{\text{UPR}}$	$\hat{\gamma}_{\text{MKT}}$	$\hat{\gamma}_{\text{SMB}}$	$\hat{\gamma}_{\text{HML}}$	$\hat{\gamma}_{\text{MP}}$	R^2
0.75								0.68	6%
(2.36)								(3.12)	
0.33					0.13	0.29	0.48		34%
(1.06)					(0.40)	(1.58)	(2.55)		
0.44					0.11	0.19	0.61	0.67	39%
(1.21)					(0.27)	(0.89)	(2.98)	(3.56)	
0.46	0.08	0.01	0.77	−0.09				0.71	32%
(0.79)	(0.80)	(0.29)	(1.47)	(−0.66)				(2.70)	

Table 6 : Explaining Average Winner-Minus-Loser Returns Using the Loading and Risk Premium on the Growth Rate of Industrial Production (January 1960–December 2004)

We report the expected WML return, E(WML), and the ratio of the expected WML return divided by average WML return in the data, E(WML)/$\overline{\text{WML}}$. We calculate the expected WML returns from the one-factor MP model (Panel A), the Fama-French (1993) three-factor model (Panel B), the Fama-French model augmented with the growth rate of industrial production, MP (Panel C), and the Chen-Roll-Ross (1986) model (Panel D). The expected WML return is calculated as: $\sum_i \hat{\beta}_i \hat{\gamma}_i$ where $\hat{\beta}_i$ is the loading of a given portfolio on factor i. $\hat{\gamma}_i$ is factor i's risk premium (reported in Table 5) that we estimate using two-stage Fama-MacBeth (1973) cross-sectional regressions with the 30 or the 125 size, book-to-market, and momentum portfolios as testing assets. Because the premium estimates vary with testing assets and estimation methods (rolling- or extending-window) in the first-stage regressions, we report four cases corresponding to four sets of risk premium estimates reported in the four panels in Table 5. For example, the column denoted "30p, rolling" reports E(WML) using the risk premiums estimated from using the 30 size, book-to-market, and momentum portfolios as the testing assets and using rolling-window regressions in the first-stage estimation.

$\overline{\text{WML}}$	E(WML) (% per month)				E(WML)/$\overline{\text{WML}}$			
(% per month)	30p, rolling	30p, extending	125p, rolling	125p, extending	30p, rolling	30p, extending	125p, rolling	125p, extending
	Panel A: The one-factor MP model							
0.77	0.14	0.51	0.07	0.30	18%	66%	9%	39%
	Panel B: The Fama-French (1993) three-factor model							
	−0.15	−0.09	−0.19	−0.21	−20%	−12%	−25%	−27%
	Panel C: Fama-French + MP							
	−0.07	0.43	−0.15	0.11	−8%	56%	−19%	14%
	Panel D: The Chen-Roll-Ross (1986) model							
	0.14	0.47	−0.03	0.08	18%	60%	−4%	10%

Table 7 : Descriptive Statistics for Subsequent Growth Rates of Dividend, Investment, and Sales for Momentum Portfolios (January 1965–December 2004)

This table reports the means and volatilities for dividend growth, investment growth, and sales growth for ten momentum portfolios. The means and volatilities are all annualized. The t-statistics in the last column test the null hypothesis that the average spread in growth rates between the winner and loser portfolios equals zero. All the t-statistics are adjusted for heteroscedasticity and autocorrelations of up to 12 lags. Accounting variables are from the COMPUSTAT annual files. We measure investment as capital expenditure from cash flow statement (item 128), dividend as common stock dividends (item 21), and sales as net sales (item 12). The sample period is from January 1965 to December 2004, where the starting point is chosen to avoid sample selection bias.

	Loser	2	3	4	5	6	7	8	9	Winner	WML	t_{WML}
Panel A: Dividend growth												
mean	−0.12	0.00	0.04	0.07	0.08	0.09	0.09	0.12	0.15	0.19	0.31	7.79
vol	0.27	0.12	0.07	0.05	0.07	0.06	0.08	0.09	0.19	0.37	0.45	
Panel B: Investment growth												
mean	−0.09	0.01	0.05	0.07	0.07	0.10	0.11	0.15	0.18	0.30	0.39	15.63
vol	0.17	0.13	0.12	0.12	0.12	0.14	0.18	0.19	0.18	0.29	0.27	
Panel C: Sales growth												
mean	0.03	0.06	0.07	0.08	0.09	0.09	0.10	0.11	0.14	0.18	0.15	17.12
vol	0.09	0.08	0.07	0.06	0.07	0.06	0.06	0.07	0.08	0.10	0.09	

Table 8 : Annual Cross-Sectional Regressions of Dividend, Sales, and Investment Growth Rates on Past Six-Month and 12-Month Returns (January 1965–December 2004)

This table reports the annual cross-sectional regressions of future dividend growth, investment growth, and sales growth on past six-month return $r_{t-5,t}$ and past 12-month return $r_{t-11,t}$ with and without controlling for the one-period lagged growth rates. We consider one-year-ahead ($\tau = 12$) and two-year-ahead ($\tau = 24$) growth rates. The Fama-MacBeth (1973) t-statistics reported in parentheses are adjusted for heteroscedasticity and serial correlations of up to six lags in the slopes using the method from Pontiff (1996). Because many firms have zero or negative dividend and investment, we measure firm-level growth rates by normalizing changes in dividend, investment, and sales, denoted $\triangle d, \triangle i$, and $\triangle s$, respectively, by book value of equity, b. We obtain accounting variables from the Compustat annual files. We measure investment as capital expenditure from cash flow statement (item 128); dividend as common stock dividends (item 21); sales as net sales (item 12); and book value of equity as from common equity (item 60) plus deferred taxes (item 74). We also report the average cross-sectional R^2s.

	Panel A: Predicting $\frac{\triangle d_{t,t+\tau}}{b_t}$				Panel B: Predicting $\frac{\triangle i_{t,t+\tau}}{b_t}$				Panel C: Predicting $\frac{\triangle s_{t,t+\tau}}{b_t}$			
Horizon	$r_{t-5,t}$	$r_{t-11,t}$	$\frac{\triangle d_{t-12,t}}{b_{t-12}}$	R^2	$r_{t-5,t}$	$r_{t-11,t}$	$\frac{\triangle i_{t-12,t}}{b_{t-12}}$	R^2	$r_{t-5,t}$	$r_{t-11,t}$	$\frac{\triangle s_{t-12,t}}{b_{t-12}}$	R^2
$\tau = 12$	0.07			2.62%	0.65			2.42	2.47%			1.97%
	(5.62)				(10.69)				(11.68)			
		0.09		2.53%		0.97		2.79%		4.12		2.71%
		(3.88)				(10.90)				(12.20)		
	0.06		−0.13	10.68%	0.65		−0.04	8.43%	1.97		0.25	9.90%
	(5.90)		(−1.31)		(9.75)		(−0.54)		(10.47)		(8.47)	
		0.09	−0.13	10.52%		0.98	−0.05	8.92%		2.94	0.24	10.15%
		(4.07)	(−1.33)			(9.88)	(−0.61)			(10.30)	(8.16)	
$\tau = 24$	0.10			2.47%	0.86			2.23%	3.65			1.44%
	(5.64)				(10.38)				(8.64)			
		0.13		2.20%		1.15		2.37%		6.87		2.36%
		(4.54)				(7.30)				(10.62)		
	0.10		−0.04	9.85%	0.85		−0.11	8.73%	2.80		0.40	8.23%
	(5.84)		(−0.32)		(8.97)		(−1.30)		(7.74)		(5.77)	
		0.12	−0.04	9.55%		1.17	−0.12	8.96%		4.87	0.38	8.62%
		(4.42)	(−0.33)			(7.05)	(−1.37)			(12.35)	(5.60)	

Table 9 : Momentum and Expected Growth Risk (January 1965–December 2004)

We report the correlations and their p-values for testing zero correlations between expected growth and the monthly growth rates of industrial production, MP, for ten six/six momentum portfolios. We sum up the dividends for all the firms in a given portfolio to obtain portfolio dividends, and calculate dividend growth as the changes of dividends in the past six months divided by the dividends six months ago. We estimate expected growth as the fitted component from the Fama-MacBeth (1973) cross-sectional regressions of the dividend growth over the future six months on the past-six-month dividend growth and the past-six-month changes in market equity divided by the book equity six months ago (Panel A). In Panel B, the regressors in cross-sectional regressions are the dividend growth and portfolio returns over the past six months. The estimated expected growth is time-varying because the regressors and the slopes are time-varying.

	Panel A: Using the ratio of changes in market equity over book equity as one instrument for expected growth									
	Loser	2	3	4	5	6	7	8	9	Winner
Correlation	0.17	0.20	0.23	0.17	0.16	0.11	0.13	0.13	0.12	0.09
p-value	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.04
	Panel B: Using past realized stock returns as one instrument for expected growth									
	Loser	2	3	4	5	6	7	8	9	Winner
Correlation	0.23	0.29	0.27	0.23	0.23	0.15	0.17	0.14	0.10	0.08
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.09

Figure 1 : Event-Time Factor Loadings on the Growth Rate of Industrial Production (January 1960–December 2004)

For each portfolio formation month t from January 1960 to December 2004, we calculate the equally-weighted returns for winner and loser quintiles for month $t+m$, where $m = 0, 1, \cdots, 18$. 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 (1993) 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.

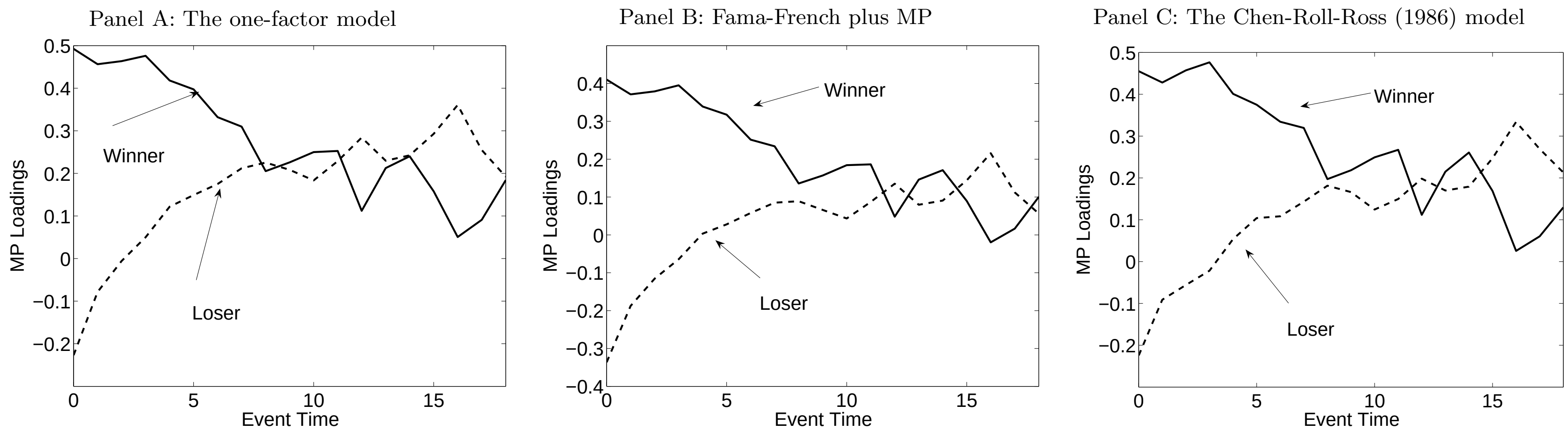

Figure 2 : Quarterly Average Growth Rates for Winner and Loser Portfolios 36 Months Before and After Portfolio Formation (January 1965–December 2004)

For each portfolio formation month from $t =$ July 1965 to December 2004, we calculate growth rates and return on equity for $t{+}m, m = -36, \ldots, 36$ 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 2004 for investment growth. To capture the effects of monthly changes in stock composition of winner and loser portfolios, we divide quarterly observations of dividend, earnings, investment, and sales data by three to obtain monthly observations. We exclude firm/month observations with negative book values.