Momentum Profits, Factor Pricing, and Macroeconomic Risk

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Recent winners have temporarily higher loadings than recent losers on the growth rate of industrial production. The loading spread derives mostly from the positive loadings of winners. The growth rate of industrial production is a priced risk factor in standard asset pricing tests. In many specifications, this macroeconomic risk factor explains more than half of momentum profits. We conclude that risk plays an important role in driving momentum profits. (*JEL* G12, E44)

We provide direct evidence of risk underlying momentum profits. A satisfactory rational explanation of momentum needs to do two things: identify a plausible pricing kernel, and show how and why the risk exposures of momentum winners on the pricing kernel differ from those of momentum losers. We focus on the growth rate of industrial production (MP) as a common risk factor driving the pricing kernel. This choice is in part motivated by Chen, Roll, and Ross (1986), whose early empirical work shows that MP is a priced risk factor. Our use of a growth-related macroeconomic variable to study momentum is also motivated by the theoretical work of Johnson (2002) and Sagi and Seasholes (2007). Both papers argue that apparent momentum profits can reflect temporary increases in growth-related risk for winner-minus-loser portfolios.

Our central findings are easy to summarize. First, winners have temporarily higher MP loadings than losers. 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. However, six months later, the

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loadings are similar: 0.33 versus 0.38; and twelve months later, the loadings for winners are lower than those for losers: 0.29 versus 0.18. The MP loadings are also asymmetric: Most of the high MP loadings occur in high-momentum deciles. Second, MP is a priced risk factor. Depending on model specification, the MP risk premiums estimated from the two-stage Fama-MacBeth (1973) cross-sectional regressions range from 0.29% to 1.47% per month and are mostly significant. Third, and most important, in many of our tests, the combined effect of MP loadings and risk premiums accounts for more than half of momentum profits.

Motivated by the theoretical work of Johnson (2002), we also study why the risk exposures of winners on MP differ from those of losers. Johnson argues that the log price-dividend ratio is a convex function of expected growth, meaning that changes in log price-dividend ratios or stock returns should be more sensitive to changes in expected growth when the 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. Consistent with this argument, we document that winners have temporarily higher average future growth rates than losers. And the duration of the expected-growth spread matches roughly that of momentum profits. More important, we find that the expected-growth risk as defined by Johnson is priced and that the expected-growth risk increases with expected growth.

The pioneering work of Jegadeesh and Titman (1993) shows that stocks with high recent performance continue to earn higher average returns over the next three to twelve months than stocks with low recent performance. This finding has been refined and extended in different contexts by many subsequent studies.[1] The momentum literature has mostly followed Jegadeesh and Titman in interpreting momentum profits as behavioral underreaction to firm-specific information.[2] Perhaps an important reason is that the empirical literature has so far failed to document direct evidence of risk that might drive momentum. For example, Jegadeesh and Titman show that momentum cannot be explained by market risk. Fama and French (1996) show that their three-factor model cannot explain momentum either. Grundy and Martin (2001) and Avramov and

1 For example, Rouwenhorst (1998) finds a similar phenomenon in international markets. Moskowitz and Grinblatt (1999) document a strong momentum effect in industry portfolios, and Lewellen (2002) documents a similar effect in size and book-to-market portfolios. Jegadeesh and Titman (2001) show that momentum remains large in the post-1993 sample. Lee and Swaminathan (2000) document that momentum is more prevalent in stocks with high trading volume. Hong, Lim, and Stein (2000) report that small firms with low analyst coverage display more momentum. Avramov et al. (2007) show that momentum profits are large and significant among firms with low-grade credit ratings but are nonexistent among firms with high-grade credit ratings. Finally, Jiang, Lee, and Zhang (2005) and Zhang (2006) report that momentum profits are higher among firms with higher information uncertainty that can be measured by size, age, return volatility, cash flow volatility, and analyst forecast dispersion.

2 Indeed, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) have attempted to explain the underreaction-related empirical patterns by relying on a variety of psychological biases such as conservatism, self-attributive overconfidence, and slow information diffusion.

Chordia (2006) find that controlling for time-varying exposures to common risk factors does not affect momentum profits.

Most relevant to our work, Griffin, Ji, and Martin (2003) show that the Chen, Roll, and Ross (1986) model does not "provide any evidence that macroeconomic risk variables can explain momentum" (p. 2515). Using an empirical framework similar to that of Griffin et al., we show that their basic inferences can be overturned with two reasonable changes in test design. First, we use thirty portfolios based on one-way sorts on size, book-to-market, and momentum to replace Griffin et al.'s twenty-five two-way sorted size and book-to-market portfolios as testing assets in estimating risk premiums. Because our economic question is what drives momentum, it seems natural to include momentum deciles as a part of testing portfolios. Second, we use not only rolling-window regressions but also extending-window and full-sample regressions in the first stage of risk premium estimation. Both additional regression methods have been used before in empirical finance (e.g., Black, Jensen, and Scholes 1972; Fama and French 1992; Ferson and Harvey 1999; Lettau and Ludvigson 2001). We find that using risk premiums estimated from the thirty testing portfolios with either extending-window or full-sample first-stage regressions yields different inferences from Griffin et al.'s. We also point out that the overall evidence in Griffin et al.'s Table III does not (literally) support their conclusion that macroeconomic risk variations do not play any role in explaining momentum (see Section 3.2.3).

Several other papers also explore risk explanations of momentum. Conrad and Kaul (1998) argue that cross-sectional variations in the mean returns of individual securities can potentially drive momentum. Ahn, Conrad, and Dittmar (2003) show that their nonparametric risk adjustment can account for roughly half of momentum profits. Pastor and Stambaugh (2003) document that a liquidity risk factor also accounts for half of momentum profits. Bansal, Dittmar, and Lundblad (2005) show that the consumption risk embodied in cash flows can explain the average return differences across momentum portfolios. Chen and Zhang (2008) document that winner-minus-loser portfolios have positive exposures on a low-minus-high investment factor, which can be motivated from neoclassical reasoning. We add to this literature by providing direct risk evidence on a macroeconomic variable that has not been considered in these studies.

Our story proceeds as follows. Section 1 describes our sample. Section 2 presents evidence on the MP loadings across momentum portfolios. Section 3 quantifies the effect of MP loadings in driving momentum profits and explains why our inferences differ from Griffin, Ji, and Martin's (2003). Section 4 connects the MP loadings of momentum portfolios to Johnson's (2002) expected-growth risk hypothesis. Finally, Section 5 summarizes and interprets our results.

1. 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 firms without December fiscal year-end. Financial statement data are from the Compustat merged annual and quarterly data files.

To construct momentum portfolios, we follow Jegadeesh and Titman (1993) and 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 equal-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. The momentum strategy is profitable in our sample: the average winner-minus-loser (WML) decile return is 0.77% per month ($t = 4.19$). Standard factor models such as the Capital Asset Pricing Model (CAPM) cannot explain momentum. The WML alpha from the CAPM regression is 0.81% per month ($t = 4.73$), and the WML alpha from the Fama-French (1993) three-factor model is 0.96% ($t = 4.56$). Thus, controlling for size and book-to-market exacerbates the momentum puzzle.

We primarily analyze factor loadings of momentum portfolios on MP. We define $\text{MP}_t \equiv \log \text{IP}_t - \log \text{IP}_{t-1}$, where IP_t is the index of industry production in month t from the 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%. Motivated by Chen, Roll, and Ross (1986) and Griffin, Ji, and Martin (2003), we also use other macroeconomic factors. We define unexpected inflation and change of expected inflation as $\text{UI}_t \equiv I_t - E[I_t|t-1]$ and $\text{DEI}_t \equiv E[I_{t+1}|t] - E[I_t|t-1]$, respectively. We measure the inflation rate from time $t-1$ to t as $I_t \equiv \log \text{CPISA}_t - \log \text{CPISA}_{t-1}$, in which CPISA_t is the seasonally adjusted consumer price index at time t from the Federal Reserve Bank of St. Louis. The expected inflation is $E[I_t|t-1] = r_{ft} - E[\text{RHO}_t|t-1]$, where r_{ft} is the one-month Treasury bill rate from CRSP, and $\text{RHO}_t \equiv r_{ft} - I_t$ is the *ex post* real return on Treasury bills in period t.

We use Fama and Gibbons's (1984) method to measure the *ex ante* real rate, $E[\text{RHO}_t|t-1]$. The difference between RHO_t and RHO_{t-1} is modeled as $\text{RHO}_t - \text{RHO}_{t-1} = u_t + \theta u_{t-1}$, so $E[\text{RHO}_t|t-1] = (r_{ft-1} - I_{t-1}) - \hat{u}_t - \hat{\theta}\hat{u}_{t-1}$. We define the term premium, UTS, as the yield spread between the long-term and the one-year Treasury bonds from the Ibbotson database, and the default premium, UPR, as the yield spread between Moody's Baa and Aaa corporate bonds from the Federal Reserve Bank of St. Louis.

2. Macroeconomic Risk in Momentum Strategies

This section presents evidence on systematic variations in MP risk exposure across momentum portfolios. Section 2.1 reports MP loadings using calendar-time regressions. Section 2.2 examines how MP loadings evolve during the twelve-month period after the portfolio formation. Section 2.3 demonstrates the robustness of our basic results by varying the length of the sorting and holding periods in constructing the testing momentum portfolios.

2.1 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. 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 an MP loading of 0.04, and portfolio W_B has an MP loading of 0.60. The hypothesis that all the MP loadings are jointly zero can be rejected (p-value = 0.02). However, the hypothesis that portfolio W_B has an MP loading lower than or equal to that of portfolio L_A can be rejected only at the 10% level (p-value = 0.07).

It can be inferred from panel A of Table 1 that the difference in MP loadings is mostly driven by the top four winner deciles. Decile six has an 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 equal-weighted portfolio of momentum deciles one through nine (p-value = 0.01) and one through eight (p-value = 0.01). And the equal-weighted portfolio of momentum deciles nine and ten has a higher MP loading than the equal-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 materially affect 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. 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, and Ross factors, the MP loading of portfolio W_B becomes 0.52 and the MP loading of

Table 1
Factor loadings of momentum portfolio returns on the growth rate of industrial production: January 1960–December 2004, 540 months

MP loadings												*p*-values of hypothesis tests				
L_A	L_B	2	3	4	5	6	7	8	9	W_A	W_B	$b_L = \cdots = b_W$	$b_W \leq b_{L\sim 9}$	$b_W \leq b_{L\sim 8}$	$b_{9\sim W} \leq b_{L\sim 8}$	$b_{W_B} \leq b_{L_A}$
Panel A: One-factor MP model, $r_{it+1} = a_i + b_i\,\text{MP}_{t+1} + \epsilon_{it+1}$																
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: Fama-French + MP model, $r_{it+1} = a_i + b_i\,\text{MP}_{t+1} + c_i\,\text{MKT}_{t+1} + s_i\,\text{SMB}_{t+1} + h_i\,\text{HML}_{t+1} + \epsilon_{it+1}$																
−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: Chen, Roll, and Ross model, $r_{it+1} = a_i + b_i\,\text{MP}_{t+1} + c_i\,\text{UI}_{t+1} + d_i\,\text{DEI}_{t+1} + e_i\,\text{UTS}_{t+1} + f_i\,\text{UPR}_{t+1} + \epsilon_{t+1}$																
−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

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 monthly from January 1960 to December 2004. MKT, SMB, and HML are the Fama-French (1993) three factors obtained from Kenneth French's web site. The Chen, Roll, and 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 MP loadings, b_i, and their corresponding t-statistics. 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 $b_W \leq b_{L\sim 9}$, in which $b_{L\sim 9}$ is the factor loading on the equal-weighted portfolio of momentum deciles one to nine. The third p-value is for the one-sided t-test of $b_W \leq b_{L\sim 8}$, in which $b_{L\sim 8}$ is the factor loading on the equal-weighted portfolio return of momentum deciles one to eight. The fourth p-value is for the one-sided t-test on $b_{9\sim W} \leq b_{L\sim 8}$, in which $b_{9\sim W}$ is the factor loading on the equal-weighted portfolio return of momentum deciles nine and ten. The last column reports the p-value for the t-test $b_{W_B} \leq b_{L_A}$. We lead the growth rate of industrial production by one period to align the timing of macroeconomic and financial variables. The t-statistics (in parentheses) are adjusted for heteroskedasticity and autocorrelations of up to twelve lags.

portfolio L_A becomes -0.19. The asymmetric pattern in MP loadings continues to hold.[3]

2.2 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 averaged over the six months. Thus, it is informative to see how these loadings evolve month by month after portfolio formation. We are particularly interested in whether the loading spreads are temporary. To this end, we perform an event-time factor regression à la Ball and Kothari (1989) for each month after portfolio formation. For each month t from January 1960 to December 2004, we calculate equal-weighted returns for all the ten momentum portfolios for $t + m$, where $m = 0, 1, \ldots, 12$. We pool together across calendar time the observations of momentum portfolio returns, the Fama-French (1993) three factors, and the Chen, Roll, and Ross (1986) factors for event month $t + m$. We estimate the factor loadings using pooled time-series factor regressions.

Table 2 reports the MP loadings of momentum portfolios for every month during the twelve-month holding period after portfolio formation. The underlying model is the one-factor MP model. The results are dramatic. The first row in panel A shows that in 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. The winner decile has a reliably higher loading than the equal-weighted portfolio of momentum deciles one to eight and the equal-weighted portfolio of deciles one to nine. Moreover, the equal-weighted portfolio of the top two winner deciles has a reliably higher loading than the equal-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. The remaining rows of Table 2 show that 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, and Ross (1986) factors into the regressions yields similar patterns of MP

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

Table 2
Factor loadings of momentum portfolios on the growth rate of industrial production for each month after portfolio formation, the one-factor MP model: January 1960–December 2004, 540 months

	Panel A: MP loadings												Panel B: p-values of hypothesis tests				
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

For each portfolio formation month t from January 1960 to December 2004, we calculate the equal-weighted returns for momentum deciles for $t+m$, where $m = 1, \ldots, 12$. 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 factor 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 hypothesis tests. The first column of p-values is associated with the Wald test on $b_L = b_2 = \cdots = b_W$, in which 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 $b_W \leq b_{L\sim 9}$, in which $b_{L\sim 9}$ denotes the factor loading of the equal-weighted portfolio of momentum deciles one to nine. Similarly, the third column of p-values is for the one-sided t-test of $b_W \leq b_{L\sim 8}$, in which $b_{L\sim 8}$ is the factor loading of the equal-weighted portfolio of momentum deciles one to eight. The fourth column of p-values is for the one-sided t-test of $b_{9\sim W} \leq b_{L\sim 8}$, in which $b_{9\sim W}$ is the factor loading of the equal-weighted portfolio of momentum deciles nine and ten. The last column reports the p-values for the t-test of $b_{W_B} \leq b_{L_A}$.

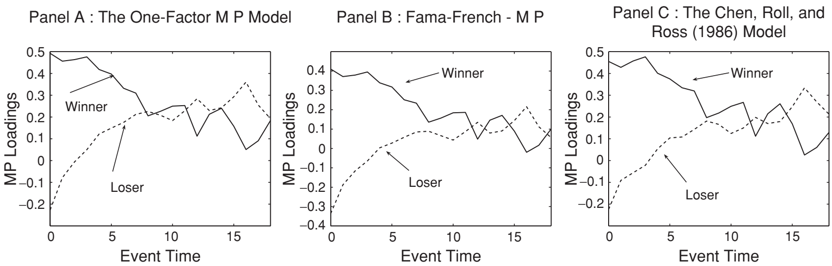

Figure 1
Event-time factor loadings on the growth rate of industrial production
Event-time factor loadings on the growth rate of industrial production, January 1960–December 2004, 540 months. For each portfolio formation month t from January 1960 to December 2004, we calculate the equal-weighted returns 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, and Ross (1986) model that includes 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. (A) One-factor MP model; (B) Fama-French + MP; (C) Chen, Roll, and Ross (1986) model.

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, and Ross five-factor model. To avoid redundancy with Table 2, we report the MP loadings for the winner and loser quintiles.

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 basic pattern of MP loadings. The winner quintile continues to have disproportionately higher loadings than the loser quintile. And the spread is temporary: it converges around month seven after portfolio formation.

2.3 Alternative momentum strategies

We have shown so far 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. We now show that this evidence is robust to the general J/K construction that sorts stocks based on their prior J-month returns, skips one month, and holds the resulting portfolios for the subsequent K months.

Table 3 reports the detailed evidence. For brevity, we display only the MP loadings for the zero-cost portfolio that buys the equal-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.

Table 3
Factor loadings of top quintile less bottom four quintiles on the growth rate of industrial production: January 1960–December 2004, 540 months

Panel A: One-factor MP model						Panel B: Fama-French + MP model						Panel C: Chen, Roll, and Ross model					
J/K	12	9	6	3	1	J/K	12	9	6	3	1	J/K	12	9	6	3	1
12	0.15	0.20	0.27	0.36	0.40	12	0.22	0.27	0.33	0.41	0.45	12	0.11	0.16	0.23	0.31	0.36
	(0.18)	(0.12)	(0.07)	(0.03)	(0.02)		(0.05)	(0.03)	(0.02)	(0.01)	(0.01)		(0.27)	(0.18)	(0.12)	(0.06)	(0.04)
9	0.20	0.25	0.33	0.42	0.50	9	0.26	0.31	0.38	0.47	0.54	9	0.16	0.20	0.27	0.37	0.44
	(0.09)	(0.06)	(0.03)	(0.01)	(0.01)		(0.02)	(0.01)	(0.01)	(0.00)	(0.00)		(0.16)	(0.11)	(0.06)	(0.03)	(0.02)
6	0.24	0.28	0.36	0.41	0.40	6	0.28	0.32	0.39	0.45	0.43	6	0.19	0.24	0.31	0.36	0.34
	(0.04)	(0.02)	(0.01)	(0.01)	(0.02)		(0.01)	(0.01)	(0.00)	(0.00)	(0.01)		(0.09)	(0.06)	(0.03)	(0.03)	(0.05)
3	0.23	0.27	0.31	0.38	0.40	3	0.26	0.30	0.34	0.40	0.42	3	0.19	0.23	0.27	0.33	0.33
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)		(0.00)	(0.00)	(0.00)	(0.00)	(0.01)		(0.05)	(0.03)	(0.03)	(0.02)	(0.03)

This table reports the factor loadings on the growth rate of industrial production (MP) of the momentum strategy that buys the equal-weighted portfolio of momentum deciles nine and ten and sells the equal-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, and Ross (1986) model with five factors. These factors are MP, unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and 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, 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.

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 0.15 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, panels B and C show that adding the Fama-French (1993) factors or the Chen, Roll, and Ross (1996) factors into the regressions yields largely similar results.

3. Explaining Momentum Profits with MP Loadings

Given that winners have higher MP loadings than losers, a natural question is how much of momentum profits these MP loadings can explain. To answer this question, we first estimate the risk premium for the MP factor in Section 3.1. Section 3.2 then uses these risk premium estimates to calculate expected momentum profits and test whether they differ significantly from observed momentum profits in the data. In Section 3.3, we directly use short-term prior returns as a regressor in Fama-MacBeth (1973) cross-sectional regressions. We then quantify the explanatory power of the MP factor by comparing the slopes of prior returns with and without controlling for MP loadings.

3.1 Estimating MP 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 portfolios that display wide spreads in average returns. We use thirty testing portfolios including ten size, ten book-to-market, and ten momentum portfolios, all of which are based on one-way sorts. The same set of testing portfolios is also used by Bansal, Dittmar, and Lundblad (2005).[4]

Following Ferson and Harvey (1999), we use sixty-month rolling windows as well as extending windows in the first-stage regressions. The extending windows always start at January 1960 and end at 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. The advantage of using the extending windows over the rolling windows is that more sample observations are used to obtain more precise estimates of the factor loadings. We also use the full sample to estimate factor loadings, following Black, Jensen, and Scholes (1972); Fama and French (1992); and Lettau and

[4] In untabulated results, we also have used 125 portfolios based on a three-way sort on size, book-to-market, and prior six-month returns as in Daniel, Grinblatt, Titman, and Wermers (1997) and obtained largely similar inferences.

Ludvigson (2001).[5] If the true factor loadings are constant, the full-sample estimates should be the most precise. As usual, we regress portfolio excess returns on factor loadings in the second stage to estimate risk premiums as the average slopes. We start the second-stage regressions in January 1962 to ensure that we have at least twenty-four monthly observations in the first-stage rolling window and extending window regressions.

3.1.1 First-stage estimation. The full-sample first-stage regressions using ten momentum portfolios are in Table 1. Table 4 reports the first-stage regressions using ten size and ten book-to-market portfolios. Small stocks have higher MP loadings than big stocks, and value stocks have higher MP loadings than growth stocks. Combined with the evidence in Table 1, these results suggest that MP-related risk is potentially important for understanding the driving forces behind the cross-section of expected stock returns.

Specifically, Table 4 reports the MP loadings from monthly regressions of ten size and ten book-to-market portfolios from January 1960 to December 2004. The portfolio data are from Kenneth French's web site. The overall pattern is remarkable. 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. The MP loadings are individually insignificant, but the null hypothesis that all ten loadings are jointly zero is rejected at the 5% significance level (p-value = 0.03). From the next two rows, the high book-to-market (value) decile has an MP loading of 0.43, which is higher than that of the low book-to-market (growth) decile, −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).

These results from the one-factor MP model are not materially affected by including the Fama-French (1993) three factors or the factors other than MP from the Chen, Roll, and 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, and Ross model does not affect by much the estimates of MP loadings, but their standard errors are higher, as shown in the higher p-values. Liew and Vassalou (2000) report that SMB and HML are linked to future GDP growth using quarterly and annual predictive regressions. We extend their evidence by documenting that size and book-to-market portfolio returns also covary contemporaneously with MP.

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

Table 4
Factor loadings of size and book-to-market portfolios on the growth rate of industrial production: January 1960–December 2004, 540 months

Panel A: 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)	

Panel B: Fama-French + MP model

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)	

Panel C: Chen, Roll, and 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)	

This table reports the loadings on the growth rate of industrial production (MP) for the one-way-sorted ten size portfolios and ten book-to-market portfolios. 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, and Ross (1986) model with five factors: MP, unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR). For all the testing portfolios, we report the MP loadings and their corresponding t-statistics (in parentheses) adjusted for heteroskedasticity and autocorrelations of up to twelve 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 the testing portfolios are from Kenneth French's web site.

3.1.2 Second-stage estimation. Table 5 reports the MP risk premiums estimated from the two-stage Fama-MacBeth (1973) cross-sectional regressions. Depending on empirical specifications, the MP premium estimates range from 0.29% to 1.47% per month and are mostly significant.

Specifically, the MP risk premium is 0.31% per month in the one-factor MP model when we use rolling-window loadings in the first-stage regression. Using

Table 5
Risk premium estimates from two-stage Fama-MacBeth (1973) cross-sectional regressions: January 1960–December 2004, 540 months

$\hat{\gamma}_0$	$\hat{\gamma}_{UI}$	$\hat{\gamma}_{DEI}$	$\hat{\gamma}_{UTS}$	$\hat{\gamma}_{UPR}$	$\hat{\gamma}_{MKT}$	$\hat{\gamma}_{SMB}$	$\hat{\gamma}_{HML}$	$\hat{\gamma}_{MP}$	$\overline{R}^2$(%)
Panel A: Rolling windows in the first-stage regressions									
0.90								0.31	20
(3.46)								(2.52)	
[3.12]								[1.14]	
1.33					−0.73	0.41	0.32		52
(4.41)					(−2.43)	(2.03)	(1.60)		
[3.94]					[−1.87]	[1.89]	[1.82]		
0.83					−0.28	0.37	0.44	0.29	60
(2.99)					(−0.89)	(1.82)	(2.52)	(2.09)	
[2.18]					[−0.67]	[1.80]	[2.68]	[1.14]	
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)	
[1.36]	[−0.08]	[−0.78]	[0.42]	[−0.14]				[2.33]	
Panel B: Extending windows in the first-stage regressions									
0.77								1.16	16
(1.68)								(3.32)	
[1.26]								[2.57]	
1.65					−1.09	0.18	0.52		52
(3.29)					(−2.18)	(0.92)	(3.32)		
[3.48]					[−2.06]	[0.88]	[3.29]		
0.34					0.37	0.01	0.71	1.29	62
(0.42)					(0.43)	(0.04)	(4.18)	(3.12)	
[0.42]					[0.45]	[0.03]	[3.38]	[1.79]	
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)	
[0.79]	[0.93]	[0.37]	[0.63]	[0.42]				[2.08]	
Panel C: Full-sample window in the first-stage regressions									
0.66								1.15	21
(1.57)								(2.85)	
[1.13]								[2.75]	
0.81					−0.31	0.13	0.71		53
(2.02)					(−0.76)	(0.58)	(3.87)		
[2.12]					[−0.76]	[0.63]	[4.25]		
0.25					0.51	−0.38	0.91	1.21	62
(0.40)					(0.85)	(−1.14)	(3.78)	(3.18)	
[0.33]					[0.74]	[−0.82]	[3.37]	[2.47]	
0.73	0.15	−0.01	0.42	0.25				1.47	66
(0.93)	(0.50)	(−0.19)	(0.36)	(0.52)				(2.08)	
[0.79]	[0.58]	[−0.22]	[0.31]	[0.49]				[2.10]	

We estimate risk premiums of the growth rate of industrial production (MP), the Fama-French (1993) factors, and the other four Chen, Roll, and Ross (1986) factors, including unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR) from two-stage Fama-MacBeth (1973) cross-sectional regressions. In the first stage, we estimate factor loadings using sixty-month rolling-window regressions, extending-window regressions, and full-sample regressions. The extending windows always start at January 1960 and end at 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 start the second-stage regressions in January 1962 to ensure that we have at least twenty-four monthly observations in the first-stage rolling-window and extending-window regressions. We use thirty testing portfolios, including the ten size, ten book-to-market, and ten six/six momentum portfolios. We report the second-stage cross-sectional regressions, including the intercepts ($\hat{\gamma}_0$), risk premiums ($\hat{\gamma}$), and average cross-sectional $\overline{R}^2$s. The intercepts and the risk premiums are in percentage per month. The Fama-MacBeth t-statistics calculated from the Shanken (1992) method are reported in parentheses. The t-statistics from estimating two-stage regressions simultaneously via GMM are reported in square brackets.

extending-window or full-sample loadings in the first stage yields much higher MP risk premiums of around 1.15% per month. Untabulated results show that the first-stage loadings are estimated much more precisely from extending-window and full-sample regressions than from sixty-month rolling regressions. The standard errors for the extending-window loadings range from one-fifth to one-third of the corresponding standard errors for the rolling-window loadings across the testing portfolios. Because the attenuation bias is less severe, using extending-window or full-sample loadings in the second-stage regressions is expected to yield higher and less biased risk premium estimates.

The Fama-French (1993) model cannot explain the average returns of the thirty portfolios. For example, from the second regressions in all panels of Table 5, the intercept $\hat{\gamma}_0$ is 1.33% per month when we use rolling-window regressions to estimate loadings, 1.65% per month when we use extending-window regressions, and 0.81% per month when we use the full-sample regressions. The intercept is significant in all three cases. Adding MP loadings into the Fama-French model improves the performance dramatically. The intercept drops from 1.33% to 0.83% per month with rolling windows, which represents a reduction of 38%. The intercept with extending windows drops by 79% from 1.65% to 0.34% per month, and the intercept with the full-sample loadings drops by 69% from 0.81% to 0.25% per month. Further, controlling for the Fama-French factor loadings does not quantitatively affect the MP premium estimates. Finally, the MP premium estimates from the Chen, Roll, and Ross (1986) model are quantitatively similar to the earlier estimates.

3.2 Expected momentum profits and MP loadings

We now use the MP risk premium estimates from Table 5 to calculate expected momentum profits implied by macroeconomic factor models. We are particularly interested in the economic magnitudes of these expected momentum profits relative to those observed in the data. Our main finding is that in many specifications, the MP loadings can explain more than half of momentum profits.

3.2.1 Test design. Our basic design of time-series tests follows that of Griffin, Ji, and Martin (2003, Table III). Using a similar test design helps crystallize the reasons why Griffin et al. and we make opposite inferences about the quantitative role of the MP factor. Griffin et al. regress the WML returns on four out of five Chen, Roll, and Ross (1986) factors—unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and the growth rate of industrial production (MP):

$$\text{WML}_t = \alpha + \beta_{UI}\,\text{UI}_t + \beta_{\text{DEI}}\,\text{DEI}_t + \beta_{\text{UTS}}\,\text{UTS}_t + \beta_{\text{MP}}\,\text{MP}_t + \varepsilon_t. \quad (1)$$

Expected momentum profits, E[WML], are estimated as

$$E[\text{WML}] = \hat{\beta}_{\text{UI}}\,\hat{\gamma}_{\text{UI}} + \hat{\beta}_{\text{DEI}}\,\hat{\gamma}_{\text{DEI}} + \hat{\beta}_{\text{UTS}}\,\hat{\gamma}_{\text{UTS}} + \hat{\beta}_{\text{MP}}\,\hat{\gamma}_{\text{MP}} \quad (2)$$

in which the betas are estimated from Equation (1). Griffin et al. estimate the risk premiums from two-stage Fama-MacBeth (1973) regressions using the twenty-five size and book-to-market portfolios as testing assets. Specifically, for each portfolio j in the twenty-five-portfolio universe, its factor sensitivities are estimated using the time-series regression (1). Griffin et al. (footnote 9) do not specify whether the first-stage regression is based on rolling windows, extending windows, or the full sample. The factor sensitivities, $\hat{\beta}_j$, are then used to fit the monthly cross-sectional regressions:

$$r_{jt} = \alpha_{jt} + \gamma_{\mathrm{UI},t}\hat{\beta}_{\mathrm{UI},j} + \gamma_{\mathrm{DEI},t}\hat{\beta}_{\mathrm{DEI},j} + \gamma_{\mathrm{UTS},t}\hat{\beta}_{\mathrm{UTS},j} + \gamma_{\mathrm{MP},t}\hat{\beta}_{\mathrm{MP},j} + \varepsilon_{jt}. \quad (3)$$

The time-series averages of the estimated slopes provide the risk premiums to be used to calculate expected momentum profits in Equation (2).

3.2.2 Empirical results. Panel A of Table 6 largely replicates the long U.S. sample result reported in Griffin, Ji, and Martin (2003, Table III) on our 1960–2004 sample. The full-fledged Chen, Roll, and Ross (1986) model and its two variants all produce expected momentum profits that are slightly positive. Their magnitudes are close to Griffin et al.'s estimate of 0.04% per month ($t = 3.89$). As a result, the differences between observed and expected momentum profits are all significant. This finding is based on risk premiums estimated with rolling-window regressions in the first stage. Using extending-window or full-sample regressions in the first stage yields similar results (not reported).

The risk premiums in panel A of Table 6 and factor loadings of WML in panel B provide clues for this basic finding. First, although WML has a positive MP loading around 0.50, the MP risk premiums estimated from the twenty-five size and book-to-market portfolios are much lower than those estimated from the thirty size, book-to-market, and momentum portfolios (see Table 5). Second, WML has a large negative loading on UTS around −0.44 (the loading is −0.95 in Griffin, Ji, and Martin's [2003] sample from May 1960 to December 2000). But panel A shows that UTS can have marginally significant positive risk premiums. The magnitude of the UTS risk premium is comparable to that of the MP risk premium. As a result, macroeconomic risk models fail to explain the momentum profits.

The important innovation that we introduce into Griffin, Ji, and Martin's (2003) framework is to use the 30 one-way sorted size, book-to-market, and momentum portfolios as testing assets in estimating risk premiums. This step seems reasonable. Our economic question is what drives momentum profits, so it is only natural to include momentum portfolios as a part of the testing assets! Using this new set of testing assets, Table 5 reports that the estimated UTS premium is much smaller than the estimated MP premium: 0.15% versus 0.39% per month in the rolling-window case and 0.45% versus 1.10% in the extending-window case. In particular, none of the UTS premium estimates are significant, whereas the MP premium estimates are all significant.

Table 6
Expected momentum profits versus observed momentum profits: January 1960–December 2004, 540 months

Panel A: Replicating Griffin, Ji, and Martin (2003, Table III)

	Risk premium estimates from 25 size and book-to-market portfolios						Observed vs. expected momentum profits (rolling windows)	
	$\hat{\gamma}_0$	$\hat{\gamma}_{UI}$	$\hat{\gamma}_{DEI}$	$\hat{\gamma}_{UTS}$	$\hat{\gamma}_{UPR}$	$\hat{\gamma}_{MP}$	E[WML]	t(diff)
CRR3	0.99	0.03	−0.00	0.01			0.00	3.98
	(4.66)	(0.92)	(−0.51)	(0.05)				
CRR4	0.98	0.01	−0.00	0.20		0.26	0.05	3.35
	(4.04)	(0.44)	(−0.26)	(1.49)		(2.21)		
CRR5	1.15	0.01	−0.00	0.25	−0.14	0.24	0.02	3.55
	(4.80)	(0.22)	(−0.35)	(1.88)	(−3.72)	(2.31)		

Panel B: Test results using risk premium estimates from 30 size, book-to-market, and momentum deciles

	Full-sample factor loadings of WML								Observed vs. expected momentum profits (rolling windows)					
	β_{UI}	β_{DEI}	β_{UTS}	β_{UPR}	β_{MKT}	β_{SMB}	β_{HML}	β_{MP}	E[WML]	$\frac{E[WML]}{WML}$	t(diff1)	$E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]$	$\frac{E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]}{WML}$	t(diff2)
MP								0.44	0.14	18%	3.13	0.14	18%	3.13
FF + MP					−0.07	−0.34	−0.23	0.48	−0.07	–	4.44	0.14	18%	3.16
CRR4	0.58	−0.30	−0.43					0.52	0.13	0.17	3.23	0.22	29%	2.67
CRR5	0.58	−0.28	−0.44	0.04				0.53	0.14	18%	3.15	0.21	27%	2.76

	Observed vs. expected momentum profits (extending windows)					
	E[WML]	$\frac{E[WML]}{WML}$	t(diff1)	$E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]$	$\frac{E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]}{WML}$	t(diff2)
MP	0.51	66%	1.22	0.51	66%	1.22
FF + MP	0.43	56%	2.92	0.62	80%	0.92
CRR4	0.49	64%	2.31	0.67	87%	0.47
CRR5	0.47	61%	2.53	0.58	75%	0.96

	Observed vs. expected momentum profits (full-sample)					
	E[WML]	$\frac{E[WML]}{WML}$	t(diff1)	$E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]$	$\frac{E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]}{WML}$	t(diff2)
MP	0.50	65%	1.30	0.50	65%	1.30
FF + MP	0.47	61%	3.26	0.58	75%	1.33
CRR4	0.68	88%	2.07	0.87	113%	−0.65
CRR5	0.70	91%	1.53	0.78	101%	−0.05

Panel A replicates the tests of Griffin, Ji, and Martin (2003, Table III) using our sample. We regress the WML returns on some or all of the Chen, Roll, and Ross (1986) factors: Unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), default premium (UPR), and the growth rate of industrial production (MP): $\mathrm{WML}_t = \alpha + \beta_{UI}\,\mathrm{UI}_t + \beta_{DEI}\,\mathrm{DEI}_t + \beta_{UTS}\,\mathrm{UTS}_t + \beta_{MP}\,\mathrm{MP}_t + \epsilon_t$. Expected momentum profits are estimated as. $E[\mathrm{WML}] = \hat{\beta}_{UI}\,\hat{\gamma}_{UI} + \hat{\beta}_{DEI}\,\hat{\gamma}_{DEI} + \hat{\beta}_{UTS}\,\hat{\gamma}_{UTS} + \hat{\beta}_{MP}\,\hat{\gamma}_{MP}$. The risk premiums, $\hat{\gamma}$, are estimated from two-stage Fama-MacBeth (1973) regressions using the twenty-five size and book-to-market portfolios as testing assets. For each portfolio j in the twenty-five-portfolio universe, its factor sensitivities on the macroeconomic factors are estimated using time-series regressions. The factor sensitivities, $\hat{\beta}_j$, are then used to fit the cross-sectional regression once for each month t: $r_{jt} = \alpha_{jt} + \gamma_{UI,t}\,\hat{\beta}_{UI,j} + \gamma_{DEI,t}\,\hat{\beta}_{DEI,j} + \gamma_{UTS,t}\,\hat{\beta}_{UTS,j} + \gamma_{MP,t}\,\hat{\beta}_{MP,j} + \epsilon_{jt}$. The time-series averages of the estimated slopes are reported in panel A. Column t(diff) reports the t-statistics testing the null hypothesis that the differences between observed momentum profits and expected momentum profits are on average zero. In panel B, instead of the twenty-five size and book-to-market portfolios, we use as testing assets thirty portfolios that include ten size deciles, ten book-to-market deciles, and ten momentum deciles. Because the risk premium estimates vary with estimation methods (rolling-window, extending-window, and full-sample) in the first-stage regressions, we report three cases for each factor model. Column t(diff1) reports the t-statistics testing the null that the differences between observed momentum profits and expected momentum profits are on average zero. Column t(diff2) reports the t-statistics testing the null that the differences between observed momentum profits and expected momentum profits based on MP alone ($\hat{\beta}_{MP}\hat{\gamma}_{MP}$) are on average zero. Panel B also reports the full-sample time-series regressions of the WML returns on different factors. We consider the one-factor MP model (MP), the Fama-French (1993) model augmented with MP (FF + MP), the Chen et al. model without the default premium (UPR) or MP (CRR3), the Chen et al. model without the default premium (UPR) (CRR4), and the full-fledged Chen et al. model (CRR5).

Another innovation that we introduce into Griffin, Ji, and Martin's (2003) framework is to distinguish risk premiums with rolling-window, extending-window, and full-sample regressions in the first stage. This step is important: rolling-window regressions yield lower risk premiums because first-stage factor loadings are less precisely estimated. From panel B of Table 6, with rolling-window regressions, the macroeconomic models can explain only about 18% of the average WML return.

Using extending-window or full-sample first-stage regressions dramatically changes the results. With the extending windows, for example, the one-factor MP model predicts the expected WML return to be 0.51% per month, which is 66% of the observed average WML return. And the difference between the observed and expected WML returns is insignificant ($t = 1.22$). The Chen, Roll, and Ross (1986) model (CRR5) produces an expected WML return of 0.47%, or 61% of the observed average WML return, although the difference between the observed and expected returns is significant ($t = 2.53$). However, the incremental contribution of MP, measured by $E[\hat{\beta}_{MP}\hat{\gamma}_{MP}]$, is 0.58% per month, or 75% of the average WML return. And the remaining 25% is insignificant ($t = 0.96$).

While not affecting the one-factor MP model performance, using full-sample risk premiums further improves the performance of the Chen, Roll, and Ross (1986) model. All the macroeconomic factor specifications produce expected momentum profits that are not significantly different from observed momentum profits. The only significant case for the difference appears when we augment the Fama-French (1993) model with MP. The combined model generates an expected WML return of 0.47% per month, and its difference from the average WML return is significant ($t = 3.26$). But the significance is mostly driven by the poor performance of the Fama-French model, which, when used alone, produces an expected WML return of −0.18% per month (untabulated). Most important, the expected WML return from the complete Chen et al. model is 0.70% per month, or 91% of the observed average WML return. The remaining 9% is insignificant ($t = 1.53$). The most important source for this model performance is the MP factor, which alone accounts for up to 100% of the momentum profits.

3.2.3 Discussion. Our previous analysis has focused on a long U.S. sample in which Griffin, Ji, and Martin (2003, Table III, panel A) report a significant difference between the expected and observed WML returns of 0.82% per month ($t = 3.89$). We have shown that their conclusion can be overturned with reasonable changes in estimation methods. We now argue that the overall evidence in their Table III does not (literally) support their conclusion that macroeconomic risks cannot explain momentum.

Griffin, Ji, and Martin (2003) highlight the evidence in the last line of panel A in their Table III: "The average expected momentum profit is −0.03% over all countries while the average observed momentum profit is 0.67%. The difference, 0.70%, is strongly statistically significant" (p. 2526). However, the overall evidence seems to tell a much more complicated, if not the opposite, story. Panel A of their Table III reports the difference between the average expected momentum profit and the average observed momentum profit for twenty-two different cases including twenty countries and two average cases (world excluding the United States and world including the United States). A majority, twelve out of the twenty-two cases, shows insignificant differences between the average expected and observed momentum profits!

The evidence reported in panel B of Griffin, Ji, and Martin (2003, Table III) does not support their conclusion either. We observe that sixteen out of twenty-two cases show insignificant differences between the average expected and observed momentum profits. In particular, for the U.S. sample from February 1990 to December 2000, the MP loading of WML is 0.24, albeit insignificant. The average observed momentum profit is 0.92% per month, whereas the average expected momentum profit is 0.43%. And the difference is insignificant ($t = 0.47$). It is likely that the estimates are noisy because of the shorter sample. However, based on the available evidence, we cannot reject the null hypothesis that the Chen, Roll, and Ross (1986) model captures the observed momentum profits.

3.3 Cross-sectional regression tests

Besides the empirical framework similar to that of Griffin, Ji, and Martin (2003, Table III), we also use short-term prior returns directly as a characteristic-based regressor in Fama-MacBeth (1973) cross-sectional regressions. The explanatory power of the MP factor can be quantified by comparing the slopes of prior returns before and after controlling for the MP loadings of the testing assets.

We again use the thirty portfolios formed on size, book-to-market, and six-month prior returns as testing portfolios. In the first stage, we estimate factor loadings using rolling-window, extending-window, or full-sample regressions. As before, we require the rolling-window and extending-window regressions to have at least twenty-four monthly observations. In the second stage, we regress portfolio excess returns on the loadings and prior six-month returns, denoted r^6. We run the regressions with and without controlling for MP loadings, and quantify the importance of MP as the percentage reduction of the r^6 slope from adding the MP loading into the regressions. Because r^6 is a characteristic, we do not use the Shanken (1992) adjustment for the slopes. Instead, we report t-statistics from estimating the two-stage cross-sectional regressions simultaneously via generalized methods of moments (GMM).

Table 7 reports the detailed results. Without MP, prior six-month returns have significant positive slopes in all nine specifications. These include univariate regressions, multiple regressions with loadings on the Fama-French (1993) three factors, and multiple regressions with loadings on the four Chen, Roll, and Ross (1986) factors other than MP. Our evidence is consistent with that of Lewellen (2002), who shows that size and book-to-market portfolios exhibit momentum

Table 7
Using short-term prior returns as a characteristic in two-stage Fama-MacBeth (1973) cross-sectional regressions, with and without controlling for MP loadings: January 1960–December 2004, 540 months

γ_0	$\hat{\gamma}_{UI}$	γ_{DEI}	γ_{UTS}	γ_{UPR}	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{r^6}	γ_0	γ_{UI}	γ_{DEI}	γ_{UTS}	γ_{UPR}	γ_{MKT}	γ_{SMB}	γ_{HML}	γ_{MP}	γ_{r^6}	$\Delta\gamma_{r^6}/\gamma_{r^6}$
Panel A: Rolling-window regressions in the first stage																			
0.69								0.05	0.61								0.15	0.03	29%
[2.87]								[3.45]	[2.48]								[0.51]	[1.72]	
1.11					−0.71	0.48	0.35	0.06	0.71					−0.35	0.48	0.43	0.12	0.05	8%
[3.72]					[−1.97]	[2.02]	[1.84]	[4.10]	[2.01]					[−0.82]	[2.33]	[2.39]	[0.62]	[3.20]	
0.34	0.05	0.00	0.33	0.00				0.04	0.27	0.04	0.01	0.29	0.02				0.05	0.04	7%
[1.40]	[0.86]	[0.28]	[2.61]	[−0.10]				[3.47]	[1.12]	[0.74]	[0.37]	[1.99]	[0.45]				[0.20]	[3.16]	
Panel B: Extending-window regressions in the first stage																			
0.69								0.05	0.65								0.59	0.03	42%
[2.87]								[3.45]	[1.46]								[1.20]	[0.59]	
0.71					−0.40	0.27	0.70	0.06	0.77					−0.32	0.18	0.79	0.46	0.03	39%
[2.21]					[−1.02]	[1.40]	[4.00]	[3.70]	[1.80]					[−0.66]	[0.81]	[3.92]	[3.14]	[1.82]	
0.67	0.27	0.06	0.64	0.07				0.04	0.62	0.24	0.05	0.79	0.00				0.38	0.03	32%
[1.63]	[2.65]	[2.88]	[2.10]	[0.76]				[2.01]	[1.36]	[2.27]	[2.31]	[2.07]	[0.02]				[1.41]	[1.18]	
Panel C: Full-sample regressions in the first stage																			
0.69								0.05	0.68								0.97	0.01	74%
[2.87]								[3.45]	[1.16]								[1.46]	[0.23]	
−0.30					0.54	0.35	0.73	0.05	−0.06					0.50	0.10	0.82	0.64	0.02	54%
[−0.91]					[1.52]	[1.65]	[4.09]	[3.11]	[−0.13]					[1.03]	[0.39]	[3.60]	[2.69]	[0.77]	
1.07	0.40	0.06	0.94	0.20				0.06	0.90	0.31	0.03	1.17	0.03				0.59	0.04	34%
[1.87]	[2.11]	[1.97]	[1.27]	[0.68]				[2.12]	[1.54]	[1.80]	[1.22]	[1.42]	[0.11]				[1.64]	[1.25]	

MP is the growth rate of industrial production. The other Chen, Roll, and Ross (1986) factors are unexpected inflation (UI), change in expected inflation (DEI), term premium (UTS), and default premium (UPR). We use the prior six-month return, denoted r^6, as a characteristic in the second-stage Fama-MacBeth (1973) cross-sectional regressions. In the first stage, we estimate factor loadings using rolling-window regressions, extending-window regressions, and full-sample regressions. The extending windows always start at January 1960 and end at month t, in which we perform second-stage cross-sectional regressions of portfolio excess returns from t to $t+1$ on loadings estimated using information up to month t. The rolling-window and extending-window regressions contain at least twenty-four monthly observations. As testing portfolios, we use thirty portfolios that include the ten size, ten book-to-market, and ten six/six momentum portfolios. We report second-stage cross-sectional regressions including the intercepts (γ_0) and slopes in percent per month. In each panel, the left subpanel reports the cross-sectional regressions without the MP loading as a regressor, and the right subpanel reports those with the MP loading. The last column in the right subpanel, denoted $\Delta\gamma_{r^6}/\gamma_{r^6}$, reports the percentage reduction of the magnitude of the r^6 slope when the MP loading is added into the regression. The t-statistics in square brackets are obtained from estimating the two-stage regressions simultaneously via GMM.

as strong as that in individual stocks and industries. More important, adding the MP loading into the regressions reduces the magnitude of the slopes of prior six-month returns by 7–29% with rolling-window first-stage regressions. The percentage reduction increases to 32–42% with extending-window first-stage regressions and further to 34–74% with full-sample first-stage regressions. Notably, the slopes of the prior six-month returns are no longer significant in seven out of nine specifications. Thus, MP is quantitatively important for driving momentum profits.

4. What Drives the MP Loadings of Momentum Portfolios?

We now investigate potential driving forces behind the MP loading pattern across momentum portfolios under the theoretical guidance of Johnson (2002).

Johnson (2002) argues that the log price-dividend ratio is a convex function of expected growth, meaning that changes in log price-dividend ratio or stock returns are more sensitive to changes in expected growth when expected growth is high.[6] If MP is a common factor summarizing aggregate changes in expected growth, and if winners have higher expected growth than losers, 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. This simulation evidence is 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. First, expected growth rates should differ monotonically across the momentum portfolios (Section 4.1). Second, the expected-growth risk as defined by Johnson should be priced in the cross-section of returns (4.2). Third, the expected-growth risk should increase with expected growth (Section 4.2). In what follows, we present evidence consistent with all three conditions.

4.1 Momentum and expected growth

This subsection establishes the empirical link between short-term prior returns and expected growth. In particular, we show that winners have temporarily higher expected growth than losers and that past returns predict future growth rates.

We consider dividend growth as well as investment growth and sales growth. Shocks to aggregate and firm-specific profitabilities are typically reflected in large movements of investment and sales rather than in movements of relatively

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[6] Pastor and Veronesi (2003, 2006) use the same logic to explain the high stock valuation levels in the late 1990s. Sagi and Seasholes (2007) 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.

smooth dividends. Thus, investment growth and sales growth are 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 and annual frequency. We obtain monthly measures of these flow variables by dividing their current year annual observations by twelve 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 it provides a crude adjustment, this method takes into account monthly changes in stock composition of momentum strategies. We also have tried to measure the portfolio fundamentals at the end of a quarter or a year. This method avoids the crude adjustment from low-frequency to monthly flow variables, but it ignores the monthly changes of stock composition within a quarter or a year. Nevertheless, this approach yields quantitatively similar results (not reported).

4.1.1 Expected growth across momentum portfolios. Table 8 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, winners also have higher growth rates than losers in almost every year in the sample.

We also study how average growth evolves 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. We obtain financial statement data from Compustat quarterly files. Using quarterly rather than annual data can better illustrate the month-to-month evolution of growth rate measures. Figure 2 shows that momentum portfolios display temporary shifts in expected growth. At the portfolio formation month, the expected-growth spreads are sizable: 14% per quarter in dividend growth, 22% in investment growth, and 5% in sales growth. These spreads converge in about ten to twenty months before and, more important, twelve to twenty months after the month of portfolio formation. Thus, the durations of the expected-growth spreads roughly match the duration of momentum profits.

4.1.2 Predicting future growth rates with short-term prior returns. Collectively, Table 8 and Figure 2 show that average growth differs almost monotonically across momentum portfolios. This evidence is conditional on firms being categorized into momentum portfolios. We also study the relation between

Table 8
Descriptive statistics for subsequent growth rates of dividend, investment, and sales for momentum portfolios: January 1965–December 2004, 480 months

	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
Std	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
Std	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
Std	0.09	0.08	0.07	0.06	0.07	0.06	0.06	0.07	0.08	0.10	0.09	

This table reports the means and standard deviations 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 heteroskedasticity and autocorrelations of up to twelve 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). Stock returns are monthly and momentum involves monthly rebalancing, but accounting variables such as investment and dividend are available at quarterly and annual frequency. We obtain monthly measures of these flow variables by dividing their current year annual observations by twelve. 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. The starting point of the 1965–2004 sample is chosen to avoid sample selection bias.

expected growth and past returns directly at the firm level. 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 affirmative.

Because many firm-year observations have zero dividend or investment, the usual growth rate definition is not meaningful at the firm level. Thus, we 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. 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). The sample is from 1965 to 2004. To adjust standard errors for the persistence in the slopes, we regress the time series of slopes on an intercept term and model the residuals as a sixth-order autoregressive process. The standard error of the intercept term is used as the corrected standard error in calculating the Fama-MacBeth (1973) t-statistics.

Table 9 reports the annual cross-sectional regressions of future growth rates on past returns. Past six- and twelve-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

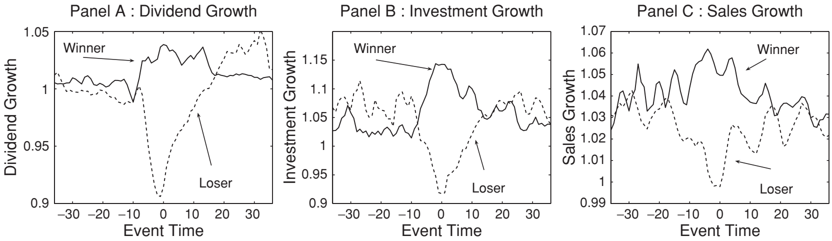

Figure 2
Quarterly average growth rates
Quarterly average growth rates for winner and loser portfolios for 36 months before and after portfolio formation, January 1965–December 2004, 480 months. For each portfolio formation month from t = July 1965 to December 2004, we calculate growth rates for $t + m$, $m = -36, \ldots, 36$ for all the stocks in each portfolio. The measures for $t + m$ are then averaged across portfolio formation months. To construct 10 six/six 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. We hold the resulting portfolios for six months. All stocks are equal-weighted within a given portfolio. We obtain dividend from Compustat quarterly item 20, sales from item two, and investment from item 90. For 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. (A) Dividend growth; (B) Investment growth; (C) Sales growth.

ranges from 1.4% to 10.7%, depending on whether lagged growth rates are used. In sum, contemporaneous stock returns positively predict future growth rates at the firm level.

Our evidence contrasts with that of 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 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

Having established the empirical link between past returns and expected growth, we now connect momentum to the expected-growth risk as defined by Johnson (2002) and quantify how far Johnson's expected-growth risk hypothesis goes in explaining the MP loadings of momentum portfolios.

4.2.1 Hypothesis development. The basic intuition underlying Johnson (2002) 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 relation between the log price-dividend ratio and expected growth is convex, meaning that the ratio is more sensitive to changes in expected growth when expected growth is high. Johnson generalizes this intuition in a stochastic framework,

Table 9
Annual cross-sectional regressions of dividend, sales, and investment growth rates on prior six-month and 12-month returns: January 1965–December 2004, 480 months

	Panel A: Predicting dividend growth, $\triangle d_{t,t+\tau}/b_t$				Panel B: Predicting investment growth, $\triangle i_{t,t+\tau}/b_t$				Panel C: Predicting sales growth, $\triangle s_{t,t+\tau}/b_t$			
Horizon	r^6	r^{12}	$\triangle d_{t-12,t}/b_{t-12}$	$\overline{R}^2(\%)$	r^6	r^{12}	$\triangle i_{t-12,t}/b_{t-12}$	$\overline{R}^2(\%)$	r^6	r^{12}	$\triangle s_{t-12,t}/b_{t-12}$	$\overline{R}^2\%$
$\tau = 12$	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)	

This table reports the annual cross-sectional regressions of future dividend growth, investment growth, and sales growth on prior six-month returns, r^6, and prior twelve-month returns, r^{12}, 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. To adjust standard errors for the persistence in the slopes, we regress the time series of slopes on an intercept term and model the residual as a six-order autoregressive process. The standard error of the intercept term is used as the corrected standard error in calculating the Fama-MacBeth (1973) t-statistics. 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, denoted by $\overline{R}^2$.

in which expected growth is stochastic and its covariation with the pricing kernel is nonzero. The convexity amplifies the covariation between expected growth and the pricing kernel when expected growth is high, and dampens the covariation when expected growth is low.

The expected-growth risk is defined by Johnson (2002) as the covariance of expected dividend growth with the pricing kernel. In practice, both the expected growth and the pricing kernel are unobservable, meaning that we make auxiliary assumptions to operationalize our tests. Motivated by our evidence in Section 2, we specify the pricing kernel as a linear function of MP and directly use the covariance of expected growth rates with MP as the measure of the expected-growth risk.

To quantify the effects of expected growth on the MP loadings of momentum portfolios, we decompose the covariance between the return of momentum decile j and MP, $\mathrm{Cov}(r_{jt}, \mathrm{MP}_t)$, as

$$\mathrm{Cov}(r_{jt}, \mathrm{MP}_t) = \mathrm{Cov}(r_{jt}|g_{jt}, \mathrm{MP}_t) + \mathrm{Cov}(r_{jt} \perp g_{jt}, \mathrm{MP}_t), \tag{4}$$

in which g_{jt} is the expected growth rate of momentum portfolio j, $r_{jt}|g_{jt}$ is the projection of r_{jt} on g_{jt}, and $r_{jt} \perp g_{jt}$ is the component of r_{jt} orthogonal to the expected growth rate g_{jt}.

Hinged on expected growth rates, Johnson's (2002) explanation of the MP loading spread across momentum portfolios primarily works through the first term in Equation (4), $\mathrm{Cov}(r_{jt}|g_{jt}, \mathrm{MP}_t)$. Let $\beta_{r_j|g_j}$ denote the projection coefficient of r_{jt} on g_{jt}. We can decompose $\mathrm{Cov}(r_{jt}|g_{jt}, \mathrm{MP}_t)$ further as

$$\mathrm{Cov}(r_{jt}|g_{jt}, \mathrm{MP}_t) = \mathrm{Cov}(\beta_{r_j|g_j}\, g_{jt}, \mathrm{MP}_t) = \beta_{r_j|g_j} \times \mathrm{Cov}(g_{jt}, \mathrm{MP}_t) \tag{5}$$

$$= \rho(r_{jt}, g_{jt})\sigma_{r_j} \times \rho(g_{jt}, \mathrm{MP}_t)\sigma_{\mathrm{MP}}, \tag{6}$$

in which we have used the relation $\beta_{r_j|g_j} = \mathrm{Cov}(r_{jt}, g_{jt})/\sigma^2_{g_j}$ to derive the last equation. In Equation (6), $\rho(\cdot, \cdot)$ denotes the correlation between the two time series in parentheses, σ_{r_j} is the return volatility of momentum decile j, and σ_{MP} is the MP volatility.

Equation (6) formalizes the necessary conditions on the expected-growth risk for Johnson's (2002) model to explain momentum. First, to see if the expected-growth risk is priced, we test the null hypothesis that $\rho(g_{jt}, \mathrm{MP}_t) = 0$. Because Table 5 shows that the MP risk is priced in the cross-section of returns, a rejection of the null establishes the empirical relevance of the expected-growth risk. Second, to examine whether the expected-growth risk increases with expected growth, we test whether $\rho(r_{jt}, g_{jt})\sigma_{r_j}$ increases with the portfolio index j (the portfolios are in ascending order).

4.2.2 Test design. Firms often pay zero dividends, making dividend growth not well defined at the firm level, so we conduct our tests at the portfolio level. And because Johnson's (2002) model is developed to explain momentum profits, we use 10 six/six momentum portfolios as our testing assets. Using twenty-five momentum portfolios yields similar results (not reported). In each month t, each of the testing portfolios has 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 dividend changes in the past six months divided by the dividends from 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. 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, the expected-growth risk and its risk premium estimates are affected by measurement errors. This problem is more challenging than the measurement-error problem of estimating betas 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 shifts in the expected-growth risk is reduced. However exploratory, our tests provide a first cut into the pricing of the expected-growth risk predicted by Johnson (2002).

4.2.3 Empirical results. Table 10 presents evidence consistent with Johnson's (2002) expected-growth risk hypothesis. $\mathrm{Cov}(r_j|g_j, \mathrm{MP})$ increases from -0.09×10^{-4} for the loser decile to 0.06×10^{-4} for the winner decile, meaning that expected growth is potentially important for driving the MP loading pattern across momentum portfolios. As a first decomposition, we rewrite $\mathrm{Cov}(r_j|g_j, \mathrm{MP})$ as $\beta_{r_j|g_j} \mathrm{Cov}(g_{jt}, \mathrm{MP}_t)$. Panel A shows that the near-monotonic pattern in the covariance is largely driven by a similar pattern in $\beta_{r_j|g_j}$. Also, the $\beta_{r_j|g_j}$ estimates are significant for most momentum deciles.

More important, panel B of Table 10 decomposes $\mathrm{Cov}(r_j|g_j, \mathrm{MP})$ as the product of $\rho(r_{jt}, g_{jt})\sigma_{r_j}$ and $\rho(g_{jt}, \mathrm{MP}_t)\sigma_{\mathrm{MP}}$. The panel shows that $\rho(r_{jt}, g_{jt})\sigma_{r_j}$ increases almost monotonically from -0.77×10^{-2} for the loser decile to 1.35×10^{-2} for the winner decile. Because $\rho(r_{jt}, g_{jt})\sigma_{r_j}$ is the portfolio-specific component of the expected-growth risk measure $\mathrm{Cov}(r_j|g_j,\mathrm{MP})$, the evidence lends support to Johnson's (2002) hypothesis that the expected-growth risk increases with expected growth or equivalently the momentum decile index j. Finally, panel C shows that the estimated correlations between expected growth and MP, $\rho(g_j, \mathrm{MP})$, are all positive. From their associated p-values, the correlations are all significantly different from zero. This evidence establishes the empirical relevance of the expected-growth risk.

Table 10
Momentum profits and the expected-growth risk: January 1965–December 2004, 540 months

Momentum decile	$\text{Cov}(r_j \mid g_j, \text{MP}) \times 10^4$	Panel A: Decomposition I $\beta_{r_j \mid g_j}$	$t(\beta_{r_j \mid g_j})$	$\text{Cov}(g_j, \text{MP}) \times 10^4$	Panel B: Decomposition II $\rho(r_j, g_j)\sigma_{r_j} \times 10^2$	$\rho(g_j, \text{MP})\sigma_{\text{MP}} \times 10^2$	Panel C: Test $\rho(g_j, \text{MP}) = 0$ $\rho(g_j, \text{MP})$	$p_{\rho(g_j, \text{MP})=0}$
Loser	−0.090	−0.11	(−1.24)	0.82	−0.77	0.12	0.17	0.00
2	−0.007	−0.02	(−0.06)	0.40	−0.07	0.10	0.20	0.00
3	0.059	0.19	(0.89)	0.31	0.35	0.17	0.23	0.00
4	0.088	0.46	(3.11)	0.19	0.77	0.11	0.17	0.00
5	0.038	0.34	(2.35)	0.11	0.53	0.07	0.16	0.00
6	0.079	0.67	(2.49)	0.12	0.94	0.08	0.11	0.02
7	0.066	0.52	(3.04)	0.13	0.75	0.09	0.13	0.00
8	0.017	0.14	(1.71)	0.12	0.35	0.05	0.13	0.00
9	0.103	0.51	(2.65)	0.20	1.30	0.08	0.12	0.01
Winner	0.069	0.18	(1.51)	0.38	1.35	0.05	0.09	0.04

For 10 six/six momentum portfolios, we report summary statistics related to the expected-growth risk. $\rho(g_j, \text{MP})$ is the correlation between the expected growth rates of momentum decile j (in the ascending order) and the monthly growth rates of industrial production (MP). $p_{\rho(g_j, \text{MP})=0}$ is the p-value associated with testing $\rho(g_j, \text{MP}) = 0$. $\beta_{r_j \mid g_j}$ is the slope from regressing the returns of decile j on its expected growth rates. $t(\beta_{r_j \mid g_j})$ is the t-statistic associated with testing $\beta_{r_j \mid g_j} = 0$. $\text{Cov}(r_j \mid g_j, \text{MP})$ is the covariance between the projections of the returns of decile j on its expected growth rates and MP. $\text{Cov}(g_j, \text{MP})$ is the covariance between the expected growth rate of momentum decile j and MP. $\rho(r_j, g_j)$ is the correlation between the returns of decile j and its expected growth rates. σ_{r_j} is the return volatility of momentum decile j and σ_{MP} is the volatility of MP. Panel A presents the decomposition of $\text{Cov}(r_j \mid g_j, \text{MP})$ as the product of $\beta_{r_j \mid g_j}$ and $\text{Cov}(g_j, \text{MP})$. Panel B presents the decomposition of $\text{Cov}(r_j \mid g_j, \text{MP})$ as the product of $\rho(r_j, g_j)\sigma_{r_j}$ and $\rho(g_j, \text{MP})\sigma_{\text{MP}}$. Panel C reports $\rho(g_j, \text{MP})$ and its associated p-value, testing the null hypothesis that the correlation is zero. 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 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.

5. Summary, Interpretation, and Future Work

Our findings suggest that the combined effect of MP risk and risk premium goes a long way in explaining momentum profits. Winners have temporarily higher MP loadings than losers. In many of our tests, the MP factor explains more than half of momentum profits. Further, consistent with the expected-growth risk hypothesis of Johnson (2002), we document that winners have temporarily higher future average growth rates than losers and that the duration of the expected-growth spread roughly matches that of momentum profits. Our evidence also suggests that the expected-growth risk is priced and that the expected-growth risk increases with the expected growth.

We interpret our results as suggesting that risk is an important driver of momentum. These results are important. Many previous studies have failed to document direct evidence of risk on momentum portfolios. An incomplete list includes Jegadeesh and Titman (1993); Fama and French (1996); Grundy and Martin (2001); Griffin, Ji, and Martin (2003); and Moskowitz (2003). Consequently, the bulk of the momentum literature has followed Jegadeesh and Titman in interpreting momentum as a result of behavioral underreaction to firm-specific information. Our results suggest that the case of behavioral underreaction might have been vastly exaggerated.

What gaps remain in making the case that momentum is a risk-driven phenomenon? First, we can quantify the role of macroeconomic risk in driving momentum by using a broader set of testing portfolios. We have focused only on the momentum deciles. But as noted, researchers have uncovered tantalizing evidence linking momentum profits to characteristics such as trading volume, size, analyst coverage, institutional ownership, book-to-market, credit rating, and information uncertainty. We can test whether macroeconomic risk can explain momentum using double-sorted testing portfolios formed on short-term prior returns and these aforementioned characteristics. And to the extent that Chan, Jegadeesh, and Lakonishok (1996) have shown that price momentum coexists, but differs from, the earnings momentum of Ball and Brown (1968) and Bernard and Thomas (1989, 1990), we can test whether macroeconomic risk can explain earnings momentum profits.

Second, several aspects of momentum other than mean returns are particularly intriguing. Chordia and Shivakumar (2002) and Cooper, Gutierrez, and Hameed (2004) document that momentum profits are strong in economic expansions but are nonexistent in recessions. Working with the 1990–2001 sample, Schwert (2003) shows that many anomalies tend to attenuate after their initial discovery. But the estimate of momentum profits is even larger in magnitude than that documented by Jegadeesh and Titman (1993) in their 1965–1989 sample. The procyclical nature of expected momentum profits seems at odds with risk-based explanations, which usually rely on downside risk. But it remains to be seen whether macroeconomic risk can account for this pattern. Cooper et al. present some negative evidence in this regard, but they use aggregate conditioning variables instead of the Chen, Roll, and Ross (1986) macroeconomic factors.

Moreover, Jegadeesh and Titman (2001) and Griffin, Ji, and Martin (2003) stress that momentum profits reverse over one- to five-year horizons, a pattern that seems inconsistent with existing risk-based explanations (e.g., Conrad and Kaul 1998; Berk, Green, and Naik 1999; Johnson 2002). This concern can be (somewhat) alleviated by our evidence that the MP loading spread across momentum deciles converges in about six post-formation months. However, the existing risk-based theories are silent about why momentum profits are more short-lived than profits from other anomaly-based strategies such as the value strategy. Further research on this question seems warranted.

Finally, the MP loading spread across momentum deciles derives mostly from winners. A more complete investigation of momentum profits can combine the expected-growth risk with the drivers of the loser returns. One possibility is liquidity: Pastor and Stambaugh (2003) show that a liquidity risk factor can account for a large portion of momentum profits. Another possibility is trading-related market frictions, as shown in Korajczyk and Sadka (2004).

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