Economic Fundamentals, Risk, and Momentum Profits

Laura X.L. Liu[*], Jerold B. Warner[†], and Lu Zhang[‡]

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Abstract

We study empirically the changes in economic fundamentals for firms with recent stock price momentum. We find that: (i) winners have temporarily higher dividend, investment, and sales growth rates, and losers have temporarily lower dividend, investment, and sales growth rates; (ii) the duration of the growth rate dispersion matches approximately that of the momentum profits; (iii) past returns are strong, positive predictors of future growth rates; and (iv) factor-mimicking portfolios on expected growth rates earn significantly positive returns on average. This evidence is consistent with the theoretical predictions of Johnson (2002), in which momentum returns reflect compensation for temporary shifts in risk associated with expected growth. Additional tests do not provide much support for a risk-based explanation, however.

[*]Doctoral Student in Finance, William E. Simon Graduate School of Business Administration, University of Rochester; Tel: (585)275-4604; Email: liuxi@simon.rochester.edu.

[†]Fred H. Gowen Professor of Finance, William E. Simon Graduate School of Business Administration, University of Rochester; Tel: (585)275-2678; Email: warner@simon.rochester.edu.

[‡]Assistant Professor of Finance, William E. Simon Graduate School of Business Administration, University of Rochester; Tel: (585)275-3491; Email: zhanglu@simon.rochester.edu.

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1 Introduction

The momentum literature, e.g., Jegadeesh and Titman (1993), finds that strategies that buy past winners and short past losers earn significantly positive average returns over the subsequent six to 12 months. There are two lines of explanation for the momentum profits. First, some argue that behavioral biases can give rise to momentum.[1] A second, more recent, line of explanation retains the assumption of rational expectations.[2]

Along the second line, Johnson (2002) proposes a direct mechanism for momentum effects within a rational pricing model. His model examines asset prices when firms' expected dividend growth rates are stochastic. As detailed below (Section 2), there are two key predictions. First, recent winners have temporarily higher expected growth rates than recent losers, therefore a sort on momentum is also a sort on expected growth rates. Second, expected growth rate risk is priced, such that stocks with higher expected growth rates have higher risk and earn higher average returns.[3] This paper investigates changes in economic fundamentals for momentum firms, and studies the empirical merits of both predictions. More generally, our paper is related to many papers that have explored expected growth rates and their asset pricing implications.[4]

We find strong evidence supporting the first prediction of Johnson (2002) that a sort on past momentum is a sort on expected growth rates. Concerning the second premise, we find that stocks with higher expected growth rates earn higher returns on average. However, evidence that this is driven by risk is weak. We find that:

- Past winners have much higher dividend, investment, and sales growth rates on average than losers.

[1]Some examples are self-attributive overconfidence in Daniel, Hirshleifer, and Subrahmanyam (1998), conservatism in Barberis, Shleifer, and Vishny (1998), and the slow information diffusion in Hong and Stein (1999).

[2]For example, Berk, Green, and Naik (1999) demonstrate that slow turnover in firms' projects gives rise to persistence in their systematic risk, making expected returns positively correlated with lagged expected returns. See also Conrad and Kaul (1998).

[3]See also Sagi and Seasholes (2001) for a model with similar economic insights.

[4]Examples include Chen, Roll, and Ross (1986), Bansal and Yaron (2002), Bansal, Dittmar, and Lundblad (2002), Li, Vassalou, and Xing (2002), Lettau and Ludvigson (2003), Menzly, Santos, and Veronesi (2003), Campbell and Vuolteenaho (2003), and Vassalou (2003).

- Expected growth rates are time-varying at the firm level and past returns are strong, positive predictors of future growth rates.

- Factor mimicking portfolios constructed on expected dividend growth rates earn significantly positive average returns.

- The dispersion in growth rates as well as that in the loadings of the winner and loser portfolios on expected growth factors are both *temporary*. Their durations also match approximately that of the momentum profits.

- Covariance-based, cross-sectional tests do not provide much support for a risk-based explanation of momentum, despite a battery of such tests. Shocks to firms' expected growth rates are positively correlated with shocks to some aggregate growth variables, such as the growth rate of industrial production. There is only weak evidence, however, that winners have higher growth-related risk than losers, or that any risk premium associated with the growth variables is relevant for explaining momentum returns.

Like our work, several other papers also examine the role of economic fundamentals and risk in explaining momentum profits. Bansal, Dittmar, and Lundblad (2002) show that the exposure of dividends to aggregate consumption helps explain the cross-sectional variation of returns. Vassalou and Apedjinou (2003) find that a strategy based on corporate innovation, defined as the proportion of a firm's gross profit margin not explained by the capital and labor it utilizes, has similar characteristics and performance to a price momentum strategy. Finally, Pastor and Stambaugh (2003) find that a liquidity risk factor accounts for half of the momentum profits over the period from 1966 to 1999. Our empirical analysis and its theoretical motivation are very different from these papers.

In Section 2, we summarize testable hypotheses from Johnson (2002). Section 3 examines growth rate measures for ten momentum portfolios. Section 4 constructs factor mimicking portfolios on expected growth rates, and examines whether momentum profits survive after controlling for expected growth rates. Section 5 provides further tests on the pricing of growth rate risk, using covariance based measures. Section 6 concludes.

2 Testable Hypotheses

To explain the relation between expected growth and risk, we begin with a simple perpetuity model with deterministic growth rates. We then review Johnson's (2002) model, which extends the intuition to a general framework with stochastic expected growth rates, and summarize testable propositions.

2.1 Constant Expected Growth Rate

Some basic intuition can be illustrated using a simple dividend growth model, e.g., Gordon (1962), 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 expected growth rate of dividends, and $k > g$. Let $U = P/D$ be the price dividend ratio. Simple algebra yields $\partial \log U / \partial g = 1/(k-g)$, which always increases with g.

This comparative static analysis says that the sensitivity of log price dividend ratio with respect to g is higher for firms with higher expected growth rates. Intuitively, the curvature of log price dividend ratio with respect to expected growth is *convex*: log price dividend ratio will be more sensitive to changes in expected growth rate when expected growth rate is high.

2.2 Stochastic Expected Growth

There is no source of uncertainty in the above model, where both discount rate and expected growth rate are constant. Johnson (2002) generalizes this intuition about price/return sensitivity in a stochastic framework with endogenously determined discount rates. He assumes that g is stochastic and its covariation with the pricing kernel, e.g., common risk factors, is nonzero. This covariation will then be one dimension of risk to be compensated. Johnson (2002) shows that the convexity in log equity price with respect to expected growth will amplify the amount of covariation between expected growth and the pricing kernel when expected growth is high, and dampen the covariation when expected growth is low.

Details

To make the idea precise, we follow Johnson (2002, p. 587) and assume that the marginal utility of a representative agent or the state price density, Λ_t, follows a geometric Brownian motion:

$$\frac{d\Lambda_t}{\Lambda_t} = -r\,dt + \sigma_\Lambda\,dW_{\Lambda t}$$

where r and σ_Λ are fixed constants. Stock j is a claim to its perpetual, nonnegative cash flow, D_t^j, with a stochastic, expected growth rate, g_t^j:

$$\begin{aligned} \frac{dD_t^j}{D_t^j} &= g_t^j\,dt + \sigma_D^j\,dW_{Dt}^j \\ dg_t^j &= \kappa^j\left(\bar{g}^j - g_t^j\right)\,dt + \sigma_g^j\,dW_{gt}^j \end{aligned}$$

where $\sigma_D^j, \kappa^j, \bar{g}^j$, and σ_g^j are constant, and the correlations among the Brownian motions, $\rho_{\Lambda D}^j, \rho_{\Lambda g}^j$, and ρ_{Dg}^j are nonzero constants.

Under these assumptions, Johnson (2002, p. 588) shows that the expected excess return of stock j, denoted EER_t^j, equals:

$$\text{EER}_t^j = -\rho_{\Lambda D}^j\sigma_\Lambda\sigma_D^j - \rho_{\Lambda g}^j\sigma_\Lambda\sigma_g^j\frac{d\log U_t^j}{dg_t^j} \tag{1}$$

where $U_t^j \equiv U(g_t^j)$ denotes the price dividend ratio of stock j, which is a function of expected growth rate g_t^j.

Equation (1) says that the expected excess return has two components. The first part, $-\rho_{\Lambda D}^j\sigma_\Lambda\sigma_D^j$, is the compensation for the covariation between the *realized* dividend growth rate and the pricing kernel. The second part, $-\rho_{\Lambda g}^j\sigma_\Lambda\sigma_g^j(d\log U_t^j/dg_t^j)$, is the compensation for the covariation between the stochastic, *expected* growth rate and the pricing kernel. The covariance is defined as the expected growth rate risk.[5]

Importantly, stock j's expected growth rate risk is proportional to $d\log U_t^j/dg_t^j$. The convexity of log equity price with respect to expected growth rate, which Johnson (2002, Lemma 1, p. 589) formally proves under the general framework with stochastic, expected

[5]Johnson (2002, p. 589) defines expected growth rate risk as the equity price elasticity with respect to the expected growth rate. Here we define the whole term of $-\rho_{\Lambda g}^j\sigma_\Lambda\sigma_g^j(d\log U_t^j/dg_t^j)$ to be expected growth rate risk to emphasize its covariance-based nature, i.e., $\rho_{\Lambda g}^j \neq 0$.

growth, implies that compensation for the expected growth risk, and hence EER_t^j, increases with expected growth rate g_t^j.

Discussion

There are two crucial, explicit predictions in Johnson's explanation for the momentum anomaly.

> **Hypothesis 1.** *Recent winners have temporarily higher expected growth rates than recent losers, such that a sort on momentum tends to be a sort on expected growth rates.*

and

> **Hypothesis 2.** *The expected growth rate risk is priced, such that stocks with higher expected growth rates have higher expected growth rate risk and earn higher returns on average.*

Testing hypothesis 1 is straightforward (Section 3). Testing hypothesis 2 is more complicated. We examine whether firms with higher expected growth rates earn higher returns, on average (Section 4). This is a necessary, though not sufficient, condition for Johnson's (2002) expected growth risk story. Whether the higher average returns are expected and due to risk associated with expected growth, i.e., $\rho_{\Lambda g}^j \neq 0$, is harder to establish. The higher average returns could occur because of investor sentiment, e.g., underreaction to information about future growth. To discriminate between risk and sentiment, covariance-based tests are required (Section 5).

These covariance-based tests are somewhat exploratory, however, because Johnson (2002) does not identify the common factors with respect to which firms' expected growth rates covary. Rather, his model's basic mechanism is that whatever these common factors are, expected growth rate risk enters into expected return determination via the covariance of expected growth with these factors. Shifts in expected growth will shift the covariance, and hence shift the risk with respect to common factors.

We use several aggregate measures to test for the pricing of expected growth rate risk, and a number of alternative specifications for expected growth. These aggregate measures include the growth rate of industrial production (Chen, Roll, Ross [1996]), and cash flow news (Campbell and Vuolteenaho [2003]). These variables go beyond those in the Fama-French (1993) three factor model. This seems natural since the three-factor model does not explain momentum (Fama and French [1996]), and (as documented below) changes in loadings on their three factors are not supportive of a risk-shifting explanation. A caution concerning our aggregate measures is that rejection of a risk-shifting story could result from the failure of our measures to capture the relevant common factors, rather than a failure of the risk-shifting story itself.

Besides dividend growth, we also use investment growth and sales growth in our empirical tests. Shocks to aggregate and firm-level productivity are typically reflected in large movements of capital investment and sales, rather than the relatively smooth dividend or payout series. Ex ante, investment growth and sales growth are thus more likely to contain useful information than dividend growth on expected returns.[6]

3 Growth Rates

In this section we study whether momentum portfolios differ in growth rates, and how persistent these growth rate differences are.

3.1 Sample Construction

We obtain data on stock return, stock price, and outstanding shares from the Center for Research in Security Prices (CRSP) monthly return file. Financial statement data, such as book value of equity, investment expenditure, and earnings are from the Compustat merged annual and quarterly data files. We use the common stocks listed on the NYSE, AMEX, and Nasdaq from July 1965 through December 2001, but exclude closed-end funds, Real Estate Investment Trust, American Depository Receipts, and foreign stocks (we use only stocks with share code of ten or 11). We ignore firms with negative book values, and only December fiscal year-end firms are used.

[6]Cochrane (1991, 1996) relies on similar motivation for using investment growth and sales growth in asset pricing tests.

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. To avoid potential microstructure biases, we impose one-month lag between the end of ranking period and the beginning of holding period.

We focus on three growth rates measures for momentum portfolios: dividend growth, investment growth, and sales growth. Even though return on equity is not directly motivated from Johnson (2002), we consider this measure as a robustness check (see also Fama and French [1995]). Stock returns are observable monthly and the momentum strategies involve monthly rebalancing. Fundamental variables such as investment and dividend are available at quarterly or annual frequency. We obtain monthly measures of flow variables by dividing their current year annual observations by 12 or by dividing their current quarterly observations by three. Profitability is measured as monthly earnings divided by book value at last fiscal year end. Each month after ranking all stocks on their past six-month returns, we aggregate the individual stock fundamentals for the 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.

As a robustness check, we also measure all the fundamentals of momentum portfolios at the end of a quarter or a year. In this case, all the flow and stock variables are current quarterly or annual observations. This method avoids the *ad hoc* adjustment from low-frequency flow to monthly flow variables, but it ignores the monthly changes of stock composition within the quarter or the year. These two different methods of measuring fundamentals yield quantitatively similar results, however.

3.2 Descriptive Statistics

Table 1 reports the summary statistics for stock returns, dividend growth, investment growth, sales growth, and return on equity, for ten momentum portfolios and the spreads between winner and loser portfolios. The data source for the fundamental variables is the Compustat merged annual files: investment is capital expenditure from cash flow statement (item 128); earnings is income before extraordinary items (item 18) plus deferred taxes (item

Table 1 : Summary Statistics, Returns and Economic Fundamentals, Ten Momentum Portfolios (July 1965 to December 2001, 438 observations)

This table reports the mean m and volatility σ of returns, dividend growth, investment growth, sales growth, and return on equity for ten momentum portfolios. Average returns and volatilities are in monthly percent, and so are the intercepts, α, from market regressions. The mean and volatility in Panels B–E are annualized. The t-statistics in the last column are for testing the average spread in average return or growth rates between winner and loser portfolios equals zero. All the t-statistics are adjusted for heteroscedasticity and autocorrelations up to six lags. Significant spreads and their t-statistics are highlighted.

	Loser	2	3	4	5	6	7	8	9	Winner	Spread	t_{Spread}
	Panel A: Excess Returns											
m	0.40	0.41	0.54	0.60	0.63	0.68	0.72	0.77	0.92	1.19	**0.78**	**3.30**
σ	8.14	6.37	5.55	5.07	4.91	4.83	4.91	5.23	5.87	7.23	4.96	
α	-0.74	-0.62	-0.45	-0.37	-0.33	-0.29	-0.26	-0.25	-0.13	0.06	0.80	
t_α	-2.94	-3.34	-2.92	-2.68	-2.60	-2.35	-2.10	-1.90	-0.80	0.26	4.34	
β	1.24	1.09	1.01	0.96	0.95	0.95	0.98	1.04	1.12	1.27	0.03	
	Panel B: Dividend Growth											
m	-0.12	0.00	0.04	0.06	0.07	0.08	0.08	0.11	0.14	0.18	**0.30**	**4.50**
σ	0.27	0.12	0.07	0.05	0.06	0.05	0.07	0.08	0.15	0.34	0.42	
	Panel C: Investment Growth											
m	-0.08	0.03	0.06	0.08	0.08	0.11	0.12	0.16	0.20	0.33	**0.41**	**9.53**
σ	0.16	0.13	0.12	0.11	0.12	0.14	0.18	0.20	0.18	0.27	0.27	
	Panel D: Sales Growth											
m	0.03	0.06	0.07	0.08	0.09	0.09	0.10	0.12	0.14	0.18	**0.15**	**10.69**
σ	0.08	0.07	0.06	0.06	0.07	0.06	0.06	0.07	0.07	0.10	0.09	
	Panel E: Profitability											
m	-0.01	0.09	0.12	0.13	0.14	0.15	0.16	0.16	0.17	0.16	**0.17**	**22.10**
σ	0.05	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.05	

50) minus preferred dividends (item 19); dividend is common stock dividends (item 21); sales are net sales (item 12); and book value is for common equity (item 60) plus deferred taxes (item 74). The sample period is from July 1965 to December 2001.

Panel A of Table 1 reports that the momentum strategy is profitable in our sample, consistent with previous studies. The average winner-minus-loser return in excess of three-month Treasury bill is 9.37% per year with a t-statistic of 3.30. Panels B–E report summary statistics for momentum portfolios' growth and profitability. The results are striking. Winner stocks have much higher growth rates, on average, than loser stocks, and the spreads between winner and loser portfolios are highly significant. For example, the dividends of winner stocks grow at an annual rate of 18 percent; while the dividends of loser stocks fall at a rate of 12 percent. Wide spreads between winners and losers are also evident for the other growth variables. Winners are also on average more profitable than losers. The average return on equity of winners is 16 percent per year, while that of losers is only minus one percent. We have also examined the time series of growth variables and profitability. Except for a few years, winners have higher growth rates and profitability than losers.

3.3 Event Time Evidence

This subsection examines how economic fundamentals and stock return moments evolve before and after firms are classified as winners and losers on past returns.

Growth Rates and Profitability

For each portfolio formation month t from January 1965 to December 2001, we calculate growth rates and return on equity for $t+m$, where $m = -36, \ldots, 36$. We then average the measures for $t+m$ across portfolio formation months, thus capturing average growth rates and profitability for three years before and three years after the portfolio formation.

We obtain financial statement data from Compustat merged quarterly files. Using quarterly data rather than annual data can better illustrate the month-to-month evolution of growth rate measures before and after portfolio formation.[7] We obtain book value of equity from quarterly data item 59; earnings are income before extraordinary items (item eight); dividend from item 20, sales from item two, and investment from item 90. For capital investment, Compustat quarterly data begin at 1984, so we use the sample from 1984 to 2001 for investment growth. To capture the effects of monthly changes in stock composition of winner and loser portfolios, we continue to dividend quarter dividend, earnings, investment, and sales data by three to obtain monthly observations. We exclude firm/month observations with negative book values.

Figure 1 shows the results. Panels A–C report that momentum is mainly associated with *temporary* differences in growth rates. At the month of portfolio formation, the dispersion

[7] We have also used Compustat merged annual files to generate Figure 1 below and obtained qualitatively similar results.

in growth rates between winners and losers is sizable: 11 percent in dividend growth, 22 percent in investment growth, and five percent per quarter in sales growth. The growth rate differences converge quickly for about ten to 20 months before and 15 to 20 months after the month of portfolio formation. In contrast, the difference in average profitability persists for at least three years after portfolio formation.

Stock Returns, Market Beta, and Volatility

To see the behavior of return moments in the same event window, we use the following procedure. 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. For each portfolio formation month from $t =$ January 1965 to December 2001, we calculate equally-weighted excess returns for winner and loser portfolios for $t+m, m = -36, \ldots, 36$. We then pool together the observations of winner and loser excess returns and market excess returns for event month $t+m$ across calendar time. All the return moments, including average excess returns, Jensen's α, market beta, and total volatility, are computed based on the pooled time series for a given event month.

From Panel A of Figure 2, there is a huge dispersion in average returns between winners and losers from month -6 to month 0. Winners gain on average more than ten percent per month, and losers lose on average about seven to eight percent per month. The magnitudes are not surprising given that we construct momentum portfolios based on past returns, and suggest large changes in firms' fundamentals. Winners continue to beat losers for about ten months, and then a reversal in stock returns kicks in. A similar pattern can be observed in Jensen's α from Panel B. The panel shows further that significant intercepts of winners are clustered around the portfolio formation month, while those of the losers tend to be distributed about 20 months before and ten months after portfolio formation.

From Panel C, the observed pattern of returns is not matched by shifts in market beta. Even though winners have much higher market betas than losers from month -6 to 0, they have lower market betas than losers for about four months after portfolio formation. From Panel D, except for a few months around month ten, losers are generally more volatile than winners after the month of portfolio formation. Panels C and D do not support a risk-shift

Figure 1 : Quarterly Growth Rates and Profitability of Winner and Loser Portfolio in Event Time (36 Months Before and After Portfolio Formation)

For each portfolio formation month from $t =$ July 1965 to December 2001, 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.

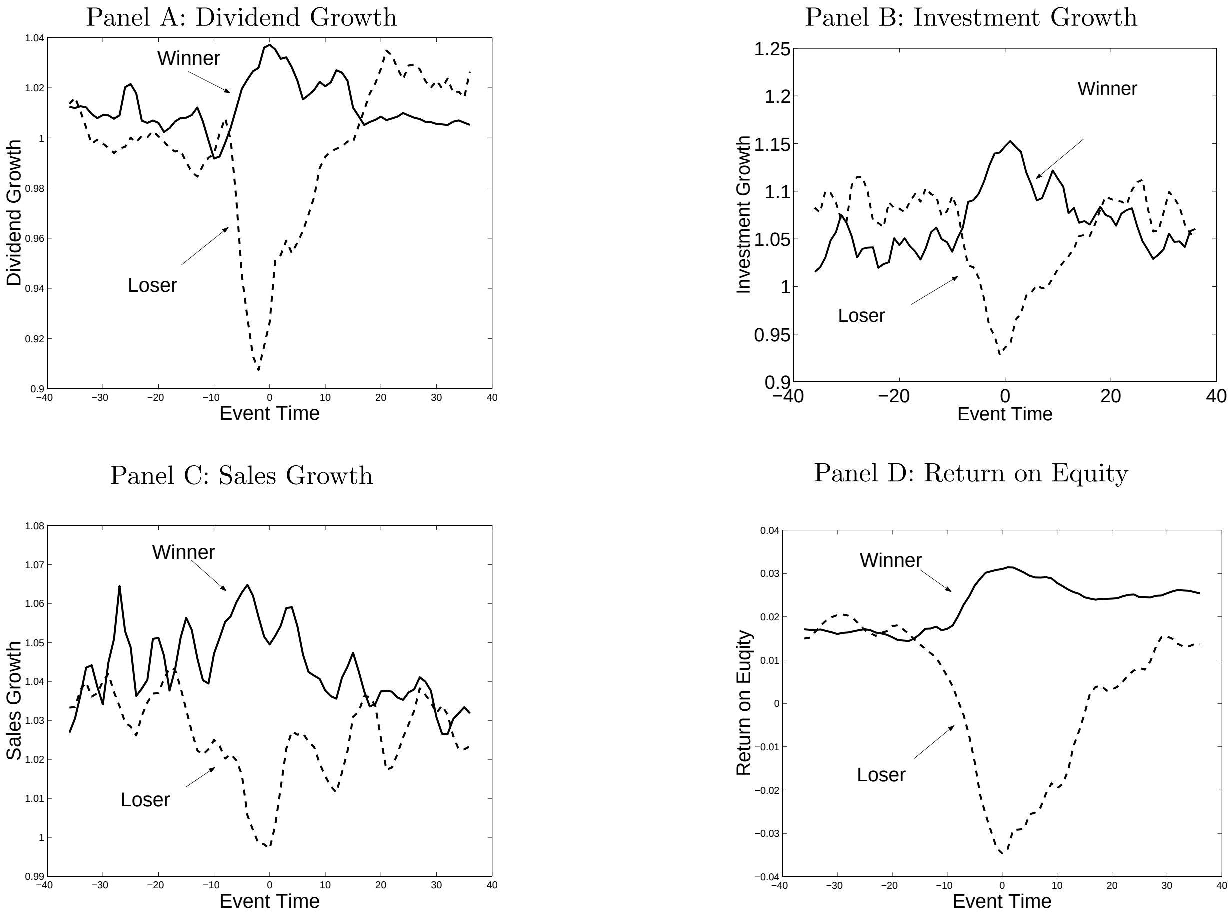
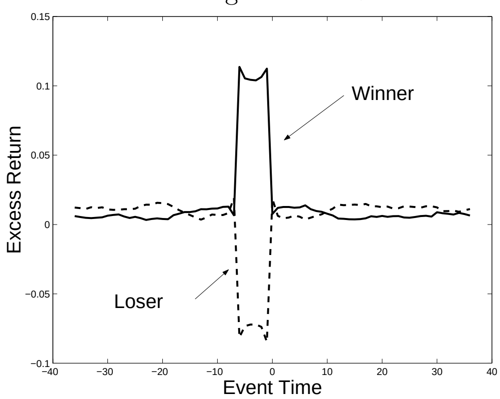


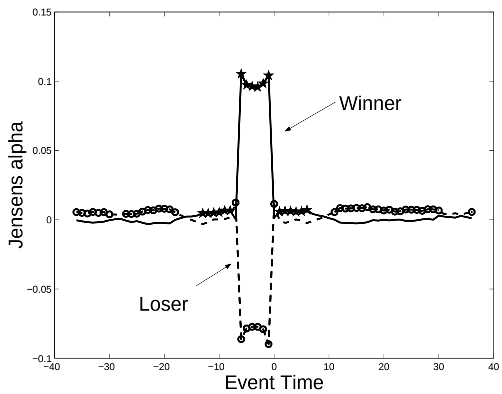
Figure 2 : Average Excess Returns, Jensen's α, Market β, and Total Volatility of Winner and Loser Portfolio in Event Time (36 Months Before and After Portfolio Formation)

For each portfolio formation month from $t =$ January 1965 to December 2001, we calculate equally-weighted excess returns for winner and loser portfolios for $t+m, m = -36, \ldots, 36$. The observations of winner and loser excess returns and market excess returns for event month $t+m$ are pooled together across calendar time. All the return moments, including average excess returns (Panel A), Jensen's α (Panel B), market beta (Panel C), and total volatility (Panel D), are computed based on the pooled time series for a given event month. In Panel B, all the significant intercepts for the winner portfolio are highlighted with stars, and all the significant intercepts for the loser portfolio are highlighted with circles.

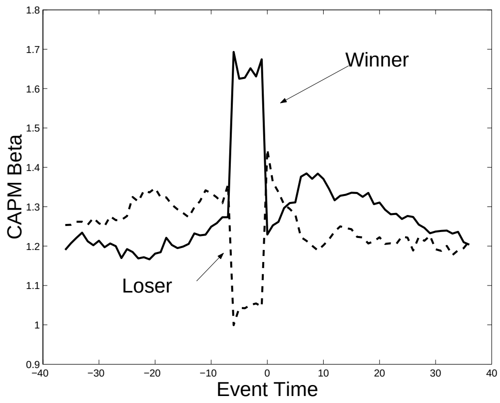
Panel A: Average Excess Returns



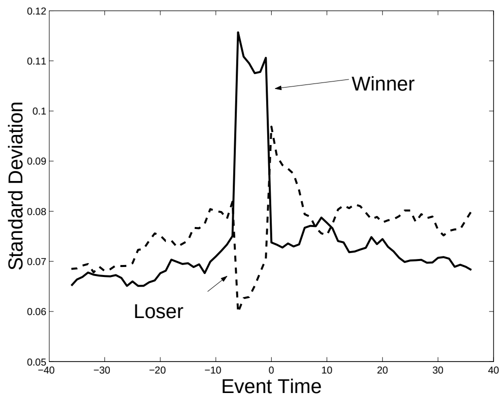
Panel B: Jensen's α



Panel C: Market β



Panel D: Volatility



explanation of momentum, but the paper's later tests are needed for a more complete picture.

3.4 Predicting Future Growth Rates with Past Returns

An important hypothesis in the theoretical model of Johnson (2002) is that recent performance in stock returns is correlated with levels of *expected* growth rates, such that a price momentum sort will tend to sort firms on future growth rates. To examine whether future growth rates are predictable from past returns, we run Fama-MacBeth (1973) cross-sectional regressions to predict future dividend growth, investment growth, and sales growth, over one-year and two-year horizons. The explanatory variables are past six-month return or 12-month return, both with and without lagged growth rates. The cross-sectional regressions are run annually from 1965 to 2001.

Since some firm/year observations have zero dividend and zero or negative capital investment, rendering the normal definition of growth rates meaningless, we measure firm-level growth by normalizing changes of dividend, investment, and sales by beginning-of-period book value. To adjust standard errors for the resulting persistence in the slope coefficients, we follow Pontiff (1996) by regressing the time-series of slope coefficients on an intercept term and modeling the residuals as a sixth-order autoregressive process. The standard error of the intercept term is then used as the corrected standard error in constructing Fama-MacBeth t-statistics.

Table 2 reports the results. From Panels A–C, past six- or 12-month returns are significant, positive predictors of future one-year and two-year growth rates. This is also true after controlling for lagged values of growth rates, and is consistent with Johnson (2002). The average R^2 ranges from one to six and half percent, depending on whether the lagged growth rates are used. Finally, Panel D shows that past stock returns are also positively correlated with future profitability. The values of average R^2 are higher than those from predictive regressions of growth rates, possibly due to the fact that profitability is more persistent than growth rates, as indicated in Figure 1.

Table 2 : Cross-Sectional Regressions of Growth Rates on Past Returns

This table reports the annual cross-sectional regressions of future dividend growth, investment growth, sales growth, and return on equity on past six-month return $r_{t-5,t}$, past 12-month return $r_{t-11,t}$ with and without controlling for an autoregressive term. We consider one-year-ahead ($\tau = 12$) and two-year-ahead ($\tau = 24$) growth rates and profitability. The Fama-MacBeth t-statistics adjusted for serial correlations in the slope coefficients (see Pontiff [1996]) are reported in parentheses. Since some firms have zero or negative dividend and investment, we measure growth rates by normalizing changes in dividend, investment, and sales by book value. The sample is from 1965 to 2000 with 36 cross-sections when $\tau = 12$ and from 1965 to 1999 with 35 cross-sections when $\tau = 24$. The average R^2 values are in percent. All the significant slopes and t-statistics are highlighted.

	Panel A: Predicting $\triangle D_{t,t+\tau}/B_t$				Panel B: Predicting $\triangle I_{t,t+\tau}/B_t$			
Horizon	$r_{t-5,t}$	$r_{t-11,t}$	$\triangle D_{t-12,t}/B_{t-12}$	R^2(%)	$r_{t-5,t}$	$r_{t-11,t}$	$\triangle I_{t-12,t}/B_{t-12}$	R^2(%)
$\tau = 12$	**0.044**			1.27	**0.620**			1.67
	(3.42)				**(5.80)**			
		0.063		1.06		**1.165**		1.61
		(3.36)				**(8.50)**		
	0.039		-0.051	6.36	**0.658**		-0.041	6.53
	(2.34)		(-0.70)		**(4.95)**		(-0.75)	
		0.059	-0.050	6.04		**1.065**	-0.046	6.72
		(2.53)	(-0.69)			**(7.44)**	(-0.84)	
$\tau = 24$	**0.075**			1.62	0.615			1.55
	(8.77)				(1.65)			
		0.088		1.50		**1.444**		1.46
		(6.49)				**(3.67)**		
	0.074		0.012	4.54	**0.885**		**-0.103**	4.00
	(9.87)		(0.18)		**(2.75)**		**(-2.02)**	
		0.085	0.013	4.43		**1.261**	**-0.109**	4.17
		(6.61)	(0.20)			**(5.43)**	**(-2.08)**	

	Panel C: Predicting $\triangle S_{t,t+\tau}/B_t$				Panel D: Predicting $E_{t+\tau}/B_t$			
Horizon	$r_{t-5,t}$	$r_{t-11,t}$	$\triangle S_{t-12,t}/B_{t-12}$	R^2(%)	$r_{t-5,t}$	$r_{t-11,t}$	E_t/B_{t-12}	R^2(%)
$\tau = 12$	**1.825**			0.90	**1.263**			1.91
	(4.84)				**(4.10)**			
		4.50		1.32		**1.960**		1.72
		(7.43)				**(3.80)**		
	1.645		**0.098**	3.25	**1.005**		**0.329**	10.71
	(4.42)		**(3.81)**		**(3.49)**		**(5.31)**	
		3.124	**0.093**	3.43		**1.145**	**0.331**	10.40
		(5.56)	**(3.64)**			**(2.81)**	**(5.30)**	
$\tau = 24$	**2.982**			0.90	**1.200**			1.33
	(3.40)				**(2.90)**			
		7.964		1.40		**1.217**		1.47
		(6.34)				**(2.86)**		
	2.364		**0.154**	3.16	**0.975**		**0.273**	7.22
	(3.41)		**(3.12)**		**(2.24)**		**(6.26)**	
		5.626	**0.146**	3.36		0.671	**0.273**	7.25
		(6.39)	**(3.00)**			(1.73)	**(6.26)**	

4 Expected Growth and Average Returns

If the market expects higher growth for winner firms and if expected growth is a priced risk factor, higher expected growth rates should entail higher average returns (Johnson [2002], p. 589), and momentum profits should be lower after controlling for it. This section examines these issues using factor-mimicking portfolios on expected growth rates. Later (Section 5), we use portfolios based on stocks' covariances with aggregate growth variables.

4.1 Portfolio Construction

To obtain measures of expected growth rates, we first perform cross-sectional regressions of future growth rates on past returns and lagged growth rates, i.e.,

$$\triangle F_{t,t+12} = \alpha + \beta_1 r_{t-12,t-6} + \beta_2 \triangle F_{t-24,t-12} + \epsilon_{t,t+12} \tag{2}$$

where $\triangle F_{t,t+12}$ denotes the future growth rates of dividend, investment, or sales in the year from month t to month t+12, $r_{t-12,t-6}$ is the six-month lagged cumulative stock return from month t–12 to month t–6, and $\triangle F_{t-24,t-12}$ is the two-year lagged growth rates. As in Section 3.4, we continue to measure firm-level growth as the changes in dividend, investment, and sales divided by book value at the beginning of the year. We then assume that the regression coefficients are constant and use the fitted components in (2) as our measures of expected growth rates. The regression results from (2) are quantitatively similar to those reported in Table 2, despite the timing differences in the regressors.

Our timing convention avoids potential look-ahead bias. We use six-month lagged past returns, instead of those from month $t-11$ to month t, $r_{t-11,t}$, and two-year lagged growth rates, instead of one-year lagged growth rates $\triangle F_{t-11,t}$, as the instruments to model the expected growth rates. Dividend, investment, and sales are annual averages, whereas stock returns are point-to-point. Investment growth at December of 1980, from dividing investment at December of year 1980 by that at the end of year 1979, corresponds roughly to the *actual* investment growth from July of year 1979 to June of year 1980. Thus we choose June as the point of annual portfolio rebalancing. Chen, Roll, and Ross (1986) and Cochrane (1991, 1996) use similar techniques to correct for the timing difference between stock returns and

Table 3 : Descriptive Statistics for MKT, SMB, HML, WML, and Factor Mimicking Portfolios on Growth Rates (July 1965 to December 2001, 432 Observations)

This table reports summary statistics for market excess return (MKT), SMB, HML, WML, and factor mimicking portfolios on dividend growth (FAC^D), investment growth (FAC^I), and sales growth (FAC^S). The data for MKT, SMB, and HML are from Kenneth French's website. Panel A reports the means, volatilities, and t-statistics (reported in parentheses) adjusted for heteroscedasticity and autocorrelations up to six lags. Average returns and volatilities are in monthly percent. Panel B reports the correlation matrix of all the factors. We sort all stocks into three groups at June of each year t, and then record all the portfolio returns from July of year t to June of year $t+1$. The factor-mimicking portfolios are then constructed as return spreads between the equally weighted return of the bottom 30 percent stocks and that of the top 30 percent stocks in an ascending sort with NYSE breakpoints. Significant average returns and their t-statistics are highlighted.

	Panel A: Summary Statistics						
	MKT	SMB	HML	WML	FAC^I	FAC^D	FAC^S
m	**0.476**	0.118	**0.459**	**0.728**	0.470	**0.560**	0.466
	(**2.14**)	(0.65)	(**2.67**)	(**3.46**)	(1.82)	(**2.49**)	(1.79)
σ	4.542	3.334	3.042	5.559	5.240	4.940	5.248
	Panel B: Correlation Matrix						
	MKT	SMB	HML	WML	FAC^I	FAC^D	FAC^S
MKT	1	0.281	-0.427	-0.003	0.070	-0.019	0.132
SMB		1	-0.287	-0.148	0.039	-0.106	0.064
HML			1	-0.041	-0.111	-0.017	-0.166
WML				1	0.464	0.455	0.419
FAC^I					1	0.847	0.954
FAC^D						1	0.846
FAC^S							1

economic fundamentals.

To construct the factor-mimicking portfolios, at the beginning of June of each year, we rank all the stocks into ten deciles based on the expected growth rates, measured as the fitted components from (2). We then record equally-weighted portfolio returns from the beginning of July of the current year through June of the next year. The factors are the high-minus-low expected growth portfolios.

Table 3 reports descriptive statistics for market excess return, SMB, HML, WML, and factor-mimicking portfolios constructed from the expected growth measures. WML is constructed from buying the top 30 percent winners and selling the bottom 30 percent losers. From Panel A, the average WML factor return is 0.73 percent per month (t-statistic of 3.46). Further, stocks with higher expected growth rates earn higher average returns than stocks with lower expected growth rates. The expected dividend growth factor earns an average return of 0.56 percent per month which is significant with a t-statistic of 2.49. The factors of expected investment growth and expected sales growth both earn about 0.47 percent per month that are marginally significant with t-statistics around 1.80. From Panel B, the growth factors are highly correlated with WML, with the correlations ranging from 0.42 to 0.46.

The general tenor of these results (as well as those in Section 4.2) is robust to alternative specifications of expected growth rates. We also find that past earnings surprise measured as the Standardized Unexpected Earnings, the ratio of change of earnings divided by book value, and the ratio of cash flow divided by book value are all strong positive predictors of future growth rates. Using these instruments to model expected growth yields quantitatively similar results (not reported).

4.2 Time Series Tests

We examine whether the factor-mimicking portfolios can potentially explain the momentum profits in the time series tests, using the framework of Fama and French (1996). To ensure that our results are comparable to theirs, we construct momentum portfolios following their procedure, i.e., sorting on past 12-month returns, skipping the portfolio formation month in ranking stocks to reduce bid-ask bias, and holding the portfolios for one month in the future. In the sample from July 1965 to December 2001, the average return spread between the 12/1 winner and loser deciles is 0.79% per month and is significant with a t-statistic of 2.92. The alpha from the unconditional CAPM for the winner decile is 0.72% per month with a t-statistic of 2.82, and the GRS test for the intercepts being jointly zero has a p-value of 0.008.

Time Series Regressions

Table 4 replicates Fama and French (1996 Table VII) using our sample, with similar results. The intercepts of the ten momentum portfolios increase monotonically from −0.22

Table 4 : Ten 12/1 Momentum Portfolios: Time Series Regressions with Fama-French Three Factor Model (July 1965 to December 2001, 432 Observations)

To ensure that our results are comparable with Fama and French (1996), we follow their procedure and construct momentum portfolios by sorting on past 11-month returns, skipping the portfolio formation month in ranking stocks to reduce bid-ask bias, and holding the portfolios for one month in the future. We report the multiple regressions with Fama-French three factor model, including the coefficients, t-statistics, and goodness-of-fit, denoted R^2, for the monthly excess returns (in percent) on ten momentum deciles. The ten regression equations are estimated together as a system by GMM, where the t-statistic are adjusted with heteroscedasticity and autocorrelation consistent standard errors. Significant t-statistics associated with the intercepts are highlighted. We also report the GRS statistic and p-value on testing that all the intercepts are jointly zero.

	$r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + e_{it+1}$									
	Loser	2	3	4	5	6	7	8	9	Winner
a_i	-0.22	-0.37	-0.24	-0.21	-0.12	0.00	0.14	0.22	0.42	0.73
t_a	-0.98	**-2.49**	**-2.40**	**-2.65**	-1.69	0.07	**2.04**	**2.62**	**3.51**	**3.86**
b_i	1.11	1.00	0.97	0.95	0.95	0.98	0.99	1.04	1.11	1.19
t_b	13.87	16.80	21.30	25.49	33.47	38.29	30.96	23.42	15.09	11.31
s_i	1.17	0.85	0.69	0.61	0.55	0.56	0.52	0.54	0.62	0.83
t_s	5.86	6.22	6.91	6.78	7.44	8.44	6.50	5.60	3.93	3.80
h_i	0.28	0.40	0.43	0.45	0.46	0.47	0.40	0.33	0.23	-0.04
t_h	1.22	2.94	4.49	5.62	6.68	7.54	7.06	5.35	2.84	-0.31
R^2	0.59	0.73	0.83	0.88	0.91	0.93	0.91	0.88	0.80	0.71

percent per month for the losers to 0.73 percent per month for the winners. The GRS test on the null hypothesis that the intercepts are jointly zero has a statistic of 2.50 and a p-value of 0.006. The loadings of Loser on SMB and HML are markedly higher than those of Winner, indicating that momentum strategy is not risky along these dimensions.

Table 5 augments the Fama-French three factor model with WML or one of the three expected growth rate factors in the time series regression. From Panel A, except for the loser portfolio and the two top deciles of momentum portfolios, the four factor model with MKT, SMB, HML, and WML can account for most of the momentum portfolio returns.[8] From Panel B, except for the two top deciles of momentum portfolios, the augmented model with expected dividend growth factor can account for all the other eight momentum portfolio returns. The GRS test statistic on the null hypothesis that all the intercepts are jointly zero

[8]Stronger results apply using average realized growth rates for portfolio formation. These results are not reported because of a potential look-ahead bias: realized growth rates are correlated with realized returns.

is 1.52 and is not rejected at conventional significance levels.

The next two rows of Panel B indicates that the loadings on the expected dividend growth factor increase monotonically from a significant -0.41 for the loser portfolio to a significant 0.21 for the winner portfolio. Except for that of portfolio six, these loadings on dividend growth factor are highly significant. The role of the expected dividend growth factor seems very similar to that of WML in the time series regressions. Similar patterns are also observed in Panels C and D, which augment the Fama-French three factor model with investment growth and sales growth factors, respectively. However, the GRS test statistics are now significant at the five percent level.

Factor Loadings in Event Time

Figure 3 shows the behavior of factor loadings of the winner and loser portfolios on three expected growth factors during the periods 36 months before and 36 months after the portfolio formation. For each portfolio formation month from t = January 1965 to December 2001, we calculate equally-weighted excess returns for winner and loser portfolios for $t+m, m = -36, \ldots, 36$. The observations of winner and loser excess returns, market excess returns, SMB, HML, expected growth factors, for event month $t+m$ are pooled together across calendar time. The factor loadings are calculated using the pooled time series regressions of the winner and loser portfolio returns on the Fama-French three factors augmented with one expected growth rate factor for a given event month.

From Figure 3, Panels A–C show that the risk dispersion associated with expected growth factors between the winner and the loser portfolios converge about eight months before and about 15 months after the portfolio formation. In contrast, Panels D and E show that the loadings on SMB and HML display the "wrong" pattern. Winners have higher loadings than losers before portfolio formation, but have lower loadings after portfolio formation.

5 Covariance-Based Tests

The evidence in Sections 3 and 4 is striking, and the general findings are explicitly predicted by Johnson (2002). The evidence is also consistent with a characteristic-based

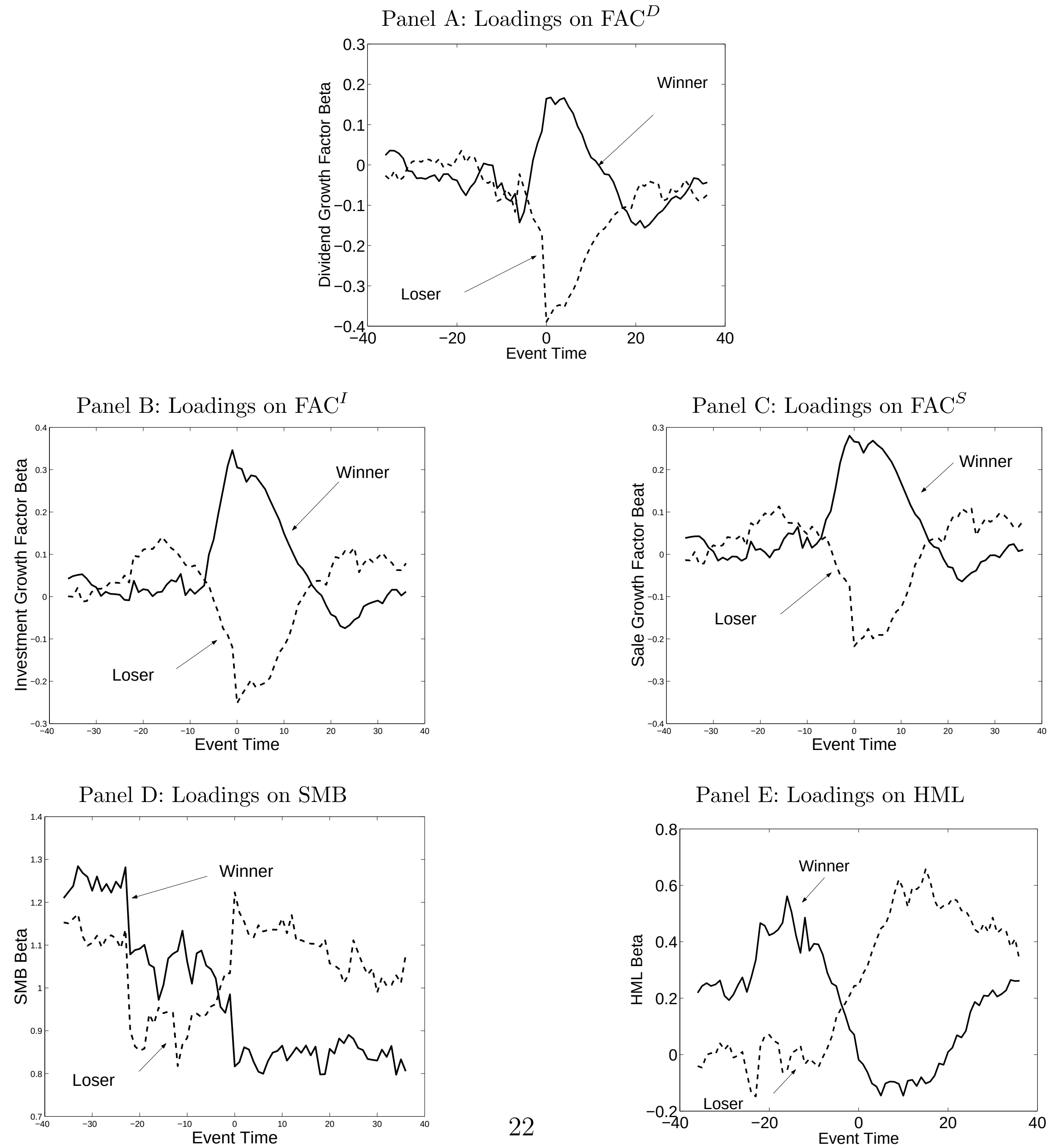
Table 5 : Time Series Regressions for Ten 12/1 Momentum Portfolios on Fama-French Three Factor Model Augmented with One Growth Rate Factor (July 1965 to December 2001, 432 Observations)

This table reports the results from multiple regressions, including the coefficients, t-statistics, and goodness-of-fit, denoted R^2, for the monthly excess returns on ten momentum deciles. The regression equations are: $\mathrm{r}_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{FAC}_{t+1} + \epsilon_{it+1}$, where MKT, SMB, and HML are Fama-French three factors and FAC denotes WML (Panel A) or one of the three factors: dividend growth factor (FAC^D, Panel B), investment growth factor (FAC^I, Panel C), and sales growth factor (FAC^S, Panel D). The ten regression equations are estimated together as a system by GMM, where the t-statistic are adjusted with heteroscedasticity and autocorrelation consistent standard errors. We also report the GRS statistic and p-value on testing that all the intercepts are jointly zero. Significant t-statistics associated with the intercepts and GRS statistics and p-values are highlighted.

	Panel A: $r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{WML}_{t+1} + e_{it+1}$											
	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
a_i	0.49	0.05	0.02	-0.04	-0.01	0.05	0.11	0.14	0.28	0.52		
t_a	**2.59**	0.36	0.23	-0.65	-0.14	0.87	1.65	1.60	**2.17**	**2.58**	1.20	0.288
f_i	-0.85	-0.50	-0.31	-0.20	-0.13	-0.06	0.03	0.09	0.17	0.25		
t_f	-8.13	-11.48	-19.87	-10.95	-7.77	-3.29	1.08	1.65	1.86	1.54		
R^2	0.86	0.90	0.92	0.92	0.93	0.93	0.91	0.88	0.82	0.74		
	Panel B: $r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{FAC}^D_{t+1} + e_{it+1}$											
	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
a_i	0.03	-0.18	-0.12	-0.13	-0.07	0.00	0.10	0.16	0.34	0.61		
t_a	0.10	-1.11	-1.13	-1.58	-0.98	0.07	1.49	1.94	**2.77**	**3.23**	1.52	0.128
f_i	-0.41	-0.31	-0.21	-0.14	-0.08	-0.00	0.06	0.10	0.15	0.21		
t_f	-3.81	-5.56	-6.46	-5.47	-3.53	-0.00	3.14	4.13	5.00	3.90		
R^2	0.64	0.78	0.86	0.89	0.92	0.93	0.91	0.88	0.81	0.73		
	Panel C: $r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{FAC}^I_{t+1} + e_{it+1}$											
	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
a_i	-0.05	-0.22	-0.13	-0.13	-0.07	0.01	0.10	0.15	0.30	0.54		
t_a	-0.21	-1.37	-1.25	-1.70	-1.01	0.17	1.50	**2.03**	**3.14**	**3.82**	**2.44**	**0.008**
f_i	-0.31	-0.28	-0.21	-0.15	-0.09	-0.01	0.07	0.13	0.23	0.36		
t_f	-3.58	-6.01	-7.21	-6.50	-4.31	-0.66	3.69	4.51	4.23	4.13		
R^2	0.62	0.78	0.87	0.90	0.92	0.93	0.92	0.89	0.83	0.76		
	Panel D: $r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{FAC}^S_{t+1} + e_{it+1}$											
	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
a_i	-0.07	-0.23	-0.14	-0.14	-0.07	0.01	0.10	0.15	0.30	0.55		
t_a	-0.28	-1.50	-1.41	-1.84	-1.06	0.11	1.55	**2.07**	**3.16**	**3.68**	**2.27**	**0.014**
f_i	-0.28	-0.25	-0.19	-0.14	-0.08	-0.01	0.06	0.13	0.22	0.34		
t_f	-4.41	-7.52	-7.79	-6.61	-4.34	-0.32	3.69	5.21	5.30	5.17		
R^2	0.62	0.77	0.86	0.90	0.92	0.93	0.92	0.89	0.83	0.76		

Figure 3 : Factor Loadings of Winner and Loser Portfolios on SMB, HML, Investment Growth Factor, and Sales Growth Factor in Event Time (36 Months Before and After Portfolio Formation)

For each portfolio formation month from $t =$ January 1965 to December 2001, we calculate equally-weighted excess returns for winner and loser portfolios for $t+m, m = -36, \ldots, 36$. The observations of winner and loser excess returns, market excess returns, SMB, HML, investment growth factor, and sales growth factor, for event month $t+m$ are pooled together across calendar time. All the loadings, including those on SMB (Panel A), HML (Panel B), investment growth factor (Panel C), and sales growth factor (Panel D), are computed based on the pooled time series regressions (Fama-French three factor model augmented with one growth rate factor) for a given event month.



interpretation. Specifically, suppose momentum firms have subsequent extreme growth but market prices have only partially reflected this. Then the observed relation between momentum and extreme subsequent growth reflects slow reaction, not risk. This section uses covariance-based tests to provide a cleaner interpretation than the tests in Section 4.

5.1 Test Design

As reviewed in Section 2, Johnson (2002) contains a cross-sectional pricing restriction: under fairly general assumptions, the expected excess return on equity of firm j follows (1). We test this restriction explicitly.

Suppose that the pricing kernel and expected growth rate are both observable. Let $\sigma^j_R \equiv -\rho^j_{\Lambda D}\sigma_\Lambda\sigma^j_D$ denote the covariance of *realized* dividend growth with the pricing kernel, and $\sigma^j_E \equiv -\rho^j_{\Lambda g}\sigma_\Lambda\sigma^j_g$ be the covariance of *expected* dividend growth with the pricing kernel. We test (1) using the cross-sectional regression:

$$R^j_{t+1} = a + b\,\sigma^j_R + c\,\sigma^j_E + \epsilon^j_{t+1} \tag{3}$$

where R^j_{t+1} is the realized return of firm j from time t to $t+1$.

The pricing of expected growth rate risk in (1) implies $c > 0$ in (3). This is because the slope coefficient of σ^j_E in (1) corresponds to $(d\log U^j_t/dg^j_t)$, which is positive, as price dividend ratio U^j_t increases with expected growth g^j_t. Alternatively, we can interpret $c > 0$ as indicating that the risk premium associated with the covariance of expected growth with the pricing kernel, defined as the expected growth risk in Section 2, is positive.

Further, due to the convexity property of log price dividend ratio U^j_t with respect to expected growth g^j_t, $(d\log U^j_t/dg^j_t)$ increases with g^j_t. The slope of σ^j_E should increase with expected growth g^j_t. We can test this hypothesis by specifying $c = c_0 + c_1 g^j_t$ and rewriting (3) as:

$$R^j_{t+1} = a + b\,\sigma^j_R + c_0\,\sigma^j_E + c_1\left(\sigma^j_E g^j_t\right) + \epsilon^j_{t+1} \tag{4}$$

The convexity property then implies that $c_1 > 0$.

Since the pricing kernel is unobservable in practice, to operationalize our tests we specify the pricing kernel as a linear function of common factors. We then directly use the covariances of realized dividend growth and expected dividend growth with these common factors in regressions (3) and (4).[9]

5.2 Implementation

Common Factors

We use three common factors in specifying the pricing kernel: (i) market excess return; (ii) the growth rate of industrial production; and (iii) the cash flow news as in Campbell and Vuolteenaho (2003). The market excess return is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates), and is obtained from Kenneth French's website. The seasonally adjusted monthly index of real industrial production is from Federal Reserve Bank of Saint Louis. The market excess return is used to evaluate whether expected growth risk is priced in the CAPM world, which seems a natural benchmark.

The other two measures are related to aggregate growth. Both are motivated by and used in the literature. Chen, Roll, and Ross (1986) show that the growth rate of industrial production is a significant priced factor in the cross-section of returns. The idea that aggregate growth is priced with a positive premium is also implicit in Campbell and Vuolteenaho (2003). Their aggregate cash flow news is effectively a return factor on shocks to expected aggregate dividend growth.[10] Using cross-sectional regressions, Campbell and Vuolteenaho (2003) show that risk associated with cash flow news is indeed priced and its price of risk is actually higher than that of usual market beta.

More generally, our use of growth variables as common factors is consistent with many other papers that investigate asset pricing implications of growth. Cochrane (1991) shows that expected returns rise with expected investment growth. Fama and French (2002) estimate the equity premium using dividend and earnings growth rates to measure expected

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[9] Specifically, suppose that $d\Lambda_t/\Lambda_t = l_0 + l_1 f_t$, where $d\Lambda_t/\Lambda_t$ is the pricing kernel, f_t is the common factor, and l_0 and l_1 are the constant loadings of the pricing kernel on the common factor f_t. The slopes in the cross-sectional regressions will be proportional to l_1. We can thus continue to test $c>0$ and $c_1>0$.

[10] Specifically, Campbell and Vuolteenaho (2003) start from a decomposition of returns: $r_{t+1} - \mathrm{E}_t[r_{t+1}] = (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=0}^{\infty}\rho^j \triangle d_{t+1+j} - (\mathrm{E}_{t+1} - \mathrm{E}_t)\sum_{j=1}^{\infty}\rho^j r_{t+1+j} \equiv N_{CF,t+1} - N_{DR,t+1}$, where ρ is a constant. They then define $N_{DR,t+1}$ to be the discount rate news, and $N_{CF,t+1}$ to be the cash flow news.

capital gain. Other examples include Bansal and Yaron (2002), Bansal, Dittmar, and Lundblad (2002), Menzly, Santos, and Veronesi (2003), and Lettau and Ludvigson (2003).

Testing Portfolios and Expected Growth

Given that some firms pay zero or negative dividends, making dividend growth rate ill-defined at the firm level, we conduct our cross-sectional tests at portfolio level. We use 25 momentum portfolios, which are constructed using the standard six/six price momentum strategies discussed in Section 3. We have also used 100 momentum portfolios, but the results are quantitatively similar and are omitted for brevity.

In each month t, we have for each of the 25 portfolios six sub-portfolios which are formed at time $t-1, t-2, t-3, t-4, t-5$ and $t-6$, respectively. We record the dividends for all the firms in each one of the six sub-portfolios and sum them up to obtain the portfolio dividend. We also record the dividends from last month for the same set of firms. Dividend growth is now calculated as the change of dividend divided by lagged dividend.

To model expected dividend growth, we use the fitted component of Fama-MacBeth cross-sectional, predictive regressions of future dividend growth on lagged dividend growth and past six-month returns. In each month, we take previous 60 monthly observations and run 60 cross-sectional regressions on the 25 momentum portfolios. We then take the time series averages of the regression coefficients over the 60-month window. After we obtain the coefficients, we use the fitted component as the expected dividend growth.[11] To estimate σ_R^j and σ_E^j for each of the 25 momentum portfolios, we again use 60-month rolling regressions. The cross-sectional regressions in (3) and (4) can then be carried out in the usual way.

5.3 Test Results

Tables 6 and 7 report the results for the sample from July 1965 to December 2001. In general, evidence for the pricing of expected growth risk is weak.

From Panel A of Table 6, the correlation between the realized dividend growth rate and the common factors, $\rho_{\Lambda D}^j$, is generally insignificant. From Panel B, the correlation between

[11] Assuming the regression coefficients are constant in the sample yields quantitatively similar results. Details are available upon request.

Table 6 : Correlations of Realized and Expected Dividend Growth Rates of Ten Momentum Portfolios with the Common Factors

This table reports for ten momentum portfolios the correlations between their realized dividend growth rates and the common factors $\rho^j_{\Lambda D}$ (Panel A), and the correlations between their expected dividend growth rates and the common factors $\rho^j_{\Lambda g}$ (Panel B). Three common factors are considered and they are linear functions of market excess return, MKT, the growth rate of industrial production, IP, and the cash flow news, N_{CF}. All nominal variables are deflated using the growth rate of Consumer Price Index. p-values are reported in the parentheses.

Panel A: Correlations of Realized Dividend Growth with the Common Factors ($\rho^j_{\Lambda D}$)										
Factors	Loser	2	3	4	5	6	7	8	9	Winner
MKT	0.01	-0.02	-0.05	-0.02	-0.02	-0.03	-0.04	-0.05	-0.05	0.00
	(0.78)	(0.66)	(0.29)	(0.71)	(0.63)	(0.46)	(0.34)	(0.31)	(0.31)	(0.99)
IP	0.16	0.18	0.13	0.10	0.03	0.03	0.01	0.01	-0.03	0.02
	(0.00)	(0.00)	(0.01)	(0.04)	(0.52)	(0.58)	(0.81)	(0.89)	(0.54)	(0.64)
N_{CF}	-0.02	-0.02	0.02	0.02	0.04	0.03	0.04	0.05	0.08	0.02
	(0.66)	(0.61)	(0.62)	(0.62)	(0.39)	(0.50)	(0.37)	(0.29)	(0.08)	(0.59)
Panel B: Correlations of Expected Dividend Growth with the Common Factors ($\rho^j_{\Lambda g}$)										
Factors	Loser	2	3	4	5	6	7	8	9	Winner
MKT	-0.03	-0.10	-0.08	-0.06	-0.07	-0.09	-0.08	-0.08	-0.09	-0.07
	(0.54)	(0.03)	(0.09)	(0.20)	(0.12)	(0.06)	(0.08)	(0.07)	(0.06)	(0.14)
IP	0.19	0.28	0.28	0.22	0.26	0.26	0.25	0.22	0.18	0.14
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N_{CF}	-0.05	-0.04	-0.04	-0.04	-0.06	-0.07	-0.08	-0.09	-0.09	-0.09
	(0.27)	(0.30)	(0.35)	(0.38)	(0.17)	(0.13)	(0.08)	(0.06)	(0.06)	(0.07)

the expected dividend growth rate and the common factors (market excess return and cash flow news), $\rho^j_{\Lambda g}$, is also mostly insignificant. However, with the growth rate of industrial production as the common factor, $\rho^j_{\Lambda g}$ clusters around .20 and is highly significant. This positive covariation between expected growth and the pricing kernel is a necessary condition for Johnson's (2002) explanation of momentum.

Table 7 reports the results of Fama-MacBeth (1973) cross-sectional regressions (3) and (4). From the first two regressions of Panel A, the expected growth rate risk σ^j_E does not translate into higher expected returns in the CAPM world. The slope of σ^j_E has the wrong, negative sign, albeit insignificant, in both regressions. The slope of the product term $\sigma^j_E g^j_t$ is positive, but again insignificant. Regressions three and four conduct the same analysis but controlling for loadings of Fama-French three factors. The slope of σ^j_E continues to be negative, and the slope of $\sigma_E^j g_t^j$ is again positive and insignificant.

Panel B reports the results using the growth rate of industrial production as the common factor. From regression five in Panel B, σ_E^j is priced with a significant t-statistic of 2.02. However, from regression six, when we add the product term $\sigma_E^j g_t^j$, both slopes of σ_E^j and the product term become insignificant, although still positive. The product term remains positive and insignificant, once we control for loadings on Fama-French factors, as reported in regression eight. The slope of σ_E^j becomes negative and insignificant once we control for the Fama-French factors.

The evidence is again weak with cash flow news as the common factor from Panel C. All four regressions in this panel indicate that the premium associated with expected growth risk σ_E^j is negative, and in some case even significant. The slope of the product term remains positive, significant without but insignificant with the Fama-French factors.

These results are unchanged with a number of additional test variations. For example, although leverage is not modelled in Johnson (2002), it is potentially relevant. Positive momentum reduces leverage and risk, offsetting and making it more difficult to detect any predicted risk increase caused by an increase in expected growth. In unreported tests, we obtain similar results in a subsample of low leverage firms.

5.4 Further Tests

As a less model-dependent robustness check, we examine directly the loadings of momentum portfolio returns on empirical measures of aggregate growth, including the growth rate of industrial production and the cash flow news of Campbell and Vuolteenaho (2003). We find evidence that losers load negatively and winners load positively on the growth factors, indicating that winners are riskier than losers, but the overall results are not strong.

Table 8 reports the monthly and quarterly time series regressions of ten momentum portfolio returns on the Fama-French factors and the growth rate of industrial production (Panels A and B). From Panel A, losers have a negative but insignificant loading, and winners have a positive and significant loading on growth rate factor. The null hypothesis

Table 7 : Covariance-Based, Cross-Sectional Regression Tests

This table reports the results of the Fama-MacBeth cross-sectional regressions of 25 momentum portfolio returns on the covariances of their realized dividend growth rates with the pricing kernel σ_R^j, the covariances of their expected dividend growth rates with the pricing kernel σ_E^j, and the product of σ_E^j times the expected growth rates g_t^j. We again consider three pricing kernels by using market excess return, the growth rate of industrial production, and cash flow news as the common factors. t-statistics are reported in the parentheses below the slope coefficients. The slopes of the first two regressors in Panels B and C are on the order of 10^4, and those of the product term $\sigma_E^j g_t^j$ are on the order of 10^6.

	Panel A: Market Excess Return As the Common Factor					
	σ_R^j	σ_E^j	$\sigma_E^j g_t^j$	β_{MKT}	β_{SMB}	β_{HML}
1	3.48	-26.85				
	(1.60)	(-1.68)				
2	4.97	-35.25	964.31			
	2.42	(-1.57)	(1.31)			
3	3.72	-25.10		-0.30	-0.33	-1.10
	(3.25)	(-2.05)		(-0.45)	(-0.58)	(-2.61)
4	3.98	-22.24	224.33	0.12	-0.35	-0.82
	(3.71)	(-1.23)	(0.37)	(0.18)	(-0.86)	(-2.26)
	Panel B: The Growth Rate of Industrial Production As the Common Factor					
	$\sigma_R^j(\times 10^{-4})$	$\sigma_E^j(\times 10^{-4})$	$\sigma_E^j g_t^j(\times 10^{-6})$	β_{MKT}	β_{SMB}	β_{HML}
5	-0.22	1.36				
	(-1.79)	(2.06)				
6	-0.15	0.23	0.14			
	(-1.15)	(0.30)	(0.52)			
7	-0.17	-0.09		0.19	-0.71	-1.13
	(-1.51)	(-0.17)		(0.29)	(-1.45)	(-2.77)
8	-0.14	-0.18	0.27	0.09	-0.23	-0.99
	(-1.35)	(-0.35)	(1.45)	(0.14)	(-0.49)	(-2.46)
	Panel C: Cash Flow News As the Common Factor					
	$\sigma_R^j(\times 10^{-4})$	$\sigma_E^j(\times 10^{-4})$	$\sigma_E^j g_t^j(\times 10^{-6})$	β_{MKT}	β_{SMB}	β_{HML}
9	0.06	-0.39				
	(1.13)	(-1.18)				
10	0.11	-1.60	0.38			
	(2.23)	(-2.53)	(2.06)			
11	0.09	-0.51		-0.60	-0.39	-0.79
	(2.55)	(-1.93)		(-1.01)	(-0.94)	(-1.89)
12	0.09	-0.88	0.16	-0.33	-0.29	-0.72
	(2.51)	(-1.99)	(1.30)	(-0.57)	(-0.81)	(-2.01)

that all loadings are jointly equal to zero is strongly rejected with a p-value of 0.019.[12] The corresponding quarterly regressions in Panel B report quantitatively similar results. Despite the supporting evidence that losers load negatively and winners load positively on aggregate growth factor, the improvement in Jensen's alpha is relatively small. The dispersion in the intercept between winners and losers in Panel A of Table 8 is a significant .78 percent per month, only slightly lower than the .95 percent reported in Table 4.

Panels C and D of Table 8 report the results using cash flow news. From Panel C, the monthly loading of losers on cash flow news is 0.17 and that of winners is -0.25, but both are insignificant. In quarterly regressions reported in Panel D, the pattern is reversed, as the loading of losers on cash flow news is -0.51 with a significant t-statistic of -3.18, and the loading of winners on cash flow news is 0.08 though not significant. The improvement in Jensen's alpha is again negligible, which is perhaps not surprising given the weak pattern in the loadings.

6 Conclusion

We find that momentum firms are unusual, and in particular have unusual growth rates. This and some of our other findings are necessary conditions for the risk-shift explanation of momentum advocated by Johnson (2002), but they are not sufficient. We have tried to specify sharper, covariance-based tests, focusing on the relation between expected growth, expected return, and risk. Overall, support for a risk-based explanation in covariance-based tests is weak.

Our findings do not necessarily imply that expected growth is unimportant in asset pricing, however. To the contrary, we find that firms' expected growth rates are predictable and their shocks are correlated with shocks to some macroeconomic variables, such as the growth rate of industrial production. This reinforces the view that expected growth can be potentially important for asset pricing, and that further work along this line is needed.

[12]Following Chen, Roll, and Ross (1986), we lead industrial production growth by one period in the monthly regressions.

Table 8 : Time Series Regressions for Ten Momentum Portfolios on Fama-French Three Factor Model and the Growth Rate of Industrial Production or Cash Flow News

This table reports the results from multiple regressions, including the coefficients, t-statistics, and goodness-of-fit, denoted R^2, for both monthly and quarterly excess returns on ten momentum deciles. The regression equation is: $r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{FAC}_{t+1} + \epsilon_{it+1}$, where MKT, SMB, and HML are Fama-French three factors and FAC_{t+1} denotes the growth rate of industrial production or cash flow news. Following Chen, Roll, and Ross (1986), we lead the growth rate of industrial production by one period in monthly regressions. The ten regression equations are estimated together as a system by GMM, where the t-statistic are adjusted with heteroscedasticity and autocorrelation consistent standard errors. We also report the Wald statistic and p-value on testing that the loadings of ten portfolio on FAC are jointly equal to zero. Significant t-statistics associated with the intercepts and Wald statistics and p-values are highlighted.

	Loser	2	3	4	5	6	7	8	9	Winner	Wald	p
	Panel A: Monthly Regression with the Growth Rate of Industrial Production											
a_i	-0.19	-0.32	-0.19	-0.15	-0.10	0.02	0.12	0.16	0.33	0.59		
t_a	-0.77	-1.83	-1.64	-1.54	-1.34	0.35	1.79	**2.04**	**2.79**	**3.20**		
f_i	-0.11	-0.22	-0.22	-0.27	-0.07	-0.08	0.06	0.23	0.41	0.62		
t_f	-0.30	-0.95	-1.32	**-2.17**	-1.02	-1.17	0.61	1.92	**2.69**	**2.70**	**19.82**	**0.019**
R^2	0.59	0.73	0.83	0.88	0.91	0.93	0.91	0.88	0.80	0.71		
	Panel B: Quarterly Regression with the Growth Rate of Industrial Production											
	Loser	2	3	4	5	6	7	8	9	Winner	Wald	p
a_i	-0.56	-1.15	-0.88	-0.52	-0.34	-0.08	0.37	0.48	0.94	1.61		
t_a	-0.62	**-2.21**	**-2.73**	-1.75	-1.35	-0.32	1.49	1.62	**2.64**	**3.00**		
f_i	-0.51	-0.31	-0.12	-0.35	-0.12	-0.10	-0.01	0.13	0.33	0.71		
t_f	-1.03	-0.94	-0.68	**-2.16**	-0.80	-0.68	-0.06	0.85	1.41	1.76	**26.44**	**0.002**
R^2	0.68	0.81	0.89	0.92	0.94	0.94	0.91	0.86	0.78	0.72		
	Panel C: Monthly Regression with Cash Flow News											
	Loser	2	3	4	5	6	7	8	9	Winner	Wald	p
a_i	-0.17	-0.32	-0.23	-0.20	-0.12	-0.00	0.12	0.19	0.37	0.65		
t_a	-0.66	-0.93	**-2.10**	**-2.28**	-1.63	-0.06	1.82	**2.52**	**3.48**	**4.00**		
f_i	0.17	0.17	0.03	0.03	0.00	-0.03	-0.06	-0.08	-0.16	-0.25		
t_f	0.79	1.42	0.42	0.54	0.01	-0.54	-0.98	-1.07	-1.09	-1.04	**25.72**	**0.002**
R^2	0.59	0.73	0.83	0.88	0.91	0.93	0.91	0.88	0.80	0.71		
	Panel D: Quarterly Regression with Cash Flow News											
	Loser	2	3	4	5	6	7	8	9	Winner	Wald	p
a_i	-1.38	-1.65	-1.14	-0.91	-0.43	-0.18	0.31	0.61	1.21	2.21		
t_a	**-2.18**	**-4.40**	**-4.40**	**-3.74**	-1.73	-0.71	1.37	**2.02**	**3.32**	**3.54**		
f_i	-0.51	-0.31	-0.20	-0.14	-0.01	-0.03	-0.06	0.04	0.04	0.09		
t_f	**-3.18**	**-2.93**	**-2.22**	-1.75	-0.10	-0.48	-1.00	0.61	0.40	0.50	**31.67**	**0.000**
R^2	0.68	0.82	0.89	0.91	0.94	0.94	0.91	0.85	0.78	0.71		

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