Economic Fundamentals, Risk, and Momentum Profits

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Abstract

We study empirically the changes in economic fundamentals for firms with recent stock price momentum. We document that: (i) winners have temporarily higher dividend, investment, and sales growth rates than losers; (ii) past returns are positive predictors of future growth rates; (iii) factor-mimicking portfolios on expected growth rates earn significantly positive returns on average; more importantly, (iv) after expected growth rates are controlled for, momentum profits fall greatly, in some cases to insignificant levels; and finally, (v) the dispersion in the loadings of the winner and loser portfolios on expected growth factors is only temporary and its duration is surprisingly in line with that of the momentum profits. In all, our evidence indicates that, consistent with the rational expectations theory of Johnson (2002), economic fundamentals can be important sources of the momentum anomaly.

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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 explanations for these momentum profits. First, some argue that certain behavioral biases can give rise to positive medium-term return autocorrelations, such as 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). The second line of explanation retains the assumption of rational expectations. In the model of Berk, Green, and Naik (1999), slow turnover in firms' projects gives rise to persistence in their systematic risk, making expected returns positively correlated with lagged expected returns.

More recently, Johnson (2002) proposes a more direct mechanism for momentum effects within a rational model: the curvature of log equity price with respect to expected growth rate is convex. Since growth rate risk can be written as the first-order derivative of log equity price with respect to expected growth rate, the convexity property implies that growth rate risk rises with expected growth rate. Suppose growth rate risk carries a positive premium, expected return then rises with expected growth rate. As market participants correctly incorporate information on future growth rates, recent performance in equity price will be correlated with the level of expected growth rate. The upshot is that a price momentum sort will tend to sort firms by future growth rates, and hence by expected returns.

There are two key predictions in the model of Johnson (2002). First, winners have higher expected growth rates than losers so a sort on momentum is also a sort on expected growth rates. Second, growth rate risk is priced so stocks with high expected growth rates earn high average returns. Our goal in this paper is to examine the empirical merits of these two key premises.

Specifically, we first recast the basic intuition of Johnson (2002) into an investment-based asset pricing model along the lines of Cochrane (1991, 1996). This allows us to derive additional testable hypotheses relating expected returns to investment growth and sales growth, which are absent from Johnson (2002). We then ask what economic fundamentals such as dividend growth, investment growth, and sales growth rates of momentum strategies look like in the data. Do momentum portfolios actually differ in their expected growth rates? Are future growth rates predictable with past returns? Moreover, is the growth rate risk priced, i.e, are expected growth rates positively correlated with expected returns at the firm-level? Finally, we also ask whether the momentum profits persist once the expected growth rates are controlled for.

Our findings are easy to summarize. We document that:

1. Winners have much higher dividend, investment, and sales growth rates than losers.

2. Expected growth rates are time-varying and past returns are positive predictors of future growth rates.

3. Factor mimicking portfolios constructed on expected growth rates earn significantly positive average returns, suggesting that the growth rate risk is indeed priced.

4. After we control for the expected growth rates, the momentum profits fall greatly, and in some cases to insignificant levels.

5. The dispersion in the loadings of the winner and loser portfolios on expected growth factors is only *temporary* and its duration is approximately equal to that of the momentum profits.

6. The relationship between size and momentum and that between book-to-market and momentum, which have been previously interpreted as indicating investor irrationality, e.g., Hong, Lim, and Stein (2000) and Daniel and Titman (1999), reflect similar relationships between these firm characteristics and expected growth rates.

In all, our evidence suggests that, consistent with the rational expectations theory of Johnson (2002), economic fundamentals can be important sources of the momentum profits.

Our paper is related to several recent papers that explore the predictability of expected growth rate and its asset pricing implications both at the aggregate and the firm-level. At the aggregate time series level, Bansal and Yaron (2002) show that a small amount of predictable component and changing volatility of dividend growth can go a long way in explaining the equity premium puzzle. Lettau and Ludvigson (2003) document that the aggregate dividend growth is predictable and expected dividend growth is positively correlated with expected market excess return at business cycle frequencies. Menzly, Santos, and Veronesi (2003) demonstrate that, in a general equilibrium model with time-varying risk aversion and time-varying expected dividend growth, expected dividend growth increases with both price dividend ratio and expected excess return. Thus, time-varying expected dividend growth induces a positive relation between price dividend ratio and expected excess return.

At the cross-sectional level, Li, Vassalou, and Xing (2002) find that a four-factor investment growth model can explain much of the cross-sectional variation in the 25 size and book-to-market portfolios. Vassalou (2003) finds that a factor that captures news on future GDP growth along with the market factor can explain the size and book-to-market portfolios about as well as the Fama-French model. However, all the aforementioned papers do not analyze the sources of momentum profits explicitly.

Like our work, several other papers also emphasize 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 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. However, our empirical analysis and its theoretical motivation are very different from these papers.

The rest of the paper is organized as follows. In Section 2, we recast the basic intuition of Johnson (2002) into an investment-based asset pricing model, following Cochrane (1991, 1996). Section 3 presents growth rate measures for ten momentum portfolios. Section 4 investigates whether growth rate risk is priced by constructing factor mimicking portfolios of expected growth rates. This section also examines whether the momentum profits survive after expected growth rates are controlled for. Finally, Section 5 concludes.

2 Hypothesis Development

To motivate our empirical analysis linking expected returns to expected investment growth and sales growth in addition to expected dividend growth, we recast the basic intuition of Johnson (2002) into an investment-based asset pricing model similar to Cochrane (1991, 1996).

While the model in Johnson (2002) is elegant theoretically, there are some ex ante reasons to believe that other measures of growth such as investment growth and sales growth may be more capable of explaining the behavior of stock returns empirically than dividend growth. The reason is that shocks on aggregate and firm-level productivity are typically reflected in large movements of capital investment and output, rather than to the relatively smooth dividend stream. Therefore, investment growth and sales growth are likely to contain more information than dividend growth on expected returns. Cochrane (1991, 1996) uses similar reasoning to motivate his analysis of market and portfolio returns based on aggregate investment growth.

Following Cochrane (1991, 1996), Appendix A shows that stock return is linked to economic fundamentals as follows:

$$R_{t+1} = \frac{\pi_{t+1} + (\frac{a}{2}) i_{t+1}^2 + (1-\delta)(1 + a i_{t+1})}{1 + a i_t} \tag{1}$$

where R_{t+1} denotes stock return from time t to t+1, i_t is investment rate (investment-capital ratio) at time t, π_{t+1} denotes marginal product of capital at time t+1, and $a \geq 0$ and $1 > \delta > 0$ are constant parameters.[1]

While equation (1) appears technically involved, its economic interpretation is quite clear. First, it says that investment return increases with marginal product of capital. In the special case of $a = 0$, stock return equals marginal product of capital plus a constant. This relation holds ex ante as well: expected stock return equals expected marginal product of capital up to a constant. All else being equal, high expected marginal product implies high expected

[1] As shown in the appendix, (1) is derived under a set of parametric assumptions. But for our purposes of developing qualitative, testable hypotheses on momentum profits, alternative parametric assumptions deliver similar results.

sales growth and high expected dividend growth rates. Thus (1) captures the basic intuition of Johnson (2002) that expected return rises with expected dividend growth rate.

Furthermore, (1) implies that when the investment rate at time $t+1$ is *high*, the stock return from t to $t+1$ is high, and that when the investment rate at time t is *low*, the stock return from t to $t+1$ is high. The stock return also has roughly the same sensitivities (first-order derivatives) to investment rates at time t and $t+1$, although with opposite sign. Since capital stock changes much less than investment, it follows that the stock return is approximately proportional to the investment *growth* rate. From an ex ante perspective, this implies that expected return is roughly proportional to expected investment growth rate. This link between stock return and investment growth, first formulated in Cochrane (1991), is absent in Johnson (2002) because he assumes an exogenous dividend growth rate.

Applying these economic insights in the context of the momentum profits, we have the following testable hypotheses:

> **Hypothesis 1.** Winners have higher expected dividend growth, sales growth, and investment growth rates than losers. The expected growth rate spreads between winners and losers are only *temporary*, reflecting the same temporary pattern of their expected return spread.

> **Hypothesis 2.** Stocks with higher expected dividend growth, sales growth, and investment growth earn higher expected returns than stocks with lower expected growth rates. Sort on past return momentum is equivalent to sorting on the expected growth rates.

In sum, Johnson (2002) derives similar hypotheses only for expected dividend growth. Using an investment-based asset pricing framework of Cochrane (1991, 1996), we have extended these hypotheses to the cases of expected sales growth and expected investment growth.

3 Do Momentum Strategies Differ in Growth Rates?

We now test the hypotheses formulated in Section 2 above. In this section, we ask whether momentum portfolios actually differ in growth rates in the data.

3.1 Sample Construction

We obtain all the 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 also maintained by CRSP. We use the common stocks listed on the NYSE, AMEX, and Nasdaq from January 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 10 or 11). We ignore firms with negative book values. Only December fiscal year-end firms are used in order to eliminate the problems caused by overlapping observations.

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 D_t/D_{t-1}, investment growth I_t/I_{t-1}, and sales growth S_t/S_{t-1}. Even though return on equity is not directly motivated from Johnson (2002), we consider this fundamental measure in order to compare with the results in Fama and French (1995) on size and book-to-market portfolios. The data source for these variables are as follows: investment expenditure is from Compustat item 128, earnings from item 18 (plus item 50 and minus item 19 if these two items are available), dividend from item 21, sales from item 12, and book value of common equity is from item 60 (plus item 74 if it is available).

Stock returns are observable monthly and the momentum strategies involve monthly rebalancing. But fundamental variables such as investment and earnings are available at the quarterly or annual frequency. We employ two methods to measure the fundamentals of momentum strategies at the portfolio level. First, we obtain monthly measures of flow variables such as earnings by dividing their current year annual observations by 12 or by dividing their current quarterly observations by four, and we measure profitability as monthly earnings divided by last fiscal year end book value. After we rank the stocks according to their past six-month returns, we sum up the individual stock fundamentals for all the stocks held in that month in each portfolios to obtain the fundamentals at the portfolio level. Although it is a crude adjustment, this method takes into account the 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 December. In this case, all the flow and stock variables are current annual observations. This method avoids the *ad hoc* adjustment from annual flow to monthly flow variables, but it ignores all the changes of stock composition during the other months of the year. These two different methods yield quantitatively similar results, so we only report below the results using the adjusted monthly observations of fundamentals. We have also used the fundamentals from Compustat merged quarterly files maintained by CRSP and obtained quantitatively similar results.

3.2 Descriptive Statistics

Table 1 reports the summary statistics of 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 sample period is from July 1965 to December 2001. Panel A reports that the momentum strategy is profitable in our sample: the average winner-minus-loser return in excess of three-month Treasury bill is 9.37% per year and is significant with a t-statistic of 3.30. The unconditional CAPM cannot explain the momentum profits: the Jensen's α of the winner-minus-loser spread is 0.80 percent per month and is highly significant with a t-statistic of 4.34. Moreover, the dispersion in market beta between winner stocks and loser stocks is only 0.03.

Panels B–D of Table 1 report the summary statistics of dividend growth, investment growth, and sales growth for ten momentum portfolios. The panels document that winner stocks have much higher growth rates 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 30 percent; while the dividends of loser stocks growth at a negative rate of 12 percent. Similar wide spreads between winners and losers are also evident in investment and sales growth rates. Finally, Panel E indicates that 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.

Figure 1 plots the time series of dividend growth, investment growth, sales growth, and return on equity, for winners (the solid line) and losers (the broken line) from year 1965 to 2001. We measure all the flow and stock variables at the end of calendar year. This method avoids the ad hoc slicing adjustment from annual flow to monthly flow variables, but it ignores all the changes of stock composition during the year. Taking the changes into account with the slicing technique does not change the results, however, so we only report the results without slicing. Figure 1 shows that, except for a few annual observations, the winner portfolio has higher dividend growth (Panel A), investment growth (Panel B), and sales growth (Panel C) than the loser portfolio for almost every year from 1965 to 2001. Panel D shows further that winner portfolio is much more profitable than loser portfolio.

3.3 Event Time Evidence

To see how growth rates and profitability evolve before firms are classified as winners or losers on past returns, and how the fundamental measures behave after portfolio formation, Figure 2 shows the average values of dividend growth, investment growth, sales growth, and profitability for winner and loser portfolios for 72 months around the portfolio formation month. For each portfolio formation month from $t =$ January 1965 to December 2001, we calculate growth rates and return on equity for $t+m$, where $m=-36,\ldots,36$. The measures for $t+m$ are then averaged across portfolio formation months. The plots thus capture average dividend growth, investment growth, sales growth, and profitability as a function of post returns for three years before and three years after the portfolio formation.

We continue to obtain all the data on stock return, stock price, and shares outstanding from CRSP monthly return file, but get the financial statement data from COMPUSTAT merged quarterly files. We obtain book value of equity from quarterly data item 59, earnings from item eight, dividend from item 20, sales from item two, and investment from item 90. Using quarterly data rather than annual data can better illustrate the month-to-month evolution of growth rate measures before and after portfolio formation.[2] For capital investment, most firms only report this item after 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 four to obtain monthly observations. The sample selection criterion is the same as before: we restrict the share code to be 10 or 11 and exclude observations with negative book value.

Panels A–C of Figure 2 show that momentum or past return performance is mainly associated with temporary, but not permanent, differences in dividend growth, investment growth, and sales growth rates. Winners have on average higher growth rates for about 10 to 20 months before and 15 to 20 months after the month of portfolio formation. In contrast, the difference in average profitability between winners and losers is much more persistent. Unlike growth rates which converge in less than 2 years, the difference in profitability persists for at least 3 years after portfolio formation.

We also investigate the behavior of return moments in the same event window in order to compare with that of growth rates and profitability. This also provides additional insights on the risk and return of momentum strategies. 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.

The results are reported in Figure 3. Panel A shows the behavior of average excess returns of winners and losers for 36 months before and 36 months after the portfolio formation month. We observe that there exists a huge dispersion in average returns for the two extreme

[2] We have also used COMPUSTAT merged annual files to generate Figure 2 and obtained qualitatively similar results. The only quantitative difference is that with annual data the curves in Panels A–C of the figure are smoother, reflecting the fact that annual data are averaged quarterly data.

deciles during the period from month -6 to month 0. In this period, the winner decile gains on average more than ten percent per month, and the loser decile loses on average about seven to eight percent per month. These high magnitudes are not surprising given that we construct momentum portfolios based on past returns, and are indicative of large changes in firms's fundamentals. Panel A also shows that, consistent with the previous literature, the winner portfolio continues to beat the loser portfolio for about ten months, and then reversal in stock returns kicks in. A similar pattern is in Jensen's α from the market regression, as indicated by Panel B. The panel also shows that significant intercepts of the winner portfolio are clustered around the portfolio formation month, while those of the loser portfolio tend to be distributed about 20 months before and ten months after portfolio formation.

Interestingly, the observed pattern of returns is not evident in either market beta or total volatility, the two traditional measures of risk. Panel C of Figure 3 shows that, even though winners have much higher market betas than losers from month -6 to 0, they actually have lower market betas than losers for about four months after portfolio formation. After four months, winners have higher market betas than losers. This pattern of market beta is almost exactly opposite to that of average excess return, thus rendering the static CAPM completely useless in explaining the momentum profits. The behavior of total volatility of the winner and the loser portfolios is illustrated in Panel D. Except for a few months around month ten, losers are generally more volatile than winners after the month of portfolio formation. We will return to these return moments in event time in Section 4.3, after we construct factor mimicking portfolios based on expected growth rates.

In sum, this subsection has shown that winners are associated with temporarily higher dividend growth, investment growth, and sales growth than losers. The differences in growth rates between the two portfolios tend to converge in 15 to 20 months after portfolio formation. Moreover, traditional measures of risk, such as market beta and total volatility, indicate that winners are actually less risky than losers for about four to ten months after portfolio formation.

3.4 Expected Growth Rates and Past Returns

So far we have only investigated the behavior of growth rates conditional on inclusion in momentum portfolios. 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, 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 dividends and zero or negative capital investments, rendering the normal definition of growth rates meaningless, we normalize changes of dividend, investment, and sales by beginning-of-period book value.

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 true even after lagged values of growth rates are controlled for. 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, probably due to the fact that profitability is more persistent than growth rates, as indicated in Figure 2. In sum, consistent with Johnson (2002), we find that future growth rates are positively correlated with past stock returns. Therefore, a momentum sort tends to be a sort on expected growth rates.

4 Can Expected Growth Rates Explain Momentum?

We now test whether the momentum profits can survive after the dispersion in expected growth rates is controlled for. First, we construct factor mimicking portfolios on expected growth rates and test whether growth rate risk is priced. We then use these factors of growth measures in time series tests with ten momentum portfolios as target assets, as in Fama and

French (1996). Second, we cut the universe of stocks into different subsamples based on the expected growth rates, and then examine the magnitude of the momentum profits within each subsample. If momentum profits are mainly driven by growth rate risk, then within each subsample the magnitudes of the momentum profits should be much lower than those without controlling for growth rate risk.

4.1 Is Growth Rate Risk Priced?

Having shown in Section 3 that the momentum portfolios indeed differ in expected growth rates, we now ask whether growth rate risk is priced in the data. Specifically, we ask whether firms with higher expected growth rates earn higher average returns than firms with lower expected growth rates.

To this end, we construct factor-mimicking portfolios for three expected growth measures, dividend growth, investment growth, and sales growth. As in Section 3.4, we define growth rates as the changes in dividend, investment, or sales divided by book value at the beginning of the year and only use firms with positive book values of equity.

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. 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. These results are not reported to save space but are available from the authors upon request.

Our timing convention of the regressors in (2) is carefully chosen to avoid potential look-ahead bias in constructing factor-mimicking portfolios on expected growth rates. 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 instruments for modeling expected growth rates. The reason is that dividend, investment, and sales are annual averages, where stock returns are point-to-point. So investment growth at December of 1980, from dividing investment measured 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. So 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 economic fundamentals.

In sum, we construct factor-mimicking portfolios on expected growth rates as follows. At the 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 equal-weight portfolio returns from July of this year to June of next year. The factors are defined as the differences between the highest expected growth portfolio and the lowest expected growth portfolio.

Table 3 reports the descriptive statistics of market excess return, SMB, HML, WML, and the factor-mimicking portfolios constructed from the expected growth measures. The data for market excess return, SMB, and HML are from Ken French's website. WML is constructed from buying the top ten percent winners and selling the bottom ten percent losers. Consistent with previous studies, Panel A shows that the momentum strategy is profitable in our sample: the average WML factor return is 0.73 percent per month with a t-statistic of 3.46.

Panel A of Table 3 also indicates that the dividend growth factor earns an average return of 56 percent per month which is significant with a t-statistic of 2.49. The factors associated with expected investment growth and expected sales growth both earn about 47 percent per month that are marginally significant with t-statistics around 1.80. These results suggest that growth rate risk is indeed priced, i.e., stocks with higher expected growth rates earn higher average returns than stocks with lower expected growth rates.

The momentum factor also seems to be very much related to the return factors constructed on expected growth rates. Panel B of Table 3 reports the correlation matrix for all the return factors. The fourth row of Panel B shows that the momentum factor is highly positively correlated with the growth rates factors. The correlations range from 0.42 to 0.46 in monthly frequency.

4.2 Time Series Tests

We now examine whether the factor-mimicking portfolios constructed on expected growth rates can explain the momentum profits in the time series tests.

First we run time series regressions of WML on Fama-French three factors and our return factors on growth rates, both separately and jointly,

$$\mathrm{WML}_{t+1} = \alpha + b\,\mathrm{MKT}_{t+1} + s\,\mathrm{SMB}_{t+1} + h\,\mathrm{HML}_{t+1} + f\,\mathrm{FAC}_{t+1} + \epsilon_{t+1} \tag{3}$$

where MKT, SMB, and HML are Fama-French three factors and FAC denotes on of the three return factors constructed above: investment growth (FAC^I), dividend growth (FAC^D), and sales growth (FAC^S).

The results are reported in Table 4. Consistent with previous findings, the first two regressions in the table show that the static CAPM and the Fama-French three factor model cannot explain the momentum effect. The Jensen's α from the market regression is 73 basis points per month and is highly significant with a t-statistic of 3.69. Adding SMB and HML into the regression equation actually increases the intercept by 10 basis points, although its t-statistic is slightly reduced. The reason why Fama-French three factor model deepens the momentum puzzle lies in the loadings of SMB and HML, which are *negative*, albeit insignificant. Thus, if momentum profits are compensation for risk, then the source of this risk must be very different from what SMB and HML are proxy for.

Regressions 3–5 in Table 4 report the univariate regressions of WML on three expected growth rate factors. All the loadings on the three factors are positive and highly significant. The R^2's are all around 20 percent, much higher than the static CAPM or the Fama-French three factor model. Relative to the intercept in the CAPM regression, the intercepts associated with expected growth factors are lowered by about 30 to 40 percent, although they are still significant. These results are robust with respect to the inclusion of the Fama-French factors, as indicated in Regressions 6–8.

We next consider using ten momentum portfolio as target assets in our time series regressions. Fama and French (1996) find that their three-factor model cannot explain the momentum returns. The intercepts in time series regressions of ten momentum portfolios on MKT, SMB, and HML are significantly negative for loser portfolios and significantly positive for winner portfolios, and the hypothesis that all the intercepts are jointly zero is strongly rejected. To make sure that our results are comparable with those reported by Fama and French (1996), 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.

Panel A of Table 5 reports the average excess returns of ten equal-weight momentum portfolios constructed using the 12/1 strategy using the sample from July 1965 to December 2001. The average return spread between winner and loser portfolios is 79 basis points per month and is significant with a t-statistic of 2.92. We notice that, although the spread is still significant, it is 52 basis points less than 131 basis points reported in Fama and French (1996) using the sample from July 1963 to December 1993. Next, Panel B of Table 5 reports the results of market regressions on the ten momentum portfolios. Consistent with Jegadeesh and Titman (1993), the static CAPM cannot explain the momentum profits: the Jensen's α's for the winner portfolios are positive and significant and the GRS test for testing intercepts being jointly zero is rejected at one percent level. There is also no dispersion in unconditional market beta between the loser and the winner portfolio. The amount of variation explained, R^2, ranges from 42 percent for Loser to 78 percent for portfolio seven.

Panel C of Table 5 replicates Fama and French (1996 Table VII) using our data. The panel shows that the intercepts of the ten momentum portfolios increase monotonically from -0.22 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. So it seems that the Fama-French three factor model performs slightly worse than the static CAPM in accounting for the momentum profits. The loadings of Loser on SMB and HML are markedly higher than those of Winner, indicating that momentum strategy is not risky along the dimensions that SMB and HML are proxy for. On a positive note, the amount of variation in returns explained by the Fama-French three factor model is higher than that of the static CAPM.

We now augment the Fama-French three factor model with WML or one of the three expected growth rate factors in the time series regression, i.e.,

$$r_{it+1} = \alpha_i + b_i \,\mathrm{MKT}_{t+1} + s_i \,\mathrm{SMB}_{t+1} + h_i \,\mathrm{HML}_{t+1} + f_i \,\mathrm{FAC}_{t+1} + \epsilon_{it+1} \tag{4}$$

where FAC_{t+1} is WML or one of the three expected growth rate factors, including dividend growth factor FAC^D, investment growth FAC^I, and sales growth FAC^S.

Panel A in Table 6 reports that 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. Panel B shows that, 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 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 much the same as 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.

In sum, the evidence strongly indicates that the underlying expected growth rates are important sources of the momentum profits. The loser portfolio has lower average returns because it has lower risk associated with expected growth rates indicated by its negative loadings on the expected growth factors. The winner portfolio keeps winning because it has higher risk associated with expected growth rates indicated by its positive loadings.

4.3 Factor Loadings in Event Time

The momentum profits are short-lived in the data. They are positive in the range from one to 12 months and then turn negative in the longer horizons. To explain this pattern, Johnson (2002) posits that shocks on growth rates are episodic: Persistent growth rate shocks only occur in the more infrequent, short-lived state, representing technological innovations in the economy. If the profits of the momentum strategy in the data are indeed driven by its exposure to the expected growth rate factor, then this exposure must be *temporary* and it must decay over the horizons in which there are no momentum profits.

To test this hypothesis, we investigate the behavior of factor loadings of the winner and loser portfolios on three expected growth rate 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 on expected growth factors are calculated based on 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. The factor loadings on SMB and HML are based on the pooled time series regressions on the Fama-French three factor model.

Figure 4 reports the findings. Panels A–C clearly indicate that the growth rate risk is short-lived: 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. This evidence reinforces the notion that the momentum profits are likely driven by the growth rate risk. In contrast, Panels D and E of Figure 4 show that the loadings of winners and losers on SMB and HML display the "wrong" pattern. Winners have higher loadings than losers before portfolio formation but have lower loadings than losers after portfolio formation. Moreover, the dispersion in the factor loadings between winners and losers do not converge even three years after the portfolio formation.

In sum, this section shows that: (i) the risk associated with expected growth rates is priced and stocks with higher expected growth rates earn higher returns on average than stocks with lower expected growth rates; (ii) after the risk to expected growth rate factors is controlled for, momentum profits fall greatly, and in some cases to insignificant levels; and finally, (iii) the dispersion in the loadings of winner and loser portfolios on expected growth rate factors is temporary and its duration is amazingly consistent with that of the momentum profitability.

4.4 Momentum Profits, Cut Different Ways

In this subsection we investigate the cross-sectional variation of momentum profits across different samples sorted on size and book-to-market. The behavioral finance literature has interpreted this evidence as indicating investor irrationality. We argue instead that it arises naturally as a result of the cross-sectional variation of expected growth rates.

Size Effect in Momentum Profits

Previous literature, e.g., Jegadeesh and Titman (1993) and Hong, Lim, and Stein (2000), finds that the relationship between size and the magnitude of the momentum effect is a pronounced, inverted U-shape. Hong, Lim, and Stein (2000) argue that the near monotonic effect of raw size in momentum profits results from the information diffusion story in Hong and Stein (1999). Smaller firms have slower information diffusion, which leads to greater momentum profits. To reconcile this story with the evidence that momentum profits revert in the smallest size deciles, Hong, Lim, and Stein (2000) further argue that smallest firms also have more limited investor participation, which leads to the more pronounced reversals due to supply shocks.

In contrast, a perhaps more natural explanation of the inverted U-shape of the relationship between size and momentum can be based on similar relationships between size and expected growth rates underlying the momentum strategy. To investigate this possibility, at the end of each year t, we sort all the stocks into three groups independently based on its prior six-month return, expected dividend growth, expected investment growth, and expected sales growth. Both low and high groups take up 30 percent of stocks, leaving the middle group with the remaining 40 percent. We further rank all stocks independently according to its market capitalization at the end of June of year t into ten size deciles using NYSE breakpoints. We then take intersections of the three groups based on momentum or growth rates and the ten size groups. As a results we have 30 portfolios for momentum and each expected growth rates, and 120 portfolios in total. We record the returns of these portfolios from July of year $t-1$ till June of year t and calculate the return spread between high and low groups for each size decile.

Panel A of Figure 5 plots across ten size deciles the average monthly returns in percent of high-minus-low momentum (the solid line), expected dividend growth factor (the broken line), expected investment growth factor (the dash-dot line), and expected sales growth factor. Consistent with previous literature, the solid line indicates that the magnitude of momentum profits across different size groups follows an inverted U-shape. The fourth size decile has the highest momentum profits and the largest decile of firms have the lowest momentum profits. Except for the three smallest size deciles, the magnitude of momentum profits declines with firm size.

Interestingly, the other three lines in Panel A of Figure 5 show that similar inverted U-shape is also evident in the relationship between size and expected growth factors. The average returns of expected growth factors decrease with size starting from the fourth size decile and increase with size among the three smallest deciles. However, the magnitudes of the expected growth factor returns are lower than that of the momentum factor. In sum, this evidence is suggestive that the size effect in momentum is a reflection of similar size effect in expected growth rates.

Value Effect in Momentum Profits

Besides the size effect in momentum, the previous literature also examines the relationship between book-to-market and momentum. Asness (1997) and Daniel and Titman (1999) find that momentum effects are stronger for growth stocks than for value stocks. Daniel and Titman (1999) further interpret this evidence as indicating investor overconfidence: momentum effect is likely to be stronger among stocks whose valuations require deciphering more ambiguous information, which suffers more from the overconfidence bias.

In contrast, we propose an alternative interpretation of the evidence based on expected growth rates: momentum profits are higher in low book-to-market or growth firms than those in high book-to-market or value firms because growth firms have temporary higher expected growth rates than value firms.

To investigate this hypothesis, we examine the cross-sectional variation of the average returns of momentum strategy and expected growth rate factors across ten book-to-market deciles. At the end of each year t, we sort all the stocks into three groups independently based on its prior six-month return, expected dividend growth, expected investment growth, and expected sales growth. Both low and high groups take up 30 percent of stocks, and the middle group contains the remaining 40 percent. We further rank all stocks independently according to its book-to-market into ten deciles using NYSE breakpoints. Market value is measured at the end of June of year t and book value is measured at the end of year $t-1$. We then take intersections of the three groups based on momentum or expected growth rates and the ten book-to-market deciles. As a results we have 30 portfolios for momentum and each expected growth rates, and 120 portfolios in total. We record the returns of these portfolios from July of year $t-1$ till June of year t and calculate the return spread between high and low groups for each book-to-market decile.

The results are reported in Panel B of Figure 5. The solid line in the panel shows that momentum profits decrease in general with book-to-market, consistent with the evidence in Asness (1997) and Daniel and Titman (1999). Interestingly, the other three lines in Panel B show that the relationships between book-to-market and expected growth factors are also close to being monotonic. This evidence is supportive of our interpretation that the value effect in momentum is driven by the differences in underlying expected growth rates between high and low book-to-market deciles.

In sum, the relationship between size and momentum and that between book-to-market and momentum reflect similar relationships between these firm characteristics and expected growth rates. Therefore, behavioral biases, such as slow information diffusion and investor overconfidence, are not necessary to explain the cross-sectional variation of the momentum profits.

5 Conclusion

We investigate empirically whether momentum profits reflect the behavior of their underlying economic fundamentals, as predicted by Johnson (2002). We find evidence that: (i) winners have persistently higher dividend, investment, and sales growth rates than losers; (ii) past returns are positive predictors of future growth rates; (iii) factor-mimicking portfolios on expected growth rates earn significantly positive returns on average; more importantly, (iv) after expected growth rates are controlled for, momentum profits fall, in some cases to insignificant levels; and (v) the dispersion in the loadings of the winner and loser portfolios on expected growth rates is only *temporary* and its duration is surprisingly consistent with the duration of the momentum profits. Finally, we also document the expected growth factors display similar relationships to size and book-to-market to that of momentum profits. Thus, behavioral biases, e.g., slow information diffusion and investor overconfidence, are not necessary to explain the cross-sectional variation of momentum profits across the size and book-to-market deciles. In all, our evidence indicates that, consistent with the rational expectations theory of Johnson (2002), economic fundamentals can be important sources of the momentum anomaly.

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A Stock Returns and Investment Growth

The setup of the investment-based asset pricing model is standard, e.g., Cochrane (1991, 1996). A firm maximizes its net present value of future dividends by choosing corporate investment policy:

$$\max_{K_{t+1}, I_t} \; \mathrm{E}_0 \left[\sum_{t=0}^{\infty} M_t \left[\Pi(K_t, X_t) - I_t - C(I_t, K_t) \right] \right] \tag{A1}$$

subject to the capital accumulation rule:

$$K_{t+1} = (1-\delta) K_t + I_t \tag{A2}$$

In (A1), M_t is the shareholders' stochastic discount factor, K_t is the capital of the firm at time t, I_t is investment expenditure at time t, $\Pi(K_t, X_t)$ is the operating revenue as the outcome of a static optimization problem where all the variable inputs have been determined, X_t is the vector of state variables summarizing all sources of uncertainty, and $C(I_t, K_t)$ is capital adjustment cost discussed below. (A2) says that next period capital stock equals current period capital net of depreciation plus new investment.

Capital investment also entails adjustment cost, captured as deduction from the economic profit at time t:

$$C(I_t, K_t) = \frac{a}{2} \left(\frac{I_t}{K_t} \right)^2 K_t; \qquad\qquad a > 0 \tag{A3}$$

The adjustment cost is increasing and convex in investment rate I/K, thus faster capital adjustment leads to higher cost. We adopt the simple quadratic form for $C(I_t, K_t)$. Other parameterizations of the adjustment cost exist in the literature, but for our purposes of developing testable hypotheses on momentum profits, alternative functional forms deliver qualitatively similar economic inferences.

Assume constant return to scale for the production technology: $\Pi(K_t, X_t) = X_t K_t$, where X_t denotes source of uncertainty, e.g., productivity shock. The optimality condition of the firm implies that: $\mathrm{E}_t \left[M_{t+1} R^I_{t+1} \right] = 1$, where the investment return (the rate of return for the claim to the capital stock of the firm), denoted R^I_{t+1}, is defined as:

$$R^I_{t+1} = \frac{\pi_{t+1} + (a/2) i^2_{t+1} + (1-\delta)(1 + a i_{t+1})}{1 + a i_t} \tag{A4}$$

$i_t \equiv I_t / K_t$ is the investment rate and $\pi_t \equiv \Pi_t / K_t = \Pi_K(t)$ is the marginal product of capital at time $t+1$.

Next, to link investment return to stock return, we assume that these two returns for a given firm are equal, again following Cochrane (1991). This is equivalent to saying that equity is a claim to the capital stock of the firm. We have ignored the bondholders' claims to capital. This should not have much effect on the results. Since the marginal source of financing investment is often retained earnings, so the effect of marginal investment on investment return may be fully reflected in stock return alone.

Table 1 : Summary Statistics of Returns and Economic Fundamentals of Ten Momentum Portfolios and WML (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. All the data on stock return, stock price, and outstanding shares from the Center for Research in Security Prices (CRSP) monthly return file. Financial statement data are from the COMPUSTAT merged annual data files. We use the common stocks listed on the NYSE, AMEX, and Nasdaq from January 1965 through December 2001, but exclude closed-end funds, Real estate Investment Trust, trusts, American Depository Receipts, and foreign stocks. Only December fiscal year-end firms are used in order to eliminate the problems caused by overlapping observations. Method: 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. Stock returns are observable monthly and the momentum strategies involve monthly rebalancing. But fundamental variables such as investment and earnings are available only at the annual frequency. We obtain monthly measures of flow variables such as earnings by dividing their most recent annual observations by 12, and we use the most recent annual observations of stock variables such as book value in any given month. After we rank the stocks according to their past six-month returns, we sum up the individual stock fundamentals for all the stocks held in that month in each portfolios to obtain the fundamentals at the portfolio level. Although it is a crude adjustment, this method takes into account the monthly changes in stock composition of momentum strategies.

	Loser	2	3	4	5	6	7	8	9	Winner	Spread	t-stat
	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	

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 are reported in parentheses. Since some firms have zero or negative dividend and investment, we normalize all the growth rates 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.

	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
	(3.56)				(4.89)			
		0.063		1.06		1.165		1.61
		(3.36)				(8.18)		
	0.039		-0.051	6.36	0.658		-0.041	6.53
	(2.48)		(-0.73)		(5.77)		(-0.77)	
		0.059	-0.050	6.04		1.065	-0.046	6.72
		(2.67)	(-0.72)			(8.07)	(-0.87)	
$\tau=24$	0.075			1.62	0.615			1.55
	(10.51)				(1.60)			
		0.088		1.50		1.444		1.46
		(7.45)				(3.30)		
	0.074		0.012	4.54	0.885		-0.103	4.00
	(11.15)		(0.22)		(2.60)		(-2.07)	
		0.085	0.013	4.43		1.261	-0.109	4.17
		(8.13)	(0.25)			(4.39)	(-2.13)	

	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
	(4.54)				(4.04)			
		4.50		1.32		1.960		1.72
		(7.40)				(4.68)		
	1.645		0.098	3.25	1.005		0.329	10.71
	(4.01)		(4.79)		(3.20)		(6.00)	
		3.124	0.093	3.43		1.145	0.331	10.40
		(5.28)	(4.63)			(2.95)	(6.00)	
$\tau=24$	2.982			0.90	1.200			1.33
	(3.16)				(2.22)			
		7.964		1.40		1.217		1.47
		(6.03)				(2.19)		
	2.364		0.154	3.16	0.975		0.273	7.22
	(2.53)		(3.75)		(1.68)		(6.80)	
		5.626	0.146	3.36		0.671	0.273	7.25
		(4.81)	(3.57)			(2.871)	(6.85)	

Table 3 : Descriptive Statistics of MKT, SMB, HML, WML, and Factor Mimicking Portfolios of Dividend Growth, Investment Growth, and Sales Growth (July 1965 to December 2001, 432 Observations)

This table reports summary statistics of market excess return (MKT), SMB, HML, momentum (WML), and factor mimicking portfolios on dividend growth (FAC^D). investment growth (FAC^I), and sales growth (FAC^S). Panel A reports for all the return factors their means, volatilities, and t-statistics for testing zero average returns. The t-statistics (reported in parentheses) are 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. To construct factor-mimicking portfolios on growth rates, we sort all stocks into three groups at the December of each portfolio formation year t, and then record all the portfolio returns from July of year $t-1$ to June of year t. The factor-mimicking portfolios on growth rates (and the momentum factor WML) 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

Table 4 : Univariate and Multiple Regressions of WML on Fama-French three factors and Growth Rate Factors (July 1965 to December 2001, 432 Observations)

This table reports the results of regressing WML on market excess return, MKT, SMB, HML, and growth rate factors, including investment growth (FAC^I), dividend growth (FAC^D), and sales growth (FAC^S), separately and jointly. To construct factor-mimicking portfolios on growth rates, we sort all stocks into three groups at the December of each portfolio formation year t, and then record all the portfolio returns from July of year $t-1$ to June of year t. The factor-mimicking portfolios on growth rates (and the momentum factor WML) 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. All the t-statistics (reported in the parentheses) are adjusted for heteroscedasticity and autocorrelations up to six lags. Significant intercepts and their t-statistics are highlighted. The values of R^2 are in percent.

Regression	α	MKT	SMB	HML	FAC^I	FAC^D	FAC^S	R^2
1	**0.730**	-0.003						0.00
	(**3.69**)	(-0.04)						
2	**0.831**	0.012	-0.293	-0.159				2.95
	(**3.46**)	(0.15)	(-1.88)	(-0.71)				
3	**0.497**				0.492			21.52
	(**2.47**)				(6.63)			
4	**0.442**					0.512		20.71
	(**2.02**)					(5.11)		
5	**0.521**						0.444	17.59
	(**2.68**)						(8.11)	
6	**0.567**	-0.004	-0.296	-0.075	0.495			24.43
	(**2.39**)	(-0.06)	(-2.36)	(-0.34)	(6.48)			
7	**0.539**	0.007	-0.210	-0.149		0.499		22.36
	(**2.12**)	(0.11)	(-1.61)	(-0.74)		(5.17)		
8	**0.589**	-0.027	-0.296	-0.054			0.454	20.74
	(**2.58**)	(-0.41)	(-2.22)	(-0.23)			(8.06)	

Table 5 : Ten 12/1 Momentum Portfolios: Summary Statistics, Market Regressions, and Time Series Regressions with Fama-French Three Factor Model (July 1965 to December 2001, 432 Observations)

To ensure that our results are comparable with those in Fama and French (1996, Tables VI and VII), 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 results of summary statistics (Panel A), market regression (Panel B), and multiple regressions with Fama-French three factor model (Panel C), 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.

	Panel A: Average Excess Returns and Volatilities											
	Loser	2	3	4	5	6	7	8	9	Winner	Spread	t-stat
m	0.58	0.39	0.50	0.52	0.61	0.75	0.85	0.93	1.13	1.37	**0.79**	**2.92**
σ	8.92	6.47	5.56	5.13	4.89	4.96	5.05	5.49	6.37	8.03		
	Panel B: $r_{it+1} = a_i + b_i \, \mathrm{MKT}_{t+1} + e_{it+1}$											
	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
a_i	-0.02	-0.11	0.03	0.07	0.17	0.29	0.38	0.43	0.58	0.72		
t_a	-0.09	-0.54	0.16	0.48	1.32	**2.16**	**3.00**	**2.95**	**3.06**	**2.82**	**2.42**	**0.008**
b_i	1.28	1.06	0.99	0.95	0.93	0.96	0.98	1.06	1.18	1.34		
t_b	15.46	17.68	18.79	20.86	22.27	22.48	25.83	26.16	23.23	20.00		
R^2	0.42	0.55	0.66	0.71	0.75	0.77	0.78	0.77	0.70	0.60		
	Panel C: $r_{it+1} = a_i + b_i \, \mathrm{MKT}_{t+1} + s_i \, \mathrm{SMB}_{t+1} + h_i \, \mathrm{HML}_{t+1} + e_{it+1}$											
	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
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**	**2.50**	**0.006**
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		

Table 6 : 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.

	Loser	2	3	4	5	6	7	8	9	Winner	GRS	p
	Panel A: $r_{it+1} = a_i + b_i\,\mathrm{MKT}_{t+1} + s_i\,\mathrm{SMB}_{t+1} + h_i\,\mathrm{HML}_{t+1} + f_i\,\mathrm{WML}_{t+1} + e_{it+1}$											
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 1 : Growth Rates and Profitability of Winners and Losers in Calendar Time (1965–2001, 37 Observations)

This figure plots the time series of growth measures, including dividend growth (Panel A), investment growth (Panel B), sales growth (Panel C), and return on equity (Panel D), measured at the end of calendar year, for winner portfolio (the solid line) and loser portfolio (the broken line). Data source: All the data on stock return, stock price, and outstanding shares from the Center for Research in Security Prices (CRSP) monthly return file. Financial statement data are from the COMPUSTAT merged annual data files. We use the common stocks listed on the NYSE, AMEX, and Nasdaq from January 1965 through December 2001, but exclude closed-end funds, Real estate Investment Trust, trusts, American Depository Receipts, and foreign stocks. Only December fiscal year-end firms are used in order to eliminate the problems caused by overlapping observations. Method: 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 measure all the flow and stock variables at the end of calendar year. This method avoids the *ad hoc* slicing adjustment from annual flow to monthly flow variables, but it ignores all the changes of stock composition during the year.

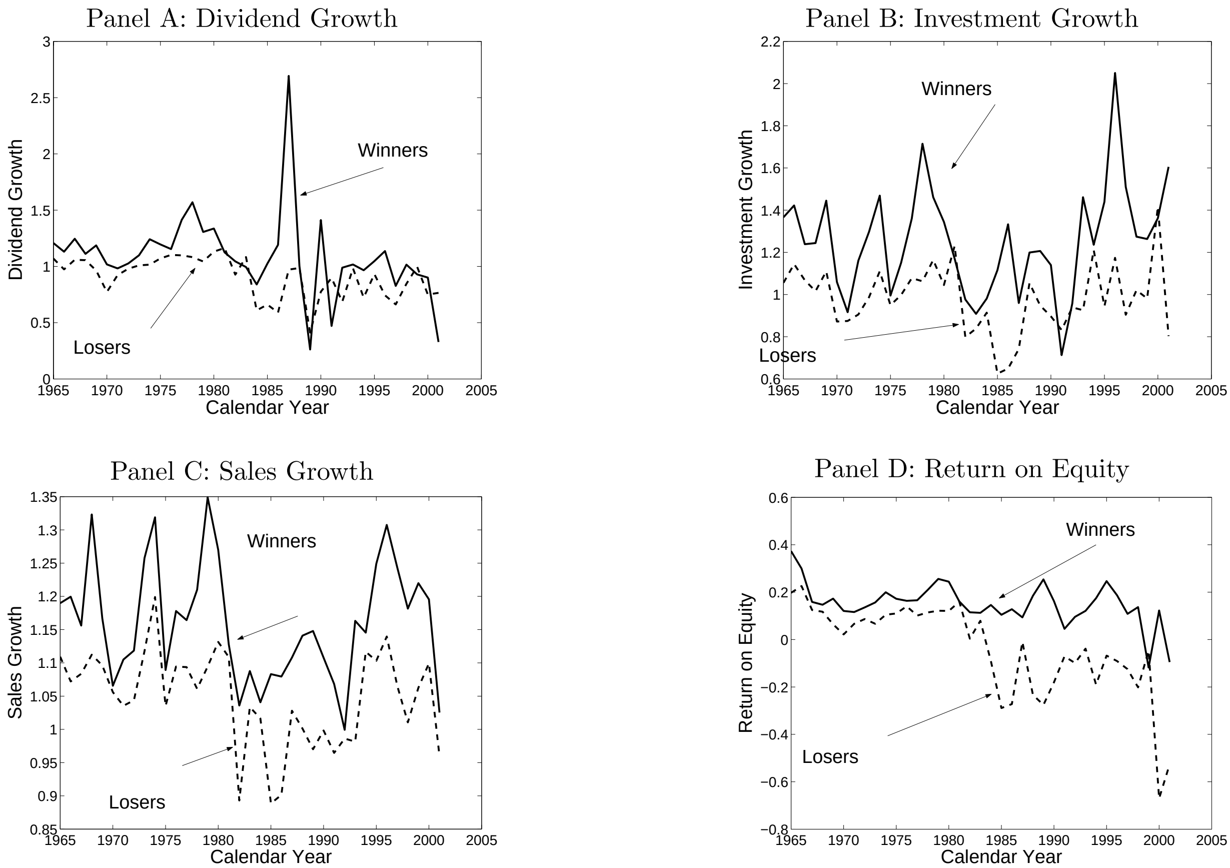
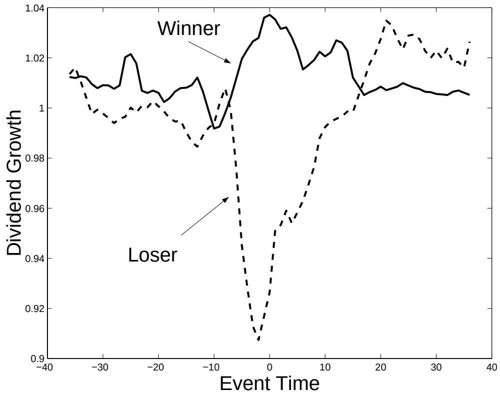


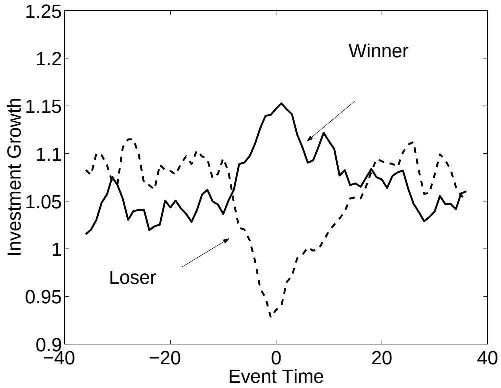
Figure 2 : Growth Rates and Profitability of Winner and Loser Portfolio in Event Time (36 Months Before and After Portfolio Formation)

For each portfolio formation month from $t =$ January 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. To avoid potential microstructure biases, we impose one-month lag between the end of ranking period and the beginning of holding period. All the data on stock return, price, and shares outstanding are from CRSP monthly return file. Financial statement data are from COMPUSTAT merged quarterly files. We use the common stocks listed on NYSE, AMEX, and NASDAQ from January 1965 to December 2001, but exclude closed-end funds, Real Estate Investment Trust, American Depository Receipts, foreign stocks, and firms with negative book value.

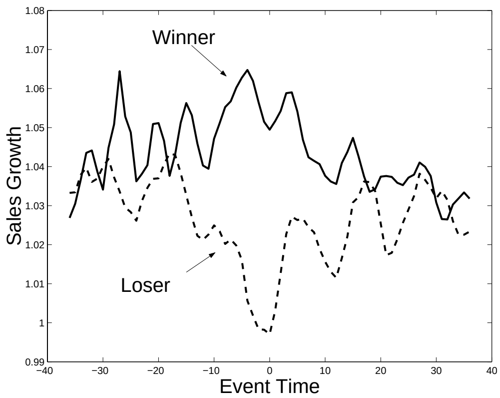
Panel A: Dividend Growth



Panel B: Investment Growth



Panel C: Sales Growth



Panel D: Return on Equity

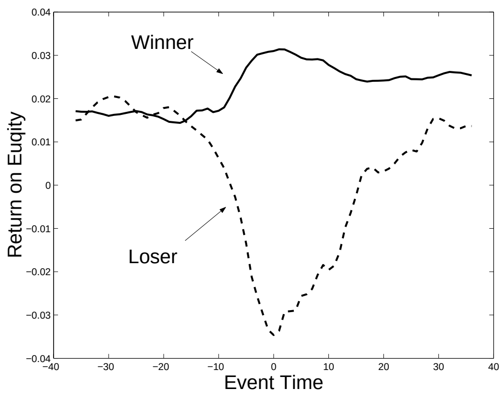


Figure 3 : Average Excess Returns, Jensen's α, Market β, and Total Volatility of Winner and Loser Portfolio in Event Time (36 Months Before and After Portfolio Formation)

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. 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. All the data on stock return, price, and shares outstanding are from CRSP monthly return file. We use the common stocks listed on NYSE, AMEX, and NASDAQ from January 1965 to December 2001, but exclude closed-end funds, Real Estate Investment Trust, American Depository Receipts, foreign stocks, and firms with negative book value.

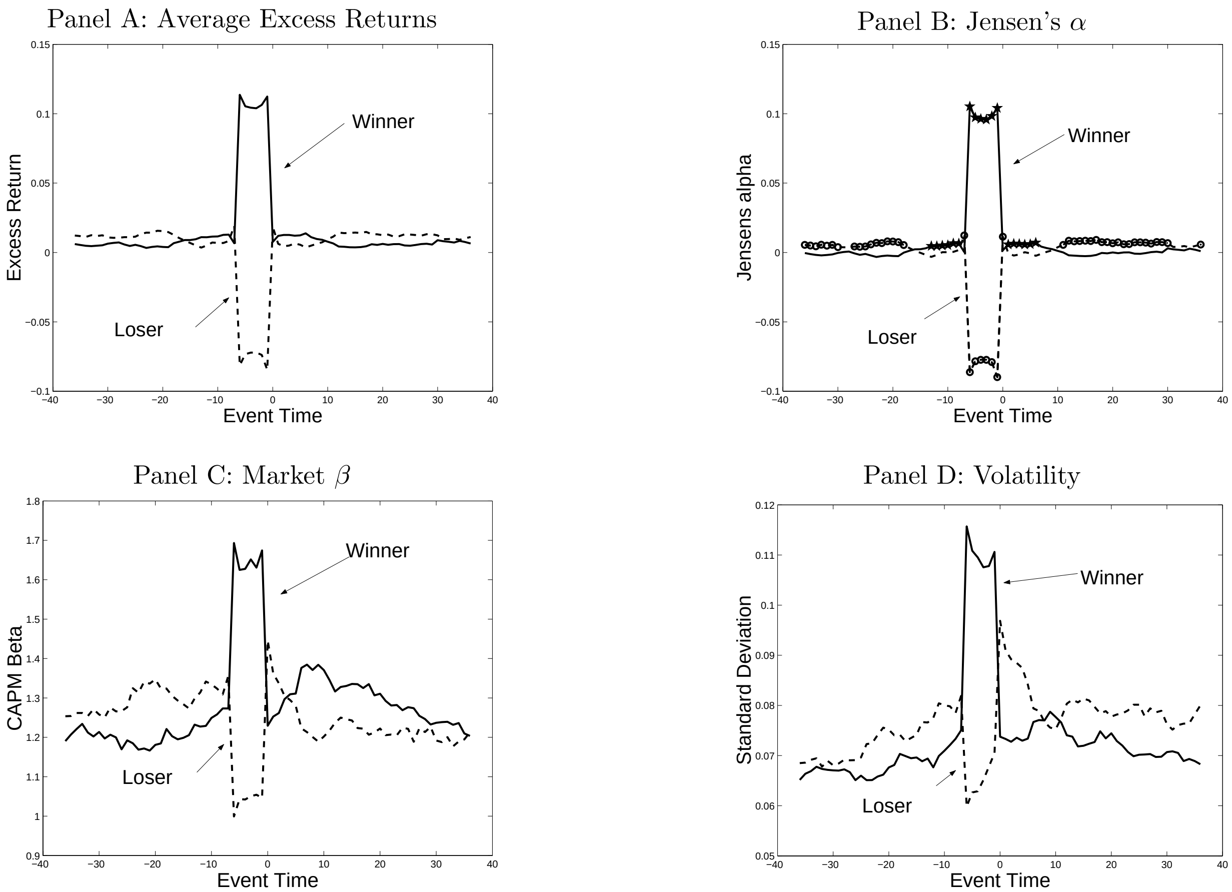
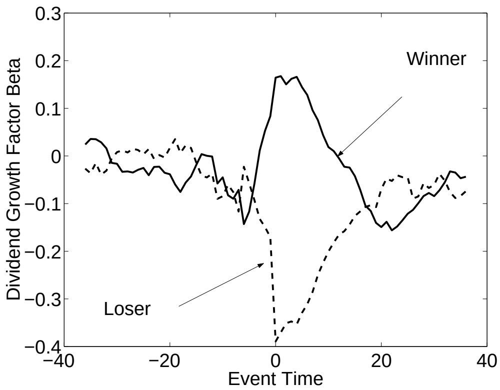


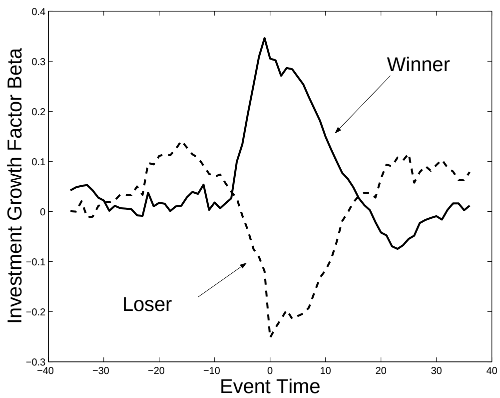
Figure 4 : Factor Loadings of Winner and Loser Portfolios on SMB, HML, Investment Growth Factor, and Sales Growth Factor in Event Time (36 Months Before and After Portfolio Formation)

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.

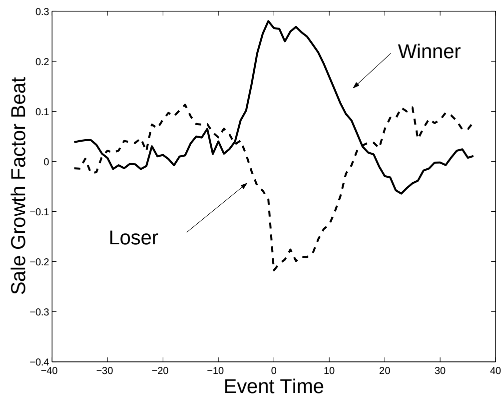
Panel A: Loadings on FAC^D



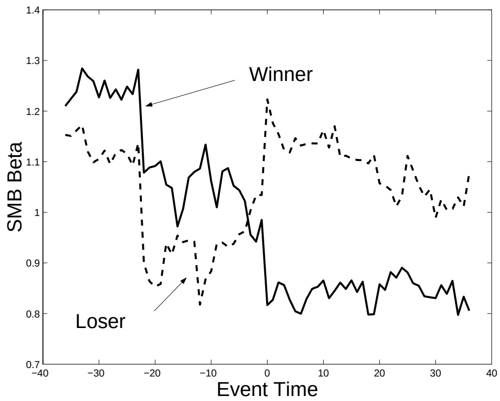
Panel B: Loadings on FAC^I



Panel C: Loadings on FAC^S



Panel D: Loadings on SMB



Panel E: Loadings on HML

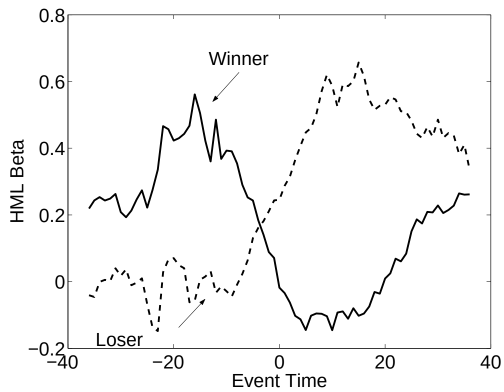


Figure 5 : Average Returns of WML, Expected Dividend Growth, Expected Investment Growth, and Expected Sales Growth Factor Returns Across Ten Subsamples Sorted on Size or Book-to-Market

Panel A of this figure plots the relationship between size and the magnitude of the moment effect (the solid line), that between size and the average return of expected dividend growth factor (the broken line), that between size and the average return of expected investment growth factor (the dash-dot line), and that between size and the average return of expected sales growth factor (the dotted line). Panel B of this figure plots the relationship between book-to-market and the magnitude of the moment effect (the solid line), that between book-to-market and the average return of expected dividend growth factor, (the broken line), that between book-to-market and the average return of expected investment growth factor (the dash-dot line), and that between book-to-market and the average return of expected sales growth factor (the dotted line). At the end of each year t, we sort all the stocks according to its prior six-month return, expected dividend growth, expected investment growth, or expected sales growth into three groups. Both low and high groups take up 30 percent of stocks, leaving the middle group with 40 percent of stocks. We further rank all stocks independently according to its market capitalization or book-to-market at the end of June of year t into ten size deciles using NYSE breakpoints. We then take intersections and obtain 30 portfolios. We calculate the average returns of these portfolios from July of year $t-1$ till June of year t and calculate the return spreads between high and low momentum, expected dividend growth, expected investment growth, and expected sales growth groups controlling for size or book-to-market.