

Investment-Specific Shocks and Momentum Profits *

(Job Market Paper)

Jun Li[†]

November 21, 2011

Abstract

This paper explores the relationship between investment-specific shocks (i.e., technological innovations in equipment and software), firm investment, and momentum profits. Empirically, momentum profits comove positively with investment-specific shocks with a correlation coefficient of 0.32. An unconditional two-factor model, with investment-specific shocks and market excess returns as the risk factors, explains 90% of the average returns of momentum portfolios. Consistent with investment dynamics, I propose a rational explanation for momentum profits: Past winners are those who had good idiosyncratic productivity in the recent past; they initiate more investment, make greater investment commitments, and hence have a higher risk exposure to investment-specific shocks than past losers. A simple investment-based asset pricing model is developed to elaborate this story, with the key ingredients of investment commitment and investment-specific shocks. The model generates reasonably large momentum profits and investment dynamics of momentum portfolios as in the data.

JEL Classifications: G12, E44

Keywords: Momentum, Investment-specific shocks, Investment commitment, Investment-based asset pricing

*I am indebted to my advisors Frederico Belo and Robert Goldstein for their continuous support and encouragement. I am grateful to Rajesh Aggarwal, Santiago Bazdresch, Philip Bond, John Boyd, Ian Cooper, Philip Dybvig, Murray Frank, Vito Gala, Satadru Hore, Ben Jacobsen, Ronald Masulis, Rick Nelson, Frans de Roon, Patricio Valenzuela, Fan Yang, Lu Zhang, and especially Xiaoji Lin and Jianfeng Yu for valuable discussions and comments. I also thank seminar participants at the University of Minnesota, the Econometric Society North American Summer Meeting, the 2011 EFA Doctor Tutorial, and the 2011 FMA Annual Meeting. All errors are my own.

[†]Department of Finance, University of Minnesota, 321 19th Ave. South., #4-273, Minneapolis, MN 55455. e-mail: lixx353@umn.edu.

1 Introduction

The profitability of momentum-based investment strategies is one of the most enduring anomalies identified in the asset pricing literature. From 1930 to 2009, the difference in average returns between past winners and past losers in the U.S. stock market is about 13% per year, and more than 90% of the momentum profits in a five-year window are positive. Further, momentum profits have persisted long after being documented in Jegadeesh and Titman (1993).¹ Most of the literature on momentum profits focus on behavioral rather than rational explanations. One major reason for this focus is the failure of standard risk factor models, such as the capital asset pricing model (CAPM) and the Fama and French (1993) three-factor model, in capturing momentum portfolio returns, and no one has yet been able to identify an underlying risk factor that strongly covaries with momentum to support a rational explanation. As such, momentum is one of the biggest challenges for the efficient market hypothesis.

In this paper, I try to fill this gap by proposing investment-specific shocks (i.e., the aggregate technological innovations on new investment such as equipment and software) as a potential candidate for the underlying risk factor that justifies momentum profits. In particular, I provide a link for momentum profits to investment-specific shocks through the channel of firms' real investment dynamics. Intuitively, past winners are firms with high recent profitability; they initiate more investment, make greater investment commitments, and have a higher sensitivity to technological progress in equipment. In contrast, loser firms are those with low recent profitability; they initiate more disinvestment, make greater disinvestment commitments, and have a lower (or negative) exposure to investment-specific shocks. The investment-specific shock is an aggregate risk factor bearing a positive price of risk. Therefore, winner firms have a higher expected return than loser firms.

Introduced in macroeconomic literature, investment-specific shocks measure the technological innovations in investment goods, such as equipment and software. Greenwood, Hercowitz, and Krusell (1997) and subsequent papers show that investment-specific shocks can explain a substantial fraction of growth and variation in output and hours over the business cycle. One key feature of these innovations is that, unlike neutral technological changes, firms have to invest in equipment that embodies the latest technology in order to reap the benefits. This implies that firms with a higher investment commitment are more sensitive to technological innovations in investment goods, and hence have a higher exposure to investment-specific shocks.

¹These values are calculated using the momentum portfolios from Kenneth French's Web site. Different portfolio formation strategies will generate different moments. See Jegadeesh and Titman (2005) for an excellent review on momentum.

I start by exploring the empirical relationship between investment-specific shocks and momentum profits. The main findings can be summarized as follows. First, momentum profits comove strongly and positively with investment-specific shocks. For the annual sample from 1930 to 2009, the correlation between the momentum factor and investment-specific shocks is 0.32, which is significant at a 5% level. Second, an unconditional two-factor model, with investment-specific shocks and market excess returns as the risk factors, can capture well the relative movements of 10 portfolios sorted by momentum. The factor loadings on investment-specific shocks from the time series regression are monotonically increasing from the loser portfolio (-4.05 with a t -statistic of -1.93) to the winner portfolio (1.61 with a t -statistic of 2.31). Third, in a cross-sectional regression of average momentum portfolio returns on unconditional factor loadings, the model explains 90% of the portfolio returns. The mean absolute pricing error is only 0.9% per year, and the χ^2 test fails to reject the model. In addition, this model does not suffer from the critique of Lewellen, Nagel, and Shanken (2010) on the cross-sectional asset pricing tests on portfolios with a strong factor structure. The high GLS- R^2 of more than 60% indicates that these two factors are mean-variance efficient in pricing momentum portfolios. Fourth, the main results hold in a quarterly sample, with the control for firm characteristics such as value premium and size, and for industry momentum portfolios as well.

The above empirical findings naturally raise another question: Why do past winners have a high risk exposure to investment-specific shocks, whereas past losers have a low or even negative exposure? To answer this question, I look into the dynamics of momentum portfolios by focusing on the profitability and investment rate of momentum portfolios in an 11-year window around the portfolio formation year. Winner firms have higher profitability than loser firms, which is consistent with the existing literature such as Liu and Zhang (2011). More interestingly, the investment spread between winner and loser portfolios is not at peak in the event year as one might expect. Instead, it peaks one year after the portfolio formation, when the investment spread is *five times greater*.

It is worth noting that standard Q-theory models with convex adjustment costs cannot generate such hump-shaped investment responses. When a positive idiosyncratic productivity shock arrives, standard Q-theory models predict that capital expenditure shoots up immediately and then gradually decays because of the convex adjustment cost. The hump-shaped investment dynamics observed in momentum portfolios suggest that another type of friction — namely, investment commitment — may play an important role.

Based on this analysis, I propose a rational explanation for momentum profits: Winner firms are those that experienced high profitability in the recent past. They initiate more investment and make a greater commitment to future investment. Investment commitment

is risky because it is in terms of future capital expenditure. In a world in which the price of investment goods is stochastic, winner firms will therefore have a higher risk exposure to investment-specific shocks. On the other hand, loser firms suffer from past low profitability. They initiate more disinvestment and commit to greater disinvestment in the future. The commitment to disinvest serves as a hedge to loser firms, as a higher price of investment goods in the future implies that fewer units of existing capital need to be resold, which to some extent relieves the pain originating from low profitability. Therefore, loser firms have a low (or even a negative) exposure to investment-specific shocks.

I then develop a simple investment-based asset pricing model in a rational framework to elaborate this story. In this model, firms optimally choose capital expenditure to maximize their value. Two ingredients are key to the model: First, the investment-specific shock, or the per unit price of investment goods, is a risk factor that is stochastic and priced by investors. The total capital stock in the following period therefore depends not only on the capital expenditure, but also on the price of the investment goods. In addition, firms with different exposures to investment-specific shocks are priced differently.

The second key ingredient is investment commitment. Departing from the standard business cycle literature, I assume a two-period investment structure: Firms make investment decisions today, but can complete only a small fraction of these investments. A commitment is made at the same time to complete the remaining larger fraction in the next period. Together with investment-specific shocks, this implies that firms with more investment commitments will have higher levels of risk exposure to investment-specific shocks.

With the interaction of these two key ingredients, this model generates large momentum profits in the cross section. Using simulated data from the model, I repeat the tests that are performed in the empirical part and find good performance overall. The model captures the success of the two-factor model in explaining momentum portfolios. In particular, a large fraction of the momentum spread can be explained by the difference in risk exposures to investment-specific shocks between winners and losers. In addition to asset prices, the model also generates realistic dynamics of profitability and investment.

To explore in detail the mechanism in generating the risk premium for the momentum spread, I sort firms into 10 portfolios by committed investment rate using simulated data from the benchmark calibration. Firms with a high committed investment rate have a higher average return than those with low commitments, which confirms the intuition that investment commitment serves as a good proxy for risk exposure to investment-specific shocks. In a separate exercise, I turn off the investment-specific shocks and resimulate the model. Without exposure to investment-specific shocks, the momentum spread is much smaller than in the benchmark calibration. Taken together, these tests show that both investment

commitment and investment-specific shocks are important in generating sizable momentum profits.

The paper proceeds as follows: Section 2 reviews the literature. Section 3 documents the empirical findings about the relationship between momentum profits, investment-specific shocks and firm investment. Motivated by the empirical results, I propose an investment-based equilibrium model to rationalize these findings in Section 4. Section 5 concludes with some remarks. Details about data construction and numerical solutions are found in the Appendix.

2 Related literature

This paper is closely related to the current finance literature along several dimensions. First, my paper enriches the growing body of literature that strives to rationalize momentum profits. Johnson (2002) is one of the first papers to argue that momentum can be generated in a rational expectations framework. In his model, the growth rate of dividends is stochastic. The convex nature of the price of risk with respect to the growth rate predicts a positive relationship between the expected return and the growth rate, and hence predicts a positive autocorrelation of stock returns. Sagi and Seasholes (2007) extend the idea of Johnson (2002) and find that a firm's revenues, costs, and growth options combine to determine the stock return autocorrelation. These papers start from a theoretical perspective to analyze possible channels through which momentum profits can be generated or enhanced. In contrast, my paper starts from empirical findings and shows a direct link between momentum return spreads, real investment, and risk exposure to investment-specific shocks.

One particular line of research in this literature is searching for the underlying macroeconomic risk factors that capture momentum profits. For example, Liu and Zhang (2008) find that the growth rate of industrial production can explain more than half of momentum profits, as recent winners have temporarily higher loadings than recent losers on the growth rate of industrial production. They argue that if the industry production factor summarizes the firm-level changes in expected growth, then the factor loading should be high among stocks with high expected growth. Consistent with their argument, they do find that winner firms tend to have higher expected growth than loser firms.

Another example is Bansal, Dittmar, and Lundblad (2005), who document that the aggregate consumption risks embodied in cash flows can account for the large spread in momentum portfolios. They model dynamics of aggregate consumption and cash flow growth rates in a vector autoregression and find that differences in cash flow betas account for more than 60% of the cross-sectional variation. In contrast to the consumption side, my

paper focuses on the production side of the economy and explores the relationship between momentum profits and investment-specific shocks, a type of exogenous shock that is shown to be very important in the macroeconomic literature.

Liu and Zhang (2011) also study momentum profits in a rational framework. They use structural estimation of Q-theory of investment on momentum portfolios and find that the investment-based model can capture well the cross-sectional return variations of momentum portfolios. In particular, they document that the higher expected growth rate of the investment-to-capital ratio and the high expected sales-to-capital ratio are the two most important sources of momentum profits. My paper goes one step further and explores how interactions between investment commitment and investment specific-shocks can simultaneously generate a high (low) expected investment and expected return for winners (losers).

Second, this paper is related to the literature on time-to-build and the investment commitment (or investment plan). Lamont (2000) documents that in the United States, investment and stock returns have a significant negative contemporaneous covariation, contrary to the basic intuition that investment should rise as the discount rate falls. He then argues that investment-based models can capture this negative correlation, once they allow for the fact that the lags in investment prevent firms from immediately adjusting investment when the discount rate changes. More recently, Kuehn (2007) studies the effect of long-term investment commitment on asset prices in a general equilibrium model. The combination of investment commitment with Epstein-Zin preference in his model contributes to the countercyclical first and second moments of the aggregate market risk premium. My model extends the idea of investment commitment to momentum profits, and explores its distinctive implications for asset pricing, especially for stock returns in the cross section, even though the time-to-build or investment commitment feature may not be crucial for a theory of fluctuations. (See, for example, Rouwenhorst (1991).)

A large macroeconomic literature studies the impact of investment-specific shocks on economic growth and business cycles. For example, Greenwood, Hercowitz, and Krusell (1997), Greenwood, Hercowitz, and Krusell (2000), and Fisher (2006) show that investment-specific shocks can explain a large fraction of the growth and variations in output. Papanikolaou (2011) introduces investment-specific shocks into a two-sector general equilibrium model and explores the asset pricing implications of this type of shock. Kogan and Papanikolaou (2010) study the differential impact of investment-specific shocks on assets-in-place and growth options and provide a potential explanation for the value premium. Yang (2011) investigates the relationship between investment-specific shocks and the basis spread in the commodity market.

My paper also extends a fast-growing literature that studies the cross section of asset

returns in an investment-based framework. (See, for example, Berk, Green, and Naik (1999), Zhang (2005), Carlson, Fisher, and Giammarino (2004), Cooper (2006), and Bazdrech, Belo, and Lin (2009).) This strand of models usually specifies the pricing kernel exogenously and solves a firm’s problem by optimally choosing investment/labor hiring to maximize the firm’s value. This framework is proven to be effective in studying asset pricing anomalies in the cross section.

3 Empirical findings

In this section, I explore the empirical relationship between investment-specific shocks, firm-level investment, and momentum profits. Section 3.1 describes the data sources, variable definitions, and summary statistics. Further detail about variable construction is provided in the Appendix A-1. In Section 3.2, I propose an unconditional two-factor model and test it on momentum portfolios. The main finding is that winners and losers have different risk exposures to investment-specific shocks, and these differences in exposures can explain the majority of momentum profits. To understand the sources of risk exposure, I study in Section 3.3 the dynamics of momentum portfolios by looking into profitability and investment in an 11-year window around the portfolio formation year. The salient features of these dynamics motivate an investment-based story.

3.1 Benchmark sample and summary statistics

Following Greenwood, Hercowitz, and Krusell (1997), the investment-specific shock (*Ishock*) is defined as the negative change in the price deflator of investment goods relative to that of non-durable consumption goods from National Income and Product Accounts (NIPA):

$$Ishock_t = -\Delta \log \left(\frac{P_{Eqpmt,t}}{P_{NonDur,t}} \right). \quad (1)$$

By definition, a positive investment-specific shock implies technological progress in the investment sector that induces a lower price for investment goods.

Strictly speaking, two consequences for investment goods are usually associated with technological progress: lower price and better quality. The Bureau of Economic Analysis (BEA) has incorporated quality adjustment when constructing NIPA data. However, some economists contend that a significant amount of quality change goes unmeasured in the official statistics.² Nevertheless, much of the debate is about the growth rate of the tech-

²See, for example, Gordon (1990).

nological progress, instead of its fluctuations. For this reason, I adopt the above simpler definition, by which the sample can be easily extended as far back as the early 1930s.³

The 10 standard momentum portfolio returns and risk factors are from Kenneth French's Web site. These factors include the market factor (MKT), value premium factor (HML), and size factor (SMB) used in the Fama and French (1993) three-factor model, and the momentum factor (MOM) in the Carhart (1997) four-factor model. I choose the 10 standard momentum portfolios in the benchmark factor model analysis (in Section 3.2.1) because of their popularity in the literature. In the following sections, I also form portfolios and calculate firm-level characteristics using monthly firm-level stock returns from the Center for Research in Security Prices (CRSP) and annual accounting variables from COMPUSTAT.

The benchmark sample is annual from 1930 to 2009, where the starting year is constrained by the availability of price deflators from NIPA. Table 1 summarizes the aggregate variables by reporting the mean, standard deviation, maximum, median, minimum, and correlations. As can be seen in the left side of the table, the annual mean and volatility of Ishock are 0.43% and 1.55%, an indication of positive stable technological progress during the past 80 years. The average market excess return is about 7% per year, with a Sharpe ratio of around 0.35. The momentum strategy, proxied by the factor MOM, is more profitable than the value and size strategies, but it also generates higher return volatility.

[Insert Table 1 Here]

The right side of Table 1 displays the correlation matrix for these variables. In the sample period, Ishock has an almost zero correlation with market excess returns (MKT), but it is highly correlated with the momentum factor (MOM). The annual correlation coefficient between MOM and Ishock is 0.32, with a t -statistic of 2.5. This positive and significant correlation indicates that investment-specific shocks have the potential to be an underlying risk factor capturing momentum profits. In the next section, I will formally test this idea in a two-factor model.

It is worth noting that the momentum factor comoves negatively with HML and SMB. This serves as a warning flag for asset pricing tests in the following sections. In particular, it is important and necessary to control for the value premium and size effect when interpreting the relationship between investment-specific shocks and momentum profits.

³In an unreported analysis, I use the alternative measure of investment-specific shocks from Israelsen (2010) and Papanikolaou (2011), who make additional quality adjustment. This alternative measure generates very similar results as my definition in the overlapped sample period.

3.2 Investment-specific shocks and momentum profits

This section provides the main empirical tests on the relationship between investment-specific shocks and momentum profits.

3.2.1 A two-factor model

If momentum profits can be rationally captured by investment-specific shocks, portfolios sorted by recent past performance should display a monotonic trend in risk exposure. In this section, I propose an unconditional two-factor model. The first risk factor is the market excess return (MKT), as used in CAPM, and the second factor is the investment-specific shocks (Ishock). The two-factor model is tested on the 10 standard momentum portfolios in two steps. In step one, the excess returns of each portfolio are regressed on the time series of the two factors, generating factor loadings β_j^i , which measure the risk exposure of portfolio j to factor i . Factor loadings are constant since the two-factor model is assumed to be an unconditional factor model:

$$R_{jt}^e = Cte_j + \beta_j^{MKT} \times MKT_t + \beta_j^{Ishock} \times Ishock_t + \epsilon_{jt}. \quad (2)$$

In step two, the factor loadings are used as independent variables in the cross-sectional regression

$$E_T(R_{jt}^e) = \beta_j^{MKT} \times \lambda^{MKT} + \beta_j^{Ishock} \times \lambda^{Ishock} + \eta_j, \quad (3)$$

where E_T is the unconditional expectation over the sample and λ^i is the estimated price of risk i . With risk prices and factor loadings, the model-predicted average return for portfolio j is then equal to

$$R_j^{Pred} = \beta_j^{MKT} \times \lambda^{MKT} + \beta_j^{Ishock} \times \lambda^{Ishock}. \quad (4)$$

Table 2 reports the two-stage test results. Panel A provides the regression coefficients and their t -statistics for the 10 momentum portfolios and the spread portfolio with a long position in the past winner stocks and a short position the past loser stocks, from time series regressions. The market beta β^{MKT} for the loser portfolio is 1.55, compared with 1.05 for the winner portfolio (see top left panel of Figure 1). This pattern in market betas of momentum portfolios provides direct evidence for the failure of CAPM, since if CAPM holds, winners are expected to have lower average return than losers.

On the other hand, the betas for investment-specific shocks display a strong monotonic trend across these portfolios, as shown in the top right panel of Figure 1. In particular, the loser portfolio has a negative exposure to investment-specific shocks of -4.05, while the

winner portfolio has a positive and significant exposure of 1.61. The large difference in risk exposures implies the potential explanatory power of investment-specific shocks in the momentum spread, but this also depends on the risk prices from the second stage test. The last row in Panel A of Table 2 presents the ordinary least squares (OLS) R^2 of the time series regression for momentum portfolios. Individual portfolio R^2 ranges from 76.91% to 93.20%, and the two-factor model explains 24% of the time series variations of the spread portfolio.

[Insert Table 2 Here]

[Insert Figure 1 Here]

Panel B of Table 2 provides the results from the second-stage cross-sectional regression. The first two columns report the implied prices of risk for the two factors. The risk price of the market factor is about 8% per year, close to the sample average of market excess returns. For investment-specific shocks, the estimated risk price is approximately 2.67% per year (with a t -stat of 2.90). The positive sign is consistent with the procyclical (countercyclical) movement of winners (losers) with investment-specific shocks. This risk price, together with the corresponding large beta spread between the winners and losers, contributes 15% to annual momentum profits, a percentage even larger than the average return of 13.3% for the spread portfolio.

This two-factor model fits the data exceptionally well. The mean absolute error (MAE) is only less than 1%, a significant improvement upon CAPM. In addition, the χ^2 test, which tests if the pricing errors are sufficiently significant, fails to reject the model at the conventional significance level. The high OLS- R^2 from the cross-sectional regression indicates that 90% of the variations in momentum portfolio returns can be explained by this two-factor model.

To get a better sense of the improvement, I graphically compare performances of CAPM and the two-factor model in matching the average returns of the momentum portfolios. In the bottom left panel of Figure 1, I plot the CAPM-predicted portfolio returns against the average realized portfolio returns for the 10 portfolios. Not surprisingly, CAPM does a poor job: the circles are sitting on a curve that is almost perpendicular to the 45-degree line. When Ishock is added, as the bottom right panel of Figure 1 shows, all 10 circles are well in line with the 45-degree line, indicating the significant role played by investment-specific shocks in capturing momentum profits.

Lewellen, Nagel, and Shanken (2010) critique the empirical methods in cross-sectional asset pricing literature that report only a high OLS- R^2 and low pricing errors, particularly for size and boom-to-market (BM) portfolios that have a strong factor structure. They argue that for testing portfolios with a strong factor structure, the power of the test is fairly low.

Lewellen, Nagel, and Shanken (2010) then propose several prescriptions to improve the test power for such portfolios.

One prescription is to impose restrictions on factor prices. If one risk factor is a traded asset, the risk premium on the factor should be close to its average excess return. In the two-factor model of this paper, the only traded risk factor is market excess return MKT, and I already show that the implied risk price is fairly close to its sample mean. Therefore, imposing this restriction should not have a significant impact on the test results reported above.

Another useful prescription is to report GLS cross-sectional R^2 . The rationale, as emphasized in Kandel and Stambaugh (1995), is that when expected returns are regressed on betas with respect to a factor portfolio, the GLS- R^2 has the economic interpretation in terms of the relative mean-variance efficiency of the factor-mimicking portfolios. In fact, most factor models revisited in Lewellen, Nagel, and Shanken (2010) suffer from this GLS- R^2 test, even though many of them are able to successfully produce a high OLS- R^2 .

Following this prescription, I report the GLS cross-sectional R^2 in the last column of Panel B in Table 2. Even though it is not as impressive as OLS- R^2 , the GLS- R^2 is still 66.5%. This indicates that the space spanned by the two factor-mimicking portfolios are not far away from the mean-variance frontier of the 10 momentum portfolios, and therefore, it is able to price momentum profits efficiently.

3.2.2 Quarterly samples

The analysis in the previous section was done at an annual frequency. An obvious disadvantage is that there are too few observations in the sample, and one may wonder if the results still hold at a higher frequency. Fortunately, NIPA collects the price deflator data both annually and quarterly, which allows me to examine the robustness of previous findings with more observations and at a higher frequency. In this section, I repeat the above analysis for the sample 1948Q1-2009Q4.

One concern with quarterly data is its seasonality. It is therefore inappropriate to use negative changes to the relative price of investment goods from the previous quarter as a proxy for investment-specific shocks. To overcome this problem, I take the Hodrick-Prescott (HP) filter on the time series of the relative price deflator at a quarterly frequency and define investment-specific shocks as the residuals.⁴

⁴An alternative definition of quarterly investment-specific shocks is negative changes to the relative price from the same quarter in the previous year. This is essentially similar to the earning announcement in quarterly financial statements, where current earnings are compared with the same-quarter earnings from the previous year. The results are very similar with this alternative definition.

[Insert Table 3 Here]

Table 3 reports the test results. Consistent with annual sample, the beta for investment-specific shocks increases from -5.60 for the loser portfolio to 0.91 for the winner portfolio, as reported in Panel A. The risk exposures for the spread portfolio in the last column confirm that the difference in betas of investment-specific shocks between winners and losers is positive and significant.

Panel B presents the results for the cross-sectional regression. Even though prices and quantities at a quarterly frequency are known to be a lot noisier than annual data, the two-factor model is still capable of pricing momentum portfolios very well. Specifically, the annualized price of risk for the market factor is 8.34%, and for investment-specific shocks is 2.54%. Both values are very close to the estimates from the benchmark annual sample. The p -value for the χ^2 test is 0.90, suggesting that the pricing errors from the cross-sectional regression are fairly small. The proposed two factors have both high explanatory power and mean-variance efficiency, as manifested in a high OLS- R^2 of 86.44% and a GLS- R^2 of 61.52%, respectively.

In summary, the two-factor model tested on a quarterly sample strongly supports the findings from the previous section. In the next section, I show that the main results still hold after controlling for firm-level characteristics such as size and book-to-market.

3.2.3 Controlling for size and book-to-market

One feature of the momentum factor from summary statistics of Table 1 is its significant correlations with the value premium factor HML and the size factor SMB. It can be the case, for example, that investment-specific shocks correlate with momentum profits through the channel of book-to-market or market capitalization. In this section, I take this effect into account and explore the relationship between investment-specific shocks and momentum profits after controlling for size and book-to-market effects.

Following Hou and Robinson (2006), I generate the time series of after-control momentum profits in a Fama and MacBeth (1973) regression. In the first stage, the cross-sectional stock returns for all firms at year t are regressed onto their characteristics, including size, book-to-market (BM), and momentum (MOM):

$$R_{jt}^e = a_t + \lambda_t^{SIZE} \times SIZE_{jt} + \lambda_t^{BM} \times BM_{jt} + \lambda_t^{MOM} \times MOM_{jt} + \epsilon_{jt} \quad (5)$$

The after-control momentum profits at year t are then given by the coefficient λ_t^{MOM} . Similarly, λ_{BM} and λ_{SIZE} are the after-control size and book-to-market, respectively. It should be noted that λ_t^{MOM} is not the expected risk premium for the momentum strategy at time

t . Instead, it is similar to the momentum factor MOM_t and should be interpreted as realized momentum profits at t , but after controlling for firm characteristics including size and book-to-market.

Panel A of Table 4 reports the Fama and MacBeth (1973) regression for the full sample 1930-2009 and the short subsample 1963-2009.⁵ In line with existing literature, size negatively predicts stock returns, whereas book-to-market and momentum have a positive prediction for stock returns. These patterns are strongly significant in both a statistical and an economic sense and hold in both samples.

[Insert Table 4 Here]

In the second stage, I regress the risk premium λ_t^{MOM} on MKT_t and $Ishock_t$ in the two-factor model:

$$\lambda_t^{MOM} = Cte_0 + b_0^{MKT} \times MKT_t + b_0^{Ishock} \times Ishock_t + \epsilon_{0t}. \quad (6)$$

If the investment-specific shock is indeed the risk factor that drives momentum profits, b_0^{Ishock} is expected to be consistent with findings from previous sections and remains positive and significant.

The results displayed in Panel B of Table 4 confirm this. The correlation between the after-control momentum profits and MKT is negative, whereas the coefficient for investment-specific shocks b_0^{Ishock} is 0.39 (with a t -stat of 1.75) for the full sample and 0.69 (with a t -stat of 2.48) for the short sample. One possible explanation for the relatively lower significance in the full sample is that during the period before year 1963, both momentum profits and the value premium are positively correlated with $Ishock$. Controlling the book-to-market effect might weaken the comovement between momentum profits and $Ishock$ as well.

Overall, this section excludes the possibility that size and book-to-market effects are the driving force behind the relationship between investment-specific shocks and momentum profits. This reinforces the role of investment-specific shocks as the potential risk factor.

3.2.4 Industry momentum

Moskowitz and Grinblatt (1999) document a strong and prevalent momentum effect in industries. In particular, they find that once the industry momentum effect is controlled, momentum profits from individual stocks are significantly weaker and are statistically insignificant for the most part. However, other papers such as Grundy and Martin (2001)

⁵I explore the shorter sample starting from 1963 because it is conventional for many empirical studies on the stock market. In addition, the correlation between the value premium and momentum profits is much higher before 1963 than in the periods after 1963. This could affect the results, as will be discussed soon.

and Lewellen (2002) suggest that neither industry momentum nor individual stock momentum subsume one another, but they are both important. It is therefore interesting to see if investment-specific shocks can capture the industry momentum effect as well, and that is the focus of this section.

Following Moskowitz and Grinblatt (1999), I use two-digit Standard Industrial Classification (SIC) codes from CRSP to form industry portfolios in order to maximize coverage of individual stocks while maintaining a manageable number of industries and ensuring that each industry contains a large number of stocks for diversification. The stock return of an industry is then calculated as the value-weighted average of stock returns for all firms in that industry. Table 5 reports the industry definitions and stock return summary statistics. Across industries, the average annual excess return ranges from 5.81% for the utilities industry to 9.47% in the petroleum industry, consistent with the findings in existing literature that there is no significant spread in industry portfolio returns.

[Insert Table 5 Here]

The last two columns of Table 5 also report industry exposures to investment-specific shocks when industry returns are regressed onto market excess returns and investment-specific shocks. Unlike stock returns, there is a relatively large variation of exposures to investment-specific shocks across industries. The industry with the highest exposure is railroads, with a β^{Ishock} of 2.94, whereas the industry with the lowest exposure is transportation equipment, with a β^{Ishock} of -1.89.

The industries are then sorted into 10 momentum portfolios by their past performance in each month. One feature of industry momentum, as documented in Moskowitz and Grinblatt (1999), is that industry momentum is strongest in the short term (at a one-month horizon). Therefore, I define industry momentum at month t as its past cumulative returns from $t - 12$ to $t - 2$, sort industries by their momentum into 10 momentum portfolios, and hold for only one month. These monthly portfolio returns are then aggregated into an annual frequency.

[Insert Table 6 Here]

Table 6 reports the test results. Panel A provides the means and standard deviations of the 10 industry momentum portfolio returns. The large annual spread of 5.78% between the winner and loser portfolios confirms the finding of Moskowitz and Grinblatt (1999) that industry portfolios exhibit significant momentum profits. When the 10 portfolios are tested on the same two-factor model, as reported in Panels B and C, similar patterns are found as in the individual stock momentum portfolios. In particular, there is an upward pattern in betas of investment-specific shocks from loser to winner portfolios. The implied risk prices

are quantitatively close to what are found in Section 3.2.1. In addition, the model generates small mean absolute errors and explains more than 67% of the industry momentum profits.

To conclude this section, even though industry momentum and individual stock momentum may be different from each other in many aspects, they are both captured well by investment-specific shocks.

3.3 Dynamics of profitability and investment

In previous sections, I proposed a two-factor model and showed that the winner (loser) portfolio has a high (low) exposure to investment-specific shocks, and this difference in risk exposures explains a large fraction of the momentum spread. However, the mechanism through which investment-specific shocks affect momentum portfolios differently is still not clear. In particular, investment-specific shocks measure technological innovations in investment goods, including equipment and software. As such, the underlying mechanism has to be closely related to the firm’s capital expenditure. In this section, I explore the dynamics of the momentum portfolios in an 11-year window — five years before and five years after — around the portfolio formation year. I focus on the profitability and investment rate for momentum portfolios.

It is well known that momentum strategies are profitable from 3 to 12 months, so in order to accurately match with the annual frequency of COMPUSTAT accounting data, I make the following modifications to the standard momentum strategy:

1. I form portfolios based on the past one-year cumulative return and hold them for the following one year;
2. Instead of rebalancing every month, I form portfolios only once per year at the end of December. This treatment may have some quantitative effect on the momentum spread, but not qualitatively.
3. I exclude firms that do not have fiscal-year-end (FYR) in December. In this way, the fiscal years exactly match the calendar years, and one-year cumulative return from CRSP in a specific year is well aligned with accounting variables from COMPUSTAT.

To be specific, at the end of year t , I form 10 portfolios based on the past one-year stock performance and keep track of the profitability (EK) and investment-to-capital ratio (IK) of these portfolios over the 11 years around t . Then I take the average over the time series of 11 windows for the whole sample period, which gives the average dynamics of these portfolio characteristics over the 11-year window. This type of “event study” procedure is used in

Lakonishok, Shleifer, and Vishny (1994) and Fama and French (1995), followed by many others.

Accounting data are from COMPUSTAT Annual: Profitability (EK) is defined as the earnings over the lagged capital. The investment-capital ratio is the ratio of capital expenditure to the lagged capital. Stock returns are from CRSP monthly. Annual portfolio returns are calculated first by taking the value-weighted average across all firms in each portfolio every month and then aggregating over 12 months in that calendar year. The sample is from 1950 to 2009.

[Insert Figure 2 Here]

The top two panels of Figure 2 plot the dynamics of profitability (top left) and the investment-capital ratio (top right). Winner firms are persistently more profitable than loser firms, and the profitability spread gradually converges after the portfolio formation. This result looks similar to the existing explanations for the value premium that value firms (firms with high book-to-market) have higher average returns than growth firms (firms with low book-to-market). For example, Zhang (2005) explains the differences between growth firms and value firms in a dynamic equilibrium model, where value firms are risky because they had bad idiosyncratic shocks in the past and are burdened by their extra capital stock during bad times when the price of risk is high.⁶ The explanation is supported by the evidence from Fama and French (1995), who empirically demonstrate that the difference in profitability is associated with book-to-market.⁷ Here I add another source of risk, i.e., the investment-specific shocks. Firms with sudden positive profitability shocks (past winners) will have higher exposure to this risk, so their expected return is higher than past losers. I will further discuss the difference between momentum and the value premium in Section 4.3.4.

In top right panel of Figure 2, I plot the dynamics of the investment-capital ratio (IK) for winner and loser portfolios. One interesting feature is that the winner firms invest more than the loser firms in the year during which the portfolios are formed. However, the difference is *even greater* the following year. Indeed, the investment spread is more than five times larger in the following year. It is worth noting that these investment dynamics cannot be

⁶Besides Zhang (2005), several other papers have explored mechanisms of generating the value premium in theoretical models. Among others, Carlson, Fisher, and Giammarino (2004) emphasize the importance of operating leverage, Cooper (2006) studies the effect of investment irreversibility and fixed adjustment cost, and Lettau and Wachter (2007) adopt a duration-based explanation for the difference between value and growth stocks.

⁷However, Wang and Yu (2011) challenge this explanation by separating data into groups using measures of limits to arbitrage. They find that the groups with high limits to arbitrage have a more pronounced value premium, but there is no significant negative correlation between book-to-market and profitability.

generated from the standard Q-theory model of investment with convex adjustment costs. In the standard Q-theory model, investment takes one period before it becomes productive. As such, firms that had good idiosyncratic productivity shocks in the past would optimally choose to invest more in that period. With frictions like convex adjustment costs for capital expenditure, this would imply an immediate spike in the investment rate, followed by gradual decay.

This finding motivates a different type of friction in capital accumulation: investment commitment.⁸ Intuitively, firms with very positive idiosyncratic shocks (winners) initiate more investment, but investment takes more than one period to finish. Investment commitment is risky because it is in terms of total expenditure. In an economy where the price of investment goods in the following period is stochastic, firms with greater investment commitment will have a higher exposure to fluctuations in the price of investment goods, or investment-specific shocks. On the other hand, firms with very negative idiosyncratic shocks (losers) initiate more disinvestment commitment. This disinvestment commitment serves as a hedge to loser firms, since a higher price of investment goods in the future implies that fewer units of existing capital need to be resold, which to some extent relieves the pain originating from recent low profitability. Therefore, loser firms have a low exposure (or even negative exposure) to investment-specific shocks.

This proposed mechanism provides a plausible explanation for the empirical findings from the two-factor model. In the next section, I elaborate on this explanation and develop a simple investment-based equilibrium model to rationalize the empirical findings.

4 An investment-based asset pricing model

Previous sections document the empirical links for momentum profits, investment-specific shocks, and real investment. In particular, i) past winners have a higher exposure to investment-specific shocks than do past losers, and this translates to higher expected returns; ii) past winners are more profitable than past losers; and iii) winners have a higher investment rate than losers in the event year, but the investment spread between them is even greater the following year. In this section, I follow the intuition proposed from the previous sections and develop a simple investment-based asset pricing model to capture these salient features.

⁸An alternative type of friction is adjustment cost on investment growth. However, Lucca (2007) shows that to the first-order linearization, the investment growth friction models are equivalent to models with time-to-build, and they generate similar hump-shaped impulse responses.

4.1 The model

I develop a dynamic partial equilibrium model with heterogenous production units (or firms),⁹ where the pricing kernel is exogenously specified. This framework was first developed in Berk, Green, and Naik (1999) and was later adopted by many others to study asset prices in the cross section. The two key components of the model are: (1) investment-specific shocks; and (2) two-period investment commitment.

4.1.1 Production

The economy has a large number of firms, and the decision of each firm is independent of each other. Firms use physical capital to produce outputs and make a choice between dividend payout and investment expenditure to maximize the firm's value. The output Y_{it} of firm i at time t is given by production function

$$Y_{it} = X_t Z_{it} K_{it}^\alpha, \quad (7)$$

where X_t is the level of aggregate productivity, and Z_{it} is the level of firm-specific productivity. The coefficient $\alpha < 1$ features the decreasing returns to scale of the production function, capturing the fact that the investment opportunity is less for larger firms.

In each period, firms decide on the amount of output to pay out as dividends (negative dividends are considered as equity issuance), and the remaining is used as capital expenditure. Departing from standard real business cycle models, investment has a two-period structure: Firms that initiate new investment at time t can complete only a small fraction in that period; they also make a commitment to complete the remaining large fraction in the following period $t+1$.¹⁰ One may impose the restriction that the newly installed capital can be productive only after both fractions are completed, but this adds one more state variable, making the numerical solution even more computationally demanding. Therefore, I make the simplifying assumption, as Kuehn (2007) does, that the fraction of capital is productive immediately after it is installed.

Denote the small fraction of the first period by w , the newly initiated investment expenditure at time t by L_{it} , the depreciation rate of physical capital by δ , and the investment-specific

⁹One can also think of the production units as industries to address industry momentum effects. Accordingly, the idiosyncratic productivity shocks below can be considered as industry-specific shocks.

¹⁰My investment commitment structure is similar to Kuehn (2007). In his dynamic general equilibrium model, Kuehn (2007) considers an infinite horizon investment commitment, with the committed amount geometrically decaying over time. This structure greatly simplifies the solution of his model, as all previous committed investments can be captured by a single state variable. My commitment structure is slightly different in that the committed investment is only one period ahead.

technological level by Q_t . The capital accumulation follows:

$$K_{it+1} = (1 - \delta)K_{it} + I_{it}Q_t \quad (8)$$

$$I_{it} = wL_{it} + (1 - w)L_{it-1}. \quad (9)$$

There are two ways to interpret Q_t . First, as discussed above, $1/Q_t$ can be thought of as representing the cost of producing a new unit of equipment in terms of final output. Equation (8) can be read as follows. The next period capital stock is the sum of non-depreciated capital and the new investment, which equals the ratio of total capital expenditure to the price of equipment. Alternatively, Q_t can also be interpreted as the efficiency of transforming outputs to physical capital, while keeping the cost of producing one new unit of equipment constant over time. An increase in efficiency implies that one unit of output can be transformed to more units of physical capital. Throughout the rest of this paper, I will stick to the first interpretation, as it corresponds to the definition of investment-specific shocks from empirical analysis.

Equation (9) indicates that the total capital expenditure of a firm at time t has two components: one from the large fraction of investment committed in the previous period $(1-w)L_{it-1}$, and the second from the small fraction of newly initiated investment wL_{it} . This structure of capital accumulation implies that when firms make an investment commitment, they will have to take into account the stochastic feature of investment goods prices. The more capital expenditure a firm commits to, the higher exposure it has to investment-specific shocks. Put another way, the investment commitment rate is a proxy for the risk exposure to investment-specific shocks in this model.

An adjustment cost is incurred when firms initiate investment, and it takes the following quadratic form:

$$G(L_{it}, K_{it}) = \frac{c}{2} \left(\frac{L_{it}}{K_{it}} \right)^2 K_{it}, \quad (10)$$

where the adjustment cost coefficient c controls the curvature and takes different values when firms make investment and disinvestment decisions. In particular,

$$c = \begin{cases} c_+ & \text{if } L_{it} > 0 \\ c_- & \text{otherwise} \end{cases} \quad (11)$$

and $c_- > c_+ \geq 0$, capturing the effect that it is more costly to disinvest than invest. Zhang (2005) shows that this asymmetry is crucial in generating the value premium in his dynamic equilibrium model.

A firm's output Y_{it} equals the sum of its investment I_{it} , capital adjustment cost $G(L_{it}, K_{it})$,

operating costs fK_{it} , and dividend payout D_{it} :

$$Y_{it} = I_{it} + D_{it} + G(L_{it}, K_{it}) + fK_{it}, \quad (12)$$

where the operating cost is assumed to be proportional to firm-level capital, and f controls for the operating leverage.

4.1.2 Equilibrium

Given the pricing kernel $\{m_t\}$ and shock processes for $\{X_t\}$, $\{Q_t\}$, $\{Z_{it}\}$, which I will specify in the next subsection, the firm's problem can be described in the following recursive form:

$$\begin{aligned} V(K_{it}, L_{it-1}, X_t, Q_t, Z_{it}) &= \max_{L_{it}} D_{it} + E_t[M_{t+1}V(K_{it+1}, L_t, X_{t+1}, Q_{t+1}, Z_{it+1})] \\ &\text{s.t. (7) - (12)} \\ &\text{Given } \{m_t\}, \{X_t\}, \{Q_t\}, \{Z_{it}\}. \end{aligned} \quad (13)$$

Intuitively, a firm's cum-dividend market value is the sum of the dividend (the first term in the right hand side) and the present value of the firm's continuation value (the second term in the right-hand side), when the firm optimally chooses an investment commitment to maximize the firm's value. The optimal investment commitment is determined by the first-order condition in the right-hand side of (13) and depends on the economy-wide and firm-specific states. When a firm experiences a high level of productivity, it may choose to make a greater investment commitment, since the benefit from continuation value dominates the cost from the dividend payout, especially when the productivity process is persistent. On the other hand, when a firm has excess capital and experiences a low level of productivity, it may choose to initiate less investment or even greater disinvestment.

When numerically solving this model, it is more convenient to scale the second state variable L_{it-1} by firm-level capital. As such, the firm's problem can be translated to

$$\begin{aligned} V(K_{it}, LK_{it-1}, X_t, Q_t, Z_{it}) &= \max_{LK_{it}} D_{it} + E_t[M_{t+1}V(K_{it+1}, LK_{it}, X_{t+1}, Q_{t+1}, Z_{it+1})] \\ &\text{s.t. (7) - (12)} \\ LK_{it} &= \frac{L_{it}}{K_{it+1}} \\ &\text{Given } \{m_t\}, \{X_t\}, \{Q_t\}, \{Z_{it}\}, \end{aligned} \quad (14)$$

and the gross return for firm i is calculated as

$$R_{it+1}^U = V_{it+1}/(V_{it} - D_{it}). \quad (15)$$

Up to this point, firms are assumed to be all equity financed, and the stock return in (15) is interpreted as an unleveled return. In practice, most firms have a certain amount of outstanding debt, which affects both the mean and standard deviation of stock returns. To address this issue, I follow Boldrin, Christiano, and Fisher (2001), Kuehn (2007), and Croce (2010) and assume the same constant leverage ratio Φ for all firms. Therefore, the levered excess return for stock i is

$$R_{it+1} - R_f = (R_{it+1}^U - R_f)(1 + \Phi), \quad (16)$$

where R_f is the gross risk-free rate.

4.1.3 Exogenous shocks and pricing kernel

The three exogenous state variables in the model — aggregate productivity X_t , idiosyncratic productivity Z_{it} , and investment-specific technological level Q_t — are assumed to follow AR(1) processes, which represent a detrended economy:

$$\log(X_{t+1}) = \rho_x \log(X_t) + (1 - \rho_x) \log(\bar{X}) + \epsilon_{t+1}^x, \quad \epsilon_{t+1}^x \sim N(0, \sigma^x) \quad (17)$$

$$\log(Q_{t+1}) = \rho_q \log(Q_t) + (1 - \rho_q) \log(\bar{Q}) + \epsilon_{t+1}^q, \quad \epsilon_{t+1}^q \sim N(0, \sigma^q) \quad (18)$$

$$\log(Z_{it+1}) = \rho_z \log(Z_{it}) + \epsilon_{t+1}^z, \quad \epsilon_{t+1}^z \sim N(0, \sigma^z). \quad (19)$$

The bars above X and Q stand for their means, ρ_x , ρ_q , and ρ_z measure the persistence, and the innovations ϵ_{t+1}^x , ϵ_{t+1}^q , ϵ_{t+1}^z are assumed to be normally distributed and independent from each other.

The pricing kernel is specified as a function of the aggregate productivity shock and the investment-specific shock:

$$M_{t+1} = \exp(-r_f) \times \frac{\exp\{-\gamma_x \epsilon_{t+1}^x - \gamma_q \epsilon_{t+1}^q\}}{E_t[\exp\{-\gamma_x \epsilon_{t+1}^x - \gamma_q \epsilon_{t+1}^q\}]}, \quad (20)$$

where $\gamma_x > 0$, $\gamma_q > 0$ measures the constant risk prices. E_t denotes the time- t conditional expectation. This specification of the pricing kernel, following Yang (2011), guarantees the interpretation of r_f as the risk-free rate. To see this, one can simply take the conditional expectation on both sides of equation (20) and get

$$E_t(M_{t+1}) = \exp(-r_f). \quad (21)$$

In words, the market price of a one-period risk-free bond (the right-hand side) equals the

sum of one-period state prices across all states (the left-hand side).

4.2 Calibration

To align with the investment commitment feature in the empirical data, I calibrate the model at an annual frequency. Therefore, it takes two years to complete an initiated investment, which is consistent with the empirical findings by Koeva (2001), who documents that the average length of time-to-build is approximately two years in most industries.

The key parameter values in the model are summarized in Table 7. I break down all the parameters into two groups. The first group includes parameters that can be restricted by empirical or quantitative studies, whereas the second group has limited guidance from previous literature or requires special discussion. The key moments from simulation of the model are reported in Table 8.

[Insert Table 7 Here]

[Insert Table 8 Here]

The top panel of Table 7 reports the parameters in the first group. The elasticity of output with respect to capital α in the production function equals 0.5, well between 0.30 used in Zhang (2005) and 0.75 from Lin (2011). The annual depreciation rate is set to 0.13, close to the empirical estimate of 0.12 by Cooper and Haltiwanger (2006). The adjustment cost coefficient θ_+ is set to 1.0, close to the midpoint of the range between 0.5 and 2 reported by Whited (1992). θ_- is set to 20, capturing the effect that it is very costly to disinvest. These two adjustment cost parameters combined generate an average ratio of adjustment cost to output of around 2.8% per year, well within the range between 1% and 20% estimated from Hamermesh and Pfann (1996). They also imply an average disinvestment rate of 2% reported by Abel and Eberly (2002). The operating cost coefficient f is set to 0.19, generating an average fixed cost-output ratio of 0.17, very close to 0.18 from Eberly, Rebelo, and Vincent (2009).

The persistence of aggregate productivity process ρ_x is set to 0.92, following King and Rebelo (1999). The persistence of investment-specific shocks equals 0.6, roughly the same magnitude as the empirical estimate of 0.62. The conditional volatility of investment-specific shocks relative to aggregate productivity shocks is set to 1.0 from the real data. The average level of aggregate productivity, \bar{X} , is a scaling variable. It is set to 0.32 to make the average long-run capital stock at 1/4. The average level of investment-specific technological state \bar{Q} set to 0.84, matching an average investment rate of 15% reported by Abel and Eberly (2002). To calibrate the persistence ρ_z and the conditional volatility σ_z of idiosyncratic productivity

shocks, I impose restrictions on the volatilities of firm-level stock returns and the investment rate. As such, I set $\rho_z = 0.85$ and $\sigma_z = 0.50$. This implies an average firm-level stock return volatility of 30.1% per year, well within the range of 25% reported by Campbell, Lettau, Malkiel, and Xu (2001) and 32% from Vuolteenaho (2002). The implied investment rate volatility is around 0.21, close to 0.22 estimated from real data. The real risk-free rate is constant and equals the historical average of 1.8% per year. Following Boldrin, Christiano, and Fisher (2001), I set the leverage ratio parameter Φ to 1.667.

The second group of parameters has only limited guidance from prior studies or requires special discussion. The fraction of investment expenditure in the first period w is set to 0.2, consistent with the finding of Lamont (2000) that more than three-quarters of the annual variations in aggregate investment growth are explained by investment plans.

The risk price γ_x and volatility σ^x of aggregate productivity shocks are used to match the market excess return and Sharpe ratio. Therefore, I set $\gamma_x = 2.5$ and $\sigma^x = 0.2$, which generates an average excess return of 6.79% and Sharpe ratio of 0.47, very close to 6.69% and 0.43 from Campbell and Cochrane (1999). The annual volatility of aggregate productivity shocks is 20% and is significantly higher than the empirical estimate of about 1.4% per year from the data. The reason is that in standard investment-based asset pricing models, exogenous shocks tend to be well absorbed by quantities such as investment or labor hiring, leaving asset prices that are too smooth. The purpose of this paper is to try to understand momentum returns in the cross section, given the properties in the time series. Therefore, I choose this parameter to match a reasonably large equity premium. Finally, the risk price γ^q for investment-specific shocks is set to 20.

It is interesting to note that even though this paper is aimed at capturing the individual stock momentum in the cross section, it does not generate an aggregate market momentum, as the autocorrelation in the time series of the market excess return is 7%, slightly higher than the 5% reported by Campbell and Cochrane (1999).

4.3 Model results

The model has no analytical solution, so I resort to value function iterations to solve it numerically. The details of the numerical solution can be found in Appendix A-2.

4.3.1 Value function and investment policy function

The value function for the case $X = \bar{X}$, $Q = \bar{Q}$, and $Z = 1$ is plotted in the top graph of Figure 3 against capital (K_t) and the committed investment rate (LK_{t-1}). The firm's value is increasing in capital when the committed investment rate is low, consistent with

the implication from standard investment-based models. However, when the committed investment rate is high, the relationship between capital and value becomes non-monotonic. In particular, at a smaller capital region, the firm’s value increases with capital, since capital is below steady state and extra committed investment is valuable for the firm. When capital is large enough, the firm’s value actually drops with additional units of capital. This is intuitive because when the committed investment rate is high, it is extremely costly to reduce the redundant capital due to the asymmetric specification of the capital adjustment cost. Along the direction of the committed investment rate, the value function decreases with committed investment, again, because of the high cost of disinvestment.

[Insert Figure 3 Here]

The bottom panel of Figure 3 plots the policy function for the newly committed investment rate. A higher stock of capital is associated with a lower initiated investment rate, and the optimal committed investment decreases the committed investment rate.

4.3.2 Momentum portfolio returns and dynamics

In this section, I explore the benchmark model implications for momentum profits and the dynamics of profitability and the investment rate for momentum portfolios. I simulate the model 100 times, with each sample 80 years and 2,000 firms. The empirical procedure is implemented on each simulated sample, and cross simulation results are reported. As a comparison, I report in the top panel of Table 9 the momentum portfolio returns and asset pricing test results from the same procedure as in the data.

[Insert Table 9 Here]

In each year, 10 momentum portfolios are formed by sorting past one-year stock return performance. The first two rows of Table 9 report the means and standard deviations of portfolio excess returns from the data and the model. In line with the data, the investment-based model generates a large momentum profit: The average excess return for the simulated loser portfolio is 3.91% (with a standard deviation of 11.14%), compared with the winner portfolio of 9.91% (with a standard deviation of 17.19%). The average momentum profit of 5.99% per annum is slightly lower than 7.56% in the data.

The middle five rows of Table 9 report the time series regression coefficients from CAPM. Departing from the empirical findings, CAPM works much better in simulated data: The market beta increases from the loser portfolio to the winner portfolio, which captures a large fraction of momentum profits (see also top panel of Figure 4). The abnormal return for the

spread portfolio W-L is only 1.91% per year from the simulated data, in contrast to 9.84% in the empirical data. However, the $\alpha(CAPM)$ is still more than three standard deviations from zero.¹¹ This counterfactual success of CAPM in the model indicates that a large fraction of investment-specific shocks is captured by market excess return, so that they are not as orthogonal to each other as in the real data.

[Insert Figure 4 Here]

When the investment-specific shocks are included in the asset pricing test, there is a substantial improvement in the model fit (see the bottom panel of Figure 4). The bottom seven rows of Table 9 show that the risk exposure of momentum portfolios to investment-specific shocks using simulated data increases from -1.90 for the loser portfolio to 2.55 for the winner portfolio, a pattern that is very consistent with the empirical counterpart.

To compare the dynamics of profitability and the investment rate for momentum portfolios with the data, I repeat the same procedure as in Section 3.3. The bottom left panel of Figure 2 presents profitability dynamics in an 11-year window. As in the data, the winner portfolio's profitability is higher in the event year than the loser portfolio, and their difference gradually decays in the following years.

The bottom right panel of Figure 2 plots the dynamics of the investment rate for winner and loser portfolios. With high-level idiosyncratic productivity, winner firms initiate more investment. However, the investment initiation cannot immediately translate into productive capital, due to the two-period investment commitment structure. When winners initiate high investment, they also make a greater commitment to invest in the following period, generating a hump-shaped investment profile that is consistent with the data.

In summary, this simple investment-based model can generate a reasonably large momentum profit and realistic investment dynamics. This profit can be well explained by the exposures to investment-specific shocks in a two-factor model, consistent with empirical data. In the following sections, I inspect the mechanism in generating the momentum profits in more detail. In particular, I explore the contributions of the investment commitment and investment-specific shocks to momentum profits separately.

4.3.3 Inspecting mechanism

The risk premium in rational models can be expressed as the product of quantities of risks (i.e., betas) and risk prices. As discussed previously, the committed investment rate LK_{it-1}

¹¹It is worth noting that CAPM could fail substantially in a separate (unreported) calibration, where I decrease the volatility of aggregate productivity shocks relative to the investment-specific shocks. The cost with that calibration is that the simulated value premium is significantly negative. I will explore the value premium and its mechanism in Section 4.3.4.

serves as a natural proxy for the risk exposure to investment-specific shocks, since firms with a higher committed investment rate will be more exposed to the variation in the relative prices of investment goods. This is clear from capital accumulation equation (9). To check on this point, I use the same simulated data from the benchmark calibration and form 10 portfolios based on LK_{it-1} . If the above argument is true, we should expect to see that these investment commitment portfolios are closely related to the momentum portfolios.

Panel A of Table 10 reports the descriptive statistics of these LK portfolios. Consistent with the previous hypothesis, firms with a higher committed investment rate have higher average stock returns. The return spread between high and low investment commitment portfolios is about 6.32% per year, even higher than the 5.99% of momentum spread from Table 9. Intuitively, the committed investment rate LK is a better proxy for exposure to investment-specific shocks than past performance. As such, portfolios sorted by LK will generate a larger return spread than momentum portfolios. This confirms the key role of investment commitment in capturing the risk exposure to investment-specific shocks. Unfortunately, it would be difficult to test this empirically, because well-documented data on disaggregate investment commitment are rare.

[Insert Table 10 Here]

Another question is: How important are investment-specific shocks in the model? The two-factor model test on simulated data implies that market beta contribute to the momentum profits. Is it possible to generate a similar momentum spread while keeping only the aggregate and idiosyncratic productivity shocks? The answer is no. To see this, I shut down investment-specific shocks and keep the rest of the benchmark model unchanged. I recalibrate the risk price and volatility of aggregate productivity shocks to match the first and second moments of aggregate market returns, and I form 10 new momentum portfolios based on the one-year performance from the simulated data. The mean and standard deviation of the momentum portfolio returns are reported in Panel B of Table 10. Without investment-specific shocks, the momentum spread is only 2.88%, less than half of the spread from the benchmark model. However, it is very interesting that momentum profits remain positive in the absence of investment-specific shocks. The reason is the following. The capital accumulation equation (8) explicitly describes the exposure of investment commitment on investment-specific shocks, but indirectly, investment commitment is also related to aggregate productivity shocks. With time-varying levels of aggregate productivity, the value of installed capital is changing over time, as is the value of the committed capital that is yet to be installed. The more commitment to invest, the higher the risk exposure to aggregate productivity shocks. This explains why we could still observe momentum profits from the

calibration without investment-specific shocks.

4.3.4 Value premium

The investment-based framework was initially introduced by Berk, Green, and Naik (1999), Zhang (2005), Carlson, Fisher, and Giammarino (2004) among others to explain the value premium. In Zhang (2005), value firms are those with low idiosyncratic productivity shocks, like loser firms in momentum portfolios. In contrast, growth firms are those with high idiosyncratic productivity shocks, similar to winner firms. Not surprisingly, while his model can successfully generate a positive value premium, it also implies a counterfactual negative momentum profit.

Similarly, one might ask: what are the implications of this model for the value premium? To address this question, the first two rows of Table 11 report the stock returns for 10 book-to-market portfolios using empirical and simulated data. The return spread between firms with high book-to-market and firms with low book-to-market is about 0.35% per year from simulated data, even though it is smaller than the empirical counterpart of 5.59%. This is impressive, given the negative signs of the value premium and momentum profits from the Zhang (2005) model. In addition, ignoring the extremely high book-to-market portfolio, the spread between portfolio 9 and Lo is as high as 2.89% per year.

[Insert Table 11 Here]

To understand these results, it is worth emphasizing two important differences between my model and the model of Zhang (2005). First, Zhang (2005) has only one type of aggregate shock — aggregate productivity shocks — so CAPM holds conditionally in his model. In contrast, my model has two types of aggregate shocks — aggregate productivity shocks and investment-specific shocks — therefore, my model implies a two-factor model.¹²

Second, in terms of mechanisms, Zhang (2005) emphasizes the role of the time-varying price of risk, asymmetric adjustment cost, and operating leverage in generating the value premium. The intuition, as discussed before, is that value firms are burdened with excess capital, since they are unable to disinvest without incurring a large adjustment cost, and hence they are very sensitive to aggregate productivity shocks. In my model, winners and losers have different exposures to investment-specific shocks, capturing the momentum profits. In addition, the channel of asymmetric adjustment cost and operating leverage from Zhang (2005) also plays an important role, generating a positive value premium. Therefore,

¹²More precisely, my model implies a conditional two-factor model. However, in both the empirical and simulated data, the unconditional two-factor model is already a very good approximation of the conditional two-factor model.

even though winners (losers) look similar to growth (value) firms in terms of past productivity shocks, the two opposing channels help to create both positive momentum profits and a positive value premium.

One implication of the second channel is that value and growth firms are exposed to aggregate productivity shocks (or TFP shocks in the data) differently. The bottom five rows of Table 11 report the results of a one-factor model where 10 book-to-market portfolio returns are regressed onto aggregate productivity shocks. Both the data and the model imply an upward trend in β_{TFP} from growth firms to value firms, consistent with Gourio (2007), who tries to capture the value premium in a two-factor framework where the aggregate productivity shock is one of the factors.

5 Conclusion

Motivated by the strong comovement between momentum profits and investment-specific shocks, and the dynamics of profitability and investment for momentum portfolios, I propose a rational explanation for momentum profits that is consistent with firm investment dynamics. Intuitively, past winners had high idiosyncratic profitability in the recent past; they initiate more investment, make greater investment commitments, and have a higher exposure to investment-specific shocks. In contrast, past losers had low idiosyncratic profitability; they make fewer investment commitments (or more disinvestment commitments), and therefore have a lower or even negative exposure to investment-specific shocks. The investment-specific shock is a priced risk factor; this translates to higher expected returns for past winners and lower expected returns for past losers. I then develop a simple investment-based asset pricing model to elaborate this explanation. Calibrated to match the first and second moments of aggregate market returns and firm-level investment, this model generates a large momentum profit and realistic investment dynamics.

It should be emphasized that I do not intend to rule out existing behavioral explanations. Instead, the purpose of this paper is to propose a potential rational explanation for momentum profits that is consistent with salient features of the data. It can be the case that the observed comovement between investment-specific shocks and momentum profits is due to some unobservable behavioral force from investors' psychology. In particular, the measure of investment-specific shocks is a relative price, which is susceptible to psychological influence.

On the other hand, the findings also raise the bar for behavioral explanations of momentum. Many behavioral stories focus on firms' underreaction or overreaction to firm-level information, ignoring the interaction between momentum profits and the macroeconomy.

The empirical findings in this paper indicate that behavioral explanations should generate not only an unconditional momentum spread, but also its correlation with macroeconomic variables, such as investment-specific technological innovations. For example, it would be interesting to understand why a positive investment-specific shock is associated with a higher degree of overreaction or overreaction of investors to firm-level information. It is beyond the scope of this paper to carefully distinguish the roles of rational and behavioral forces in generating momentum profits, but this is a very interesting topic that is left for future research.

Another direction of future research is to connect with existing literature on conditional momentum profits. Jegadeesh and Titman (1993) find that there is greater momentum for smaller firms. Hong, Lim, and Stein (2000) document that even after controlling for size, firms that are followed by fewer stock analysts exhibit greater momentum. Daniel and Titman (1999) find that momentum profits are significantly larger when the strategy is implemented with growth stocks rather than value stocks. More recently, Avramov, Chordia, Jostova, and Philipov (2007) and Cooper, Gutierrez, and Hameed (2004) document that momentum profits are related to credit ratings and market states, respectively. It would be interesting to see how these conditional momentum phenomena are linked to investment-specific technological progress. From a theoretical perspective, a model with endogenous technological innovations, explicit debt issuance decisions, and bankruptcy options may be promising in capturing many of these aspects.

APPENDIX

A-1 Variable definitions

A-1.1 Investment-specific shocks

The data used to construct time series of investment-specific shocks are from the National Income and Product Accounts (NIPA) at the Bureau of Economic Analysis (BEA). Following Greenwood, Hercowitz, and Krusell (1997), the relative price of investment goods to nondurable consumption goods is defined as the ratio between the price deflator for nondurable goods of personal consumption expenditures (row 5 of NIPA table 1.1.9) and the price deflator for equipment and software of gross private domestic investment (row 11 of NIPA table 1.1.9). For the benchmark annual sample, the investment-specific shock is the negative percentage change of this relative price from the previous year in an annual sample. For the quarterly sample, I take the HP filter to detrend the time series of the price of investment goods relative to nondurable consumption goods and define investment-specific shocks as the negative residual.

A-1.2 Standard risk factors, momentum portfolios and book-to-market portfolios

The data for the three Fama-French factors, the momentum factor, and the standard momentum and book-to-market portfolios are from Kenneth French's Web site.

The three factors are: (i) the market excess return on a value-weighted portfolio of NYSE, Amex, and Nasdaq stocks minus the T-bill rate; (ii) SMB, which is the return on the small-minus-big portfolio; and (iii) HML, which is the return on the high-minus-low portfolio. The SMB and HML portfolios are based on the six Fama-French benchmark portfolios sorted by size (breakpoint at the median) and book-to-market equity (breakpoints at the 30th and 70th percentiles). The SMB return is the difference in average returns between three small and three big stock portfolios. The HML return is the difference in average returns between two high and two low book-to-market portfolios. The momentum factor is formed using six value-weighted portfolios based on size and prior (2-12) returns. These portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. The momentum factor is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. The

10 momentum portfolios are constructed monthly using NYSE prior (2-12) return decile breakpoints. Value-weighted average returns of momentum portfolios are used throughout the paper.

The 10 momentum portfolios are constructed monthly using NYSE prior (2-12) return decile breakpoints. The portfolios constructed each month include NYSE, Amex, and NASDAQ stocks with prior return data. To be included in a portfolio for month t (formed at the end of month $t - 1$), a stock must have a price for the end of month $t - 13$ and a good return for $t - 2$. In addition, any missing returns from $t - 12$ to $t - 3$ must be -99.0, CRSP's code for a missing price. Each included stock also must have ME for the end of $t - 1$.

The 10 book-to-market portfolios are formed on BE/ME at the end of each June using NYSE breakpoints. The BE used in June of year t is the book equity for the last fiscal year end in $t - 1$. ME is price times shares outstanding at the end of December of $t - 1$. All NYSE, Amex, and NASDAQ stocks with available ME for December of $t - 1$ and June of t , and BE for $t - 1$ are included.

A-2 Numerical solution

The investment-based asset pricing model is solved via the value function iteration. The state space is discretized on 5-dimensional grids. In particular, the AR(1) processes for aggregate productivity $\log(X)$, investment-specific technology $\log(Q)$, and idiosyncratic productivity $\log(Z)$ are each modeled as a Markov chain. The discretization approach follows Rouwenhorst (1995), and I use 5 grid points for $\log(X)$ and $\log(Q)$ processes, and 3 grids for $\log(Z)$ process. Since the curvature of the value function is higher when capital stock is low, I choose the capital grid points following a geometric series, so that more grid points are concentrated in the small capital region. For the grid of the committed investment rate, I use the equal space. I specify 21 grid points for capital stocks and 11 grid points for the committed investment rate.

With the grids set up, I iterate the value functions by searching the optimal policy committed investment rate continuously. In calculating the next period firm value against capital and the committed investment rate, I extensively use quadratic polynomial interpolations. All results are robust to finer grids for the state space.

References

- Abel, Andrew, and Janice Eberly, 2002, Investment and q with fixed costs: An empirical analysis, working paper, Northwestern University.
- Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2007, Momentum and credit rating, *Journal of Finance* 62, 2503–2520.
- Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad, 2005, Consumption, dividends, and the cross section of equity returns, *Journal of Finance* 60, 1639–1672.
- Bazdrech, Santiago, Frederico Belo, and Xiaoji Lin, 2009, Labor hiring, investment and stock return predictability in the cross section, working paper, Carlson School of Management, University of Minnesota.
- Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553–1607.
- Boldrin, Michele, Lawrence J. Christiano, and Jonas D. M. Fisher, 2001, Habit persistence, asset returns, and the business cycle, *American Economic Review* 91, 149–166.
- Campbell, John Y., and John Cochrane, 1999, Force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107, 205–251.
- Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1–43.
- Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.
- Cooper, Ilan, 2006, Asset pricing implications of nonconvex adjustment costs and irreversibility of investment, *Journal of Finance* 61, 139–170.
- Cooper, Michael J., Roberto C. Gutierrez, and Allaudeen Hameed, 2004, Market states and momentum, *Journal of Finance* 59, 1345–1365.

- Cooper, Russell W., and John C. Haltiwanger, 2006, On the nature of capital adjustment costs, *Review of Economic Studies* 73, 611–633.
- Croce, Mariano Massimiliano, 2010, Long-run productivity risk: A new hope for production-based asset pricing?, working paper, University of North Carolina, Chapel Hill.
- Daniel, Kent, and Sheridan Titman, 1999, Market efficiency in an irrational world, *Financial Analysts Journal* 55, 28–40.
- Davis, James, Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929-1997, *Journal of Finance* 55, 389–406.
- Eberly, Janice, Sergio Rebelo, and Nicolas Vincent, 2009, Investment and value: A neoclassical benchmark, working paper, Northwestern University.
- Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.
- , 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–55.
- Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–36.
- Fisher, Jonas D. M., 2006, The dynamic effects of neutral and investment-specific technology shocks, *Journal of Political Economy* 114, 413–451.
- Gordon, Robert J., 1990, *The Measurement of Durable Goods Prices*. NBER Books (National Bureau of Economic Research, Inc).
- Gourio, Francois, 2007, Labor leverage, firms’ heterogeneous sensitivities to the business cycle, and the cross-section of expected returns, working paper, Boston University.
- Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, 1997, Long-run implications of investment-specific technological change, *American Economic Review* 87, 342–62.
- , 2000, The role of investment-specific technological change in the business cycle, *European Economic Review* 44, 91–115.
- Grundy, Bruce D, and J Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *Review of Financial Studies* 14, 29–78.

- Hamermesh, Daniel S., and Gerard A. Pfann, 1996, Adjustment costs in factor demand, *Journal of Economic Literature* 34, 1264–1292.
- Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.
- Hou, Kewei, and David T. Robinson, 2006, Industry concentration and average stock returns, *Journal of Finance* 61, 1927–1956.
- Israelsen, Ryan, 2010, Investment based valuation and managerial expectations, working paper, Indiana University, Bloomington.
- Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.
- , 2005, Momentum, in Richard Thaler, ed.: *Advances in Behavioral Finance II* (Princeton Press, NJ).
- Johnson, Timothy C., 2002, Rational momentum effects, *Journal of Finance* 57, 585–608.
- Kandel, Shmuel, and Robert F. Stambaugh, 1995, Portfolio inefficiency and the cross-section of expected returns, *Journal of Finance* 50, 157–84.
- King, Robert G., and Sergio T. Rebelo, 1999, Resuscitating real business cycles, in J. B. Taylor, and M. Woodford, ed.: *Handbook of Macroeconomics*, vol. 1 of *Handbook of Macroeconomics*. chap. 14, pp. 927–1007 (Elsevier).
- Koeva, Petya, 2001, The facts about time-to-build, working paper, International Monetary Fund.
- Kogan, Leonid, and Dimitris Papanikolaou, 2010, Growth opportunities, technology shocks and asset prices, working paper, Kellogg School of Management, Northwestern University.
- Kuehn, Lars-Alexander, 2007, Asset pricing with real investment commitment, working paper, Sauder School of Business, University of British Columbia.
- Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, 1541–78.
- Lamont, Owen A., 2000, Investment plans and stock returns, *Journal of Finance* 55, 2719–2745.

- Lettau, Martin, and Jessica A. Wachter, 2007, Why is long-horizon equity less risky? a duration-based explanation of the value premium, *Journal of Finance* 62, 55–92.
- Lewellen, Jonathan, 2002, Momentum and autocorrelation in stock returns, *Review of Financial Studies* 15, 533–564.
- , Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.
- Lin, Xiaoji, 2011, Endogenous technological progress and the cross section of stock returns, *Journal of Financial Economics*, forthcoming.
- Liu, Laura Xiaolei, and Lu Zhang, 2008, Momentum profits, factor pricing, and macroeconomic risk, *Review of Financial Studies* 21, 2417–2448.
- , 2011, A model of momentum, working paper, Fisher College of Business, The Ohio State University.
- Lucca, David O., 2007, Resuscitating time-to-build, working paper, Board of Governors of the Federal Reserve System.
- Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.
- Papanikolaou, Dimitris, 2011, Investment shocks and asset prices, *Journal of Political Economy* 119, 639 – 685.
- Rouwenhorst, Geert K., 1991, Time to build and aggregate fluctuations: A reconsideration, *Journal of Monetary Economics* 27, 241–254.
- , 1995, Asset pricing implications of equilibrium business cycle models, in Ed T.F. Cooley, ed.: *In Frontiers of business cycle research* (Princeton Press, NJ).
- Sagi, Jacob S., and Mark S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, *Journal of Financial Economics* 84, 389–434.
- Shanken, Jay, 1992, On the estimation of beta-pricing models, *Review of Financial Studies* 5, 1–33.
- Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns?, *Journal of Finance* 57, 233–264.

- Wang, Huijun, and Jianfeng Yu, 2011, An empirical assessment of models of the value premium, working paper, University of Minnesota.
- Whited, Toni M., 1992, Debt, liquidity constraints, and corporate investment: Evidence from panel data, *Journal of Finance* 47, 1425–60.
- Yang, Fan, 2011, Investment shocks, capacity constraints, and the commodity basis spread, working paper Carlson School of Management, University of Minnesota.
- Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

Table 1: Summary statistics

This table reports the summary statistics for the benchmark annual sample. The left part of the table presents the mean, standard deviation, maximum, median, and minimum of investment-specific shocks (Ishock) and standard risk factors. The investment-specific shock is defined as the negative change in the price deflator of investment goods relative to that of non-durable consumption goods. MKT is the market return in excess of the risk-free rate, MOM is the momentum factor, HML is the high-minus-low book-to-market factor, and SMB is the small-minus-big size factor. The right part of the table calculates the contemporaneous correlation coefficients of these variables. The symbols ***, **, * stand for statistical significance at 1%, 5%, and 10%, respectively. The sample is annual from 1930 to 2009.

(%)	Mean	Std	Max	Median	Min	Correlation coefficients				
						Ishock	MKT	MOM	HML	SMB
Ishock	0.43	1.55	4.65	0.64	-4.47	1.00				
MKT	7.08	20.03	57.77	10.19	-49.21	0.01	1.00			
MOM	7.83	16.04	37.81	9.94	-64.58	0.32**	-0.28***	1.00		
HML	4.89	12.81	35.85	4.78	-29.40	0.14	0.15	-0.30*	1.00	
SMB	3.49	12.23	42.09	3.26	-28.07	0.01	0.38***	-0.21**	0.10	1.00

Table 2: Two-factor model on standard momentum portfolios: Benchmark annual sample

This table reports the test results of a two-factor model on the standard 10 momentum portfolios from Kenneth French's Web site. The first factor is market excess returns (MKT), and the second factor is investment-specific shocks (Ishock). In the first-stage time series regressions, the 10 portfolio excess returns are regressed on the two factors, generating factor loadings (or betas), as reported in Panel A. The second stage regresses the average portfolio returns on the factor loadings estimated from the first stage, generating prices of risks, as reported in Panel B. Panel B also reports the mean absolute error (MAE), p -value for the χ^2 test, OLS- R^2 , and GLS- R^2 from the cross-sectional regression. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation. To address the problem that the risk exposures are estimated from the first stage, I adjust the standard errors from the second-stage regression as proposed in Shanken (1992). The sample is annual from 1930 to 2009.

Panel A: Time series regression: $R_{jt}^e = Cte_j + \beta_j^{MKT} \times MKT_t + \beta_j^{Ishock} \times Ishock_t + \epsilon_{jt}$

	2	3	4	5	6	7	8	9	Winner	W-L
Cte_j	-8.36 (-3.66)	-2.16 (-1.57)	-0.87 (-0.81)	0.22 (0.27)	0.41 (0.82)	1.14 (1.22)	2.50 (4.39)	2.66 (2.74)	6.00 (4.18)	14.35 (5.34)
β_j^{MKT}	1.55 (15.45)	1.12 (14.94)	1.06 (12.21)	0.94 (16.83)	1.01 (24.07)	0.94 (19.25)	0.94 (25.78)	1.01 (21.82)	1.05 (12.18)	-0.49 (-3.23)
β_j^{Ishock}	-4.05 (-1.93)	-1.24 (-1.89)	-0.05 (-0.11)	-1.16 (-2.26)	-0.48 (-1.53)	0.19 (0.27)	0.95 (2.70)	1.08 (2.01)	1.61 (2.31)	5.66 (2.41)
$R^2(\%)$	76.91	86.14	84.27	87.16	93.20	90.86	90.70	88.97	79.18	23.84

Panel B: Cross-sectional regression: $E_T(R_{jt}^e) = \beta_j^{MKT} \times \lambda^{MKT} + \beta_j^{Ishock} \times \lambda^{Ishock} + \eta_j$

	λ^{MKT}	λ^{Ishock}	MAE (%)	p -(χ^2 test)	OLS- $R^2(\%)$	GLS- $R^2(\%)$
Est.	8.04 (3.47)	2.67 (2.90)	0.92	0.71	89.70	66.53

Table 3: Two-factor model on standard momentum portfolios: Quarterly samples

This table reports the test results of a two-factor model on the standard 10 momentum portfolios from Kenneth French's Web site. The first factor is market excess returns (MKT), and the second factor is investment-specific shocks (Ishock). The quarterly investment-specific shocks are defined as the residuals of the time series of the quarterly relative price deflator after taking the HP filter. In the first-stage time series regressions, the 10 portfolio excess returns are regressed on the two factors, generating factor loadings (or betas), as reported in Panel A. The second stage regresses the average portfolio returns on the factor loadings estimated from the first stage, generating prices of risks, as reported in Panel B. Panel B also reports the mean absolute error (MAE), p -value for the χ^2 test, OLS- R^2 , and GLS- R^2 from the cross-sectional regression. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation. To address the problem that the risk exposures are estimated from the first stage, I adjust the standard errors from the second-stage regression as proposed in Shanken (1992). The sample is quarterly from 1948Q1 to 2009Q4.

Panel A: Time series regression: $R_{jt}^e = Cte_j + \beta_j^{MKT} \times MKT_t + \beta_j^{Ishock} \times Ishock_t + \epsilon_{jt}$

	Loser	2	3	4	5	6	7	8	9	Winner	W-L
Cte_j	-11.49 (-5.86)	-4.69 (-3.19)	-1.84 (-1.68)	-0.53 (-0.46)	-0.32 (-0.36)	0.27 (0.42)	1.23 (1.49)	3.25 (4.65)	3.41 (3.69)	6.61 (4.88)	18.11 (10.74)
β_j^{MKT}	1.44 (19.10)	1.21 (18.11)	1.02 (18.61)	0.95 (19.86)	0.92 (24.34)	0.96 (28.94)	0.87 (22.52)	0.89 (29.89)	0.95 (28.84)	1.14 (21.17)	-0.30 (2.08)
β_j^{Ishock}	-5.60 (-1.85)	-1.57 (-1.10)	-1.62 (-1.19)	-0.10 (-0.11)	-0.14 (-0.16)	-0.03 (-0.04)	-0.53 (-0.86)	0.97 (1.75)	0.68 (0.76)	0.91 (0.71)	6.51 (2.55)
$R^2(\%)$	71.13	76.96	76.88	80.83	85.37	88.72	86.50	86.73	85.18	75.23	4.10

Panel B: Cross-sectional regression: $E_T(R_{jt}^e) = \beta_j^{MKT} \times \lambda^{MKT} + \beta_j^{Ishock} \times \lambda^{Ishock} + \eta_j$

	λ^{MKT}	λ^{Ishock}	MAE(%)	p -(χ^2 test)	OLS- R^2 (%)	GLS- R^2 (%)
Est.	8.34	2.54	1.27	0.90	86.44	61.52
	(3.73)	(2.61)				

Table 4: Two-factor model with control for size and book-to-market

This table reports the relationship between momentum profits and investment-specific shocks after controlling for the effects of size and book-to-market. Following Fama and French (1993), the book value of equity is defined as the COMPUSTAT book value of common equity (CEQ) plus balance-sheet deferred taxes (TXDB) and investment tax credits (ITCB), minus book value of preferred stock. Depending on availability, I use the redemption (PSTKRV), liquidation (PSTKL), or carrying value of preferred stock (PSTK). When CEQ is unavailable, the liquidation value of common equity (CEQL) is used. When the book value of equity is not available from COMPUSTAT, it is supplemented by the book equity data for NYSE stocks in Davis, Fama, and French (2000). Size is defined as the stock price times shares outstanding at the end of June of year t from CRSP. Book-to-market is the ratio of the book value of equity to the market value of equity, which is price times shares outstanding at the end of December of year t from CRSP. The momentum is the prior (2-12) return. I match the CRSP monthly stock from July of year t to June of year $t + 1$ with the accounting data of fiscal year $t - 1$ from CRSP/COMPUSTAT Merged database. In the first-stage Fama and MacBeth (1973) regression, firm-level stock returns are regressed on firm-level natural log of size, natural log of book-to-market, and momentum, and the estimates are reported in Panel A.

$$R_{jt}^e = a_t + \lambda_t^{SIZE} \times SIZE_{jt} + \lambda_t^{BM} \times BM_{jt} + \lambda_t^{MOM} \times MOM_{jt} + \epsilon_{jt}$$

In the second stage, the time series coefficients on firm-level momentum estimated from the first stage (i.e. the after-control momentum risk premium) is then tested onto the two-factor model, with market excess returns (MKT) and investment-specific shocks (Ishock) as risk factors.

$$\lambda_t^{MOM} = Cte_0 + b_0^{MKT} \times MKT_t + b_0^{Ishock} \times Ishock_t + \epsilon_{0t}$$

The estimates are reported in Panel B. Two annual sample periods are tested: the full sample 1930-2009, and the short sample 1963-2009. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation.

Panel A: Fama and MacBeth (1973) regression

Sample	Intercept	Size	BM	MOM	OLS- R^2 (%)
1930-2009	1.34 (4.95)	-0.12 (-3.35)	0.21 (4.29)	0.72 (3.23)	4.85
1963-2009	1.37 (4.11)	-0.08 (-2.13)	0.19 (4.04)	0.84 (3.95)	3.86

Panel B: Two-factor model

Sample	Cte_0	b_0^{MKT}	b_0^{Ishock}	OLS- R^2 (%)
1930-2009	0.79 (2.85)	-0.03 (-4.13)	0.39 (1.75)	18.60
1963-2009	0.32 (0.72)	-0.02 (-2.40)	0.69 (2.48)	27.73

Table 5: Industry definition

This table reports the definitions of 20 industries used in Moskowitz and Grinblatt (1999) and their stock return summary statistics. Two-digit Standard Industrial Classification (SIC) codes from CRSP are used to form industry portfolios, and the return of an industry is calculated as the value-weighted average of stock returns for all firms in that industry. Columns 4 and 5 report the sample mean and standard deviation of industry portfolio returns. Columns 6 and 7 report the exposures of industry portfolios to investment-specific shocks and the corresponding t -stats, when industry portfolio returns are regressed on a two-factor model, with market excess returns and investment-specific shocks as the risk factors. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation. The sample is annual from 1930 to 2009.

Industry	Description	SIC Codes	E(R)-Rf (%)	Std(%)	β^{Ishock}	$t(\beta^{Ishock})$
1	Mining	10-14	7.60	24.70	2.67	(2.79)
2	Food	20	8.12	17.32	-0.10	(-0.13)
3	Apparel	22-23	7.39	31.34	-1.68	(-1.31)
4	Paper	26	9.13	27.84	0.59	(0.43)
5	Chemical	28	8.17	19.53	-0.02	(-0.03)
6	Petroleum	29	9.47	20.33	1.57	(1.87)
7	Construction	32	7.95	28.11	-0.74	(-1.29)
8	Prim. Metals	33	7.77	30.54	0.96	(0.70)
9	Fab. Metals	34	7.53	22.92	0.47	(0.79)
10	Machinery	35	8.06	25.60	0.50	(0.63)
11	Electrical Eq.	36	7.78	26.23	-0.54	(-0.81)
12	Transport Eq.	37	9.22	28.97	-1.89	(-2.39)
13	Manufacturing	38-39	8.76	22.32	-0.23	(-0.20)
14	Railroads	40	8.63	24.75	2.94	(2.99)
15	Other Transport.	41-47	6.51	27.95	0.01	(0.01)
16	Utilities	49	5.81	19.97	-0.29	(-0.28)
17	Dept. Stores	53	8.18	23.50	-0.10	(-0.08)
18	Retail	50-52, 54-59	8.47	22.28	-1.39	(-1.59)
19	Financial	60-69	7.91	23.74	0.02	(0.02)
20	Other	other	6.13	17.65	-0.24	(-0.54)

Table 6: Industry momentum

This table reports test results for 10 industry momentum portfolios. Industries are defined by two-digit SIC codes as in Table 5. Industry momentum for time t equals the cumulative industry return from $t - 12$ to $t - 2$, and the portfolio holding period is one month. Panel A presents the mean and standard deviation of the annualized returns of the 10 industry momentum portfolios and the spread portfolio with a long position in the past winner industries and a short position in the past loser industries. The 10 industry momentum portfolios are tested in a two-factor model, with market excess returns (MKT) and investment-specific shocks (Ishock) as the risk factors. In the first-stage time series regressions, the 10 portfolio excess returns are regressed on the two factors, generating factor loadings, or betas, reported in Panel B. The second stage regresses the average portfolio returns on the factor loadings from the first stage, generating prices of risks, as reported in Panel C. Panel C also reports the mean absolute error (MAE), p -value for the χ^2 test, and OLS- R^2 from the cross-sectional regression. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation. To address the problem that the risk exposures are estimated from the first stage, I adjust the standard errors from the second-stage regression as proposed in Shanken (1992). The sample is annual from 1930 to 2009.

		Panel A: Portfolio Returns										
		Loser	2	3	4	5	6	7	8	9	Winner	W-L
E(R)-Rf (%)		5.91	4.92	6.13	6.06	7.77	7.75	7.50	8.82	10.14	11.69	5.78
std(%)		23.33	23.61	23.01	24.62	22.81	19.24	20.56	21.23	22.79	22.66	17.03

		Panel B: Time Series Regression: $R_{jt}^e = Cte_j + \beta_j^{MKT} \times MKT_t + \beta_j^{Ishock} \times Ishock_t + \epsilon_{jt}$										
		Loser	2	3	4	5	6	7	8	9	Winner	W-L
Cte_j		-0.58 (-0.47)	-2.60 (-2.84)	-1.07 (-0.92)	-1.97 (-1.69)	0.13 (0.17)	1.38 (1.15)	1.04 (1.23)	1.80 (1.79)	2.70 (2.23)	4.04 (3.21)	4.62 (2.95)
β_j^{MKT}		0.98 (17.26)	1.09 (21.65)	1.04 (14.31)	1.14 (10.39)	1.08 (23.81)	0.84 (12.42)	0.94 (15.89)	0.97 (18.20)	0.99 (13.51)	1.01 (19.23)	0.03 (0.37)
β_j^{Ishock}		-0.96 (-1.15)	-0.37 (-0.61)	-0.28 (-0.38)	-0.06 (-0.12)	0.00 (-0.01)	0.99 (1.33)	-0.44 (-0.64)	0.38 (0.37)	1.01 (1.47)	1.19 (1.70)	2.15 (2.43)
R^2 (%)		70.47	84.83	81.22	85.71	89.81	77.49	83.98	83.83	76.28	80.42	4.04

		Panel C: Cross-sectional Regression: $E_T(R_{jt}^e) = \beta_j^{MKT} \times \lambda^{MKT} + \beta_j^{Ishock} \times \lambda^{Ishock} + \eta_j$				
		λ^{MKT}	λ^{Ishock}	MAE(%)	p -(χ^2 test)	OLS- R^2 (%)
Est.		7.19 (3.05)	2.65 (1.92)	1.12	0.71	67.43

Table 7: Parameter values under benchmark calibration

This table lists the parameters values for the benchmark calibration. Group I reports the parameters that can be restricted by empirical or quantitative studies. Group II reports the parameters with limited guidance from prior studies or that require special discussion.

Parameter	Symbol	Value
Group I		
Elasticity of output w.r.t. capital	α	0.5
Depreciation rate of capital	δ	0.13
Capital adjustment coefficient when invests	c_+	1
Capital adjustment coefficient when disinvests	c_-	20
Operating cost coefficient	f	0.19
Persistence of aggregate productivity	ρ^x	0.92
Long-run average of aggregate productivity	\bar{X}	0.32
Persistence of investment-specific technological state	ρ^q	0.6
Long-run average of investment-specific technological state	\bar{Q}	0.84
Volatility of investment-specific shocks relative to aggregate productivity shocks	$\frac{\sigma^q}{\sigma^x}$	1.0
Persistence of idiosyncratic productivity	ρ^z	0.85
Volatility of idiosyncratic productivity shocks	σ^z	0.5
Constant risk-free rate	r_f	1.8%
Leverage ratio	Φ	1.667
Group II		
Proportion of investment completed when initiated	w	0.2
Volatility of aggregate productivity shocks	σ^x	0.2
Risk price for aggregate productivity shocks	γ_x	2.5
Risk price for investment-specific shocks	γ_q	20

Table 8: Key moments

This table reports unconditional moments generated from the simulated data and real data. 100 samples are simulated, with each sample spanning 80 years and for 2,000 firms, and the cross-simulation average annual moments are reported. The mean, Sharpe ratio, and AR(1) coefficient of market excess returns are from Campbell and Cochrane (1999), and the volatility of firm-level stock returns is reported by Campbell, Lettau, Malkiel, and Xu (2001) and Vuolteenaho (2002). The average investment rate and disinvestment rate are from Abel and Eberly (2002). I estimate the standard deviation of firm-level investment rates using pooled sample from 1950-2009, where the investment rate is the ratio between capital expenditure (CAPX) and lagged capital (PPENT) from COMPUSTAT. The range for average adjustment cost-output ratio is reported by Hamermesh and Pfann (1996), and the average fixed cost-output ratio is from Eberly, Rebelo, and Vincent (2009).

Moments	Data	Model
Average annual market excess return (%)	6.69	6.79
Average annual Sharpe ratio	0.43	0.47
AR(1) coefficient of annual market excess return	0.05	0.07
Volatility of annual firm-level stock return (%)	25.0–32.0	30.1
Annual average investment rate	0.15	0.15
Annual average disinvestment rate	0.02	0.02
Standard deviation of firm-level investment rate	0.22	0.21
Average adjustment cost-output ratio (%)	1–20	2.8
Average fixed cost-output ratio (%)	0.18	0.17

Table 9: Momentum profits

This table shows the momentum portfolio returns and asset pricing test results. The top panel presents the results with empirical data, where I rebalance momentum portfolios in December of each year and hold for one year. Momentum at year t is defined as the cumulative returns from January to November of year $t - 1$ to avoid microstructure concerns. The sample is annual from 1930 to 2009. The bottom panel shows the results from simulated data, where 100 samples are simulated, with each sample spanning 80 years and for 2,000 firms. The first two rows of each panel report the annual mean and standard deviation of the excess returns of momentum portfolios and the spread portfolio with a long position in the past winners and a short position in the past losers. The middle five rows report the CAPM tests results, including abnormal returns $\alpha(CAPM)$, market exposure $\beta_{MKT}(CAPM)$. The bottom seven rows report the two-factor model (TF) test results, with market excess returns and investment-specific shocks as risk factors, including the intercept $Cte(TF)$, market exposure $\beta_{MKT}(TF)$, and exposure to investment-specific shocks $\beta_{Ishock}(TF)$. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation.

	Data										
	Los.	2	3	4	5	6	7	8	9	Win.	W-L
E(R)-Rf (%)	3.03	7.22	7.21	7.96	7.34	6.77	7.18	8.70	9.70	10.58	7.56
std(%)	32.91	26.92	23.35	21.88	20.22	19.95	19.06	19.75	21.41	24.52	21.89
$\alpha(CAPM)$	-7.05	-1.35	-0.34	0.69	0.71	0.09	1.00	2.12	2.60	2.78	9.84
	(-3.45)	(-0.94)	(-0.32)	(0.71)	(0.62)	(0.12)	(1.14)	(2.86)	(3.25)	(1.93)	(4.27)
$\beta_{MKT}(CAPM)$	1.43	1.21	1.07	1.03	0.94	0.94	0.87	0.93	1.00	1.10	-0.32
	(11.03)	(13.52)	(13.66)	(17.85)	(13.65)	(20.82)	(15.92)	(21.67)	(22.23)	(17.50)	(-2.27)
$R^2(CAPM)(\%)$	75.24	81.25	83.77	88.36	86.18	89.81	84.39	89.13	88.40	81.14	8.72
$Cte(TF)(\%)$	-5.80	-0.68	0.41	1.26	0.78	0.19	0.80	1.69	2.18	2.12	7.92
	(-3.17)	(-0.50)	(0.46)	(1.32)	(0.62)	(0.23)	(0.97)	(2.89)	(2.41)	(1.28)	(3.65)
$\beta_{MKT}(TF)$	1.43	1.21	1.07	1.03	0.94	0.94	0.87	0.93	1.00	1.10	-0.32
	(12.55)	(12.98)	(13.77)	(16.53)	(13.43)	(20.58)	(16.21)	(26.01)	(22.27)	(15.47)	(-2.44)
$\beta_{Ishock}(TF)$	-2.97	-1.60	-1.77	-1.34	-0.17	-0.23	0.47	1.01	0.97	1.58	4.54
	(-2.12)	(-2.03)	(-2.55)	(-2.19)	(-0.24)	(-0.52)	(0.98)	(3.40)	(1.63)	(1.70)	(3.13)
$R^2(TF)(\%)$	77.20	82.10	85.16	89.28	86.19	89.84	84.54	89.76	88.90	82.13	19.13

	Model										
	Los.	2	3	4	5	6	7	8	9	Win.	W-L
E(R)-Rf(%)	3.91	3.35	3.68	5.12	5.52	5.68	5.84	8.57	9.17	9.91	5.99
std(%)	11.14	7.99	8.61	12.69	12.30	12.28	12.34	18.39	19.19	17.19	7.39
$\alpha(CAPM)$	-0.77	-0.15	-0.13	-0.49	-0.16	-0.04	0.04	0.00	0.18	1.14	1.91
	(-2.98)	(-0.65)	(-0.58)	(-2.30)	(-0.90)	(-0.22)	(0.16)	(0.02)	(0.70)	(3.32)	(3.42)
$\beta_{MKT}(CAPM)$	0.76	0.53	0.57	0.88	0.85	0.85	0.85	1.28	1.33	1.19	0.43
	(26.17)	(11.91)	(11.61)	(32.28)	(37.58)	(33.70)	(24.53)	(26.14)	(17.06)	(27.21)	(6.39)
$R^2(CAPM)(\%)$	95.39	90.38	90.43	96.79	97.36	97.02	96.42	97.19	96.60	97.24	67.45
$Cte(TF)(\%)$	-1.12	-0.33	-0.25	-0.70	-0.22	-0.07	0.09	0.00	0.29	1.60	2.72
	(-3.64)	(-1.22)	(-0.98)	(-2.72)	(-0.95)	(-0.29)	(0.37)	(-0.01)	(0.97)	(4.00)	(4.21)
$\beta_{MKT}(TF)$	0.76	0.53	0.57	0.88	0.85	0.85	0.85	1.28	1.33	1.19	0.43
	(26.94)	(11.89)	(11.62)	(32.82)	(37.81)	(33.44)	(24.48)	(25.95)	(16.94)	(28.81)	(6.68)
$\beta_{Ishock}(TF)$	-1.90	-0.96	-0.65	-1.17	-0.35	-0.12	0.30	-0.10	0.58	2.55	4.45
	(-2.67)	(-1.24)	(-0.77)	(-1.94)	(-0.59)	(-0.21)	(0.53)	(-0.10)	(0.64)	(2.82)	(3.16)
$R^2(TF)(\%)$	95.94	90.77	90.68	96.97	97.41	97.06	96.46	97.24	96.65	97.66	73.97

Table 10: Roles of investment commitment and investment-specific shocks

This table studies the mechanism in generating momentum profits from the model. In panel A, I sort simulated firms from benchmark calibration by committed investment rate LK_{t-1} into 10 portfolios. Panel A reports the mean and standard deviation of stock returns for these portfolios. In panel B, I shut down the investment-specific shocks from the benchmark model, and form 10 momentum portfolio from simulation. All parameters remain the same as the benchmark calibration, except that the risk price and volatility of aggregate productivity shocks is re-calibrated so that the equity premium and the market Sharpe ratio are matched. Panel B reports the mean and standard deviation of stock returns for these portfolios. 100 samples are simulated, with each sample spanning 80 years and for 2000 firms.

Panel A: Portfolios sorting by LK_{t-1}

	Low	2	3	4	5	6	7	8	9	High	H-L
E(R)-Rf(%)	3.88	3.98	4.23	4.70	5.69	6.69	7.46	7.96	8.70	10.20	6.32
Std(%)	11.36	10.84	10.49	10.91	13.04	15.09	16.51	16.84	16.98	16.70	6.76

Panel B: Momentum portfolios without investment-specific shocks

	Loser	2	3	4	5	6	7	8	9	Winner	W-L
E(R)-Rf(%)	4.90	3.92	4.02	5.60	5.54	5.57	5.68	7.95	8.35	7.78	2.88
Std(%)	12.13	8.93	9.30	13.35	13.31	13.32	14.03	19.80	21.43	19.25	8.18

Table 11: Value premium

This table shows the book-to-market portfolio returns and asset pricing test results. The top panel presents the results with empirical data, where book-to-market portfolio returns are from Kenneth French's Web site, and the sample is annual from 1930 to 2009. The bottom panel shows the results from simulated data, where 100 samples are simulated, with each sample spanning 80 years and for 2000 firms. Book-to-market for firm i at time t in the model is defined as the ratio of capital K_{it} at the beginning of year t to the ex-dividend firm value $V_{it-1} - D_{it-1}$ at the end of year $t - 1$. The first two rows of each panel report the annual mean and standard deviation of the excess returns of the book-to-market portfolios and the spread portfolio with a long position in the value firms and a short position in the growth firms. The bottom five rows in each panel report the one-factor model (OF) test results, with the aggregate productivity shocks (or TFP growth in the data) as the risk factor, including the intercept $Cte(OF)$ and exposure to aggregate productivity shocks $\beta_{TFP}(OF)$. Newey-West t -stats given in parentheses control for heteroscedasticity and autocorrelation.

	Data										
	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
E(R)-Rf (%)	6.09	6.98	7.28	6.96	8.28	8.30	7.97	9.99	10.42	11.68	5.59
std(%)	20.20	16.36	16.32	17.10	17.37	17.20	18.60	19.32	18.83	23.93	18.27
$Cte(OF)$	4.83	6.12	6.71	5.33	6.70	5.83	6.12	7.06	7.74	8.22	3.39
	(1.44)	(2.14)	(2.66)	(1.78)	(2.19)	(1.97)	(2.11)	(2.76)	(2.99)	(2.77)	(1.36)
$\beta_{TFP}(OF)$	0.96	0.66	0.43	1.25	1.21	1.89	1.42	2.25	2.05	2.64	1.68
	(0.74)	(0.56)	(0.43)	(0.98)	(1.01)	(1.57)	(1.13)	(2.06)	(1.70)	(1.93)	(1.64)
$R^2(OF)(\%)$	0.78	0.56	0.24	1.84	1.67	4.16	2.01	4.66	4.09	4.21	2.93

	Model										
	Lo	2	3	4	5	6	7	8	9	Hi	Hi-Lo
E(R)-Rf (%)	4.89	6.64	6.96	6.39	6.04	6.69	7.34	7.86	7.78	5.23	0.35
std	8.76	11.50	12.77	12.84	12.54	13.67	15.46	17.47	18.36	14.86	7.62
$Cte(OF)$	10.94	14.24	15.37	14.99	14.37	15.49	17.19	19.11	19.69	14.66	3.73
	(5.22)	(5.93)	(6.67)	(6.33)	(6.28)	(6.25)	(6.51)	(6.00)	(5.27)	(5.11)	(1.22)
$\beta_{TFP}(OF)$	7.45	9.43	10.20	10.16	9.74	10.42	11.59	12.99	13.42	10.26	2.81
	(3.16)	(3.53)	(3.80)	(3.63)	(3.83)	(3.74)	(3.87)	(3.82)	(3.74)	(4.01)	(1.44)
$R^2(OF)(\%)$	35.29	32.79	30.94	30.27	29.10	28.14	27.25	26.57	25.49	22.98	7.79

Figure 1: Risk exposures and performance of the two-factor model

This figure plots the asset pricing test results on 10 standard momentum portfolios from Kenneth French's Web site. The top left(right) panel plots the average momentum portfolio returns against exposure to market excess returns (investment-specific shocks), where the risk exposures are estimated from a two-factor model, with market excess returns and investment-specific shocks as the risk factors. The bottom left plot compares the CAPM predicted momentum portfolio returns with average realized returns. The bottom right plot compares the two-factor model-predicted momentum portfolio returns with average realized returns. The sample is annual from 1930 to 2009.

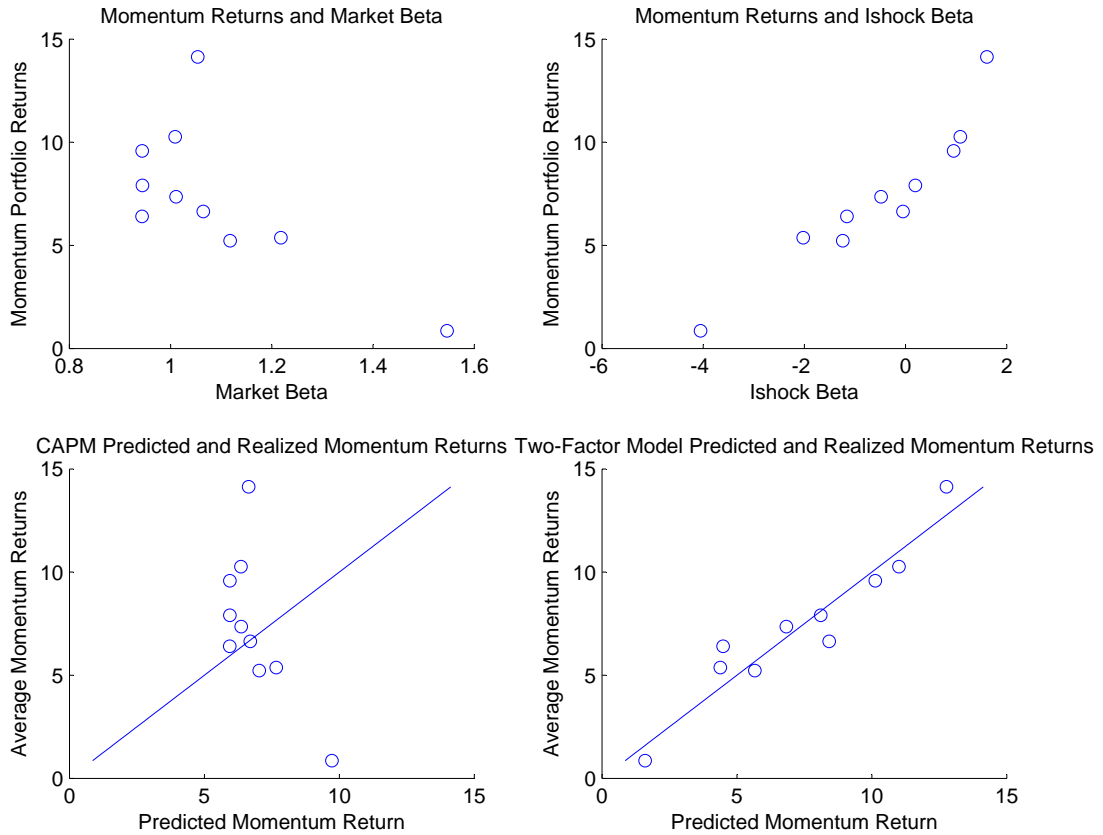


Figure 2: 11-year event windows of momentum portfolios

The figure plots the dynamics of profitability and the investment rate of momentum portfolios in an 11-year event window around the portfolio-forming year. The top two panels show the results for the empirical data. Profitability is proxied by return on equity, defined as the ratio between income before extraordinary items (IB) and lagged capital (PPENT) from COMPUSTAT. The investment rate is the ratio between capital expenditure (CAPX) and lagged capital (PPENT) from COMPUSTAT. At the end of December of each year, 10 momentum portfolios are rebalanced based on the cumulative stock returns in that year. The profitability and investment rate of the same firms in a portfolio are tracked for five years before and five years after the portfolio formation year, and the averages over calendar years are plotted in the 11-year window. The sample keeps only firms that have a fiscal year end (FYR) of December, and is annual from 1950 to 2009. The bottom two panels show the results for the simulated data, where 100 samples are simulated, with each sample spanning 80 years and for 2,000 firms.

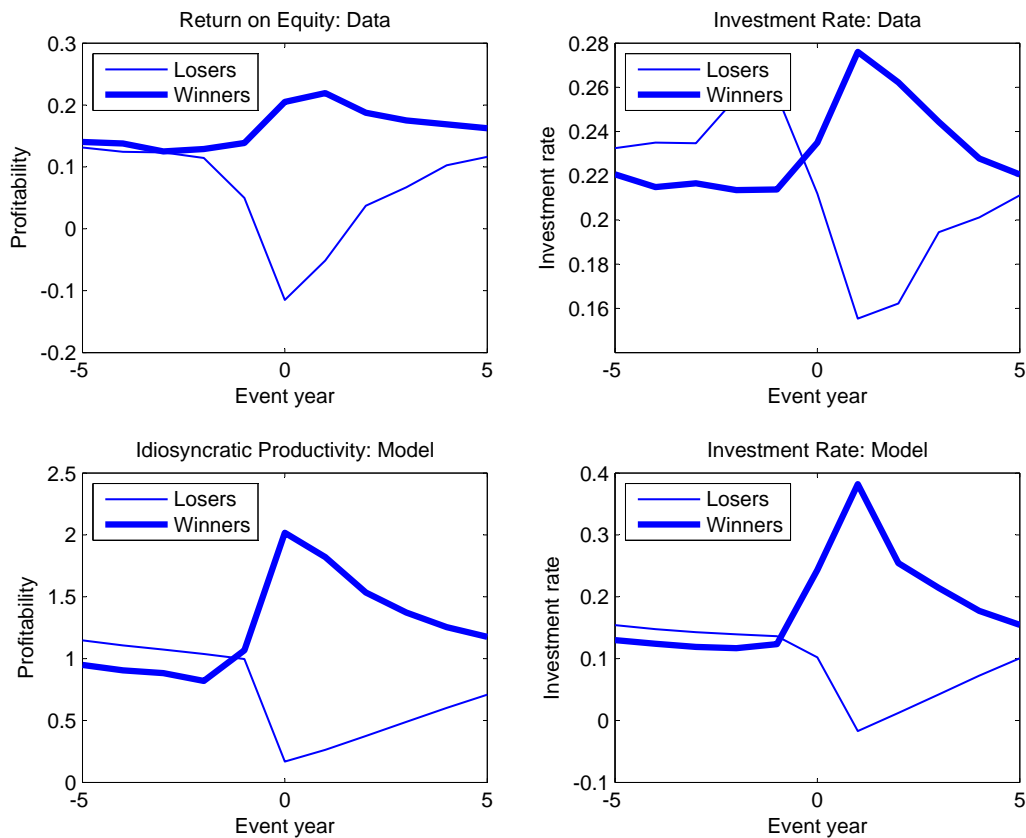


Figure 3: Value function and policy function

The figure presents the value function (top panel) and policy committed investment rate (bottom panel) against two state variables: capital and committed investment rate, when the other state variables are set to their steady states, i.e., $X = \bar{X}$, $Q = \bar{Q}$, and $Z = 1$. The value function and policy function are generated through value function iterations.

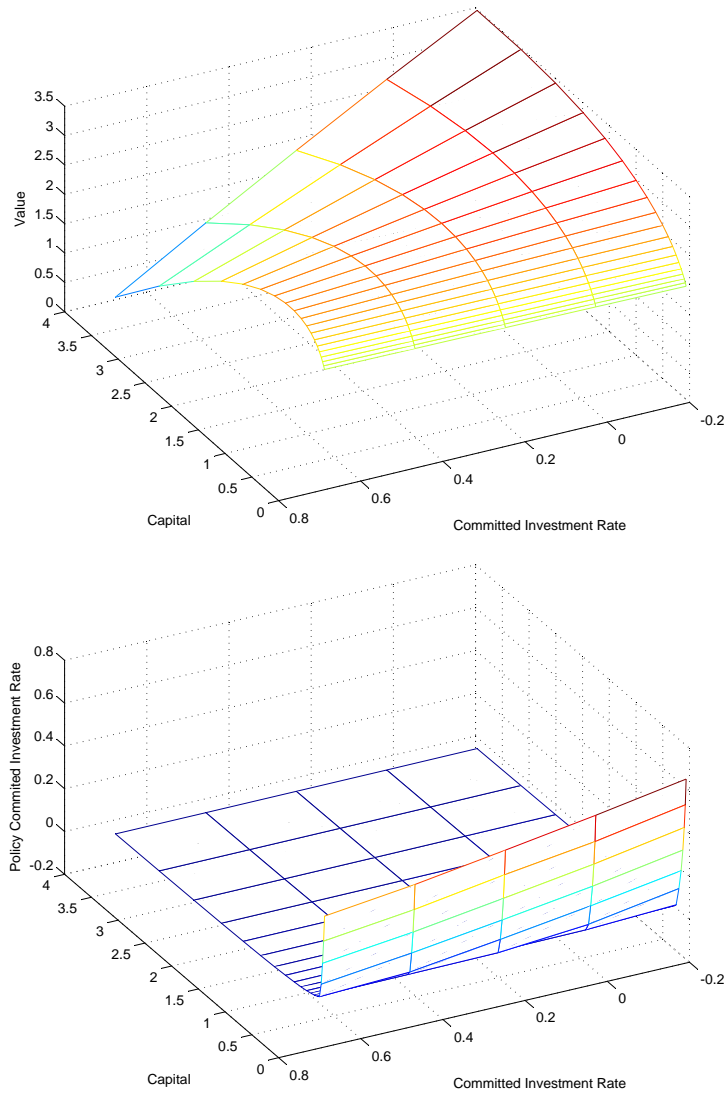


Figure 4: Predicted return and actual return of 10 momentum portfolios: Simulated data

This figure plots the performance of CAPM and the two-factor model on 10 simulated momentum portfolios. The top panel compares CAPM predicted momentum portfolio returns with realized returns. The bottom panel compares the two-factor model predicted momentum portfolio returns with realized returns. 1000 samples are simulated, with each sample 80 years and 2000 firms.

