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ABSTRACT

Momentum is consistent with value maximization of firms. The neoclassical theory of investment implies that expected stock returns are connected with the ratio of expected marginal benefits of investment divided by marginal costs of investment. Winners have higher expected growth and expected marginal productivity (two major components of marginal benefits of investment), and consequently earn higher expected stock returns than losers. Our model outperforms traditional asset pricing models in explaining average momentum profits. The model also succeeds in reproducing reversal of momentum in long horizons and long run risks across momentum portfolios. However, the model fails to explain the procyclicality of momentum profits.

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1 Introduction

In an influential paper, Jegadeesh and Titman (1993) document that stocks with high recent performance continue to earn higher average returns over the next three to twelve months than stocks with low recent performance. Many subsequent studies have confirmed and refined Jegadeesh and Titman's original finding.[1] For the most part, the literature has followed Jegadeesh and Titman in interpreting momentum profits as irrational underreaction to firm-specific information. In particular, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) have constructed behavioral models to explain momentum using psychological biases such as conservatism, self-attributive overconfidence, and slow information diffusion.

Deviating from the bulk of the momentum literature, we propose and quantitatively evaluate an investment-based explanation of momentum. Under constant returns to scale, the neoclassical theory of investment implies that stock returns equal (levered) investment returns (e.g., Cochrane (1991) and Liu, Whited, and Zhang (2009)). The investment returns, defined as the next-period marginal benefits of investment divided by the current-period marginal costs of investment, are linked to firm characteristics through firms' optimality conditions. Intuitively, winners have higher expected growth and higher expected marginal productivity (two major components of expected marginal benefits of investment), and consequently earn higher expected stock returns than losers.

We use generalized method of moments (GMM) to match the means of levered investment returns with those of stock returns. As testing portfolios we use Jegadeesh and Titman's (1993) momentum deciles, Moskowitz and Grinblatt's (1999) industry momentum quintiles, and two-way (three by three) portfolios on momentum and one of the following characteristics: size, firm age,

[1] Asness (1997) shows that momentum is stronger in growth firms than in value firms. Rouwenhorst (1998) documents momentum profits in international markets. Moskowitz and Grinblatt (1999) document large momentum profits in industry portfolios. Hong, Lim, and Stein (2000) show that small firms with low analyst coverage display stronger momentum. Lee and Swaminathan (2000) document that momentum is more prevalent in stocks with high trading volume. Jegadeesh and Titman (2001) show that momentum remains large in the post-1993 sample. Lewellen (2002) shows that momentum profits also exist in size and book-to-market portfolios. Jiang, Lee, and Zhang (2005) and Zhang (2006) report that momentum profits are higher among firms with higher information uncertainty measured by size, age, return volatility, cash flow volatility, and analyst forecast dispersion.

trading volume, stock return volatility, cash flow volatility, and book-to-market. The investment-based model does a good job in explaining average momentum profits. The winner-minus-loser decile has a small alpha of 0.4% per annum, which is negligible compared to the CAPM alpha of 17.0% and the alpha of 19.2% from the Fama-French (1993) model. (We equal-weight all testing portfolios following Jegadeesh and Titman (1993).) The winner-minus-loser industry momentum quintile has a small alpha of 0.4% in the investment-based model. In contrast, the alphas are 9.2% in the CAPM and 9.4% in the Fama-French model. The alphas of individual portfolios in our model are also substantially smaller in magnitude than those in the traditional models.

For the double sorted momentum portfolios, the investment-based model outperforms the traditional models. In particular, our alphas do not vary systematically with short-term prior returns. For example, the winner-minus-loser tercile alphas are −0.9%, −1.0%, and −0.8% per annum across the small, median, and big size terciles, respectively. In contrast, the alphas from the CAPM are 10.2%, 7.9%, and 6.1%, and the alphas from the Fama-French model are 11.6%, 9.6%, and 7.8%, respectively. However, the investment-based model delivers large individual alphas for several testing portfolios. The model has its worst fit in the nine cash flow volatility and momentum portfolios. The individual alphas range from −6.9% to 6.9%. Although the alphas do not vary systematically with momentum, their magnitude is comparable with those from the CAPM and the Fama-French model.

Our model suggests several determinants of expected stock returns. All else equal, firms with low investment-to-capital, high expected growth of investment-to-capital, high expected sales-to-capital, high market leverage, low expected rate of depreciation, and low expected corporate bond returns should earn high expected stock returns. Using extensive comparative statics, we show that the expected growth of investment-to-capital is the most important, and the expected sales-to-capital is the second most important source of momentum. Eliminating the cross-sectional variation in the expected growth of investment-to-capital would increase the winner-minus-loser decile alpha to 11.4% per annum from 0.4% in the benchmark estimation. And eliminating the cross-sectional variation in the expected sales-to-capital would increase the winner-minus-loser decile alpha to 7.1%.

Going beyond the average returns of momentum portfolios, we also use the investment-based model to understand the dynamics of momentum. Consistent with the data, momentum profits predicted in the model revert beyond the second year after portfolio formation. The low persistence of the expected growth of investment-to-capital is the key driving force of this result. Moreover, the predicted momentum profits cannot be explained by the CAPM and the Fama-French model. We also show that the cash flow component of the investment returns displays long run risks similar to the dividend component of the stock returns per Bansal, Dittmar, and Lundblad (2005). However, contrary to Cooper, Gutierrez, and Hameed's (2004) evidence based on stock returns, the predicted momentum profits are not substantially higher following up markets than down markets.

Our investment-based explanation of momentum is related to Johnson (2000) and Sagi and Seasholes (2007). Johnson argues that the log price-to-dividend ratio is convex in expected growth, meaning that stock returns (changes in the log price-to-dividend ratio) are more sensitive to changes in expected growth when expected growth is high. Winners are more likely to have positive shocks to expected growth than losers. If the expected growth risk is priced, winners should earn higher expected returns than losers. Sagi and Seasholes argue that winners have more risky growth options as a fraction of equity value, and should earn higher expected returns than losers. Both papers rely on the expected growth spread between winners and losers. Complementing their work, we derive the same positive relation between expected growth and expected stock returns using the dynamic investment framework with endogenous cash flows. More important, we also show empirically via structural estimation that the expected growth is the most important driving force of momentum.

The rest of the paper is organized as follows. Section 2 sets up the model. Section 3 describes our test design and data. Section 4 presents our estimation results. Finally, Section 5 concludes.

2 The Investment-Based Model of Expected Stock Returns

We adopt the model of Liu, Whited, and Zhang (2009), who study the relations of stock returns with earnings surprises, book-to-market, and investment. We instead examine momentum. Firms use capital and costlessly adjustable inputs to produce a homogeneous output. These inputs are chosen each period to maximize operating profits, defined as revenues minus expenditures on the inputs. Taking operating profits as given, firms choose investment to maximize the market value of equity. Let $\Pi(K_{it}, X_{it})$ denote the operating profits of firm i at time t, in which K_{it} is capital and X_{it} is a vector of exogenous aggregate and firm-specific shocks. We assume $\Pi(K_{it}, X_{it})$ has constant returns to scale, meaning that $\Pi(K_{it}, X_{it}) = K_{it}\partial\Pi(K_{it}, X_{it})/\partial K_{it}$. We further assume that firms have a Cobb-Douglas production function, meaning that the marginal product of capital is given by $\partial\Pi(K_{it}, X_{it})/\partial K_{it} = \kappa Y_{it}/K_{it}$, in which $\kappa > 0$ is the capital's share in output and Y_{it} is sales.

Capital evolves as $K_{it+1} = I_{it} + (1 - \delta_{it})K_{it}$, in which capital depreciates at an exogenous proportional rate of δ_{it}. We allow δ_{it} to be firm-specific and time-varying as in the data. Firms incur adjustment costs when investing. The adjustment cost function, denoted $\Phi(I_{it}, K_{it})$, is increasing and convex in I_{it}, decreasing in K_{it}, and has constant returns to scale in I_{it} and K_{it}. In particular, we use the standard quadratic functional form: $\Phi(I_{it}, K_{it}) = (a/2)(I_{it}/K_{it})^2 K_{it}$, in which $a > 0$.

Firms can borrow by issuing one-period debt. At the beginning of time t, firm i can issue debt, denoted B_{it+1}, which must be repaid at the beginning of t+1. Firms take as given the risky interest rate on B_{it}, denoted r^B_{it}, which can vary across firms and over time. Taxable corporate profits equal operating profits less capital depreciation, adjustment costs, and interest expenses: $\Pi(K_{it}, X_{it}) - \delta_{it}K_{it} - \Phi(I_{it}, K_{it}) - (r^B_{it} - 1)B_{it}$. Let τ_t denote the corporate tax rate at time t, so $\tau_t\delta_{it}K_{it}$ is the depreciation tax shield, and $\tau_t(r^B_{it} - 1)B_{it}$ is the interest tax shield. Firm i's payout is then:

$$D_{it} \equiv (1 - \tau_t)[\Pi(K_{it}, X_{it}) - \Phi(I_{it}, K_{it})] - I_{it} + B_{it+1} - r^B_{it}B_{it} + \tau_t\delta_{it}K_{it} + \tau_t(r^B_{it} - 1)B_{it}. \quad (1)$$

Let M_{t+1} be the stochastic discount factor from t to $t+1$. Taking M_{t+1} as given, firm i maximizes its cum-dividend market value of equity:

$$V_{it} \equiv \max_{\{I_{it+s}, K_{it+s+1}, B_{it+s+1}\}_{s=0}^{\infty}} E_t\left[\sum_{s=0}^{\infty} M_{t+s}D_{it+s}\right], \quad (2)$$

subject to a transversality condition: $\lim_{T\to\infty} E_t\left[M_{t+T}\, B_{it+T+1}\right] = 0$. The firm's first-order condition for investment implies $E_t[M_{t+1} r^I_{it+1}] = 1$, where r^I_{it+1} is the investment return, defined as:

$$r^I_{it+1} \equiv \frac{(1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right] + \tau_{t+1}\delta_{it+1} + (1-\delta_{it+1})\left[1+(1-\tau_{t+1})a\left(\frac{I_{it+1}}{K_{it+1}}\right)\right]}{1+(1-\tau_t)a\left(\frac{I_{it}}{K_{it}}\right)}. \quad (3)$$

The investment return is the ratio of the marginal benefits of investment at period $t+1$ divided by the marginal costs of investment at t. The optimality condition $E_t[M_{t+1} r^I_{it+1}] = 1$ means that the marginal costs of investment equal the marginal benefits of investment discounted to time t. In the numerator of the investment return, $(1-\tau_{t+1})\kappa Y_{it+1}/K_{it+1}$ is the after-tax marginal product of capital, $(1-\tau_{t+1})(a/2)(I_{it+1}/K_{it+1})^2$ is the after-tax marginal reduction in adjustment costs, and $\tau_{t+1}\delta_{it+1}$ is the marginal depreciation tax shield. The last term in the numerator is the marginal continuation value of the extra unit of capital net of depreciation, in which the marginal continuation value equals the marginal costs of investment in the next period.

Define the after-tax corporate bond return as $r^{Ba}_{it+1} \equiv r^B_{it+1} - (r^B_{it+1} - 1)\tau_{t+1}$, then firm i's first-order condition for new debt implies that $E_t[M_{t+1} r^{Ba}_{it+1}] = 1$. Define $P_{it} \equiv V_{it} - D_{it}$ as the ex-dividend market value of equity, $r^S_{it+1} \equiv (P_{it+1} + D_{it+1})/P_{it}$ as the stock return, and $w_{it} \equiv B_{it+1}/(P_{it} + B_{it+1})$ as the market leverage. Then the investment return equals the weighted average of the stock return and the after-tax corporate bond return:

$$r^I_{it+1} = w_{it}\, r^{Ba}_{it+1} + (1-w_{it})\, r^S_{it+1} \quad (4)$$

(see Liu, Whited, and Zhang (2009, Appendix A) for a detailed proof). Solving for r^S_{it+1} gives:

$$r^S_{it+1} = r^{Iw}_{it+1} \equiv \frac{r^I_{it+1} - w_{it}\, r^{Ba}_{it+1}}{1-w_{it}}, \quad (5)$$

in which r^{Iw}_{it+1} is the levered investment return. If $w_{it} = 0$, equation (5) collapses to the equivalence between stock returns and investment returns, a relation first derived by Cochrane (1991).

3 Econometric Design

We lay out the GMM application in Section 3.1, and describe our data in Section 3.2.

3.1 GMM Estimation and Tests

We use GMM to test the first moment restriction implied by equation (5):

$$E\left[r_{it+1}^{S} - r_{it+1}^{Iw}\right] = 0. \tag{6}$$

In particular, we define the expected return error (alpha) from the investment-based model as:

$$\alpha_i^q \equiv E_T\left[r_{it+1}^{S} - r_{it+1}^{Iw}\right], \tag{7}$$

in which $E_T[\cdot]$ is the sample mean of the series in brackets.

We estimate the parameters a and κ using GMM on equation (6) applied to momentum portfolios. We use one-stage GMM with the identity weighting matrix to preserve the economic structure of the portfolios (e.g., Cochrane (1996)). This choice befits our economic question because short-term prior returns are economically important in providing a wide spread in the cross section of average stock returns. The identity weighting matrix also gives more robust (but less efficient) estimates.

Specifically, following the standard GMM procedure (e.g., Hansen and Singleton (1982)), we estimate the parameters, $\mathbf{b} \equiv (a, \kappa)$, by minimizing a weighted combination of the sample moments (6). Let $\mathbf{g}_T$ be the sample moments. The GMM objective function is a weighted sum of squares of the model errors across a given set of assets, $\mathbf{g}_T'\mathbf{W}\mathbf{g}_T$, in which we use $\mathbf{W} = \mathbf{I}$, the identity matrix. Let $\mathbf{D} = \partial \mathbf{g}_T / \partial \mathbf{b}$ and $\mathbf{S}$ a consistent estimate of the variance-covariance matrix of the sample errors $\mathbf{g}_T$. We estimate $\mathbf{S}$ using a standard Bartlett kernel with a window length of five. The estimate of $\mathbf{b}$, denoted $\hat{\mathbf{b}}$, is asymptotically normal with variance-covariance matrix:

$$\mathrm{var}(\hat{\mathbf{b}}) = \frac{1}{T}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\mathbf{S}\mathbf{W}\mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}. \tag{8}$$

To construct standard errors for the alphas on individual portfolios or a subset of alphas, we use the variance-covariance matrix for the model errors, $\mathbf{g}_T$:

$$\text{var}(\mathbf{g}_T) = \frac{1}{T}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]\mathbf{S}\left[\mathbf{I} - \mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\right]'. \tag{9}$$

We follow Hansen (1982, lemma 4.1) to form a χ^2 test that all model errors are jointly zero:

$$\mathbf{g}_T'\left[\text{var}(\mathbf{g}_T)\right]^+\mathbf{g}_T \quad \sim \quad \chi^2(\#\,\text{moments} - \#\,\text{parameters}), \tag{10}$$

in which χ^2 denotes the chi-square distribution, and the superscript + denotes pseudo-inversion.

3.2 Data

Firm-level data are from the Center for Research in Security Prices (CRSP) monthly stock file and the annual 2008 Standard and Poor's Compustat industrial files. Firms with primary SIC classifications between 4900 and 4999 or between 6000 and 6999 are omitted (the neoclassical theory of investment is unlikely to apply to regulated or financial firms). The sample is from 1963 to 2008.

3.2.1 Testing Portfolios

When forming momentum portfolios, we keep only firm-year observations with positive total asset (Compustat annual item AT $>$ 0), positive sales (SALE $>$ 0), nonnegative debt (DLTT + DTC $\geq$ 0), positive market value of asset (DLTT + DTC + CSHO $\times$ PRCC_F $>$ 0), positive gross capital stock (PPEGT $>$ 0) at the most recent fiscal year end, and positive gross capital stock one year prior to the most recent fiscal year. Following Jegadeesh and Titman (1993), we also exclude stocks with prices per share less than \$5 at the portfolio forming month.

We construct momentum portfolios by sorting all stocks at the end of every month t on the basis of their past six-month returns from $t-6$ to $t-1$, and hold the resulting ten deciles for the subsequent six months from $t+1$ to $t+6$. We skip one month between the end of the ranking period and the beginning of the holding period (month t) to avoid potential microstructure biases.

We equal-weight all stocks within a given portfolio. Because we use the six-month holding period while forming the portfolios monthly, we have six sub-portfolios for each decile in a given holding month. We average across these six sub-portfolios to obtain monthly returns of a given decile.

Moskowitz and Grinblatt (1999) document that trading strategies that buy stocks from past winning industries and sell stocks from past losing industries are profitable. We use their 20 industry classifications. Because we exclude financial firms and regulated utilities, we have 18 industries left in our sample. At the end of each portfolio formation month t, we sort the 18 industry portfolios into quintiles based on their prior six-month value-weighted returns from $t-6$ to $t-1$. The top and bottom quintiles each have three industries while the other three quintiles each have four industries. (We form quintiles instead of deciles because the number of industries is too small to construct deciles.) We hold the resulting quintile portfolios (value-weighted across industry portfolios) for the subsequent six months from $t+1$ to $t+6$.

For the double sorted portfolios, we need to measure size, age, trading volume, stock return volatility, cash flow volatility, and book-to-market. All these variables used in two-way sorts in conjunction with the prior six-month return are updated monthly. Size is market capitalization at the end of the portfolio formation month t. We require firms to have positive market capitalization before including them in the sample. Firm age is the number of months elapsed between the month when a firm first appears in the monthly CRSP database and the portfolio formation month t. Trading volume is the average daily turnover during the past six months from $t-6$ to $t-1$, in which daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. Following Lee and Swaminathan (2000), we restrict our sample to include NYSE and AMEX stocks only when forming the nine trading volume and momentum portfolios. The reason is that the number of shares traded for Nasdaq stocks is inflated relative to NYSE and AMEX stocks because of the double counting of dealer trades.

Following Lim (2001) and Zhang (2006), we measure stock return volatility as the standard deviation of weekly excess returns over the past six months. Weekly returns are from Thursday to Wednesday to mitigate bid-ask effects in daily prices. We calculate weekly excess returns as raw weekly returns minus weekly risk-free rates. The daily risk-free rates are from Ken French's Web site. The daily rates are available only after July 1, 1964. For days prior to that date, we use the monthly rate for a given month divided by the number of trading days within the month to obtain daily rates. We require a stock to have at least 20 weeks of data to enter the sample.

Cash flow volatility is the standard deviation of the ratio of cash flow from operations scaled by total assets in the most recent five years prior to the portfolio forming month. We require at least three years of data available. Cash flow from operations is earnings before extraordinary items minus total accruals, scaled by total assets, in which total accruals are changes in current assets minus changes in cash, changes in current liabilities, and depreciation expense plus changes in short-term debt (Compustat annual item (IB $-$ (ΔACT $-$ ΔCHE $-$ ΔLCT $-$ DP + ΔDLC))/TA). We measure book equity as common equity (Compustat annual item CEQ) plus balance sheet deferred tax (item TXDB) at the most recent fiscal yearend. The market equity is market capitalization from CRSP measured at the most recent month.

To form a given set of double sorted portfolios such as, for example, the nine size and momentum portfolios, we sort stocks independently into terciles at the end of each portfolio formation month t on the market capitalization at the end of the month, and then on the prior six-month return from $t-6$ to $t-1$. Taking intersections of the three size terciles and the three momentum terciles, we form nine size and momentum portfolios. Skipping the current month t, we hold the resulting portfolios for the subsequent six months from month $t+1$ to $t+6$. We equal-weight all stocks within a given portfolio when calculating returns for the portfolio.

3.2.2 Variable Measurement

The capital stock, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). Investment, I_{it}, is capital expenditures (CAPX) minus sales of property, plant, and equipment

(SPPE). We set the sales of property, plant, and equipment to be zero if item SPPE is missing. The capital depreciation rate, δ_{it}, is the amount of depreciation (DP) divided by the capital stock. Output, Y_{it}, is sales (SALE). Total debt, B_{it+1}, is long-term debt (DLTT) plus short term debt (DLC). Market leverage, w_{it}, is the ratio of total debt to the sum of total debt and the market value of equity. The tax rate, τ_t, is the statutory corporate income tax from the Commerce Clearing House's annual publications. Both stock and flow variables in Compustat are recorded at the end of year t. But in the model stock variables dated t are measured at the beginning of year t and flow variables dated t are over the course of year t. We take, for example, for the year 2003 any beginning-of-period stock variable K_{i2003} from the 2002 balance sheet and I_{i2003} from the 2003 income or cash flow statement.

Firm-level corporate bond data are rather limited, and few or even none of the firms in several testing portfolios have corporate bond returns. To measure the pre-tax corporate bond returns in a broad sample, we follow Blume, Lim, and MacKinlay (1998) to impute the credit ratings for firms with no crediting rating data in Compustat, and assign the corporate bond returns for a given credit rating (from Ibbotson Associates) to the firms with the same credit ratings.[2] Portfolio corporate bond returns are equal-weighted across firms in a given portfolios.

[2]Liu, Whited, and Zhang (2009) describe in detail the imputation procedure. Specifically, we first estimate an ordered probit model that relates credit ratings to observed explanatory variables. The model is estimated using all the firms that have data on credit ratings (Compustat annual item SPLTICRM). We then use the fitted value to calculate the cutoff value for each credit rating. For firms without credit ratings we estimate their credit scores using the coefficients estimated from the ordered probit model and impute credit ratings by applying the cutoff values of different credit ratings. We assign the corporate bond returns for a given credit rating from Ibbotson Associates to all the firms with the same credit ratings. The ordered probit model contains the following explanatory variables: interest coverage, the ratio of operating income after depreciation (item OIADP) plus interest expense (item XINT) to interest expense; the operating margin, the ratio of operating income before depreciation (item OIBDP) to sales (item SALE), long-term leverage, the ratio of long-term debt (item DLTT) to assets (item AT); total leverage, the ratio of long-term debt plus debt in current liabilities (item DLC) plus short-term borrowing (item BAST) to assets; the natural logarithm of the market value of equity (item PRCC_C times item CSHO) deflated to 1973 by the consumer price index; as well as the market beta and residual volatility from the market regression. We estimate the beta and residual volatility for each firm in each calendar year with at least 200 daily returns from CRSP. We adjust for nonsynchronous trading with one leading and one lagged values of the market return.

3.2.3 Timing

Momentum portfolios are rebalanced monthly, but variables from accounting statements are available annually.[3] Aligning the timing of stock returns of momentum portfolios with the timing of their investment returns is intricate because the composition of the momentum portfolios changes monthly. The difficulty in measuring economic fundamentals for momentum portfolios should, ex ante, go against our effort in identifying the fundamental driving forces underlying momentum profits. Also, any timing misalignment should have less impact on the average returns of momentum portfolios than on the dynamics of momentum profits. And the former is the focus of our study.

We design a more elaborate procedure than Liu, Whited, and Zhang's (2009) procedure for earnings surprises deciles. We construct *monthly* levered investment returns of a momentum portfolio from its *annual* accounting variables to match with the portfolio's monthly stock returns. Consider the loser decile. In any given month we have six sub-portfolios for the loser decile because of the six-month holding period. For instance, for the loser decile in July of year t, the first sub-portfolio is formed at the end of January of year t based on the prior six-month return from July to December of year $t-1$. Skipping the month of January of year t, this sub-portfolio's holding period is from February to July of year t. The second sub-portfolio is formed at the end of February of year t, based on the prior six-month return from August of year $t-1$ to January of year t, and its holding period is from March to August of year t. The last (sixth) sub-portfolio is formed at the end of June of year t, and its holding period is from July to December of year t.

Our procedure contains three steps. The first, and the most important step in our procedure is to determine the timing of firm-level characteristics. This step is done at the sub-portfolio level.

[3] We have explored the use of quarterly Compustat data. The results on matching average returns of momentum portfolios are largely similar to those obtained with annual Compustat data (not reported). We opt to use annual Compustat data for several reasons. First, doing so provides a longer sample starting from 1963. In contrast, because of the data availability of quarterly property, plant, and equipment, the quarterly sample can only start from 1977. Second, quarterly data display strong seasonality that can affect the dynamic properties of momentum portfolios. A common way of controlling for seasonality is to average the quarterly observations within a given year. But doing so is largely equivalent to using annual Compustat data. Finally, the annual dataset is of higher quality than the quarterly dataset because quarterly accounting statements are not required by law to be audited by an independent auditor.

The general principle is to combine the holding period information with the time interval from the midpoint of the current fiscal year to the midpoint of the next fiscal year to determine from which fiscal yearend we take firm-level characteristics. We do so because in Compustat, stock variables are measured at the end of the fiscal year and flow variables are realized over the course of the fiscal year. As such, the investment returns constructed from annual accounting variables go roughly from the midpoint of the current fiscal year to the midpoint of the next fiscal year. For firms with December fiscal yearend, for example, the midpoint time interval is from July of year t to June of year $t+1$. For firms with June fiscal yearend, the time interval is from January to December of year $t+1$.

Figure 1 illustrates the timing of firm-level characteristics for firms with December fiscal yearend.[4] Take, for example, the first sub-portfolio of the loser decile in July of year t. As noted, the sub-portfolio's holding period is from February of year t to July of year t. For firms in this sub-portfolio with December fiscal yearend, the first five months (February to June) lie to the left of the applicable time interval. For these five months we use accounting variables at the fiscal yearend of t to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of $t-1$ to measure economic variables dated t in the model.

However, for the last month in the holding period (July), because the month is within the time interval, we use accounting variables at the fiscal yearend of $t+1$ to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of t to measure economic variables dated t in the model. For the firms with December fiscal yearend in the sixth sub-portfolio of the loser decile in July of year t, all the holding period months (July to December of year t) lie within the applicable time interval. As such, we use accounting variables at the fiscal yearend of $t+1$ to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of t to measure economic variables dated t in the model. We apply the same general principle to firms with non-December fiscal yearend (see Appendix A for more details).

[4] In the Compustat sample from 1961 to 2009, the five most frequent months in which firms end their fiscal year are December (60.4%), June (8.7%), September (6.9%), March (5.3%), and January (3.9%).

The second step in our procedure is to construct various components of the levered investment returns at the sub-portfolio level. For each month we calculate sub-portfolio characteristics for a given sub-portfolio by aggregating firm characteristics over the firms in the sub-portfolio. This cross-sectional aggregation follows the practice in Fama and French (1995). For example, sub-portfolio investment-to-capital for month t, I_{it}/K_{it}, is the sum of investment for all the firms within the sub-portfolio in month t divided by the sum of capital for the same set of firms in month t. Other components such as Y_{it+1}/K_{it+1} and I_{it+1}/K_{it+1} are calculated analogously. Because portfolio composition changes from month to month at the sub-portfolio level, the portfolio characteristics also change from month to month.

The final step in our procedure is to construct the levered investment returns for a given testing portfolio to match with its stock returns. Continue to use the loser decile as an example. After obtaining the decile's sub-portfolio characteristics, for each month we take the cross-sectional averages of these characteristics over the six sub-portfolios to obtain the characteristics for the loser decile for that month. we then use these characteristics to construct the investment returns for each month for the loser decile using equation (3). The investment returns are in annual terms but vary monthly (because, as noted, the sub-portfolio characteristics change monthly). After obtaining firm-level corporate bond returns from Blume, Lim, and MacKinlay's (1998) imputation procedure, we construct portfolio bond returns for a testing portfolio in the same way as portfolio stock returns. We equal-weight all firm-level corporate bond returns within a given portfolio. Finally, we construct levered investment returns at the portfolio level using equation (5).

4 Empirical Results

To set the background, we first report the tests of the CAPM and the Fama-French model in Section 4.1. We then use the investment-based expected stock return model to explain average momentum profits in Section 4.2. Finally, we examine the dynamics of momentum profits in Section 4.3.

4.1 Descriptive Statistics

Panel A of Table 1 reports the tests of the CAPM and the Fama-French model for the ten momentum deciles. The average return increases monotonically from the loser decile to the winner decile. The winner-minus-loser decile earns an average return of 17.4% per annum, which is more than seven standard errors from zero. The CAPM alpha and the Fama-French alphas of the winner-minus-loser portfolio are 17.0% and 19.2%, respectively, which are both more than eight standard errors from zero. Both models are strongly rejected by the Gibbons, Ross, and Shanken (1989, GRS) test. Panel B reports industry momentum profits. The average return goes from 11.0% per annum for the loser quintile to 20.2% for the winner quintile. The spread of 9.2% is more than three standard errors from zero. The CAPM alpha and the Fama-French alpha for the winner-minus-loser quintile are 9.2% and 9.4%, respectively, which are both more than 4.5 standard errors from zero.

Momentum profits are larger in small firms than in big firms (Panel C). The winner-minus-loser tercile in the small size tercile has a CAPM alpha of 10.2% per annum, which is larger than that in the big size tercile, 6.1%. The average return and the Fama-French alpha follow a similar pattern. From Panel D, the magnitude of momentum profits decreases with firm age. The average return, the CAPM alpha, and the Fama-French alpha in young firms are 12.1%, 12.0%, and 13.3%, which are higher than those in old firms, 5.1%, 5.0%, and 6.1%, respectively. Consistent with Lee and Swaminathan (2000), the magnitude of momentum profits increases with trading volume (Panel E). Momentum also increases with stock return volatility and cash flow volatility. From Panel F, the average return of the winner-minus-loser tercile increases from 6.6% in the low return volatility tercile to 13.7% in the high return volatility tercile. The CAPM alpha and the Fama-French alpha of the winner-minus-loser tercile are both lower in the low return volatility tercile than in the high return volatility tercile: 6.5% and 8.4% versus 13.6% and 15.2%, respectively. From Panel G, the results for the nine cash flow volatility and momentum portfolios are largely similar. Consistent with Asness (1997), momentum profits are stronger in growth firms than in value firms (Panel H).[5]

[5]In addition to the CAPM and the Fama-French model, we have also implemented the tests on the standard

4.2 Explaining Average Momentum Profits with the Investment-Based Model

4.2.1 Point Estimates and Overall Model Performance

Table 2 reports the GMM parameter estimates and tests of overidentification for each set of momentum portfolios. There are only two parameters: the adjustment cost parameter, a, and the capital's share, κ. The estimates of a, ranging between 2.8 and 4.8, are similar in magnitude across different sets of testing portfolios. The estimate is 3.1 for the industry momentum portfolios with a standard error of 2.2. All the other sets of testing portfolios deliver significantly positive estimates of a. The evidence implies that the adjustment cost function is increasing and convex in investment. The estimates of the capital's share, κ, are also similar across different sets of testing portfolios, ranging from 0.10 to 0.13. The κ estimates are precise with small standard errors no larger than 0.02. Overall, the parameter estimates seem reasonable, and are close to those obtained in prior studies.

The overidentification tests show that the investment-based model is not formally rejected with ten momentum deciles and with five industry momentum quintiles. The p-values of the tests are 0.10 and 0.11, respectively. However, the model is strongly rejected for the remaining six sets of momentum portfolios. This evidence suggests that our test design has sufficient power to reject the null hypothesis that all the individual alphas for a given set of momentum portfolios are jointly zero. This benefit results from our construction of monthly levered investment returns. In contrast, Liu, Whited, and Zhang (2009) fail to reject the investment-based model by constructing annual levered investment returns to match with annual stock returns.

Table 2 also shows that except for the cash flow volatility and momentum portfolios, the mean absolute errors (m.a.e. hereafter) from the investment-based model are smaller than those from the

consumption-CAPM. We use the pricing kernel implied by the power utility, $M_{t+1} = \rho(C_{t+1}/C_t)^{-\gamma}$, in which ρ is the time preference, γ is risk aversion, and C_t is annual per capita consumption of nondurables and services from the Bureau of Economic Analysis. The moment conditions are $E[M_{t+1}(r^S_{it+1} - r_{ft+1})] = 0$ and $E[M_{t+1}r_{ft+1}] = 1$, in which r^S_{it+1} is the stock return of testing portfolio i, and r_{ft+1} is the risk-free interest rate. The consumption-CAPM alpha is calculated as $E_T[M_{t+1}(r^S_{it+1} - r_{ft+1})]/E_T[M_{t+1}]$. Without showing the details, we can report that the consumption-CAPM results are largely similar to those for the CAPM and the Fama-French model. In particular, the winner-minus-loser consumption-alphas have a similar magnitude as the CAPM alphas and the Fama-French alphas. In addition, the time preference estimates are above two, and the risk aversion estimates are above 75.

CAPM and the Fama-French model. In particular, the m.a.e. of the momentum deciles is 0.8% per annum, which is lower than those from the CAPM (3.7%) and the Fama-French model (4.1%). The m.a.e. of the age and momentum portfolios is 1.2% in the investment-based model, which is smaller than those from the CAPM (3.5%) and the Fama-French model (3.7%). The results from the other sets of testing portfolios are largely similar. For the cash flow volatility and momentum portfolios, our model produces an m.a.e. of 4.1%, which is slightly larger than the m.a.e. from the CAPM (3.7%) and that from the Fama-French model (4.0%).

4.2.2 Alphas

Table 3 reports for each individual testing portfolio the alpha from the investment-based model, α_i^q, defined in equation (7). The levered investment returns are constructed using the parameter estimates in Table 2. We also report the t-statistics that test that a given α_i^q equals zero, using standard errors calculated from one-stage GMM.

From Panel A of Table 3, the alphas for the momentum deciles range from -1.5% per annum for the loser decile to 1.4% for the fifth decile. The winner-minus-loser decile has a small alpha of 0.4%, which is within 0.2 standard errors from zero. In terms of economic magnitude, this alpha is negligible compared to the large alphas from the CAPM (17.0%) and the Fama-French model (19.2%). Figure 2 shows the performance of the alternative models by plotting the average predicted returns of the momentum deciles against their average realized returns. If a model's performance is perfect, all the observations should lie exactly on the 45-degree line. From Panel A, the scatter plot from the investment-based model is closely aligned with the 45-degree line. In contrast, Panel B shows that the scatter plot from the Fama-French model is roughly horizontal. The evidence shows that the investment-based alphas do not vary systematically across the momentum deciles, in contrast to the Fama-French alphas. Across all testing portfolios, the scatter plots from the CAPM are largely horizontal (similar to those from the Fama-French model), and are omitted for brevity.

The investment-based model also fits well the industry momentum quintiles. From Panel B of

Table 3, the alphas range from −1.0% to 0.9% per annum, all of which are within 0.4 standard errors from zero. The winner-minus-loser quintile has a small alpha of 0.4%, which is within 0.2 standard errors from zero. This alpha is smaller than those from the traditional models by an order of magnitude: 9.2% from the CAPM and 9.4% from the Fama-French model. Figure 3 further confirms the superior fit of the investment-based model for the industry momentum portfolios.

Panel C of Table 3 reports larger alphas for the nine size and momentum portfolios. The individual alphas range from −4.0% to 5.8% per annum. The winner-minus-loser alphas are −0.9%, −1.0%, and −0.8% across the small, median, and big size terciles, and are all within one standard error from zero. These alphas are all lower in magnitude than those from the CAPM: 10.2% in the small tercile, 7.9% in the median tercile, and 6.1% in the big tercile, as well as those from the Fama-French model: 11.6%, 9.6%, and 7.8%, respectively. Panel A of Figure 4 shows that the scatter plot from the investment-based model is largely aligned with the 45-degree line, but the fit is worse than the fit for the momentum deciles and the industry momentum quintiles. In contrast, the scatter plot from the Fama-French model is largely horizontal (Panel B).

Panel D of Table 3 reports somewhat smaller individual alphas but larger winner-minus-loser alphas for the firm age and momentum portfolios. The individual alphas range from −2.4% to 2.5% per annum, and the winner-minus-loser alphas are 2.5%, −1.4%, and −3.6% across the young, median, and old firm age terciles. However, the winner-minus-loser alphas are still smaller in magnitude than those from the CAPM and the Fama-French model. The scatter plots in Figure 5 confirm the clear difference in performance between the investment-based model and the traditional models. From Panel E of Table 3, the individual alphas from the investment-based model across the nine volume and momentum portfolios range from −1.9% to 4.7% per annum. However, despite their large magnitude, none of the alphas are significant at the 5% level, likely due to measurement errors in portfolio characteristics. As such, we only emphasize the economic magnitude of the alphas, instead of their statistical insignificance. More important, the individual alphas do not vary systematically with short-term prior returns. The winner-minus-loser alphas are −1.8%, −0.1%, and -0.3% in the low, median, and high volume terciles, respectively. These alphas are again all lower in magnitude than those from the CAPM and the Fama-French model. Figure 6 illustrates the model fit graphically for volume and momentum portfolios.

From Panel F of Table 3, the individual alphas from the investment-based model across the stock return volatility and momentum portfolios are large, ranging from -3.7% to 3.6% per annum. The winner-minus-loser alphas are $-1.9\%, 0.4\%$, and -2.9% in the low, median, and high return volatility terciles, respectively, which are again lower in magnitude than those from the traditional models. Figure 7 illustrates the investment-based model's fit for the return volatility and momentum portfolios in comparison with the CAPM and the Fama-French model. Although the individual alphas can sometimes be large, the alphas do not vary systematically with prior short-term returns. In contrast, the scatter plot from the Fama-French model is largely horizontal.

Panel G of Table 3 shows that the fit of the investment-based model for the cash flow volatility and momentum portfolios leaves much to be desired. The individual alphas range from -6.9% to 6.9% per annum. Five out of nine portfolios have individual alphas with magnitude higher than 5%, and an additional portfolio has an alpha larger than 3.0%. Although still smaller in magnitude than those from the CAPM and the Fama-French model, the winner-minus-loser alphas are quite large: -1.7%, -3.6%, and -5.7% in the low, median, and high cash flow volatility terciles, respectively. From Figure 8, although the overall fit of the investment-based model is still better than that for the Fama-French model, the individual alphas from the investment-based model are the largest in magnitude among the different sets of momentum portfolios.

From Panel H of Table 3, the individual alphas for the book-to-market and momentum portfolios are also large, ranging from -6.0% to 5.3% per annum. Four out of nine portfolios have alphas with magnitude larger than 4.5%. Although smaller in magnitude than those from the CAPM and the Fama-French model, the winner-minus-loser alphas are 4.2%, 0.0%, and -7.1% in the low, median, and high book-to-market terciles. Figure 9 shows that the investment-based model still outperforms the Fama-French model overall, despite the large individual alphas.

4.2.3 Sources of Momentum Profits

What drives our estimation results? The investment return equation (3) and the levered investment return equation (5) suggest several cross-sectional determinants of expected stock returns. Each determinant comes from a specific component of the levered investment return.

The first source is investment-to-capital, I_{it}/K_{it}, in the denominator of the investment return. The second source is the growth rate of marginal q, defined as $q_{it} \equiv 1 + (1 - \tau_t)a(I_{it}/K_{it})$. This term can be viewed as the "capital gain" portion of the investment return because marginal q is related to the stock price. The third source is the marginal product of capital, Y_{it+1}/K_{it+1}, in the numerator of the investment return. The fourth source is the depreciation rate, δ_{it+1}. Collecting terms involving δ_{it+1} in the numerator of the investment return shows a negative relation between δ_{it+1} and the expected return. The fifth source is the market leverage, w_{it}, in the levered investment return, which shows a positive relation between w_{it} and the expected return. The sixth source is the after-tax corporate bond return, r^{Ba}_{it+1}. In all, all else equal, firms with low I_{it}/K_{it}, high expected q_{it+1}/q_{it}, high expected Y_{it+1}/K_{it+1}, low expected δ_{it+1}, high w_{it}, and low expected r^{Ba}_{it+1} should earn higher expected stock returns at time t.

To dig deeper behind our estimation results, Table 4 reports the averages of four components of the levered investment returns across the testing portfolios including $I_{it}/K_{it}, q_{it+1}/q_{it}, Y_{it+1}/K_{it+1}$, and w_{it}. The averages of the depreciate rate and the after-tax corporate bond return are largely flat across the momentum portfolios, and their impact on the estimation results is small (not reported). In the case of the growth rate of q, because q involves the unobserved adjustment cost parameter, a, we instead report the average growth rate of investment-to-capital, $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$.

Panel A of Table 4 shows that the winner decile has a substantially higher growth rate of investment-to-capital, $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$, than the loser decile: 1.16 versus 0.83 per annum. The spread of 0.33 is highly significant. The winner decile also has a higher next-period sales-to-capital, Y_{it+1}/K_{it+1}, than the loser decile: 4.19 versus 3.18, and the spread of 1.01 is more than 5.5 standard errors from zero. Both components go in the right direction to explain the expected stock returns across the momentum deciles. However, going in the wrong direction, the winner decile has significantly higher current-period investment-to-capital, I_{it}/K_{it}, than the loser decile, 0.26 versus 0.22. However, the magnitude of the spread is small. The winner decile also has lower market leverage than the loser decile, and the spread of -0.12 is more than seven standard errors from zero. The basic patterns for industry momentum are largely similar (Panel B).

The remainder of Table 4 shows how the economically important cross-sectional spreads in $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$ and Y_{it+1}/K_{it+1} between winners and losers vary across terciles formed on size, firm age, trading volume, stock return volatility, cash flow volatility, and book-to-market. From Panel C, the market leverage spread does not vary across the size terciles. However, the spread in the growth rate of investment-to-capital is higher in small firms than in big firms: 0.24 versus 0.14. The spread in sales-to-capital follows the same pattern: 0.83 versus 0.45. These variations across the size terciles go in the right direction in explaining expected stock returns. The spread in the current-period investment-to-capital is small across extreme momentum portfolios.

Panel D shows that the spread in the growth rate of investment-to-capital is only slightly higher in young firms than in old firms, 0.19 versus 0.15. However, going in the wrong direction in explaining expected stock returns, the next-period sales-to-capital spread across the momentum terciles is lower in the young firm tercile than that in the old firm tercile: 0.34 versus 0.52. The evidence helps explain why the winner-minus-loser alphas are large across the firm age terciles. From Panel E, the spread in the growth rate of investment-to-capital across the momentum terciles increases with trading volume: 0.14 in the low volume tercile and 0.23 in the high volume tercile. However, albeit not monotonic, the sales-to-capital spread moves in the wrong direction: 0.65 in the low volume tercile, 0.34 in the median tercile, and 0.49 in the high volume tercile. Also going in the wrong direction, the market leverage spread is -0.05 in the low volume tercile but -0.11 in the high volume tercile.

Panel F shows that the spread in the growth rate of investment-to-capital across the momentum terciles increases with stock return volatility: 0.14 in the low volatility tercile and 0.30 in the high volatility tercile. This variation goes in the right direction in explaining expected stock returns. The sales-to-capital spread and the market leverage spread are largely flat across the return volatility terciles. The spreads in both the growth rate of investment-to-capital and sales-to-capital increase with cash flow volatility (Panel G). However, the spread in investment-to-capital growth is only somewhat higher in the high volatility tercile than in the low volatility tercile: 0.23 versus 0.16. The evidence helps explain the large winner-minus-loser alphas in the cash flow volatility and momentum portfolios. The same pattern also holds for the book-to-market and momentum portfolios (Panel H). In addition, the sales-to-capital spread is largely flat across the book-to-market terciles.

4.2.4 Accounting for Average Momentum Profits

To quantify the role of each component in explaining momentum profits, we conduct comparative static experiments. We set a given component to its cross-sectional average in each month at the sub-portfolio level. We use the parameter estimates in Table 2 to reconstruct levered investment returns, while fixing all the other components. We examine the resulting change in the magnitude of the alphas. A large change would mean that the component in question is quantitatively important.

Table 5 shows that, on balance, the growth rate of marginal q is the most important source of momentum, and the sales-to-capital ratio is the second most important. From Panel A, without the cross-sectional variation in the growth rate of q, the winner-minus-loser alpha inflates to 11.4% per annum from the level of 0.4% in the benchmark estimation. Eliminating the cross-sectional variation in sales-to-capital gives rise to a winner-minus-loser alpha of 7.1%. Because market leverage goes to the wrong direction to explain the expected returns, eliminating its cross-sectional variation across the momentum deciles reduces the winner-minus-loser alpha slightly to 0.3%. The industry momentum results are largely similar (Panel B).

The remainder of Table 5 quantifies the role of the growth rate of q and sales-to-capital in the double sorted momentum portfolios. From Panel C, fixing the growth rate of q to its cross-sectional averages produces alphas of 6.5%, 4.9%, and 3.1% per annum for the winner-minus-loser tercile across the size terciles. Eliminating the cross-sectional variation in the next-period sales-to-capital generates alphas of 3.4%, 2.4%, and 2.1%, respectively. In contrast, in the benchmark estimation these alphas are $-0.9\%, -1.0\%$, and -0.8%, respectively. From Panel D, fixing the growth rate of q to its cross-sectional averages produces winner-minus-loser alphas of 8.8% and 3.9% in the young and median age terciles, which are larger in magnitude than 2.5% and -1.4% in the benchmark estimation. Panel E also shows that the growth rate of q and the next-period sales-to-capital are the two most important sources of momentum in the trading volume and momentum portfolios. From Panel F, because the sales-to-capital spread is largely flat across the return volatility terciles, eliminating its cross-sectional variation has a small effect on the alphas.

The growth rate of q is also important for explaining the cash flow volatility and momentum portfolios. From Panel G, without its cross-sectional variation, the individual alphas and the winner-minus-loser alphas both increase in magnitude. However, despite its small spread across the portfolios, investment-to-capital has a surprisingly large effect. Without its cross-sectional variation, we observe a winner-minus-loser alpha of -13.7% in the high cash flow volatility tercile. The evidence suggests that nonlinearity in the investment-based model goes beyond the cross-sectional means of the levered investment return components: because of Jensen's inequality, a change in the alphas can also result from the change in cross-sectional volatility of a given component.

4.3 The Dynamics of Momentum Profits

So far we have only focused on the average returns of momentum portfolios. However, several stylized facts of momentum involve its dynamics. The dynamics of momentum are particularly interesting because the model parameters are estimated only based on average momentum profits. As such, the dynamic properties of momentum can serve as additional diagnostics on the model performance.

4.3.1 Reversal of Momentum Profits in Long Horizons

Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996) show that momentum profits are short-lived. In particular, Chan et al.'s Table II shows that the winner-minus-loser return is on average 15.4% per annum at the one-year horizon, but is close to zero during the second year and the third year after portfolio formation. Table 6 replicates their evidence in our sample. From the first row in each panel, the winner-minus-loser return is on average 9.2% over the six-month period, 11.0% for the first year, −5.9% for the second year, and −5.4% for the third year after portfolio formation. As such, instead of short-term continuation, we observe reversal at longer horizons.

More important, the second row in each panel of Table 6 shows that the investment-based model is consistent with reversal at long horizons. In particular, the levered investment return for the winner-minus-loser decile is 8.6% for the six-month period and 12.1% for the first year after portfolio formation. However, the predicted momentum profits turn negative afterward: −1.9% for the second year and −4.9% for the third year after portfolio formation.

The remaining three rows in each panel of Table 6 show that it is the expected growth component of levered investment returns that drives the short-lived nature of momentum profits. Using the average growth rate of q to measure expected growth, we observe that it starts at 10% for the first six-month period, weakens to 7% at the one-year horizon, and turns negative afterward. Using the average growth rate of investment-to-capital yields a similar pattern: 34% at the six-month horizon, 24% at the one-year horizon, −8% for the second year, and −11% for the third year after portfolio formation.[6] In contrast, the sales-to-capital ratio is more persistent: it starts at 1.02 for the first six-month period and remains at 0.44 for the third year after portfolio formation.

4.3.2 The Failure of the Traditional Asset Pricing Models

Jegadeesh and Titman (1993) show that the CAPM cannot explain momentum because the market beta of the winner-minus-loser decile is weakly negative. Fama and French (1996) show that their

[6] Using average dividend, investment, and sales growth rates in the future to measure expected growth, Liu and Zhang (2008, Figure 2) also show that winners have temporarily higher expected growth than losers.

three-factor model cannot explain momentum either because the loser decile tends to load positively, and the winner decile tends to load negative on their value factor. Table 1 replicates these findings: The CAPM alpha and the Fama-French alpha for the winner-minus-loser decile are 17.0% and 19.2%, respectively, both of which are more than eight standard errors from zero. In untabulated results, we find that the winner-minus-loser decile has a weakly positive market beta of 0.08, which is within one standard error of zero. In the Fama-French regression, the winner-minus-loser decile has a weakly negative market beta of -0.08 ($t = -1.05$), an insignificantly positive SMB beta of 0.22 ($t = 1.12$), and a significantly negative HML beta of -0.40 ($t = -2.03$).

To see if the investment-based model explains the failure of the traditional factor models, Table 7 performs the CAPM and the Fama-French regressions using levered investment returns of the momentum deciles as the dependent variables. From the contemporaneous regressions in Panel A, the winner-minus-loser alphas are 16.6% and 16.2% in the CAPM and in the Fama-French model, respectively, consistent with the evidence based on stock returns. However, inconsistent with the stock returns evidence, the winner-minus-loser betas are significantly positive: 0.83 in the CAPM and 0.73 in the Fama-French model, both of which are more than 2.4 standard errors from zero.

Lamont (2000) and Lettau and Ludvigson (2002) argue that investment lags (time lags between investment decision and actual investment expenditure) can temporally shift the correlations between investment returns and stock returns.[7] Liu, Whited, and Zhang (2009) show that the contemporaneous correlation between stock returns and investment returns for the earnings surprises, book-to-market, and corporate investment portfolios is negative, but that the correlation between one-year lagged stock returns and investment returns is positive. We verify in untabulated results that a similar correlation structure also holds for the momentum deciles.

To see how the temporal shift in the correlation structure affects the factor regressions, Panel B

[7] Consider a one-year lag. A discount rate fall in year t increases investment only in year $t+1$. As the discount rate falls, stock returns rise in year t, and investment growth as well as investment returns increase in year $t+1$. As such, lagged stock returns are positively correlated with investment returns. The discount rate fall in year t also means lower stock returns in year $t+1$, giving rise to negative correlations between stock returns and investment returns in year $t+1$.

of Table 7 regresses levered investment returns of the momentum deciles on the six-month lagged factor returns. The winner-minus-loser alphas are unaffected. The CAPM beta of the winner-minus-loser decile becomes insignificantly negative, -0.21 ($t = -0.88$), and its market beta in the Fama-French model becomes insignificantly positive, 0.18 ($t = 0.75$). However, the HML beta remains insignificantly positive, whereas the HML beta is significantly negative in stock returns.

4.3.3 Market States and Momentum

Momentum profits depend on market states. Cooper, Gutierrez, and Hameed (2004) show that the average winner-minus-loser decile return during the six-month period after portfolio formation is 0.93% per month following non-negative prior 36-month market returns (UP markets), but is −0.37% following negative prior 36-month market returns (DOWN markets). There is also evidence that the subsequent reversal of momentum profits is stronger following DOWN markets.

The first six rows in each panel of Table 8 largely replicate Cooper, Gutierrez, and Hameed's (2004) evidence in our sample. For example, if we categorize the UP and DOWN markets based on the value-weighted CRSP index returns over the prior 12-month period, Panel A shows that the winner-minus-loser decile return over the six-month period after portfolio formation is on average 10.7% following the UP markets but 3.8% following the DOWN markets. Changing the holding period from six months to 12 months makes the evidence even stronger: the winner-minus-loser return is on average 13.7% following the UP markets versus 1.6% following the DOWN markets.

The investment-based model fails to explain the procyclicality of momentum profits. From rows seven to 12 in Panels A and B of Table 8, if anything, the investment-based model predicts that momentum profits are larger in DOWN markets. In particular, Panel B shows that with market states based on prior 12-month market returns, the predicted winner-minus-loser return over the 12-month period after portfolio formation is 10.8% following the UP markets, but 16.8% following the DOWN markets. The temporal shift in the correlation structure between stock returns and investment returns is partially responsible for this counterfactual result. As noted, investment lags cause stock returns to lead investment returns by six to 12 months. Panel B of Table 8 shows that if we lead the levered investment returns by 12 months, the predicted winner-minus-loser returns over the 12-month period after portfolio formation are weakly procyclical: 12.8% following the UP markets and 11.3% following the DOWN markets. However, the degree of procyclicality predicted from the model substantially falls short of that observed in the data.

Panels C and D of Table 8 show that, consistent with Cooper, Gutierrez, and Hameed (2004), reversal of momentum profits is stronger following the DOWN markets. Without describing the results in detail, we can report that the investment-based model is more consistent with this evidence.

4.3.4 Long Run Risks in Investment Returns

Bansal, Dittmar, and Lundblad (2005) show that aggregate consumption risks in cash flows help explain the average return spread across momentum portfolios. Panel A of Table 9 replicates their based results on our 1963–2008 sample. Specifically, we perform the following regression:

$$g_{i,t} = \gamma_i \left(\frac{1}{K} \sum_{k=1}^{K} g_{c,t-k} \right) + u_{i,t}, \tag{11}$$

in which $K = 8$, $g_{i,t}$ is demeaned log real dividend growth rates on momentum decile i, and $g_{c,t}$ is demeaned log real growth rate of aggregate consumption.[8] The projection coefficient, γ_i, measures the cash flow's exposure to the long-term growth rate of aggregate consumption (long run risk). Consistent with Bansal, Dittmar, and Lundblad (2005), winners have higher long run risk than losers: 15.9 versus 0.3. The cash flow risk spread between the two extreme deciles is 17.1, albeit with a large standard error of 13.5. Winners also have a higher cash flow growth rate than losers: 2.9% versus −2.1% per annum. The growth rate spread of 4.5% again has a large standard error of 3.5%.[9]

[8]Aggregate consumption is seasonally adjusted real per capital consumption of nondurables and services. The quarterly real per capita consumption data are from the NIPA tables from the Bureau of Economic Analysis. We use personal consumption expenditures (PCE) deflator from the NIPA tables to convert nominal variables to real variables. Portfolio dividend growth rates are calculated in exactly the same way as described in Bansal, Dittmar, and Lundblad (2005, p. 1648–1649). In particular, we take into account stock repurchases in the calculation of dividends. We also use a trailing four-quarter average of the quarterly cash flows to construct the quarterly dividends adjusted for seasonality.

[9]Because of a few observations with negative cash flows (dividends plus net repurchases), which we treat as missing, the projection coefficient, γ_i, for the winner-minus-loser decile is not identical to the spread in γ_i between winners and losers. For the same reason, the cash flow growth rate of the winner-minus-loser decile is not exactly the growth

In Panel B of Table 9, we document similar, if not stronger evidence of long run risks in investment returns. Specifically, based on the investment return in equation (3), we define a new fundamental cash flow measure as $D^{\star}_{it+1} \equiv (1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right] + \tau_{t+1}\delta_{it+1}$. To see its economic interpretation, we note that the denominator of the investment return equals marginal q. As such, equation (3) implies that the ratio of $D^{\star}_{it+1}/\left[1+(1-\tau_t)a\frac{I_{it}}{K_{it}}\right]$ is analogous to the dividend yield, and that the remaining piece of the investment return, $(1-\delta_{it+1})\left[1+(1-\tau_{t+1})a\frac{I_{it+1}}{K_{it+1}}\right]/\left[1+(1-\tau_t)a\frac{I_{it}}{K_{it}}\right]$ is analogous to the rate of capital gain.

The first column in Panel B of Table 9 shows that the fundamental cash flow growth rate has higher long run consumption risk in winners than in losers: 13.2 versus 5.2. The spread of 8.0 is significant with a standard error of 3.2. The fundamental cash growth rates are also higher in winners than in losers: 17.1% versus -2.5%, and the spread is highly significant. The remainder of Panel B provides additional evidence that winners have significantly higher cash flow risks than losers in the sales-to-capital growth and in the growth of depreciation rate, but not in the growth rate of squared investment-to-capital. This evidence is intriguing because it connects long run risk in dividends documented by Bansal, Dittmar, and Lundblad (2005) to the long run risks in the sales-to-capital growth and in the growth of depreciation rate via firms' optimal investment conditions. As such, our evidence helps explain why winners have higher long run risk than losers.

5 Conclusion

We offer an investment-based explanation of momentum profits. The neoclassical theory of investment suggests that expected stock returns are connected with expected marginal benefits of investment divided by current-period marginal costs of investment. Using GMM, we show that the investment-based model matches reasonably well with the expected stock returns across a wide array of momentum portfolios. Intuitively, winners have higher expected growth of investment-

rate spread between winners and losers. In particular, if we do not include net repurchases into the calculation of cash flows, then the projection coefficients for losers, winners, and the winner-minus-loser decile are 0.8, 12.1, and 11.3, and the cash flow growth rates are $-2.0\%, 1.8\%$, and 3.8% per annum, respectively. The γ_i for the winner-minus-loser decile has a large standard error of 12.1, and the growth rate spread has a large standard error of 3.2%.

to-capital and expected sales-to-capital (two major components of expected marginal benefits of investment), and consequently earn higher expected stock returns than losers. Differing from the bulk of the momentum literature, our framework does not assume any form of behavioral biases. On balance, our results suggest that the momentum effect can be understood in the context of a model in which markets are efficient and managers are maximizing the market value of equity.

It is important to point out that the fundamental equation of asset pricing, $E[M_{t+1}r^S_{t+1}] = 1$, holds in our framework. While the investment-based approach is immune to consumption measurement errors that plague most consumption-based studies, we do not identify the stochastic discount factor, M_{t+1}. Our risk story is indirect. Firm A with high expected growth of investment-to-capital and high expected marginal productivity must be riskier than firm B with low expected growth of investment-to-capital and low expected marginal productivity. Otherwise, firm A would have a lower cost of equity and invest more than firm B today, so as to make the spread in expected investment-to-capital growth between the two firms disappear. Although our long run risk tests go in the right direction, more work on linking macroeconomic risk to momentum profits is needed.

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A Details of Timing Alignment

As noted in Section 3.2.3, we align the timing of firm-level characteristics with the timing of stock returns at the sub-portfolio level. Our basic idea is to combine the holding period information with the time interval from the midpoint of the current fiscal year to the midpoint of the next fiscal year to determine from which fiscal yearend take take firm-level characteristics. Section 3.2.3 describes the timing convention for firms with December fiscal yearend. This appendix details how we handle firms with non-December fiscal yearend.

Panel A of Figure A.1 shows the timing of firm-level characteristics for firms with June fiscal yearend. Their applicable midpoint time interval is from January to December of year $t + 1$. For those firms in the first sub-portfolio of the loser decile in July of year t, all the holding period months (February to July of year t) lie to the left of the time interval. As such, we use accounting variables at the fiscal yearend of t to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of $t-1$ to measure economic variables dated t in the model. For firms with June fiscal yearend in the sixth sub-portfolio of the loser decile in July of year t, their holding period months (July to December of year t) again lie to the left of the applicable time interval. As such, their timing is the exactly same as that for the firms in the first sub-portfolio.

Panel B of Figure A.1 shows the timing of firm-level characteristics for firms with September fiscal yearend. Their midpoint time interval is from April of year $t+1$ to March of year $t+2$. For those firms in the first sub-portfolio of the loser decile in July of year $t+1$, two months out of the holding period (February and March of year $t+1$) lie to the left of the time interval, and the remaining four months (from April to July) lie within the time interval. For February and March of year $t+1$, we use accounting variables at the fiscal yearend of t to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of $t-1$ to measure economic variables dated t in the model. For the months from April to July of $t+1$, we use accounting variables at the fiscal yearend of $t+1$ to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of t to measure economic variables dated t in the model. For the firms in the sixth sub-portfolio of the loser decile in July of year $t+1$, all the holding period months (from July to December of $t+1$) lie within the midpoint time-interval. As such, we use accounting variables at the fiscal yearend of $t+1$ to measure economic variables dated $t+1$ in the model, and use accounting variables at the fiscal yearend of t to measure economic variables dated t in the model.

Table 1 : Descriptive Statistics for Testing Portfolios

For all testing portfolios, we report (in annual percent) average stock returns, r^S, stock return volatilities, σ^S, the CAPM alphas from monthly market regressions, α, the alphas from monthly Fama-French (1993) three-factor regressions, α_{FF}, and their t-statistics adjusted for heteroscedasticity and autocorrelations. m.a.e. is the mean absolute error for a given set of testing portfolios. W−L is the winner-minus-loser portfolio. The p-values (p-val) in the last column in each panel are from the Gibbon, Ross, and Shanken (1989) tests of the null that the alphas for a given set of testing portfolios are jointly zero. Section 3.2 describes the testing portfolios in detail.

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L	m.a.e.	p-val
r^S	3.39	8.49	10.45	11.66	12.69	13.49	13.81	15.47	17.56	20.75	17.36		
σ^S	25.56	20.95	19.24	18.39	18.06	18.07	18.59	19.88	21.99	26.97	16.22		
α	−9.50	−3.35	−0.98	0.41	1.48	2.23	2.40	3.72	5.32	7.45	16.95	3.68	0.00
$[t]$	−4.32	−1.77	−0.55	0.25	0.93	1.43	1.56	2.30	2.91	2.99	8.49		
α_{FF}	−11.51	−6.37	−4.28	−2.79	−1.52	−0.48	−0.08	1.89	4.23	7.64	19.15	4.08	0.00
$[t]$	−7.49	−5.69	−4.08	−3.14	−1.82	−0.67	−0.14	3.23	5.19	5.18	8.22		

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L	m.a.e.	p-val
r^S	11.04	13.38	14.25	18.19	20.20	9.16		
σ^S	21.77	21.10	20.84	20.98	21.71	12.80		
α	−0.62	1.68	2.56	6.51	8.53	9.15	3.98	0.00
$[t]$	−0.27	0.80	1.27	3.08	3.84	4.84		
α_{FF}	−4.23	−1.67	−0.83	3.11	5.17	9.40	3.00	0.00
$[t]$	−2.74	−1.80	−0.88	3.34	3.50	4.55		

Panel C: Nine size and momentum portfolios

	Small				2				Big					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
r^S	8.20	14.14	18.71	10.51	8.34	12.76	16.36	8.01	8.38	11.02	14.55	6.17		
σ^S	22.27	19.24	22.93	8.68	22.31	18.80	22.44	11.00	19.55	16.27	19.24	11.95		
α	−3.69	3.05	6.47	10.16	−4.09	1.22	3.80	7.89	−3.35	0.03	2.74	6.09	3.16	0.00
$[t]$	−1.61	1.40	2.66	8.59	−2.35	0.82	2.38	5.73	−2.90	0.04	2.48	3.52		
α_{FF}	−7.50	−1.01	4.05	11.55	−6.24	−1.52	3.40	9.64	−3.94	−0.91	3.83	7.77	3.60	0.00
$[t]$	−6.41	−1.20	4.36	9.26	−4.59	−1.55	3.78	6.08	−2.87	−1.20	4.00	4.09		

Panel D: Nine firm age and momentum portfolios

	Young				2				Old					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
r^S	6.10	12.94	18.19	12.09	9.82	14.01	17.49	7.66	10.23	12.82	15.32	5.08		
σ^S	22.65	19.77	22.11	9.79	20.59	18.13	20.27	9.51	18.51	16.18	18.00	9.16		
α	−6.00	1.45	5.99	11.98	−1.77	2.91	5.80	7.57	−0.91	2.14	4.07	4.98	3.45	0.00
$[t]$	−2.44	0.70	2.53	9.24	−0.79	1.58	2.91	5.99	−0.49	1.52	2.80	3.84		
α_{FF}	−10.15	−2.39	3.19	13.34	−6.09	−0.86	2.83	8.92	−4.97	−1.30	1.15	6.12	3.66	0.00
$[t]$	−5.73	−1.66	2.12	10.60	−4.63	−0.78	2.70	7.04	−3.73	−1.32	1.21	4.76		

	Low				2				High					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
Panel E: Nine trading volume and momentum portfolios														
r^S	10.98	14.30	18.10	7.12	9.75	13.91	17.64	7.90	5.95	12.07	17.88	11.94		
σ^S	16.90	15.08	16.45	7.60	20.09	18.04	19.16	8.55	24.90	22.47	23.89	11.29		
α	0.70	4.26	7.67	6.97	−1.80	2.74	6.13	7.93	−7.01	−0.46	5.10	12.11	3.98	0.00
$[t]$	0.37	2.65	4.41	6.97	−0.84	1.57	3.37	6.36	−2.89	−0.22	2.11	7.46		
α_{FF}	−3.86	0.46	4.27	8.13	−6.12	−1.01	3.03	9.15	−10.85	−3.58	2.81	13.65	4.00	0.00
$[t]$	−2.82	0.41	3.67	7.78	−4.30	−0.88	2.57	7.42	−6.16	−2.37	1.81	8.20		
Panel F: Nine stock return volatility and momentum portfolios														
r^S	11.12	13.99	17.77	6.64	8.56	13.58	19.24	10.68	2.86	8.87	16.52	13.66		
σ^S	15.75	14.39	15.31	7.55	21.11	19.41	20.54	9.13	28.58	26.63	28.23	11.43		
α	0.90	3.95	7.40	6.50	−3.35	1.97	7.33	10.68	−10.89	−4.52	2.75	13.63	4.78	0.00
$[t]$	0.50	2.71	5.31	6.31	−1.69	1.10	4.14	9.66	−4.26	−1.85	1.01	8.22		
α_{FF}	−3.02	0.77	5.36	8.38	−6.90	−1.11	5.64	12.54	−12.31	−5.64	2.85	15.15	4.84	0.00
$[t]$	−2.65	0.81	6.20	8.66	−5.99	−1.41	7.36	10.05	−8.12	−5.70	1.97	7.93		
Panel G: Nine cash flow volatility and momentum portfolios														
r^S	10.14	13.68	17.87	7.73	9.03	13.63	18.56	9.53	6.46	11.75	17.92	11.46		
σ^S	18.92	16.06	19.31	10.61	20.68	17.98	21.55	10.45	24.25	20.92	25.40	10.89		
α	−1.18	3.00	6.34	7.52	−2.74	2.45	6.44	9.17	−6.09	−0.08	4.93	11.02	3.69	0.00
$[t]$	−0.66	2.12	3.87	5.33	−1.39	1.51	3.43	6.99	−2.74	−0.04	2.10	8.06		
α_{FF}	−4.52	0.03	4.43	8.94	−6.01	−0.73	5.02	11.03	−8.56	−2.69	4.37	12.93	4.04	0.00
$[t]$	−3.67	0.04	5.45	5.87	−5.02	−0.99	6.05	7.59	−7.58	−3.56	3.75	8.61		
Panel H: Nine book-to-market and momentum portfolios														
r^S	1.68	9.23	16.47	14.78	7.78	12.91	18.49	10.70	10.59	15.61	19.65	9.06		
σ^S	24.57	20.70	25.61	11.31	22.20	18.29	21.39	10.32	20.38	17.52	19.43	8.61		
α	−11.31	−2.94	3.29	14.60	−4.42	1.62	6.46	10.89	−0.72	5.01	8.44	9.17	4.92	0.00
$[t]$	−5.54	−1.99	1.48	8.52	−2.35	0.97	3.21	8.84	−0.33	2.47	3.94	7.62		
α_{FF}	−10.85	−2.29	4.93	15.78	−6.78	−1.46	4.14	10.92	−5.85	−0.30	3.61	9.46	4.47	0.00
$[t]$	−7.72	−2.91	3.90	7.86	−5.56	−1.84	5.13	7.65	−5.05	−0.32	3.82	7.58		

Table 2 : GMM Parameter Estimates and Tests of Overidentification

Results are from one-stage GMM with an identity weighting matrix. a is the adjustment cost parameter and κ is the capital's share. The standard errors ([ste]) are reported beneath the point estimates. χ^2, d.f., and p-val are the statistic, the degrees of freedom, and the p-value testing that the expected return errors across a given set of testing assets are jointly zero. m.a.e. is the mean absolute expected return error in annualized percent for a given set of testing portfolios.

	Momentum	Industry momentum	Size and momentum	Age and momentum	Volume and momentum	Return volatility and momentum	Cash flow volatility and momentum	Book-to-market and momentum
a	2.81	3.08	2.54	2.80	3.10	3.57	4.78	3.76
[ste]	0.96	2.19	0.72	0.94	0.87	0.77	1.09	1.03
κ	0.12	0.12	0.10	0.12	0.13	0.13	0.12	0.13
[ste]	0.02	0.02	0.01	0.01	0.01	0.02	0.02	0.01
χ^2	13.21	6.03	21.14	23.80	20.21	18.44	30.31	25.91
d.f.	8	3	7	7	7	7	7	7
p-val	0.10	0.11	0.00	0.00	0.01	0.01	0.00	0.00
m.a.e.	0.80	0.76	3.33	1.19	1.51	2.05	4.11	2.98

Table 3 : Alphas from the Investment-Based Expected Stock Return Model

The alphas (in annual percent) and t-statistics are from one-stage GMM with an identity weighting matrix. The moment conditions are $E\left[r_{it+1}^{S} - r_{it+1}^{Iw}\right] = 0$, in which r_{it+1}^{S} is the stock return, and r_{it+1}^{Iw} is the levered investment return. The alphas are calculated from $\alpha_i^q \equiv E_T\left[r_{it+1}^{S} - r_{it+1}^{Iw}\right]$, in which $E_T[\cdot]$ is the sample mean of the series in brackets. L denotes losers, W winners, and W−L the differences between the loser and winner portfolios.

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L
α^q	−1.50	0.37	1.01	0.87	1.39	0.64	−0.06	−0.63	−0.43	−1.07	0.44
$[t]$	−0.36	0.10	0.30	0.27	0.45	0.22	−0.02	−0.21	−0.13	−0.25	0.13

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L
α^q	0.44	0.58	−0.97	−0.92	0.88	0.44
$[t]$	0.15	0.21	−0.37	−0.36	0.32	0.19

Panel C: Nine size and momentum portfolios

	Small				2				Big			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
α^q	−3.06	−3.88	−3.98	−0.93	1.68	0.71	0.70	−0.98	5.79	5.26	4.96	−0.83
$[t]$	−0.77	−1.14	−1.02	−0.56	0.48	0.24	0.22	−0.56	1.82	2.03	1.70	−0.42

Panel D: Nine firm age and momentum portfolios

	Young				2				Old			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
α^q	−2.40	−0.40	0.06	2.46	0.60	0.99	−0.78	−1.38	2.05	1.89	−1.54	−3.59
$[t]$	−0.59	−0.12	0.02	1.23	0.16	0.33	−0.25	−0.74	0.61	0.71	−0.59	−1.89

	Low				2				High			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
Panel E: Nine trading volume and momentum portfolios												
α^q	2.28	4.68	0.46	−1.82	−0.35	0.29	−0.44	−0.09	−1.60	−1.54	−1.94	−0.34
$[t]$	0.70	1.64	0.18	−1.07	−0.09	0.09	−0.15	−0.05	−0.39	−0.42	−0.53	−0.17
Panel F: Nine stock return volatility and momentum portfolios												
α^q	3.28	3.61	1.36	−1.93	0.67	0.40	1.07	0.40	−0.71	−3.72	−3.62	−2.91
$[t]$	1.05	1.36	0.56	−1.23	0.17	0.12	0.33	0.22	−0.16	−0.87	−0.80	−1.18
Panel G: Nine cash flow volatility and momentum portfolios												
α^q	6.91	6.07	5.24	−1.67	3.24	1.85	−0.36	−3.61	−1.22	−5.18	−6.94	−5.73
$[t]$	2.05	2.13	1.73	−0.95	0.87	0.59	−0.11	−1.83	−0.28	−1.35	−1.56	−1.98
Panel H: Nine book-to-market and momentum portfolios												
α^q	−6.01	−4.64	−1.85	4.16	0.51	1.09	0.54	0.03	5.26	5.06	−1.83	−7.09
$[t]$	−1.48	−1.33	−0.46	1.91	0.14	0.35	0.16	0.02	1.23	1.40	−0.51	−2.82

Table 4 : Economic Characteristics of Testing Portfolios

For each testing asset i we report the averages (in annual terms) of investment-to-capital (I_{it}/K_{it}), the growth rate of investment-to-capital ($(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$), sales-to-capital ($Y_{it+1}/K_{it+1}$), and market leverage ($w_{it}$). L denotes losers, W winners, and W−L the differences between the winner and loser portfolios. [t] denotes the t-statistics for the differences.

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L	[t]
I_{it}/K_{it}	0.22	0.21	0.20	0.20	0.20	0.20	0.21	0.21	0.23	0.26	0.04	3.71
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.83	0.92	0.94	0.97	0.99	1.02	1.03	1.07	1.09	1.16	0.33	16.05
Y_{it+1}/K_{it+1}	3.18	3.04	2.99	3.00	3.00	3.14	3.23	3.43	3.65	4.19	1.01	5.86
w_{it}	0.34	0.29	0.27	0.25	0.25	0.24	0.23	0.22	0.21	0.22	−0.12	−7.44

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L	[t]
I_{it}/K_{it}	0.20	0.20	0.20	0.20	0.21	0.01	0.89
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.95	0.97	0.99	1.02	1.06	0.11	8.71
Y_{it+1}/K_{it+1}	3.02	3.08	3.15	3.24	3.26	0.24	1.24
w_{it}	0.28	0.26	0.25	0.25	0.24	−0.04	−3.29

Panel C: Nine size and momentum portfolios

	Small					2					Big				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
I_{it}/K_{it}	0.20	0.20	0.22	0.02	5.14	0.20	0.20	0.22	0.02	4.53	0.21	0.19	0.21	0.01	1.43
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.88	1.01	1.12	0.24	16.97	0.89	1.00	1.09	0.20	15.33	0.93	1.00	1.07	0.14	11.68
Y_{it+1}/K_{it+1}	4.26	4.63	5.09	0.83	8.00	3.46	3.73	3.98	0.53	5.59	2.70	2.71	3.15	0.45	4.50
w_{it}	0.38	0.33	0.29	−0.09	−11.95	0.34	0.28	0.25	−0.09	−9.81	0.27	0.23	0.21	−0.07	−5.79

Panel D: Nine firm age and momentum portfolios

	Young					2					Old				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
I_{it}/K_{it}	0.23	0.21	0.24	0.02	2.27	0.21	0.20	0.22	0.01	2.67	0.19	0.19	0.20	0.00	0.79
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.88	0.99	1.07	0.19	13.85	0.90	1.00	1.08	0.17	11.45	0.93	1.00	1.09	0.15	11.41
Y_{it+1}/K_{it+1}	3.33	3.36	3.67	0.34	2.12	3.14	3.21	3.60	0.45	3.84	2.84	2.83	3.36	0.52	4.35
w_{it}	0.30	0.24	0.22	−0.08	−6.62	0.28	0.22	0.22	−0.07	−5.44	0.31	0.26	0.25	−0.07	−4.61

	Low					2					High				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
Panel E: Nine trading volume and momentum portfolios															
I_{it}/K_{it}	0.19	0.18	0.20	0.01	1.53	0.20	0.19	0.20	0.00	0.91	0.22	0.22	0.23	0.01	1.15
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.94	0.99	1.08	0.14	7.57	0.93	1.01	1.09	0.16	10.49	0.87	1.00	1.10	0.23	14.85
Y_{it+1}/K_{it+1}	2.86	2.66	3.50	0.65	4.00	3.20	3.22	3.54	0.34	3.06	3.16	3.22	3.64	0.49	4.08
w_{it}	0.25	0.21	0.20	−0.05	−4.54	0.30	0.26	0.23	−0.07	−4.96	0.38	0.32	0.27	−0.11	−8.15
Panel F: Nine stock return volatility and momentum portfolios															
I_{it}/K_{it}	0.20	0.19	0.21	0.01	2.20	0.22	0.22	0.24	0.02	3.38	0.25	0.25	0.26	0.00	0.51
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.94	1.00	1.09	0.14	9.27	0.90	1.00	1.08	0.18	14.13	0.82	0.97	1.12	0.30	14.30
Y_{it+1}/K_{it+1}	2.88	2.82	3.41	0.53	3.56	3.34	3.43	3.82	0.48	3.70	3.62	3.97	4.14	0.52	3.69
w_{it}	0.27	0.23	0.20	−0.07	−6.04	0.32	0.26	0.21	−0.10	−8.12	0.34	0.30	0.25	−0.08	−7.47
Panel G: Nine cash flow volatility and momentum portfolios															
I_{it}/K_{it}	0.19	0.18	0.20	0.01	1.31	0.22	0.22	0.23	0.02	2.90	0.25	0.24	0.28	0.03	3.75
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.93	1.00	1.08	0.16	11.86	0.91	1.00	1.11	0.20	15.09	0.86	1.00	1.10	0.23	10.74
Y_{it+1}/K_{it+1}	2.50	2.50	2.83	0.32	3.43	3.52	3.73	4.11	0.59	4.91	4.74	5.06	5.79	1.05	5.44
w_{it}	0.27	0.21	0.21	−0.05	−4.32	0.25	0.19	0.19	−0.06	−5.18	0.28	0.23	0.20	−0.08	−6.12
Panel H: Nine book-to-market and momentum portfolios															
I_{it}/K_{it}	0.30	0.27	0.30	0.01	0.65	0.22	0.20	0.21	−0.01	−2.23	0.17	0.16	0.15	−0.02	−3.69
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.90	0.99	1.07	0.17	11.00	0.91	1.00	1.08	0.17	15.48	0.90	1.00	1.12	0.22	11.40
Y_{it+1}/K_{it+1}	3.84	4.05	4.31	0.46	3.67	3.14	2.99	3.50	0.35	2.27	2.68	2.57	3.12	0.44	3.50
w_{it}	0.15	0.12	0.13	−0.02	−1.70	0.27	0.26	0.26	−0.01	−1.46	0.46	0.42	0.41	−0.05	−3.66

Table 5 : Accounting for Average Momentum Profits

We perform four comparative static experiments: $\overline{I_{it}/K_{it}}$, $\overline{q_{it+1}/q_{it}}$, $\overline{Y_{it+1}/K_{it+1}}$, and $\overline{w}_{it}$, in which $q_{it+1}/q_{it} = [1 + (1 - \tau_{t+1})a(I_{it+1}/K_{it+1})]/[1 + (1 - \tau_t)a(I_{it}/K_{it})]$. In the experiment denoted $\overline{Y_{it+1}/K_{it+1}}$, we set Y_{it+1}/K_{it+1} for a given set of testing portfolios to be its cross-sectional average in year $t+1$. We use the parameters reported in Panel A of Table 2 to reconstruct the levered investment returns, while keeping all the other characteristics unchanged. The other three experiments are designed analogously. We report the alphas calculated as $\alpha_i^q \equiv E_T\left[r_{it+1}^S - r_{it+1}^{Iw}\right]$ for the testing portfolios and the winner-minus-loser portfolios.

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L
$\overline{I_{it}/K_{it}}$	−2.65	0.87	2.71	3.65	4.26	2.81	1.55	−0.39	−2.69	−8.16	−5.51
$\overline{q_{it+1}/q_{it}}$	−7.90	−2.33	−0.76	−0.01	1.02	1.04	0.72	1.20	2.17	3.47	11.37
$\overline{Y_{it+1}/K_{it+1}}$	−2.41	−1.43	−1.14	−1.26	−0.70	−0.50	−0.58	0.33	1.93	4.73	7.14
$\overline{w}_{it}$	−1.50	0.10	1.01	0.76	1.24	0.47	−0.12	−0.96	−0.86	−1.25	0.25

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L
$\overline{I_{it}/K_{it}}$	0.88	0.51	−0.95	−0.43	0.35	−0.53
$\overline{q_{it+1}/q_{it}}$	−1.34	−0.22	−1.09	−0.21	2.71	4.06
$\overline{Y_{it+1}/K_{it+1}}$	−0.64	0.17	−1.02	−0.37	1.39	2.03
$\overline{w}_{it}$	0.42	0.51	−1.01	−0.95	0.90	0.48

Panel C: Nine size and momentum portfolios

	Small				2				Big			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
$\overline{I_{it}/K_{it}}$	−1.96	−2.17	−6.82	−4.86	2.68	2.20	−1.57	−4.25	5.75	7.11	4.03	−1.73
$\overline{q_{it+1}/q_{it}}$	−7.00	−3.66	−0.50	6.50	−1.67	0.72	3.20	4.87	3.74	5.23	6.79	3.05
$\overline{Y_{it+1}/K_{it+1}}$	0.74	2.07	4.10	3.36	−0.50	0.54	1.88	2.38	−0.38	−0.60	1.75	2.13
$\overline{w}_{it}$	−1.85	−2.67	−3.49	−1.64	1.71	0.71	0.31	−1.40	5.50	4.99	4.38	−1.12

Panel D: Nine firm age and momentum portfolios

	Young				2				Old			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
$\overline{I_{it}/K_{it}}$	−5.17	−0.24	−5.05	0.12	1.23	2.12	−2.30	−3.53	4.63	5.13	0.66	−3.97
$\overline{q_{it+1}/q_{it}}$	−6.46	−0.59	2.35	8.81	−2.21	1.15	1.68	3.89	0.26	2.25	1.03	0.76
$\overline{Y_{it+1}/K_{it+1}}$	−2.25	−0.26	2.50	4.76	−0.21	0.68	1.48	1.69	−0.90	−1.00	−0.64	0.26
$\overline{w}_{it}$	−2.33	−0.68	−0.25	2.09	0.82	0.69	−1.31	−2.13	1.88	1.79	−1.42	−3.30

	Low				2				High			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
Panel E: Nine trading volume and momentum portfolios												
$\overline{I_{it}/K_{it}}$	4.81	8.23	1.77	−3.03	0.56	2.06	−0.10	−0.66	−5.34	−4.59	−6.28	−0.94
$\overline{q_{it+1}/q_{it}}$	0.52	4.54	2.64	2.12	−2.80	0.54	2.06	4.86	−6.80	−1.59	1.37	8.17
$\overline{Y_{it+1}/K_{it+1}}$	−0.33	0.81	2.52	2.84	−0.37	0.26	1.82	2.19	−2.32	−1.82	0.80	3.12
$\overline{w}_{it}$	1.76	4.18	−0.59	−2.36	−0.52	0.12	−0.90	−0.38	−0.86	−0.67	−1.56	−0.71
Panel F: Nine stock return volatility and momentum portfolios												
$\overline{I_{it}/K_{it}}$	9.17	10.36	5.08	−4.08	2.35	2.16	−1.17	−3.51	−5.31	−8.34	−9.00	−3.69
$\overline{q_{it+1}/q_{it}}$	1.86	4.33	4.60	2.73	−3.03	0.86	4.19	7.22	−8.22	−4.82	0.87	9.10
$\overline{Y_{it+1}/K_{it+1}}$	−1.13	−1.06	0.65	1.78	−0.45	−0.09	3.15	3.60	−0.11	−0.70	0.48	0.59
$\overline{w}_{it}$	2.88	3.26	0.42	−2.47	0.76	0.11	0.22	−0.53	−0.28	−2.91	−3.14	−2.86
Panel G: Nine cash flow volatility and momentum portfolios												
$\overline{I_{it}/K_{it}}$	14.13	15.22	11.37	−2.76	4.72	3.24	−2.60	−7.32	−6.27	−9.15	−19.97	−13.71
$\overline{q_{it+1}/q_{it}}$	3.82	6.28	8.49	4.67	−0.62	2.13	4.20	4.82	−7.83	−5.36	−2.94	4.89
$\overline{Y_{it+1}/K_{it+1}}$	−1.83	−2.18	−1.04	0.79	1.13	1.05	0.99	−0.14	3.89	1.45	3.36	−0.54
$\overline{w}_{it}$	6.73	6.10	5.36	−1.37	3.12	1.56	−0.82	−3.94	−1.14	−5.34	−6.82	−5.68
Panel H: Nine book-to-market and momentum portfolios												
$\overline{I_{it}/K_{it}}$	−19.22	−14.02	−17.23	1.99	−0.06	6.17	2.58	2.64	19.75	22.08	18.27	−1.48
$\overline{q_{it+1}/q_{it}}$	−9.87	−4.60	0.90	10.77	−2.85	1.46	3.70	6.55	0.95	5.35	2.99	2.04
$\overline{Y_{it+1}/K_{it+1}}$	−3.27	−0.78	3.27	6.54	−0.96	−1.69	1.44	2.40	−1.66	−2.82	−4.23	−2.56
$\overline{w}_{it}$	−6.51	−6.57	−4.50	2.01	0.51	0.90	0.40	−0.11	4.87	6.22	2.30	−2.57

Table 6 : Reversal of Momentum Profits in Long Horizons

For each momentum decile we report the average buy-and-hold stock returns (r^S_{it+1}) over periods following portfolio formation (in the following six months and in the first, second, and third subsequent years). The table also reports the levered investment returns (r^{Iw}_{it+1}), sales-to-capital (Y_{it+1}/K_{it+1}), the growth rate of q (q_{it+1}/q_{it}), and the growth rate of investment-to-capital ($\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$) over the same time horizons. Stock returns and levered investment returns are in semi-annual percent in Panel A, and are in annual percent in the remaining panels. The three other characteristics are in annual terms.

	L	2	3	4	5	6	7	8	9	W	W−L
Panel A: Six months after portfolio formation											
r^S_{it+1}	1.84	4.53	5.52	6.14	6.67	7.07	7.23	8.11	9.24	11.00	9.16
r^{Iw}_{it+1}	2.42	4.02	4.71	5.34	5.59	6.43	6.92	8.10	9.05	11.01	8.59
Y_{it+1}/K_{it+1}	3.17	3.04	3.00	2.99	3.00	3.14	3.23	3.44	3.66	4.19	1.02
q_{it+1}/q_{it}	0.95	0.98	0.99	0.99	1.00	1.00	1.01	1.02	1.03	1.05	0.10
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.83	0.92	0.95	0.97	0.99	1.02	1.04	1.07	1.10	1.17	0.34
Panel B: First year after portfolio formation											
r^S_{it+1}	6.66	10.51	12.07	12.85	13.51	14.09	14.47	15.08	16.24	17.68	11.02
r^{Iw}_{it+1}	6.92	8.81	9.89	10.94	11.09	12.52	13.36	15.26	16.75	19.01	12.09
Y_{it+1}/K_{it+1}	3.18	3.05	3.00	2.99	3.00	3.14	3.22	3.43	3.63	4.14	0.96
q_{it+1}/q_{it}	0.96	0.98	0.99	0.99	1.00	1.00	1.01	1.01	1.02	1.03	0.07
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.87	0.93	0.95	0.98	0.99	1.01	1.03	1.05	1.07	1.11	0.24
Panel C: Second year after portfolio formation											
r^S_{it+1}	16.19	14.52	14.20	14.19	14.02	14.09	13.68	13.54	12.53	10.29	−5.90
r^{Iw}_{it+1}	14.24	11.97	11.57	11.51	11.37	11.84	12.08	12.34	12.66	12.31	−1.93
Y_{it+1}/K_{it+1}	3.27	3.09	3.03	3.01	3.01	3.13	3.20	3.38	3.53	3.94	0.67
q_{it+1}/q_{it}	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.98	−0.02
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	1.03	1.00	1.00	0.99	0.99	0.99	0.99	0.98	0.97	0.95	−0.08
Panel D: Third year after portfolio formation											
r^S_{it+1}	17.54	16.03	15.25	14.80	14.63	14.41	14.15	13.94	13.47	12.10	−5.43
r^{Iw}_{it+1}	16.13	13.26	12.60	11.81	11.90	11.90	11.86	12.24	11.78	11.20	−4.93
Y_{it+1}/K_{it+1}	3.38	3.15	3.07	3.01	3.03	3.13	3.19	3.36	3.48	3.82	0.44
q_{it+1}/q_{it}	1.01	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.99	0.98	−0.03
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	1.05	1.02	1.01	1.00	1.01	0.99	0.99	0.98	0.96	0.94	−0.11

Table 7 : Explaining Levered Investment Returns with the CAPM and the Fama-French Model

For each momentum decile we conduct monthly CAPM regressions and monthly Fama-French three-factor regressions using levered investment returns. The levered investment returns are constructed using the parameter estimates in Table 2. For each regression, we report the intercept and factor loadings as well as their t-statistics adjusted for heteroscedasticity and autocorrelations.

	L	2	3	4	5	6	7	8	9	W	W−L
Panel A: Levered investment returns regressed on contemporaneous factor returns											
α	5.00	8.06	9.29	10.62	11.14	12.65	13.66	15.86	17.72	21.56	16.56
[t]	3.12	6.59	8.62	11.26	12.47	14.20	16.46	17.87	17.62	10.26	6.93
β	−1.30	−0.92	−0.70	−0.71	−0.68	−0.61	−0.59	−0.52	−0.46	−0.47	0.83
[t]	−4.59	−4.40	−5.01	−5.99	−5.39	−5.30	−5.53	−4.66	−4.39	−2.34	2.85
α_{FF}	5.67	8.52	9.59	10.88	11.35	12.86	13.91	16.07	17.92	21.90	16.24
[t]	3.75	7.39	9.32	11.87	13.05	14.60	17.05	18.69	18.19	11.14	7.01
β_{MKT}	−1.44	−1.00	−0.77	−0.78	−0.72	−0.66	−0.65	−0.58	−0.54	−0.71	0.73
[t]	−5.65	−5.58	−5.62	−6.83	−5.80	−5.84	−6.21	−5.30	−4.92	−3.80	2.45
β_{SMB}	−0.67	−0.49	−0.26	−0.19	−0.23	−0.18	−0.21	−0.16	−0.08	0.23	0.90
[t]	−1.90	−2.03	−1.71	−1.59	−1.99	−1.37	−1.91	−1.26	−0.51	1.05	2.44
β_{HML}	−1.05	−0.71	−0.48	−0.43	−0.34	−0.35	−0.41	−0.34	−0.34	−0.71	0.34
[t]	−3.04	−3.74	−2.92	−3.25	−2.57	−2.41	−2.59	−1.96	−1.76	−1.62	0.90
Panel B: Levered investment returns regressed on six-month lagged factor returns											
α	4.20	7.51	8.91	10.25	10.75	12.31	13.31	15.52	17.38	21.22	17.02
[t]	2.56	5.67	7.91	10.30	11.43	13.45	15.86	17.63	17.87	10.63	7.14
β	0.48	0.31	0.15	0.14	0.19	0.16	0.20	0.23	0.30	0.27	−0.21
[t]	2.70	1.49	1.13	1.30	1.73	1.66	2.19	2.61	3.05	1.45	−0.88
α_{FF}	4.36	7.51	8.92	10.24	10.71	12.21	13.19	15.38	17.17	20.64	16.27
[t]	2.68	5.46	7.97	10.37	11.45	13.53	16.11	17.62	17.77	9.36	6.29
β_{MKT}	0.31	0.26	0.17	0.14	0.20	0.16	0.22	0.24	0.31	0.49	0.18
[t]	1.77	1.29	1.22	1.33	1.92	1.81	2.42	2.61	3.04	2.67	0.75
β_{SMB}	0.32	0.17	−0.06	0.02	0.03	0.14	0.13	0.23	0.32	0.21	−0.11
[t]	1.11	0.64	−0.32	0.15	0.16	0.87	0.91	1.51	1.70	0.62	−0.29
β_{HML}	−0.36	−0.03	−0.01	0.01	0.06	0.14	0.18	0.21	0.29	1.00	1.36
[t]	−1.05	−0.11	−0.03	0.09	0.46	1.11	1.32	1.58	1.54	1.48	1.74

Table 8 : Market States and Momentum Profits

At the end of each month t, all NYSE, AMEX, and NASDAQ firms are sorted into deciles based on their prior six-month returns from $t-5$ to $t-1$, skipping month t. Stocks with prices per share under \$5 at month t are excluded. We categorize month t as UP (DOWN) markets if the value-weighted CRSP index returns over months $t-N$ to $t-1$ with $N = 36, 24$, or 12 are nonnegative (negative). Profits of the winner-minus-loser decile are cumulated across four holding periods: months $t+1$ to $t+6$ (Panel A), months $t+1$ to $t+12$ (Panel B), months $t+13$ to $t+24$ (Panel C), and months $t+25$ to $t+36$ (Panel D). Profits (average returns) are in semi-annual percent in Panel A and in annual percent in the remaining panels. Profits are reported as average stock returns (r^S), average contemporaneous levered investment returns (r^{Iw}), average six-month leading levered investment returns ($r^{Iw}_{[+6]}$), and average 12-month leading levered investment returns ($r^{Iw}_{[+12]}$).

Panel A: Months 1–6					Panel B: Months 1–12				
State	Profits	[t]	N-month market	Returns	State	Profits	[t]	N-month market	Returns
DOWN	6.14	3.76	36	r^S	DOWN	5.34	1.81	36	r^S
DOWN	4.64	4.08	24	r^S	DOWN	−0.49	−0.19	24	r^S
DOWN	3.77	2.18	12	r^S	DOWN	1.58	0.46	12	r^S
UP	9.51	7.84	36	r^S	UP	11.67	5.25	36	r^S
UP	9.75	8.11	24	r^S	UP	12.49	5.81	24	r^S
UP	10.68	9.02	12	r^S	UP	13.68	5.90	12	r^S
DOWN	9.49	4.86	36	r^{Iw}	DOWN	15.60	3.97	36	r^{Iw}
DOWN	9.25	4.67	24	r^{Iw}	DOWN	15.41	4.05	24	r^{Iw}
DOWN	10.57	6.87	12	r^{Iw}	DOWN	16.86	6.06	12	r^{Iw}
UP	8.03	5.95	36	r^{Iw}	UP	11.69	4.42	36	r^{Iw}
UP	8.04	5.91	24	r^{Iw}	UP	11.67	4.37	24	r^{Iw}
UP	7.50	5.20	12	r^{Iw}	UP	10.75	3.73	12	r^{Iw}
DOWN	8.98	6.81	36	$r^{Iw}_{[+6]}$	DOWN	14.74	5.12	36	$r^{Iw}_{[+6]}$
DOWN	7.58	3.97	24	$r^{Iw}_{[+6]}$	DOWN	12.09	3.14	24	$r^{Iw}_{[+6]}$
DOWN	9.83	7.57	12	$r^{Iw}_{[+6]}$	DOWN	15.77	6.12	12	$r^{Iw}_{[+6]}$
UP	8.28	6.13	36	$r^{Iw}_{[+6]}$	UP	12.14	4.57	36	$r^{Iw}_{[+6]}$
UP	8.45	6.25	24	$r^{Iw}_{[+6]}$	UP	12.45	4.66	24	$r^{Iw}_{[+6]}$
UP	7.93	5.29	12	$r^{Iw}_{[+6]}$	UP	11.45	3.81	12	$r^{Iw}_{[+6]}$
DOWN	7.10	5.12	36	$r^{Iw}_{[+12]}$	DOWN	10.85	4.87	36	$r^{Iw}_{[+12]}$
DOWN	7.24	4.48	24	$r^{Iw}_{[+12]}$	DOWN	11.54	3.75	24	$r^{Iw}_{[+12]}$
DOWN	6.60	4.91	12	$r^{Iw}_{[+12]}$	DOWN	11.30	3.85	12	$r^{Iw}_{[+12]}$
UP	8.54	6.27	36	$r^{Iw}_{[+12]}$	UP	12.60	4.67	36	$r^{Iw}_{[+12]}$
UP	8.54	6.25	24	$r^{Iw}_{[+12]}$	UP	12.54	4.64	24	$r^{Iw}_{[+12]}$
UP	8.90	5.79	12	$r^{Iw}_{[+12]}$	UP	12.75	4.25	12	$r^{Iw}_{[+12]}$

Panel C: Months 13–24				
State	Profits	[t]	N-month market	Returns
DOWN	−0.38	−0.15	36	r^S
DOWN	−0.65	−0.21	24	r^S
DOWN	−2.45	−1.50	12	r^S
UP	−6.54	−3.42	36	r^S
UP	−6.59	−3.42	24	r^S
UP	−6.90	−3.26	12	r^S
DOWN	3.28	0.82	36	r^{Iw}
DOWN	2.19	0.51	24	r^{Iw}
DOWN	4.58	1.43	12	r^{Iw}
UP	−2.54	−1.01	36	r^{Iw}
UP	−2.47	−0.97	24	r^{Iw}
UP	−3.82	−1.40	12	r^{Iw}
DOWN	4.03	1.12	36	$r^{Iw}_{[+6]}$
DOWN	0.41	0.10	24	$r^{Iw}_{[+6]}$
DOWN	2.96	0.88	12	$r^{Iw}_{[+6]}$
UP	−2.46	−0.97	36	$r^{Iw}_{[+6]}$
UP	−2.07	−0.80	24	$r^{Iw}_{[+6]}$
UP	−3.17	−1.12	12	$r^{Iw}_{[+6]}$
DOWN	−1.40	−0.36	36	$r^{Iw}_{[+12]}$
DOWN	−0.54	−0.12	24	$r^{Iw}_{[+12]}$
DOWN	−0.74	−0.21	12	$r^{Iw}_{[+12]}$
UP	−1.93	−0.75	36	$r^{Iw}_{[+12]}$
UP	−2.05	−0.80	24	$r^{Iw}_{[+12]}$
UP	−2.21	−0.78	12	$r^{Iw}_{[+12]}$

Panel D: Months 25–36				
State	Profits	[t]	N-month market	Returns
DOWN	0.59	0.29	36	r^S
DOWN	0.24	0.15	24	r^S
DOWN	−1.67	−0.83	12	r^S
UP	−6.15	−3.04	36	r^S
UP	−6.20	−2.97	24	r^S
UP	−6.56	−2.90	12	r^S
DOWN	−0.02	−0.01	36	r^{Iw}
DOWN	−0.74	−0.24	24	r^{Iw}
DOWN	1.16	0.42	12	r^{Iw}
UP	−5.51	−2.48	36	r^{Iw}
UP	−5.49	−2.47	24	r^{Iw}
UP	−6.74	−2.96	12	r^{Iw}
DOWN	−0.57	−0.23	36	$r^{Iw}_{[+6]}$
DOWN	−2.99	−1.14	24	$r^{Iw}_{[+6]}$
DOWN	−1.22	−0.55	12	$r^{Iw}_{[+6]}$
UP	−5.20	−2.31	36	$r^{Iw}_{[+6]}$
UP	−4.93	−2.18	24	$r^{Iw}_{[+6]}$
UP	−5.75	−2.31	12	$r^{Iw}_{[+6]}$
DOWN	−3.70	−1.11	36	$r^{Iw}_{[+12]}$
DOWN	−2.74	−0.76	24	$r^{Iw}_{[+12]}$
DOWN	−3.03	−1.20	12	$r^{Iw}_{[+12]}$
UP	−4.85	−2.17	36	$r^{Iw}_{[+12]}$
UP	−5.00	−2.22	24	$r^{Iw}_{[+12]}$
UP	−5.25	−2.11	12	$r^{Iw}_{[+12]}$

Table 9 : Long Run Risks in Momentum Profits

Panel A reports the long run risk measure per Bansal, Dittmar, and Lundblad (2005) across momentum deciles. The data are quarterly from 1963 to 2008. γ_i is the projection coefficient from the regression: $g_{i,t} = \gamma_i \left(\frac{1}{8}\sum_{k=1}^{8} g_{c,t-k}\right) + u_{i,t}$, in which $g_{i,t}$ is demeaned log real cash flow growth rates on portfolio i, and $g_{c,t}$ is demeaned log real growth rate in aggregate consumption. Negative cash flow observations are treated as missing. $\bar{g}_i$ is the sample average log real dividend growth rate. Standard errors are reported in the columns denoted "ste." In Panel B, $\gamma_i^\star$ is the projection coefficient from the regression: $g_{i,t}^\star = \gamma_i^\star \left(\frac{1}{8}\sum_{k=1}^{8} g_{c,t-k}\right) + u_{i,t}$, in which $g_{i,t}^\star$ is demeaned log real cash flow growth rates on portfolio i. The cash flow is defined as $D_{it+1}^\star \equiv (1-\tau_{t+1})\left[\kappa\frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right] + \tau_{t+1}\delta_{it+1}$, in which τ_{t+1} is corporate tax rate, Y_{it+1} is sales, K_{it+1} is capital, I_{it+1} is investment, δ_{it+1} is the rate of capital depreciation, κ is the capital's share, and a is the adjustment cost parameter. The parameter values of κ and a are given by Table 2. $\bar{g}_i^\star$ is the sample average log real cash flow growth rate. $\gamma_{1i}^\star$ is the projection coefficient from regressing $g_{1i,t}^\star$ on $\frac{1}{8}\sum_{k=1}^{8} g_{c,t-k}$, in which $g_{1i,t}^\star$ is demeaned log real growth rate of $(1-\tau_{t+1})\kappa\frac{Y_{it+1}}{K_{it+1}}$. $\gamma_{2i}^\star$ is the projection coefficient from regressing $g_{2i,t}^\star$ on $\frac{1}{8}\sum_{k=1}^{8} g_{c,t-k}$, in which $g_{2i,t}^\star$ is demeaned log real growth rate of $(1-\tau_{t+1})\frac{a}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2$. $\gamma_{3i}^\star$ is the projection coefficient from regressing $g_{3i,t}^\star$ on $\frac{1}{8}\sum_{k=1}^{8} g_{c,t-k}$, in which $g_{3i,t}^\star$ is demeaned log real growth rate of $\tau_{t+1}\delta_{it+1}$. Nominal variables are converted to real variables using the personal consumption expenditures (PCE) deflator. The growth rates are in annual percent.

	Panel A: Stock returns				Panel B: Investment returns									
	γ_i	ste	$\bar{g}_i$	ste	$\gamma_i^\star$	ste	$\bar{g}_i^\star$	se	$\gamma_{1i}^\star$	ste	$\gamma_{2i}^\star$	ste	$\gamma_{3i}^\star$	ste
L	0.33	4.95	−2.07	1.29	5.18	2.27	−2.46	0.60	5.44	1.76	16.79	8.91	−0.43	2.34
2	−1.01	2.66	−0.65	0.69	6.44	1.60	1.48	0.43	5.59	1.40	19.85	7.11	0.40	1.77
3	−2.22	1.93	−0.33	0.50	6.80	1.51	2.45	0.41	5.47	1.35	23.67	6.52	1.20	1.70
4	−0.43	1.98	−0.05	0.52	6.87	1.32	3.47	0.37	5.87	1.31	22.45	5.50	0.92	1.57
5	−0.70	1.47	0.05	0.38	6.41	1.29	4.30	0.36	5.83	1.30	17.40	5.60	1.40	1.64
6	1.39	1.83	0.32	0.48	6.15	1.33	5.57	0.36	5.86	1.31	13.58	5.65	2.20	1.66
7	1.76	2.85	0.55	0.74	7.04	1.36	6.52	0.38	6.41	1.25	16.63	5.89	3.84	1.79
8	2.56	3.83	0.74	1.00	5.96	1.49	8.55	0.40	6.23	1.33	11.06	5.96	2.57	1.95
9	2.84	5.45	1.10	1.42	7.91	1.91	11.51	0.52	7.42	1.50	11.27	6.52	5.69	2.60
W	15.88	10.56	2.85	2.74	13.22	3.08	17.12	0.84	10.62	2.03	5.95	8.39	11.38	4.22
W−L	17.14	13.50	4.54	3.49	8.04	3.16	19.58	0.83	5.18	2.04	−10.85	9.93	11.81	3.66

Figure 1: Timing of Firm-Level Characteristics, Firms with December fiscal yearend

This figure illustrates the timing alignment between monthly stock returns and annual accounting variables from Compustat for firms with December fiscal yearend. r^I_{it+1} is the investment return of firm i constructed from characteristics from the current fiscal year and the next fiscal year. τ_t and I_{it} are the corporate income tax rate and firm i's investment for the current fiscal year, respectively. δ_{it+1} and Y_{it+1} are the depreciate rate and sales from the next fiscal year, respectively. K_{it} is firm i's capital observed at the end of the last fiscal year (or at the beginning of the current fiscal year).

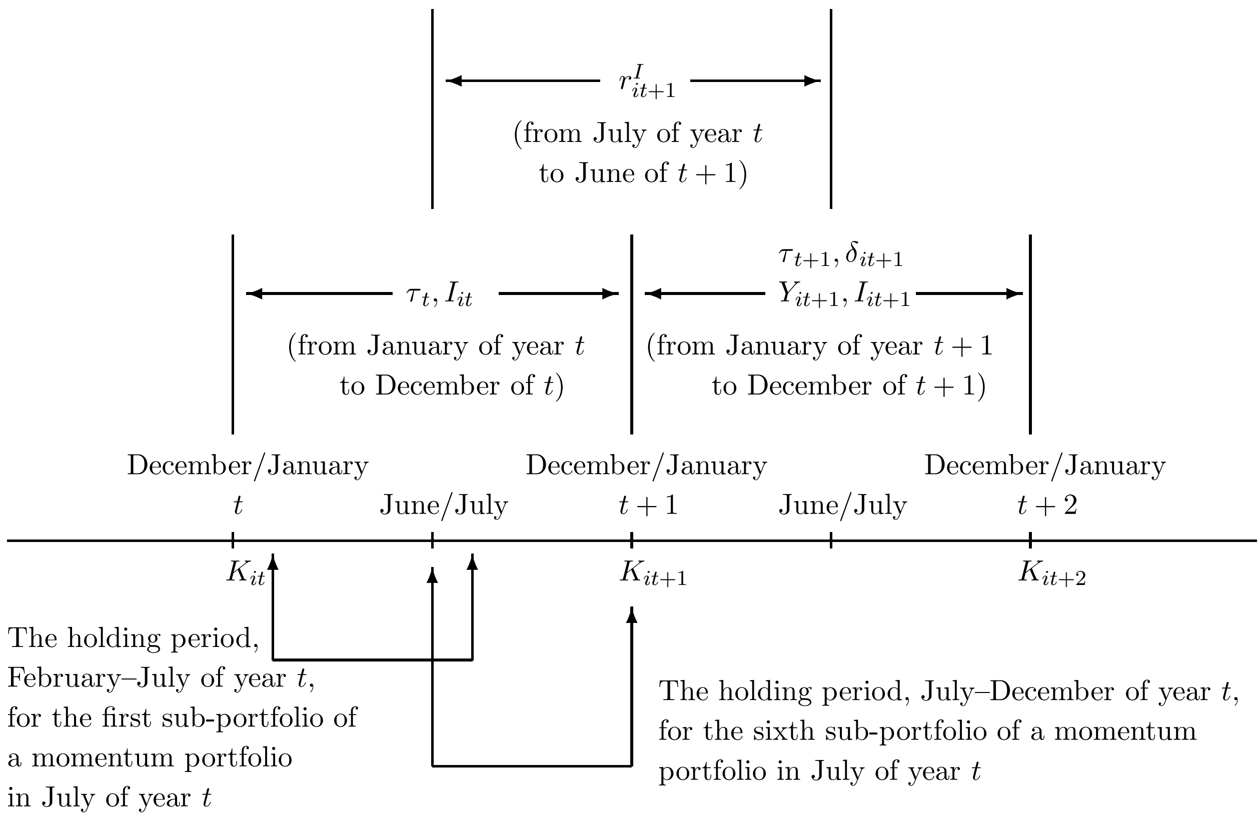


Figure 2 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Ten Momentum Deciles

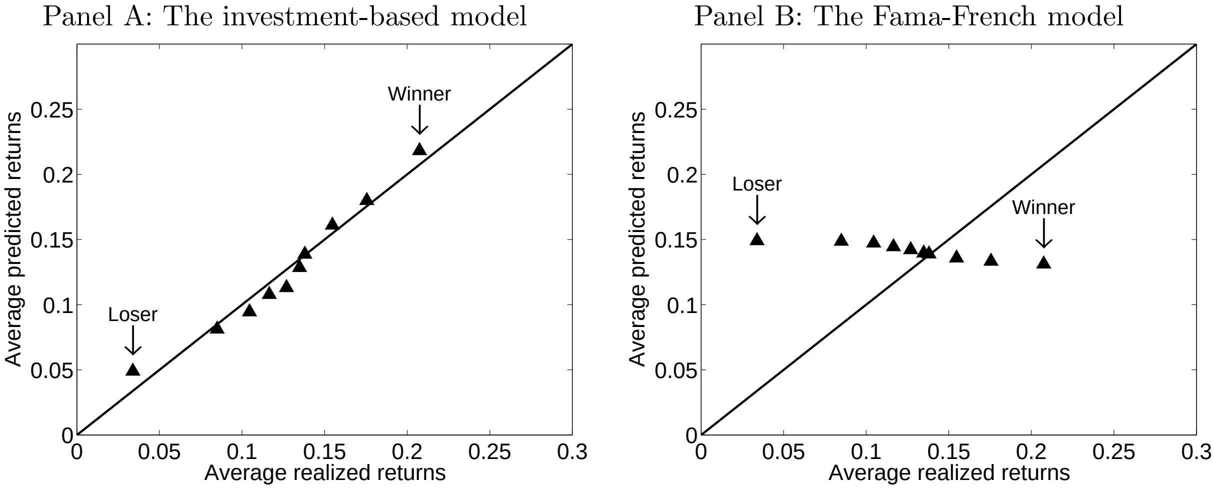


Figure 3 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Five Industry Momentum Quintiles

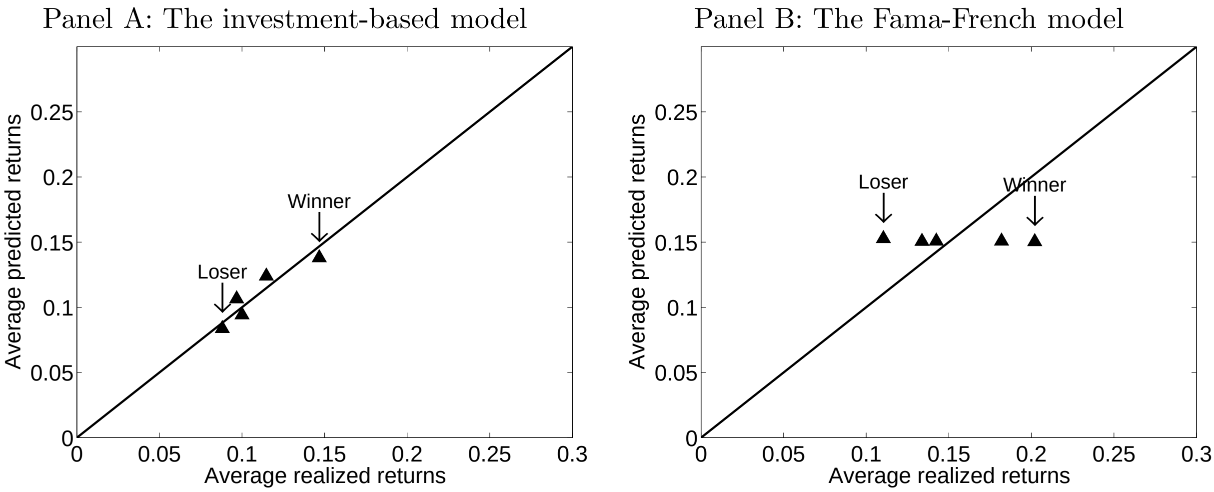


Figure 4 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Size and Momentum Portfolios

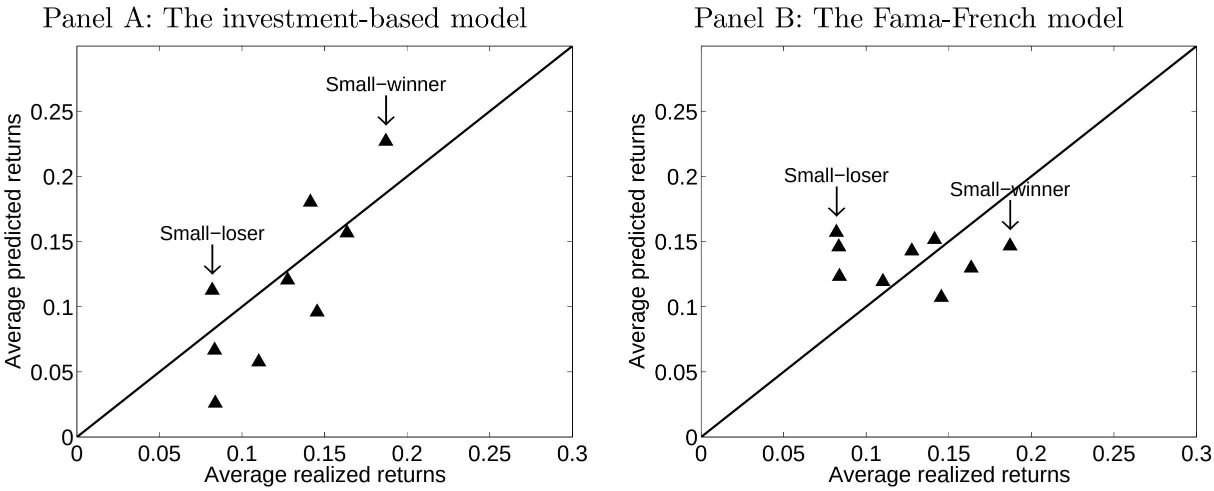


Figure 5 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Firm Age and Momentum Portfolios

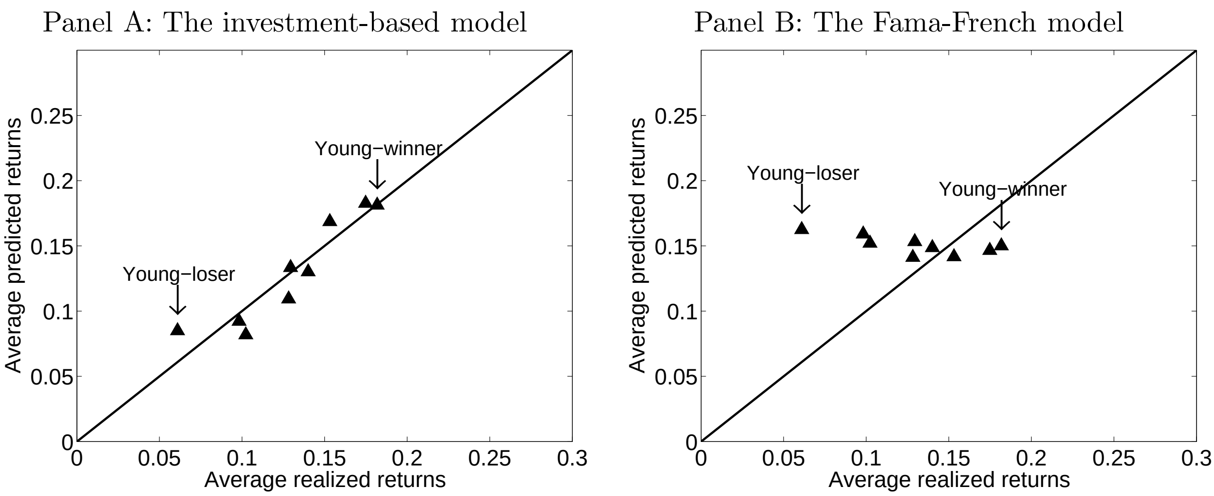


Figure 6 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Trading Volume and Momentum Portfolios

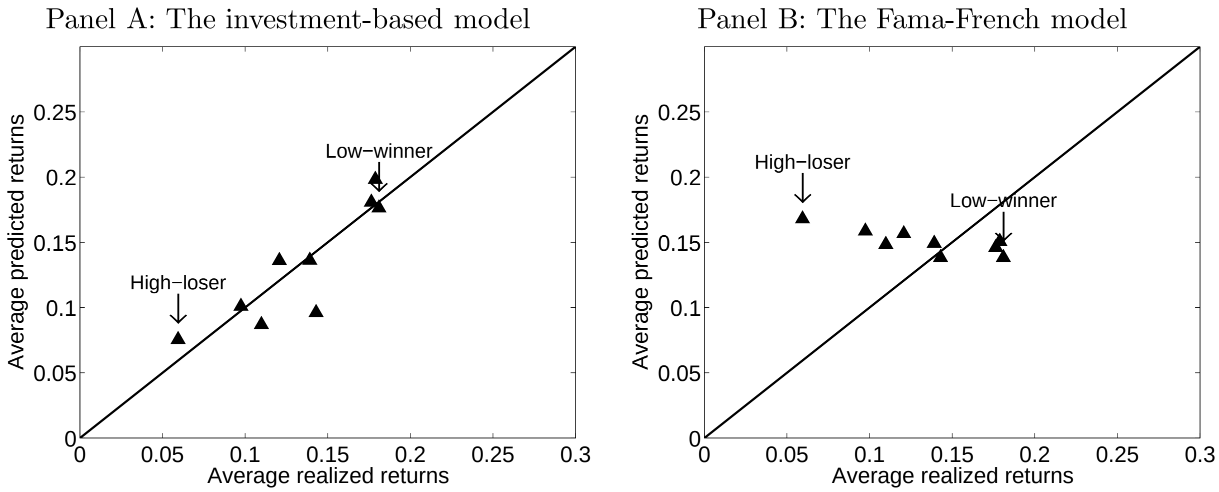


Figure 7 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Stock Return Volatility and Momentum Portfolios

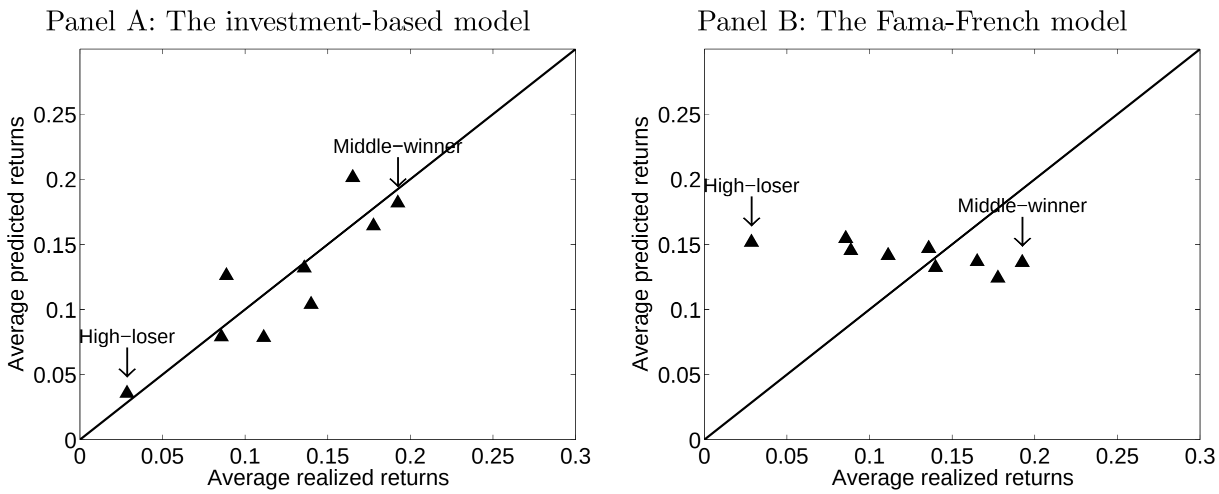


Figure 8 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Cash Flow Volatility and Momentum Portfolios

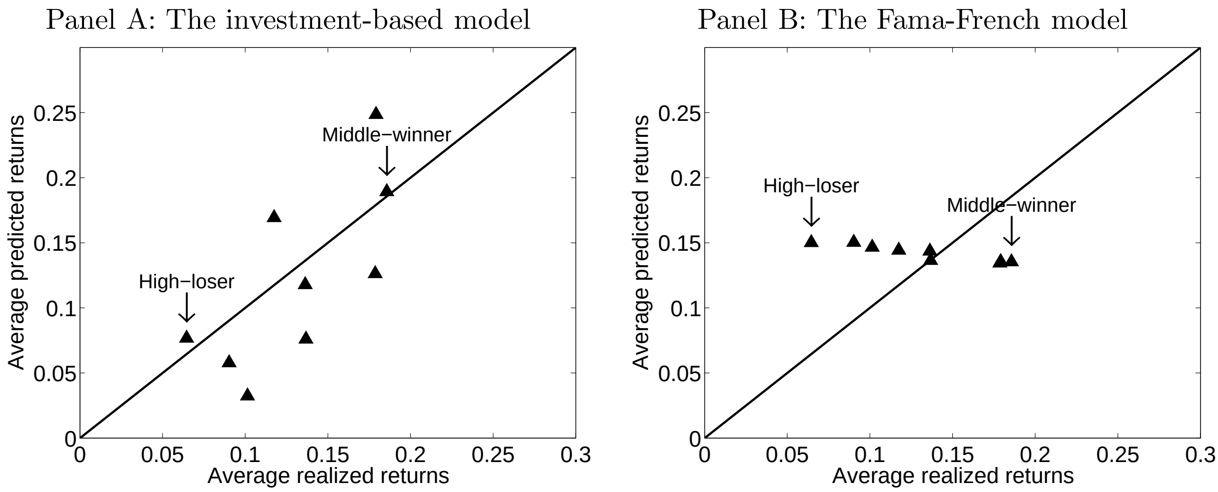


Figure 9 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Book-to-Market and Momentum Portfolios

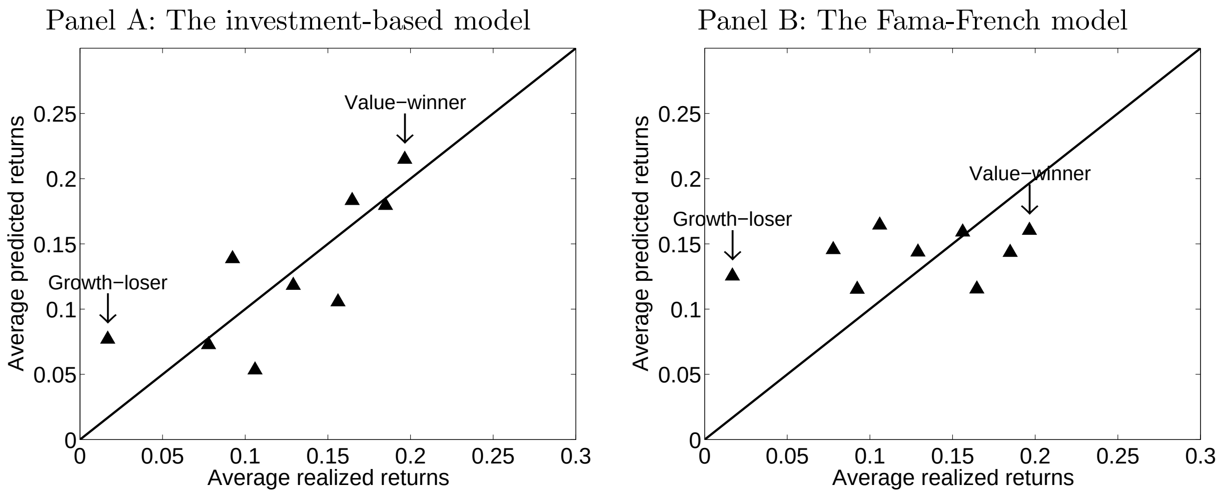
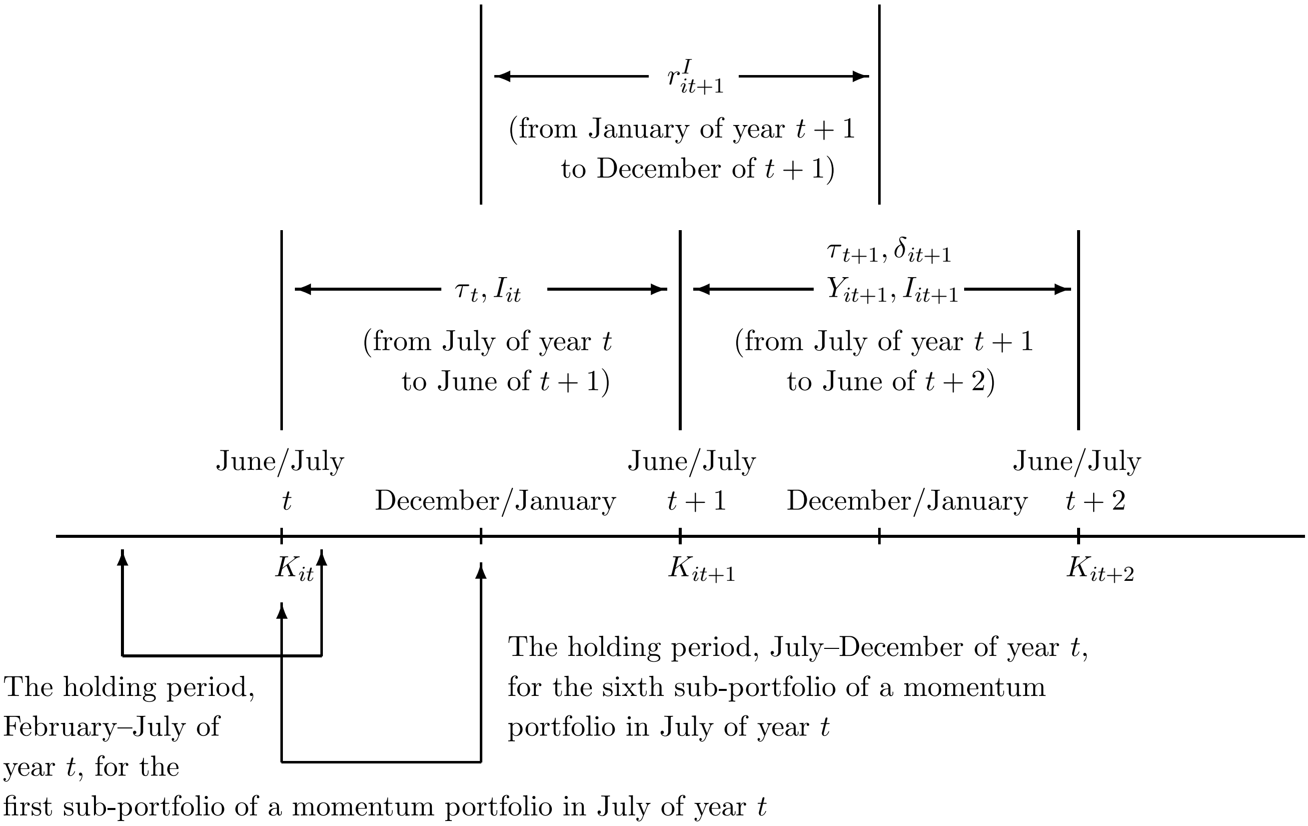


Figure A.1: Timing of Firm-Level Characteristics, Firms with Non-December fiscal yearend

This figure illustrates the timing alignment between monthly stock returns and annual accounting variables from Compustat for firms with non-December fiscal yearend. r^I_{it+1} is the investment return of firm i constructed from characteristics from the current fiscal year and the next fiscal year. τ_t and I_{it} are the corporate income tax rate and firm i's investment for the current fiscal year, respectively. δ_{it+1} and Y_{it+1} are the depreciate rate and sales from the next fiscal year, respectively. K_{it} is firm i's capital observed at the end of the last fiscal year (or at the beginning of the current fiscal year).

Panel A: Firms with June fiscal yearend



Panel B: Firms with September fiscal yearend