Investment-Based Momentum Profits

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May 2011‡

Abstract

We interpret momentum within the neoclassical theory of investment. The theory implies that expected stock returns are connected with 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 earn higher expected stock returns than losers. The investment-based model succeeds in capturing average momentum profits, reversal of momentum in long horizons, and the interaction of momentum with firm characteristics. However, the model fails to reproduce procyclical momentum profits.

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‡For helpful comments, we thank Heitor Almeida, Ilona Babenko (HKUST discussant), Frederico Belo, Jerome Detemple, Bob Dittmar, Hui Guo, Dirk Hackbarth, Kewei Hou, Jennifer Huang, Charles Khan, Neil Pearson, Marcel Rindisbacher, Mark Seasholes, Berk Sensoy, René Stulz, Mike Weisbach, Ingrid Werner, Peter Wong, Chen Xue, Frank Yu, and other seminar participants at Boston University, Cheung Kong Graduate School of Business, China Europe International Business School, The 2010 HKUST Finance Symposium on Asset Pricing/Investment, The Ohio State University, The Third Shanghai Winter Finance Conference, University of Cincinnati, and University of Illinois at Urbana-Champaign. The portfolio data and Matlab programs used for GMM estimation and tests in this work are available from the authors upon request. All remaining errors are our own.

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 their 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 based on 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 a model of momentum based on the neoclassical theory of investment. Under constant returns to scale, stock returns equal (levered) investment returns (e.g., Cochrane (1991)). The investment returns (next-period marginal benefits of investment divided by current-period marginal costs of investment) are linked to 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 earn higher expected stock returns than losers.

We use generalized method of moments (GMM) to match average levered investment returns to average stock returns. The investment-based model does a good job in capturing average momentum profits across ten momentum deciles from Jegadeesh and Titman (1993). The winner-minus-loser decile has a small alpha of 0.44% per annum, which is negligible compared to the CAPM alpha of 16.95% and the alpha of 19.15% from the Fama-French (1993) model. The alphas of individual deciles in the investment-based model are also substantially smaller than those in the CAPM and

[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. Jiang, Lee, and Zhang (2005) and Zhang (2006) report that momentum profits are higher among firms with higher information uncertainty using measures such as size, firm age, stock return volatility, and cash flow volatility.

the Fama-French model. In particular, the mean absolute error across the deciles is 0.80% in the investment-based model, 3.68% in the CAPM, and 4.08% in the Fama-French model.

The investment-based model suggests several components 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 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 alpha of the winner-minus-loser decile to 11.37% per annum from 0.44% in the benchmark estimation. Without the cross-sectional variation in the expected sales-to-capital, the winner-minus-loser alpha would jump to 7.14%.

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 the short-lived nature of momentum. As in the data, the predicted momentum profits cannot be explained by the CAPM or 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 as in Bansal, Dittmar, and Lundblad (2005). However, contrary to Cooper, Gutierrez, and Hameed's (2004) evidence on stock returns, the predicted momentum profits are not substantially higher following up markets than down markets.

In addition, the investment-based model goes a long way in capturing the interaction of momentum with firm characteristics. In particular, the model substantially outperforms the CAPM and the Fama-French model in fitting the average returns across two-way three-by-three portfolios from interacting momentum with size, firm age, trading volume, or stock return volatility. Most important, the alphas in the investment-based model do not vary systematically with prior six-month returns. For example, across the small, median, and big size terciles the winner-minus-loser tercile alphas are $-0.93\%, -0.98\%$, and -0.83% per annum, respectively. In contrast, the CAPM alphas are 10.16%, 7.89%, and 6.09%, and the Fama-French alphas are 11.55%, 9.64%, and 7.77%, respectively. However, the mean absolute error across the nine size and momentum portfolios has a similar magnitude in the investment-based model as those in the CAPM and the Fama-French model.

Following Cochrane (1991, 1996), investment-based asset pricing has built on the neoclassical investment framework to study aggregate and cross-sectional asset pricing.[2] None of the existing studies addresses what drives momentum, however. We fill this important gap in the literature. 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 Model

Firms use capital and costlessly adjustable inputs to produce a homogeneous output. These inputs are chosen each period to maximize operating profits, defined as revenue minus expenditure 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 $\Pi(K_{it}, X_{it})$ exhibits 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. Firms incur adjustment

[2] Zhang (2005) and Cooper (2006) develop dynamic investment models to study the value premium. Bazdrech, Belo, and Lin (2009) investigate the impact of labor adjustment costs on expected stock returns. Belo (2010) uses marginal rate of transformation from firms' first-order conditions as the pricing kernel in asset pricing tests. Gourio (2010) examines the effect of putty-clay technology on stock return volatility. Jermann (2010) studies the properties of the equity premium derived from firms' optimal investment conditions. Tuzel (2010) studies the relation between corporate real estate holdings and stock returns. Liu, Whited, and Zhang (2009) examine how stock returns relate to earnings surprises, book-to-market, and corporate investment.

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 exhibits 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, B_{it+1}, which must be repaid at the beginning of $t+1$. Firms take as given the gross 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 marginal benefits of investment at period $t+1$ divided by 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 $r^{Ba}_{it+1} \equiv r^{B}_{it+1} - (r^{B}_{it+1} - 1)\tau_{t+1}$. 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:

$$r^{I}_{it+1} = w_{it}\, r^{Ba}_{it+1} + (1 - w_{it})\, r^{S}_{it+1} \tag{4}$$

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

$$r^{S}_{it+1} = r^{Iw}_{it+1} \equiv \frac{r^{I}_{it+1} - w_{it}\, r^{Ba}_{it+1}}{1 - w_{it}}, \tag{5}$$

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

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

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

$$\alpha^{q}_{i} \equiv E_T\left[r^{S}_{it+1} - r^{Iw}_{it+1}\right], \tag{7}$$

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

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

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

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

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

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

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 (regulated firms) or between 6000 and 6999 (financial firms) are omitted. The sample is from 1963 to 2008. We keep only firm-year observations with positive total asset (Compustat annual item AT > 0), positive sales (SALE > 0), nonnegative debt (DLTT + DTC ≥ 0), positive market value of asset (DLTT + DTC + CSHO × PRCC_F > 0), positive gross capital stock (PPEGT > 0) at the most recent fiscal year end of the portfolio formation month, 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.

Testing Portfolios

We use ten momentum deciles as the benchmark set of testing portfolios. We construct the momentum deciles 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. As in Jegadeesh and Titman (1993), all stocks are equal-weighted 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.

Variable Measurement

The capital stock, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). Investment, I_{it}, is capital expenditures (item CAPX) minus sales of property, plant, and equipment (item SPPE). We set SPPE to be zero if it is missing. The capital depreciation rate, δ_{it}, is the amount of depreciation (item DP) divided by the capital stock. Output, Y_{it}, is sales (item SALE). Total debt, B_{it+1}, is long-term debt (item DLTT) plus short term debt (item DLC). Market leverage, w_{it}, is the ratio of total debt to the sum of total debt and market value of equity. The tax rate, τ_t, is the statutory corporate income tax rate from the Commerce Clearing House's annual publications.

Both stock and flow variables in Compustat are recorded at the end of year. But in the model time-t stock variables are at the beginning of year t, and time-t flow variables are over the course of year t. We take, for example, for the year 2003 any time-t stock variable such as K_{i2003} from the 2002 balance sheet and any flow variable such as 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 ratings data in Compustat, and assign the corporate bond returns for a given credit rating from Ibbotson Associates to the firms with the same credit rating.[3] Portfolio corporate bond returns are equal-weighted across firms in a given portfolio.

Timing

Momentum portfolios are rebalanced monthly, but variables from accounting statements are available annually.[4] 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 measurement difficulty should, ex ante, go against our effort in identifying 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.

[3]Liu, Whited, and Zhang (2009) describe the imputation procedure in detail. 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 rating. 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.

[4]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 (untabulated). 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 effectively 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.

To facilitate the timing alignment, we design a more elaborate procedure than Liu, Whited, and Zhang's (2009) procedure for earnings surprise deciles. We construct *monthly* levered investment returns of a momentum portfolio from its *annual* accounting variables to match with its 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 is to determine the timing of firm-level characteristics. This step is done at the sub-portfolio level. 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.[5] Take, for example, the first sub-portfolio of the loser decile in July of year t. As noted, this sub-portfolio's holding period is from February of year t to July of year t. For firms in this sub-

[5]In the Compustat sample from 1961 to 2008, 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%).

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 calendar year 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 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).

The second step in our procedure is to construct the various components of the levered investment returns at the sub-portfolio level. For each month we calculate characteristics for a given sub-portfolio by aggregating firm characteristics over the firms in the sub-portfolio (e.g., Fama and French (1995)). For example, the 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}, I_{it+1}/K_{it+1}, and δ_{it+1} are calculated analogously. Because portfolio composition changes from month to month at the sub-portfolio level, the sub-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. Finally, we construct levered investment returns at the portfolio level using equation (5).

4 Empirical Results

We study average momentum profits in Section 4.1 and the dynamics of momentum in Section 4.2. We examine the interaction of momentum with firm characteristics in Section 4.3.

4.1 Average Momentum Profits

We ask whether the investment-based model can capture the average returns of ten momentum deciles, and compare the model's performance with that of the CAPM and the Fama-French model.

Tests of Asset Pricing Models on the Benchmark Momentum Deciles

Panel A of Table 1 reports the tests of the CAPM and the Fama-French model for ten momentum deciles. (The data for the Fama-French factors are from Kenneth French's Web site.) The average return increases monotonically from 3.39% per annum for the loser decile to 20.75% for the winner decile. The winner-minus-loser decile earns an average return of 17.4%, which is more than seven standard errors from zero. The CAPM alpha and the Fama-French alpha of the winner-minus-loser decile 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.[6]

[6] In addition to the CAPM and the Fama-French model, we have also implemented the tests on the standard 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 consumption-CAPM alpha of the winner-minus-loser decile has a similar magnitude as the CAPM alpha and the

There are only two parameters in the investment-based model: the adjustment cost parameter, a, and the capital's share, κ. Using the momentum deciles, we estimate a to be 2.81 with a standard error of 0.96. The evidence implies that the adjustment cost function is increasing and convex in investment. The estimate of the capital's share, κ, is 0.12 with a small standard error of 0.02. Both parameter estimates seem reasonable in terms of economic magnitude. The overidentification test shows that the investment-based model is not formally rejected with the momentum deciles. From Panel A of Table 1, the p-value of the χ^2-test given by equation (10) is 0.10. The mean absolute pricing error (m.a.e. hereafter) across the momentum deciles is 0.80% per annum for the investment-based model. In contrast, the m.a.e. is 3.68% for the CAPM and 4.08% for the Fama-French model. As noted, both the CAPM and the Fama-French model are strongly rejected.

We also report individual alphas from the investment-based model, α_i^q, defined in equation (7) in the last two rows of Panel A. The levered investment returns are constructed using the estimates of a and κ from one-stage GMM. We also report t-statistics testing that a given α_i^q equals zero, using standard errors calculated from one-stage GMM. The individual alphas range from -1.50% per annum for the loser decile to 1.39% for the fifth decile. In contrast, the CAPM alphas range from -9.50% for the loser decile to 7.45% for the winner decile, and the Fama-French alphas go from -11.51% for the loser decile to 7.64% for the winner decile. The winner-minus-loser alpha in the investment-based model is 0.44%, which is within 0.2 standard errors from zero. This alpha is negligible compared to those from the CAPM (17.0%) and the Fama-French model (19.2%), both of which are more than eight standard errors from zero.

Figure 2 shows the performance of the alternative models by plotting the average predicted stock returns of the momentum deciles against their average realized stock 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, Panels B and C show that the scatter plots from the CAPM and the Fama-French model

Fama-French alpha. In addition, the time preference estimate is above two, and the risk aversion estimate is above 75.

are roughly horizontal. As such, the investment-based alphas do not vary systematically across the momentum deciles, in contrast to the CAPM alphas and the Fama-French alphas.[7]

Intuition: Components of Expected Stock Returns

How does the model capture average momentum profits? The unlevered and levered investment return equations (3) and (5) suggest several components of expected stock returns.

The first component is investment-to-capital, I_{it}/K_{it}, in the denominator of the investment return. The second component 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 component is the marginal product of capital, Y_{it+1}/K_{it+1}, in the numerator of the investment return. The fourth component 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 stock return. The fifth component is the market leverage, w_{it}, in the levered investment return, which shows a positive relation between w_{it} and the expected stock return. The sixth component is the after-tax corporate bond return, r^{Ba}_{it+1}. To summarize, 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 see the intuition behind our results, Panel B of Table 1 reports the averages for four components of levered investment returns across the momentum deciles: $I_{it}/K_{it}, q_{it+1}/q_{it}, Y_{it+1}/K_{it+1}$, and w_{it}. The averages of the depreciate rate and the after-tax corporate bond return are largely flat

[7] In untabulated results, we also find that the investment-based model fits well the industry momentum quintiles of Moskowitz and Grinblatt (1999). Moskowitz and Grinblatt 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 $t+6$. In the investment-based model, the alphas range from -0.97% to 0.88% per annum, all of which are within 0.4 standard errors from zero. The winner-minus-loser quintile has a small alpha of 0.44%, which is within 0.2 standard errors from zero. This alpha is substantially smaller than 9.15% from the CAPM and 9.40% from the Fama-French model.

across the momentum deciles, and their impact on the estimation results is trivial (untabulated).[8] In the case of the growth rate of q_{it}, because q_{it} involves the unobserved adjustment cost parameter, we instead report the average growth rate of investment-to-capital, $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$.

Panel B shows that the winner decile has a 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. The spread of 1.01 is more than 5.5 standard errors from zero. Both components go in the right direction to capture expected stock returns across the momentum deciles. However, going in the wrong direction, the winner decile has a higher current-period investment-to-capital, I_{it}/K_{it}, than the loser decile, 0.26 versus 0.22. Albeit significant, the spread is small. Also going in the wrong direction, the winner decile has a lower market leverage than the loser decile: 0.22 versus 0.34. The spread of -0.12 is more than seven standard errors from zero.

Comparative Statics: Accounting for Average Momentum Profits

To quantify the role of each component in capturing momentum profits, we conduct the following comparative static experiments. We set a given component of the levered investment return to its cross-sectional average in each month at the sub-portfolio level. We then use the estimates of a and κ to reconstruct levered investment returns, while fixing all the other components. We examine the resulting change in the magnitude of the model errors. A large change would mean that the component in question is quantitatively important for the model's success in capturing momentum.

Panel C of Table 1 shows that the growth rate of marginal q is the most important source of momentum, and sales-to-capital is the second most important. Without the cross-sectional variation

[8] The evidence that the average corporate bond returns are flat across the momentum deciles contrasts with Gebhardt, Hvidkjaer, and Swaminathan (2005), who show that stock momentum spills over to bond returns. Our evidence is different for several reasons. First, their evidence is based on a small sample from the Lehman Brothers Fixed Income Database, which is substantially smaller in the coverage of the cross section than the CRSP-Compustat universe. Second, Gebhardt et al. consider only investment grade corporate bonds, while we use both investment grade and non-investment grade credit ratings. Finally, to study the broader cross section in the CRSP-Compustat universe, we follow Blume, Lim, and MacKinlay (1998) to assign the corporate bond returns for a given credit rating to all the firms with the same credit rating. Doing so is likely to limit the cross-sectional variation in average corporate bond returns.

in the growth rate of q_{it}, the winner-minus-loser alpha in the investment-based model inflates to 11.37% per annum. In contrast, this alpha is only 0.44% in the benchmark estimation. Eliminating the cross-sectional variation in sales-to-capital gives rise to a winner-minus-loser alpha of 7.14%. Because the market leverage goes to the wrong direction, eliminating its cross-sectional variation reduces the winner-minus-loser alpha further to 0.25%. Finally, fixing investment-to-capital to its cross-sectional average produces a winner-minus-loser alpha of −5.51%.

These comparative statics complement those reported in Liu, Whited, and Zhang (2009), who show that the current-period investment-to-capital is the most important driving force of the value premium. Asness (1997) argues that book-to-market and momentum are negatively correlated across stocks, yet each is positively related to average stock returns. Asness stresses that any explanation for why value and momentum work must explain this interaction. Using a coherent economics-based framework (the investment return equation derived from first principles), our work provides such an explanation. Value works because growth stocks invest more than value stocks, and momentum works because winners have higher expected growth and profitability than losers.

4.2 The Dynamics of Momentum

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 based only on average momentum profits. As such, the dynamic properties of momentum can serve as additional diagnostics on the model performance.

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. show 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 2 replicates their evidence in our sample. From the first row in each panel, the winner-minus-loser return is on average 9.16% over the six-month period, 11.02% for the first year, −5.90% for the second year, and −5.43% for the third year after the portfolio formation. As such, we observe reversal of momentum at longer horizons.

The second row in each panel of Table 2 shows that the investment-based model reproduces reversal at longer horizons. In particular, the levered investment return for the winner-minus-loser decile is 8.59% for the six-month period and 12.09% for the first year after portfolio formation. In addition, the predicted momentum profits turn negative afterward: −1.93% for the second year and −4.93% for the third year after the portfolio formation.

The remaining three rows in each panel of Table 2 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_{it} 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 the portfolio formation.[9] 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 the portfolio formation.

The Failure of 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 three-factor model cannot explain momentum either because the loser decile tends to load positively, and the winner decile tends to load negatively on their value factor. Table 1 replicates these findings: The CAPM alpha and the Fama-French alpha for the winner-minus-loser decile are 16.95% and 19.15%, 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

[9]Using average future dividend, investment, and sales growth rates to measure expected growth, Liu and Zhang (2008, Figure 2) also show that winners have temporarily higher expected growth than losers. However, their work does not quantify the impact of short-lived expected growth spread across winners and losers on the short-lived nature of momentum profits. We provide such a quantitative exercise using the investment return framework.

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 size factor beta of 0.22 ($t = 1.12$), and a significantly negative value factor beta of -0.40 ($t = -2.03$).

To examine if the investment-based model reproduces the failure of the traditional factor models, Table 3 performs the CAPM and the Fama-French regressions using levered investment returns of the momentum deciles in excess of the one-month Treasury bill rate as the dependent variables. From the contemporaneous regressions in Panel A, the winner-minus-loser alphas are 16.56% and 16.24% in the CAPM and in the Fama-French model, respectively, consistent with the evidence based on stock returns. However, inconsistent with the evidence based on stock returns, 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. We verify in untabulated results that the contemporaneous correlation between stock returns and investment returns for the momentum deciles is negative, but that the correlation between one-year lagged stock returns and investment returns is positive. To see how the temporal shift in the correlation structure affects the factor regressions, Panel B of Table 3 regresses levered investment excess returns of the momentum deciles on the six-month lagged factor returns. The winner-minus-loser alphas are largely 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 value factor beta remains insignificantly positive, whereas it is significantly negative in stock returns.

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. We replicates their basic 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. The projection coefficient, γ_i, measures the cash flow's exposure to the long-term aggregate consumption growth (long run risk). Aggregate consumption is seasonally adjusted real per capital consumption of nondurables and services. The quarterly real per capita consumption data are from NIPA at the Bureau of Economic Analysis. We use personal consumption expenditures (PCE) deflator from NIPA to convert nominal variables to real variables. We calculate portfolio dividend growth following Bansal et al. (p. 1648–1649). In particular, we take into account stock repurchases in calculating dividends. We also use a trailing four-quarter average of the quarterly cash flows to adjust for seasonality in quarterly dividends.

Consistent with Bansal, Dittmar, and Lundblad (2005), Panel A of Table 4 shows that winners have higher long run risk than losers: 15.88 versus 0.33. The cash flow risk spread between the two extreme deciles is 17.14, albeit with a large standard error of 13.50. Winners also have a higher cash flow growth rate than losers: 2.85% versus −2.07% per annum. The growth rate spread of 4.54% again has a large standard error of 3.49%.[10]

In Panel B of Table 4, we report similar, if not stronger evidence of long run risks in investment returns. 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

[10]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 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%.

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. In other words, the role of $D^{\star}_{it+1}$ in the investment return is analogous to the role of dividends in the stock return.

The first column in Panel B of Table 4 shows that the fundamental cash flow growth rate has higher long run consumption risk in winners than in losers: 13.22 versus 5.18. The spread of 8.04 is significant with a standard error of 3.16. The fundamental cash growth rates are also higher in winners than in losers: 17.12% versus −2.46%, 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 connects long run risk in dividends documented by Bansal, Dittmar, and Lundblad (2005) to the long run risks in fundamentals such as the growth rate of sales-to-capital via firms' optimal investment conditions. As such, our evidence helps explain why winners have higher long run risks than losers.

Market States and Momentum

Momentum profits depend on market states. Cooper, Gutierrez, and Hameed (2004) show that the average return of the winner-minus-loser decile 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 is stronger following DOWN markets.

The first six rows in each panel of Table 5 largely replicate Cooper, Gutierrez, and Hameed's (2004) evidence in our sample. 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 10.68% following the UP markets but 3.77% following the DOWN markets. Changing the holding period from six months to 12 months makes the evidence stronger: The winner-minus-loser return is on average 13.68% following the UP markets but 1.58% following the DOWN markets.

The investment-based model fails to reproduce the strong procyclicality of momentum. From rows seven to 12 in Panels A and B of Table 5, if anything, the model predicts that momentum profits are larger in DOWN markets. 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 10.75% following the UP markets, but 16.86% 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 also 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: 12.75% following the UP markets and 11.30% following the DOWN markets. However, the degree of procyclicality in the model falls short of that in the data.

Panels C and D of Table 5 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 consistent with this evidence.

4.3 The Interaction of Momentum with Firm Characteristics

Going beyond the simple momentum deciles analyzed by Jegadeesh and Titman (1993), the momentum literature has documented several stylized facts on the interaction of momentum with firm characteristics (see footnote 1). In this subsection, we show that the investment-based model goes a long way in capturing these stylized facts by applying the model to two-way momentum portfolios.

Two-Way Momentum Portfolios

We use four sets of two-way (three-by-three) portfolios by interacting prior six-month returns with size, firm age, trading volume, and stock return volatility. These four firm characteristics are all 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 only NYSE and AMEX stocks when forming the trading volume and momentum portfolios (the number of shares traded for Nasdaq stocks is inflated relative to NYSE and AMEX stocks because of double counting of dealer trades).

We measure stock return volatility as the standard deviation of weekly excess returns over the past six months (e.g., Lim (2001) and Zhang (2006)). 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 Kenneth 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.

To form the two-way momentum portfolios such as, for example, the nine size and momentum portfolios, we sort stocks into terciles at the end of each portfolio formation month t on the market capitalization at the end of the month, and then independently on the prior six-month return from $t-6$ to $t-1$. Taking intersections of the three size 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.

From Panel A of Table 6, momentum is stronger in small firms than in big firms. The winner-minus-loser tercile in small firms has a CAPM alpha of 10.16% per annum, which is larger than that in big firms, 6.09%. The average return and the Fama-French alpha follow a similar pattern. From Panel B, momentum also decreases with firm age. The average return, the CAPM alpha, and the Fama-French alpha of the winner-minus-loser tercile in young firms are 12.09%, 11.98%, and 13.34%, which are higher than those in old firms, 5.08%, 4.98%, and 6.12%, respectively.

Consistent with Lee and Swaminathan (2000), momentum increases with trading volume (Panel C). The average return, the CAPM alpha, and the Fama-French alpha of the winner-minus-loser tercile in low volume firms are 7.12%, 6.97%, and 8.13%, which are lower than those in high volume firms, 11.94%, 12.11%, and 13.65%, respectively. Momentum also increases with stock return volatility (Panel D). The average return of the winner-minus-loser tercile increases from 6.64% in the low volatility tercile to 13.66% in the high volatility tercile. The CAPM alpha and the Fama-French alpha of the winner-minus-loser tercile are both lower in the low volatility tercile than in the high volatility tercile: 6.50% and 8.38% versus 13.63% and 15.15%, respectively. Across all testing portfolios, the CAPM and the Fama-French model are strongly rejected by the GRS test.

GMM Parameter Estimates and Tests of Overidentification

Table 7 reports the GMM parameter estimates and tests of overidentification for the two-way momentum portfolios. The estimates of the adjustment cost parameter, a, range from 2.54 for the size and momentum portfolios to 3.57 for the volatility and momentum portfolios. Their standard errors range from 0.72 to 0.94. As such, the estimates of a are all significantly positive, meaning that the adjustment cost function is increasing and convex in investment. The estimates of a from the two-way momentum portfolios are also close to the benchmark estimate of 2.81 from the one-way momentum deciles. The estimates of the capital's share, κ, are between 0.10 to 0.13 across different sets of two-way momentum portfolios, and are close to 0.12 in the benchmark estimation.

The mean absolute errors from the investment-based model are mostly smaller than those from the CAPM and the Fama-French model. The m.a.e. of the age and momentum portfolios is 1.19% per annum in the investment-based model, which is smaller than those from the CAPM (3.45%) and the Fama-French model (3.66%). The m.a.e. of the volume and momentum portfolios is 1.51% in the investment-based model, 3.98% in the CAPM, and 4.00% in the Fama-French model. And the m.a.e. of the volatility and momentum portfolios is 2.05% in the investment-based model, 4.78% in the CAPM, and 4.84% in the Fama-French model. For the size and momentum portfolios, the investment-based model produces an m.a.e. of 3.33%, which is slightly higher than the m.a.e. from the CAPM (3.16%) but slightly lower than that from the Fama-French model (3.60%).

However, in contrast to the benchmark estimation using the momentum deciles, the investment-based model is strongly rejected using the two-way momentum portfolios. This evidence means that our test design has sufficient power to reject the null hypothesis that all the individual alphas for a given set of testing portfolios are jointly zero. This benefit results from our construction of monthly levered investment returns to match with monthly stock 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. In untabulated results, we verify that using their annual estimation also fails to reject the model using the two-way momentum portfolios.

Individual Alphas

Panel A of Table 8 reports that the alphas from the investment-based model for the nine size and momentum portfolios range from -3.98% to 5.79% per annum. Although not small, these individual alphas do not vary systematically with momentum. In particular, across the small, median, and big size terciles the winner-minus-loser alphas are -0.93%, -0.98%, and -0.83%, which are all within one standard error from zero. These winner-minus-loser alphas are all lower in magnitude than those from the CAPM: 10.16% in the small tercile, 7.89% in the median tercile, and 6.09% in the big tercile, as well as those from the Fama-French model: 11.55%, 9.64%, and 7.77%, respectively. Panel A of Figure 3 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. In contrast, the scatter plot from the Fama-French model is largely horizontal (Panel B). The scatter plot from the CAPM is similar to that from the Fama-French model (not reported).

Panel B of Table 8 reports smaller individual alphas but larger winner-minus-loser alphas for the firm age and momentum portfolios. The individual alphas range from -2.40% to 2.46% per annum, and the winner-minus-loser alphas are 2.46%, -1.38%, and -3.59% across the young, median, and old age terciles, respectively. However, the winner-minus-loser alphas are still smaller in magnitude than those from the CAPM, 11.98%, 7.57%, and 4.98%, as well as those from the Fama-French model, 13.34%, 8.92%, and 6.12%, respectively. The scatter plots in Panels C and D of Figure 3 confirm the performance difference between the investment-based model and the Fama-French model.

From Panel C of Table 8, the individual alphas from the investment-based model across the nine volume and momentum portfolios range from -1.94% to 4.68% per annum. However, 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 prior six-month returns. The winner-minus-loser alphas are $-1.82\%, -0.09\%$, and -0.34% in the low, median, and high volume terciles, respectively. These winner-minus-loser alphas are again all lower in magnitude than those from the CAPM, 6.97%, 7.93%, and 12.11%, as well as those from the Fama-French model, 8.13%, 9.15%, and 13.65%, respectively. Panels A and B of Figure 4 illustrates the model fit graphically for the volume and momentum portfolios.

From Panel D of Table 8, the individual alphas from the investment-based model across the stock return volatility and momentum portfolios are large, ranging from -3.72% to 3.61% per annum. The winner-minus-loser alphas are $-1.93\%, 0.40\%$, and -2.91% in the low, median, and high return volatility terciles, which are again lower in magnitude than those from the CAPM, 6.50%, 10.68%, and 13.63%, as well as those from the Fama-French model, 8.38%, 12.54%, and 15.15%, respectively. Panels C and D of Figure 4 illustrates our model's fit for the volatility and momentum portfolios in comparison with the Fama-French model. Although the individual alphas can be large in the investment-based model, the alphas do not vary systematically with prior short-term returns. In contrast, the scatter plot from the Fama-French model is largely horizontal.

5 Conclusion

We offer an investment-based interpretation of momentum. The neoclassical theory of investment suggests that expected stock returns are connected with expected marginal benefits of investment divided by marginal costs of investment. Using GMM, we show that the investment-based model goes a long way in capturing average momentum profits across ten momentum deciles as well as the interaction of momentum with firm characteristics. Intuitively, winners have higher expected growth of investment-to-capital and expected sales-to-capital (two major components of expected marginal benefits of investment), and therefore earn higher expected stock returns than losers. Differing from the bulk of the momentum literature, we do not assume any behavioral bias.

However, it is important to point out that the fundamental equation of asset pricing holds in our model. While the investment-based approach is immune to consumption measurement errors that plague most consumption-based studies, we do not identify the pricing kernel. Risk mechanism works only indirectly through firms. 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 worthwhile.

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A Details of Timing Alignment

As noted in Section 3.2, 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 we take firm-level characteristics. Section 3.2 describes the timing convention for firms with December fiscal yearend. This appendix details how we handle firms with non-December fiscal yearend. We use firms with June fiscal yearend and September fiscal yearend as two examples to illustrate our procedure. Firms with fiscal year ending in other months are handled in an analogous way.

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) also lie to the left of the applicable time interval. As such, their timing is exactly the same as the timing 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 : The Benchmark Momentum Deciles, Tests of Asset Pricing Models, Economic Characteristics, and Comparative Statics on the Investment-Based Asset Pricing Model

For each momentum decile, we report (in annual percent) average stock return, r_i^S, stock return volatility, σ_i^S, the CAPM alpha from monthly market regressions, α_i, the alpha from monthly Fama-French (1993) three-factor regressions, α_i^{FF}, and their t-statistics adjusted for heteroscedasticity and autocorrelations. α_i^q is the alpha from the investment-based model, calculated as $E_T[r_{it+1}^S - r_{it+1}^{Iw}]$, in which E_T is the sample mean, and r_{it+1}^{Iw} is the levered investment return. 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. In Panel C, we perform four comparative static experiments on the investment-based model: $\overline{I_{it}/K_{it}}$, $\overline{q_{it+1}/q_{it}}$, $\overline{Y_{it+1}/K_{it+1}}$, 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 model parameters from one-stage GMM to reconstruct the levered investment returns, while keeping all the other characteristics unchanged. The other three experiments are designed analogously. We report the alpha as the average difference between stock returns and reconstructed levered investment returns for each momentum decile.

Panel A: Tests of the CAPM, the Fama-French model, and the investment-based model

	L	2	3	4	5	6	7	8	9	W	W−L	m.a.e.	p-val
r_i^S	3.39	8.49	10.45	11.66	12.69	13.49	13.81	15.47	17.56	20.75	17.36		
σ_i^S	25.56	20.95	19.24	18.39	18.06	18.07	18.59	19.88	21.99	26.97	16.22		
α_i	−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_i^{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		
α_i^q	−1.50	0.37	1.01	0.87	1.39	0.64	−0.06	−0.63	−0.43	−1.07	0.44	0.80	0.10
[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: Economic characteristics

	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 C: The investment-based alphas, α_i^q, from comparative static experiments

	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

Table 2 : Reversal of Momentum Profits in Long Horizons

Following Chan, Jegadeesh, and Lakonishok (1996), 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) for each momentum deciles. 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 3 : Regressing Levered Investment Excess Returns on the CAPM and the Fama-French Factors

For each momentum decile we conduct monthly CAPM regressions and monthly Fama-French three-factor regressions using levered investment returns in excess of the one-month Treasury bill rate. The levered investment returns are constructed using the parameter estimates in Table 7. The data for the one-month Treasury-bill rate and the Fama-French factors are from Kenneth French's Web site. 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: Regressing levered investment excess returns 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: Regressing levered investment excess returns 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 4 : 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 7. $\bar{g}_i^\star$ 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	$\bar{g}_i^\star$	ste	$\gamma_{1i}^\star$	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

Table 5 : 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					Panel D: Months 25–36				
State	Profits	$[t]$	N-month market	Returns	State	Profits	$[t]$	N-month market	Returns
DOWN	−0.38	−0.15	36	r^S	DOWN	0.59	0.29	36	r^S
DOWN	−0.65	−0.21	24	r^S	DOWN	0.24	0.15	24	r^S
DOWN	−2.45	−1.50	12	r^S	DOWN	−1.67	−0.83	12	r^S
UP	−6.54	−3.42	36	r^S	UP	−6.15	−3.04	36	r^S
UP	−6.59	−3.42	24	r^S	UP	−6.20	−2.97	24	r^S
UP	−6.90	−3.26	12	r^S	UP	−6.56	−2.90	12	r^S
DOWN	3.28	0.82	36	r^{Iw}	DOWN	−0.02	−0.01	36	r^{Iw}
DOWN	2.19	0.51	24	r^{Iw}	DOWN	−0.74	−0.24	24	r^{Iw}
DOWN	4.58	1.43	12	r^{Iw}	DOWN	1.16	0.42	12	r^{Iw}
UP	−2.54	−1.01	36	r^{Iw}	UP	−5.51	−2.48	36	r^{Iw}
UP	−2.47	−0.97	24	r^{Iw}	UP	−5.49	−2.47	24	r^{Iw}
UP	−3.82	−1.40	12	r^{Iw}	UP	−6.74	−2.96	12	r^{Iw}
DOWN	4.03	1.12	36	$r^{Iw}_{[+6]}$	DOWN	−0.57	−0.23	36	$r^{Iw}_{[+6]}$
DOWN	0.41	0.10	24	$r^{Iw}_{[+6]}$	DOWN	−2.99	−1.14	24	$r^{Iw}_{[+6]}$
DOWN	2.96	0.88	12	$r^{Iw}_{[+6]}$	DOWN	−1.22	−0.55	12	$r^{Iw}_{[+6]}$
UP	−2.46	−0.97	36	$r^{Iw}_{[+6]}$	UP	−5.20	−2.31	36	$r^{Iw}_{[+6]}$
UP	−2.07	−0.80	24	$r^{Iw}_{[+6]}$	UP	−4.93	−2.18	24	$r^{Iw}_{[+6]}$
UP	−3.17	−1.12	12	$r^{Iw}_{[+6]}$	UP	−5.75	−2.31	12	$r^{Iw}_{[+6]}$
DOWN	−1.40	−0.36	36	$r^{Iw}_{[+12]}$	DOWN	−3.70	−1.11	36	$r^{Iw}_{[+12]}$
DOWN	−0.54	−0.12	24	$r^{Iw}_{[+12]}$	DOWN	−2.74	−0.76	24	$r^{Iw}_{[+12]}$
DOWN	−0.74	−0.21	12	$r^{Iw}_{[+12]}$	DOWN	−3.03	−1.20	12	$r^{Iw}_{[+12]}$
UP	−1.93	−0.75	36	$r^{Iw}_{[+12]}$	UP	−4.85	−2.17	36	$r^{Iw}_{[+12]}$
UP	−2.05	−0.80	24	$r^{Iw}_{[+12]}$	UP	−5.00	−2.22	24	$r^{Iw}_{[+12]}$
UP	−2.21	−0.78	12	$r^{Iw}_{[+12]}$	UP	−5.25	−2.11	12	$r^{Iw}_{[+12]}$

Table 6 : Tests of the CAPM and the Fama-French Three-Factor Model for Two-Way Sorted Momentum 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.

Panel A: 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 B: 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		

Panel C: Nine trading volume and momentum portfolios

	Low				2				High					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
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 D: 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		

Table 7 : GMM Parameter Estimates and Tests of Overidentification, Two-Way Sorted Momentum Portfolios

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.

	Size and momentum	Age and momentum	Volume and momentum	stock return volatility and momentum
a	2.54	2.80	3.10	3.57
[ste]	0.72	0.94	0.87	0.77
κ	0.10	0.12	0.13	0.13
[ste]	0.01	0.01	0.01	0.02
χ^2	21.14	23.80	20.21	18.44
d.f.	7	7	7	7
p-val	0.00	0.00	0.01	0.01
m.a.e.	3.33	1.19	1.51	2.05

Table 8 : Alphas from the Investment-Based Expected Stock Return Model, Two-Way Sorted Momentum Portfolios

The alphas (in annual percent) and t-statistics are from one-stage GMM with an identity weighting matrix. The moment conditions are $E\left[r^S_{it+1} - r^{Iw}_{it+1}\right] = 0$, in which r^S_{it+1} is the stock return, and r^{Iw}_{it+1} is the levered investment return. The alphas are calculated from $\alpha^q_i \equiv E_T\left[r^S_{it+1} - r^{Iw}_{it+1}\right]$, 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: 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 B: 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 C: 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 D: 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

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).

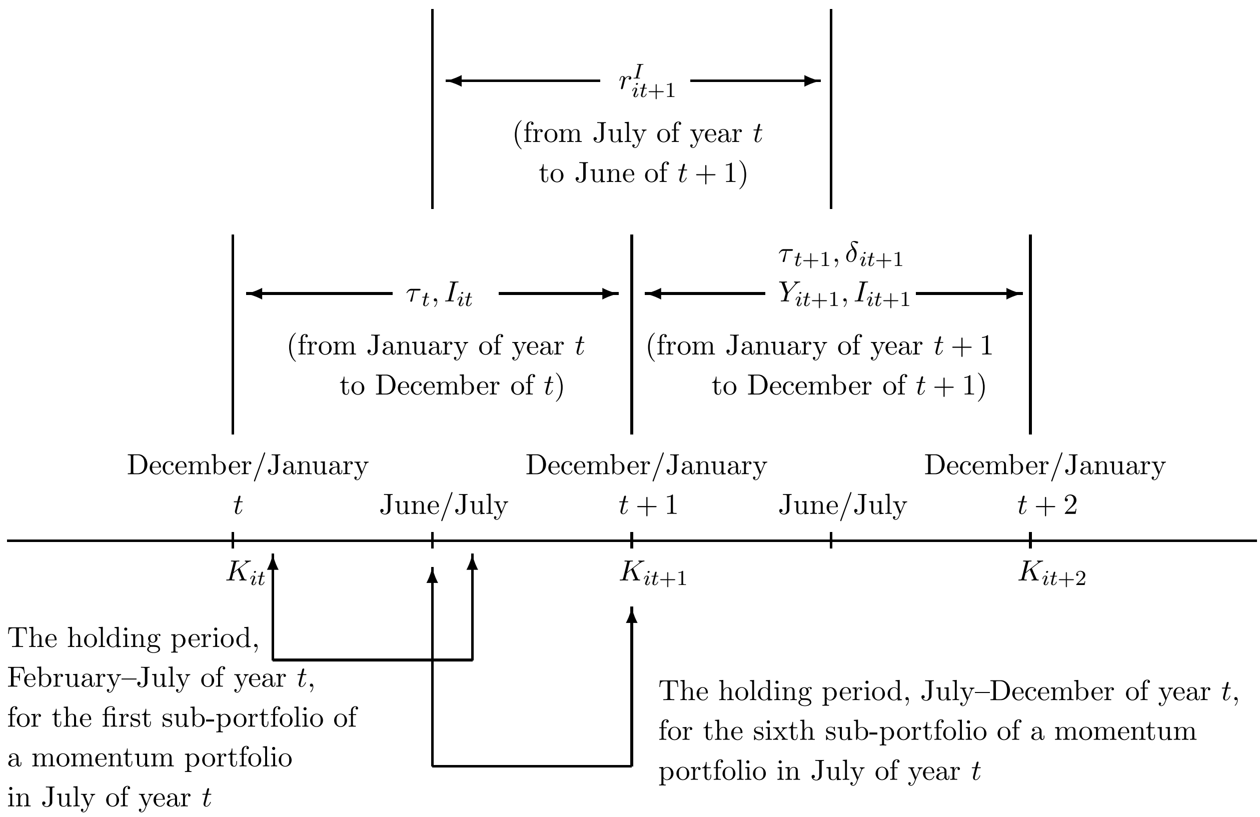


Figure 2 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Ten Momentum Deciles

In the investment-based model, the average predicted stock returns are given by $E_T[r^{Iw}_{it+1}]$, in which E_T is the sample mean, and r^{Iw}_{it+1} is levered investment returns given by equation (5). We use the parameter estimates from one-stage GMM to construct the levered investment returns. In the CAPM, the average predicted stock returns are the time series average of the product between the market beta and market excess returns. In the Fama-French model, the average predicted stock returns are the time series average of the sum of three products: the market beta times market excess returns, the size factor loading times the size factor returns, and the value factor loading times the value factor returns.

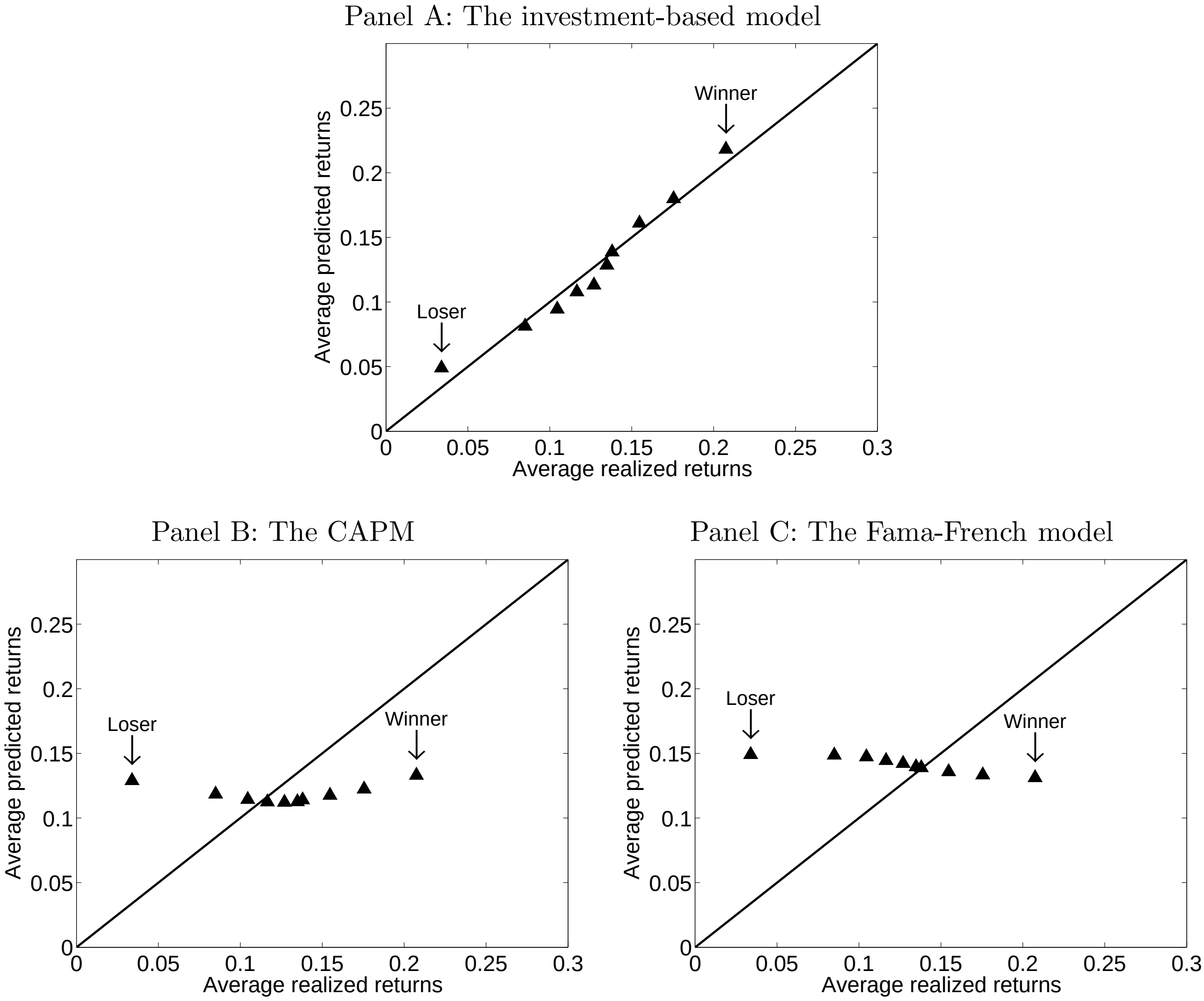


Figure 3 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Size and Momentum Portfolios and Nine Firm Age and Momentum Portfolios

In the investment-based model, the average predicted stock returns are given by $E_T[r_{it+1}^{Iw}]$, in which E_T is the sample mean, and r_{it+1}^{Iw} is levered investment returns given by equation (5). We use the parameter estimates from one-stage GMM to construct the levered investment returns. In the Fama-French model, the average predicted stock returns are the time series average of the sum of three products: the market beta times market excess returns, the size factor loading times the size factor returns, and the value factor loading times the value factor returns.

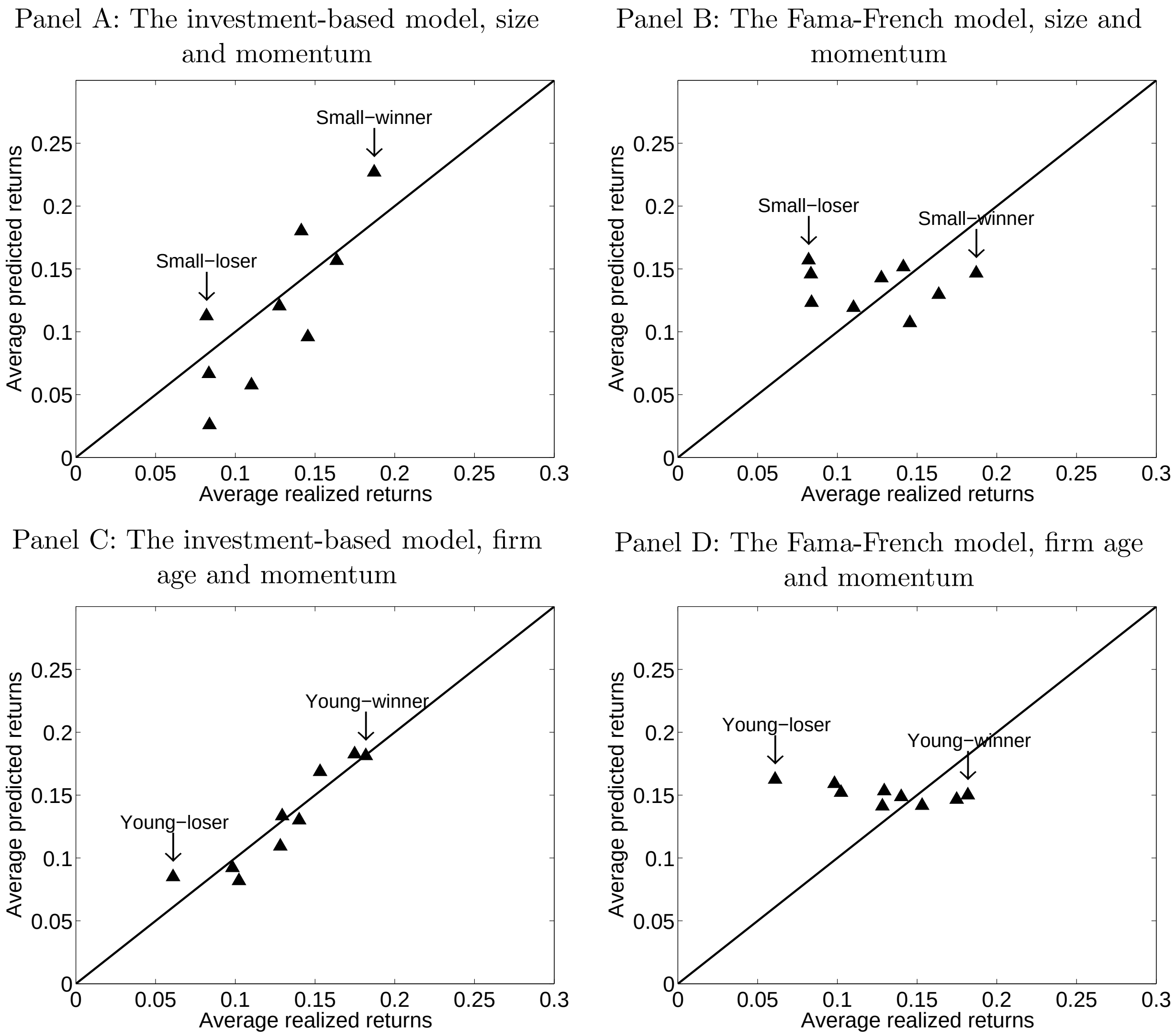
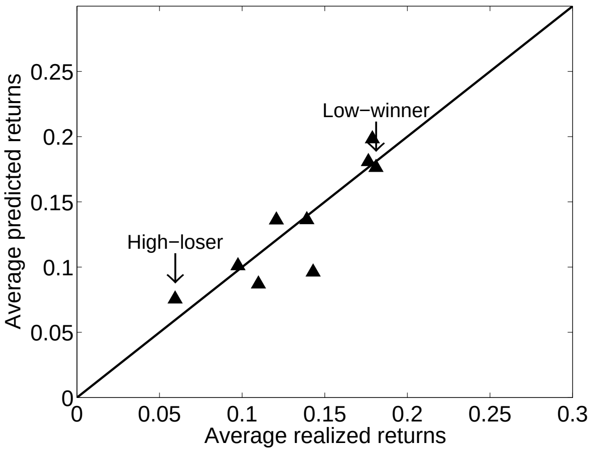


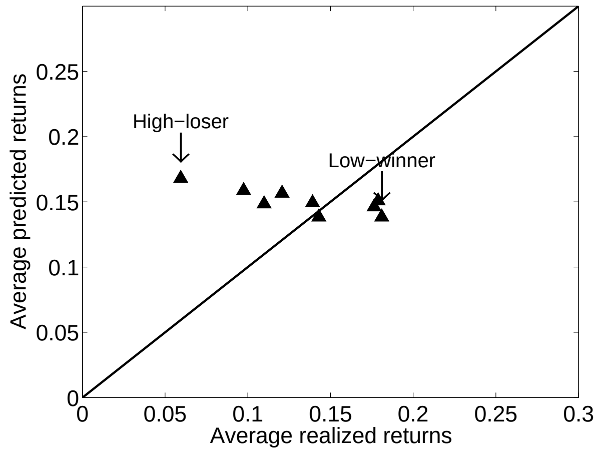
Figure 4 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Trading Volume and Momentum Portfolios and Nine Stock Return Volatility and Momentum Portfolios

In the investment-based model, the average predicted stock returns are given by $E_T[r^{Iw}_{it+1}]$, in which E_T is the sample mean, and r^{Iw}_{it+1} is levered investment returns given by equation (5). We use the parameter estimates from one-stage GMM to construct the levered investment returns. In the Fama-French model, the average predicted stock returns are the time series average of the sum of three products: the market beta times market excess returns, the size factor loading times the size factor returns, and the value factor loading times the value factor returns.

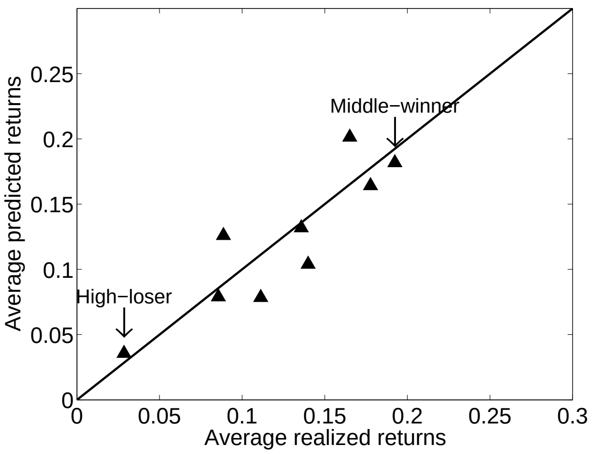
Panel A: The investment-based model, trading volume and momentum



Panel B: The Fama-French model, trading volume and momentum



Panel C: The investment-based model, stock return volatility and momentum



Panel D: The Fama-French model, stock return volatility and momentum

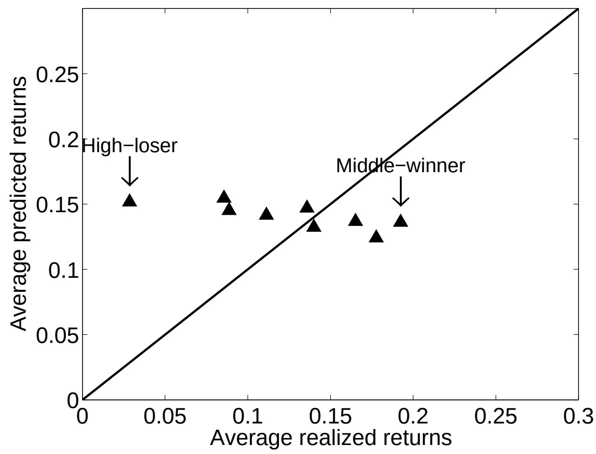
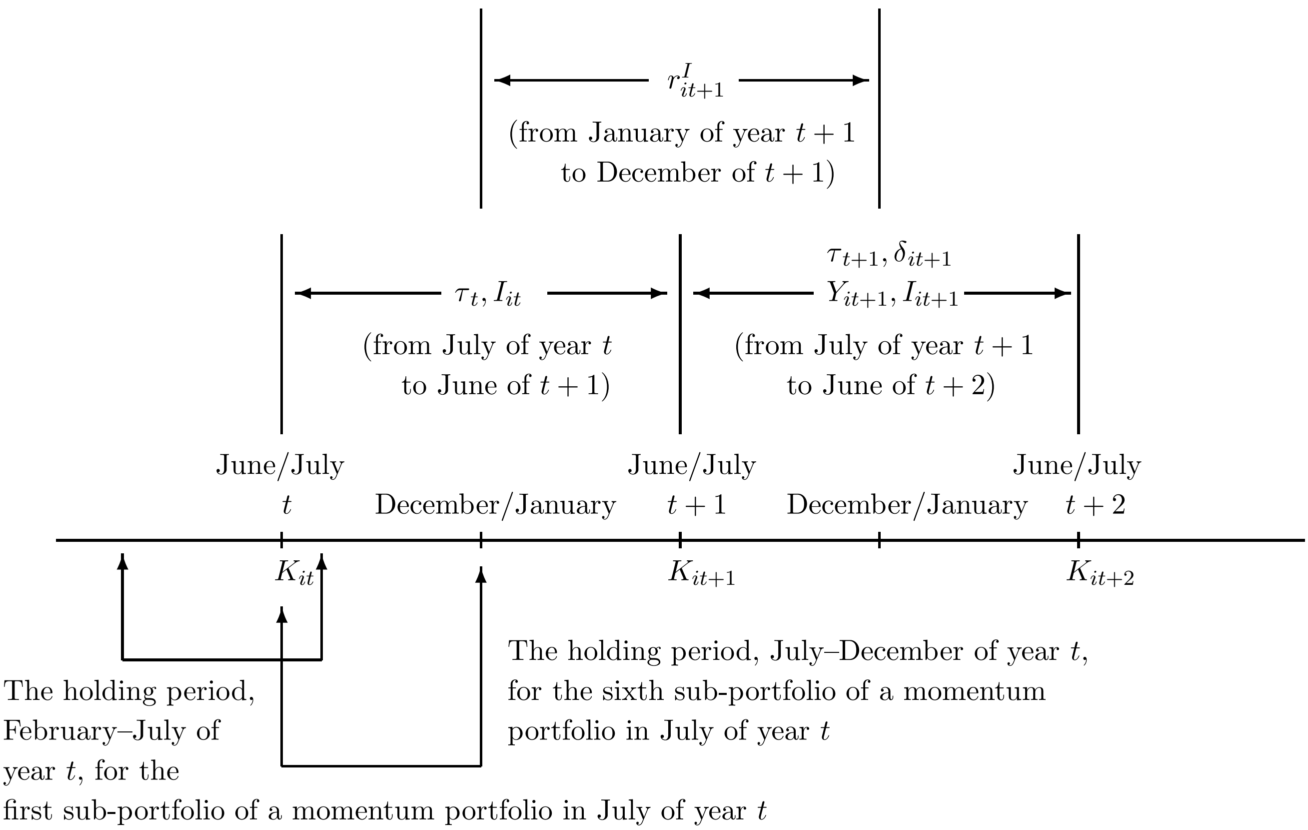


Figure A.1: Timing of Firm-Level Characteristics, Firms with Non-December fiscal yearend

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