Fisher College of Business
Working Paper Series

Charles A. Dice Center for Research in Financial Economics

Investment-Based Momentum Profits

Laura Xiaolei Liu,
Hong Kong University of Science and Technology

Lu Zhang, Department of Finance, The Ohio State University,
NBER,

Dice Center WP 2010-17
Fisher College of Business WP 2010-03-017

September 2010

Investment-Based Momentum Profits

Laura Xiaolei Liu*
Hong Kong University of Science and Technology

Lu Zhang†
Ohio State University
and NBER

September 2010‡

Abstract

We offer an investment-based explanation of momentum. The neoclassical theory of investment implies that expected stock returns are related to expected investment returns, defined as the next-period marginal benefits of investment divided by the current-period marginal costs of investment. Empirically, winners have higher expected growth of investment-to-capital and higher expected marginal product of capital and consequently higher expected stock returns than losers. The investment-based expected return model captures well the moment profits across a wide array of momentum portfolios. However, the individual alphas for several testing portfolios are large. All in all, we conclude that momentum is consistent with the value maximization of firms.

*Finance Department, School of Business and Management, Hong Kong University of Science and Technology, Kowloon, Hong Kong. Tel: (852) 2358-7661, fax: (852) 2358-1749, and e-mail: fnliu@ust.hk.

†Department of Finance, Fisher College of Business, Ohio State University, 760A Fisher Hall, 2100 Neil Avenue, Columbus OH 43210; and NBER. Tel: (614) 292-8644, fax: (614) 292-7062, and e-mail: zhanglu@fisher.osu.edu.

‡We thank Jennifer Huang, Frank Yu, and other seminar participants at Cheung Kong Graduate School of Business and China Europe International Business School for helpful comments. The portfolio level data and Matlab programs used in our GMM estimation and tests 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 Jegadeesh and Titman's original finding.[1] For the most part, the literature has followed Jegadeesh and Titman in interpreting momentum profits as irrational underreaction to firm-specific information. In particular, Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) have constructed behavioral models to explain the momentum anomaly using psychological biases such as conservatism, self-attributive overconfidence, and slow information diffusion.

Deviating from the bulk of the momentum literature, we propose and quantitatively evaluate an investment-based explanation of momentum. As shown by Cochrane (1991) and Liu, Whited, and Zhang (2009), under constant returns to scale, the neoclassical theory of investment implies that stock returns equal levered investment returns. The latter returns, defined as the next-period marginal benefits of investment divided by the current-period marginal costs of investment, are linked to firm characteristics through firms' optimality conditions for equity value maximization.

We use generalized method of moments (GMM) to match the means of levered investment returns to the means of stock returns. As testing assets we use one-way momentum deciles of Jegadeesh and Titman (1993) and industry momentum quintiles of Moskowitz and Grinblatt (1999) as well as two-way three-by-three portfolios sorted on momentum and one of the following characteristics: size, firm age, trading volume, stock return volatility, and cash flow volatility (e.g., Hong, Lim, and Stein (2000), Lee and Swaminathan (2000), Jiang, Lee, and Zhang (2005), and Zhang (2006)).

The investment-based expected return model does a good job in explaining momentum profits.

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

In particular, the winner-minus-loser decile has a small alpha of 1.23% per annum, which is negligible compared to the alphas from the traditional asset pricing models: 14.97% from the CAPM, 16.46% from the Fama-French (1993) model, and 14.87% from the standard consumption-CAPM with power utility. (All testing portfolios are equal-weighted.) For the industry momentum quintiles, the winner-minus-loser quintile has a small alpha of 0.61% in the investment-based model. In contrast, the alphas are 6.65% in the CAPM, 9.73% in the Fama-French model, and 6.76% in the standard consumption-CAPM. The alphas of individual testing portfolios are also substantially smaller in the investment-based model than those in the traditional models.

For the double sorted momentum portfolios, the investment-based model continues to do well in explaining momentum profits in that the model errors do not vary systematically with short-term prior returns. For example, the winner-minus-loser tercile alphas are $-0.46\%, 1.13\%$, and 0.75% per annum across the small, median, and big size terciles, respectively. In contrast, the alphas from the traditional models are 9.52%–10.78% in the small size tercile, 8.06%–9.98% in the median size tercile, and 5.55%–6.93% in the big size tercile. Across the trading volume terciles, the winner-minus-loser alphas are 0.55%, 2.75%, and 1.27% in the investment-based model. In contrast, the alphas from the traditional models are 3.85%–7.49% in the low volume tercile, 7.43%–8.49% in the median volume tercile, and 10.19%–15.67% in the high volume tercile. Finally, across the low, median, and high cash flow volatility terciles, the winner-minus-loser alphas are 1.24%, 1.03%, and -2.26%, respectively. In contrast, the alphas from the traditional models are 6.26%–7.62% in the low volatility tercile, 8.20%–9.95% in the median tercile, and 10.17%–12.00% in the high volatility tercile.

The shortcoming of the investment-based model is that it delivers large individual alphas for some testing portfolios. In particular, the model has its worst fit in the nine cash flow volatility and momentum portfolios. The individual alphas range from -8.35% to 7.62% per annum. Although the alphas do not vary systematically with momentum, their magnitude is comparable with the magnitude of the alphas from the traditional models. However, all the other sets of testing portfolios have individual alphas that are smaller in magnitude than those from the traditional models.

The investment-based model suggests several sources of cross-sectional variations of expected stock returns. All else equal, firms with low investment-to-capital today, high expected growth rate of investment-to-capital, high expected sales-to-capital, high market leverage today, low expected rate of depreciation, and low expected corporate bond returns should earn higher expected stock returns. Through extensive comparative statics, we show that the expected growth of investment-to-capital is the most important source of momentum profits, and the expected sales-to-capital ratio is the second most important. For example, eliminating the cross-sectional variation in the expected growth of investment-to-capital would increase the alpha of the winner-minus-loser decile to 13.17% per annum from 1.23% in the benchmark estimation. Without the cross-sectional variation in the expected sales-to-capital ratio, the winner-minus-loser alpha would be 5.44%. All the other sources of expected stock returns are largely irrelevant for explaining momentum profits.

Our investment-based explanation of momentum is related to Johnson (2000) and Sagi and Seasholes (2007). Johnson argues that the log price-to-dividend ratio is convex in expected growth, meaning that stock returns (changes in the log price-to-dividend ratio) are more sensitive to changes in expected growth when expected growth is high. Winners that have recently had large positive return shocks are more likely to have positive shocks to expected growth than losers that have recently had large negative return stocks. If the expected growth risk carries a positive premium, winners should earn higher expected returns than losers. Sagi and Seasholes argue that growth options are riskier than assets in place. Winners with good recent performance have more risky growth options that account for a larger fraction of equity value than losers with bad recent performance. As such, winners should earn higher expected returns than losers.

The economic mechanisms in both Johnson (2000) and Sagi and Seasholes (2007) rely on the expected growth spread between winners and losers. We complement their work in two ways. First, using a different framework based on the neoclassical theory of investment, we show theoretically that firms with high expected growth rates should earn higher expected stock returns than firms with low expected growth rates, all else equal. Second, we show empirically via structural estimation that the expected growth is the most important driving force of momentum profits. More generally, our work expands the investment-based asset pricing literature initiated by Cochrane (1991, 1996) and Berk, Green, and Naik (1999). We adopt the investment-based expected return model from Liu, Whited, and Zhang (2009), who study the relations of stock returns with earnings surprises, book-to-market equity, and corporate investment. We instead study the momentum puzzle.

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 empirical results, and Section 5 concludes.

2 The Model of the Firms

Because we adopt the Liu, Whited, and Zhang (2009) model, we keep its description brief. Firms use capital and costlessly adjustable inputs to produce a homogeneous output. These inputs are chosen each period to maximize operating profits, defined as revenues minus expenditures on the inputs. Taking operating profits as given, firms choose investment to maximize the market value of equity.

Let $\Pi(K_{it}, X_{it})$ denote the operating profits of firm i at time t, in which K_{it} is capital and X_{it} is a vector of exogenous aggregate and firm-specific shocks. We assume $\Pi(K_{it}, X_{it})$ has constant returns to scale, meaning that $\Pi(K_{it}, X_{it}) = K_{it}\partial\Pi(K_{it}, X_{it})/\partial K_{it}$. We further assume that firm i has a Cobb-Douglas production function, meaning that the marginal product of capital is given by $\partial\Pi(K_{it}, X_{it})/\partial K_{it} = \kappa Y_{it}/K_{it}$, in which $\kappa > 0$ is the capital's share in output and Y_{it} is sales.

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

Firms can borrow by issuing one-period debt. At the beginning of time t, firm i can issue debt, denoted B_{it+1}, which must be repaid at the beginning of $t+1$. The gross corporate bond return on B_{it}, denoted r^B_{it}, 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. Firm i's payout is then:

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

in which $\tau_t \delta_{it} K_{it}$ is the depreciation tax shield, and $\tau_t(r^B_{it} - 1)B_{it}$ is the interest tax shield.

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:

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

subject to a transversality condition: $\lim_{T\to\infty} E_t \left[M_{t+T}\, B_{it+T+1} \right] = 0$. The firm's optimality conditions imply that $E_t[M_{t+1} r^I_{it+1}] = 1$, in which r^I_{it+1} is the investment return, defined as:

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

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

Define the after-tax corporate bond return as $r^{Ba}_{it+1} \equiv r^B_{it+1} - (r^B_{it+1} - 1)\tau_{t+1}$, then $E_t[M_{t+1} r^{Ba}_{it+1}] = 1$. 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 is 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 we define r^{Iw}_{it+1} as the levered investment return.

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 brackets.

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

Specifically, following the standard GMM procedure (e.g., Hansen and Singleton (1982)), we estimate the parameters, $\mathbf{b} \equiv (a, \kappa)$, by minimizing a weighted combination of the sample moments

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

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

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

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

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

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

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

3.2 Data

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

3.2.1 Testing Portfolios

To understand the driving forces behind momentum profits, we include as testing assets two sets of one-way sorted portfolios including ten momentum deciles as in Jegadeesh and Titman (1993) and five industry momentum portfolios as in Moskowitz and Grinblatt (1999). We also use as testing assets a list of double sorted three-by-three portfolios including nine size and momentum portfolios as in Hong, Lim, and Stein (2000), nine age and momentum portfolios as in Zhang (2006), nine trading volume and momentum portfolios as in Lee and Swaminathan (2000), nine stock return volatility and momentum portfolios as in Zhang (2006), and nine cash flow volatility and momentum portfolios as in Jiang, Lee, and Zhang (2005).

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

We construct momentum portfolios by sorting all stocks at the end of every month t on the basis of their past six-month returns from $t-6$ to $t-1$, and hold the resulting ten deciles for the subsequent six months from $t+1$ to $t+6$. We skip one month between the end of the ranking period and the beginning of the holding period (month t) to avoid potential microstructure biases. We equal-weight all stocks within a given portfolio. Because we use the six-month holding period while forming the portfolios monthly, we have six portfolios for each decile in a given holding month. We first average across these six portfolios to obtain monthly returns, and then calculate buy-and-hold annual returns from July of each year to June of next year to match with annual levered investment returns. The sample is annual from July 1963 to June 2008. We time-aggregate monthly returns from July of each year to June of next year (instead of from January to December of a given year) to align the timing of annual stock returns with the timing of annual levered investment returns (see Section 3.2.3).

Moskowitz and Grinblatt (1999) document that trading strategies that buy stocks from past winning industries and sell stocks from past losing industries are profitable, even after controlling for size, book-to-market, and individual stock momentum. We use the 20 industry classifications as in Moskowitz and Grinblatt. Because we exclude financial firms and regulated utilities, we have only 18 industries in our sample. We value-weight all stocks in a given industry portfolio. At the end of each portfolio formation month t, we sort the 18 industry portfolios into quintiles based on their prior six-month 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 for the subsequent six months from $t+1$ to $t+6$. We again time-aggregate monthly returns from July of each year to June of next year to form annual stock returns.

For the double sorted portfolios, in addition to past six-month returns, we need to measure the other sorting variable including size, age, trading volume, stock return volatility, and cash flow volatility. Size is market capitalization at the beginning of the portfolio formation month t. We require firms to have positive market capitalization before including them into the sample. Firm age is the number of months elapsed between the month when the firm first appears in the monthly CRSP database and the portfolio formation month t.

Trading volume is the average daily turnover during the past six months from $t-6$ to $t-1$, in which daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. Following Lee and Swaminathan (2000), we restrict our sample to include NYSE and AMEX stocks only when forming the nine trading volume and momentum portfolios. The reason is that the number of shares traded for Nasdaq stocks is inflated relative to NYSE and AMEX stocks because of the double counting of dealer trades.

Following Lim (2001) and Zhang (2006), we measure stock return volatility as the standard deviation of weekly excess returns over the past six months from $t-6$ to $t-1$. Weekly returns are from Thursday to Wednesday to mitigate bid-ask effects in daily prices. We calculate weekly excess returns as raw weekly returns minus weekly risk-free rates. The daily risk-free rates are from Ken French's Web site. We require a stock to have at least 20 weeks of date to enter the sample. Cash flow volatility is the standard deviation of the ratio of cash flow from operations scaled by total assets in the most recent five years prior to the portfolio forming month. We require at least three years of data available to measure the standard deviation. Cash flow from operations is earnings before extraordinary items minus total accruals, scaled by total assets, in which total accruals are changes in current assets minus changes in cash, changes in current liabilities, and depreciation expense plus changes in short-term debt (Compustat annual item (IB $-$ (ΔACT $-$ ΔCHE $-$ ΔLCT $-$ DP $+$ ΔDLC))/TA).

To form a given set of double sorted portfolios, for example, the nine size and momentum portfolios, we sort stocks independently into terciles at the end of each portfolio formation month t on the market capitalization at the beginning of the month, and then on the prior six-month return from $t-6$ to $t-1$. Taking intersections of the three size terciles and the three momentum terciles, we form nine size and momentum portfolios. Skipping the current month t, we hold the resulting portfolios for the subsequent six months from month $t+1$ to $t+6$. We equal-weight all stocks within a given portfolio when calculating returns for the portfolio. Buy-and-hold annual returns are calculated from July of each year to June of next year to match with annual levered investment returns. The other sets of double sorted portfolios are constructed in a similar way.

3.2.2 Variable Measurement

We follow Liu, Whited, and Zhang (2009) in measuring characteristics used to construct the levered investment returns. The capital stock, K_{it}, is gross property, plant, and equipment (Compustat annual item PPEGT), and investment, I_{it}, is capital expenditures (CAPX) minus sales of property, plant, and equipment (SPPE). We set the sales of property, plant, and equipment to be zero when item SPPE is missing. The capital depreciation rate, δ_{it}, is the amount of depreciation (DP) divided by the capital stock. Output, Y_{it}, is sales (SALE). Total debt, B_{it+1}, is long-term debt (DLTT) plus short term debt (DLC). Market leverage, w_{it}, is the ratio of total debt to the sum of total debt and the market value of equity. We measure the tax rate, τ_t, as the statutory corporate income tax from the Commerce Clearing House's annual publications.

Both stock and flow variables in Compustat are recorded at the end of year t. But in the model stock variables dated t are measured at the beginning of year t and flow variables dated t are over the course of year t. We take, for example, for the year 2003 any beginning-of-period stock variable K_{i2003} from the 2002 balance sheet and I_{i2003} from the 2003 income or cash flow statement.

Firm-level corporate bond data are rather limited, and few or even none of the firms in several testing portfolios have corporate bond returns. To measure the pre-tax corporate bond returns, r^B_{it+1}, in a broad sample, we follow Blume, Lim, and MacKinlay (1998) to impute the credit ratings for firms with no crediting rating data from Compustat (annual item SPLTICRM). We assign the corporate bond returns for a given credit rating (from Ibbotson Associates) to the firms with the same credit ratings (see Liu, Whited, and Zhang (2009) for details of this imputation procedure).

3.2.3 Timing Alignment

We construct annual levered investment returns to match with annual stock returns. Constructing annual portfolio characteristics underlying the levered investment returns is intricate because the composition of the portfolios changes monthly. We use the following procedure analogous to Liu, Whited, and Zhang's (2009) procedure for the monthly rebalanced earnings surprises deciles.

For example, consider the 12 low momentum deciles formed in each month from July of year t to June of year $t+1$. For each month we calculate portfolio-level characteristics by aggregating firm-level characteristics over the firms in the low momentum decile. This cross-sectional aggregation follows the practice in Fama and French (1995). For example, portfolio-level investment-to-capital is the sum of investment for all the firms within the portfolio at time t divided by the sum of capital for the same set of firms at time t. Because for a given low momentum decile, there are six portfolios formed in each month of the six-month ranking period, we average the portfolio characteristics across the six portfolios. In addition, because the portfolio composition changes from month to month, the portfolio characteristics also change from month to month. As such, we average these portfolio characteristics over the 12 monthly low momentum deciles, and use these averages to construct the levered investment returns. We repeat this procedure for the remaining nine momentum deciles (deciles two to ten) (see Liu, Whited, and Zhang (2009, Appendix C) for more details of the timing alignment). We use the same timing convention for all the other sets of momentum portfolios.

4 Empirical Results

To set the background, we report the tests of the CAPM, the Fama-French model, and the standard consumption-CAPM for the momentum portfolios in Section 4.1. We then present the results from testing the investment-based expected return model in Section 4.2.

4.1 Preliminaries

Table 1 reports the tests of the traditional asset pricing models. The standard consumption-CAPM has the pricing kernel given by $\rho(C_{t+1}/C_t)^{-\gamma}$, in which ρ is 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 $E[M_{t+1}r_{ft+1}] = 1$. The standard consumption-CAPM alpha is calculated as $E_T[M_{t+1}(r^S_{it+1} - r_{ft+1})]/E_T[M_{t+1}]$.

Panel A reports the results for the ten momentum deciles. The average return increases monotonically from the loser decile to the winner decile. The winner-minus-loser portfolio earns an equal-weighted average return of 15.04% per annum, which is more than seven standard errors from zero. We use equal-weighted returns precisely because these returns are harder for asset pricing models to explain than value-weighted returns. The CAPM alpha of the winner-minus-loser portfolio is 14.9%, which is more than eight standard errors from zero. The Fama-French alpha is 16.46% ($t = 8.2$). Both models are strongly rejected by the Gibbons, Ross, and Shanken (1989, GRS) test. The standard consumption-CAPM produces an alpha of 14.87% for the zero-cost portfolio, but is within 0.7 standard errors from zero. This insignificance is probably due to large measurement errors in consumption data. The economic magnitude of the error is large. In addition, the χ^2 test of the overidentification strongly rejects the model.

From Panel B, the industry momentum strategy is profitable. The average return goes from 9.46% per annum for the loser quintile to 16.33% for the winner quintile. The spread of 6.87% is more than three standard errors from zero. The CAPM alpha and the Fama-French alpha for the winner-minus-loser quintile are 6.65% and 9.73%, respectively, both of which are more than four standard errors from zero. The consumption alpha of the zero-cost portfolio is 6.76%.

Panel C shows that momentum profits tend to be larger in small firms than in big firms. For example, the winner-minus-loser tercile in the small-firm tercile has a CAPM alpha of 9.52% per annum, which is larger than that in the big-firm tercile, 5.55%. The average return and the Fama-French alpha follow a similar pattern. However, the consumption alpha of the zero-cost tercile is slightly smaller in the small-size tercile than in the median-size tercile: 9.88% versus 9.98%. All three models are again strongly rejected by the GRS test or the χ^2 test of overidentification.

From Panel D, the magnitude of momentum profits decreases with firm age. The average return, the CAPM alpha, the Fama-French alpha, and the consumption alpha in young firms are 10.09%, 10.11%, 11.50%, and 11.21% per annum, which are higher than those in old firms, 5.34%, 5.35%, 6.46%, and 7.33% respectively. Panel E shows that consistent with Lee and Swaminathan (2000), momentum is stronger in stocks with high trading volume than in stocks with low trading volume. The average return of the winner-minus-loser tercile increases from 6.26% in the low volume tercile to 9.80% in the high volume tercile. The CAPM alpha, the Fama-French alpha, and the consumption alpha of the winner-minus-loser tercile in the low volume tercile are 6.24%, 7.49%, and 3.85%, which are lower than those in the high volume tercile, 10.19%, 11.44%, and 15.67%, respectively.

Momentum also increases with stock return and cash flow volatilities. From Panel F, the average return of the winner-minus-loser tercile increases from 4.36% in the low return volatility tercile to 10.96% in the high return volatility tercile. The CAPM alpha, the Fama-French alpha, and the consumption alpha of the zero-cost portfolio are all lower in the low return volatility tercile than in the high return volatility tercile. From Panel G, the results for the nine cash flow volatility and momentum portfolios are largely similar. All three models are again strongly rejected.

4.2 Testing the Investment-Based Expected Return Model

With this background, we turn to the tests on the investment-based expected return model.

4.2.1 Point Estimates and Overall Model Performance

Table 2 reports the GMM parameter estimates and tests of overidentification for each set of momentum portfolios. There are only two parameters in the model: the adjustment cost parameter, a, and the capital's share, κ. The estimates of a are between 3.26 and 7.82. The estimate is 7.82 for the industry momentum portfolios, and is about 1.9 standard errors from zero. All the other six sets of testing portfolios deliver significantly positive estimates of a. The evidence implies that the adjustment cost function is increasing and convex in investment. The capital's share is estimated to be between 0.14 and 0.20. The estimates are precise with small standard errors ranging from 0.02 to 0.03.

The tests of overidentification show that the investment-based model is not formally rejected. The p-values range from 0.24 to 0.41. Except for the cash flow volatility and momentum portfolios, the mean absolute errors (m.a.e. hereafter) produced from the investment-based model are no greater than those from the traditional asset pricing models. In particular, the m.a.e. of the momentum deciles is 1.72% per annum, which is lower than those from the CAPM (3.66%), the Fama-French model (3.03%), and the standard consumption-CAPM (2.75%). The m.a.e. of the industry momentum quintiles is 0.49%, which is lower than those from the CAPM (1.88%), the Fama-French model (2.89%), and the standard consumption-CAPM (1.68%).

The m.a.e. of the nine size and momentum portfolios is 3.44%, which is similar to those from the traditional models ranging from 3.16% to 3.37%. The m.a.e. of the age and momentum portfolios is 1.37% in the investment-based model, which is smaller than those from the traditional models ranging from 3.03% to 3.62%. The m.a.e.'s across the trading volume and momentum portfolios and across the stock return volatility and momentum portfolios are similar to those from the traditional models. However, the investment-based model produces a large m.a.e. of 5.62% per annum across the cash flow volatility and momentum portfolios, which is larger than those from the traditional models (ranging from 3.37% to 3.77%).

4.2.2 Alphas

Table 2 only reports overall model performance. To study whether the errors vary systematically across momentum portfolios, Table 3 reports for each individual testing portfolio the alpha from the investment-based model, α_i^q, defined in equation (7). In the equation the levered investment returns are constructed using the parameter estimates in Table 2. We also report the t-statistics that test that a given α_i^q equals zero, using standard errors calculated from one-stage GMM.

From Panel A of Table 3, the alphas for the momentum deciles range from -4.01% to 2.38% per annum. The winner-minus-loser decile has a small alpha of 1.23%, which is within 0.6 standard errors from zero. In terms of economic magnitude, this alpha is negligible compared to the large alphas from the traditional models: 14.97% from the CAPM, 16.46% from the Fama-French model, and 14.87% from the standard consumption-CAPM. Figure 1 reports graphically the performance of the different models by plotting the average predicted 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. The remaining panels of the figure show that the scatter plots from the CAPM, the Fama-French model, and the standard consumption-CAPM are all largely horizontal. The evidence shows that the errors from the investment-based model do not vary systematically across the momentum deciles, whereas the errors from the traditional models do.

The investment-based model fits even better for the industry momentum quintiles. From Panel B of Table 3, the alphas range from -0.51% to 0.94% per annum, all of which are within 0.4 standard errors from zero. The winner-minus-loser quintile has a small alpha of 0.61% ($t = 0.34$). This alpha is smaller than those from the traditional models by an order of magnitude: 6.65% from the CAPM, 9.73% from the Fama-French model, and 6.76% from the consumption-CAPM. Figure 2 further confirms the superior fit of the investment-based model for the industry momentum portfolios.

Panel C of Table 3 reports larger alphas for the nine size and momentum portfolios. The individual alphas range from -4.53% to 5.46% per annum. The winner-minus-loser alphas are $-0.46\%, 1.13\%$, and 0.75% across the small, median, and big size terciles, and are all within one standard error from zero. These alphas are all lower than those from the traditional models reported in Table 1: 9.52%–10.78% in the small tercile, 8.06%–9.98% in the middle tercile, and 5.55%–6.93% in the big tercile. 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 one-way sorted momentum portfolios. In contrast, the remainder of the figure shows that the scatter plots from the traditional models are all largely horizontal, indicating that these models fail to explain the average returns across the size and momentum portfolios.

Panel D of Table 3 reports small errors for the firm age and momentum portfolios. The individual alphas range from -2.58% to 2.99% per annum. The winner-minus-loser alphas are 0.07%, -0.17%, and -1.43% across the young, median, and old firm age terciles. The alphas are again lower than those from the traditional models: 10.11%–11.50% in the young age tercile, 6.94%–7.93% in the median age tercile, and 5.35%–7.33% in the old age tercile. The scatter plots in Figure 4 confirm the dramatic difference in performance between the investment-based model and the traditional models.

Panel E of Table 3 reports large alphas in the investment-based model across the nine volume and momentum portfolios. The individual alphas range from -5.39% to 7.27% per annum, and six out of nine alphas have magnitudes larger than 2.5%. However, none of the alphas are significant at the 5% level probably due to measurement errors in portfolio characteristics. As such, we only emphasize the economic magnitude of the alphas, instead of their insignificance. The large individual alphas do not vary systematically with short-term prior returns. The alphas of the winner-minus-loser portfolios are $0.55\%, 2.75\%$, and 1.27% in the low, median, and high volume terciles, respectively. These alphas are all lower than those from the traditional models: 3.85%–7.49% in the low tercile, 7.43%–8.49% in the median tercile, and 10.19%–15.67% in the high tercile. Figure 5 illustrates the model fit graphically. The scatter plots from the traditional models are all largely horizontal. Although the scatter plot from the investment-based model is not horizontal, it indicates large individual alphas.

From Panel F of Table 3, the individual alphas across the stock return volatility and momentum portfolios, ranging from -5.16% to 5.31% per annum, are largely similar in magnitude as those across the volume and momentum portfolios. The winner-minus-loser alphas are $-0.89\%, 1.69\%$, and 0.77% in the low, median, and high return volatility terciles, respectively. These alphas are again lower than those from the traditional models. From Figure 6, Panel A shows that the investment-based model's fit for the return volatility and momentum portfolios is similar to the fit for the trading volume and momentum portfolios. The remaining panels of the figure show largely horizontal scatter plots from the traditional models.

Panel G of Table 3 shows that the investment-based model has its worst fit in the cash flow volatility and momentum portfolios. The individual alphas range from -8.35% to 7.62% per annum. Five out of nine portfolios have individual alphas with magnitude higher than 5% per annum, and all portfolios have alphas with magnitude higher than 2.5%. However, as in the case of all the other sets of momentum portfolios, the alphas do not vary systematically with momentum. The winner-minus-loser alphas are 1.24%, 1.03%, and -2.26% in the low, median, and high cash flow volatility terciles, respectively. In contrast, the alphas from the traditional models are 6.26%–7.62% in the low volatility tercile, 8.20%–9.95% in the median tercile, and 10.17%–12.00% in the high volatility tercile. Panel A of Figure 7 shows large individual alphas from the investment-based model, but the scatter plot goes in the same direction as the 45-degree line. In contrast, the remainder of the figure shows largely horizontal scatter plots from the traditional models.

4.2.3 Sources of Momentum Profits

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

The first source is investment-to-capital, I_{it}/K_{it}, in the denominator of the investment return. The second source is the growth rate of marginal q, defined as $q_{it} \equiv 1 + (1 - \tau_t)a(I_{it}/K_{it})$. This term can be viewed as the "capital gain" portion of the investment return because marginal q is related to the stock price. The third source is the marginal product of capital, Y_{it+1}/K_{it+1}, in the numerator of the investment return. The fourth source is the depreciation rate, δ_{it+1}. Collecting terms involving δ_{it+1} in the numerator of the investment return shows a negative relation between δ_{it+1} and the expected return. The fifth source is the market leverage, w_{it}, in the levered investment return, which shows a positive relation between w_{it} and the expected return. The sixth source is the after-tax corporate bond return, r^{Ba}_{it+1}. In all, *ceteris paribus*, 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 provide intuition behind our results, Table 4 reports the averages of four components of the levered investment returns across the testing portfolios including $I_{it}/K_{it}, q_{it+1}/q_{it}, Y_{it+1}/K_{it+1}$, and w_{it}. In the case of the growth rate of q, because q involves the unobserved adjustment cost parameter, a, we instead report the average growth rate of investment-to-capital, $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$. The averages of the depreciate rate and the after-tax corporate bond return are largely flat across the momentum portfolios, and their quantitative impact on the estimation results is small. As such, we do not tabulate their averages to save space.

Panel A of Table 4 shows that there is virtually no spread in I_{it}/K_{it} across extreme momentum deciles. However, winners have significantly higher growth rates of investment-to-capital from t to $t + 1$ and sales-to-capital at $t + 1$ than losers. The spreads are 0.31 and 0.35, respectively, both of which are more than five standard errors from zero. Both components go in the right direction to explain expected stock returns. Going in the wrong direction, however, winners have lower market leverage than losers. The spread of -0.09 is more than 4.5 standard errors from zero.

From Panel B, industry momentum winners also have higher growth rates of investment-to-capital than industry momentum losers. The spread is 0.11 across the two extreme quintiles, and is more than 7.5 standard errors from zero. The winner quintile also has a higher sales-to-capital ratio than the loser quintile, although the spread of 0.13 is within 1.7 standard errors of zero. The extreme quintiles have largely identical investment-to-capital at time t. Although the winner quintile has significantly lower market leverage than the loser quintile, the spread of -0.03 is economically small.

The remainder of Table 4 shows how the economically important cross-sectional spreads in $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$ and Y_{it+1}/K_{it+1} between winners and losers vary across terciles formed on size, firm age, trading volume, stock return volatility, and cash flow volatility. From Panel C, the spread in w_{it} does not vary across the size terciles. However, the spread in the growth rate of investment-to-capital is higher in small firms than in big firms: 0.33 versus 0.14. The spread in sales-to-capital follows the same pattern: 0.37 versus 0.21. The spread in investment-to-capital again does not exist across extreme momentum portfolios. Panel D shows that the spread in the growth rate of investment-to-capital is higher in young firms than in old firms, 0.21 versus 0.14. However, the sales-to-capital spread and the market leverage spread are both flat across the firm age terciles.

From Panel E, the spread in the growth rate of investment-to-capital across the momentum terciles increases with trading volume. This spread is 0.12 in the low volume tercile, but is 0.26 in the high volume tercile. This cross-sectional variation goes in the right direction to explain the expected stock returns. However, albeit not monotonic, the sales-to-capital spread moves in the wrong direction: 0.28 in the low volume tercile, 0.16 in the median tercile, and 0.22 in the high volume tercile. Moreover, also going in the wrong direction, the market leverage spread increases in magnitude with trading volume: -0.03 in the low volume tercile but -0.09 in the high volume tercile.

The pattern that two characteristics move in the wrong direction cross-sectionally as the expected returns gives rise to the relatively large alphas across the volume and momentum portfolios.

Panel F shows that the spread in the growth rate of investment-to-capital across the momentum terciles increases with stock return volatility. The spread is 0.12 in the low volatility tercile, but is 0.28 in the high volatility tercile. This variation goes in the right direction to explain the expected returns. However, the sales-to-capital spread moves in the wrong direction: 0.25 in the low volatility tercile but 0.19 in the high volatility tercile. The market leverage spread is largely flat across the return volatility terciles. Finally, Panel G shows that both the spread in the growth rate of investment-to-capital and the spread in sales-to-capital increase with cash flow volatility. The cross-sectional variations go in the right direction to explain the expected returns.

4.2.4 Accounting for Momentum Profits

To quantify the role of each component in the levered investment return, we conduct the following comparative static analysis. We set a given component to its cross-sectional average in each year. We then use the parameter estimates in Table 2 to reconstruct levered investment returns, while keeping all the other components unchanged. We examine the resultant change in the magnitude of the alphas. A large change would mean that the component in question is quantitatively important.

Table 5 shows that the growth rate of marginal q is the most important source of momentum profits, and the sales-to-capital ratio is the second most important. From Panel A, without the cross-sectional variation in the growth rate of q, the winner-minus-loser alpha dramatically inflates to 13.17% per annum from the level of 1.23% in the benchmark estimation (see Table 3). In addition, eliminating the cross-sectional variation in sales-to-capital gives rise to a winner-minus-loser alpha of 5.44%. Without the variation in the current-period investment-to-capital, the winner-minus-loser alpha only increases slightly to 1.92%. Finally, because market leverage goes to the wrong direction to explain the expected returns (see Table 4), eliminating its cross-sectional variation across the momentum portfolios works to reduce the winner-minus-loser alpha to 0.49%. The industry momentum results are largely similar (Panel B). The alpha of the winner-minus-loser quintile in the benchmark estimation is 0.61% per annum. Eliminating the cross-sectional variations in the growth rate of q and sales-to-capital increases this alpha to 5.43% and 2.07%, respectively.

The remainder of Table 5 demonstrates the quantitative importance of the growth rate of q and sales-to-capital in the double sorted momentum portfolios. From Panel C, fixing the growth rate of q to its cross-sectional averages produces alphas of 8.22%, 6.89%, and 4.07% for the winner-minus-loser portfolio across the size terciles. Eliminating the cross-sectional variation in sales-to-capital generates alphas of 2.95%, 4.04%, and 2.92%, respectively. In contrast, in the benchmark estimation (see Table 3), these alphas are $-0.46\%, 1.13\%$, and 0.75%, respectively. The comparative statics for the firm age and momentum portfolios are similar. From Panel D, fixing the growth rate of q to its cross-sectional averages produces alphas of 8.33%, 6.06%, and 2.65% for the winner-minus-loser portfolio across the firm age terciles. Eliminating the cross-sectional variation in sales-to-capital generates alphas of 2.71%, 1.69%, and 1.49%, which are larger in magnitude than those in the benchmark estimation: $0.07\%, -0.17\%$, and -1.43%, respectively.

Panel E confirms that the growth rate of q and sales-to-capital are also the most important sources of momentum profits in the trading volume and momentum portfolios. Fixing the growth rate of q to its cross-sectional averages produces alphas of 3.68%, 6.46%, and 9.44% for the winner-minus-loser portfolio across the trading volume terciles. Eliminating the cross-sectional variation in sales-to-capital generates alphas of 4.01%, 4.50%, and 4.10%, respectively. In contrast, in the benchmark estimation, the winner-minus-loser alphas are $0.55\%, 2.75\%$, and 1.27%, respectively. From Panel F, fixing the growth rate of q to its cross-sectional averages produces alphas of 2.21%, 7.09%, and 10.52% for the winner-minus-loser portfolio across the return volatility terciles. Fixing sales-to-capital to its cross-sectional averages generates alphas of 1.97%, 3.57%, and 3.32%, respectively. In contrast, the alphas in the benchmark estimation are $-0.89\%, 1.69\%$, and 0.77%, respectively.

The growth rate of q and sales-to-capital are also the most important for driving the cash flow volatility and momentum portfolios. Panel G shows that without the cross-sectional variation in the growth rate of q the winner-minus-loser alphas are 5.52%, 6.50%, and 7.87% across the low, median, and high cash flow volatility terciles, respectively. Fixing sales-to-capital to its cross-sectional averages produces alphas of 3.29%, 3.86%, and 1.75%, respectively. In contrast, the winner-minus-loser alphas are 1.24%, 1.03%, and −2.26%, respectively, in the benchmark estimation. In particular, with the cross-sectional variation in sales-to-capital in the benchmark estimation, the investment-based model predicts an average winner-minus-loser return that is higher than that in the data by 2.26% in the high cash flow volatility tercile ($\alpha^q = -2.26\%$). Without the cross-sectional variation in sales-to-capital, the investment-based model predicts an average winer-minus-loser return that is lower than that in the data by 1.75% in the high cash flow volatility tercile ($\alpha^q = 1.75\%$).

5 Conclusion

We offer an investment-based explanation of momentum profits. The neoclassical theory of investment suggests that expected stock returns are related to the ratio of the next-period marginal benefits of investment divided by the current-period marginal costs of investment. Using GMM, we show that the investment-based model matches reasonably well with the expected stock returns across a wide array of momentum portfolios. Intuitively, winners have higher expected growth of investment-to-capital and higher expected sales-to-capital than losers. As a result, winners earn higher expected stock returns than losers. Differing from the bulk of the momentum literature, our model does not assume any form of behavioral biases. Although we do not rule out the possibility that investors can be irrational, we argue that irrationality is not necessary to explain momentum profits. In particular, our results suggest that momentum is consistent with the value maximization of firms.

References

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307–343.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1153–1607.

Blume, Marshall E., Felix Lim, and A. Craig MacKinlay, 1998, The declining credit quality of U.S. corporate debt: Myth or reality? *Journal of Finance* 53, 1389–1413.

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209–237.

Cochrane, John H., 1996, A cross-sectional test of an investment-based asset pricing model, *Journal of Political Economy* 104, 572–621.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreaction, *Journal of Finance* 53, 1839–1886.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F. and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, 131–155.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57, 1121–1152.

Hansen, Lars Peter, 1982, Large sample properties of generalized method of moments estimators, *Econometrica* 40, 1029–1054.

Hansen, Lars Peter and Kenneth J. Singleton, 1982, Generalized instrumental variables estimation of nonlinear rational expectations models, *Econometrica* 50, 1269–1288.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance*, 54, 2143–2184.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance*, 56, 699–720.

Jiang, Guohua, Charles M. C. Lee, and Yi Zhang, 2005, Information uncertainty and expected returns, *Review of Accounting Studies* 10, 185–221.

Johnson, Timothy C., 2002, Rational momentum effects, *Journal of Finance* 57, 585–608.

Lee, Charles M. C., and Bhaskaran Swaminathan, 2000, Price momentum and trading volume, *Journal of Finance* 55, 2017–2069.

Lewellen, Jonathan, 2002, Momentum and autocorrelation in stock returns, *Review of Financial Studies* 15, 533–563.

Lim, Terence, 2001, Rationality and analysts' forecast bias, *Journal of Finance* 56, 369–385.

Liu, Laura Xiaolei, Toni M. Whited, and Lu Zhang, 2009, Investment-based expected stock returns, *Journal of Political Economy* 117, 1105–1139.

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum? *Journal of Finance* 54, 1249–1290.

Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance*, 53, 267–284.

Sagi, Jacob S., and Mark S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, *Journal of Financial Economics* 84, 389–434.

Zhang, X. Frank, 2006, Information uncertainty and stock returns, *Journal of Finance* 61, 105–136.

Table 1 : Descriptive Statistics for Testing Portfolios

For all testing portfolios, we report (in annual percent) average stock returns, $\bar{r}^S$, 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 the alphas from the standard consumption-CAPM with power utility, α^C, and the t-statistics for the alphas adjusted for heteroscedasticity and autocorrelations. m.a.e. is the mean absolute error for a given set of testing portfolios. W−L denotes the winner-minus-loser portfolio. For the CAPM and the Fama-French model, the p-values (p-val) in the last column in each panel are from the Gibbon, Ross, and Shanken (1989) tests of the null hypothesis that the alphas for a given set of testing portfolios are jointly zero. For the consumption-CAPM, the p-values are for the χ^2 test from one-stage GMM that the moment restrictions for a given set of testing assets are jointly zero. See Section 3.2 for the detailed description of all the testing portfolios. In Panel A for the standard consumption-CAPM, the time preference estimate is $\rho = 2.38$ (standard error 0.51) and the risk aversion estimate is $\gamma = 81.05$ (24.26). In Panel B $\rho = 2.34$ (0.47), $\gamma = 76.93$ (25.51); in Panel C $\rho = 2.37$ (0.50), $\gamma = 86.16$ (24.69); in Panel D $\rho = 2.40$ (0.55), $\gamma = 86.18$ (23.49); in Panel E $\rho = 2.41$ (0.55), $\gamma = 86.69$ (23.25); in Panel F $\rho = 2.41$ (0.57), $\gamma = 89.13$ (24.11); and in Panel G $\rho = 2.40$ (0.54), $\gamma = 84.92$ (24.64).

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L	m.a.e.	p-val
$\bar{r}^S$	5.24	10.56	12.27	13.15	13.59	14.51	14.41	15.25	16.81	20.27	15.04		
σ^S	24.00	19.62	18.31	17.58	17.37	17.18	17.30	17.86	19.17	23.55	13.65		
α	−7.51	−1.19	0.85	1.91	2.37	3.31	3.16	3.80	5.00	7.46	14.97	3.66	0.00
[t]	−4.06	−0.79	0.62	1.46	1.86	2.66	2.56	3.14	3.66	3.82	8.16		
α^{FF}	−9.53	−4.34	−2.27	−1.31	−0.65	0.33	0.51	1.42	3.05	6.92	16.46	3.03	0.00
[t]	−6.42	−4.26	−2.62	−1.70	−0.83	0.50	0.77	2.28	4.52	6.12	8.20		
α^C	−9.94	−3.18	−1.49	−0.52	0.51	1.18	1.37	1.41	2.92	4.93	14.87	2.75	0.00
[t]	−2.05	−0.86	−0.44	−0.17	0.19	0.42	0.50	0.45	0.84	1.16	0.67		

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L	m.a.e.	p-val
$\bar{r}^S$	9.46	11.59	11.38	13.78	16.33	6.87		
σ^S	19.05	17.75	18.53	19.10	20.22	14.87		
α	−1.81	0.51	0.01	2.22	4.84	6.65	1.88	0.00
[t]	−1.78	0.67	0.02	2.59	3.49	5.32		
α^{FF}	−4.87	−1.50	−2.03	1.20	4.87	9.73	2.89	0.00
[t]	−2.75	−1.10	−1.29	1.05	3.43	4.18		
α^C	−3.11	0.32	−0.96	0.38	3.65	6.76	1.68	0.01
[t]	−1.01	0.14	−0.29	0.12	1.07	0.36		

Panel C: Nine size and momentum portfolios

	Small				2				Big					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
$\bar{r}^S$	9.40	15.57	19.18	9.78	9.28	13.64	17.34	8.05	8.97	11.69	14.50	5.53		
σ^S	22.18	18.97	22.25	8.89	21.86	18.19	21.41	11.23	18.78	15.62	18.13	11.74		
α	−2.64	4.35	6.88	9.52	−3.22	2.09	4.83	8.06	−2.71	0.79	2.84	5.55	3.37	0.00
[t]	−1.35	2.40	3.42	8.02	−2.16	1.72	3.49	5.43	−2.33	1.09	2.96	3.16		
α^{FF}	−6.22	0.30	4.56	10.78	−5.06	−0.69	4.34	9.40	−3.50	−0.33	3.43	6.93	3.16	0.00
[t]	−5.31	0.38	5.37	8.70	−3.83	−0.79	4.84	5.78	−2.84	−0.46	3.68	3.88		
α^C	−5.74	0.53	4.14	9.88	−4.77	1.44	5.21	9.98	−4.35	0.62	1.81	6.17	3.18	0.00
[t]	−1.36	0.15	1.02	0.77	−1.17	0.64	1.61	0.54	−1.09	0.26	0.47	0.33		

Panel D: Nine firm age and momentum portfolios

	Young				2				Old					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
$\bar{r}^S$	8.25	15.02	18.34	10.09	11.39	14.86	18.22	6.83	11.24	13.62	16.58	5.34		
σ^S	22.10	18.94	21.12	10.12	19.90	17.31	19.04	9.75	18.53	16.04	17.70	9.82		
α	−3.90	3.55	6.21	10.11	−0.22	3.81	6.73	6.94	−0.08	2.83	5.27	5.35	3.62	0.00
$[t]$	−1.91	2.13	3.37	7.29	−0.12	2.55	4.24	5.08	−0.05	2.41	4.03	3.70		
α^{FF}	−8.32	−0.46	3.18	11.50	−4.34	0.16	3.59	7.93	−4.15	−0.72	2.31	6.46	3.03	0.00
$[t]$	−5.40	−0.44	2.44	8.21	−3.38	0.17	3.57	5.65	−3.31	−0.85	2.30	4.50		
α^C	−7.55	0.29	3.65	11.21	−3.25	2.19	4.00	7.25	−3.46	1.44	3.87	7.33	3.30	0.00
$[t]$	−1.44	0.08	0.92	0.47	−0.76	0.97	1.23	0.35	−0.97	0.63	1.84	0.44		

	Low				2				High					
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L	m.a.e.	p-val
Panel E: Nine trading volume and momentum portfolios														
$\bar{r}^S$	12.09	15.22	18.34	6.26	11.36	14.96	18.58	7.22	7.73	13.40	17.53	9.80		
σ^S	16.76	14.64	15.88	7.82	19.69	17.44	18.30	9.06	24.25	21.59	22.69	11.73		
α	1.66	5.13	7.90	6.24	−0.30	3.79	7.13	7.43	−5.24	0.95	4.96	10.19	4.12	0.00
$[t]$	1.00	3.85	5.49	5.47	−0.17	2.68	4.97	5.80	−2.48	0.54	2.45	5.89		
α^{FF}	−2.82	1.41	4.67	7.49	−4.46	−0.02	4.03	8.49	−9.47	−2.52	1.97	11.44	3.49	0.00
$[t]$	−2.37	1.60	4.30	6.59	−3.47	−0.02	4.08	6.68	−5.61	−1.86	1.33	6.43		
α^C	−1.69	1.20	2.16	3.85	−3.73	2.23	4.92	8.65	−9.02	0.77	6.65	15.67	3.60	0.00
$[t]$	−0.55	0.39	0.57	0.43	−0.86	0.91	1.58	0.46	−1.56	0.29	2.68	0.38		
Panel F: Nine stock return volatility and momentum portfolios														
$\bar{r}^S$	13.08	14.65	17.44	4.36	11.63	15.33	19.36	7.74	8.00	13.83	18.96	10.96		
σ^S	15.80	14.25	14.89	7.93	19.77	18.08	18.55	8.83	25.06	22.96	23.16	11.14		
α	2.85	4.64	7.19	4.33	0.16	4.15	8.07	7.91	−4.77	1.38	6.53	11.31	4.42	0.00
$[t]$	1.86	3.95	6.44	3.71	0.09	2.84	5.39	6.30	−2.11	0.69	3.14	7.23		
α^{FF}	−1.02	1.47	4.98	6.00	−4.33	0.28	5.01	9.33	−9.14	−2.65	3.21	12.35	3.57	0.00
$[t]$	−0.90	1.74	5.52	5.58	−3.44	0.29	4.83	7.50	−5.38	−2.23	2.39	7.57		
α^C	−0.56	2.11	4.45	5.00	−3.71	2.00	6.19	9.90	−9.63	−2.77	5.30	14.93	4.08	0.00
$[t]$	−0.20	0.95	1.39	0.40	−0.81	0.74	2.10	0.44	−1.73	−0.68	1.63	0.55		
Panel G: Nine cash flow volatility and momentum portfolios														
$\bar{r}^S$	11.34	14.37	18.07	6.73	10.89	15.03	19.12	8.24	7.64	13.06	18.52	10.88		
σ^S	18.41	15.74	18.48	10.36	20.07	17.20	19.87	10.45	23.15	20.06	24.19	11.25		
α	−0.04	3.62	6.56	6.61	−0.95	3.87	7.25	8.20	−4.81	1.23	5.63	10.44	3.77	0.00
$[t]$	−0.03	3.07	4.99	4.74	−0.60	3.07	4.94	5.84	−2.55	0.77	2.75	7.11		
α^{FF}	−3.20	0.52	4.42	7.62	−4.11	0.74	5.85	9.95	−7.17	−1.53	4.83	12.00	3.60	0.00
$[t]$	−2.75	0.67	5.13	5.17	−3.56	1.05	7.75	6.94	−6.31	−2.09	4.12	7.69		
α^C	−3.30	1.80	2.96	6.26	−4.51	1.24	5.28	9.79	−7.04	−1.11	3.13	10.17	3.37	0.00
$[t]$	−0.84	0.69	1.02	0.45	−1.05	0.46	1.65	0.54	−1.68	−0.31	0.67	0.56		

Table 2 : GMM Parameter Estimates and Tests of Overidentification

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

	(1) Momentum	(2) Industry momentum	(3) Size and momentum	(4) Age and momentum	(5) Volume and momentum	(6) Return volatility and momentum	(7) Cash flow volatility and momentum
a	5.40	7.82	3.26	4.87	4.14	4.41	4.48
[ste]	[1.14]	[4.12]	[0.55]	[1.19]	[0.96]	[0.78]	[1.02]
κ	0.20	0.19	0.14	0.20	0.19	0.19	0.17
[ste]	[0.03]	[0.03]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
χ^2	8.45	4.20	7.22	7.61	8.06	8.23	8.55
d.f.	8	3	7	7	7	7	7
p-val	0.39	0.24	0.41	0.37	0.33	0.31	0.29
m.a.e.	1.72	0.49	3.44	1.37	3.59	3.56	5.62

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

The alphas (in annual percent) and t-statistics are from one-stage GMM with an identity weighting matrix. The moment conditions are $E\left[r^S_{it+1} - r^{Iw}_{it+1}\right] = 0$, in which r^S is the stock return, and r^{Iw} 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 denotes winners, and W−L denotes the differences between the loser and winner portfolios.

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L
α^q	−4.01	0.05	1.76	2.38	1.79	2.32	0.92	0.35	−0.88	−2.78	1.23
$[t]$	−1.24	0.02	0.61	0.83	0.64	0.83	0.36	0.12	−0.30	−0.80	0.59

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L
α^q	−0.33	0.94	−0.51	−0.37	0.28	0.61
$[t]$	−0.14	0.38	−0.21	−0.14	0.11	0.34

Panel C: Nine size and momentum portfolios

	Small				2				Big			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
α^q	−4.07	−2.40	−4.53	−0.46	0.78	2.52	1.91	1.13	4.28	5.46	5.02	0.75
$[t]$	−1.07	−0.70	−1.12	−0.38	0.29	0.90	0.66	0.93	1.34	1.79	1.74	0.52

Panel D: Nine firm age and momentum portfolios

	Young				2				Old			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
α^q	−2.58	0.69	−2.51	0.07	−0.01	2.99	−0.17	−0.17	1.11	1.92	−0.32	−1.43
$[t]$	−0.66	0.20	−0.67	0.05	0.00	1.10	−0.07	−0.09	0.43	0.77	−0.14	−1.06

	Low				2				High			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
Panel E: Nine trading volume and momentum portfolios												
α^q	3.54	7.27	4.09	0.55	−0.39	1.82	2.36	2.75	−5.39	−3.37	−4.12	1.27
$[t]$	1.14	1.95	1.27	0.46	−0.14	0.69	0.80	1.61	−1.49	−1.09	−1.23	0.82
Panel F: Nine stock return volatility and momentum portfolios												
α^q	4.60	5.31	3.71	−0.89	0.66	2.46	2.35	1.69	−5.16	−3.41	−4.39	0.77
$[t]$	1.47	1.73	1.35	−0.86	0.21	0.87	0.83	1.15	−1.49	−0.96	−1.20	0.56
Panel G: Nine cash flow volatility and momentum portfolios												
α^q	6.38	7.58	7.62	1.24	2.57	4.40	3.60	1.03	−6.10	−4.00	−8.35	−2.26
$[t]$	1.85	2.04	2.17	0.92	0.91	1.60	1.12	0.80	−1.73	−1.33	−1.93	−0.99

Table 4 : Economic Characteristics of Testing Portfolios

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

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L	$[t]$
I_{it}/K_{it}	0.13	0.12	0.11	0.11	0.11	0.11	0.11	0.11	0.12	0.13	0.00	−0.19
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.85	0.94	0.96	0.97	1.00	1.01	1.03	1.05	1.09	1.16	0.31	16.89
Y_{it+1}/K_{it+1}	1.57	1.47	1.45	1.44	1.45	1.47	1.51	1.58	1.70	1.92	0.35	5.15
w_{it}	0.34	0.29	0.27	0.26	0.26	0.24	0.24	0.24	0.24	0.25	−0.09	−4.82

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L	$[t]$
I_{it}/K_{it}	0.11	0.11	0.11	0.11	0.11	0.00	−0.26
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.95	0.97	0.99	1.03	1.06	0.11	7.87
Y_{it+1}/K_{it+1}	1.47	1.50	1.54	1.58	1.60	0.13	1.61
w_{it}	0.29	0.27	0.27	0.26	0.26	−0.03	−2.19

Panel C: Nine size and momentum portfolios

	Small					2					Big				
	L	2	W	W−L	$[t]$	L	2	W	W−L	$[t]$	L	2	W	W−L	$[t]$
I_{it}/K_{it}	0.12	0.11	0.12	0.00	−1.69	0.11	0.11	0.12	0.00	1.50	0.12	0.11	0.12	0.00	−0.55
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.86	1.01	1.19	0.33	13.05	0.90	1.01	1.13	0.23	17.25	0.94	1.00	1.08	0.14	9.79
Y_{it+1}/K_{it+1}	2.13	2.29	2.50	0.37	5.32	1.62	1.69	1.88	0.26	5.73	1.34	1.34	1.55	0.21	4.11
w_{it}	0.39	0.34	0.31	−0.07	−10.77	0.34	0.29	0.28	−0.07	−7.16	0.28	0.24	0.23	−0.05	−4.72

Panel D: Nine firm age and momentum portfolios

	Young					2					Old				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
I_{it}/K_{it}	0.14	0.12	0.14	0.00	0.12	0.12	0.11	0.12	0.00	−0.61	0.11	0.10	0.11	0.00	−1.02
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.88	0.99	1.09	0.21	9.53	0.91	1.01	1.11	0.20	13.44	0.94	1.00	1.08	0.14	8.86
Y_{it+1}/K_{it+1}	1.69	1.70	1.92	0.22	2.88	1.56	1.48	1.74	0.18	2.20	1.39	1.39	1.62	0.22	4.00
w_{it}	0.30	0.24	0.25	−0.05	−3.77	0.30	0.24	0.25	−0.05	−2.95	0.31	0.26	0.26	−0.05	−4.56

Panel E: Nine trading volume and momentum portfolios

	Low					2					High				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
I_{it}/K_{it}	0.11	0.10	0.11	0.00	0.47	0.11	0.11	0.11	0.00	−0.90	0.13	0.12	0.12	−0.01	−2.90
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.95	0.99	1.07	0.12	5.87	0.94	1.01	1.09	0.15	14.32	0.87	1.01	1.12	0.26	10.55
Y_{it+1}/K_{it+1}	1.35	1.25	1.63	0.28	4.16	1.56	1.56	1.72	0.16	2.41	1.60	1.62	1.83	0.22	4.55
w_{it}	0.24	0.21	0.21	−0.03	−2.75	0.29	0.26	0.25	−0.05	−3.34	0.40	0.34	0.31	−0.09	−6.50

Panel F: Nine stock return volatility and momentum portfolios

	Low					2					High				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
I_{it}/K_{it}	0.11	0.10	0.11	0.00	0.64	0.12	0.11	0.11	0.00	−0.70	0.13	0.12	0.12	−0.01	−2.44
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.96	1.01	1.07	0.12	7.63	0.92	1.01	1.10	0.18	22.16	0.85	0.98	1.13	0.28	13.45
Y_{it+1}/K_{it+1}	1.37	1.34	1.62	0.25	3.32	1.59	1.57	1.75	0.16	2.72	1.73	1.79	1.92	0.19	3.68
w_{it}	0.26	0.23	0.21	−0.05	−5.23	0.33	0.29	0.26	−0.06	−4.46	0.40	0.35	0.32	−0.07	−8.27

Panel G: Nine cash flow volatility and momentum portfolios

	Low					2					High				
	L	2	W	W−L	[t]	L	2	W	W−L	[t]	L	2	W	W−L	[t]
I_{it}/K_{it}	0.11	0.10	0.11	0.00	−0.18	0.12	0.11	0.12	0.00	−0.03	0.13	0.12	0.14	0.00	0.29
$\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$	0.93	1.00	1.08	0.15	9.68	0.92	1.02	1.12	0.19	8.98	0.88	1.03	1.19	0.30	8.76
Y_{it+1}/K_{it+1}	1.18	1.19	1.36	0.18	3.23	1.61	1.66	1.87	0.26	5.60	2.23	2.27	2.64	0.41	4.21
w_{it}	0.27	0.22	0.23	−0.04	−2.68	0.25	0.20	0.21	−0.04	−2.73	0.28	0.23	0.23	−0.05	−3.15

Table 5 : Accounting for Momentum Profits

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

Panel A: Ten momentum deciles

	L	2	3	4	5	6	7	8	9	W	W−L
$\overline{I_{it}/K_{it}}$	−9.13	−0.57	2.39	4.35	3.99	4.68	2.77	1.39	−1.14	−7.21	1.92
$\overline{q_{it+1}/q_{it}}$	−9.35	−2.10	−0.16	0.86	0.99	1.94	1.34	1.50	1.99	3.82	13.17
$\overline{Y_{it+1}/K_{it+1}}$	−3.82	−1.01	0.48	0.93	0.50	1.19	0.38	0.60	0.74	1.63	5.44
$\overline{w}_{it}$	−3.72	0.16	1.86	2.30	1.72	2.20	0.71	0.28	−1.22	−3.23	0.49

Panel B: Five industry momentum quintiles

	L	2	3	4	W	W−L
$\overline{I_{it}/K_{it}}$	−0.77	0.59	−0.93	0.63	0.70	1.47
$\overline{q_{it+1}/q_{it}}$	−2.38	−0.36	−0.97	0.65	3.05	5.43
$\overline{Y_{it+1}/K_{it+1}}$	−1.19	0.63	−0.47	0.16	0.87	2.07
$\overline{w}_{it}$	−0.19	1.08	−0.45	−0.38	0.23	0.42

Panel C: Nine size and momentum portfolios

	Small				2				Big			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
$\overline{I_{it}/K_{it}}$	−6.03	−1.01	−5.11	0.92	1.12	4.49	1.55	0.43	3.09	6.84	4.55	1.46
$\overline{q_{it+1}/q_{it}}$	−7.41	−2.09	0.81	8.22	−1.92	2.18	4.97	6.89	1.65	4.20	5.72	4.07
$\overline{Y_{it+1}/K_{it+1}}$	0.00	3.20	2.94	2.95	−1.71	1.15	2.33	4.04	−0.36	0.94	2.56	2.92
$\overline{w}_{it}$	−2.80	−1.37	−4.05	−1.25	0.92	2.50	1.54	0.63	4.14	5.24	4.48	0.34

Panel D: Nine firm age and momentum portfolios

	Young				2				Old			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
$\overline{I_{it}/K_{it}}$	−9.28	−0.43	−9.20	0.07	0.16	4.90	0.59	0.43	3.86	6.39	3.84	−0.03
$\overline{q_{it+1}/q_{it}}$	−6.56	0.73	1.76	8.33	−2.88	2.85	3.18	6.06	−1.22	1.13	1.43	2.65
$\overline{Y_{it+1}/K_{it+1}}$	−1.67	1.47	1.04	2.71	−0.40	1.29	1.29	1.69	−1.43	−0.51	0.05	1.49
$\overline{w}_{it}$	−2.27	0.43	−2.75	−0.49	0.74	2.63	−0.52	−1.26	1.37	1.92	−0.13	−1.50

	Low				2				High			
	L	2	W	W−L	L	2	W	W−L	L	2	W	W−L
Panel E: Nine trading volume and momentum portfolios												
$\overline{I_{it}/K_{it}}$	4.43	9.81	4.67	0.24	−0.10	3.82	3.48	3.58	−10.06	−5.66	−5.96	4.10
$\overline{q_{it+1}/q_{it}}$	1.65	6.04	5.33	3.68	−2.48	1.47	3.98	6.46	−8.97	−2.03	0.47	9.44
$\overline{Y_{it+1}/K_{it+1}}$	1.06	3.54	5.07	4.01	−0.28	1.71	4.23	4.50	−4.96	−2.83	−0.86	4.10
$\overline{w}_{it}$	3.19	6.88	3.24	0.05	−0.23	1.65	2.11	2.34	−3.72	−2.26	−3.55	0.17
Panel F: Nine stock return volatility and momentum portfolios												
$\overline{I_{it}/K_{it}}$	6.71	8.66	5.42	−1.29	0.16	3.50	2.71	2.55	−9.86	−5.65	−6.21	3.65
$\overline{q_{it+1}/q_{it}}$	2.42	4.17	4.63	2.21	−2.20	2.23	4.89	7.09	−9.11	−2.92	1.41	10.52
$\overline{Y_{it+1}/K_{it+1}}$	1.58	2.05	3.55	1.97	0.20	1.64	3.77	3.57	−3.92	−1.36	−0.59	3.32
$\overline{w}_{it}$	4.43	4.92	2.66	−1.77	1.00	2.26	1.91	0.91	−3.93	−2.53	−3.65	0.29
Panel G: Nine cash flow volatility and momentum portfolios												
$\overline{I_{it}/K_{it}}$	8.58	12.00	10.04	1.47	2.36	6.14	3.67	1.31	−10.83	−5.56	−13.21	−2.38
$\overline{q_{it+1}/q_{it}}$	3.37	6.32	8.90	5.52	−0.40	3.62	6.10	6.50	−9.60	−3.54	−1.73	7.87
$\overline{Y_{it+1}/K_{it+1}}$	−0.07	1.56	3.22	3.29	0.72	3.20	4.57	3.86	−1.21	0.85	0.55	1.75
$\overline{w}_{it}$	6.50	7.67	7.72	1.22	2.59	4.17	3.36	0.78	−5.54	−4.34	−8.62	−3.08

Figure 1 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Ten Momentum Portfolios

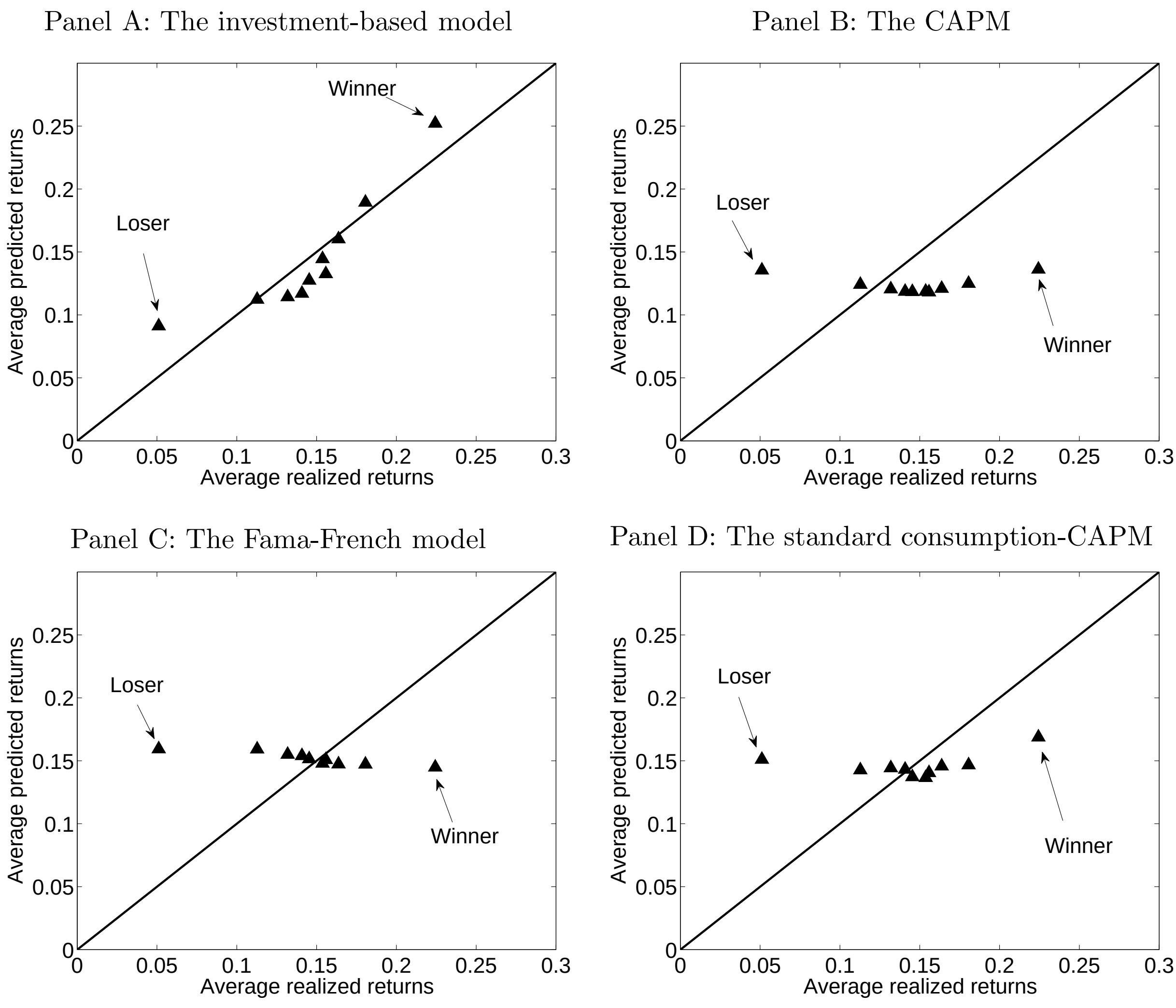

Figure 2 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Five Industry Momentum Portfolios

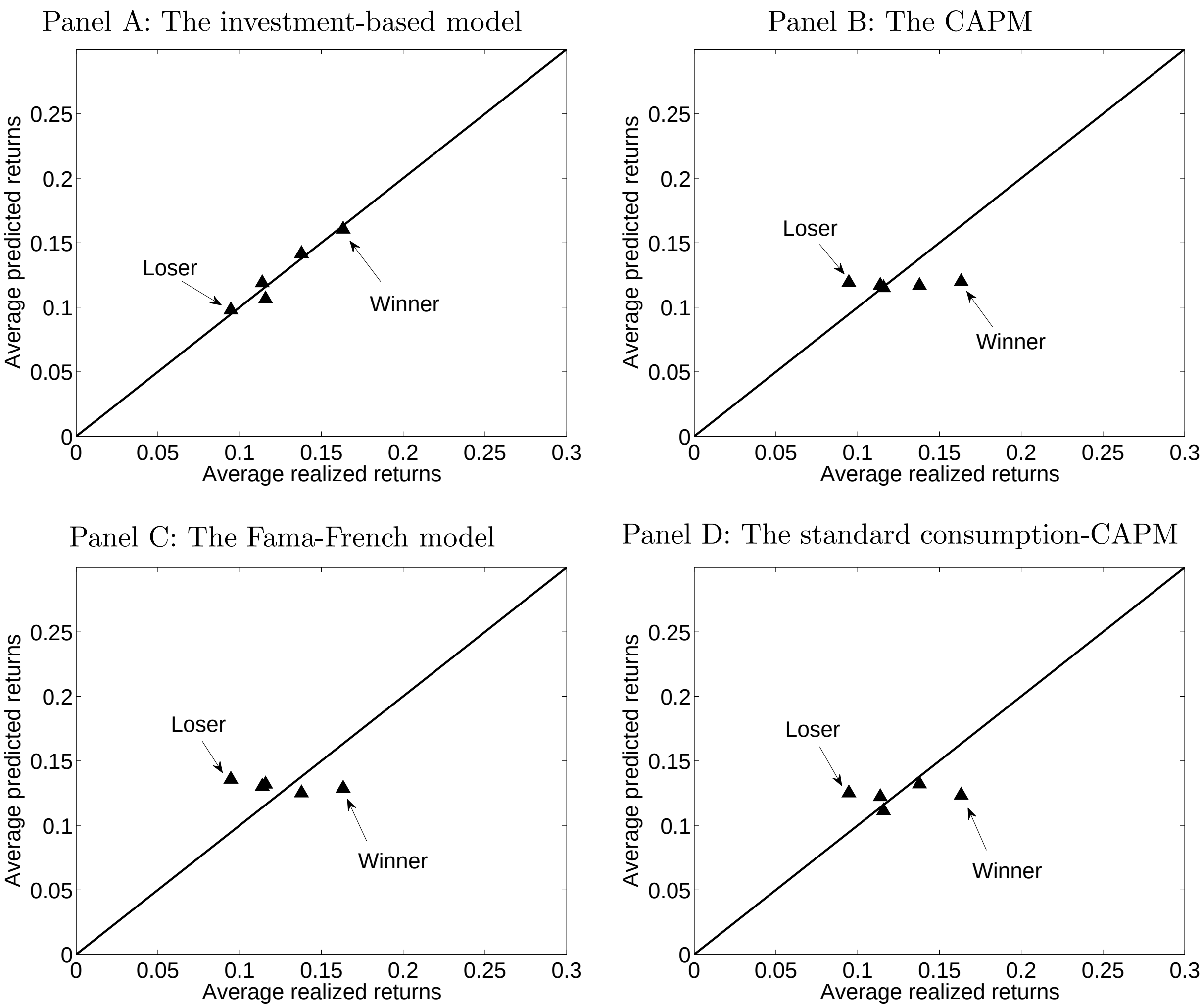

Figure 3 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Size and Momentum Portfolios

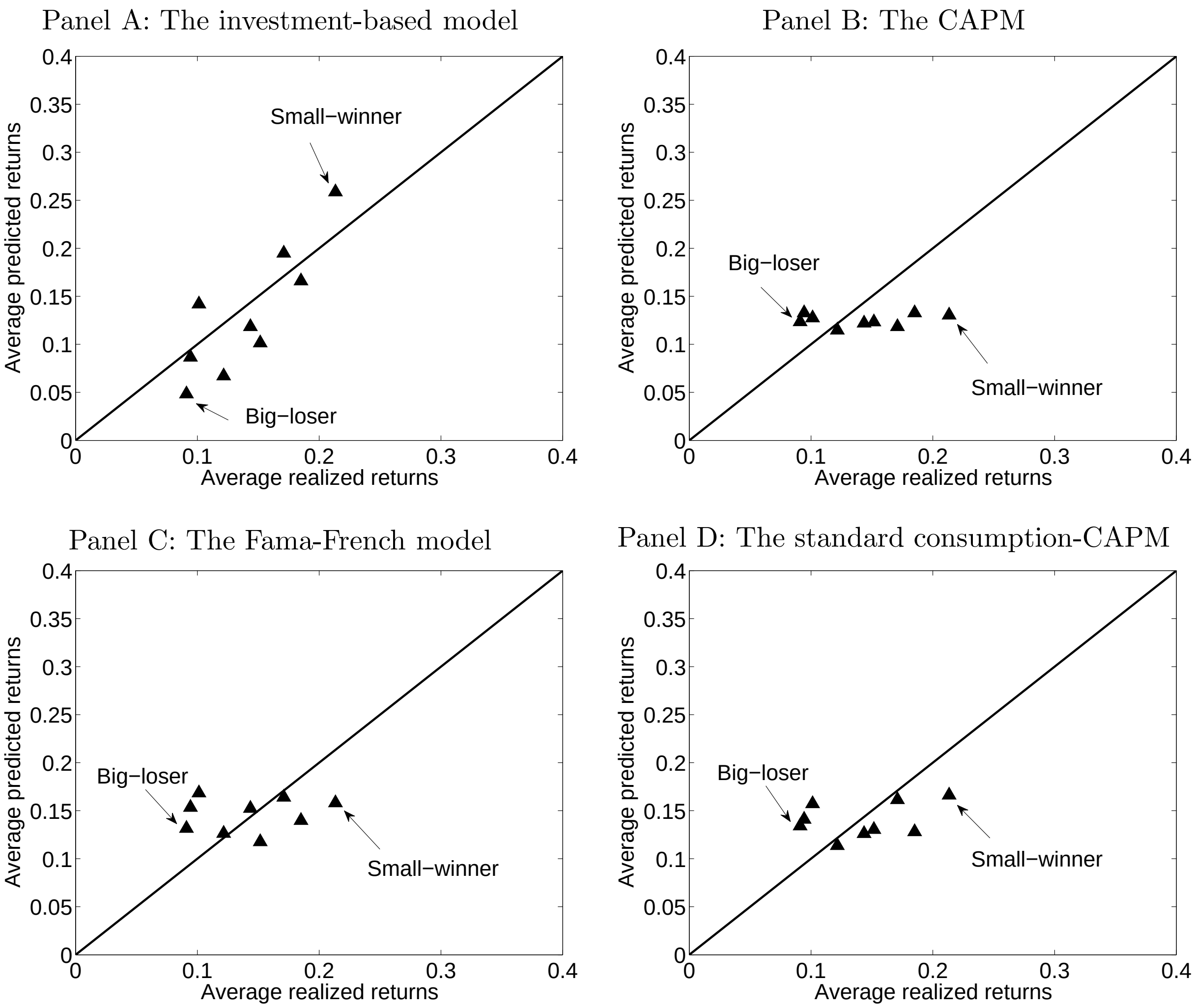

Figure 4 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Firm Age and Momentum Portfolios

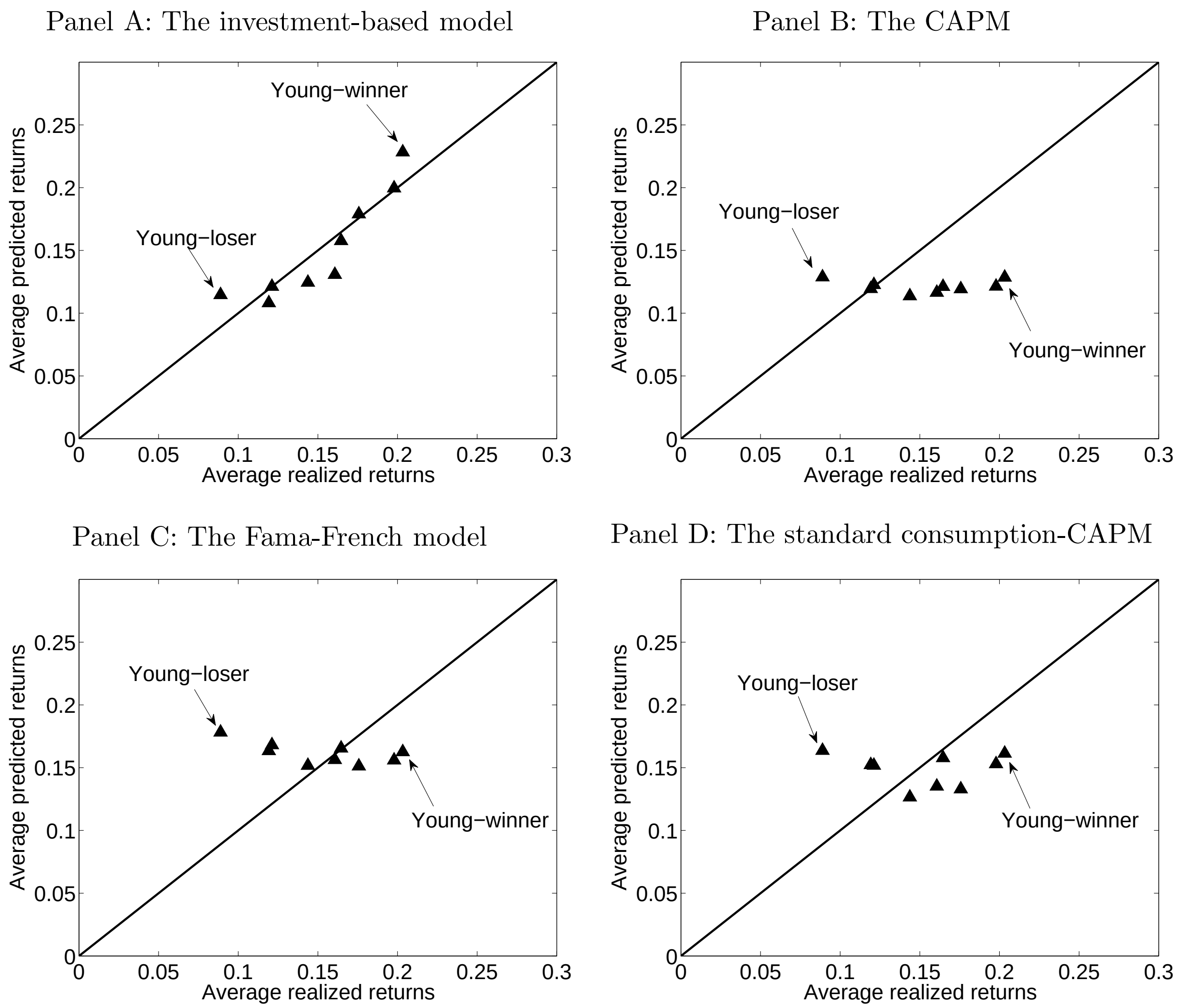

Figure 5 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Trading Volume and Momentum Portfolios

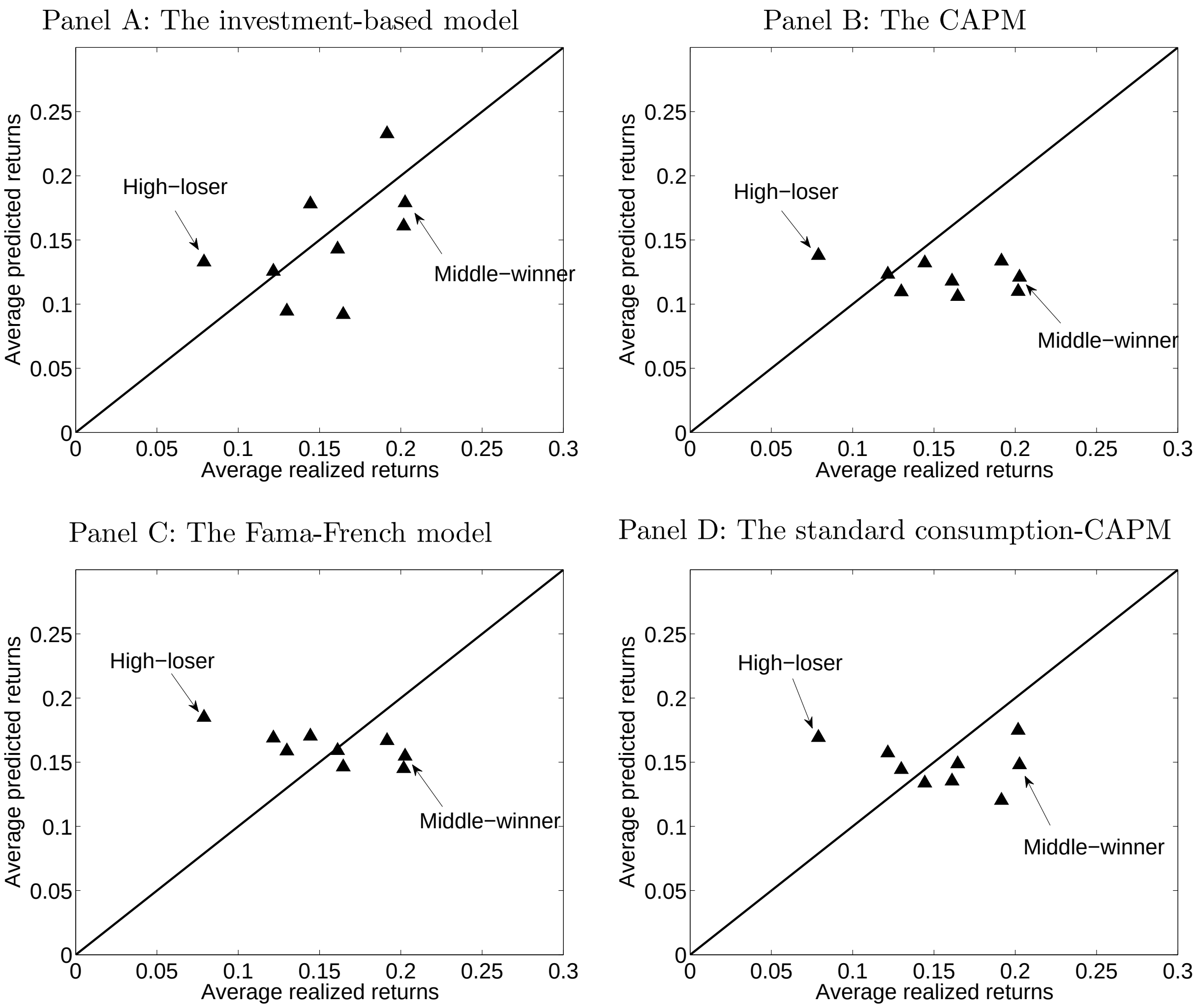

Figure 6 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Stock Return Volatility and Momentum Portfolios

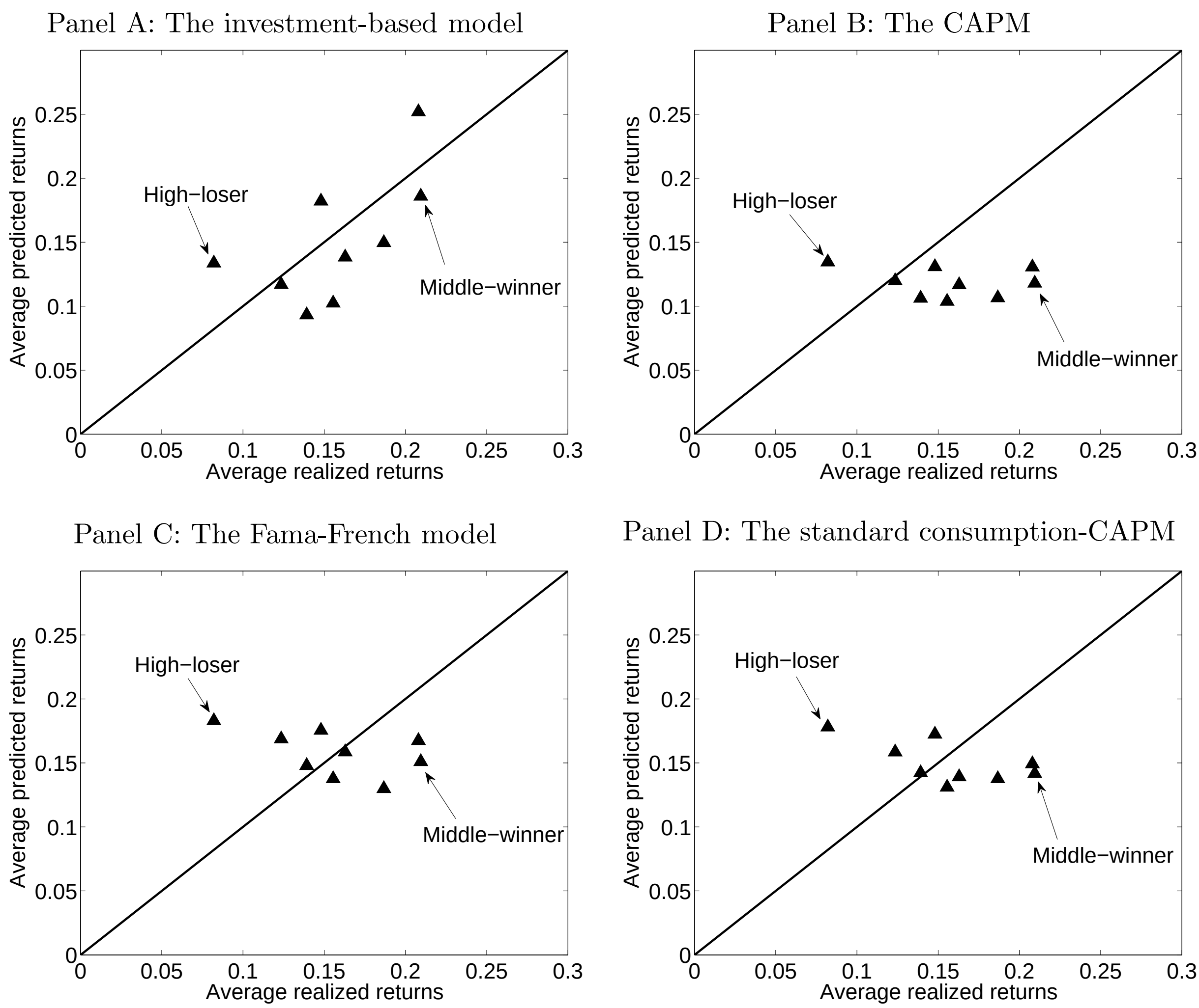

Figure 7 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Nine Cash Flow Volatility and Momentum Portfolios