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A MODEL OF MOMENTUM

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ABSTRACT

Optimal investment of firms implies that expected stock returns are tied with the expected marginal benefit of investment divided by the marginal cost 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. Theinvestment-based model succeeds in capturing average momentum profits, reversal of momentum in long horizons, as well as the interaction of momentum with with market capitalization, firm age, trading volume, and stock return volatility. However, the model fails to reproduce procyclical momentum profits.

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1 Introduction

Momentum is a major puzzle in financial economics. 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. They interpret the evidence as saying that "investor expectations are systematically biased (p. 90)."[1] The subsequent literature has mostly followed their interpretation. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999), in particular, have constructed behavioral models to reproduce momentum with psychological biases such as conservatism, self-attributive overconfidence, and slow information diffusion. This interpretation is disturbing because it calls into question rational expectations, an assumption underlying the bulk of the modern literature on finance and macroeconomics.

We use the neoclassical theory of investment to examine whether momentum in asset prices is correctly connected to investment through first-order conditions of firms. Under constant returns to scale, the stock return equals the (levered) investment return (e.g., Cochrane (1991)). The investment return (the next-period marginal benefit of investment divided by the current-period marginal cost of investment) is tied with firm characteristics via firms' optimality conditions. Intuitively, winners have higher expected growth and higher expected marginal productivity (two major components of the expected marginal benefit of investment). As such, winners 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 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 model error (alpha) of 0.44% per annum, which is negligible compared to the alpha of 16.95% from the capital asset pricing model (CAPM) and the

[1] Many subsequent studies have confirmed and refined this finding. Rouwenhorst (1998) documents momentum profits in international markets. Moskowitz and Grinblatt (1999) report 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 measured by, for example, size, firm age, and stock return volatility.

alpha of 19.15% from the Fama-French (1993) three-factor model. The alphas of individual deciles in our model are also substantially smaller than those in the two alternative models. In particular, the mean absolute error across the deciles is 0.80% per annum in our model, but is 3.68% in the CAPM and 4.08% in the Fama-French model.

The model suggests several connections between asset price momentum and quantity variables. All else equal, firms with low investment-to-capital, high expected investment-to-capital growth, high expected sales-to-capital, high market leverage, low expected rates of depreciation, and low expected corporate bond returns should earn high expected stock returns. Comparative statics show that expected investment-to-capital growth is the most important, and expected sales-to-capital is the second most important component of momentum. Without the cross-sectional variation in the expected growth, the alpha of the winner-minus-loser decile jumps to 11.37% per annum from 0.44% in the benchmark estimation. Without the cross-sectional variation in the expected sales-to-capital, the alpha becomes 7.14%.

Going beyond matching average momentum profits via GMM, the model is also consistent with several other stylized facts of momentum. Momentum predicted in the model reverts beyond the second year after portfolio formation. The low persistence of the expected investment-to-capital growth is the underlying force of this reversal. As in the data, the predicted momentum profits cannot be captured by the CAPM or the Fama-French model. The cash flow component of the investment return also displays long run risks similar to the dividend component of the stock return 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.

Finally, our model goes a long way in capturing the interaction of momentum with firm characteristics. The model 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. The alphas in our model do not vary systematically with prior six-month returns. In particular, 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 our model as those in the CAPM and the Fama-French model.

Cochrane (1991, 1996, 1997) is the first to use the neoclassical investment model to study asset prices. Lettau and Ludvigson (2002) examine the impact of time-varying risk premiums on aggregate investment. Merz and Yashiv (2007) quantify the role of labor in stock market valuation. Belo (2010) uses the marginal rate of transformation as the stochastic discount factor. Gourio (2010) examines the effect of putty-clay technology on stock market volatility. Jermann (2010) studies the equity premium derived from firms' optimality conditions. While these prior studies focus on aggregate stock market, we focus on the cross section of returns. How to interpret the cross section is one of the biggest questions in financial economics.[2] Liu, Whited, and Zhang (2009) start to use the neoclassical investment model to examine how stock returns relate to earnings surprises, book-to-market equity, and investment in the cross section. We study momentum, which, as noted, is a major puzzle in financial economics.

The rest of the paper unfolds as follows. Section 2 sets up the model. Section 3 describes our research design and data. Section 4 presents our estimation results. Section 5 concludes.

2 The Model of the Firms

The neoclassical investment model is standard. 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 the 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 that $\Pi(K_{it}, X_{it})$ exhibits

[2]For example, Barberis and Thaler (2003, p. 1085) argue: "While the behavior of the aggregate stock market is not easy to understand from the rational point of view, promising rational models have nonetheless been developed and can be tested against behavioral alternatives. Empirical studies of the behavior of *individual* stocks have unearthed a set of facts which is altogether more frustrating for the rational paradigm. Many of these facts are about the *cross-section* of average returns: they document that one group of stocks earns higher average returns than another. These facts have come to be known as 'anomalies' because they cannot be explained by the simplest and most intuitive model of risk and return in the financial economist's toolkit, the Capital Asset Pricing Model, or CAPM (original emphasis)."

constant returns to scale, that is, $\Pi(K_{it}, X_{it}) = K_{it}\partial\Pi(K_{it}, X_{it})/\partial K_{it}$. In addition, firms have a Cobb-Douglas production function, meaning that the marginal product of capital is $\partial\Pi(K_{it}, X_{it})/\partial K_{it} = \kappa Y_{it}/K_{it}$, 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 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 of constant returns to scale in I_{it} and K_{it}. 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 with one-period debt. At the beginning of time t, firm i issues 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 varies 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 be the corporate tax rate, $\tau_t\delta_{it}K_{it}$ be the depreciation tax shield, and $\tau_t(r^B_{it} - 1)B_{it}$ be the interest tax shield. Firm i's payout is:

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

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 $E_t[M_{t+1}r^I_{it+1}] = 1$, in which r^I_{it+1} is the investment return:

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

The investment return is the marginal benefit of investment at $t+1$ divided by the marginal cost of investment at t. The optimality condition says that the marginal cost of investment equals the marginal benefit of investment discounted to 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 an extra unit of capital net of depreciation, in which the marginal continuation value equals the marginal cost 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 $E_t[M_{t+1}r^{Ba}_{it+1}] = 1$. 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. The investment return then equals the weighted average of the stock return and the after-tax corporate bond return:

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

Equations (3) and (4) provide the microfoundation for the weighted average cost of capital approach to capital budgeting in corporate finance (e.g., Berk and DeMarzo (2010, chapter 18)). Intuitively, firm i will optimally choose investment such that the marginal benefit of investment at $t+1$ discounted by the weighted average cost of capital equals the marginal cost of investment. At the margin, the net present value of the last infinitesimal project is zero.

Solving for the stock return, r^{S}_{it+1}, from equation (4) yields:

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

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 model error (alpha) from the 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. 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 $\mathbf{W} = \mathbf{I}$, 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, 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:

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

in which χ^2 is the chi-square distribution, and the superscript + is 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 assets (Compustat annual item AT>0), positive sales (item SALE>0), nonnegative debt (item DLTT+DTC≥0), positive market value of assets (item DLTT+DTC+CSHO×PRCC_F>0), positive gross capital stock (item PPEGT>0) at the most recent fiscal yearend as of portfolio formation, and positive gross capital stock one year prior to the most recent fiscal year. Following Jegadeesh and Titman (1993), we exclude stocks with prices per share less than $5 at the portfolio formation month.

3.2.1 Testing Portfolios

We use ten momentum deciles as the benchmark set of testing portfolios. We construct the 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 holding the resulting 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. Following Jegadeesh and Titman (1993), we equal-weight all stocks within a given portfolio. Because we use the six-month holding period while forming the portfolios monthly, we have six sub-portfolios for each decile in a given holding month. We average across these six sub-portfolios to obtain the monthly returns of a given decile.

3.2.2 Variable Measurement

The capital stock, K_{it}, is net property, plant, and equipment (Compustat annual item PPENT). Investment, I_{it}, is capital expenditures (item CAPX) minus sales of property, plant, and equipment (item SPPE). We set SPPE to be zero if the item 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.

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. However, both stock and flow variables in Compustat are recorded at the end of year. 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. We then assign the corporate bond returns for a given credit rating from Ibbotson Associates to the firms with the same credit rating.[3] Corporate bond returns are equal-weighted across the firms in a given portfolio.

3.2.3 Timing

Momentum portfolios are rebalanced monthly, but Compustat variables are available annually.[4] Aligning the timing of portfolio stock returns with the timing of portfolio investment

[3]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 quarterly Compustat data set. The results on matching average momentum profits are largely similar to those obtained with annual Compustat data. We opt to use annual data for several reasons. First, doing so provides a longer sample starting from 1963. In contrast, because of data availability of

returns is intricate because the momentum portfolios' composition changes monthly. This measurement difficulty should, ex ante, go against any effort in identifying fundamental driving forces underlying momentum profits. Also, any timing misalignment should have less impact on the magnitude of average momentum profits than on the dynamics of momentum.

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 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 timing alignment contains three steps. The first step is to determine the timing of firm-level characteristics at the sub-portfolio level. The general approach 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 decide from which fiscal yearend we take firm-level characteristics. As noted, in Compustat stock variables are measured at the end of the fiscal year and flow variables are over the course of the fiscal year. As such, the investment return constructed from annual accounting variables goes 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

quarterly property, plant, and equipment, the quarterly sample can only start from 1977. Second, quarterly data display strong seasonality that affects the dynamic properties of momentum profits. A common way of controlling for seasonality is to average the quarterly observations within a given year. But doing so is equivalent to using the annual data. Finally, the annual data are of higher quality than the quarterly data because quarterly accounting statements are not required by law to be audited by an independent auditor.

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-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 approach to firms with non-December fiscal yearend (see Appendix A).

The second step is to construct the components of the levered investment return 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, the sub-portfolio characteristics also change from month to month.

The final step 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 the example. After obtaining the decile's sub-portfolio characteristics, for each month we take the cross-sectional average

[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%).

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 using equation (3). The investment returns are in annual terms but vary monthly because 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 Estimation Results

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

4.1 Average Momentum Profits

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

4.1.1 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. 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 average return spread of 17.36% is more than seven standard errors from zero. The CAPM alpha and the Fama-French alpha of the winner-minus-loser decile are 16.95% and 19.15%, respectively, both of which are more than eight standard errors from zero. Both models are strongly rejected by the Gibbons, Ross, and Shanken (1989, GRS) test.[6]

[6]We have also tested the standard consumption-CAPM. The stochastic discount factor is given 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. The consumption-CAPM alpha of the winner-minus-loser decile has a similar magnitude as its CAPM and Fama-French alphas. In addition, the time preference estimate is above two, and the risk aversion estimate is above 75.

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

We also report individual alphas from our 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 our model is 0.44%, which is within 0.2 standard errors from zero. This alpha is negligible compared to those from the CAPM, 16.95%, and the Fama-French model, 19.15%, both of which are more than eight standard errors from zero.

Figure 2 illustrates the performance of different models by plotting the average predicted returns of the momentum deciles against their average realized returns. If a model's performance is perfect, all the observations should lie exactly on the 45-degree line. From Panel A, the scatter plot from our 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 are roughly horizontal. As such, the investment-based alphas do not vary systematically across the momentum deciles, whereas the CAPM alphas and the Fama-French alphas do.[7]

[7]In untabulated results, we also find that our model fits well Moskowitz and Grinblatt's (1999) industry momentum quintiles. They document that trading strategies buying stocks from past winning industries and selling stocks from past losing industries are profitable. Excluding financial firms and regulated utilities from their 20 industry classifications, 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

4.1.2 Expected Return Components

How does the model match average momentum profits? The unlevered and levered investment return equations (3) and (5) identify 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 $q_{it} \equiv 1+(1-\tau_t)a(I_{it}/K_{it})$. The growth rate of q can be interpreted 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}, which has a negative relation between δ_{it+1} and the investment 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}. In all, all else equal, firms with low I_{it}/K_{it}, high expected q_{it+1}/q_{it}, high expected Y_{it+1}/K_{it+1}, low expected δ_{it+1}, high w_{it}, and low expected r^{Ba}_{it+1} should earn higher expected stock returns at time t.

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}. For 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, $(I_{it+1}/K_{it+1})/(I_{it}/K_{it})$. We see that the winner decile has a higher average growth rate of investment-to-capital than the loser decile: 1.16 versus 0.83 per annum. 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. Both components go in the right direction to capture average momentum profits. 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. Also going in the wrong direction, the winner decile has a lower market leverage than the loser decile: 0.22 versus 0.34. Finally, the averages of the depreciate rate and the after-tax corporate bond return are largely flat across the momentum deciles, and

across industry portfolios) for the subsequent six months from $t+1$ to $t+6$. The investment-based 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 smaller than 9.15% from the CAPM and 9.40% from the Fama-French model.

their impact on the estimation results is small.[8]

4.1.3 Accounting for Average Momentum Profits

To quantify the sources of momentum, 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 performance.

From Panel C of Table 1, the growth rate of marginal q is the most important, and sales-to-capital is the second most important source of moment. Without the cross-sectional variation in the growth rate of q_{it}, the winner-minus-loser alpha in our model jumps to 11.37% per annum. In contrast, this alpha is only 0.44% in the benchmark estimation. Without the cross-sectional variation in sales-to-capital, the winner-minus-loser alpha becomes 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%.

4.2 The Dynamics of Momentum

We have so far only examined average momentum profits. However, several stylized facts of momentum involve its dynamics. The dynamics are particularly interesting because the model parameters are estimated from matching average momentum profits. As such, the dynamics of momentum can serve as additional diagnostics on the model's performance.

[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. This procedure likely restricts the cross-sectional variation in average corporate bond returns.

4.2.1 Reversal of Momentum Profits in Long Horizons

Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996) show that momentum profits are short-lived. In particular, Chan et al. 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 first 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.

The second row in each panel of Table 2 shows that our model reproduces this reversal behavior at longer horizons. The levered investment return, r^{Iw}_{it+1}, for the winner-minus-loser decile is on average 8.59% for the first six-month period and 12.09% for the first year after portfolio formation. Afterward, the average predicted return turns negative: −1.93% for the second year and −4.93% for the third year after the portfolio formation.

The remaining three rows in each panel show that it is the expected growth component of the levered investment return that drives the short-lived nature of momentum profits. Using the average growth rate of q_{it} to measure the 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 −2% and −3% at the two-year and the three-year horizons, respectively. 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. 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.

Jegadeesh and Titman (1993, Table IX) document that the average three-day returns (from day −2 to 0) around quarterly earnings announcement dates represent about 25% of momentum for the first six-month holding period, and the announcement date returns also display reversal in long horizons. Unfortunately, we cannot replicate this pattern quantitatively because daily data on characteristics are not available due to data limitations. Qualitatively, however, equation (5) implies that levered investment returns should equal stock returns in *realization*, state by state and period by period. If daily investment returns were available, it is not inconceivable that their ex post pattern mimics that of daily stock returns. Intuitively, positive earnings shocks at $t+1$ would increase the marginal product of capital at $t+1$, and increase the investment returns from t to $t+1$. The positive earnings shocks should also increase the investment-to-capital growth from t to $t+1$ because investment increases with the marginal product of capital. Given the low persistence of the expected investment-to-capital growth documented in Table 2, the investment returns around earnings announcement dates should then inherit the reversal of announcement date stock returns.

4.2.2 The Failure of Traditional Asset Pricing Models

Jegadeesh and Titman (1993) show that the CAPM cannot capture 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 capture momentum either because the loser decile loads positively and the winner decile loads negatively on their value factor. We confirm 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 (see Table 1). In untabulated results, the winner-minus-loser decile has a weakly positive market beta of 0.08, which is within one standard error of zero. In the Fama-French regression, the winner-minus-loser decile has a weakly negative market beta of -0.08 ($t=-1.05$), a size factor beta of 0.22 ($t=1.12$), and a value factor beta of -0.40 ($t=-2.03$).

To examine if our model replicates this evidence, 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 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 stock returns. However, inconsistent with 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.

Lettau and Ludvigson (2002) argue that investment lags (time lags between investment decision and actual investment expenditure) can temporally shift the correlation between investment returns and stock returns. The contemporaneous correlation is negative, but that between lagged stock returns and current investment returns is positive. To see how this temporal shift affects the factor regressions, Panel B of Table 3 regresses levered investment excess returns of the momentum deciles on the six-month lagged factor (stock) returns. The winner-minus-loser alphas are unaffected. But the factor loadings are more in line with the data: the CAPM beta of the winner-minus-loser decile becomes -0.21 ($t = -0.88$), and its market beta in the Fama-French model becomes 0.18 ($t = 0.75$). However, the value factor loading remains insignificantly positive, whereas it is significantly negative in stock returns.

4.2.3 Long Run Risks in Investment Returns

Bansal, Dittmar, and Lundblad (2005) show that aggregate consumption risks in cash flows help interpret the average return spread across momentum portfolios. We replicate their basic results in 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 slope, γ_i, measures the cash flow's exposure to the long-term aggregate consumption growth (long run risk).[9] Consistent with Bansal et al., Panel A of Table 4 shows that winners have a higher slope than losers: 15.88 versus 0.33. The 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 spread of 4.54% again has a large standard error of 3.49%.[10]

[9] 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.

[10] Because of a few observations with negative cash flows (dividends plus net repurchases), which we treat as missing, the slope, γ_i, for the winner-minus-loser decile is not identical to the spread in γ_i between winners and losers. Similarly, the cash flow growth rate of the winner-minus-loser decile is not exactly the growth rate spread between winners and losers. If we do not include net repurchases into the calculation of cash flows, 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 standard error of 12.1, and the growth rate spread has a standard error of 3.2%.

In Panel B of Table 4, we report similar evidence of long run risks in investment returns. Based on the investment return equation (3), we define a new fundamental cash flow measure as $D^{\star}_{it+1} \equiv (1 - \tau_{t+1}) \left[\kappa \frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2} \left(\frac{I_{it+1}}{K_{it+1}} \right)^2 \right] + \tau_{t+1} \delta_{it+1}$. Because the denominator of the investment return equals marginal q, equation (3) implies that $D^{\star}_{it+1} / \left[1 + (1 - \tau_t) a \frac{I_{it}}{K_{it}} \right]$ is analogous to the dividend yield, and the remaining piece of the investment return, $(1 - \delta_{it+1}) \left[1 + (1 - \tau_{t+1}) a \frac{I_{it+1}}{K_{it+1}} \right] / \left[1 + (1 - \tau_t) a \frac{I_{it}}{K_{it}} \right]$, is analogous to the rate of capital gain. As such, $D^{\star}_{it+1}$ in the investment return is analogous to 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 rate is also higher in winners than in losers: 17.12% versus −2.46%, and the spread is highly significant. The remainder of Panel B shows further 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 risks in dividends documented in Bansal, Dittmar, and Lundblad (2005) to long run risks in fundamentals such as the growth rate of sales-to-capital via firms' optimality conditions. As such, our evidence sheds light on *why* winners have higher long run risks than losers.

4.2.4 Market States and Momentum

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

The first six rows in each panel of Table 5 replicate Cooper, Gutierrez, and Hameed's (2004) results. 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. Over the 12-month period after portfolio formation, the winner-minus-loser return is on average 13.68% following the UP markets but 1.58% following the DOWN markets.

Our model fails to reproduce the procyclicality of momentum. From rows seven to 12 in Panels A and B of Table 5, if anything, the model predicts that momentum is stronger in DOWN markets. Panel B shows that 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 result. If we lead the levered investment returns by 12 months, the predicted winner-minus-loser return over the 12-month holding period is 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.

4.3 The Interaction of Momentum with Firm Characteristics

Going beyond the momentum deciles, the literature has documented stylized facts on the interaction of momentum with firm characteristics (see footnote 1). By applying our model to two-way sorted momentum portfolios, we show that it goes a long way to capture these facts.

4.3.1 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)). 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%. From Panel B, momentum also decreases with firm age. The CAPM alpha and the Fama-French alpha of the winner-minus-loser tercile in young firms are 11.98% and 13.34%, which are higher than those in old firms, 4.98% and 6.12%, respectively. Consistent with Lee and Swaminathan (2000), momentum increases with trading volume (Panel C). The CAPM alpha and the Fama-French alpha of the winner-minus-loser tercile in low volume firms are 6.97% and 8.13%, which are lower than those in high volume firms, 12.11% and 13.65%, respectively. Finally, momentum also increases with stock return volatility (Panel D). The CAPM alpha of the winner-minus-loser tercile increases from 6.50% in the low volatility tercile to 13.63% in the high volatility tercile. Across all testing portfolios, both the CAPM and the Fama-French model are strongly rejected by the GRS test.

4.3.2 GMM Parameter Estimates and Tests of Overidentification

Table 7 reports the GMM estimation 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. These estimates are close to the benchmark estimate of 2.81 from the benchmark 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 our model are mostly smaller than those from the CAPM and the Fama-French model. For example, the m.a.e. of the age and momentum portfolios is 1.19% per annum in our model, which is smaller than those from the CAPM, 3.45%, and the Fama-French model, 3.66%. The only exception is the size and momentum portfolios. Our model produces an m.a.e. of 3.33%, which is slightly higher than that from the CAPM, 3.16%, but slightly lower than that from the Fama-French model, 3.60%.

In contrast to the benchmark estimation with the momentum deciles, our 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.

4.3.3 Individual Alphas

From the last two rows in Panel A of Table 6, the alphas from our model for the nine size and momentum portfolios range from -3.98% to 5.79% per annum. Although not small, these 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 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 our model is largely aligned with the 45-degree line. However, the fit is not as good as the fit for the momentum deciles. In contrast, the scatter plot from the Fama-French model is largely horizontal (Panel B). The evidence the CAPM is similar to that from the Fama-French model (untabulated).

The last two rows in Panel B of Table 6 report 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 our model and the Fama-French model.

From the last two rows in Panel C of Table 6, the individual alphas from our model across the nine volume and momentum portfolios range from −1.94% to 4.68% per annum. None of the alphas are significant at the 5% level, likely due to measurement errors in 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 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 E and F of Figure 3 illustrate the model fit graphically for the volume and momentum portfolios.

From the last two rows in Panel D of Table 6, the individual alphas from our model across the 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 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 G and H of Figure 3 illustrate 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 our 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 Summary and Interpretation

Optimal investment implies that expected stock returns are tied with the expected marginal benefit of investment divided by the marginal cost of investment. We show via GMM that the investment model captures average momentum profits. Intuitively, winners have higher expected investment-to-capital growth and expected sales-to-capital (two major components of the expected marginal benefit), and earn higher expected stock returns than losers. The model also captures the reversal of momentum in long horizons, the failure of traditional asset pricing models in capturing momentum, long run risks in the momentum deciles, as well as the interaction of momentum with market capitalization, firm age, trading volume, and stock return volatility. However, the model fails to reproduce procyclical momentum profits.

Momentum is often interpreted as a sign of investor irrationality. For example, Jegadeesh and Titman (1993, p. 90) write "the market underreacts to information about the short-term prospects of firms but overreacts to information about their long-term prospects," and conclude that "investor expectations are systematically biased." Our results show that firms' investment decisions are connected properly to the momentum phenomenon in asset markets: firms invest more when expected returns and the cost of capital are low, and vice versa. This observation directly says nothing about investor rationality or irrationality. A low cost of capital could reflect rationally low market prices of risk demanded by investors, or it could reflect sentiment of investors who are irrationally optimistic.

Our results do provide some implications for the "rationality" of equilibrium asset prices. We see that firms invest more when prices are high. Such investment expands the supply of investment to match the demand, whatever the source of such demand. If adjustment costs were zero and firms acted rationally, then no amount of investor sentiment could affect prices. It would only affect quantities instead. Our finding that firms react with greater, but not infinite investment, reflecting adjustment costs, indicates that the room for any investor irrationality to affect prices is limited by firms' offsetting response.

In contrast to standard asset pricing theories that have predictions only about *expected* returns, equation (5) speaks to not only expected returns but also *ex-post* returns. It predicts that the levered investment return should equal the stock return for every stock, every period, and every state of the world. Because no choice of parameters satisfies such an extremely refutable prediction, the equation is rejected at any level of significance. Although we only use GMM to test the ex-ante prediction that expected levered investment returns equal expected stock returns across momentum portfolios, this test design befits our economic question: why winners earn higher returns *on average* than losers. As noted (see Section 4.2.1), the ex-post prediction in fact helps us interpret the ex-post pattern of earnings announcement returns.

We do not claim that the investment model "explains" momentum. The investment model is based on first-order conditions of firms, which do not establish causality from investment to expected returns. The model is as consistent with the view that investment growth "explains" expected returns as with the view that expected returns "explain" investment growth.

However, our finding is *no more and no less* important or "explanatory" than a would-be finding that momentum was consistent with consumption Euler equation, $E_t[M_{t+1}r^S_{it+1}] = 1$.[11] Suppose one found a utility function and consumption data such that $E_t[M_{t+1}r^S_{it+1}] = 1$ holds across ten momentum deciles. It is tempting to claim that the consumption model "explains" momentum. However, the would-be finding does not support this claim. Consumption first-order conditions say that consumers adjust consumption correctly in response to asset price movements. If the stock price moves arbitrarily with the lunar cycle, consumption first-order conditions will just line up consumption accordingly. Consumption is as endogenous to consumption first-order conditions as investment to investment first-order conditions.

In general equilibrium, consumption (consumption betas), expected returns, and investment (characteristics) are all endogenous variables determined by a system of simultaneous equilibrium conditions. Neither consumption nor investment *causes* expected returns to vary across firms. Neither consumption nor investment is more primitive than the other in "explaining" expected returns. Instead of causality, we can only learn about structural corre-

[11]This equation holds in our framework as well. Rewriting firm i's objective function given by equation (2) in recursive form yields: $V_{it} - D_{it} = E_t[M_{t+1}V_{it+1}]$. Dividing both sides by $P_{it} = V_{it} - D_{it}$ yields $E_t[M_{t+1}r^S_{it+1}] = 1$, in which $r^S_{it+1} = (P_{it+1} + D_{it+1})/P_{it}$.

lations between consumption, expected returns, and investment from equilibrium conditions.

The investment approach thinks about asset pricing very differently from the consumption approach, but in a complementary way. The consumption approach tries to figure out unobservable and hard-to-measure expected returns from equally unobservable and hard-to-measure consumption betas. In contrast, the investment approach tries to figure out expected returns from *observable* and *easier-to-measure* characteristics. Standard finance textbooks teach students to estimate the discount rate from the CAPM or multifactor models, and then use the estimated discount rate to calculate net present values for new projects to decide which ones to take in capital budgeting. The investment approach turns finance on its head: because the levered investment return equals the weighted average cost of capital, we can back out the discount rate from observable investment decisions. The investment approach *completes* the consumption approach in general equilibrium!

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Table 1 : The Benchmark Momentum Deciles, Tests of Asset Pricing Models, Economic Characteristics, and Comparative Statics on the Investment 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 our 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. The p-values (p-val) are from the Gibbon, Ross, and Shanken (1989) tests of the null that the alphas across the ten momentum deciles are jointly zero. Panel B reports average characteristics for each momentum decile including current-period investment-to-capital, I_{it}/K_{it}; the growth rate of investment-to-capital, $\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$; next-period sales-to-capital, Y_{it+1}/K_{it+1}; market leverage, w_{it}; the next-period rate of depreciation, δ_{it+1}; and the corporate bond returns in annualized percent, r_{it+1}^B. In Panel C, we perform four comparative static experiments on our 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. α_i^q is the average difference between stock returns and reconstructed levered investment returns. L is the loser decile, W is the winner decile, and W−L is the winner-minus-loser portfolio.

Panel A: Tests of the CAPM, the Fama-French model, and the investment 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
δ_{it+1}	0.14	0.14	0.13	0.13	0.13	0.13	0.13	0.14	0.14	0.18	0.03	1.92
r_{it+1}^B	0.68	0.66	0.65	0.65	0.65	0.65	0.65	0.65	0.66	0.68	0.00	0.11

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 in Long Horizons

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 decile as in Chan, Jegadeesh, and Lakonishok (1996). We also report the levered investment return, 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 investment-to-capital growth, $\frac{I_{it+1}/K_{it+1}}{I_{it}/K_{it}}$, 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 characteristics are in annual terms. L is the loser decile, W is the winner decile, and W−L is the winner-minus-loser decile.

	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 i, we conduct monthly CAPM regressions and Fama-French regressions using levered investment returns in excess of the one-month Treasury bill rate. The data for the Treasury-bill rate and the Fama-French factors are from Kenneth French's Web site. For the CAPM regressions, we report the intercept, α_i, and the market beta, β_i. For the Fama-French regressions, we report the intercept, α_i^{FF}, and the loadings on the market factor, β_i^{MKT}, the size factor, β_i^{SMB}, and the value factor, β_i^{HML}. We also report 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											
The CAPM regressions											
α_i	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_i	−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
The Fama-French three-factor regressions											
α_i^{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_i^{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_i^{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_i^{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											
The CAPM regressions											
α_i	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_i	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
The Fama-French three-factor regressions											
α_i^{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_i^{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_i^{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_i^{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 the momentum deciles. The data are quarterly from 1963 to 2008. γ_i is the projection coefficient from the regression:

$$g_{i,t} = \gamma_i \left(\frac{1}{8} \sum_{k=1}^{8} g_{c,t-k} \right) + u_{i,t}, \tag{12}$$

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:

$$g_{i,t}^\star = \gamma_i^\star \left(\frac{1}{8} \sum_{k=1}^{8} g_{c,t-k} \right) + u_{i,t}, \tag{13}$$

in which $g_{i,t}^\star$ is demeaned log real fundamental cash flow growth rates on decile i. This cash flow is $D_{it+1}^\star \equiv (1 - \tau_{t+1}) \left[\kappa \frac{Y_{it+1}}{K_{it+1}} + \frac{a}{2} \left(\frac{I_{it+1}}{K_{it+1}} \right)^2 \right] + \tau_{t+1}\delta_{it+1}$, 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 depreciation, κ is the estimated capital's share, and a is the estimated adjustment cost parameter. $\bar{g}_i^\star$ is the sample average of log real fundamental cash flow growth rates. $\gamma_{1i}^\star$ is the slope from regressing $g_{1i,t}^\star$, demeaned log real growth rates of $(1 - \tau_{t+1})\kappa \frac{Y_{it+1}}{K_{it+1}}$, $\gamma_{2i}^\star$ is the slope from regressing $g_{2i,t}^\star$, demeaned log real growth rates of $(1 - \tau_{t+1}) \frac{a}{2} \left(\frac{I_{it+1}}{K_{it+1}} \right)^2$, and $\gamma_{3i}^\star$ is the slope from regressing $g_{3i,t}^\star$, demeaned log real growth rates of $\tau_{t+1}\delta_{it+1}$ on $\frac{1}{8} \sum_{k=1}^{8} g_{c,t-k}$. We convert nominal 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 two holding periods: months $t+1$ to $t+6$ (Panel A) and months $t+1$ to $t+12$ (Panel B). Profits (average returns) are in semi-annual percent in Panel A and in annual percent in Panel B. We report 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	$r^{Iw}_{[+12]}$

Table 6 : Tests of the CAPM, the Fama-French Model, and the Investment Model for Two-Way Sorted Momentum Portfolios

For each testing portfolio, we report (in annual percent) the CAPM alphas, α_i, the Fama-French alphas, α_i^{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. The p-values (p-val) 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. The investment-based alphas and t-statistics are from one-stage GMM with an identity weighting matrix. These alphas are calculated as $\alpha_i^q \equiv E_T\left[r_{it+1}^S - r_{it+1}^{Iw}\right]$, in which $E_T[\cdot]$ is the sample mean of the series in brackets, r_{it+1}^S is stock returns, and r_{it+1}^{Iw} is levered investment returns. L is the loser tercile, W is the winner tercile, and W−L is the winner-minus-loser tercile.

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
α_i	−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_i^{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		
α_i^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	m.a.e.	p-val
α_i	−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_i^{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		
α_i^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	m.a.e.	p-val

Panel C: Nine trading volume and momentum portfolios

α_i	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_i^{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		
α_i^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_i	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_i^{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		
α_i^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		

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, denoted [ste], are 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 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

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).

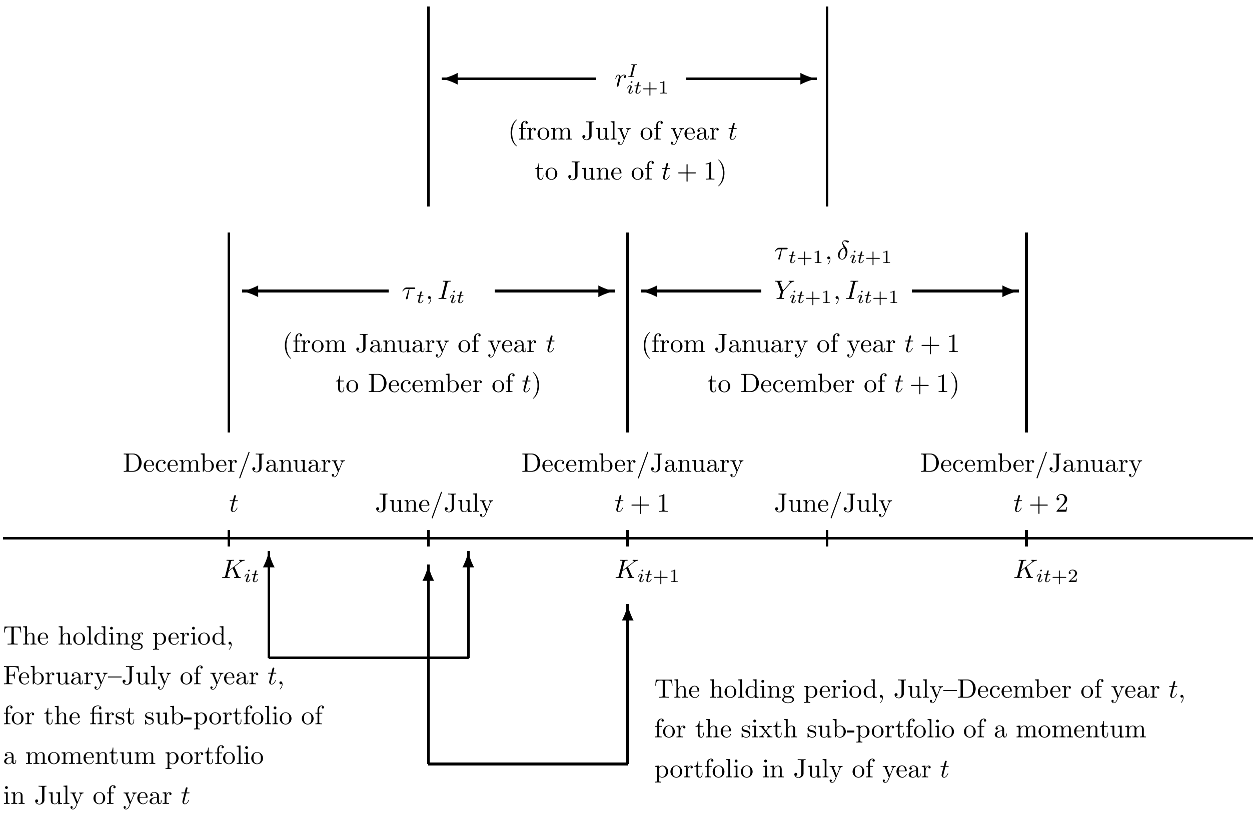


Figure 2 : Average Predicted Stock Returns vs. Average Realized Stock Returns, Ten Momentum Deciles

In our 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.

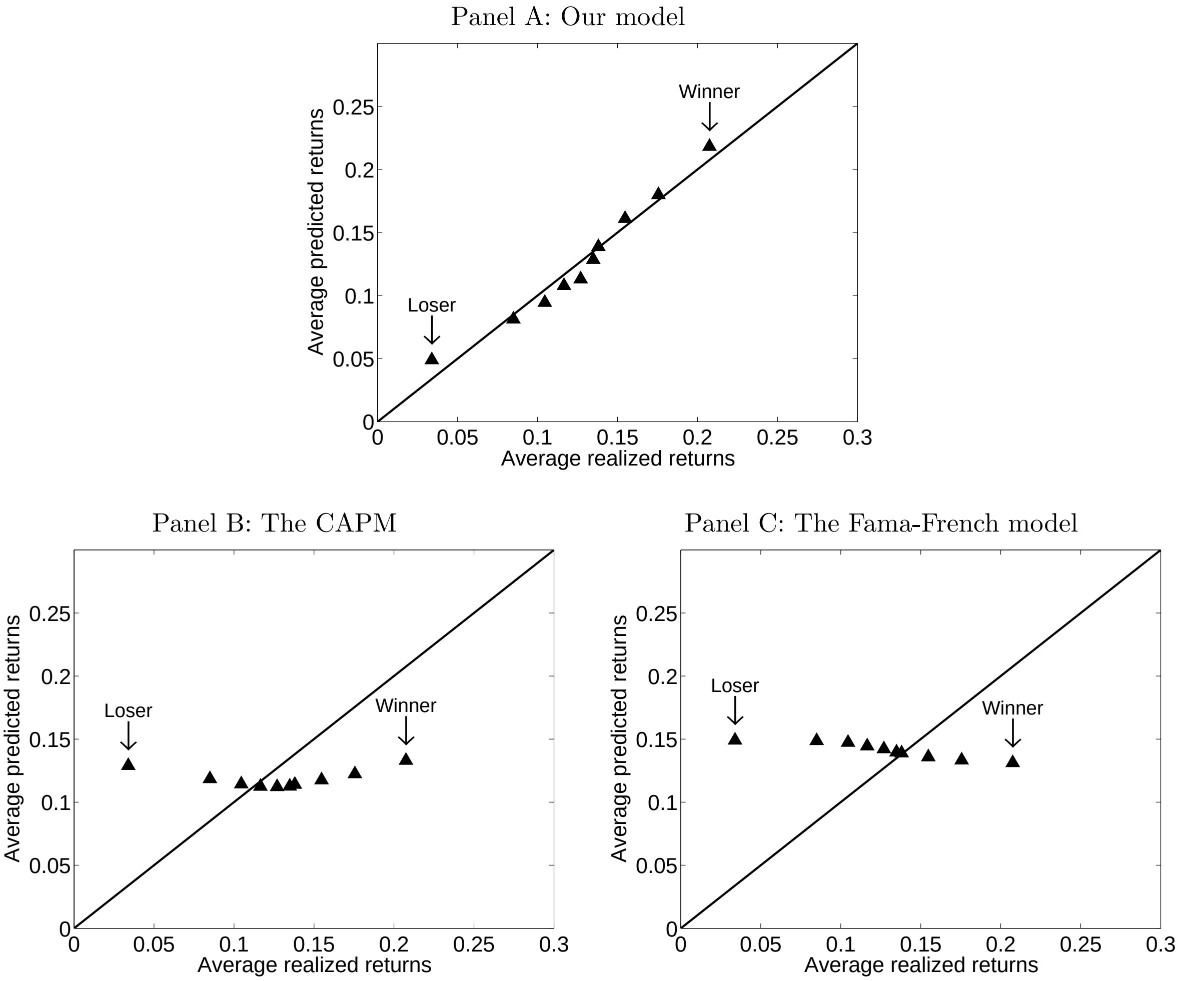
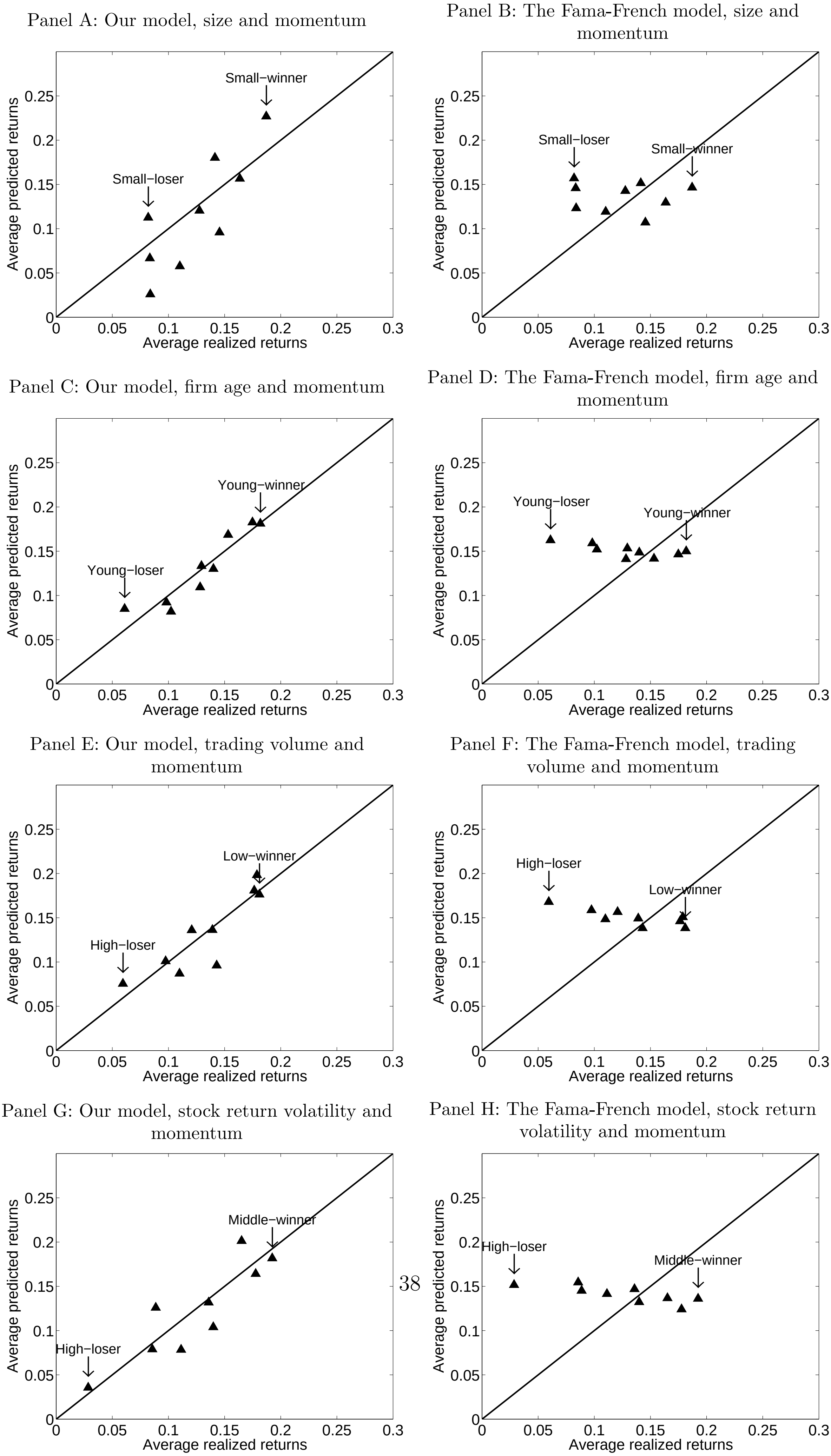


Figure 3 : Average Predicted Stock Returns vs. Average Realized Stock Returns



A Timing Alignment: Further Details

Section 3.2.3 describes the timing convention for firms with December fiscal yearend. This appendix details how we handle firms with non-December fiscal yearend. We use firms with June fiscal yearend as an example to illustrate our procedure. Firms with fiscal year ending in other months are handled in an analogous way.

Figure A1 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.

Figure A1: 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 June 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).