An Alternative Three-Factor Model

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April 2010§

Abstract

We propose a new factor model consisting of the market factor, an investment factor, and a return on assets factor for explaining the cross-section of expected stock returns. The new factor model outperforms traditional asset pricing models in explaining anomalies such as those associated with short-term prior returns, failure probability, *O*-score, earnings surprises, accruals, net stock issues, and stock valuation ratios. The new model's performance, combined with its economic intuition, suggests that it can be used to obtain expected return estimates in practice.

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§For helpful comments we thank Andrew Ang, Jonathan Berk (CEPR discussant), Patrick Bolton, Sreedhar Bharath, Ken French, Gerald Garvey (BGI discussant), Joao Gomes (AFA discussant), Hong Liu (FIRS discussant), Scott Richardson, Tyler Shumway, Richard Sloan, Alan Timmermann, Motohiro Yogo (UBC discussant), and other seminar participants at AllianceBernstein, Barclays Global Investors, Case Western Reserve University, Hong Kong University of Science and Technology, National University of Singapore, Pennsylvania State University, Renmin University of China, Rutgers Business School, Singapore Management University, Tel Aviv University, University of California at San Diego, University of Michigan, University of Washington, CRSP Forum 2008, Society of Quantitative Analysts, the Sanford C. Bernstein Conference on Controversies in Quantitative Finance and Asset Management, the UBC PH&N Summer Finance Conference in 2007, the 2008 Financial Intermediation Research Society Conference on Banking, Corporate Finance, and Intermediation, the 2009 American Finance Association Annual Meetings, and the 2009 CEPR Asset Pricing Week in Gerzensee. Cynthia Jin and Chen Xue provided valuable research assistance. Cam Harvey (the Editor), two anonymous Associated Editors, and an anonymous referee deserve special thanks. An Internet Appendix available at the authors' Web sites contains supplementary results not tabulated in the paper. A data library containing the new factors and all the testing portfolios used in the paper is also available on the authors' Web sites. Previous drafts of the paper were circulated under the titles "Neoclassical factors," "An equilibrium three-factor model," "Production-based factors," and "A better three-factor model that explains more anomalies."

1 Introduction

Although an elegant theoretical contribution, the empirical performance of the Sharpe (1964) and Lintner (1965) Capital Asset Pricing Model (CAPM) has been abysmal.[1] Fama and French (1993), among others, have augmented the CAPM with certain factors to explain what the CAPM cannot.[2] However, it has become increasingly clear over the past two decades that even the extremely influential Fama-French model cannot explain many anomalies. Prominent examples include the positive relations of average returns with momentum and earnings surprises, as well as the negative relations of average returns with financial distress, accruals, net stock issues, and asset growth.[3]

We propose a new three-factor model and show that it goes a long way toward explaining many patterns in cross-sectional returns that the Fama-French model cannot. In the new model the expected return on portfolio i in excess of the risk-free rate, denoted $E[r_i] - r_f$, is described by the sensitivity of its return to three factors: the market excess return (r_{MKT}), the difference between the return of a portfolio of low-investment stocks and the return of a portfolio of high-investment stocks (r_{INV}), and the difference between the return of a portfolio of stocks with high returns on assets and the return of a portfolio of stocks with low returns on assets (r_{ROA}). Formally,

$$E[r_i] - r_f = \beta^i_{MKT} E[r_{MKT}] + \beta^i_{INV} E[r_{INV}] + \beta^i_{ROA} E[r_{ROA}], \tag{1}$$

where $E[r_{MKT}]$, $E[r_{INV}]$, and $E[r_{ROA}]$ are expected premiums, and β^i_{MKT}, β^i_{INV}, and β^i_{ROA} are the

[1] DeBondt and Thaler (1985), Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994) show that average returns are associated with book-to-market, earnings-to-price, dividend-to-price, long-term past sales growth, and long-term prior returns, even after one controls for market betas. Jegadeesh and Titman (1993) show that stocks with higher short-term prior returns earn higher average returns.

[2] In particular, Fama and French (1993, 1996) show that their three-factor model, which includes the market excess return, a factor mimicking portfolio based on market equity (SMB), and a factor mimicking portfolio based on book-to-market (HML) can explain many CAPM anomalies such as average returns across portfolios formed on size and book-to-market, earnings-to-price, dividend-to-price, and long-term prior returns.

[3] An incomplete list of the important contributions to the anomalies literature includes Ball and Brown (1968), Bernard and Thomas (1989), Ritter (1991), Jegadeesh and Titman (1993), Ikenberry, Lakonishok, and Vermaelen (1995), Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), Chan, Jegadeesh, and Lakonishok (1996), Fama and French (1996, 2008), Sloan (1996), Dichev (1998), Campbell, Hilscher, and Szilagyi (2008), and Cooper, Gulen, and Schill (2008). The bulk of the literature argues that anomalies are due to mispricing. For example, Campbell, Hilscher, and Szilagyi (2008) suggest that their evidence "is a challenge to standard models of rational asset pricing in which the structure of the economy is stable and well understood by investors" (p. 2934).

factor loadings from regressing portfolio i' excess returns on r_{MKT}, r_{INV}, and r_{ROA}, respectively.

In the sample from January 1972 to June 2009, r_{INV} and r_{ROA} earn average returns of 0.28% ($t = 3.21$) and 0.76% per month ($t = 3.84$), respectively. These average returns persist after adjusting for their exposures to the Fama-French factors. The new factor model outperforms traditional asset pricing models in explaining the average returns of the 25 size and momentum portfolios. The winner-minus-loser alphas across five size quintiles range from 0.67% to 0.91% per month in the new factor model. Albeit significant, these alphas are smaller than those from the CAPM, which range from 0.99% to 1.44%, and those from the Fama-French model, which range from 1.14% to 1.58%.

The new factor model goes a long way toward explaining the negative relation between average returns and financial distress. The high-minus-low decile formed on Campbell, Hilscher, and Szilagyi's (2008) failure probability earns an alpha of −0.42% per month ($t = -1.45$) in the new factor model. The model cannot be rejected across the ten deciles by the Gibbons, Ross, and Shanken (1989, GRS) test. In contrast, the high-minus-low alphas are −1.51% ($t = -4.23$) in the CAPM and −1.80% ($t = -5.78$) in the Fama-French model. Both models are strongly rejected by the GRS test. The high-minus-low decile formed on Ohlson's (1980) O-score earns an alpha of −0.18% ($t = -0.84$) in the new factor model. In contrast, the high-minus-low alphas are −0.88% ($t = -3.41$) in the CAPM and −1.24% ($t = -6.27$) in the Fama-French model. Intuitively, more distressed firms have lower returns on assets (ROA), load less on the high-minus-low ROA factor, and earn lower expected returns than less distressed firms. All prior studies fail to recognize the connection between the distress effect and the positive ROA-expected return relation, and, not surprisingly, find the negative distress-expected return relation anomalous.

Several other anomaly variables such as earnings surprises, total accruals, net stock issues, and asset growth have also gained prominence since Fama and French (1996). We show that the new factor model outperforms traditional asset pricing models in explaining these anomalies, often by a big margin. For example, the high-minus-low earnings surprise decile earns an alpha of 0.26% per month ($t = 1.76$) in the new factor model. In contrast, the CAPM alpha is 0.45% ($t = 3.25$), and the Fama-French alpha is 0.53% ($t = 3.64$). The high-minus-low net stock issues decile earns an alpha of −0.34% ($t = -3.03$) in the new factor model. In contrast, the CAPM alpha is −0.60% ($t = -5.24$), and the Fama-French alpha is −0.53% ($t = -4.81$). Finally, the new factor model is comparable with the Fama-French model in explaining the average returns of portfolios formed on stock valuation ratios. Low-valuation stocks have fewer growth opportunities, invest less, load more on the low-minus-high investment factor, and earn higher average returns than high-valuation stocks.[4]

We motivate the new factor model from investment-based asset pricing. Intuitively, investment predicts returns because given expected cash flows, high costs of capital imply low net present values of new capital and low investment, whereas low costs of capital imply high net present values of new capital and high investment. ROA predicts returns because high expected ROA relative to low investment implies high discount rates. The high discount rates are necessary to offset the high expected ROA and induce low net present values of new capital and low investment. If the discount rates were not high enough to offset the high expected ROA, firms would observe high net present values of new capital and invest more. Similarly, low expected ROA relative to high investment (such as small-growth firms in the late 1990s) implies low discount rates. If the discount rates were not low enough, these firms would observe low net present values of new capital and invest less.

Our contribution is to provide a new workhorse model for estimating expected returns. We offer an update of Fama and French (1996), who show that their three-factor model summarizes what we know about the cross-section of returns as of the mid-1990s. Similarly, we show that the new factor model is a good start to understanding the cross-section of returns as of the early 2010s. We also elaborate a conceptual framework in which many anomalies can be interpreted simultaneously in an economically meaningful way. The model's performance, combined with its economic intuition,

[4]More generally, the new factor model is largely comparable with the Fama-French model in capturing the average returns of the testing portfolios that Fama and French (1996) show that their three-factor model is capable of explaining. The list includes earnings-to-price, dividend-to-price, reversal, five-year sales growth rank, and market leverage (total assets-to-market equity). We only report the results of the 25 size and book-to-market portfolios to save space: Fama and French show that book-to-market largely subsumes the aforementioned variables in predicting future returns. The Internet Appendix reports detailed factor regressions for all the other testing portfolios.

suggests that it can be used in many practical applications. The list includes evaluating mutual fund performance, measuring abnormal returns in event studies, estimating expected returns for portfolio choice, and obtaining cost of equity estimates for capital budgeting and stock valuation.

Most prior studies motivate common factors from the consumption side of the economy (e.g., Ferson and Harvey (1992, 1993); Lettau and Ludvigson (2001)). We instead motivate our factors by exploiting a direct link between returns and characteristics from the production side (e.g., Cochrane (1991)). Titman, Wei, and Xie (2004) show that investment predicts returns, and a long literature dated back to Ball and Brown (1968) shows that earnings surprise predicts returns. We show that ROA subsumes earnings surprise, and that the combined effect of investment and ROA largely explains the big picture of the cross-sectional variation of expected stock returns.

The rest of the paper is organized as follows. Section 2 motivates the new factors, and Section 3 constructs them empirically. Section 4 tests the new factor model, and Section 5 concludes.

2 Hypothesis Development

To develop testable hypotheses, we outline a two-period toy model that illustrates the basic intuition. There are two periods, 0 and 1, and heterogeneous firms, indexed by i. Firm i's operating profits are given by $\Pi_{i0}A_{i0}$ in date 0 and $\Pi_{i1}A_{i1}$ in date 1, where A_{i0} and A_{i1} are the firm's scale of productive assets and Π_{i0} and Π_{i1} are the firm's ROA in dates 0 and 1, respectively. Firm i starts with assets A_{i0}, invests in date 0, produces in both dates, and exits at the end of date 1 with a liquidation value of $(1-\delta)A_{i1}$, where δ is the rate of depreciation. Assets evolve according to $A_{i1} = I_{i0} + (1-\delta)A_{i0}$, where I_{i0} is investment. Investment entails quadratic adjustment costs given by $(a/2)(I_{i0}/A_{i0})^2 A_{i0}$, where $a > 0$ is a constant parameter. Firm i has a gross discount rate of r_i, which varies across firms due to, for example, firm-specific loadings on macroeconomic risk factors. The firm chooses A_{i1} to maximize the market value at the beginning of date 0:

$$\max_{\{A_{i1}\}} \quad \Pi_{i0}A_{i0} - [A_{i1} - (1-\delta)A_{i0}] - \frac{a}{2}\left[\frac{A_{i1}}{A_{i0}} - (1-\delta)\right]^2 A_{i0} + \frac{1}{r_i}\left[\Pi_{i1}A_{i1} + (1-\delta)A_{i1}\right]. \qquad (2)$$

The market value is date 0's free cash flow, $\Pi_{i0}A_{i0} - I_{i0} - (a/2)(I_{i0}/A_{i0})^2 A_{i0}$, plus the discounted value of date 1's free cash flow, $[\Pi_{i1}A_{i1} + (1-\delta)A_{i1}]/r_i$. With only two dates the firm does not invest in date 1, so date 1's free cash flow equals the sum of operating profits and the liquidation value.

The tradeoff of firm i is as follows: forgoing date 0's free cash flow in exchange for higher free cash flow in date 1. Setting the first-order derivative of equation (2) with respect to A_{i1} to zero yields:

$$r_i = \frac{\Pi_{i1} + 1 - \delta}{1 + a(I_{i0}/A_{i0})}. \tag{3}$$

This optimality condition is intuitive. The numerator in the right-hand side is the marginal benefit of investment, including the marginal product of capital (ROA), Π_{i1}, and the marginal liquidation value of capital, $1-\delta$. The denominator is the marginal cost of investment, including the marginal purchasing cost of investment (unity) and the marginal adjustment cost, $a(I_{i0}/A_{i0})$. Because the marginal benefit of investment is in date 1's dollar terms and the marginal cost of investment is in date 0's dollar terms, the first-order condition says that the marginal benefit of investment discounted to date 0 should equal the marginal cost of investment. Equivalently, the investment return, defined as the ratio of the marginal benefit of investment in date 1 divided by the marginal cost of investment in date 0, should equal the discount rate, as in Cochrane (1991).

2.1 The Investment Hypothesis

We use the first-order condition (3) to develop testable hypotheses for cross-sectional returns.

> H1: Given the expected ROA, the expected return decreases with investment-to-assets. This mechanism drives the negative relations of average returns with net stock issues, asset growth, valuation ratios, long-term past sales growth, and long-term prior returns.

Figure 1 illustrates the investment hypothesis.

Economic Intuition

The negative relation between expected returns and investment is intuitive. Firms invest more when their marginal q (the net present value of future cash flows generated from one additional unit of capital) is high. Given expected ROA or cash flows, low discount rates give rise to high marginal q and high investment, and high discount rates give rise to low marginal q and low investment. This discount rate intuition is probably most transparent in the capital budgeting language of Brealey, Myers, and Allen (2006). In our setting capital is homogeneous, meaning that there is no difference between project-level costs of capital and firm-level costs of capital. Given expected cash flows, high costs of capital imply low net present values of new projects and in turn low investment, and low costs of capital imply high net present values of new projects and in turn high investment.

The negative investment-discount rate relation has a long tradition in financial economics. In a world without uncertainty, Fisher (1930) and Fama and Miller (1972, Figure 2.4) show that the interest rate and investment are negatively correlated. Equivalently, the investment demand curve is downward sloping. Cochrane (1991), Li, Livdan, and Zhang (2009), and Liu, Whited, and Zhang (2009) extend this insight into a world with uncertainty.[5] Carlson, Fisher, and Giammarino (2004) also predict the negative investment-expected return relation. In their real options model expansion options are riskier than assets in place. Investment converts riskier expansion options into less risky assets in place. As such, high-investment firms are less risky and earn lower expected returns.

Portfolio Implications

The negative investment-expected return relation is conditional on expected ROA. Investment is not disconnected with ROA: more profitable firms tend to invest more than less profitable firms. This conditional relation provides a natural portfolio interpretation of the investment hypothesis. Sorting on net stock issues, asset growth, book-to-market, and other valuation ratios is closer to

[5] Cochrane (1991) and Liu, Whited, and Zhang (2009) demonstrate the negative investment-expected return relation via the discount rate intuition in a dynamic setting with constant returns to scale. Li, Livdan, and Zhang (2009) also illustrate a cash flow channel underlying the negative investment-expected return relation. Under decreasing returns to scale, more investment reduces the marginal product of capital, which in turn lowers expected returns.

sorting on investment than sorting on expected ROA. Equivalently, these sorts produce wider spreads in investment than in expected ROA. As such, we can interpret the average return spreads generated from these diverse sorts using their common implied sort on investment.

The negative relations of average returns with net stock issues and asset growth are consistent with the negative investment-expected return relation. The balance-sheet constraint of firms implies that a firm's uses of funds must equal the firm's sources of funds, meaning that issuers must invest more and earn lower average returns than nonissuers.[6] Cooper, Gulen, and Schill (2008) document that asset growth predicts future returns with a negative slope and interpret the evidence as investor underreaction to overinvestment. However, asset growth is the most comprehensive measure of investment-to-assets, where investment equals the change in total assets. As such, the asset growth effect can potentially be consistent with optimal investment.

The value premium can also be interpreted using the negative investment-expected return relation. Investment-to-assets is an increasing function of marginal q (the denominator of equation (3)), and the marginal q equals the average q under constant returns to scale. The average q and market-to-book equity are highly correlated, and are identical without debt financing. As such, value firms with high book-to-market invest less, and earn higher average returns than growth firms with low book-to-market. In general, firms with high valuation ratios have more growth opportunities, invest more, and should earn lower expected returns than firms with low valuation ratios.

We also include market leverage in this category. Fama and French (1992) measure market leverage as the ratio of total assets to the market equity. Empirically, the new factor model captures the market leverage-expected return relation better than the Fama-French model (not tabulated). Intuitively, because the market equity is in the denominator, high leverage signals fewer growth opportunities, low investment, and high expected returns, while low leverage signals more growth opportunities, high investment, and low expected returns. This investment mechanism differs from

[6] Lyandres, Sun, and Zhang (2008) show that adding the investment factor to the CAPM and the Fama-French model reduces the magnitude of the underperformance following initial public offerings, seasoned equity offerings, and convertible debt offerings. Lyandres et al. also report the part of Figure 1 related to the new issues puzzle.

the standard leverage effect in corporate finance texts. According to the textbook argument, high leverage means a high proportion of asset risk shared by equity holders, inducing high expected equity returns. This argument implicitly assumes that the investment policy is fixed and that asset risk does not vary with investment. In contrast, the investment mechanism allows investment and leverage to be jointly determined, giving rise to a negative relation between market leverage and investment and consequently a positive relation between market leverage and expected returns.

High valuation ratios can result from a stream of positive shocks on fundamentals, and low valuation ratios can result from a stream of negative shocks on fundamentals. As such, high valuation ratios of growth firms can manifest as high past sales growth and high long-term prior returns. These firms should invest more and earn lower average returns than firms with low long-term prior returns and low past sales growth. Therefore, the investment mechanism also helps explain DeBondt and Thaler's (1985) reversal effect and Lakonishok, Shleifer, and Vishny's (1994) sales growth effect.

2.2 The ROA Hypothesis

In addition to the investment hypothesis, equation (3) implies the following ROA hypothesis:

> H2: Given investment-to-assets, firms with high expected ROA should earn higher expected returns than firms with low expected ROA. This ROA-expected return relation drives the positive relations of average returns with short-term prior returns and earnings surprises, as well as the negative relation of average returns with financial distress.

Economic Intuition

Why should high expected ROA firms earn higher expected returns than low expected ROA firms? We explain the intuition in two ways: via discounting and via capital budgeting.

First, the marginal cost of investment in the denominator of the right-hand side of equation (3) equals marginal q, which in turn equals average q or market-to-book. As such, equation (3) says that the expected return is the expected ROA divided by market-to-book. Equivalently, the expected return equals the expected cash flow divided by the market equity. This relation is analogous to the Gordon Growth Model. In a two-period world price equals the expected cash flow divided by the discount rate. High expected cash flows relative to low market equity (or high expected ROAs relative to low market-to-book) mean high discount rates; low expected cash flows relative to high market equity (or low expected ROAs relative to high market-to-book) mean low discount rates.

This discounting intuition from valuation theory is also noted by Fama and French (2006). Using the residual income model, Fama and French argue that expected stock returns are related to three variables (book-to-market equity, expected profitability, and expected investment). Controlling for book-to-market and expected investment, more profitable firms earn higher expected returns. However, Fama and French do not motivate the ROA effect from economic theory or connect the ROA-expected return relation to the momentum and distress anomalies, as we do in Section 4.

We also provide the intuition for the positive ROA-expected return relation via capital budgeting. Equation (3) says that the expected return equals the expected ROA divided by an increasing function of investment-to-assets. High expected ROA relative to low investment must mean high discount rates. The high discount rates are necessary to offset the high expected ROA to induce low net present values of new capital and therefore low investment. If the discount rates were not high enough to counteract the high expected ROA, firms would instead observe high net present values of new capital and invest more. Similarly, low expected ROA relative to high investments (such as small-growth firms in the 1990s) must mean low discount rates. If the discount rates were not low enough to counteract the low expected ROA, these firms would instead observe low net present values of new capital and invest less.

Portfolio Implications

The ROA-expected return relation has important portfolio implications. For any sorts that produce wider spreads in expected ROA than in investment, the average return patterns across the sorted portfolios can be interpreted using the common implied sort on expected ROA. We explore three such sorts, including sorts on short-term prior returns, financial distress, and earnings surprises.

First, sorting on short-term prior returns should generate an expected ROA spread. Intuitively, shocks to earnings are positively correlated with contemporaneous shocks to stock returns. Firms with positive earnings surprises are likely to experience immediate stock price increases, whereas firms with negative earnings surprises are likely to experience immediate stock price decreases. As such, winners with high short-term prior returns should have higher expected ROA and earn higher average returns than losers with low short-term prior returns. Second, less distressed firms are more profitable (with higher expected ROA) and, all else equal, should earn higher average returns, whereas more distressed firms are less profitable (with lower expected ROA) and should earn lower average returns. As such, the distress anomaly can be interpreted using the positive ROA-expected return relation. Finally, sorting on earnings surprises should generate an expected ROA spread between extreme portfolios. Intuitively, firms that have experienced large positive earnings surprises should be more profitable than firms that have experienced large negative earnings surprises.

3 The Explanatory Factors

We test the investment and ROA hypotheses using the Fama-French portfolio approach. We construct new common factors based on investment-to-assets and ROA in a similar way that Fama and French (1993, 1996) construct their size and value factors. Because the new factors are motivated from the production side of the economy, we also include the market factor from the consumption side, and use the resulting three-factor model as a parsimonious description of cross-sectional returns. In the same way that Fama and French test their three-factor model, we use calendar-time factor regressions to evaluate the new factor model's performance. The simplicity of the portfolio approach allows us to test the new factor model on a wide array of testing portfolios.

Monthly returns, dividends, and prices come from the Center for Research in Security Prices (CRSP) and accounting information from the Compustat Annual and Quarterly Industrial Files. The sample is from January 1972 to June 2009. The starting date is restricted by the availability of quarterly earnings and assets data. We exclude financial firms and firms with negative book equity.

3.1 The Investment Factor

We define investment-to-assets (I/A) as the annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus the annual change in inventories (item INVT) divided by the lagged book value of assets (item AT). Changes in property, plant, and equipment capture capital investment in long-lived assets used in operations over many years such as buildings, machinery, furniture, and other equipment. Changes in inventories capture working capital investment in short-lived assets used in a normal operating cycle such as merchandise, raw materials, supplies, and work in progress. This definition is consistent with the practice of National Income Accounting. The Bureau of Economic Analysis measures gross private domestic investment as the sum of fixed investment and the net change in business inventories. Also, investment and growth opportunities are closely related: growth firms invest more than value firms. However, growth opportunities can manifest in other forms such as high employment growth and large R&D expense that are not captured by I/A.

We construct the investment factor, r_{INV}, from a two-by-three sort on size and I/A. The asset growth effect varies across different size groups (e.g., Fama and French (2008)). The effect is strong in microcaps and small stocks, but is largely absent in big stocks. Because asset growth is in effect the most comprehensive measure of investment (divided by lagged assets), it makes sense to control for size when constructing r_{INV}. The two-by-three sort is also used by Fama and French (1993) in constructing SMB and HML to control for the correlation between size and book-to-market.

In June of each year t we break NYSE, Amex, and NASDAQ stocks into three I/A groups based on the breakpoints for the low 30%, medium 40%, and high 30% of the ranked values. We also use the median NYSE market equity (stock price times shares outstanding from CRSP) to split NYSE, Amex, and NASDAQ stocks into two groups. We form six portfolios from the intersections of the two size and the three I/A groups. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of $t+1$.

Designed to mimic the common variation in returns related to I/A, the investment factor is the difference (low-minus-high I/A), each month, between the simple average of the returns of the two low-I/A portfolios and the simple average of the returns of the two high-I/A portfolios.

From Table 1, the average return of r_{INV} in our sample is 0.28% per month ($t = 3.21$). Regressing r_{INV} on the market factor produces an alpha of 0.32% ($t = 3.45$) and an R^2 of 7%. The average return subsists after controlling for the Fama-French factors. However, augmenting the Fama-French model with the momentum factor produces an insignificant alpha for r_{INV}, 0.14%, which is within 1.7 standard errors of zero. (The data of the Fama-French factors and the momentum factor are from Kenneth French's Web site.) The investment factor has a high correlation of 0.45 with HML, consistent with the evidence in Titman, Wei, and Xie (2004) and Xing (2008).[7] Sorting on I/A produces a large I/A spread. The small-size-low-I/A portfolio has an average I/A of -4.22% per annum, whereas the small-size-high-I/A portfolio has an average of 28.88% (not tabulated).

The impact of industries on the investment factor is negligible. We conduct an annual two-by-three sort on industry size and I/A using Fama and French's (1997) 48 industries. Following Fama and French (1995), we define industry size as the sum of market equity across all firms in a given industry and industry I/A as the sum of investment for all firms in the industry divided by the sum of lagged assets for the same firms. We construct the industry-level investment factor as the average low-I/A industry returns minus the average high-I/A industry returns. If the industry effect is important for the firm-level investment factor, the industry-level investment factor should earn significant average returns.[8] However, untabulated results show that the average return for the

[7] Titman, Wei, and Xie (2004) sort stocks on $CE_{t-1}/[(CE_{t-2}+CE_{t-3}+CE_{t-4})/3]$, where CE_{t-1} is capital expenditure (Compustat annual item CAPX) scaled by sales (item SALE) in the fiscal year ending in calendar year $t-1$. The prior three-year moving average of CE aims to capture the benchmark investment level. We sort stocks directly on I/A because it is more closely connected to theory. Xing (2008) shows that an investment growth factor contains information similar to HML and can explain the value premium approximately as well as HML. We differ in several ways. First, equation (3) says that investment-to-assets is a more direct predictor of returns than past investment growth. Second, empirically, firm-level investment can often be zero or negative, making investment growth ill-defined. Measuring investment as capital expenditure ignores firms with zero or negative investment. By using data on changes of property, plant, and equipment, we include these firms in our construction. Finally, we use a more comprehensive measure of investment that includes both long-term fixed capital investment and short-term working capital investment.

[8] Moskowitz and Grinblatt (1999) use a similar test design to construct industry-level momentum and show that it accounts for much of the firm-level momentum.

industry-level investment factor is only 0.09% per month ($t = 0.79$). Its CAPM alpha and the Fama-French alpha are 0.10% and 0.02%, respectively, neither of which is significant. Finally, each of the six firm-level size-I/A portfolios draws observations from a wide range of industries, and the industry distribution of firm-month observations does not vary much across the portfolios (not tabulated).

3.2 The ROA Factor

We construct the ROA factor, r_{ROA}, by sorting on the current ROA (as opposed to the expected ROA) because ROA is highly persistent. Fama and French (2006) show that current profitability is the strongest forecaster of future profitability, and that adding more regressors in the expected profitability specification decreases its explanatory power for future stock returns. Moreover, because r_{ROA} is most relevant for explaining earnings surprises, momentum, and distress anomalies, which are all rebalanced monthly, we use a similar approach to construct the ROA factor.[9]

We measure ROA as income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged total assets (item ATQ). At the beginning of each month from January 1972 to June 2009, we categorize NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, medium 40%, and high 30% of the ranked values of quarterly ROA. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). For example, if the earnings for the fourth fiscal quarter of last year are publicly announced on March 5 (or March 25) of this year, we use the announced earnings (divided by the quarterly assets from last year's third quarter) to form portfolios at the beginning of April of this year. We also use the NYSE median at the beginning of each month to split NYSE, Amex, and NASDAQ stocks into two size groups. We form six portfolios from the intersections of the two size and three ROA groups. Monthly value-weighted returns on

[9] In untabulated results, we show that the earnings surprises, momentum, and the distress anomalies do not exist in annually rebalanced portfolios. In June of each year t we sort all NYSE, Amex, and NASDAQ stocks into deciles based on, separately, the Standardized Unexpected Earnings, Campbell, Hilscher, and Szilagyi's (2008) failure probability, and Ohlson's (1980) O-score measured at the fiscal year ending in calendar year $t-1$, as well as the 12-month prior return from June of year $t-1$ to May of year t. We calculate monthly value-weighted returns from July of year t to June of $t+1$, and rebalance the portfolios in June of $t+1$. None of these strategies produces mean excess returns or CAPM alphas that are significantly different from zero at the 5% level.

the six portfolios are calculated for the current month, and the portfolios are rebalanced monthly. Meant to mimic the common variation in returns related to firm-level ROA, the ROA factor is the difference (high-minus-low ROA), each month, between the simple average of the returns on the two high-ROA portfolios and the simple average of the returns on the two low-ROA portfolios.

Panel A of Table 1 shows that r_{ROA} earns an average return of 0.76% per month ($t = 3.84$) from January 1972 to June 2009. Controlling for the market factor, the Fama-French factors, and the momentum factor does not materially affect the average return. From Panel B, r_{ROA} and the momentum factor have a correlation of 0.31, suggesting that shocks to earnings are positively correlated with shocks to returns contemporaneously. In untabulated results we show that sorting on ROA generates a large ROA spread. For example, the small-size-low-ROA portfolio has an average ROA of -3.34% per quarter, whereas the small-size-high-ROA portfolio has an average ROA of 3.40%. The large ROA spread corresponds to a large spread in prior six-month returns, 5.30% versus 16.25%, helping explain the high correlation between r_{ROA} and the momentum factor.

The correlation between the investment factor and the ROA factor is close to zero, meaning that there is no need to neutralize the two factors against each other. Untabulated results show that the large ROA spread in small firms only corresponds to a small spread in I/A: 10.50% versus 12.03% per annum. The timing difference between I/A and ROA helps explain the low correlation between the two factors. In particular, I/A is for the fiscal year ending in the last calendar year, whereas ROA is calculated with the most recently announced quarterly earnings.

The industry effect on the ROA factor is small. We conduct a monthly two-by-three sort on industry size and ROA using Fama and French's (1997) 48 industries. We define industry ROA as the sum of earnings across all the firms in a given industry divided by the sum of lagged assets across the same firms. The industry ROA factor is constructed as the average high-ROA industry returns minus the average low-ROA industry returns. If the industry effect matters for the firm-level ROA factor, the industry-level ROA factor should show large average returns. From untabulated results, the average return of the industry-level ROA factor is 0.28% per month ($t = 2.18$), and the CAPM alpha and the Fama-French alpha are 0.31% ($t = 2.45$) and 0.41% ($t = 3.23$), respectively. Although significant, the industry effect is small in magnitude relative to the firm-level ROA factor that earns an average return of 0.76% ($t = 3.84$). Finally, each of the six firm-level size-ROA portfolios draws observations from a wide range of industries, and the industry distribution of firm-month observations does not vary much across the six portfolios.

4 Calendar-time Factor Regressions

We confront the new factor model with testing portfolios formed on a wide range of anomaly variables using factor regressions of the following form:

$$r_i - r_f = \alpha_Q^i + \beta_{MKT}^i r_{MKT} + \beta_{INV}^i r_{INV} + \beta_{ROA}^i r_{ROA} + \epsilon_i. \qquad (4)$$

If the model's performance is adequate, α_Q^i should be statistically indistinguishable from zero.

4.1 Short-term Prior Returns

Following Jegadeesh and Titman (1993), we construct the 25 size and momentum portfolios using the "6/1/6" convention. At the beginning of each month t, we sort NYSE, Amex, and NASDAQ stocks into quintiles on their prior returns from month t–2 to t–7, skip month t–1, and calculate the subsequent portfolio returns from month t to t+5. We also use NYSE market equity breakpoints to sort the stocks independently each month into quintiles. The 25 portfolios are formed monthly from taking the intersection of the size and prior six-month returns quintiles.[10]

Regression Results

Table 2 reports large momentum profits. From Panel A, the average winner-minus-loser return varies from 0.93% ($t = 3.27$) to 1.37% per month ($t = 5.90$). The CAPM alphas of the winner-

[10] Using the 25 size and momentum portfolios with the "11/1/1" convention of momentum from Kenneth French's Web site yields similar results (not tabulated). The "11/1/1" convention means that, for each month t, we sort stocks on their prior returns from month $t-2$ to $t-12$, skip month $t-1$, and calculate portfolio returns for the current month t.

minus-loser portfolios are significantly positive across all five size quintiles. In particular, the small-stock winner-minus-loser portfolio earns a CAPM alpha of 1.44% per month ($t = 6.49$). Consistent with Fama and French (1996), their three-factor model exacerbates momentum. The small-stock winner-minus-loser portfolio earns a Fama-French alpha of 1.58% per month ($t = 7.08$). Losers have higher HML loadings than winners, meaning that the Fama-French model counterfactually predicts that losers should earn higher average returns.

Panel B reports the new factor model's performance. Although still significant, the winner-minus-loser alphas are smaller in magnitude than those from the CAPM and the Fama-French model. The small-stock winner-minus-loser portfolio has an alpha of 0.91% per month ($t = 3.48$), which represents a reduction of 37% in magnitude from its CAPM alpha and 42% from its Fama-French alpha. However, all three models are rejected by the GRS test at the 1% level.

The new factor model's relative performance derives from two sources. First, winners have higher r_{ROA} loadings than losers across all size quintiles, going in the right direction to explain momentum. The loading spreads range from 0.25 to 0.49, and (given the average r_{ROA} return of 0.76%) explain 0.19% to 0.37% per month of momentum profits. Second, somewhat surprisingly, winners also have higher r_{INV} loadings than losers. The loading spreads range from 0.18 to 0.36. Combined with an average r_{INV} return of 0.28%, these loadings account for additional 0.05% to 0.10% per month of momentum profits. Although quantitatively less important than the ROA factor loadings, the investment factor loadings also go in the right direction to explain momentum.

Understanding the Factor Loadings of Momentum Portfolios

The r_{INV} loading pattern is counterintuitive. Our prior was that winners with high valuation ratios should invest more and have lower loadings on the (low-minus-high) investment factor than losers with low valuation ratios. To understand what drives the loading pattern, we use the event-study approach of Fama and French (1995) to examine how I/A varies across momentum portfolios. To preview the results, we find that winners indeed have higher contemporaneous I/A than losers at the portfolio formation month. However, winners also have lower I/A than losers starting from two to three quarters prior to the portfolio formation. Because r_{INV} is rebalanced annually, the higher r_{INV} loadings for winners capture their lower I/A several quarters prior to the portfolio formation.

For each portfolio formation month t from January 1972 to June 2009, we calculate the annual I/A for month $t+m$, where $m = -60, \ldots, 60$, and then average the I/A for $t+m$ across portfolio formation months t. For a given portfolio we plot the median I/A among the firms in the portfolio. Panel A of Figure 2 shows that although small winners have higher I/A at the portfolio formation than small losers, small winners have lower I/A than small losers from the event quarter -20 to -3. Although big winners have higher I/A at the portfolio formation than big losers, big winners also have lower I/A than big losers from the event quarter -20 to -2.

Turning to calendar time, Panel B of Figure 2 shows that small winners have higher contemporaneous I/A than small losers. We define the contemporaneous I/A as the I/A at the current fiscal year-end. For example, if the current month is March or September 2003, the contemporaneous I/A is the I/A for the fiscal year ending in 2003. However, Panel C shows that small winners also have lower lagged (sorting-effective) I/A than small losers. We define the sorting-effective I/A as the I/A on which an annual sort on I/A in each June would be based. For example, if the current month is March 2003, the sorting-effective I/A is the I/A for the fiscal year ending in calendar year 2001 because the annual sort on I/A is in June 2002. If the current month is September 2003, the sorting-effective I/A is the I/A for the fiscal year ending in calendar year 2002 because the annual sort on I/A is in June 2003. Because r_{INV} is rebalanced annually, the lower sorting-effective I/A of winners explains their higher investment factor loadings than losers.

Finally, as expected, Figure 2 also shows that winners have higher ROA than losers both before and after the portfolio formation (Panel D). In calendar time, winners have consistently higher ROA than losers, especially in the small-size quintile (Panels E and F). This evidence explains the higher ROA factor loadings for winners documented in Table 2.

4.2 Financial Distress

A big portion of the distress anomaly is explained by the ROA factor loadings. At the beginning of each month, we sort all NYSE, Amex, and NASDAQ stocks into deciles on Campbell, Hilscher, and Szilagyi's (2008) failure probability and Ohlson's (1980) O-score (see Appendix A for the variable definitions). Earnings and other accounting data for a fiscal quarter are used in portfolio sorts in the months immediately after the quarter's public earnings announcement month (Compustat quarterly item RDQ). The starting point of the sample for the failure probability deciles is January 1975, and is restricted by the data requirement for failure probability. For comparison, Campbell, Hilscher, and Szilagyi (2008) start their sample in 1981. Monthly value-weighted portfolio returns are calculated for the current month, and the portfolios are rebalanced at the beginning of next month.

Panel A of Table 3 shows that more distressed firms earn lower average returns than less distressed firms. The high-minus-low failure probability decile earns an average return of -1.10% per month ($t = -2.85$). Controlling for risk only makes things worse because more distressed firms appear riskier in traditional factor models. The high-minus-low decile has a CAPM beta of 0.76, which produces an alpha of -1.51% ($t = -4.23$). In the Fama-French model the high-minus-low portfolio has a market beta of 0.59, an SMB beta of 1.11, and an HML beta of 0.17. The positive betas produce a large Fama-French alpha of -1.80%, which is more than 5.5 standard errors from zero.

The new factor model reduces the high-minus-low alpha to -0.42% per month, which is within 1.5 standard errors of zero. This alpha represents reductions in magnitude of 72% from the CAPM alpha and 77% from the Fama-French alpha. The new factor model is not rejected by the GRS test. In contrast, the CAPM and the Fama-French model are both strongly rejected. The r_{ROA} loading moves in the right direction to explain the distress anomaly. More distressed firms have lower r_{ROA} loadings than less distressed firms. The loading spread is -1.26, which is more than 13 standard errors from zero. This evidence makes sense because failure probability has a strong negative relation with profitability (see Appendix A), meaning that more distressed firms are less profitable than less distressed firms. From untabulated results, the average portfolio ROA decreases monotonically from 3.45% per quarter for the low failure probability decile to −3.44% for the high failure probability decile, and the ROA spread of −6.88% is highly significant.

From Panel B of Table 3, the high O-score decile underperforms the low O-score decile by an average of −0.72% per month ($t = -2.60$). The CAPM alpha for the high-minus-low decile is −0.88% ($t = -3.41$), and the Fama-French alpha −1.24% ($t = -6.27$). In contrast, the new factor model largely explains the abnormal return: the alpha is reduced to −0.18%, which is within one standard error of zero. The driving force behind the improved performance is again the large ROA factor loading, −0.90 ($t = -12.91$) for the high-minus-low decile. From untabulated results, the average portfolio ROA decreases monotonically from 2.89% per quarter for the low O-score decile to −3.59% for the high O-score decile, and the ROA spread of −6.48% is highly significant.

4.3 Earnings Surprises

The new factor model largely explains the post-earnings announcement drift. Following Chan, Jegadeesh, and Lakonishok (1996), we define Standardized Unexpected Earnings (SUE) as the change in the most recently announced quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of the change in quarterly earnings over the prior eight quarters (at least six quarters). We rank all NYSE, Amex, and NASDAQ stocks at the beginning of each month based on their most recent past SUE. Monthly value-weighted portfolio returns are calculated for the current month, and the portfolios are rebalanced at the beginning of next month.

From Panel A of Table 4, the new factor model is not rejected by the GRS test using the SUE deciles, whereas both the CAPM and the Fama-French model are rejected at the 1% significance level. The high-minus-low SUE portfolio earns an average return of 0.40% per month ($t = 2.77$), a CAPM alpha of 0.45% ($t = 3.25$), and a Fama-French alpha of 0.53% ($t = 3.64$). The new factor model reduces the alpha to 0.26% ($t = 1.76$). The reason is that the high-minus-low portfolio has an ROA factor loading of 0.28, which is more than six standard errors from zero. From untabulated results, the average portfolio ROA increases monotonically from 0.64% per quarter for the low SUE decile to 2.53% for the high SUE decile, and the ROA spread of 1.89% is highly significant.

4.4 Total Accruals

Sloan (1996) documents that firms with high total accruals earn abnormally lower average returns than firms with low total accruals. Sloan's work has spawned a large literature in capital markets research in accounting. We show that the new factor model can largely capture the accrual anomaly, whereas the traditional asset pricing models cannot.

In June of each year t we sort all NYSE, Amex, and NASDAQ stocks into deciles based on the ranked values of total accruals for the fiscal year ending in calendar year $t-1$. Value-weighted portfolio returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of year $t+1$. Following Sloan (1996), we define total accruals as $(\triangle CA - \triangle CASH) - (\triangle CL - \triangle STD - \triangle TP) - DEP$, in which $\triangle CA$ is the change in current assets (Compustat annual item ACT), $\triangle CASH$ is the change in cash or cash equivalents (item CHE), $\triangle CL$ is the change in current liabilities (item LCT), $\triangle STD$ is the change in debt included in current liabilities (item DLC), $\triangle TP$ is the change in income taxes payable (item TXP), and DEP is depreciation and amortization expense (item DP). We scale total accruals for the fiscal year ending in calendar year $t-1$ with average total assets (the mean of the total assets [item AT] for the fiscal years ending in t–1 and t–2).

From Panel B of Table 4, the high-minus-low accrual decile earns an average return of -0.54% per month ($t = -2.88$). The CAPM alpha and the Fama-French alpha are -0.61% and -0.58%, respectively, which are both more than three standard errors from zero. The new factor model reduces the alpha to an insignificant -0.30%, which is within 1.6 standard errors of zero. The reason is the large investment factor loading for the high-minus-low decile, -0.72, which is more than 5.5 standard errors from zero. From untabulated results, the average portfolio I/A increases monotonically from 3.08% per annum for the low accrual decile to 31.76% for the high accrual decile, and the I/A spread of 28.68% is highly significant. However, the new factor model is still rejected by the GRS test, as in the case of the CAPM and the Fama-French model.

4.5 Net Stock Issues

Following Fama and French (2008), we measure net stock issues as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end in $t-1$ to the split-adjusted shares outstanding at the fiscal year-end in $t-2$. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item ADJEX_C). In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into deciles based on net stock issues for the fiscal year ending in calendar year $t-1$. Because a disproportionately large number of firms have zero net stock issues, we group all the firms with negative net issues into the lowest decile, and all the firms with zero net issues into decile two. We then sort the firms with positive net issues into the remaining eight (equal-numbered) deciles. Monthly value-weighted portfolio returns are calculated from July of year t to June of year $t+1$, and the deciles are rebalanced in June of $t+1$.

From Panel A of Table 5, firms with high net issues earn lower average returns than firms with low net issues, 0.10% vs. 0.63% per month. The high-minus-low decile earns an average return of -0.52% ($t = -4.33$), a CAPM alpha of -0.60% ($t = -5.24$), and a Fama-French alpha of -0.53% ($t = -4.81$). The new factor model reduces the high-minus-low alpha to -0.34%, albeit still significant ($t = -3.03$). The high-minus-low portfolio has an investment factor loading of -0.36 ($t = -5.10$), moving in the right direction to explain the average returns. This loading pattern is consistent with the underlying investment pattern. From untabulated results, the average portfolio I/A increases virtually monotonically from 6.82% per annum for the low net issues decile to 30.65% for the high net issues decile, and the I/A spread is highly significant.

In addition, the ROA factor loading also moves in the right direction to explain the average returns. The high-minus-low net issues decile has an ROA factor loading of -0.17 ($t = -5.28$), meaning that firms with high net issues are less profitable than firms with low net issues at the portfolio formation. This evidence differs from Loughran and Ritter's (1995) evidence that equity issuers are more profitable than nonissuers. While Loughran and Ritter only examine new equity issues, net issues also include share repurchases. Our evidence is consistent with Lie's (2005) that repurchasing firms exhibit superior operating performance relative to industry peers.

4.6 Asset Growth

In June of each year t we sort all NYSE, Amex, and NASDAQ stocks into deciles based on the ranked values of asset growth for the fiscal year ending in calendar year $t-1$. Following Cooper, Gulen, and Schill (2008), we measure asset growth as total assets (Compustat annual item AT) at the fiscal year-end of $t-1$ minus total assets at the fiscal year-end of $t-2$ divided by total assets at the fiscal year-end of $t-2$. Monthly value-weighted portfolio returns are calculated from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of $t+1$.

Panel B of Table 5 reports that the high asset growth decile earns a lower average return than the low asset growth decile with a spread of -0.83% per month ($t = -4.58$). The high-minus-low portfolio earns a CAPM alpha of -0.90% ($t = -5.14$) and a Fama-French alpha of -0.54% ($t = -3.42$). The new factor model produces a high-minus-low alpha of -0.62% ($t = -3.77$). As such, the new model's performance is somewhat worse than the performance of the Fama-French model.

While the Fama-French model gets the explanatory power from HML, the new factor model works through the investment factor. The high-minus-low portfolio has an investment factor loading of -1.06 ($t = -11.08$). From untabulated results, the average portfolio I/A increases monotonically from -8.69% per annum for the low asset growth decile to 38.55% for the high asset growth decile, and the spread is highly significant. Although asset growth and I/A capture firm-level investment, the investment factor fails to fully capture the asset growth anomaly. The reason is probably that asset growth is a more comprehensive measure of investment than I/A.

4.7 Book-to-Market Equity

Table 6 reports factor regressions of Fama and French's (1993) 25 size and book-to-market portfolios (the data for the portfolio returns are from Kenneth French's Web site). Value stocks earn higher average returns than growth stocks. The average high-minus-low return is 0.99% per month ($t = 4.84$) in the small-size quintile and 0.22% ($t = 1.10$) in the big-size quintile. The small-stock high-minus-low portfolio has a CAPM alpha of 1.15% ($t = 6.15$), and a Fama-French alpha of 0.65% ($t = 5.70$). In particular, the small-growth portfolio has a Fama-French alpha of −0.53%, which is more than 4.5 standard errors from zero.[11] The big-stock high-minus-low portfolio has a CAPM alpha of 0.29 ($t = 1.48$), but a Fama-French alpha of −0.31% ($t = -2.38$).

On balance, the new factor model performs roughly as well as the Fama-French model in explaining the average returns across the 25 size and book-to-market portfolios. The small-stock high-minus-low alpha is 0.61% per month ($t = 3.14$), and has a similar magnitude with the Fama-French alpha. The new factor model does exceptionally well in capturing the low average returns of the small-growth portfolio. In contrast to the high Fama-French alpha of −0.53%, the alpha is virtually zero in the new factor model. Also, unlike the significantly negative alpha in the Fama-French model, the big-stock high-minus-low portfolio has an insignificant alpha of 0.17% in the new factor model. However, the small-value portfolio has an alpha of 0.61% ($t = 3.42$) in the new factor model. In contrast, the Fama-French alpha is only 0.12%, which is within 1.8 standard errors of zero.

From Panel B of Table 6, value stocks have higher r_{INV} loadings than growth stocks. The loading spreads, ranging from 0.58 to 0.87, are all more than 4.5 standard errors from zero. This evidence shows that growth firms invest more than value firms. The r_{ROA} loading pattern is more complicated. In the small-size quintile, the high-minus-low portfolio has a positive loading of 0.38 ($t = 4.80$) because the small-growth portfolio has a large negative loading of −0.62. However, in the big-size quintile, the high-minus-low portfolio has a negative ROA factor loading of −0.08, albeit in-

[11] The small-growth effect is notoriously difficult to explain. Campbell and Vuolteenaho (2004), for example, show that the small-growth portfolio is particularly risky in their two-beta model: it has higher cash flow and discount rate betas than the small-value portfolio. As a result, their two-beta model fails to explain the small-growth effect.

significant. It is somewhat surprising that the small-growth portfolio has a lower ROA factor loading than the small-value portfolio. Using an updated sample through 2009, we show in untabulated results that growth firms indeed have persistently higher ROA than value firms in the big-size quintile in event time and in calendar time, consistent with Fama and French (1995). However, in the small-size quintile growth firms have persistently lower ROA than value firms before and after the portfolio formation. In calendar time, a dramatic downward spike of ROA appears for the small-growth portfolio from 1995 to 2005. This downward spike explains the abnormally low ROA factor loadings.

4.8 Industries, CAPM Betas, and Market Equity

Lewellen, Nagel, and Shanken (2008) argue that asset pricing tests are often misleading because apparently strong explanatory power (such as high cross-sectional R^2) provides only weak support for a model. Our tests are immune to this critique because we focus on the intercepts from factor regressions as the yardstick for evaluating competing models. Following Lewellen et al.'s prescription, we also confront the new factor model with a wide array of testing portfolios formed on characteristics other than size and book-to-market. We test the new model further with industry and CAPM beta portfolios. Because these portfolios do not display much cross-sectional variation in average returns, the model's performance is roughly comparable with that of the CAPM and the Fama-French model.

From Table 7, the CAPM explains the returns of ten industry portfolios with an insignificant GRS statistic. Both the Fama-French model and the new factor model are rejected by the GRS test. The reason is that the point estimates are more precise than those from the CAPM, meaning that even an economically small deviation from the null is significant. The average magnitude of the alphas is comparable across three models: 0.16% in the CAPM, 0.20% in the Fama-French model, and 0.18% in the new factor model. One out of ten individual alphas in the CAPM, three in the Fama-French model, and two in the new factor model are significant.

Panel A of Table 8 shows that none of the models is rejected by the GRS test using the CAPM beta deciles. The high-minus-low decile even earns a significantly negative CAPM alpha of -0.54%

per month ($t = -1.99$). The high-minus-low alphas are -0.21% and 0.25% in the Fama-French model and the new factor model, respectively, and both are within one standard error of zero.

Panel B reports a weakness of the new factor model. Small firms earn slightly higher average returns than big firms. The average return, CAPM alpha, and the Fama-French alpha for the small-minus-big portfolio are smaller than 0.25% in magnitude and are all within 1.5 standard errors of zero. In contrast, although not rejected by the GRS test, the new factor model delivers an alpha of 0.50% ($t = 2.07$). The new model inflates the size premium because small firms have significantly lower r_{ROA} loadings than big firms, going in the opposite direction as the average return. However, this weakness is also the strength that allows the new model to explain the small-growth anomaly.

5 Summary and Interpretation

We offer a new factor model consisting of the market factor, a low-minus-high investment factor, and a high-minus-low ROA factor. The new factor model outperforms traditional asset pricing models in explaining a wide range of anomalies in the cross-section of returns. Our pragmatic approach means that the new factor model can be used in many applications that require expected return estimates. The list includes evaluating mutual fund performance, measuring abnormal returns in event studies, estimating expected returns for asset allocation, and calculating costs of equity for capital budgeting and stock valuation. The applications depend primarily on the model's performance. The economic intuition of the model also raises the likelihood that such performance can persist in the future.

We interpret the new factor model as providing a parsimonious factor structure for the cross-section of expected stock returns. In particular, differing from Fama and French (1993, 1996), who interpret their similarly constructed SMB and HML as risk factors in the context of ICAPM or APT, we do not interpret the investment and ROA factors as risk factors. On the one hand, investment-based asset pricing ties expected returns to firm characteristics without assuming mispricing. Unlike size and book-to-market that directly involve market equity, which behaviorists often use as a mispricing proxy (e.g., Daniel, Hirshleifer, and Subrahmanyam (2001)), the new factors are constructed on economic fundamentals. Fundamentals are less likely to be affected by mispricing, at least directly. On the other hand, while motivated from economic theory, our tests are not meant to be formal tests. More important, investment-based asset pricing is largely silent on the investor behavior, which can be rational or irrational. As such, our tests do not aim to, and cannot distinguish whether anomalies are driven by rational or irrational forces.

We also conduct horse races between covariances and characteristics following the test design of Daniel and Titman (1997, Table III). In untabulated results, we document that after controlling for investment-to-assets, investment factor loadings are unrelated to average returns, but controlling for investment factor loadings does not affect the explanatory power of investment-to-assets. Similarly, after controlling for ROA, ROA factor loadings are unrelated to average returns, but controlling for ROA factor loadings does not affect the explanatory power of ROA. Consistent with Daniel and Titman, the evidence suggests that low-investment stocks and high-ROA stocks earn high average returns regardless of whether these stocks have return patterns (covariances) that are similar to other low-investment and high-ROA stocks.

We reiterate that, differing from Fama and French (1993) but echoing Daniel and Titman (1997), we do not consider the new factors necessarily as risk factors. As noted, we view the new factor model agnostically as a parsimonious description of cross-sectional returns. The factor loadings explain returns because the factors are based on characteristics. Time-series and cross-sectional regressions are largely equivalent ways of summarizing correlations. If a characteristic is significant in cross-sectional regressions, its factor is likely to load significantly in time-series regressions. If a factor has significant loadings in time-series regressions, its characteristic is likely significant in cross-sectional regressions. Factor loadings are no more primitive than characteristics, and characteristics are no more primitive than factor loadings, as far as explaining the expected returns is concerned.

The evidence in Daniel and Titman (1997) is sometimes interpreted as suggesting that risk does not determine expected returns. In our view this interpretation is too strong. Theoretically, investment-based asset pricing predicts an array of relations between characteristics and expected returns, relations that are consistent with the data (see equation (3)). The derivation of that equation is not based on mispricing, and is consistent with the risk hypothesis. In particular, the derivation retains rational expectations in the purest form of Muth (1961) and Lucas (1972). Empirically, it is not inconceivable that characteristics provide more precise estimates of the true betas than the estimated betas (e.g., Miller and Scholes (1972)). The betas are estimated using rolling-window regressions "run between 42 months and 6 months prior to the formation date (June of year t)" (Daniel and Titman, p. 18), and are in effect average betas at 24 months prior to portfolio formation. It seems reasonable to imagine that it would be hard, for example, for the 24-month-lagged ROA factor loading to compete with the most recently announced ROA in explaining monthly returns.[12] Future work can sort out the different interpretations. However, because true conditional betas are unobservable, reaching a definitive verdict is virtually impossible.

[12]The conditioning approach uses up-to-date information to estimate betas (e.g., Harvey (1989, 1991); Ferson and Harvey (1999)). However, linear specifications contain specification errors due to nonlinearity (e.g., Harvey (2001)), and the conditional CAPM often performs no better than the unconditional CAPM (e.g., Ghysels (1998); Lewellen and Nagel (2006)). Ang and Chen (2007) document better news for the conditional CAPM, however.

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A Variable Definitions

We construct the distress measure following Campbell, Hilscher, and Szilagyi (2008, the third column in Table IV):

$$\text{Distress}(t) \equiv -9.164 - 20.264\, NIMTAAVG_t + 1.416\, TLMTA_t - 7.129\, EXRETAVG_t$$
$$+1.411\, SIGMA_t - 0.045\, RSIZE_t - 2.132\, CASHMTA_t + 0.075\, MB_t - 0.058\, PRICE_t \quad \text{(A1)}$$
$$NIMTAAVG_{t-1,t-12} \equiv \frac{1-\phi^3}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}\right) \quad \text{(A2)}$$
$$EXRETAVG_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12}\right), \quad \text{(A3)}$$

where $\phi = 2^{-1/3}$, meaning that the weight is halved each quarter. $NIMTA$ is net income (Compustat quarterly item NIQ) divided by the sum of market equity and total liabilities (item LTQ). The moving average $NIMTAAVG$ is designed to capture the idea that a long history of losses is a better predictor of bankruptcy than one large quarterly loss in a single month. $EXRET \equiv \log(1+R_{it}) - \log(1+R_{\text{S\&P500},t})$ is the monthly log excess return on each firm's equity relative to the S&P 500 index. The moving average $EXRETAVG$ is designed to capture the idea that a sustained decline in stock market value is a better predictor of bankruptcy than a sudden stock price decline in a single month. $TLMTA$ is the ratio of total liabilities (item LTQ) divided by the sum of market equity and total liabilities. $SIGMA$ is the annualized three-month rolling sample standard deviation: $\sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$, in which k is the index of trading days in months $t-1, t-2$, and $t-3$, r_k^2 is the firm-level daily return, and N is the total number of trading days in the three-month period. $SIGMA$ is treated as missing if there are less than six nonzero observations over the three months in the rolling window. $RSIZE$ is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index. $CASHMTA$, used to capture the liquidity position of the firm, is the ratio of cash and short-term investments (item CHEQ) divided by the sum of market equity and total liabilities. MB is the market-to-book equity, in which book equity is defined as in Cohen, Polk, and Vuolteenaho (2003). Following Campbell et al., we add 10% of the difference between market and book equity to the book equity to alleviate measurement issues for extremely small book equity values. For firm-month observations that still have negative book equity after this adjustment, we replace these negative values with \$1 to ensure that the market-to-book ratios for these firms are in the right tail of the distribution. $PRICE$ is each firm's log price per share, truncated above at \$15. We further eliminate stocks with prices less than \$1 at the portfolio formation date.

We follow Ohlson (1980, Model One in Table 4) to construct the O-score: $-1.32 - 0.407\log(MKTASSET/CPI) + 6.03\,TLTA - 1.43\,WCTA + 0.076\,CLCA - 1.72\,OENEG - 2.37\,NITA - 1.83\,FUTL + 0.285\,INTWO - 0.521\,CHIN$, where $MKTASSET$ is market assets defined as book assets with book equity replaced by market equity. We calculate $MKTASSET$ as total liabilities (Compustat quarterly item LTQ) + market equity (CRSP price times shares outstanding) + 0.1×(market equity − book equity). The adjustment of $MKTASSET$ using 10% of the difference between market equity and book equity follows Campbell, Hilscher, and Szilagyi (2008) to ensure that assets are not close to zero. The construction of book equity follows Fama and French (1993). CPI is the consumer price index. $TLTA$ is the leverage ratio defined as the book value of debt (item DLCQ plus item DLTTQ) divided by $MKTASSET$. $WCTA$ is working capital divided by market assets (item ACTQ − item LCTQ)/$MKTASSET$. $CLCA$ is current liabilities (item LCTQ) divided by current assets (item ACTQ). $OENEG$ is one if total liabilities (item LTQ) exceeds total assets (item ATQ) and is zero otherwise. $NITA$ is net income (item NIQ) divided by assets, $MKTASSET$. $FUTL$ is the fund provided by operations (item PIQ) divided by liabilities (item LTQ). $INTWO$ is equal to one if net income (item NIQ) is negative for the last two years and zero otherwise. $CHIN$ is $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income (item NIQ) for the most recent quarter.

Table 1 : Properties of the Investment Factor (r_{INV}) and the ROA Factor (r_{ROA}) 1/1972–6/2009 (450 Months)

Investment-to-assets (I/A) is annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus annual change in inventories (item INVT) divided by lagged book assets (item AT). In each June we break NYSE, Amex, and NASDAQ stocks into three I/A groups using the breakpoints for the low 30%, medium 40%, and high 30% of the ranked I/A. We also use median NYSE size to split NYSE, Amex, and NASDAQ stocks into two groups. Taking intersections, we form six size-I/A portfolios. We calculate monthly value-weighted returns for the six portfolios from July of year t to June of year $t+1$, and sort the portfolios again in June of year $t+1$. r_{INV} is the difference (low-minus-high I/A), each month, between the average returns on the two low-I/A portfolios and the average returns on the two high-I/A portfolios. Each month we sort NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, medium 40%, and the high 30% of the ranked quarterly ROA. Return on assets (ROA) is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). Each month we sort NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, medium 40%, and the high 30% of the ranked quarterly ROA. Quarterly earnings are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (Compustat quarterly item RDQ). We also use the NYSE median each month to split NYSE, Amex, and NASDAQ stocks into two size groups. We form six portfolios from the intersections of the two size and the three ROA groups. Monthly value-weighted returns on the six portfolios are calculated for the current month, and the portfolios are rebalanced monthly. r_{ROA} is the difference (high-minus-low ROA), each month, between the simple average of the returns on the two high-ROA portfolios and the simple average of the returns on the two low-ROA portfolios. In Panel A we regress r_{INV} and r_{ROA} on traditional factors including the market factor, SMB, HML, and WML (from Kenneth French's Web site). The t-statistics (in parentheses) are adjusted for heteroskedasticity. Panel B reports the correlation matrix of the new factors and the traditional factors. The p-values (in parentheses) test the null hypothesis that a given correlation is zero.

Panel A: Descriptive statistics of r_{INV} and r_{ROA}

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2
r_{INV}	0.28	0.32	−0.10				0.07
	(3.21)	(3.45)	(−4.39)				
		0.18	−0.06	0.09	0.26		0.23
		(2.08)	(−2.86)	(2.75)	(7.73)		
		0.14	−0.05	0.09	0.28	0.04	0.24
		(1.66)	(−2.51)	(2.90)	(8.71)	(1.62)	
r_{ROA}	0.76	0.85	−0.23				0.07
	(3.84)	(4.06)	(−3.50)				
		0.87	−0.12	−0.50	0.08		0.21
		(4.62)	(−2.00)	(−5.02)	(0.63)		
		0.58	−0.06	−0.50	0.18	0.28	0.30
		(3.10)	(−1.19)	(−4.25)	(1.56)	(4.24)	

Panel B: Correlation matrix (p-values in parentheses)

	r_{ROA}	r_{MKT}	SMB	HML	WML
r_{INV}	−0.03	−0.26	0.00	0.45	0.04
	(0.57)	(0)	(0.96)	(0)	(0.41)
r_{ROA}		−0.26	−0.43	0.20	0.31
		(0)	(0)	(0)	(0)
r_{MKT}			0.27	−0.36	−0.14
			(0)	(0)	(0)
SMB				−0.26	−0.01
				(0)	(0.81)
HML					−0.15
					(0)

Table 2 : Descriptive Statistics and Calendar-Time Factor Regressions for Monthly Percent Excess Returns of 25 Size and Momentum Portfolios, 1/1972–9/2009 (450 Months)

The data for the one-month Treasury bill rate (r_f) and the Fama-French factors are obtained from Kenneth French's Web site. The monthly constructed size and momentum portfolios are the intersections of quintiles formed on market equity and quintiles formed on prior two- to seven-month returns. The monthly size breakpoints are the NYSE quintiles. For each portfolio formation month t, we sort stocks on their prior returns from month $t-2$ to $t-7$ (skipping month $t-1$), and calculate the subsequent portfolio returns from month t to $t+5$. We value-weight all portfolio returns. Panel A reports mean percent excess returns and their t-statistics, CAPM alphas (α) and their t-statistics, and the intercepts (α_{FF}) and their t-statistics from Fama-French three-factor regressions. Panel B reports the new three-factor regressions: $r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$. See Table 1 for the description of r_{INV} and r_{ROA}. The t-statistics are adjusted for heteroskedasticity. F_{GRS} is the Gibbons, Ross, and Shanken (1989) F-statistic testing that the intercepts of all 25 portfolios are jointly zero, and p is its associated p-value. We only report the results of quintiles 1, 3, and 5 for size and momentum to save space.

	Loser	3	Winner	W−L	Loser	3	Winner	W−L	Loser	3	Winner	W−L	Loser	3	Winner	W−L
	Panel A: Means, CAPM alphas, and Fama-French alphas								Panel B: The new three-factor regressions							
	Mean				t_{Mean}				α_Q				t_{α_Q} ($F_{GRS} = 2.63, p = 0$)			
Small	−0.44	0.58	0.93	1.37	−1.07	2.32	2.82	5.90	−0.18	0.31	0.72	0.91	−0.72	1.96	3.26	3.48
3	−0.18	0.45	0.83	1.01	−0.48	1.87	2.59	3.82	−0.08	0.06	0.59	0.67	−0.39	0.63	3.07	2.13
Big	−0.33	0.21	0.60	0.93	−0.96	0.98	2.18	3.27	−0.39	−0.15	0.31	0.71	−1.76	−2.13	2.05	2.10
	α				t_α ($F_{GRS} = 3.93, p = 0$)				β_{INV}				$t_{\beta_{INV}}$			
Small	−0.84	0.32	0.60	1.44	−3.24	2.26	3.02	6.49	−0.07	0.32	0.29	0.36	−0.60	4.18	2.84	3.12
3	−0.58	0.17	0.48	1.06	−2.85	1.77	3.00	4.13	−0.21	0.24	−0.02	0.18	−1.82	4.09	−0.27	1.24
Big	−0.70	−0.05	0.29	0.99	−3.55	−0.72	2.30	3.52	−0.33	0.07	−0.11	0.22	−2.85	1.72	−1.54	1.30
	α_{FF}				$t_{\alpha_{FF}}$ ($F_{GRS} = 3.61, p = 0$)				β_{ROA}				$t_{\beta_{ROA}}$			
Small	−1.17	−0.02	0.41	1.58	−6.13	−0.27	4.02	7.08	−0.79	−0.13	−0.30	0.49	−8.18	−2.44	−3.09	3.92
3	−0.75	−0.11	0.45	1.20	−4.07	−1.60	4.12	4.53	−0.52	0.02	−0.12	0.40	−6.44	0.65	−1.33	2.66
Big	−0.69	−0.07	0.45	1.14	−3.30	−1.22	3.52	3.85	−0.22	0.10	0.03	0.25	−2.56	3.62	0.50	1.81

Table 3 : Descriptive Statistics and Factor Regressions for Monthly Percent Excess Returns of Deciles Formed on Campbell, Hilscher, and Szilagyi's (2008) Failure Probability and on Ohlson's (1980) *O*-Score

The data on the one-month Treasury bill rate (r_f) and the Fama-French three factors are from Kenneth French's Web site. See Table 1 for the description of r_{INV} and r_{ROA}. We sort all NYSE, Amex, and NASDAQ stocks at the beginning of each month into deciles based on the most recent failure probability and, separately, on *O*-score. See Appendix A for the detailed variable definitions of failure probability and *O*-score. Earnings and other accounting data for a fiscal quarter are used in portfolio sorts in the months immediately after the quarter's public earnings announcement month (Compustat quarterly item RDQ). Monthly value-weighted returns on the portfolios are calculated for the current month, and the portfolios are rebalanced monthly. We report the mean excess returns in monthly percent and their *t*-statistics, the CAPM regressions ($r_i - r_f = \alpha^i + \beta^i r_{MKT} + \epsilon_i$), the Fama-French regressions ($r_i - r_f = \alpha^i_{FF} + b^i r_{MKT} + s^i SMB + h^i HML + \epsilon_i$), and the new three-factor regressions ($r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$). For each asset pricing model we also report the Gibbons, Ross, and Shanken (1989) *F*-statistic (F_{GRS}) testing that the intercepts are jointly zero and its *p*-value (in parentheses). The *t*-statistics are adjusted for heteroskedasticity. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space.

	Low	5	High	H−L	F_{GRS} (p)	Low	5	High	H−L	F_{GRS} (p)
	Panel A: The failure probability deciles (1/1975–6/2009, 426 months)					Panel B: The *O*-score deciles (1/1972–6/2009, 450 months)				
Mean	0.86	0.58	−0.24	−1.10		0.39	0.36	−0.33	−0.72	
t_{Mean}	3.64	2.37	−0.50	−2.85		1.73	1.48	−0.84	−2.60	
α	0.36	0.03	−1.15	−1.51	3.01	0.00	−0.04	−0.87	−0.88	2.05
β	0.93	1.02	1.68	0.76	(0)	1.00	1.02	1.40	0.40	(0.03)
t_α	3.18	0.33	−3.74	−4.23		0.04	−0.39	−3.69	−3.41	
α_{FF}	0.43	−0.05	−1.38	−1.80	4.46	0.16	−0.21	−1.08	−1.24	5.10
b	0.90	1.08	1.49	0.59	(0)	0.96	1.02	1.23	0.28	(0)
s	−0.01	−0.08	1.10	1.11		−0.14	0.32	1.07	1.22	
h	−0.14	0.18	0.04	0.17		−0.28	0.26	0.15	0.43	
$t_{\alpha_{FF}}$	3.93	−0.59	−5.24	−5.78		3.13	−2.49	−5.76	−6.27	
α_Q	0.25	−0.02	−0.17	−0.42	1.51	0.07	0.00	−0.11	−0.18	1.06
β_{MKT}	0.96	1.04	1.38	0.42	(0.13)	0.98	1.01	1.19	0.21	(0.39)
β_{INV}	−0.10	0.08	0.02	0.12		−0.28	0.09	−0.09	0.19	
β_{ROA}	0.16	0.02	−1.10	−1.26		0.03	−0.08	−0.87	−0.90	
t_{α_Q}	1.80	−0.18	−0.73	−1.45		1.07	0.00	−0.57	−0.84	
$t_{\beta_{MKT}}$	32.26	36.35	22.27	5.98		57.58	33.95	25.73	4.00	
$t_{\beta_{INV}}$	−1.51	1.65	0.15	0.77		−6.65	1.39	−0.84	1.57	
$t_{\beta_{ROA}}$	2.47	0.58	−16.28	−13.30		1.29	−2.28	−14.01	−12.91	

Table 4 : Descriptive Statistics and Factor Regressions for Monthly Percent Excess Returns of Deciles Formed on Standardized Unexpected Earnings (SUE) and on Total Accruals, 1/1972–9/2009 (450 Months)

The data on the one-month Treasury bill rate (r_f) and the Fama-French three factors are from Kenneth French's Web site. See Table 1 for the description of r_{INV} and r_{ROA}. We define SUE as the change in the most recently announced quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of the earnings change over the prior eight quarters. In Panel A we rank all NYSE, Amex, and NASDAQ stocks into deciles at the beginning of each month by their most recent past SUE. Monthly value-weighted returns on the SUE portfolios are calculated for the current month, and the portfolios are rebalanced monthly. In Panel B we assign all NYSE, Amex, and NASDAQ stocks into deciles in June of year t based on total accruals for the fiscal year ending in calendar year $t-1$. See Section 4.4 for the detailed definition of total accruals. Value-weighted portfolio returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of $t+1$. We report the mean excess returns in monthly percent and their t-statistics, the CAPM regressions ($r_i - r_f = \alpha^i + \beta^i r_{MKT} + \epsilon_i$), the Fama-French three-factor regressions ($r_i - r_f = \alpha^i_{FF} + b^i r_{MKT} + s^i SMB + h^i HML + \epsilon_i$), and the new three-factor regressions ($r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$). For each asset pricing model we also report the Gibbons, Ross, and Shanken (1989) F-statistic (F_{GRS}) testing that the intercepts are jointly zero and its p-value (in parentheses). The t-statistics are adjusted for heteroskedasticity. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space.

	Low	5	High	H−L	F_{GRS} (p)	Low	5	High	H−L	F_{GRS} (p)
	Panel A: The SUE deciles					Panel B: The total accruals deciles				
Mean	0.29	0.29	0.69	0.40		0.61	0.36	0.08	−0.54	
t_{Mean}	1.15	1.28	3.21	2.77		2.02	1.66	0.22	−2.88	
α	−0.12	−0.10	0.33	0.45	3.35	0.13	−0.01	−0.48	−0.61	3.15
β	1.05	0.99	0.91	−0.14	(0)	1.24	0.93	1.42	0.18	(0)
t_α	−1.21	−1.39	4.27	3.25		0.94	−0.11	−3.07	−3.35	
α_{FF}	−0.18	−0.13	0.35	0.53	3.97	0.23	−0.04	−0.36	−0.58	3.84
b	1.09	1.00	0.94	−0.15	(0)	1.13	0.97	1.25	0.12	(0)
s	−0.05	0.00	−0.17	−0.12		0.26	−0.11	0.49	0.23	
h	0.13	0.06	0.00	−0.13		−0.25	0.09	−0.35	−0.10	
$t_{\alpha_{FF}}$	−1.74	−1.83	4.72	3.64		1.66	−0.60	−2.71	−3.06	
α_Q	−0.11	−0.08	0.15	0.26	1.40	0.29	−0.08	−0.01	−0.30	2.97
β_{MKT}	1.05	0.99	0.96	−0.09	(0.18)	1.19	0.95	1.28	0.09	(0)
β_{INV}	0.11	−0.01	−0.02	−0.12		−0.09	−0.01	−0.81	−0.72	
β_{ROA}	−0.06	−0.02	0.22	0.28		−0.15	0.09	−0.24	−0.09	
t_{α_Q}	−0.96	−1.07	2.14	1.76		1.85	−0.95	−0.08	−1.56	
$t_{\beta_{MKT}}$	32.21	55.12	53.86	−2.01		35.12	50.36	34.34	1.94	
$t_{\beta_{INV}}$	1.39	−0.17	−0.40	−1.22		−1.02	−0.18	−8.95	−5.88	
$t_{\beta_{ROA}}$	−1.57	−0.61	10.31	6.24		−3.38	2.52	−5.83	−1.36	

Table 5 : Descriptive Statistics and Factor Regressions for Monthly Percent Excess Returns of the Net Stock Issues Deciles and the Asset Growth Deciles, 1/1972–9/2009 (450 Months)

The data on the Treasury bill rate (r_f) and the Fama-French three factors are from Kenneth French's Web site. See Table 1 for the description of r_{INV} and r_{ROA}. We measure net stock issues as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end in $t-1$ divided by the split-adjusted shares outstanding at the fiscal year-end in $t-2$. The split-adjusted shares outstanding is the Compustat shares outstanding (Compustat annual item CSHO) times the Compustat adjustment factor (item ADJEX_C). In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into deciles on the net stock issues for the fiscal year ending in calendar year $t-1$. Because a disproportionately large number of firms have zero net stock issues, we group all the firms with negative net issues into the lowest decile, and all the firms with zero net issues into decile two. We then sort the firms with positive net stock issues into the remaining eight (equal-numbered) deciles. Monthly value-weighted portfolio returns are calculated from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of $t+1$. In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into deciles based on asset growth measured at the end of the last fiscal year-end $t-1$. Asset growth for fiscal year $t-1$ is the change in total assets (item AT) from the fiscal year-end of $t-2$ to the year-end of $t-1$ divided by total assets at the fiscal year-end of $t-2$. Monthly value-weighted returns are calculated from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of $t+1$. We report the mean excess returns in monthly percent and their t-statistics, the CAPM regressions ($r_i - r_f = \alpha^i + \beta^i r_{MKT} + \epsilon_i$), the Fama-French regressions ($r_i - r_f = \alpha^i_{FF} + b^i r_{MKT} + s^i SMB + h^i HML + \epsilon_i$), and the new three-factor regressions ($r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$). We also report the Gibbons, Ross, and Shanken (1989) F-statistic (F_{GRS}) and p-value (in parentheses) testing that the intercepts are jointly zero for a given model. The t-statistics are adjusted for heteroskedasticity. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space.

	Low	5	High	H−L	F_{GRS} (p)	Low	5	High	H−L	F_{GRS} (p)
	Panel A: The net stock issues deciles					Panel B: The asset growth deciles				
Mean	0.63	0.57	0.10	−0.52		0.86	0.50	0.03	−0.83	
t_{Mean}	2.97	2.56	0.40	−4.33		2.99	2.44	0.10	−4.58	
α	0.26	0.19	−0.33	−0.60	5.13	0.41	0.15	−0.49	−0.90	4.13
β	0.92	0.97	1.11	0.19	(0)	1.13	0.88	1.33	0.20	(0)
t_α	4.40	2.68	−3.64	−5.24		2.84	2.26	−4.55	−5.14	
α_{FF}	0.19	0.19	−0.34	−0.53	4.45	0.16	0.03	−0.38	−0.54	2.81
b	0.98	0.97	1.10	0.11	(0)	1.12	0.95	1.24	0.12	(0)
s	−0.11	0.01	0.08	0.19		0.54	−0.05	0.14	−0.39	
h	0.16	0.00	−0.01	−0.17		0.37	0.25	−0.24	−0.61	
$t_{\alpha_{FF}}$	3.70	2.68	−3.51	−4.81		1.24	0.45	−3.67	−3.42	
α_Q	0.08	0.18	−0.26	−0.34	3.15	0.31	0.01	−0.31	−0.62	2.30
β_{MKT}	0.98	0.97	1.09	0.12	(0)	1.17	0.92	1.27	0.10	(0.01)
β_{INV}	0.19	−0.11	−0.17	−0.36		0.62	0.26	−0.44	−1.06	
β_{ROA}	0.15	0.06	−0.02	−0.17		−0.11	0.08	−0.04	0.07	
t_{α_Q}	1.47	2.41	−2.54	−3.03		2.09	0.09	−2.86	−3.77	
$t_{\beta_{MKT}}$	70.81	48.12	48.36	4.70		31.03	44.33	49.94	2.76	
$t_{\beta_{INV}}$	6.31	−2.61	−2.91	−5.10		6.96	6.44	−6.66	−11.08	
$t_{\beta_{ROA}}$	7.00	1.94	−0.55	−5.28		−2.18	3.26	−1.39	1.04	

Table 6 : Descriptive Statistics and Factor Regressions for Monthly Percent Excess Returns of 25 Size and Book-to-Market Equity Portfolios, 1/1972–9/2009 (450 Months)

The data for the one-month Treasury bill rate (r_f), the Fama-French factors, and the 25 size and book-to-market equity portfolios are obtained from Kenneth French's Web site. For all testing portfolios, Panel A reports mean percent excess returns and their t-statistics, CAPM alphas (α) and their t-statistics, and the intercepts (α_{FF}) and their t-statistics from Fama-French three-factor regressions. Panel B reports the new three-factor regressions: $r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$. See Table 1 for the description of r_{INV} and r_{ROA}. The t-statistics are adjusted for heteroskedasticity. F_{GRS} is the Gibbons, Ross, and Shanken (1989) F-statistic testing that the intercepts of all 25 portfolios are jointly zero, and p is its associated p-value. We only report the results of quintiles 1, 3, and 5 for size and book-to-market to save space.

	Low	3	High	H−L	Low	3	High	H−L	Low	3	High	H−L	Low	3	High	H−L
	Panel A: Means, CAPM alphas, and Fama-French alphas								Panel B: The new three-factor regressions							
	Mean				t_{Mean}				α_Q				t_{α_Q} ($F_{GRS} = 2.78, p = 0$)			
Small	0.00	0.73	1.00	0.99	0.01	2.61	3.48	4.84	0.00	0.43	0.61	0.61	0.01	2.37	3.42	3.14
3	0.34	0.69	0.97	0.63	1.03	2.93	3.75	2.86	0.16	0.18	0.40	0.25	0.98	1.60	2.60	1.18
Big	0.33	0.42	0.55	0.22	1.40	1.94	2.32	1.10	−0.08	−0.10	0.08	0.17	−1.01	−0.94	0.50	0.81
	α				t_α ($F_{GRS} = 3.65, p = 0$)				β_{INV}				$t_{\beta_{INV}}$			
Small	−0.55	0.33	0.60	1.15	−2.39	1.99	3.34	6.15	−0.08	0.36	0.57	0.65	−0.66	4.06	5.74	5.51
3	−0.18	0.32	0.59	0.77	−1.22	2.84	3.89	3.72	−0.36	0.27	0.50	0.87	−4.31	3.93	4.88	7.32
Big	−0.07	0.08	0.22	0.29	−0.78	0.77	1.47	1.48	−0.22	0.18	0.36	0.58	−4.67	2.54	3.47	4.69
	α_{FF}				$t_{\alpha_{FF}}$ ($F_{GRS} = 2.89, p = 0$)				β_{ROA}				$t_{\beta_{ROA}}$			
Small	−0.53	0.06	0.12	0.65	−4.86	0.92	1.75	5.70	−0.62	−0.26	−0.24	0.38	−6.29	−3.18	−3.70	4.80
3	−0.03	0.02	0.12	0.16	−0.47	0.26	1.24	1.36	−0.26	0.06	0.03	0.29	−3.72	1.44	0.47	2.73
Big	0.16	−0.05	−0.15	−0.31	2.71	−0.59	−1.32	−2.38	0.11	0.14	0.03	−0.08	4.49	3.23	0.35	−0.91

Table 7 : Descriptive Statistics and Factor Regressions for Monthly Percent Excess Returns of 10 Industry Portfolios, 1/1972–9/2009 (450 Months)

The Treasury bill rate (r_f), the Fama-French three factors, and 10 industry portfolio returns are from Kenneth French's Web site. See Table 1 for the description of r_{INV} and r_{ROA}. We report the mean excess returns in monthly percent and their t-statistics, the CAPM regressions ($r_i - r_f = \alpha^i + \beta^i r_{MKT} + \epsilon_i$), the Fama-French three-factor regressions ($r_i - r_f = \alpha^i_{FF} + b^i r_{MKT} + s^i SMB + h^i HML + \epsilon_i$), and the new three-factor regressions ($r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$). For each asset pricing model we also report the Gibbons, Ross, and Shanken (1989) F-statistic (F_{GRS}) testing that the intercepts are jointly zero and its p-value (in parentheses). The t-statistics are adjusted for heteroskedasticity.

	NoDur	Durbl	Manuf	Enrgy	HiTec	Telcm	Shops	Hlth	Utils	Other	F_{GRS} (p)
Mean	0.60	0.25	0.46	0.68	0.42	0.42	0.46	0.51	0.43	0.39	
t_{Mean}	2.79	0.84	1.90	2.55	1.28	1.83	1.75	2.10	2.17	1.54	
α	0.29	−0.18	0.06	0.37	−0.08	0.12	0.06	0.19	0.23	−0.03	1.68
β	0.79	1.10	1.03	0.78	1.29	0.77	1.00	0.82	0.51	1.07	(0.08)
t_α	2.28	−1.00	0.62	1.83	−0.49	0.75	0.45	1.16	1.37	−0.26	
α_{FF}	0.19	−0.50	−0.04	0.28	0.21	0.11	−0.01	0.40	−0.01	−0.23	3.50
b	0.86	1.22	1.08	0.88	1.10	0.82	1.01	0.80	0.67	1.16	(0)
s	−0.09	0.15	−0.03	−0.25	0.22	−0.21	0.13	−0.32	−0.18	−0.03	
h	0.21	0.59	0.19	0.24	−0.61	0.06	0.11	−0.33	0.49	0.39	
$t_{\alpha_{FF}}$	1.53	−3.08	−0.46	1.37	1.47	0.68	−0.07	2.57	−0.05	−2.48	
α_Q	−0.07	−0.26	−0.12	0.33	0.38	0.18	−0.09	−0.03	0.02	−0.30	2.00
β_{MKT}	0.89	1.13	1.08	0.78	1.15	0.75	1.05	0.88	0.57	1.14	(0.03)
β_{INV}	0.31	0.32	0.08	−0.35	−0.50	0.24	0.01	−0.07	0.18	0.39	
β_{ROA}	0.31	−0.03	0.17	0.19	−0.35	−0.17	0.18	0.29	0.18	0.17	
t_{α_Q}	−0.64	−1.29	−1.35	1.50	2.34	1.06	−0.63	−0.19	0.10	−2.90	
$t_{\beta_{MKT}}$	31.75	19.87	48.66	16.67	31.60	19.96	25.68	19.03	13.56	44.28	
$t_{\beta_{INV}}$	4.33	2.62	1.44	−2.52	−5.34	2.40	0.10	−0.76	1.87	6.72	
$t_{\beta_{ROA}}$	7.91	−0.30	5.23	3.37	−7.75	−2.87	4.02	4.52	3.07	4.46	

Table 8 : Descriptive Statistics and Factor Regressions for Monthly Percent Excess Returns of Deciles Formed on Pre-ranking CAPM Betas and on Market Equity, 1/1972–6/2009 (450 Months)

The one-month Treasury bill rate (r_f), the Fama-French three factors, and size decile returns are from Kenneth French's Web site. See Table 1 for the description of r_{INV} and r_{ROA}. We estimate pre-ranking CAPM betas on 60 (at least 24) monthly returns prior to July of year t. In June of year t we sort all stocks into deciles based on the pre-ranking betas. The value-weighted monthly returns on the deciles are calculated from July of year t to June of year $t+1$. We report the mean excess returns in monthly percent and their t-statistics, the CAPM regressions ($r_i - r_f = \alpha^i + \beta^i r_{MKT} + \epsilon_i$), the Fama-French three-factor regressions ($r_i - r_f = \alpha^i_{FF} + b^i r_{MKT} + s^i SMB + h^i HML + \epsilon_i$), and the new three-factor regressions ($r_i - r_f = \alpha^i_Q + \beta^i_{MKT} r_{MKT} + \beta^i_{INV} r_{INV} + \beta^i_{ROA} r_{ROA} + \epsilon_i$). For each asset pricing model we also report the Gibbons, Ross, and Shanken (1989) F-statistic (F_{GRS}) testing that the intercepts are jointly zero and its p-value (in parentheses). The t-statistics are adjusted for heteroskedasticity. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space.

	Panel A: The pre-ranking beta deciles					Panel B: The market equity deciles				
	Low	5	High	H−L	F_{GRS} (p)	Small	5	Big	S−B	F_{GRS} (p)
Mean	0.38	0.41	0.29	−0.09		0.59	0.61	0.35	0.24	
t_{Mean}	2.12	1.88	0.68	−0.24		1.96	2.26	1.65	1.04	
α	0.16	0.05	−0.38	−0.54	1.03	0.17	0.17	−0.02	0.19	1.59
β	0.55	0.92	1.70	1.15	(0.42)	1.05	1.13	0.93	0.12	(0.11)
t_α	1.19	0.59	−1.93	−1.99		0.92	1.57	−0.36	0.84	
α_{FF}	−0.02	−0.08	−0.23	−0.21	0.93	−0.08	0.01	0.06	−0.13	1.97
b	0.61	1.00	1.47	0.85	(0.51)	0.89	1.04	0.97	−0.08	(0.04)
s	0.08	−0.06	0.70	0.62		1.17	0.68	−0.30	1.47	
h	0.33	0.28	−0.44	−0.77		0.22	0.15	−0.08	0.30	
$t_{\alpha_{FF}}$	−0.16	−1.10	−1.47	−0.91		−0.87	0.24	1.99	−1.47	
α_Q	−0.03	−0.17	0.22	0.25	1.24	0.42	0.28	−0.08	0.50	1.42
β_{MKT}	0.61	0.99	1.53	0.93	(0.27)	0.99	1.10	0.95	0.04	(0.17)
β_{INV}	0.16	0.17	−0.43	−0.60		0.30	0.06	−0.05	0.35	
β_{ROA}	0.17	0.20	−0.54	−0.70		−0.41	−0.15	0.09	−0.49	
t_{α_Q}	−0.24	−1.97	1.14	0.96		2.11	2.47	−1.42	2.07	
$t_{\beta_{MKT}}$	14.41	43.99	30.77	12.80		19.42	32.94	63.37	0.69	
$t_{\beta_{INV}}$	2.16	3.81	−3.92	−4.22		3.15	1.01	−1.63	3.00	
$t_{\beta_{ROA}}$	3.58	5.24	−9.15	−8.70		−4.92	−3.06	4.14	−4.92	

Figure 1. Investment-to-assets as a first-order determinant of the cross-section of expected stock returns.

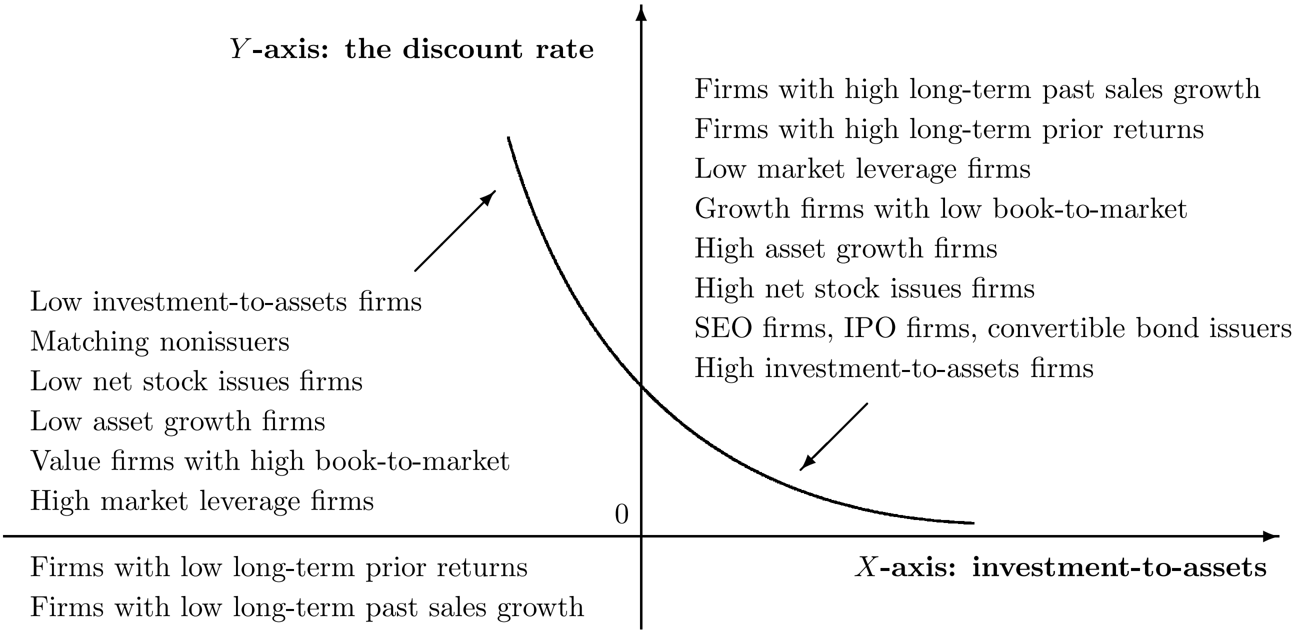

Figure 2. Investment-to-assets in annual percent (I/A, contemporaneous and lagged) and ROA in quarterly percent for the 25 size and momentum portfolios, 1972:Q1 to 2009:Q2 (150 quarters). I/A is the annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus the annual change in inventories (item INVT) divided by lagged book assets (item AT). ROA is quarterly earnings (Compustat quarterly item IBQ) divided by one-quarter-lagged assets (item ATQ). The 25 size and momentum portfolios are constructed monthly as the intersections of quintiles formed on market equity and quintiles formed on prior two- to seven-month returns (skipping one month). For each portfolio formation month t, from January 1972 to June 2009, we calculate annual I/As and quarterly ROAs for $t+m, m=-60,\ldots,60$. The I/A and ROA for month $t+m$ are averaged across portfolio formation months t. In calculating ROA for formation month t, we use the quarterly earnings from the most recent public earnings announcement month (item RDQ). Panels A and D plot the median I/As and ROAs across firms in the four extreme portfolios, respectively. In Panel B I/A is the current year-end I/A relative to month t. In Panel C the lagged I/A is the I/A on which an annual sorting on I/A in each June is based. Panels E and F plot the times series of ROA for the four extreme portfolios.