A Better Three-Factor Model That Explains More Anomalies

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ABSTRACT

The market factor, an investment factor, and a return-on-assets factor combine to summarize the cross-sectional variation of expected stock returns. The new three-factor model substantially outperforms traditional asset pricing models in explaining anomalies associated with short-term prior returns, financial distress, net stock issues, asset growth, earnings surprises, and valuation ratios. The model's performance, combined with its economic intuition based on q-theory, suggests that it can be used to obtain expected return estimates in practice.

*Long Chen is from John M. Olin Business School at Washington University, and Lu Zhang is from Stephen M. Ross School of Business at University of Michigan and NBER. For helpful discussions, we thank Andrew Ang, 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 Barclays Global Investors, Hong Kong University of Science and Technology, Renmin University of China, Rutgers Business School, Tel Aviv University, University of California at San Diego, University of Michigan, Sanford C. Bernstein Conference on Controversies in Quantitative Finance and Asset Management, UBC PH&N Summer Finance Conference in 2007, the 2008 Financial Intermediation Research Society Conference on Banking, Corporate Finance, and Intermediation, and the 2009 American Finance Association Annual Meetings. Cynthia Jin provided valuable research assistance. Cam Harvey (the Editor), an anonymous Associated Editor, and an anonymous referee deserve special thanks. In particular, the title of the paper is due to the referee. An Internet Appendix containing supplementary results is available at http://www.afajof.org/supplements.asp. A data library containing the new factors and all the testing portfolios used in this study is posted on the authors' Web sites. Previous drafts of the paper were circulated under the titles "Neoclassical Factors," "An Equilibrium Three-Factor Model," and "Production-based Factors."

Although an elegant theoretical contribution, the empirical performance of the Sharpe (1964) and Lintner (196) 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, over the past two decades, it has become increasingly clear that even the highly influential Fama-French model cannot explain many cross-sectional patterns. Prominent examples include the positive relations of average returns with short-term prior returns and earnings surprises as well as the negative relations of average returns with financial distress, net stock issues, and asset growth.[3]

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

$$E\ r^j] - r_f \quad \beta^j_{MKT} E\ r_{MKT}] + \beta^j_{INV} E\ r_{INV}] + \beta^j_{ROA} E\ r_{ROA}] \qquad (1)$$

in which $E\ r_{MKT}]$, $E\ r_{INV}]$, and $E\ r_{ROA}]$ are expected premiums, and β^j_{MKT}, β^j_{INV}, and β^j_{ROA} are factor loadings from regressing portfolio excess returns on r_{MKT}, r_{INV}, and r_{ROA}.

In our 19 – 6 sample, r_{INV} and r_{ROA} earn average returns of .43% (t 4.) and .96% per month (t .1), respectively. These average returns subsist after adjusting for their exposures to the Fama-French factors and the Carhart (199) factors. Most important,

the q-theory factor model does a good job in describing the average returns of size and momentum portfolios. None of the winner-minus-loser portfolios across five size quintiles have significant alphas. The alphas, ranging from .8% to .4% per month, are all within 1. standard errors from zero. For comparison, the alphas vary from .9 % (t 1) to 1. % per month (t . 8) in the CAPM and from .9 % (t .8) to 1.44% (t . 4) in the Fama-French model.

The q-theory factor model fully explains the negative relation between average returns and financial distress as measured by Campbell, Hilscher, and Szilagyi's (8) failure probability. The high-minus-low distress decile earns an alpha of − . % per month (t −1. 9) in our model, which cannot be rejected across the distress deciles by the Gibbons, Ross, and Shanken (1989, GRS) test at the % significance level. In contrast, the alpha is −1.8 % (t − . 8) in the CAPM and − .14% (t − .4) in the Fama-French model, and both models are strongly rejected by the GRS test. Using Ohlson's (198) O-score to measure distress yields largely similar results. 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 link between distress and ROA and the positive ROA-expected return relation, and, not surprisingly, find the negative distress-expected return relation anomalous.

Several other anomaly variables including net stock issues, asset growth, and earnings surprises also have received much attention since Fama and French (199). We show that the q-theory factor model outperforms traditional asset pricing models in capturing these effects, often by a big margin. For example, the high-minus-low net stock issues decile earns an alpha of − . 8% per month (t −1. 9) in our model. In contrast, the CAPM alpha is

$-1.$ [illegible]$\%$ $(t$ $-$ $.$

elaborate a simple conceptual framework in which many anomalies can be interpreted in a unified and economically meaningful way. The model's performance, combined with its economic intuition, suggests that the model can be used in many practical applications such as evaluating mutual fund performance, measuring abnormal returns in event studies, estimating expected returns for portfolio choice, and obtaining the cost of equity estimates for capital budgeting and stock valuation.

Most empirical finance studies motivate common factors from the consumption side of the economy (e.g., Breeden, Gibbons, and Litzenberger (1989), Ferson and Harvey (199 , 199), and Lettau and Ludvigson (1)). We instead exploit a direct link between firm-level returns and characteristics from the production side. Cochrane (1991) launches this production-based approach by studying stock market returns. We study anomalies in cross-sectional returns. Liu, Whited, and Zhang (8) explore the return-characteristics link via structural estimation. We use the Fama-French portfolio approach to produce a workhorse factor model. A factor pricing model is probably more practical because of its powerful simplicity and the availability of high-quality monthly returns data.

Section I motivates the new factors from q-theory, Section II constructs the new factors, Section III tests the new factor model, and Section IV summarizes and interprets the results.

I. Hypothesis Development

We develop testable hypotheses from q-theory (e.g., Tobin (19 9) and Cochrane (1991)). We outline a two-period structure to fix the intuition, but the basic insights hold in more general settings. There are two periods, and 1, and heterogeneous firms, indexed by j. Firm j's operating profits are given by $\Pi_{j0}A_{j0}$ in date and $\Pi_{j1}A_{j1}$ in date 1, in which

A_{j0} and A_{j1} are the firm's scale of productive assets and Π_{j0} and Π_{j1} are the firm's return on assets in dates 0 and 1, respectively. Firm j starts with assets, A_{j0}, invests in date 0, produces in both dates, and exits at the end of date 1 with a liquidation value of $(1-\delta)A_{j1}$, in which δ is the rate of depreciation. Assets evolve as $A_{j1} = I_{j0} + (1-\delta)A_{j0}$, in which I_{j0} is investment. Investment entails quadratic adjustment costs of $(a/2)(I_{j0}/A_{j0})^2 A_{j0}$, in which $a > 0$ is a constant parameter. Firm j has a gross discount rate of r_j. The discount rate varies across firms due to, for example, firm-specific loadings on macroeconomic risk factors. The firm chooses A_{j1} to maximize the market value at the beginning of date 0:

$$\max_{\{A_{j1}\}} \; \Pi_{j0}A_{j0} - [A_{j1} - (1-\delta)A_{j0}] - \frac{a}{2}\left[\frac{A_{j1}}{A_{j0}} - (1-\delta)\right]^2 A_{j0} + \frac{1}{r_j}\left[\Pi_{j1}A_{j1} + (1-\delta)A_{j1}\right]. \quad (1)$$

The market value is date 0's free cash flow, $\Pi_{j0}A_{j0} - I_{j0} - (a/2)(I_{j0}/A_{j0})^2 A_{j0}$, plus the discounted value of date 1's free cash flow, $[\Pi_{j1}A_{j1} + (1-\delta)A_{j1}]/r_j$. With only two dates the firm does not invest in date 1, so date 1's free cash flow is simply the sum of operating profits and the liquidation value.

The tradeoff of firm j is simple: forgoing date 0's free cash flow in exchange for higher date 1's free cash flow. Setting the first-order derivative of equation (1) with respect to A_{j1} to zero yields

$$r_j = \frac{\Pi_{j1} + 1 - \delta}{1 + a(I_{j0}/A_{j0})}. \quad (2)$$

This optimality condition is intuitive. The numerator in the right-hand side is the marginal benefit of investment including the marginal product of capital (return on assets), Π_{j1}, and the marginal liquidation value of capital, $1-\delta$. The denominator is the marginal cost of investment including the marginal purchasing cost of investment (one) and the marginal adjustment cost, $a(I_{j0}/A_{j0})$. Because the marginal benefit of investment is in date 1's dollar

terms and the marginal cost of investment is in date 's dollar terms, the first-order condition says that the marginal benefit of investment discounted to date 's dollar terms 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 , should equal the discount rate, as in Cochrane (1991).

A. The Investment Hypothesis

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

HYPOTHESIS 1 *Given the expected ROA, the expected return decreases with investment-to-*

present values of new projects and thereby low investment, and low costs of capital imply high net present values of new projects and thereby high investment.

Without uncertainty, it is well-known that the interest rate and investment are negatively correlated, meaning that the investment demand curve is downward sloping (e.g., Fisher (19[illegible]) and Fama and Miller (19 , Figure .4)). With uncertainty, more investment leads to lower marginal product of capital under decreasing returns to scale, giving rise to lower expected returns (e.g., Li, Livdan, and Zhang (8)).[5]

A.2. Portfolio Implications

The negative investment-expected return relation is conditional on expected *ROA*. *ROA* is not disconnected with investment 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 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 is consistent with the negative investment-expected return relation. The balance-sheet constraint of firms says that the uses of funds must equal the sources of funds, meaning that issuers must invest more and earn lower average returns than nonissuers.[6] Cooper, Gulen, and Schill (8) document that asset growth negatively predicts future returns and interpret the evidence as investor underreacting to overinvestment. However, asset growth

is the most comprehensive measure of investment-to-assets, in which investment is simply defined as the change in total assets, meaning that the asset growth effect is potentially consistent with optimal investment.

The value premium also can be interpreted using the negative investment-expected return relation investment-to-assets is an increasing function of marginal q (the denominator of equation ([illegible])). With constant returns to scale the marginal q equals the average q. But the average q of the firm 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 into this category. Fama and French (199[illegible]) measure market leverage as the ratio of total assets divided by market equity. Empirically, the new factor model captures the market leverage-expected return relation roughly as well as the Fama-French model (see the Internet Appendix). Intuitively, because market equity is in the denominator, high leverage signals low growth opportunities, low investment, and high expected returns, and low leverage signals high growth opportunities, high investment, and low expected returns. This investment mechanism differs from the standard leverage effect in corporate finance texts. The leverage effect says that high leverage means high proportion of asset risk shared by equity holders, inducing high expected equity returns. This mechanism 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 thereby 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 be manifested 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. As such, the investment mechanism also helps explain DeBondt and Thaler's (198[illegible]) reversal effect and Lakonishok, Shleifer, and Vishny's (1994) sales growth effect.

B. The ROA Hypothesis

The first-order condition ([illegible]) also implies the following ROA hypothesis

HYPOTHESIS *Given investment-to-assets, firms with high expected ROA should earn higher expected returns than firms with low expected ROA. This positive 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.*

B.1. Intuition

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

First, the marginal cost of investment in the denominator of the right-hand side of the first-order condition ([illegible]) equals marginal q, which in turn equals average q or market-to-book. As such, equation ([illegible]) says that the expected return is the expected ROA divided by market-

to-book, or equivalently, the expected cash flow divided by the market equity. This relation is analogous to the Gordon (1962) 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, and 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 also is noted by Fama and French (2006). Using the residual income model, Fama and French argue that expected stock returns are related to three variables: the book-to-market equity, expected profitability, and expected investment, and that 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 q-theory or construct the ROA factor and use it to capture the momentum and distress effects, as we do in Section III.

In addition to the discounting intuition, q-theory also provides capital budgeting intuition for the positive ROA-expected return relation. Equation ([illegible]) 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 thereby low investment. If the discount rates are not high enough to counteract the high expected ROA, firms would instead observe high net present values of new capital and thereby 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 are not low enough to counteract the low expected ROA, these firms would instead observe low

net present values of new capital and thereby invest less.

B.2. Portfolio Implications

The positive ROA-expected return relation has important portfolio implications for any sorts that generate wider spreads in expected ROA than in investment, their average return patterns can be interpreted using the common implied sort on expected ROA. We explore three such sorts in Section III, sorts on short-term prior returns, on financial distress, and on 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, and more distressed firms are less profitable (with lower expected ROA) and, all else equal, should earn lower average returns. As such, the distress effect 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.

II. The Explanatory Factors

We test the investment and ROA hypotheses via the Fama-French portfolio approach. We construct new common factors based on investment-to-asset and ROA in a similar way that Fama and French (199 199) 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 (dubbed the q-theory 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 model's performance. The simplicity of the portfolio approach allows us to test the new model on a wide range of testing portfolios.

Monthly returns, dividends, and prices are from the Center for Research in Security Prices (CRSP) and accounting information from Compustat Annual and Quarterly Industrial Files. The sample is from January 19 to December . The starting date is restricted by the availability of quarterly earnings and assets data. We exclude financial firms and firms with negative book equity.

A. The Investment Factor

We define investment-to-assets (I/A) as the annual change in gross property, plant, and equipment (Compustat annual item) plus the annual change in inventories (item) divided by the lagged book value of assets (item). 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 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 with high market-to-book equity invest more than value firms with low market-to-book equity. 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. Fama and French ([illegible]8) show that the magnitude of the asset growth effect varies across different size groups: it is strong in microcaps and small stocks, but is largely absent in big stocks. To the extent that asset growth is effectively the most comprehensive measure of investment (divided by assets), it seems necessary to control for size when constructing r_{INV}. The two-by-three sort also is 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%, middle 40%, and high 30% of the ranked values. We also use the median NYSE market equity (stock price times shares outstanding) 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), each month, between the simple average of the returns on the two low-I/A portfolios and the simple average of the returns on the two high-I/A portfolios.

From Table I, the average r_{INV} return in the 19[illegible]–[illegible] sample is .43% per month (t

4.). Regressing r_{INV} on the market factor generates an alpha of .1% per month (t 4.1) and an R^2 of 14%. The average return also subsists after controlling for the Fama-French and Carhart factors (the data are from Kenneth French's Web site). The r_{INV} factor also has a high correlation of .1 with HML, consistent with Titman, Wei, and Xie (4), Anderson and Garcia-Feijóo (4), and Xing (8).[7] From the Internet Appendix, sorting on I/A produces a large I/A spread the small and low-I/A portfolio has an average I/A of $-4.$ % per annum, whereas the small and high-I/A portfolio has an average of .1 %.

Insert Table I Here]

The impact of industries on the investment factor is relatively small (see the Internet Appendix). We conduct an annual two-by-three sort on industry size and I/A using Fama and French's (199) 48 industries. Following Fama and French (199), 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 a given industry divided by the sum of assets for the same set of 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. (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.) However, the average return for the industry-level investment factor is only .1 % per month (t 1.). The CAPM alpha, Fama-French alpha, and Carhart alpha are .19%, .14%, and . % per month, respectively, none of which are significant at the % level. 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.

B. The ROA Factor

We construct r_{ROA} by sorting on current ROA (as opposed to expected ROA) because ROA is highly persistent. Fama and French ([illegible]) show that current profitability is the strongest predictor of future profitability, and that adding more regressors in the specification of the expected profitability decreases its explanatory power for future stock returns. Also, because r_{ROA} is most relevant for explaining earnings surprises, prior returns, and distress effects that are constructed monthly, we use a similar approach to construct the ROA factor.[8]

We measure ROA as income before extraordinary items (Compustat quarterly item 8) divided by last quarter's total assets (item 44). Each month from January 19[illegible] to December [illegible], we categorize NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of quarterly ROA from four months ago. We impose the four-month lag to ensure that the required accounting information is known before forming the portfolios. The choice of the four-month lag is conservative using shorter lags only strengthens our results. We also use the NYSE median each month to split NYSE, Amex, and NASDAQ stocks into two groups. We form six portfolios from the intersections of the two size and three ROA groups. Monthly value-weighted returns on 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), 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.

From Panel A of Table I, r_{ROA} earns an average return of .9% per month (t .1) from January 19 to December . Controlling for the market factor, the Fama-French factors, and the Carhart factors does not affect the average r_{ROA} return. This evidence means that, like r_{INV}, r_{ROA} also captures average return variation not subsumed by existing common factors. From Panel B, r_{ROA} and the momentum factor have a correlation of . , suggesting that shocks to earnings are positively correlated with contemporaneous shocks to returns. The correlation between r_{INV} and r_{ROA} is only .1 (p-value .), meaning that there is no need to neutralize the two factors against each other. From the Internet Appendix, sorting on ROA generates a large ROA spread: the small and low-ROA portfolio has an average ROA of -1 % per annum, whereas the small and high-ROA portfolio has an average ROA of 1 48%. The large ROA spread only corresponds to a modest spread in I/A: 11.49% versus 1 . % per annum, helping explain the low correlation between r_{INV} and r_{ROA}. The ROA spread in small firms corresponds to a large spread in prior -1 month returns: 9. % versus 44%, helping explain the high correlation between r_{ROA} and the momentum factor.

The industry effect on the ROA factor is small (see the Internet Appendix). We conduct a monthly two-by-three sort on industry size and ROA using Fama and French's (199) 48 industries. We define industry ROA as the sum of earnings across all firms in a given industry divided by the sum of assets across the same set of 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 is important for the firm-level ROA factor, the industry ROA factor should show significant average returns. The evidence says otherwise. The average return of the industry ROA factor is only .19% per month (t 1.), and the CAPM

alpha, Fama-French alpha, and Carhart alpha are .1% (t 1.), .1% (t .), and .14% (t 1.), respectively. Relative to the firm-level *ROA* factor with an average return of .9% (t .1), the industry effect seems small in magnitude. Finally, each of the six firm-level size-*ROA* portfolios draws observations from a wide range of industries, and the industry distribution of observations does not vary much across the portfolios.

III. Calendar-Time Factor Regressions

We use simple time series regressions to confront the q-theory factor model with testing portfolios formed on a wide range of anomaly variables

$$r^j - r_f \quad \alpha_q^j + \beta_{MKT}^j r_{MKT} + \beta_{INV}^j r_{INV} + \beta_{ROA}^j r_{ROA} + \epsilon^j. \qquad (4)$$

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

A. Short-Term Prior Returns

Following Jegadeesh and Titman (199), we construct the size and momentum portfolios using the " /1/ convention. For each month t, we sort stocks on their prior returns from month $t-$ to $t-$, skip month $t-1$, and calculate the subsequent portfolio returns from month t to $t+$. We also use NYSE market equity quintiles to sort all stocks independently each month into five size portfolios. The portfolios are formed monthly as the intersection of the five size quintiles and the five quintiles based on prior – month returns.[9]

Table II reports large momentum profits. From Panel A, the winner-minus-loser (W-L) average return varies from .8 % (t 1) to 1. % per month (t .49). The CAPM

alphas for the W-L portfolios are significantly positive across all five size quintiles. The small-stock W-L strategy, in particular, earns a CAPM alpha of 1.% per month (t . 8). Consistent with Fama and French (199), their three-factor model exacerbates momentum. In particular, the small-stock W-L portfolio earns a Fama-French alpha of 1.44% per month (t . 4). Losers have higher HML-loadings than winners, so their model counterfactually predicts that losers should earn higher average returns. Panel B reports the new model's performance. *None* of the W-L strategies across five size quintiles earn significant alphas. The small-stock W-L strategy has an alpha of . 4% per month (t 1.), which represents a reduction of 9% in magnitude from its CAPM alpha and % from its Fama-French alpha. The average magnitude of the W-L alphas in the new model is .% per month, whereas it is 1. 8% in the CAPM and 1.1 % in the Fama-French model.

Insert Table II Here]

The q-theory factor model's success derives from two sources. First, from Table II, winners have higher r_{ROA}-loadings than losers across all size groups, going in the right direction in explaining the average returns. The loading spreads range from . to .4 , which, given an average r_{ROA} return of .9% per month, explain . 1% to .4% per month of momentum profits. Second, surprisingly, the r_{INV}-loading also goes in the right direction because winners have higher r_{INV}-loadings than losers. The loading spreads, ranging from . to .8 are all significant across the size groups. Combined with an average r_{INV} return of .4% per month, the loadings explain . % to .% per month of momentum profits.

This 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 (199) to examine how I/A varies across momentum portfolios. We find that winners indeed have higher contemporaneous I/A than losers at the portfolio formation month. More important, winners also have lower I/A than losers starting from two to four quarters prior to the portfolio formation. Because r_{INV} is rebalanced annually, the higher r_{INV}-loadings for winners accurately reflect their lower I/A several quarters prior to the portfolio formation.

Specifically, for each portfolio formation month t from January 19 to December , we calculate annual I/As for $t+m, m \quad -, \ldots,$. The I/As for $t+m$ are then averaged across portfolio formation months t. For a given portfolio, we plot the median I/As among the firms in the portfolio. From Panel A of Figure , although winners have higher I/As at the portfolio formation month t, winners have lower I/As than losers from month $t-$ to month $t-8$. Panel B shows that winners have higher contemporaneous I/As than losers in the calendar time in the small-size quintile. We define the contemporaneous I/A as the I/A at the current fiscal yearend. For example, if the current month is March or September the contemporaneous I/A is the I/A at the fiscal yearend of More important, Panel C shows that winners also have lower lagged (sorting-effective) I/As than losers in the small-size quintile. We define the sorting-effective I/A as the I/A on which an annual sort on I/A in each June is based. For example, if the current month is March the sorting-effective I/A is the I/A at the fiscal yearend of because the annual sort on I/A is in June . If the current month is September the sorting-effective I/A is the I/A at the fiscal yearend of because the corresponding sort on I/A is in June Because r_{INV} is rebalanced annually, the lower sorting-effective I/As of winners explain their higher

r_{INV}-loadings than losers.

Insert Figure Here]

Finally, as expected, Figure also shows that winners have higher ROAs than losers for about five quarters before and quarters after the portfolio formation month (Panel D). In the calendar time, winners have consistently higher ROAs than losers, especially in small-size quintile (Panels E and F). This evidence explains the higher r_{ROA}-loadings for winners documented in Table II.

B. Distress

The q-theory factor model fully explains the negative relation between financial distress and average returns. We form ten deciles based on Ohlson's (198) O-score and Campbell, Hilscher, and Szilagyi's (8) failure probability. Appendix A details the variable definitions.[10]

Each month from June 19 to December , we sort all stocks into ten deciles on failure probability from four months ago. The starting point of the sample is restricted by the availability of data items required to construct failure probability for comparison, Campbell, Hilscher, and Szilagyi (8) start their sample in 198 . Monthly value-weighted portfolio returns are calculated for the current month. Panel A of Table III reports that more distressed firms earn lower average returns than less distressed firms. The high-minus-low (H-L) distress portfolio has an average return of $-1.\ 8$% per month (t $-$). Controlling for traditional risk measures only makes things worse more distressed firms are riskier per traditional factor models. The H-L portfolio has a market beta of . (t .9) in the CAPM, producing an alpha of -1.8 % per month (t $-$. 8). The portfolio also has a

loading of 1.1 (t .4) on SMB and a market beta of . (t 4.) in the Fama-French model, producing an alpha of − .14% per month (t −.4).

Insert Table III Here]

The q-theory factor model reduces the H-L alpha to an insignificant level of − . % per month (t −1. 9). Although two out of ten deciles have significant alphas, the model is not rejected by the GRS test. In contrast, both CAPM and the Fama-French model are rejected at the % significance level. The r_{ROA}-loading goes in the right direction in explaining the distress ect. More distressed firms have lower r_{ROA}-loadings than less distressed firms the loading spread is −1.4 , which is more than 14 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 the Internet Appendix, the average portfolio ROA decreases monotonically from 11. % per annum for the low distress decile to −1 . % for the high distress decile, and the ROA-spread of − % is more than ten standard errors from zero.

Panel B of Table III reports similar results for deciles formed on O-score. The high O-score decile underperforms the low O-score decile by an average of − .9 % per month (t − .84), even though the high O-score decile has a higher market beta than the low O-score decile, 1. 8 versus 1. . The CAPM alpha for the H-L portfolio is −1.1 % per month (t −). The high O-score decile also has significantly higher SMB and HML loadings than the low O-score decile, producing a H-L Fama-French alpha of −1.44% per month (t −.49). More important, the new model eliminates the abnormal return the alpha is reduced to a tiny − . 9% per month (t − .). Again, the driving force is the

large and negative r_{ROA}-loading of $-1.$ (t $-11.$[illegible]) for the H-L portfolio. The average portfolio ROA decreases monotonically from 9.[illegible]8% per annum for the low O-score decile to $-$.[illegible]% for the high O-score decile, and the ROA-spread of $-$[illegible].1[illegible]% is more than ten standard errors from zero (see the Internet Appendix).

In all, the evidence suggests that the distress effect is largely subsumed by the positive ROA-expected return relation. Once we control for ROA in factor regressions, the distress effect disappears.

C. Net Stock Issues

In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on net stock issues at the last fiscal yearend. Following Fama and French (8), we measure net stock issues as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal yearend in $t-1$ divided by the split-adjusted shares outstanding at the fiscal yearend in $t-$. The split-adjusted shares outstanding is shares outstanding (item) times the adjustment factor (item). Monthly value-weighted portfolio returns

earns an alpha of $-$. 8% per month (t -1.9). The H-L portfolio has an r_{INV}-loading of $-$. (t $-4.$), going in the right direction in explaining the average returns. This loading pattern is consistent with the underlying investment pattern. The average portfolio I/A increases virtually monotonically from . % per annum for the low net issues decile to .8 % for the high net issues decile, and the I/A-spread of 4. 8% is more than ten standard errors from zero (see the Internet Appendix). Intriguingly, the r_{ROA}-loading also goes in the right direction the H-L portfolio has an r_{ROA}-loading of $-$ .9 (t $-$.), meaning that the portfolio formation the high net issues decile has a significantly lower average ROA than the low net issues decile. This evidence differs from Loughran and Ritter's (199) that equity issuers are more profitable than nonissuers. While Loughran and Ritter only examine new issues, net stock issues also include share repurchases. Our evidence makes sense in light of Lie ( ), who shows that firms announcing repurchases exhibit superior operating performance relative to industry peers.

D. Asset Growth

In June of each year t we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on asset growth at the fiscal yearend of $t-1$. Following Cooper, Gulen, and Schill (8), we measure asset growth as total assets (Compustat annual item) at fiscal yearend of $t-1$ minus total assets at fiscal yearend of $t-$ divided by total assets at fiscal yearend of $t-$. Panel B of Table IV reports that the high asset growth decile earns a lower average return than the low asset growth decile with a spread of $-1.$ 4% per month (t $-$ .19). The H-L portfolio earns a CAPM alpha of -1.1 % (t $-$ .9) and a Fama-French alpha of $-$. % per month (t $-$).

The q-theory factor model reduces the magnitude of the H-L alpha to $-$. % per month

(t $-$[illegible]). While the Fama-French model gets its explanatory power from HML, our model works through the investment factor. The H-L portfolio has an r_{INV}-loading of $-$[illegible].[illegible]8 (t $-$[illegible].[illegible]). The average portfolio I/A increases monotonically from -8.8[illegible]% per annum for the low asset growth decile to [illegible].[illegible]9% for the fifth decile and to [illegible].[illegible]% per annum for the high asset growth decile. The spread of [illegible].[illegible]% per annum is highly significant (see the Internet Appendix). Both asset growth and I/A capture firm-level investments, and r_{INV} fails to fully capture the asset growth effect probably because asset growth is a more comprehensive measure of investment than I/A.

E. Earnings Surprises

The q-theory factor model outperforms traditional asset pricing models in capturing the earnings surprise effect. Following Chan, Jegadeesh, and Lakonishok (199[illegible]), we define Standardized Unexpected Earnings (SUE) as the change in quarterly earnings (Compustat quarterly item 8) per share from its value four quarters ago divided by the standard deviation of the change in quarterly earnings over the prior eight quarters. We rank all NYSE, Amex, and NASDAQ stocks 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 monthly. From Panel A of Table V, the H-L SUE portfolio earns an average return of [illegible].[illegible]8% per month (t 8.[illegible]), a CAPM alpha of is [illegible].[illegible]% (t 8.[illegible]), and a Fama-French alpha of [illegible].[illegible]% (t 8.[illegible]9). The q-theory factor model reduces the alpha to [illegible].9[illegible]% (t [illegible].[illegible]), which only represents a modest reduction of [illegible]% from the Fama-French alpha.

Insert Table V Here]

While we follow Chan, Jegadeesh, and Lakonishok (199[illegible]) in constructing the SUE

portfolios on the most recent past earnings, we impose a four-month lag between the sorting-effective earnings and the return holding period in constructing the ROA factor. Our conservative timing (to guard against look-ahead bias) partially explains why r_{ROA} is only modestly useful in explaining the SUE effect. In Panel B of Table V we reconstruct the SUE portfolios while imposing the four-month lag. The H-L SUE portfolio earns only . % per month (t), but it still cannot be explained by the CAPM or the Fama-French model with alphas of . % and . % (t 98 and 4.), respectively. Both models are rejected by the GRS test at the 1% level. The new model reduces the H-L alpha to . % (t . 4), and the model is not rejected by the GRS test.

F. Book-to-Market Equity

Table VI reports factor regressions of Fama and French's (199) size and book-to-market portfolios (the data are from Kenneth French's Web site). Value stocks earn higher average returns than growth stocks. The average H-L return is 1. 9% per month (t . 8) in the small-size quintile and is . % (t 1.) in the big-size quintile. The small-stock H-L portfolio has a CAPM alpha of 1. % per month (t .1). The Fama-French model reduces the small-stock H-L alpha to . 8% per month, albeit still significant (t .). The q-theory factor model performs roughly as well as the Fama-French model the small-stock H-L earns an alpha of . % per month (t .). The new model does exceptionally well in capturing the low average returns of the small-growth portfolio. This portfolio earns a CAPM alpha of − . % per month (t − .), a Fama-French alpha of − . % (t −4.48), but only a tiny alpha of . 8% (t .) in the new model.[11]

Insert Table VI Here]

The r_{INV}- and r_{ROA}-loadings shed light on the explanatory power. From Panel B of Table VI, value stocks have higher r_{INV}-loadings than growth stocks. The loading spreads, ranging from .8 to .9, are all more than five standard errors from zero. This evidence shows that growth firms invest more than value firms, consistent with Fama and French (199). The r_{ROA}-loading pattern is more complicated. In the small-size quintile, the H-L portfolio has a positive loading of .9 (t 4.) because the small-growth portfolio has a large negative loading of $-$. (t $-$.). However, in the big-size quintile, the H-L portfolio has an insignificantly negative r_{ROA}-loading of $-$ . . It is somewhat surprising that the small-growth portfolio has a lower r_{ROA}-loading than the small-value portfolio. Using an updated sample through , the Internet Appendix documents that growth firms indeed have persistently higher ROAs than value firms in the big-size quintile both in the event time and in the calendar time. In the small-size quintile, however, growth firms have higher ROAs than value firms before, but lower ROAs after, the portfolio formation. In the calendar time, a dramatic downward spike of ROA appears for the small-growth portfolio over the past decade. This downward spike explains their abnormally low r_{ROA}-loadings.

G. Industries, CAPM Betas, and Market Equity

Lewellen, Nagel, and Shanken (8) argue that asset pricing tests are often misleading because apparently strong explanatory power (such as high cross-sectional R^2s) provides quite weak support for a model. Our tests are largely immune to this critique because we focus on the intercepts from factor regressions as a yardstick for evaluating competing models. Following Lewellen, Nagel, and Shanken's (8) prescription, we also confront our 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 VII, the CAPM captures the returns of ten industry portfolios with an insignificant GRS statistic of [illegible]. Both the Fama-French model and our model are rejected by the GRS test, probably because the regression R^2s are higher than those from the CAPM, so even an economically small deviation from the null is statistically significant. The average magnitude of the alphas is comparable across three models [illegible]% in the CAPM, [illegible]% in the Fama-French model, and [illegible]% in the new model.

Insert Table VII Here]

Panel A of Table VIII shows that none of the models are rejected by the GRS test using the ten portfolios formed on pre-ranking CAPM betas. The average magnitude of the alphas is again comparable [illegible]% in the CAPM, [illegible]% in the Fama-French model, and [illegible]% in our model. Panel B reports a weakness of our 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 [illegible]% in magnitude and are within [illegible] standard errors of zero. The new model delivers an alpha of [illegible]%, albeit insignificant, and the model is not rejected by the GRS test. The new model inflates the size premium because small firms have lower r_{ROA}-loadings than big firms, going in the wrong direction in explaining returns. However, this weakness also is the strength that allows the new model to fully capture the low average returns of small-growth firms.

Insert Table VIII Here]

IV. 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 model's performance is fairly remarkable. With only three factors, the q-theory factor model captures many patterns anomalous to the Fama-French model, and performs roughly as well as their model in explaining the portfolio returns which Fama and French (199[illegible]) show that their model is capable of explaining. 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. These applications primarily depend on the model's performance, and the economic intuition based on q-theory also raises the likelihood that the performance can persist in the future.

We interpret the q-theory factor model as providing a parsimonious description of the cross-section of expected stock returns. In particular, differing from Fama and French (199[illegible], 199[illegible]), 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, q-theory allows us to tie expected returns with firm characteristics in an economically meaningful way without assuming mispricing. Unlike size and book-to-market that directly involve market equity, which behaviorists often use as a proxy for mispricing (e.g., Daniel, Hirshleifer, and Subrahmanyam ([illegible])), the new factors are constructed on economic fundamentals that are less likely to be affected by mispricing, at least directly. On the other hand, our tests are only (intuitively) motivated from q-theory, and are not

formal structural evaluation of the theory. More important, q-theory is silent on investors' behavior, which can be rational or irrational. As such, our tests are not aimed to, and cannot, distinguish whether the anomalies are driven by rational or irrational forces.

We also have conducted horse races between covariances and characteristics following the research design of Daniel and Titman (199 , Table III). We find that after controlling for investment-to-assets, r_{INV}-loadings are not related to average returns, but controlling for r_{INV}-loadings does not affect the explanatory power of investment-to-assets. Similarly, after controlling for ROA, r_{ROA}-loadings are not related to average returns, but controlling for r_{ROA}-loadings does not affect the explanatory power of ROA (see the Internet Appendix). Consistent with Daniel and Titman, the evidence suggests that low-investment stocks and high-ROA stocks have high average returns whether or not they have similar return patterns (covariances) of other low-investment and high-ROA stocks.

We reiterate that, deviating from Fama and French (199 , 199) but echoing Daniel and Titman (199), we do not interpret the new factors 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 constructed on characteristics. In our view time series and cross-sectional regressions as largely equivalent ways of summarizing empirical correlations. If a characteristic is significant in cross-sectional regressions, its factor is likely to be significant in time series regressions. And if a factor is significant in time series regressions, its characteristic is likely to be significant in cross-sectional regressions. Factor loadings are no more primitive than characteristics, and characteristics are no more primitive than factor loadings.

The evidence in Daniel and Titman (199) is sometimes interpreted as saying that

risk does not determine expected returns. In our view this interpretation is too strong. Theoretically, q-theory predicts an array of relations between characteristics and expected returns, as observed in the data (see equation ([illegible]) and Section I). The simple derivation of that equation is not based on mispricing, and is potentially consistent with the risk hypothesis. In particular, the theoretical analysis retains rational expectations in the purest form of Muth (19[illegible]1) and Lucas (19[illegible]). Empirically, it is not inconceivable that characteristics provide more precise estimates of the true betas than the estimated betas (e.g., Miller and Scholes (19[illegible])). In particular, the betas are estimated with rolling-window regressions "run between [illegible] months and [illegible] months prior to the formation date (June of year t)" (Daniel and Titman, p. [illegible]8), and are in effect average betas at [illegible] months prior to portfolio formation. It seems reasonable to imagine that it would be hard, for example, for the [illegible]-month-lagged ROA factor loading to compete with four-month-lagged ROA in explaining monthly returns.[12] Future work can sort out the different interpretations. However, because true conditional betas are unobservable in reality, reaching a definitive verdict is virtually impossible.

Appendix A. The Distress Measures

We construct the distress measure following Campbell, Hilscher, and Szilagyi (8, the third column in Table 4)

$$\text{Distress}(t) \equiv -9.1\ 4 - \ .\ 4\,NIMTAAVG_t + 1.41\,TLMTA_t - \ .1\ 9\,EXRETAVG_t$$
$$+1.411\,SIGMA_t - \ .\ 4\ \ RSIZE_t - \ .1\ \,CASHMTA_t + \ .\ \ \ MB_t - \ .\ \ 8\,PRICE_t \quad (\text{A}1)$$
$$NIMTAAVG_{t-1,t-12} \equiv \frac{1-\phi^2}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}\right) \quad (\text{A}\ )$$
$$EXRETAVG_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12}\right) \quad (\text{A}\ )$$

The coefficient ϕ $^{-1/3}$, meaning that the weight is halved each quarter. $NIMTA$ is net income (Compustat quarterly item 9) divided by the sum of market equity and total liabilities (item 4). 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 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 divided by the sum of market equity and total liabilities. $SIGMA$ is the volatility of each firm's daily stock return over the past three months. $RSIZE$ is the relative size of each firm measured as the log ratio of its market equity to that of the S&P index. $CASHMTA$, used to capture the liquidity position of the firm, is the ratio of cash and short-term investments divided by the sum of market equity and total liabilities. MB is the market-to-book equity. $PRICE$ is the log price per share of the firm.

We follow Ohlson (198 , Model One in Table 4) to construct O-score $-1.\ -$ $.4\ \ \log(MKTASSET/CPI) + \ .\ \ TLTA - 1.4\ \ WCTA + \ .\ \ CLCA - 1.\ \ OENEG -$ $.\ \ NITA - 1.8\ \ FUTL + \ .\ 8\ \ INTWO - \ .\ \ 1\ CHIN$, in which $MKTASSET$ is market assets defined as book asset with book equity replaced by market equity. We calculate

$MKTASSET$ as total liabilities + Market Equity + .1 $\times$(Market Equity $-$ Book Equity), where total liabilities are given by Compustat quarterly item 4. The adjustment of $MKTASSET$ using ten percent of the difference between market equity and book equity follows Campbell, Hilscher, and Szilagyi (8) to ensure that assets are not close to zero. The construction of book equity follows Fama and French (199). CPI is the consumer price index. $TLTA$ is the leverage ratio defined as the book value of debt divided by $MKTASSET$. $WCTA$ is working capital divided by market assets, (item 4 $-$ item 49)$/MKTASSET$. $CLCA$ is current liability (item 4) divided by current assets (item 49). $OENEG$ is one if total liabilities exceeds total assets and is zero otherwise. $NITA$ is net income (item 9) divided by assets, $MKTASSET$. $FUTL$ is the fund provided by operations (item) divided by liability (item 4). $INTWO$ is equal to one if net income (item 9) 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 9) for the most recent quarter.

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Notes

[1]DeBondt and Thaler (1985), Rosenberg, Reid, and Lanstein (1985), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994) show that average returns covary with book-to-market, earnings-to-price, cash flow-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]Specifically, 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, cash flow-to-price, dividend-to-price, and long-term prior returns.

[3]See, for example, Ritter (1991), Ikenberry, Lakonishok, and Vermaelen (1995), Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), Chan, Jegadeesh, and Lakonishok (1996), Fama and French (1996, 2008), Dichev (1998), Griffin and Lemmon (2002), Daniel and Titman (2006), Campbell, Hilscher, and Szilagyi (2008), and Cooper, Gulen, and Schill (2008). Many of these papers argue that the evidence is driven by mispricing due to investors' over- or underreaction to news. 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)."

[4]More generally, our model's performance is comparable with that of the Fama-French model in capturing the average returns of testing portfolios which Fama and French (1996) show that their three-factor model is capable of explaining. The list includes earnings-to-price, dividend-to-price, prior 13–60 month returns, five-year sales 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 because Fama and French (1996) 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.

[5]The real options models of Berk, Green, and Naik (1999) and Carlson, Fisher, and Giammarino (2004) also imply the negative investment-expected return relation. In their models expansion options are riskier than assets in place. Investment converts riskier expansions options into less risky assets in place, meaning that high-investment firms are less risky and earn lower expected returns than low-investment firms.

[6]Lyandres, Sun, and Zhang (2008) show that adding the investment factor into the CAPM and the Fama-French model substantially reduces the magnitude of the underperformance following initial public offerings, seasoned equity offerings, and convertible debt offerings. Lyandres, Sun, and Zhang (2008) also report the

part of Figure 1 related to the new issues puzzle.

[7]Titman, Wei, and Xie (2004) sort stocks on $CE_{t-1}/[(CE_{t-2} + CE_{t-3} + CE_{t-4})/3]$, in which CE_{t-1} is capital expenditure (Compustat annual item 128) scaled by sales as the fiscal year $t-1$. The prior three-year moving average of CE is designed to capture the benchmark investment level. We sort stocks directly on I/A because it is more closely connected to q-theory. Xing (2008) shows that an investment growth factor contains information similar to HML and can explain the value premium roughly as well as HML. The average return of the investment growth factor is only 0.20% per month, albeit significant. Our investment factor is more powerful for several reasons. In principle, q-theory (see equation (3)) says that investment-to-assets is a more direct predictor of returns than past investment growth. Empirically, firm-level investment can often be zero or negative, making investment growth ill-defined. Xing measures investment as capital expenditure, in effect ignoring firms with zero or negative capital investment. By using annual change in property, plant, and equipment, we include these firms in our factor construction. Finally, we also use a more comprehensive measure of investment that includes both long-term investment and short-term working capital investment.

[8]The Internet Appendix shows that the original earnings surprises, momentum, and the distress effects do not exist in portfolios that are annually rebalanced. Specifically, in June of each year t we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on, separately, the Standardized Unexpected Earnings measured at the fiscal yearend of $t-1$, the 12-month prior return from June of year $t-1$ to May of year t, and Campbell, Hilscher, and Szilagyi's (2008) failure probability and Ohlson's (1980) O-score measured at the fiscal yearend of $t-1$. We calculate monthly value-weighted returns from July of year t to June of $t+1$ and rebalance the portfolios in June. None of these strategies produce mean excess returns or CAPM alphas that are significantly different from zero. Because the targeted effects only exist in monthly frequency, it seems natural to construct the explanatory ROA factor in the same frequency.

[9]Using the 25 portfolios with the "11/1/1" convention from Kenneth French's Web site yields largely similar results (see the Internet Appendix). 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.

[10]We also have experimented with portfolios formed on Altman's (1968) Z-score, but the CAPM adequately captures the average returns of these portfolios in our sample.

[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.

[12]The conditioning approach uses up-to-date information to estimate betas (e.g., Harvey (1989, 1991), Shanken (1990), and Ferson and Harvey (1993, 1999)). However, linear specifications likely 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) and Lewellen and Nagel (2006)). Ang and Chen (2007) and Kumar, Srescu, Boehme, and Danielsen (2008) document better news for the conditional CAPM, however.

Table I

Properties of the Investment Factor, r_{INV}, and the ROA Factor, r_{ROA}, 1/1972–12/2006, 420 Months

Investment-to-assets (I/A) is annual change in gross property, plant, and equipment (Compustat annual item 7) plus annual change in inventories (item 3) divided by lagged book assets (item 6). In each June we break NYSE, Amex, and NASDAQ stocks into three I/A groups using the breakpoints for the low 30%, middle 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, small and big. Taking intersections, we form six size-I/A portfolios. Monthly value-weighted returns on the six portfolios are calculated from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of year $t+1$. r_{INV} is the difference (low-minus-high), each month, between the average returns on the two low-I/A portfolios and the average returns on the two high-I/A portfolios. Return on assets (ROA) is quarterly earnings (Compustat quarterly item 8) divided by one-quarter-lagged assets (item 44). Each month from January 1972 to December 2006, we sort NYSE, Amex, and NASDAQ stocks into three groups based on the breakpoints for the low 30%, middle 40%, and the high 30% of the ranked quarterly ROA from four months ago. 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), 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 heteroscedasticity and autocorrelations. 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: Means and factor regressions of r_{INV} and r_{ROA}

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2
r_{INV}	0.43	0.51	−0.16				0.16
	(4.75)	(6.12)	(−8.83)				
		0.33	−0.09	0.06	0.27		0.31
		(4.23)	(−4.79)	(2.27)	(9.47)		
		0.22	−0.08	0.05	0.29	0.10	0.36
		(2.87)	(−4.11)	(2.29)	(10.65)	(5.89)	
r_{ROA}	0.96	1.05	−0.16				0.04
	(5.10)	(5.61)	(−4.00)				
		1.01	−0.05	−0.40	0.11		0.31
		(5.60)	(−1.23)	(−7.14)	(1.74)		
		0.74	−0.02	−0.41	0.18	0.26	0.24
		(4.16)	(−0.38)	(−7.56)	(2.81)	(6.43)	

Panel B: Correlation matrix (p-value in parenthesis)

	r_{ROA}	r_{MKT}	SMB	HML	WML
r_{INV}	0.10	−0.40	−0.09	0.51	0.20
	(0.05)	(0.00)	(0.07)	(0.00)	(0.00)
r_{ROA}		−0.19	−0.38	0.22	0.26
		(0.00)	(0.00)	(0.00)	(0.00)
r_{MKT}			0.26	−0.45	−0.07
			(0.00)	(0.00)	(0.14)
SMB				−0.29	0.02
				(0.00)	(0.62)
HML					−0.11
					(0.02)

Table II

Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on 25 Size and Momentum Portfolios, 1/1972–12/2006, 420 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 five portfolios formed on market equity and five portfolios formed on prior 2–7 month returns. The monthly size breakpoints are the NYSE market equity 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. All portfolio returns are value-weighted. Panel A reports mean percent excess returns and their t-statistics, CAPM alphas (α) and their t-statistics, and the intercepts (α^j_{FF}) and their t-statistics from Fama-French three-factor regressions. Panel B reports the new three-factor regressions: $r^j - r_f = \alpha^j_q + \beta^j_{MKT} r_{MKT} + \beta^j_{INV} r_{INV} + \beta^j_{ROA} r_{ROA} + \epsilon^j$. See Table I for the description of r_{INV} and r_{ROA}. All the t-statistics are adjusted for heteroscedasticity and autocorrelations. F_{GRS} is the Gibbons, Ross, and Shanken (1989) F-statistic testing that the intercepts of all 25 portfolios are jointly zero, and p_{GRS} is its associated p-value. We only report the results of quintiles 1, 3, and 5 for size and momentum to save space (see the Internet Appendix for the unabridged table).

Panel A: Means, CAPM alphas, and Fama-French alphas

	Loser	3	Winner	W-L	Loser	3	Winner	W-L
	Mean				t_{Mean}			
Small	−0.04	0.80	1.21	1.25	−0.09	2.78	3.54	5.49
3	0.03	0.58	0.98	0.95	0.08	2.29	3.03	3.63
Big	−0.22	0.29	0.68	0.90	−0.65	1.37	2.46	3.17
	α				t_α ($F_{GRS} = 3.28$, $p_{GRS} = 0$)			
Small	−0.59	0.40	0.73	1.33	−2.01	2.22	3.39	5.78
3	−0.51	0.18	0.48	1.00	−2.21	1.56	2.88	3.67
Big	−0.69	−0.07	0.25	0.94	−3.08	−0.91	1.86	3.15
	α_{FF}				$t_{\alpha_{FF}}$ ($F_{GRS} = 3.40$, $p_{GRS} = 0$)			
Small	−0.93	−0.05	0.51	1.44	−3.67	−0.54	4.89	5.54
3	−0.62	−0.17	0.47	1.09	−2.58	−1.91	4.26	3.57
Big	−0.60	−0.05	0.46	1.06	−2.41	−0.74	3.31	3.19

Panel B: The new three-factor regressions

	Loser	3	Winner	W-L	Loser	3	Winner	W-L
	α_q				t_{α_q} ($F_{GRS} = 2.20$, $p_{GRS} = 0$)			
Small	0.38	0.49	0.92	0.54	1.04	2.40	3.75	1.70
3	0.35	0.12	0.63	0.28	1.23	0.94	3.12	0.77
Big	−0.10	−0.10	0.31	0.41	−0.38	−1.15	1.99	1.13
	β_{INV}				$t_{\beta_{INV}}$			
Small	−0.31	0.25	0.29	0.60	−1.70	2.21	2.25	4.66
3	−0.58	0.05	0.00	0.58	−3.90	0.59	−0.04	3.75
Big	−0.67	−0.11	−0.10	0.57	−5.16	−2.56	−1.38	3.35
	β_{ROA}				$t_{\beta_{ROA}}$			
Small	−0.80	−0.24	−0.35	0.45	−6.62	−3.56	−4.01	3.48
3	−0.53	0.03	−0.14	0.39	−5.36	0.67	−1.75	2.62
Big	−0.21	0.09	0.00	0.22	−2.41	2.89	0.07	1.72

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

The data on the one-month Treasury bill rate (r_f), the Fama-French three factors are from Kenneth French's Web site. See Table I 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 failure probability and on *O*-score from four months ago. Monthly value-weighted returns on the portfolios are calculated for the current month, and the portfolios are rebalanced monthly. We report the average return in monthly percent and its *t*-statistics, the CAPM regression ($r^j - r_f = \alpha^j + \beta^j r_{MKT} + \epsilon^j$), the Fama-French three-factor regression ($r^j - r_f = \alpha^j_{FF} + b^j r_{MKT} + s^j SMB + h^j HML + \epsilon^j$), and the new three-factor regression ($r^j - r_f = \alpha^j_q + \beta^j_{MKT} r_{MKT} + \beta^j_{INV} r_{INV} + \beta^j_{ROA} r_{ROA} + \epsilon^j$). 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 parenthesis). All the t-statistics are adjusted for heteroscedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H-L) to save space (see the Internet Appendix for the unabridged table).

	Low	5	High	H-L	F_{GRS} (p)	Low	5	High	H-L	F_{GRS} (p)
	Panel A: The failure probability deciles (6/1975–12/2006, 379 months)					Panel B: The O-score deciles (1/1972–12/2006, 420 months)				
Mean	1.03	0.72	−0.35	−1.38		0.48	0.50	−0.44	−0.92	0.32

Table IV
Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on the Net Stock Issues Deciles and the Asset Growth Deciles, 1/1972–12/2006, 420 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 I for the description of r_{INV} and r_{ROA}. We measure net stock issues as the the natural log of the ratio of the split-adjusted shares outstanding at the fiscal yearend in t–1 (Compustat annual item 25 times the Compustat adjustment factor, item 27) divided by the split-adjusted shares outstanding at the fiscal yearend in $t-2$. In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the breakpoints of net stock issues measured at the end of last fiscal yearend. Monthly value-weighted returns are calculated from July of year t to June of year $t+1$. In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on asset growth measured at the end of last fiscal year $t-1$. Asset growth for fiscal year $t-1$ is the change of total assets (item 6) from the fiscal yearend of $t-2$ to yearend of $t-1$ divided by total assets at the fiscal yearend of $t-2$. Monthly value-weighted returns are calculated from July of year t to June of year $t+1$. We report the average return in monthly percent and its t-statistics, the CAPM regression ($r^j - r_f = \alpha^j + \beta^j r_{MKT} + \epsilon^j$), the Fama-French three-factor regression ($r^j - r_f = \alpha^j_{FF} + b^j r_{MKT} + s^j SMB + h^j HML + \epsilon^j$), and the new three-factor regression ($r^j - r_f = \alpha^j_q + \beta^j_{MKT} r_{MKT} + \beta^j_{INV} r_{INV} + \beta^j_{ROA} r_{ROA} + \epsilon^j$). 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 parenthesis). All the t-statistics are adjusted for heteroscedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H-L) to save space (see the Internet Appendix for the unabridged table).

	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	1.00	0.82	0.16	−0.84		1.10	0.63	0.05	−1.04	
t_{Mean}	4.73	3.61	0.55	−4.64		3.48	3.03	0.15	−5.19	
α	0.42	0.17	−0.64	−1.06	3.97	0.49	0.18	−0.67	−1.16	5.82
β	0.88	0.99	1.21	0.33	(0)	1.21	0.89	1.43	0.23	(0)
t_α	3.68	1.98	−4.34	−5.07		2.92	2.59	−4.77	−5.92	
α_{FF}	0.22	0.13	−0.59	−0.82	3.10	0.17	0.01	−0.48	−0.65	3.71
b	0.99	1.01	1.14	0.15	(0)	1.20	0.98	1.27	0.07	(0)
s	0.01	0.00	0.26	0.25		0.65	0.00	0.31	−0.34	
h	0.32	0.08	−0.07	−0.39		0.40	0.26	−0.33	−0.72	
$t_{\alpha_{FF}}$	2.39	1.36	−3.89	−4.33		1.15	0.10	−3.84	−3.57	
α_q	0.09	0.24	−0.19	−0.28	2.67	0.45	0.03	−0.10	−0.55	3.05
β_{MKT}	0.96	0.96	1.08	0.12	(0)	1.26	0.94	1.28	0.02	(0)
β_{INV}	0.11	−0.17	−0.43	−0.55		0.59	0.24	−0.79	−1.38	
β_{ROA}	0.21	0.02	−0.18	−0.39		−0.25	0.03	−0.16	0.09	
t_{α_q}	0.90	2.49	−1.10	−1.39		2.49	0.41	−0.72	−3.06	
$t_{\beta_{MKT}}$	45.73	42.35	29.85	2.67		27.15	45.42	43.03	0.44	
$t_{\beta_{INV}}$	1.66	−3.47	−4.74	−4.25		5.99	5.19	−9.47	−15.04	
$t_{\beta_{ROA}}$	5.06	0.53	−4.09	−6.53		−4.06	0.85	−4.25	1.30	

Table V
Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Most Recent (and Four-Month-Lagged) Standardized Unexpected Earnings (SUE), 1/1972–12/2006, 420 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 I for the description of r_{INV} and r_{ROA}. We define SUE as the change in quarterly earnings per share from its value announced four quarters ago divided by the standard deviation of earnings change over the prior eight quarters. In Panel A we rank all NYSE, Amex, and NASDAQ stocks into ten 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 use the same procedure but instead of the most recent SUE we sort on the SUE from four months ago. We report the average return in monthly percent and its t-statistics, the CAPM regression ($r^j - r_f = \alpha^j + \beta^j r_{MKT} + \epsilon^j$), the Fama-French three-factor regression ($r^j - r_f = \alpha^j_{FF} + b^j r_{MKT} + s^j SMB + h^j HML + \epsilon^j$), and the new three-factor regression ($r^j - r_f = \alpha^j_q + \beta^j_{MKT} r_{MKT} + \beta^j_{INV} r_{INV} + \beta^j_{ROA} r_{ROA} + \epsilon^j$). 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 parenthesis). All the t-statistics are adjusted for heteroscedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H-L) to save space (see the Internet Appendix for the unabridged table).

	Low	5	High	H-L	F_{GRS} (p)	Low	5	High	H-L	F_{GRS} (p)
	Panel A: Deciles on most recent SUE					Panel B: Deciles on four-month-lagged SUE				
Mean	−0.10	0.26	1.08	1.18		0.34	0.32	0.86	0.52	
t_{Mean}	−0.41	1.09	4.84	8.34		1.36	1.37	3.86	3.61	
α	−0.62	−0.25	0.61	1.22	10.65	−0.18	−0.18	0.39	0.57	3.65
β	1.02	1.01	0.94	−0.08	(0)	1.04	1.00	0.94	−0.10	(0)
t_α	−6.65	−2.86	7.22	8.76		−1.83	−2.10	4.52	3.98	
α_{FF}	−0.58	−0.32	0.64	1.22	11.01	−0.16	−0.20	0.45	0.62	4.60
b	1.02	1.02	0.95	−0.07	(0)	1.05	1.00	0.94	−0.11	(0)
s	−0.03	0.08	−0.10	−0.07		−0.06	0.03	−0.13	−0.08	
h	−0.04	0.09	−0.03	0.01		−0.02	0.04	−0.08	−0.06	
$t_{\alpha_{FF}}$	−6.16	−3.65	7.14	8.19		−1.57	−2.28	5.21	4.03	
α_q	−0.43	−0.17	0.47	0.90	5.56	−0.02	−0.11	0.30	0.33	1.79
β_{MKT}	0.98	0.99	0.96	−0.02	(0)	1.00	0.98	0.96	−0.04	(0.06)
β_{INV}	−0.17	0.02	−0.01	0.16		−0.14	−0.01	−0.04	0.10	
β_{ROA}	−0.10	−0.09	0.14	0.23		−0.12	−0.08	0.13	0.25	
t_{α_q}	−4.47	−1.88	5.53	6.52		−0.22	−1.26	3.51	2.24	
$t_{\beta_{MKT}}$	40.67	41.41	39.62	−0.54		31.24	41.53	39.09	−0.88	
$t_{\beta_{INV}}$	−2.86	0.32	−0.22	1.87		−1.97	−0.18	−0.73	1.14	
$t_{\beta_{ROA}}$	−3.08	−2.20	4.47	4.61		−3.45	−2.01	4.40	5.03	

Table VI

Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on 25 Size and Book-to-Market Portfolios, 1/1972–12/2006, 420 Months

The data for the one-month Treasury bill rate (r_f), the Fama-French factors, and the 25 size and book-to-market 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: $r^j - r_f = \alpha_q^j + \beta_{MKT}^j r_{MKT} + \beta_{INV}^j r_{INV} + \beta_{ROA}^j r_{ROA} + \epsilon^j$. See Table I for the description of r_{INV} and r_{ROA}. All the t-statistics are adjusted for heteroscedasticity and autocorrelations. F_{GRS} is the Gibbons, Ross, and Shanken (1989) F-statistic testing that the intercepts of all 25 portfolios are jointly zero, and p_{GRS} 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 (see the Internet Appendix for the unabridged table).

	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} ($F_{GRS} = 2.72$, $p_{GRS} = 0$)			
Small	0.10	0.88	1.19	1.09	0.25	3.10	4.21	5.08	0.08	0.46	0.64	0.57	0.27	2.23	3.31	2.72
3	0.41	0.74	1.07	0.66	1.22	3.14	4.12	2.86	0.19	0.07	0.31	0.13	1.05	0.60	1.86	0.57
Big	0.40	0.59	0.65	0.25	1.67	2.75	2.80	1.20	−0.11	−0.04	0.03	0.14	−1.17	−0.39	0.16	0.61
	α				t_α ($F_{GRS} = 4.25$, $p_{GRS} = 0$)				β_{INV}				$t_{\beta_{INV}}$			
Small	−0.63	0.37	0.70	1.32	−2.61	2.15	3.82	7.10	−0.11	0.35	0.58	0.69	−0.76	3.22	4.68	5.63
3	−0.27	0.27	0.59	0.86	−1.74	2.32	3.71	3.96	−0.43	0.24	0.50	0.93	−4.43	3.39	4.20	7.03
Big	−0.11	0.16	0.25	0.36	−1.29	1.54	1.61	1.81	−0.26	0.14	0.42	0.68	−5.17	2.19	3.76	5.05
	α_{FF}				$t_{\alpha_{FF}}$ ($F_{GRS} = 3.08$, $p_{GRS} = 0$)				β_{ROA}				$t_{\beta_{ROA}}$			
Small	−0.52	0.09	0.16	0.68	−4.48	1.35	2.16	5.50	−0.62	−0.26	−0.23	0.39	−5.65	−3.00	−3.50	4.53
3	−0.03	−0.12	−0.02	0.01	−0.37	−1.50	−0.22	0.08	−0.23	0.07	0.02	0.24	−2.95	1.55	0.25	2.10
Big	0.17	−0.02	−0.26	−0.43	2.75	−0.28	−2.34	−3.34	0.12	0.12	0.01	−0.11	4.75	2.61	0.11	−1.23

Table VII
Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Ten Industry Portfolios, 1/1972–12/2006, 420 Months

The one-month Treasury bill rate (r_f), the Fama-French three factors and ten industry portfolio returns are from Kenneth French's Web site. See Table I for the description of r_{INV} and r_{ROA}. For each portfolio we report the average return in monthly percent and its t-statistics, the CAPM regression ($r^j - r_f = \alpha^j + \beta^j r_{MKT} + \epsilon^j$), the Fama-French three-factor regression ($r^j - r_f = \alpha^j_{FF} + b^j r_{MKT} + s^j SMB + h^j HML + \epsilon^j$), and the new three-factor regression ($r^j - r_f = \alpha^j_q + \beta^j_{MKT} r_{MKT} + \beta^j_{INV} r_{INV} + \beta^j_{ROA} r_{ROA} + \epsilon^j$). 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 parenthesis). All the t-statistics are adjusted for heteroscedasticity and autocorrelations.

Panel A: Ten industry portfolios

	NoDur	Durbl	Manuf	Enrgy	HiTec	Telcm	Shops	Hlth	Utils	Other	F_{GRS} (p)
Mean	0.67	0.41	0.56	0.76	0.49	0.55	0.55	0.58	0.51	0.59	
t_{Mean}	3.04	1.43	2.31	2.82	1.44	2.35	2.03	2.31	2.52	2.36	
α	0.27	−0.11	0.05	0.37	−0.17	0.17	0.02	0.15	0.25	0.06	1.35
β	0.81	1.03	1.01	0.77	1.32	0.75	1.04	0.85	0.50	1.04	(0.20)
t_α	1.99	−0.64	0.49	1.79	−0.98	1.02	0.16	0.91	1.47	0.64	
α_{FF}	0.10	−0.47	−0.08	0.17	0.22	0.16	−0.09	0.41	−0.13	−0.17	2.88
b	0.91	1.17	1.08	0.91	1.09	0.81	1.06	0.81	0.72	1.16	(0.00)
s	−0.08	0.11	−0.03	−0.20	0.21	−0.22	0.12	−0.35	−0.15	−0.04	
h	0.27	0.53	0.20	0.33	−0.64	0.04	0.16	−0.35	0.61	0.35	
$t_{\alpha_{FF}}$	0.76	−2.75	−0.90	0.82	1.45	0.90	−0.63	2.50	−0.89	−1.81	
α_q	−0.24	−0.25	−0.20	0.30	0.47	0.26	−0.21	−0.10	−0.01	−0.24	2.17
β_{MKT}	0.92	1.07	1.06	0.76	1.18	0.76	1.08	0.88	0.56	1.11	(0.02)
β_{INV}	0.32	0.24	0.07	−0.22	−0.51	0.25	0.02	−0.08	0.22	0.25	
β_{ROA}	0.33	0.02	0.20	0.18	−0.37	−0.21	0.22	0.28	0.15	0.17	
t_{α_q}	−1.89	−1.25	−2.08	1.27	2.70	1.32	−1.46	−0.51	−0.07	−2.38	
$t_{\beta_{MKT}}$	29.52	23.18	45.36	14.75	29.79	18.57	25.34	17.39	12.06	45.91	
$t_{\beta_{INV}}$	4.39	2.20	1.10	−1.56	−5.32	2.15	0.19	−0.80	2.26	4.89	
$t_{\beta_{ROA}}$	7.47	0.19	5.91	2.75	−7.23	−3.27	4.64	3.89	2.14	4.28	

Table VIII
Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Pre-ranking CAPM Betas and the Market Equity, 1/1972–12/2006, 420 Months

The one-month Treasury bill rate (r_f), the Fama-French three factors, and ten market equity portfolio returns are from Kenneth French's Web site. See Table I 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 ten deciles based on the pre-ranking betas. The value-weighted monthly returns on the resulting ten portfolios are calculated from July of year t to June of year $t+1$. For each portfolio we report the average return in monthly percent and its t-statistics, the CAPM regression ($r^j - r_f = \alpha^j + \beta^j r_{MKT} + \epsilon^j$), the Fama-French three-factor regression ($r^j - r_f = \alpha^j_{FF} + b^j r_{MKT} + s^j SMB + h^j HML + \epsilon^j$), and the new three-factor regression ($r^j - r_f = \alpha^j_q + \beta^j_{MKT} r_{MKT} + \beta^j_{INV} r_{INV} + \beta^j_{ROA} r_{ROA} + \epsilon^j$). 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 parenthesis). All the t-statistics are adjusted for heteroscedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H-L) to save space (see the Internet Appendix for the unabridged table).

	Panel A: Ten pre-ranking CAPM beta deciles					Panel B: Ten market equity deciles				
	Low	5	High	H-L	F_{GRS} (p)	Small	5	Big	S-B	F_{GRS} (p)
Mean	0.48	0.57	0.37	−0.10		0.73	0.71	0.46	0.28	
t_{Mean}	2.26	2.55	0.80	−0.24		2.42	2.60	2.15	1.16	
α	0.16	0.10	−0.53	−0.69	1.60	0.21	0.15	−0.02	0.23	1.79
β	0.62	0.93	1.79	1.17	(0.10)	1.03	1.12	0.94	0.09	(0.06)
t_α	0.95	1.10	−2.23	−2.10		1.08	1.30	−0.31	0.96	
α_{FF}	−0.16	−0.09	−0.31	−0.15	1.23	−0.04	−0.02	0.06	−0.10	1.82
b	0.75	1.03	1.50	0.75	(0.27)	0.88	1.05	0.97	−0.10	(0.06)
s	0.08	−0.01	0.82	0.74		1.18	0.68	−0.31	1.49	
h	0.48	0.30	−0.45	−0.92		0.22	0.16	−0.08	0.31	
$t_{\alpha_{FF}}$	−0.94	−1.10	−1.54	−0.53		−0.40	−0.36	2.47	−1.11	
α_q	−0.07	−0.14	0.47	0.54	1.77	0.46	0.29	−0.07	0.53	1.57
β_{MKT}	0.67	0.98	1.57	0.91	(0.06)	1.02	1.10	0.95	0.08	(0.11)
β_{INV}	0.15	0.10	−0.70	−0.85		0.34	0.02	−0.05	0.39	
β_{ROA}	0.15	0.18	−0.62	−0.77		−0.40	−0.15	0.08	−0.48	
t_{α_q}	−0.39	−1.44	1.93	1.58		2.00	2.29	−1.20	1.91	
$t_{\beta_{MKT}}$	12.22	39.76	26.35	9.74		17.56	30.06	59.37	1.07	
$t_{\beta_{INV}}$	1.61	1.87	−4.84	−4.72		2.84	0.35	−1.55	2.68	
$t_{\beta_{ROA}}$	2.26	4.30	−8.16	−7.32		−4.44	−2.72	3.51	−4.39	

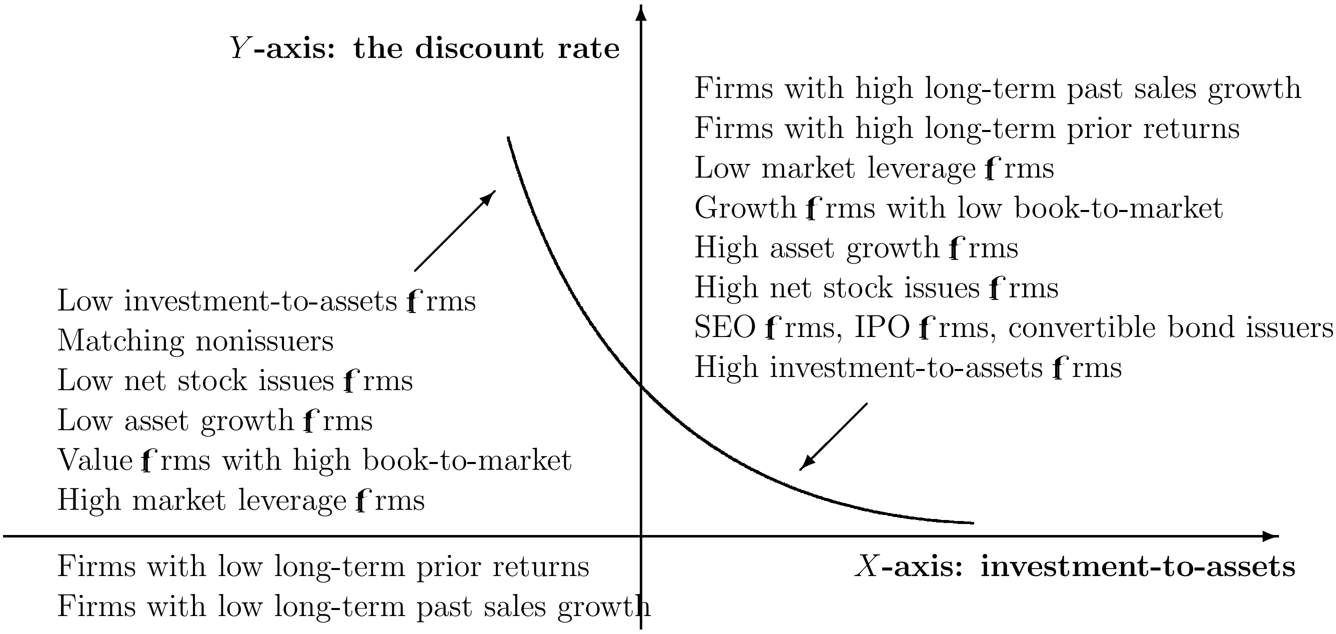

Figure 1. Investment-to-Assets As a First-Order Determinant of the Cross-Section of Expected Stock Returns.

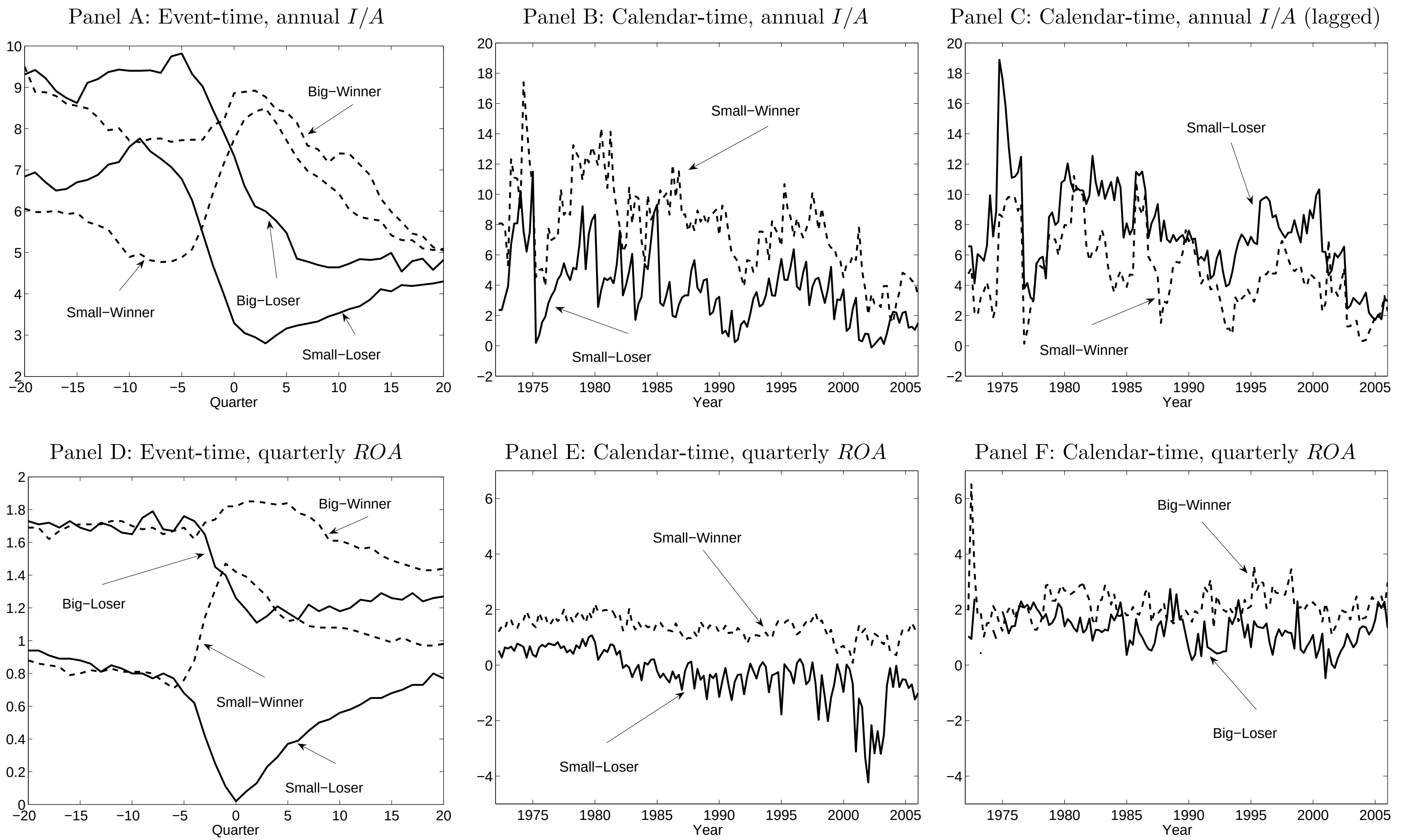

Figure 2. Investment-to-Assets (I/A, Contemporaneous and Lagged) and ROA for the 25 Size and Momentum Portfolios, 1972:Q1 to 2006:Q4, 140 Quarters. We measure I/A as the annual change in gross property, plant, and equipment (Compustat annual item 7) plus the annual change in inventories (item 3) divided by the lagged book assets (item 6). ROA is quarterly earnings (Compustat quarterly item 8) divided by one-quarter-lagged assets (item 44). The 25 size and momentum portfolios are constructed monthly as the intersections of five quintiles formed on market equity and five quintiles formed on prior 2–7 month returns (skipping one month). For each portfolio formation month t = January 1972 to December 2006, 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. ROA is the most recent ROA relative to formation month t. Panel A plots the median I/As across firms for the four extreme portfolios. In Panel B I/A is the current yearend 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.