An Alternative Three-Factor Model

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Abstract

A new factor model consisting of the market factor, an investment factor, and a return-on-equity factor is a good start to understanding the cross-section of expected stock returns. Firms will invest a lot when their profitability is high and the cost of capital is low. As such, controlling for profitability, investment should be negatively correlated with expected returns, and controlling for investment, profitability should be positively correlated with expected returns. The new three-factor model reduces the magnitude of the abnormal returns of a wide range of anomalies-based trading strategies, often to insignificance. The 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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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. Fama and French (1993, 1996) augment the CAPM with certain factors to explain what the CAPM cannot. However, it has become increasingly clear over the past two decades that even the extremely influential Fama-French model cannot explain many capital markets anomalies. Prominent examples include the positive relations of average returns with momentum and earnings surprises, and the negative relations of average returns with financial distress, idiosyncratic volatility, net stock issues, and asset growth.[1]

We show that a new three-factor model is a good start to understanding anomalies. In the new factor model, the expected return on portfolio i in excess of the risk-free rate, $E[r^i] - r^f$, is described by the sensitivity of its return to three factors: (i) the market excess return, MKT; (ii) the difference between the return of a low investment portfolio and the return of a high investment portfolio, r_{INV}; and (iii) the difference between the return of a high return-on-equity (ROE) portfolio and the return of a low return-on-equity portfolio, r_{ROE}. Formally,

$$E[r^i] - r^f = \beta^i_{MKT}\, E[MKT] + \beta^i_{INV}\, E[r_{INV}] + \beta^i_{ROE}\, E[r_{ROE}], \quad (1)$$

in which $E[MKT], E[r_{INV}]$, and $E[r_{ROE}]$ are expected premiums, and $\beta^i_{MKT}, \beta^i_{INV}$, and β^i_{ROE} are the factor loadings of portfolio i on MKT, r_{INV}, and r_{ROE}, respectively.

Theoretically, firms will invest a lot when their profitability is high and the cost of capital is low (e.g., Fama and French (2006)).[2] As such, controlling for profitability, investment should be negatively correlated with expected returns, and controlling for investment, profitability should be

[1]Seminal contributions include Ball and Brown (1968), Foster, Olsen, and Shevlin (1984), 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), Dichev (1998), Ang, Hodrick, Xing, and Zhang (2006), Campbell, Hilscher, and Szilagyi (2008), Cooper, Gulen, and Schill (2008), and Fama and French (2008). The bulk of the anomalies literature argues that anomalies are due to mispricing. In particular, Campbell et al. interpret their evidence as "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).

[2]This prediction can also be derived from the q-theory of investment (e.g., Liu, Whited, and Zhang (2009)).

positively correlated with expected returns. Empirically, consistent with theory, the low-minus-high investment factor and the high-minus-low *ROE* factor earn significantly positive average returns in the 1972–2010 sample: 0.41% ($t = 4.80$) and 0.71% per month ($t = 4.01$), respectively.

Our key message is that the combined effect of investment and *ROE* is a good start to understanding the big picture of the cross-section of expected stock returns. The investment factor plays a similar role as Fama and French's (1993) value factor. Intuitively, firms with high valuation ratios have more growth opportunities, invest more, and earn lower expected returns than firms with low valuation ratios. For example, the value-minus-growth quintile in the smallest size quintile earns an alpha of 0.67% per month ($t = 2.70$) in the new factor model. This alpha is close to the Fama-French alpha of 0.68% ($t = 5.38$). The investment factor also helps explain the net stock issues and the asset growth anomalies: Firms with high net stock issues (high asset growth) invest more and earn lower expected returns than firms with low net stock issues (low asset growth).

The *ROE* factor adds to the new factor model a new dimension of explanatory power absent in the Fama-French model. Shocks to profitability are positively correlated with contemporaneous shocks to returns. As such, winners have higher profitability and earn higher expected returns than losers. For example, the winner-minus-loser quintile in the smallest size quintile earns an alpha of 0.68% per month ($t = 2.76$) in the new factor model. Albeit significant, this alpha is less than one half of the Fama-French alpha, 1.48% ($t = 8.01$). Also, the *ROE* factor reduces to insignificance the abnormal returns of the high-minus-low deciles formed on Foster, Olsen, and Shevlin's (1984) earnings surprises, Ang, Hodrick, Xing, and Zhang's (2006) idiosyncratic volatility, Campbell, Hilscher, and Szilagyi's (2008) failure probability, and Ohlson's (1980) *O*-score. Firms with low earnings surprises, high idiosyncratic volatility, high failure probability, and high *O*-scores have lower profitability, load less on the *ROE* factor, and earn lower expected returns.

Our empirical methodology is from Fama and French (1993, 1996), who show that their three-factor model summarizes what we know about the cross-section of returns as of the mid-1990s. Most prior studies motivate common factors from the consumption side of the economy (e.g., Ferson and Harvey (1991, 1993)). We exploit a direct link between stock returns and characteristics from the production side (e.g., Cochrane (1991)). Section 2 constructs the new factors. Section 3 tests the new factor model via calendar-time factor regressions. Section 4 performs model comparison tests based on the Hansen-Jagannathan (1997) distance. Finally, Section 5 concludes.

2 The Explanatory Factors

Monthly returns, dividends, and prices are 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 December 2010. The starting date is restricted by the availability of quarterly earnings announcement dates. We exclude financials and firms with negative book equity.

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. The Bureau of Economic Analysis also measures gross private domestic investment as the sum of fixed investment and the net change in business inventories.

We measure ROE as income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock. Our definition of book equity is the quarterly version of the annual book equity in Davis, Fama, and French (2000).[3]

Following the Fama-French portfolio approach, we construct the investment factor and the ROE factor from a triple sort on I/A, ROE, and size. 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. Independently, in each month we sort NYSE, Amex, and NASDAQ stocks into three ROE groups based on the breakpoints for the low 30%, medium 40%, and high 30% of the ranked quarterly ROE. Earnings and other accounting variables in Compustat quarterly files are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (Compustat quarterly item RDQ). For example, if the earnings for the fourth fiscal quarter of year $t-1$ are publicly announced on March 5 (or March 25) of year t, we use the announced earnings (divided by the book equity from the third quarter of year $t-1$) to form portfolios at the beginning of April of year t. Also independently, in each month we split NYSE, Amex, and NASDAQ stocks into three size groups using the NYSE breakpoints for the low 30%, medium 40%, and high 30% of the ranked market equity (stock price times shares outstanding from CRSP).

Taking intersections of the I/A terciles, the ROE terciles, and the size terciles, we form 27 portfolios. Monthly value-weighted returns on the 27 portfolios are calculated for the current month, and the portfolios are rebalanced monthly. Designed to mimic the common variation in stock returns related to firm-level I/A, the investment factor is the difference (low-minus-high I/A), each month, between the simple average of the returns on the nine low I/A portfolios and the simple average of the returns on the nine high I/A portfolios. Designed to mimic the common variation in stock returns related to firm-level ROE, the ROE factor is the difference (high-minus-low ROE), each month, between the simple average of the returns on the nine high ROE portfolios and the simple average of the returns on the nine low ROE portfolios.

We sort stocks jointly on I/A and ROE in forming the new factors. The economic rationale is

[3]Fama and French (2006) measure shareholders' equity as total assets minus total liabilities. We follow Davis, Fama, and French (2000) because Compustat quarterly items SEQQ (stockholders' equity) and CEQQ (common equity) have a broader coverage than items ATQ (total assets) and LTQ (total liabilities) before 1980.

that the investment effect and the ROE effect are both conditional in nature. Firms will invest a lot when either the profitability of their investment is high, or the cost of capital is low, or both. As such, the negative relation between investment and the cost of capital is conditional on a given level of profitability. In particular, investment and the cost of capital could be positively correlated if the investment delivers exceptionally high profitability. Similarly, the positive relation between profitability and the cost of capital is conditional on a given level of investment. Profitability and the cost of capital could be negatively correlated if the profitability comes with unusually large investment. Sorting jointly on I/A and ROE controls for this conditional nature. Finally, both the investment effect and the earnings effect seem to be stronger in small firms than in big firms (e.g., Bernard and Thomas (1989) and Fama and French (2008)). As such, we control for size in the triple sort.

From Panel A of Table 1, the average return of the investment factor in our 1972–2010 sample is 0.41% per month ($t = 4.80$), and its CAPM alpha is 0.46% ($t = 5.32$). The average return subsists after controlling for the Fama-French three factors as well as the momentum factor. (The data for these factors are from Kenneth French's Web site.) From Panel B, the investment factor has a high correlation of 0.41 with the value factor, consistent with Xing (2008). The investment factor also has a significantly positive correlation of 0.15 with the momentum factor. The ROE factor earns an average return of 0.71% ($t = 4.01$). Controlling for the Fama-French and momentum factors does not reduce the average return to insignificance. The ROE factor and the momentum factor have a high correlation of 0.40, meaning that shocks to earnings are positively correlated with shocks to returns. Finally, the two new factors have an insignificantly positive correlation of 0.07.

3 Calendar-time Factor Regressions

Following Fama and French (1993, 1996), we use factor regressions to test the new factor model:

$$r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i \, MKT_t + \beta_{INV}^i \, r_{INV,t} + \beta_{ROE}^i \, r_{ROE,t} + \epsilon_t^i. \tag{2}$$

If the model's performance is adequate, α_q^i should be statistically indistinguishable from zero. The simplicity of the portfolio approach allows us to explore a wide array of testing portfolios.

3.1 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 size breakpoints to sort the stocks independently each month into quintiles. The 25 portfolios are formed monthly from taking the intersections of the size and prior six-month returns quintiles.[4]

Table 2 reports large momentum profits. From Panel A, the average winner-minus-loser return varies from 0.77% ($t = 2.96$) to 1.29% per month ($t = 6.28$). The CAPM alphas of the winner-minus-loser portfolios are significantly positive across all five size quintiles. In particular, the small-stock winner-minus-loser quintile earns a CAPM alpha of 1.37% ($t = 7.20$). Consistent with Fama and French (1996), their three-factor model exacerbates momentum. The small-stock winner-minus-loser quintile earns a Fama-French alpha of 1.48% ($t = 8.01$). The mean absolute error (m.a.e., calculated as the average magnitude of the alphas) is 0.31% both in the CAPM and in the Fama-French model. Both models are strongly rejected by the Gibbons, Ross, and Shanken (1989, GRS) test.

From Panel B, the new factor model reduces the m.a.e. only marginally to 0.26% per month. However, the winner-minus-loser alphas are substantially smaller than the CAPM alphas and the Fama-French alphas. In particular, the small-stock winner-minus-loser quintile has an alpha of 0.68% ($t = 2.76$), which is less than one half of the CAPM alpha and the Fama-French alpha. The big-stock winner-minus-loser quintile has an alpha of 0.33% ($t = 1.01$) in the new factor model, representing a reduction of more than 60% from its CAPM alpha and its Fama-French alpha.

[4] 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 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.

However, the new factor model is still rejected by the GRS test.

The new factor model's explanatory power derives from two sources. First, winners have significantly higher ROE factor loadings than losers, going in the right direction to explain momentum. The ROE loading spreads between winners and losers range from 0.41 to 0.64. Combined with the average ROE factor return of 0.71% per month, the loading spreads explain 0.29% to 0.45% per month of momentum profits. Second, surprisingly, winners also have significantly higher investment factor loadings than losers, again going in the right direction. The loading spreads range from 0.37 to 0.49. Combined with an average investment factor return of 0.41%, the loading spreads explain additional 0.15% to 0.20% per month of momentum profits.

The pattern of the investment factor loadings is counterintuitive. Our prior is 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 dig deeper, we use an event study to examine how I/A varies across momentum portfolios. For each portfolio formation month t, 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. For a given portfolio we plot the median I/A of the firms in the portfolio.

Panel A of Figure 1 shows that the winners in the smallest size quintile do have higher I/A at the portfolio formation than the losers in the smallest size quintile. More important, the winners also have lower I/A than the losers from the event quarter -20 to -3. Similarly, the winners in the biggest size quintile have higher I/A at the portfolio formation than the losers in the biggest size quintile, but the winners have lower I/A from the event quarter -20 to -1. Because we sort stocks on I/A annually in constructing the new factors, the higher investment factor loadings for winners accurately capture their lower I/A than losers' several quarters prior to the portfolio formation.

Turning to calendar time, Panel B of Figure 1 shows that the winners in the smallest size quintile have higher contemporaneous I/A than the losers in the same 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 2003, the contemporaneous I/A is the I/A for the fiscal year ending in 2003. However, Panel C shows that the winners also have lower lagged (sorting-effective) I/A than the 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 corresponding 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 corresponding annual sort on I/A is in June 2003. Because we rebalance the I/A portfolios annually when constructing the new factors, the lower sorting-effective I/A of winners explains their higher investment factor loadings than losers.

3.2 Earnings Surprises

The new factor model largely explains the post-earnings announcement drift. Following Foster, Olsen, and Shevlin (1984), we measure earnings surprises as Standardized Unexpected Earnings (SUE). We calculate 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 this change in quarterly earnings over the prior eight quarters. (We require a minimum of six quarters in calculating SUE.) 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 3, the high-minus-low SUE decile earns an average return of 0.35% per month ($t = 2.77$), a CAPM alpha of 0.40% ($t = 3.27$), and a Fama-French alpha of 0.46% ($t = 3.55$). The new factor model reduces the alpha to insignificance: 0.12%, which is within one standard error of zero. The high-minus-low decile has an ROE factor loading of 0.35, which is more than six standard errors from zero. Intuitively, firms that have recently experienced positive earnings surprises are more profitable than firms that have recently experienced negative earnings surprises. In contrast, both the market beta and the investment factor loading of the high-minus-low decile are close to zero. The new factor model also reduces the m.a.e. from 0.16% in the CAPM and 0.17% in the Fama-French model to 0.10%. While the CAPM and the Fama-French model are strongly rejected by the GRS test, the new factor model cannot be rejected at the 5% significance level.

3.3 Idiosyncratic Volatility

Following Ang, Hodrick, Xing, and Zhang (2006), we measure a stock's idiosyncratic volatility ($IVOL$) as the standard deviation of the residuals from regressing the stock's returns on the Fama-French three factors. Each month we form value-weighted deciles by sorting all NYSE, Amex, and NASDAQ stocks on their $IVOL$ estimated using daily returns over the previous month (we require a minimum of 15 daily stock returns). We hold the value-weighted deciles for the current month, and rebalance the portfolios monthly. Consistent with Ang et al., high $IVOL$ stocks earn lower average returns than low $IVOL$ stocks. From Panel B of Table 3, the high-minus-low decile earns an average return of −1.27% per month ($t = -2.98$). The CAPM alpha and the Fama-French alpha of the high-minus-low decile are −1.65% and −1.68%, respectively, both of which are at least four standard errors from zero. Both models are rejected by the GRS test.

The new factor model reduces the high-minus-low alpha to −0.45% per month ($t = -1.28$). The m.a.e. also decreases to 0.26% from 0.38% in the CAPM and 0.37% in the Fama-French model. The high $IVOL$ decile has a substantially lower ROE loading than the low $IVOL$ decile: −1.19 versus 0.15. The loading spread of −1.28 is more than 8.8 standard errors from zero. Although going in the right direction to explain the average returns, the investment factor loading of the high-minus-low decile is only −0.28, which is within 1.5 standard errors of zero. However, the new factor model is still rejected by the GRS test. Ang, Hodrick, Xing, and Zhang (2006, Table VI) show that a big portion of the idiosyncratic volatility anomaly is due to the abnormally low average returns of high $IVOL$ stocks. Our evidence suggests that the extremely low average returns are largely driven by the low profitability of high $IVOL$ stocks.

3.4 Distress

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 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 1976, which is restricted by data availability. (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 monthly.

From Panel A of Table 4, more distressed firms earn lower average returns than less distressed firms. The high-minus-low failure probability decile earns an average return of -0.90% per month ($t = -1.98$). Controlling for risk exacerbates the anomaly because more distressed firms appear riskier. The high-minus-low decile has a CAPM beta of 0.82, which gives rise to a CAPM alpha of -1.37% ($t = -3.56$). In the Fama-French model the high-minus-low portfolio has a market beta of 0.70, a size factor loading of 1.25, and a value factor loading of 0.46. These positive risk measures produce a large Fama-French alpha of -1.85% ($t = 5.81$). The m.a.e. across the deciles is 0.33 in the CAPM and 0.42 in the Fama-French model. Both models are rejected by the GRS test.

The new factor model largely captures the distress effect via the ROE factor. The high-minus-low decile has an alpha of -0.10% per month in the new factor model, which is within 0.3 standard errors of zero. Going in the right direction to explain the distress anomaly, more distressed firms have lower ROE factor loadings than less distressed firms. The loading spread is -1.56, which is more than 7.5 standard errors from zero. Intuitively, more distressed firms are less profitable than less distressed firms. In particular, profitability enters the failure probability measure with a negative coefficient, which has the highest magnitude among the coefficients for all the other components (see equation (A1) in Appendix A). In contrast, the investment factor loading of the high-minus-low decile is only 0.15, which is within 0.7 standard errors from zero. The new factor model also reduces the m.a.e. to 0.16%, but is still rejected by the GRS test.

From Panel B of Table 4, using Ohlson's (1980) O-score as an alternative measure of financial distress yields largely similar results. The CAPM alpha for the high-minus-low decile is -0.77% per month ($t = -2.90$), and the Fama-French alpha is -1.06% ($t = -5.54$). In contrast, the new factor model reduces the high-minus-low alpha virtually to nonexistence: -0.02%. The driving force is again the large ROE factor loading for the high-minus-low decile, -0.90, which is more than 7.5 standard errors from zero. The new factor model also reduces the m.a.e. from 0.18% in the CAPM and 0.28% in the Fama-French model to 0.08%, and is not rejected by the GRS test.

3.5 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 yearend in $t-1$ to the split-adjusted shares outstanding at the fiscal yearend 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, 0.12% versus 0.67% per month. The high-minus-low decile earns an average return of -0.55% ($t = -3.58$), a CAPM alpha of -0.64% ($t = -4.40$), and a Fama-French alpha of -0.63% ($t = -4.42$). The new factor model reduces the high-minus-low alpha to insignificance: -0.26% ($t = -1.79$). However, all the three factor models produce roughly the same average magnitude of the alphas around 0.17%, and the models are all rejected by the GRS test.

The high-minus-low decile has an investment factor loading of -0.41 ($t = -3.41$), going in the right direction to explain the average returns. The evidence suggests that high net issues firms invest more than low net issues firms. The ROE factor loading also moves in the right direction. The high-minus-low decile has an ROE factor loading of -0.24 ($t = -3.65$), suggesting that high net issues firms are somewhat less profitable than low net issues firms at the portfolio formation. Loughran and Ritter (1995) show that new equity issuers are more profitable than nonissuers. Because net issues equal new issues minus share repurchases, our evidence is consistent with Lie (2005), who show that repurchasing firms exhibit superior operating performance relative to industry peers.

3.6 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 yearend of $t - 1$ minus total assets at the fiscal yearend of $t - 2$ divided by total assets at the fiscal yearend 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 high asset growth firms earns lower average returns than low asset growth firms: 0.20% versus 0.99% per month. The spread of -0.79% is almost four standard errors from zero. The high-minus-low decile earns a CAPM alpha of -0.87% ($t = -4.26$) and a Fama-French alpha of -0.45% ($t = -2.53$). The new factor model produces a high-minus-low alpha of -0.52% ($t = -2.80$). As such, the new factor model underperforms the Fama-French model. The new model also generates a slightly higher m.a.e. than the Fama-French model: 0.15% versus 0.14%. The m.a.e. from the CAPM is 0.22%. All the three models are rejected by the GRS test.

While the Fama-French model derives its explanatory power for the asset growth anomaly from the value factor, the new factor model works through the investment factor. The high-minus-low decile has an investment factor loading of -1.17, which is more than ten standard errors from zero. This loading pattern goes in the right direction to explain the average returns. The investment factor fails to fully capture the asset growth anomaly probably because asset growth is a more comprehensive measure of investment than I/A. Another reason is that high asset growth firms are more profitable than low asset growth firms. As such, the high-minus-low decile has an ROE factor loading of 0.23 ($t = 2.37$), going in the wrong direction to explain the average returns.

3.7 Book-to-Market Equity

Table 6 reports factor regressions of 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 1.02% per month ($t = 4.35$) in the smallest size quintile and 0.20% ($t = 0.99$) in the biggest size quintile. The small-stock value-minus-growth quintile has a CAPM alpha of 1.19% ($t = 5.33$), and a Fama-French alpha of 0.68% ($t = 5.38$). In particular, the small-growth portfolio has a Fama-French alpha of -0.56%, which is almost five standard errors from zero.[5] The big-stock value-minus-growth quintile has a CAPM alpha of 0.27% ($t = 1.32$) and a Fama-French alpha of -0.34% ($t = -2.59$).

The new factor model's performance seems comparable the Fama-French model's. The value-minus-growth alpha in the smallest size quintile is 0.67% per month ($t = 2.70$), and has a similar magnitude as the Fama-French alpha. The new factor model does a good job in capturing the small-growth anomaly. In contrast to the high Fama-French alpha of -0.56%, the alpha is a tiny -0.03% in the new factor model. Unlike the significantly negative alpha in the Fama-French model, the big-stock value-minus-growth quintile has an insignificant alpha of 0.13% in the new factor model. However, the small-value portfolio has an alpha of 0.64% ($t = 3.25$) in the new factor model. In contrast, the Fama-French alpha is only 0.13%, which is within 1.8 standard errors of zero. The Fama-French model also outperforms the new factor model according to the metric of m.a.e.: 0.10% versus

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

0.23%. The m.a.e. in the CAPM is 0.30%. All the three models are still rejected by the GRS test.

From Panel B, value stocks have higher investment factor loadings than growth stocks. The loading spreads, ranging from 0.62 to 0.92, are all more than 4.2 standard errors from zero. Intuitively, growth firms with high valuation ratios have more growth opportunities and invest more than value firms with low valuation ratios (e.g., Fama and French (1995)). The *ROE* factor loading pattern is more complicated. In the smallest size quintile, the high-minus-low portfolio has a positive loading of 0.29 ($t = 1.96$) because the small-growth portfolio has a large negative loading of −0.65. However, in the biggest size quintile, the loading spread reverts to −0.19, albeit insignificant. The large negative *ROE* factor loading for the small-growth portfolio is due to abnormally low profitability of small growth firms in the late 1990s and early 2000s (e.g., Fama and French (2004)).

3.8 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 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 factor models. Following Lewellen et al.'s prescription, we also confront the new factor model with a wide array of testing portfolios (in addition to size and book-to-market portfolios). We test the new factor model further with industry and CAPM beta portfolios. Because these portfolios do not display large average return spreads, 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 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 the models: 0.15% per month in the CAPM and 0.19% in both the Fama-French model and the new factor model. One out of ten individual alphas in the CAPM and three out of ten in both the Fama-French model and the new factor model are significant.

From Panel A of Table 8, none of the models are rejected by the GRS test using the CAPM beta deciles. The high-minus-low decile even earns a large negative CAPM alpha of -0.59% per month ($t = -1.91$). The high-minus-low alphas are -0.32% and 0.31% in the Fama-French model and the new factor model, respectively, both of which are insignificant. 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 0.30% 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 a small-minus-big alpha of 0.52% ($t = 1.93$).

4 Hansen-Jagannathan Distance

We have so far focused on the high-minus-low alphas as the primary metric for model comparison. This section provides additional evidence based on the Hansen-Jagannathan (1997, HJ) distance. Let $M_{t+1}(\boldsymbol{\theta}) = \theta_0 + \sum_{k=1}^{K} \theta_k F_{t+1}^k$ be a linear stochastic discount factor, in which $K \geq 1$ is the number of factors, F_{t+1}^k is the k^{th} factor, and $\boldsymbol{\theta} = (\theta_0, \theta_1, \ldots, \theta_K)$ is the vector of coefficients to be estimated. To compute the HJ distance for a model across a set of N testing portfolios with gross returns R_t^i for $i = 1, \ldots, N$, we define the vector of the sample average of pricing errors as $\mathbf{g}_T(\boldsymbol{\theta}) = (g_{1T}(\boldsymbol{\theta}), \ldots, g_{NT}(\boldsymbol{\theta}))'$, in which $g_{iT}(\boldsymbol{\theta}) = (1/T) \sum_{t=1}^{T} M_t(\boldsymbol{\theta}) R_t^i - 1$. Let $\mathbf{G}_T$ denote the sample second moment matrix of the N testing assets, meaning that the (i, j)-element of $\mathbf{G}_T$ is $(1/T) \sum_{t=1}^{T} R_t^i R_t^j$ for $i, j = 1, \ldots, N$. The HJ distance is calculated as $\sqrt{\min_{\{\boldsymbol{\theta}\}} \mathbf{g}_T(\boldsymbol{\theta})' \mathbf{G}_T^{-1} \mathbf{g}_T(\boldsymbol{\theta})}$. To ensure that different models of M have comparable means to facilitate model comparison, we include one-month Treasury bill rate into each set of testing portfolios (e.g., Hodrick and Zhang (2001)).

Table 9 shows that the new factor model has the smallest HJ distance among the three models for eight out of the 11 sets of testing portfolios. Across the 25 size and momentum portfolios, the new model has an HJ distance of 0.42, which is smaller than 0.50 for the CAPM and 0.48 for the Fama-French model. Across the *SUE* deciles, the HJ distance for the new model is 0.14, which is smaller than 0.26 for the CAPM and 0.18 for the Fama-French model. The new factor model also has the smallest HJ distance across the 25 size and book-to-market portfolios: 0.40 versus 0.47 for the CAPM and 0.43 for the Fama-French model. The Fama-French model has the same HJ distance as the new factor model across the O-score deciles (0.07), but slightly smaller HJ distances across the industry portfolios (0.13 versus 0.14) and the size deciles (0.09 versus 0.10).

Moving beyond testing whether a single model is specified without errors to comparing multiple potentially misspecified models, we test the null hypothesis whether the new factor model has the smallest HJ distance among the competing models. We follow the Chen and Ludvigson (2009) procedure, which is built on White (2000). For example, to test the null hypothesis across the 25 size and momentum portfolios, we let $\delta_T^2, \delta_{FF,T}^2, \delta_{q,T}^2$ be the sample estimates of the squared HJ distances for the CAPM, the Fama-French model, and the new factor model, respectively. The White test statistic is $\mathcal{T}_W \equiv \max\left(\sqrt{T}(\delta_{q,T}^2 - \delta_T^2), \sqrt{T}(\delta_{q,T}^2 - \delta_{FF,T}^2)\right)$, in which T is the sample length. If the null is true, the sample estimate of $\mathcal{T}_W$ should not be large and positive. In particular, given a distribution of $\mathcal{T}_W$, we can reject the null at the 5% significance level if the sample statistic is greater than the 95$^{\text{th}}$ percentile of the distribution. We use block bookstrap to obtain the finite sample distribution of $\mathcal{T}_W$. Let B be the number of bootstrap samples and $\mathcal{T}_W^b$ be the White statistic computed on the b^{th} bootstrap sample.[6] The p-value for the White test is $(1/B)\sum_{b=1}^{B} \mathcal{I}_{\{\mathcal{T}_W^b > \mathcal{T}_W\}}$, in which $\mathcal{I}$ is the indicator function that takes the value of one if $\mathcal{T}_W^b > \mathcal{T}_W$ and zero otherwise. At the 5% significance level, we can reject the null if the p-value is less than 5%, but fail to reject otherwise.

From the columns denoted $\delta_{q,T}$ in Table 9, the White's (2000) test fails to reject the null hypothesis that the new factor model has the smallest HJ distance. None of the p-values are lower than 5%. Several p-values are even higher than 90%: 99.7% for the 25 size and momentum portfolios, 97.5% for the SUE deciles, 97.5% for the 25 size and book-to-market portfolios. The

[6] Specifically, the resampling works by drawing a random starting point from the historical sample and then selecting a block of observations of random length. The block length assumes a geometric distribution with a mean of ten. We continue the drawing until we reach a bootstrap sample of length T. We repeat the whole procedure to obtain a total of $B = 1,000$ bootstrap samples (see White (2000, p. 1104) for more details on the block bootstrap).

lowest p-value is 39.3% for the size deciles. Using Hansen's (2005) modified test instead of the White test yields largely similar results (see the table caption for the description of the Hansen test).

The failure to reject the null does not mean that the new factor model is better than the Fama-French model. In the columns denoted $\delta_{FF,T}$ in Table 9, we also test the null hypothesis that the Fama-French model has the smallest HJ distance among the three factor models. Both the White's (2000) and the Hansen's (2005) tests fail to reject this null for a vast majority of the testing portfolios. For example, although the HJ distance of the Fama-French model across the SUE deciles, 0.18, is higher than that of the new factor model, 0.14, the p-value for the Fama-French model is 70.8%. Across the new stock issues decile, although the HJ distance of the Fama-French model, 0.26, is higher than that of the new factor model, 0.22, we fail to reject that the Fama-French model has the smallest HJ distance (p-value = 11%). The only case in which we can formally reject the null is when we use the 25 size and momentum portfolios (p-value = 0.3%).

5 Conclusion

A new three-factor model consisting of the market factor, an investment factor, and a return-on-equity factor is a good start to understanding capital markets anomalies. As in Fama and French (1993, 1996), the new factors can be interpreted as common risk factors in the context of Merton's (1973) intertemporal CAPM or Ross's (1976) arbitrage pricing theory (APT). At a minimum, the new factor model seems a parsimonious description of the cross-section of expected stock returns. As such, it might be useful in many applications that require expected return estimates, such as 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.

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A Variable Definitions of Failure Probability and O-Score

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

$$\text{Distress}(t) \equiv -9.164 - 20.264\, NIMTAAVG_t + 1.416\, TLMTA_t - 7.129\, EXRETAVG_t$$

$$+\,1.411\, SIGMA_t - 0.045\, RSIZE_t - 2.132\, CASHMTA_t + 0.075\, MB_t - 0.058\, PRICE_t \qquad \text{(A1)}$$

$$NIMTAAVG_{t-1,t-12} \equiv \frac{1-\phi^3}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}\right) \qquad \text{(A2)}$$

$$EXRETAVG_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12}\right), \qquad \text{(A3)}$$

in which $\phi = 2^{-1/3}$. $NIMTA$ 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 (Compustat quarterly 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 five 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 measured in the same way as the denominator of ROE (see Section 2). 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. Following Campbell et al., we winsorize the variables in the right-hand side of equation (A1) at the 5th and 95th percentiles of their pooled distribution across all firm-month observations.

We follow Ohlson (1980, Model One in Table 4) to construct the O-score: $-1.32 - 0.407\log(ADJASSET/CPI) + 6.03\,TLTA - 1.43\,WCTA + 0.076\,CLCA - 1.72\,OENEG - 2.37\,NITA - 1.83\,FUTL + 0.285\,INTWO - 0.521\,CHIN$, in which $ADJASSET$ is adjusted total assets calculated as total assets (Compustat quarterly item ATQ) + 0.1×(market equity − book equity). The adjustment of $ADJASSET$ using 10% of the difference between market equity and book equity follows Campbell, Hilscher, and Szilagyi (2008) to ensure that assets are not too close to zero. Book equity is measured in the same way as the denominator of ROE (see Section 2). 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 $ADJASSET$. $WCTA$ is working capital divided by market assets (item ACTQ − item LCTQ)/$ADJASSET$. $CLCA$ 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, $ADJASSET$. $FUTL$ 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 quarters 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 : Descriptive Statistics of the Investment Factor and the *ROE* Factor (1/1972–12/2010, 468 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). We measure ROE as income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity. Book equity is the shareholders' equity, plus balance sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use the stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus liabilities (item LTQ) in that order as the shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock. 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. Independently, in 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 ROE. Earnings and other accounting variables in Compustat quarterly files are used in portfolio sorts in the months immediately after the most recent public earnings announcement month (item RDQ). Also independently, in each month we split NYSE, Amex, and NASDAQ stocks into three size groups using the NYSE breakpoints for the low 30%, medium 40%, and high 30% of the ranked market capitalization (stock price times shares outstanding from CRSP). Taking intersections of the three I/A portfolios, the three ROE portfolios, and the three size portfolios, we form 27 portfolios. Monthly value-weighted returns on the 27 portfolios are calculated for the current month, and the portfolios are rebalanced monthly. The investment factor, r_{INV}, is the difference (low-minus-high I/A), each month, between the simple average of the returns on the nine low-I/A portfolios and the simple average of the returns on the nine high-I/A portfolios. The ROE factor, r_{ROE}, is the difference (high-minus-low ROE), each month, between the simple average of the returns on the nine high-ROE portfolios and the simple average of the returns on the nine low-ROE portfolios. In Panel A, we regress r_{INV} and r_{ROE} on traditional factors including the market factor (MKT), SMB, HML, and WML (from Kenneth French's Web site). The t-statistics (in parentheses) are adjusted for heteroskedasticity 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: Descriptive statistics of r_{INV} and r_{ROE}

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2
r_{INV}	0.41	0.46	−0.09				0.06
	(4.80)	(5.32)	(−3.92)				
		0.33	−0.06	0.06	0.22		0.19
		(4.25)	(−2.64)	(1.78)	(7.50)		
		0.25	−0.04	0.06	0.25	0.08	0.23
		(3.24)	(−2.08)	(2.14)	(8.23)	(3.15)	
r_{ROE}	0.71	0.80	−0.19				0.06
	(4.01)	(4.76)	(−3.08)				
		0.88	−0.12	−0.40	−0.05		0.18
		(5.42)	(−2.10)	(−4.26)	(−0.46)		
		0.58	−0.06	−0.40	0.05	0.30	0.33
		(3.52)	(−1.43)	(−3.41)	(0.53)	(4.41)	

Panel B: Correlation matrix (p-values)

	r_{ROE}	MKT	SMB	HML	WML
r_{INV}	0.07	−0.25	−0.03	0.41	0.15
	(0.11)	(0.00)	(0.56)	(0.00)	(0.00)
r_{ROE}		−0.25	−0.40	0.10	0.40
		(0.00)	(0.00)	(0.04)	(0.00)
MKT			0.27	−0.33	−0.14
			(0.00)	(0.00)	(0.00)
SMB				−0.24	−0.01
				(0.00)	(0.88)
HML					−0.16
					(0.00)

Table 2 : Calendar-Time Factor Regressions for Monthly Percent Excess Returns of 25 Size and Momentum Portfolios (1/1972–12/2010, 468 Months)

The 25 size and momentum portfolios are the intersections of quintiles formed on market capitalization 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. All the portfolio returns are value-weighted. Panel A reports mean percent excess returns and their t-statistics, CAPM alphas (α) and their t-statistics, as well as the intercepts (α_{FF}) and their t-statistics from the Fama-French three-factor regressions. Panel B reports the new three-factor regressions: $r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i\, MKT_t + \beta_{INV}^i\, r_{INV,t} + \beta_{ROE}^i\, r_{ROE,t} + \epsilon_t^i$. See Table 1 for the description of r_{INV} and r_{ROE}. The t-statistics are adjusted for heteroskedasticity and autocorrelations. For each factor model, we report the mean absolute error (m.a.e., the average magnitude of the alphas) across the testing portfolios and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas of all the 25 portfolios are jointly zero. We only show the results for quintiles 1, 3, and 5 for size and momentum to save space. L is the loser quintile, W is the winner quintile, S is the smallest size quintile, and B is the biggest size quintile. The data for the one-month Treasury bill rate (r^f) and the Fama-French factors are from Kenneth French's Web site.

	L	3	W	W−L	L	3	W	W−L	L	3	W	W−L	L	3	W	W−L
	Panel A: Means, CAPM alphas, and Fama-French alphas								Panel B: The new three-factor regressions							
	Mean				t				α_q (m.a.e. = 0.26)				t_{α_q} ($p_{GRS} = 0$)			
S	−0.13	0.76	1.16	1.29	−0.30	2.41	3.09	6.28	0.10	0.45	0.78	0.68	0.37	2.43	3.03	2.76
3	0.09	0.65	1.02	0.93	0.25	2.51	3.22	4.10	0.21	0.20	0.56	0.35	1.01	1.78	2.82	1.16
B	0.01	0.38	0.78	0.77	0.03	1.88	2.88	2.96	0.00	−0.07	0.33	0.33	0.01	−0.95	1.98	1.01
	α (m.a.e. = 0.31)				t_α ($p_{GRS} = 0$)				β_{INV}				$t_{\beta_{INV}}$			
S	−0.78	0.28	0.59	1.37	−3.21	1.63	2.74	7.20	−0.20	0.20	0.21	0.41	−1.53	2.23	1.64	3.06
3	−0.54	0.18	0.46	1.00	−2.92	1.72	3.09	4.63	−0.45	0.05	−0.08	0.37	−3.82	0.86	−0.68	2.10
B	−0.55	−0.03	0.29	0.84	−3.05	−0.51	2.25	3.33	−0.64	−0.06	−0.22	0.42	−5.30	−1.62	−2.40	2.32
	α_{FF} (m.a.e. = 0.31)				$t_{\alpha_{FF}}$ ($p_{GRS} = 0$)				β_{ROE}				$t_{\beta_{ROE}}$			
S	−1.04	−0.01	0.44	1.48	−6.63	−0.16	3.76	8.01	−0.99	−0.34	−0.35	0.64	−9.99	−3.94	−2.19	3.58
3	−0.66	−0.03	0.46	1.12	−4.07	−0.35	4.59	5.09	−0.69	−0.06	−0.09	0.60	−6.67	−0.94	−0.60	2.50
B	−0.50	−0.01	0.45	0.95	−2.62	−0.19	3.75	3.62	−0.33	0.08	0.08	0.41	−2.88	1.90	0.82	2.02

Table 3 : Calendar-Time Factor Regressions for Monthly Percent Excess Returns of Deciles Formed on Foster, Olsen, and Shevlin's (1984) Standardized Unexpected Earnings (SUE) and on Ang, Hodrick, Xing, and Zhang's (2006) Idiosyncratic Volatility ($IVOL$) (1/1972–12/2010, 468 Months)

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 change in quarterly earnings over the prior eight quarters (at least six quarters). 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. We measure $IVOL$ as the standard deviation of the residuals from the Fama-French three-factor regression. We form value-weighted decile portfolios each month by sorting all NYSE, Amex, and NASDAQ stocks on their $IVOL$ computed using daily returns over the previous month (we require a minimum of 15 daily observations). We hold these value-weighted portfolios for one month, and the portfolios are rebalanced monthly. We report the mean monthly percent excess returns, the CAPM regressions ($r_t^i - r_t^f = \alpha^i + \beta^i\, MKT_t + \epsilon_t^i$), the Fama-French regressions ($r_t^i - r_t^f = \alpha_{FF}^i + b^i\, MKT_t + s^i\, SMB_t + h^i\, HML_t + \epsilon_t^i$), and the new three-factor regressions ($r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i\, MKT_t + \beta_{INV}^i\, r_{INV,t} + \beta_{ROE}^i\, r_{ROE,t} + \epsilon_t^i$). For each factor model, we also report the mean absolute error (m.a.e., the average magnitude of the alphas) across a given set of testing portfolios and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas are jointly zero. All the t-statistics are adjusted for heteroskedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space. 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_{ROE}.

	Low	5	High	H−L	m.a.e. (p_{GRS})	Low	5	High	H−L	m.a.e. (p_{GRS})
	Panel A: The SUE deciles					Panel B: The $IVOL$ deciles				
Mean	0.41	0.44	0.77	0.35		0.49	0.71	−0.77	−1.27	
t	1.60	1.84	3.46	2.77		2.76	2.28	−1.58	−2.98	
α	−0.07	−0.02	0.33	0.40	0.16	0.16	0.13	−1.49	−1.65	0.38
β	1.04	0.99	0.94	−0.10	(0.00)	0.72	1.26	1.54	0.82	(0.00)
t_α	−0.70	−0.25	4.67	3.27		2.03	1.08	−4.65	−4.47	
α_{FF}	−0.06	0.00	0.40	0.46	0.17	0.14	0.22	−1.54	−1.68	0.37
b	1.05	0.98	0.94	−0.10	(0.00)	0.78	1.15	1.28	0.50	(0.00)
s	−0.04	0.01	−0.12	−0.08		−0.22	0.31	1.18	1.40	
h	0.00	−0.03	−0.09	−0.09		0.09	−0.25	−0.19	−0.29	
$t_{\alpha_{FF}}$	−0.63	−0.05	5.62	3.55		2.09	2.13	−5.85	−5.72	
α_q	0.08	0.09	0.20	0.12	0.10	−0.02	0.52	−0.47	−0.45	0.26
β_{MKT}	1.00	0.96	0.97	−0.03	(0.07)	0.76	1.18	1.30	0.54	(0.00)
β_{INV}	−0.04	−0.08	−0.05	−0.01		0.13	−0.40	−0.15	−0.28	
β_{ROE}	−0.16	−0.09	0.19	0.35		0.15	−0.25	−1.19	−1.34	
t_{α_q}	0.77	1.12	2.62	0.91		−0.28	4.21	−1.52	−1.28	
$t_{\beta_{MKT}}$	36.61	43.03	44.12	−0.87		40.60	48.80	18.90	6.73	
$t_{\beta_{INV}}$	−0.56	−1.24	−0.84	−0.06		2.78	−4.48	−0.91	−1.48	
$t_{\beta_{ROE}}$	−3.28	−2.45	7.15	6.13		4.31	−6.19	−9.29	−8.84	

Table 4 : Calendar-Time 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

We sort all NYSE, Amex, and NASDAQ stocks at the beginning of each month into deciles on the most recent failure probability and, separately, on O-score. (Appendix A contains detailed variable definitions.) Earnings and other accounting variables 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 monthly percent excess returns, the CAPM regressions ($r^i_t - r^f_t = \alpha^i + \beta^i\, MKT_t + \epsilon^i_t$), the Fama-French regressions ($r^i_t - r^f_t = \alpha^i_{FF} + b^i\, MKT_t + s^i\, SMB_t + h^i\, HML_t + \epsilon^i_t$), and the new three-factor regressions ($r^i_t - r^f_t = \alpha^i_q + \beta^i_{MKT}\, MKT_t + \beta^i_{INV}\, r_{INV,t} + \beta^i_{ROE}\, r_{ROE,t} + \epsilon^i_t$). For each factor model, we also report the mean absolute error (m.a.e., the average magnitude of the alphas) across a given set of testing portfolios and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas are jointly zero. The t-statistics are adjusted for heteroskedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space. 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_{ROE}.

	Low	5	High	H−L	m.a.e. (p_{GRS})	Low	5	High	H−L	m.a.e. (p_{GRS})
	Panel A: The failure probability deciles (1/1976–12/2010, 420 months)					Panel B: The O-score deciles (1/1972–12/2010, 468 months)				
Mean	0.74	0.64	−0.16	−0.90		0.49	0.43	−0.09	−0.58	
t	3.05	2.54	−0.28	−1.98		2.04	1.75	−0.21	−1.96	
α	0.21	0.05	−1.15	−1.37	0.33	0.02	−0.02	−0.75	−0.77	0.18
β	0.91	1.04	1.73	0.82	(0.00)	1.01	0.97	1.43	0.41	(0.11)
t_α	2.04	0.55	−3.31	−3.56		0.24	−0.20	−3.01	−2.90	
α_{FF}	0.31	0.05	−1.54	−1.85	0.42	0.20	−0.21	−0.86	−1.06	0.28
b	0.87	1.03	1.57	0.70	(0.00)	0.97	0.98	1.20	0.23	(0.00)
s	0.02	0.02	1.26	1.25		−0.13	0.29	1.14	1.27	
h	−0.20	−0.02	0.26	0.46		−0.31	0.29	−0.07	0.23	
$t_{\alpha_{FF}}$	3.01	0.59	−5.70	−5.81		3.29	−2.33	−4.73	−5.54	
α_q	0.09	0.25	−0.01	−0.10	0.16	0.13	0.01	0.11	−0.02	0.08
β_{MKT}	0.95	0.99	1.44	0.49	(0.00)	0.99	0.97	1.23	0.24	(0.40)
β_{INV}	−0.12	−0.20	0.02	0.15		−0.26	0.07	−0.34	−0.08	
β_{ROE}	0.20	−0.14	−1.36	−1.56		0.01	−0.08	−0.90	−0.90	
t_{α_q}	0.62	2.36	−0.03	−0.26		1.57	0.12	0.53	−0.07	
$t_{\beta_{MKT}}$	34.21	47.07	23.24	6.86		50.52	24.41	19.28	3.43	
$t_{\beta_{INV}}$	−1.54	−3.33	0.12	0.65		−5.14	1.04	−2.45	−0.52	
$t_{\beta_{ROE}}$	2.46	−2.76	−9.74	−7.62		0.18	−1.44	−7.98	−7.77	

Table 5 : Calendar-Time Factor Regressions for Monthly Percent Excess Returns of the Net Stock Issues Deciles and the Asset Growth Deciles (1/1972–12/2010, 468 Months)

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 $t-2$. 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 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 decile one, and 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. In June of each year t, we sort NYSE, Amex, and NASDAQ stocks into deciles based on asset growth measured at the end of the last fiscal yearend $t-1$. Asset growth for fiscal year $t-1$ is the change in total assets (item AT) from the fiscal yearend of $t-2$ to the 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 $t+1$, and the portfolios are rebalanced in June. We report mean monthly percent excess returns, the CAPM regressions ($r_t^i - r_t^f = \alpha^i + \beta^i\, MKT_t + \epsilon_t^i$), the Fama-French regressions ($r_t^i - r_t^f = \alpha_{FF}^i + b^i\, MKT_t + s^i\, SMB_t + h^i\, HML_t + \epsilon_t^i$), and the new three-factor regressions ($r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i\, MKT_t + \beta_{INV}^i\, r_{INV,t} + \beta_{ROE}^i\, r_{ROE,t} + \epsilon_t^i$). For each factor model, we also report the mean absolute error (m.a.e., the average magnitude of the alphas) across a given set of testing portfolios and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas are jointly zero. The t-statistics are adjusted for heteroskedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and high-minus-low (H−L) to save space. 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_{ROE}.

	Low	5	High	H−L	m.a.e. (p_{GRS})	Low	5	High	H−L	m.a.e. (p_{GRS})
	Panel A: The net stock issues deciles					Panel B: The asset growth deciles				
Mean	0.67	0.66	0.12	−0.55		0.99	0.55	0.20	−0.79	
t	3.25	2.84	0.43	−3.58		3.04	2.67	0.59	−3.99	
α	0.25	0.20	−0.38	−0.64	0.18	0.45	0.15	−0.42	−0.87	0.22
β	0.90	0.97	1.09	0.19	(0.00)	1.17	0.88	1.33	0.16	(0.00)
t_α	3.77	2.56	−3.25	−4.40		2.66	2.13	−3.21	−4.26	
α_{FF}	0.21	0.25	−0.41	−0.63	0.16	0.22	0.07	−0.23	−0.45	0.14
b	0.94	0.95	1.03	0.09	(0.00)	1.12	0.92	1.20	0.08	(0.00)
s	−0.10	0.01	0.30	0.40		0.60	−0.07	0.22	−0.38	
h	0.10	−0.10	−0.01	−0.11		0.29	0.15	−0.42	−0.71	
$t_{\alpha_{FF}}$	3.37	3.30	−3.46	−4.42		1.50	1.18	−2.03	−2.53	
α_q	0.09	0.25	−0.18	−0.26	0.17	0.44	0.06	−0.09	−0.52	0.15
β_{MKT}	0.94	0.97	1.05	0.11	(0.00)	1.16	0.89	1.26	0.09	(0.00)
β_{INV}	0.16	−0.18	−0.25	−0.41		0.56	0.20	−0.61	−1.17	
β_{ROE}	0.12	0.04	−0.11	−0.24		−0.30	−0.01	−0.07	0.23	
t_{α_q}	1.35	2.83	−1.41	−1.79		2.47	0.95	−0.70	−2.80	
$t_{\beta_{MKT}}$	59.09	47.53	30.51	3.10		27.93	48.98	41.69	2.17	
$t_{\beta_{INV}}$	4.18	−2.96	−2.21	−3.41		5.15	3.98	−7.72	−10.22	
$t_{\beta_{ROE}}$	3.38	1.24	−2.19	−3.65		−3.84	−0.32	−1.39	2.37	

Table 6 : Calendar-Time Factor Regressions for Monthly Percent Excess Returns of 25 Size and Book-to-Market Equity Portfolios (1/1972–12/2010, 468 Months)

For all the testing portfolios, Panel A reports mean percent excess returns and their t-statistics (t), the CAPM alphas (α) and their t-statistics (t), as well as the intercepts (α_{FF}) and their t-statistics from the Fama-French three-factor regressions. Panel B reports the new three-factor regressions: $r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i MKT_t + \beta_{INV}^i r_{INV,t} + \beta_{ROE}^i r_{ROE,t} + \epsilon_t^i$. See Table 1 for the description of r_{INV} and r_{ROE}. The t-statistics are adjusted for heteroskedasticity and autocorrelations. For each factor model, we also report the mean absolute error (m.a.e., the average magnitude of the alphas) and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas are jointly zero. We only report the results of quintiles 1, 3, and 5 for size and book-to-market to save space. L is the growth quintile, H is the value quintile, S is the smallest size quintile, and B is the biggest size quintile. 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 from Kenneth French's Web site.

	L	3	H	H−L	L	3	H	H−L	L	3	H	H−L	L	3	H	H−L
	Panel A: Means, CAPM alphas, and Fama-French alphas								Panel B: The new three-factor regressions							
	Mean				t				α_q (m.a.e. = 0.23)				t_{α_q} ($p_{GRS} = 0$)			
S	0.09	0.82	1.11	1.02	0.21	2.66	3.34	4.35	−0.03	0.42	0.64	0.67	−0.11	2.18	3.25	2.70
3	0.42	0.77	1.07	0.65	1.27	3.11	3.97	2.72	0.15	0.18	0.42	0.27	0.88	1.56	2.44	1.15
B	0.39	0.49	0.58	0.20	1.62	2.32	2.37	0.99	−0.10	−0.08	0.04	0.13	−1.12	−0.74	0.23	0.66
	α (m.a.e = 0.30)				t_α ($p_{GRS} = 0$)				β_{INV}				$t_{\beta_{INV}}$			
S	−0.56	0.34	0.63	1.19	−2.31	1.96	3.11	5.33	−0.02	0.39	0.61	0.63	−0.15	3.82	5.22	5.14
3	−0.18	0.32	0.62	0.80	−1.32	2.61	3.56	3.53	−0.36	0.25	0.55	0.92	−3.91	3.81	4.50	6.70
B	−0.07	0.09	0.19	0.27	−0.82	0.84	1.26	1.32	−0.18	0.17	0.44	0.62	−3.29	2.91	3.72	4.27
	α_{FF} (m.a.e. = 0.10)				$t_{\alpha_{FF}}$ ($p_{GRS} = 0$)				β_{ROE}				$t_{\beta_{ROE}}$			
S	−0.56	0.06	0.13	0.68	−4.93	0.91	1.79	5.38	−0.65	−0.33	−0.36	0.29	−3.99	−2.98	−4.28	1.96
3	−0.05	0.03	0.14	0.18	−0.67	0.33	1.27	1.40	−0.21	0.03	−0.07	0.14	−1.94	0.49	−0.72	0.77
B	0.16	−0.03	−0.18	−0.34	2.62	−0.37	−1.61	−2.59	0.14	0.11	−0.05	−0.19	3.78	1.79	−0.45	−1.48

Table 7 : Calendar-Time Factor Regressions for Monthly Percent Excess Returns of Ten Industry Portfolios (1/1972–12/2010, 468 Months)

We report the mean excess returns in monthly percent and their t-statistics (t), the CAPM regressions ($r_t^i - r_t^f = \alpha^i + \beta^i\, MKT_t + \epsilon_t^i$), the Fama-French three-factor regressions ($r_t^i - r_t^f = \alpha_{FF}^i + b^i\, MKT_t + s^i\, SMB_t + h^i\, HML_t + \epsilon_t^i$), and the new three-factor regressions ($r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i\, MKT_t + \beta_{INV}^i\, r_{INV,t} + \beta_{ROE}^i\, r_{ROE,t} + \epsilon_t^i$). For each factor model, we also report the mean absolute error (m.a.e., the average magnitude of the alphas) across a given set of testing portfolios and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas are jointly zero. The t-statistics are adjusted for heteroskedasticity and autocorrelations. The Treasury bill rate (r^f), the Fama-French three factors, and ten industry portfolio returns are from Kenneth French's Web site. See Table 1 for the description of r_{INV} and r_{ROE}.

	NoDur	Durbl	Manuf	Enrgy	HiTec	Telcm	Shops	Hlth	Utils	Other	m.a.e. (p_{GRS})
Mean	0.65	0.43	0.56	0.73	0.50	0.51	0.52	0.54	0.46	0.46	
t	2.97	1.29	2.24	2.92	1.48	2.14	1.92	2.33	2.35	1.70	
α	0.29	−0.09	0.08	0.36	−0.10	0.15	0.06	0.16	0.22	−0.04	0.15
β	0.78	1.13	1.04	0.78	1.28	0.78	1.00	0.81	0.52	1.07	(0.07)
t_α	2.13	−0.52	0.82	1.90	−0.60	0.90	0.42	1.06	1.39	−0.33	
α_{FF}	0.21	−0.42	−0.02	0.28	0.19	0.14	0.00	0.37	0.01	−0.23	0.19
b	0.84	1.22	1.08	0.88	1.11	0.83	0.99	0.81	0.65	1.16	(0.00)
s	−0.10	0.15	−0.03	−0.25	0.22	−0.21	0.12	−0.32	−0.18	−0.03	
h	0.18	0.58	0.19	0.22	−0.59	0.07	0.09	−0.32	0.46	0.38	
$t_{\alpha_{FF}}$	1.58	−2.66	−0.22	1.48	1.34	0.86	−0.02	2.63	0.04	−2.53	
α_q	−0.09	−0.19	−0.09	0.40	0.38	0.22	−0.15	−0.07	0.01	−0.32	0.19
β_{MKT}	0.87	1.14	1.07	0.78	1.17	0.76	1.05	0.87	0.56	1.13	(0.01)
β_{INV}	0.26	0.42	0.10	−0.37	−0.39	0.20	0.05	−0.03	0.16	0.35	
β_{ROE}	0.33	−0.12	0.15	0.16	−0.38	−0.21	0.23	0.31	0.18	0.16	
t_{α_q}	−0.74	−0.92	−0.98	1.97	2.22	1.23	−0.98	−0.44	0.07	−3.00	
$t_{\beta_{MKT}}$	26.80	22.34	51.55	15.76	30.20	19.75	25.70	17.99	14.63	41.86	
$t_{\beta_{INV}}$	3.65	2.96	1.72	−2.53	−3.14	1.69	0.56	−0.24	1.36	5.30	
$t_{\beta_{ROE}}$	5.86	−0.89	2.72	2.06	−5.17	−2.48	3.67	3.80	2.28	2.57	

Table 8 : Calendar-Time Factor Regressions for Monthly Percent Excess Returns of Deciles Formed on Pre-ranking CAPM Betas and on Market Equity (1/1972–12/2010, 468 Months)

We estimate pre-ranking CAPM betas using 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 (t), the CAPM regressions ($r_t^i - r_t^f = \alpha^i + \beta^i MKT_t + \epsilon_t^i$), the Fama-French three-factor regressions ($r_t^i - r_t^f = \alpha_{FF}^i + b^i MKT_t + s^i SMB_t + h^i HML_t + \epsilon_t^i$), and the new three-factor regressions ($r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i MKT_t + \beta_{INV}^i r_{INV,t} + \beta_{ROE}^i r_{ROE,t} + \epsilon_t^i$). For each factor model, we also report the mean absolute error (m.a.e., the average magnitude of the alphas) across a given set of testing portfolios and the p-value (p_{GRS}) associated with the GRS F-statistic testing that the alphas are jointly zero. The t-statistics are adjusted for heteroskedasticity and autocorrelations. We only report the results of deciles 1 (Low), 5, 10 (High), and H−L (high-minus-low) in Panel A and deciles S (Small), 5, B (Big), and S−B (small-minus-big) to save space. 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_{ROE}.

	Panel A: The pre-ranking beta deciles					Panel B: The market equity deciles				
	Low	5	High	H−L	m.a.e. (p_{GRS})	S	5	B	S−B	m.a.e. (p_{GRS})
Mean	0.44	0.57	0.40	−0.04		0.68	0.71	0.40	0.27	
t	2.30	2.38	0.82	−0.10		1.98	2.47	1.92	1.09	
α	0.17	0.11	−0.42	−0.59	0.16	0.19	0.18	−0.03	0.21	0.13
β	0.59	0.98	1.76	1.17	(0.28)	1.06	1.14	0.93	0.13	(0.09)
t_α	1.17	1.35	−1.79	−1.91		0.91	1.76	−0.52	0.87	
α_{FF}	0.03	0.04	−0.29	−0.32	0.09	−0.09	0.02	0.05	−0.14	0.04
b	0.65	1.02	1.51	0.86	(0.54)	0.89	1.04	0.97	−0.08	(0.03)
s	−0.04	−0.05	0.81	0.85		1.17	0.68	−0.30	1.46	
h	0.27	0.15	−0.45	−0.72		0.23	0.15	−0.07	0.30	
$t_{\alpha_{FF}}$	0.22	0.49	−1.64	−1.32		−1.00	0.34	1.66	−1.50	
α_q	0.00	−0.04	0.31	0.31	0.12	0.43	0.29	−0.09	0.52	0.22
β_{MKT}	0.63	1.02	1.59	0.97	(0.22)	1.00	1.11	0.95	0.05	(0.13)
β_{INV}	0.03	0.07	−0.40	−0.43		0.32	0.08	−0.01	0.34	
β_{ROE}	0.20	0.14	−0.68	−0.88		−0.49	−0.18	0.09	−0.58	
t_{α_q}	−0.03	−0.42	1.33	1.04		1.90	2.47	−1.66	1.93	
$t_{\beta_{MKT}}$	15.05	50.65	27.87	11.45		18.78	32.98	60.64	0.82	
$t_{\beta_{INV}}$	0.33	1.38	−2.53	−2.10		2.99	1.11	−0.42	2.47	
$t_{\beta_{ROE}}$	2.74	2.76	−8.21	−6.91		−3.94	−2.81	2.78	−3.76	

Table 9 : The Chen and Ludvigson (2009) Model Comparison Tests Based on the Hansen-Jagannathan (HJ, 1997) Distance (1/1972–12/2010, 468 Months)

For each set of testing portfolios, we report the HJ distances for the CAPM, δ_T, the Fama-French model, $\delta_{FF,T}$, and the new three-factor model, $\delta_{q,T}$. Let M_{t+1} denote a linear stochastic discount factor model: $M_{t+1} = \theta_0 + \sum_{k=1}^{K} \theta_k F_{t+1}^k$, in which $K \geq 1$ is the number of factors, F_{t+1}^k is the k^{th} factor, and θ_0 and θ_k are parameters. Let $\boldsymbol{\theta}$ be the vector of parameters in a model M, $R_t^i, i = 1, \ldots, N$ and $t = 1, \ldots, T$ be the gross returns for a set of N testing portfolios, $\mathbf{g}_T(\boldsymbol{\theta}) = (g_{1T}(\boldsymbol{\theta}), \ldots, g_{NT}(\boldsymbol{\theta}))'$ be the vector of the sample average of pricing errors, that is, $g_{iT}(\boldsymbol{\theta}) = (1/T)\sum_{t=1}^{T} M_t(\boldsymbol{\theta}) R_t^i - 1$, $\mathbf{G}_T$ be the sample second moment matrix of the N testing portfolios, that is, the (i,j)-element of $\mathbf{G}_T$ is $(1/T)\sum_{t=1}^{T} R_t^i R_t^j$ for $i, j = 1, \ldots, N$. The HJ distance is $\sqrt{\min_{\{\boldsymbol{\theta}\}} \mathbf{g}_T(\boldsymbol{\theta})' \mathbf{G}_T^{-1} \mathbf{g}_T(\boldsymbol{\theta})}$. To pin down the means of the stochastic discount factors, we include one-month Treasury bill (gross) rate into each set of testing portfolios. We report two sets of p-values in percent: The White (2000) p-values (in parenthesis) and the Hansen (2005) p-values (in brackets). The null hypothesis tested in a given column is that the underlying model has the smallest HJ distance among the three models. For example, to test whether the new factor model has the smallest HJ distance, we employ White's (2000) test statistic, $\mathcal{T}_W \equiv \max\left(\sqrt{T}(\delta_{q,T}^2 - \delta_T^2), \sqrt{T}(\delta_{q,T}^2 - \delta_{FF,T}^2)\right)$, and Hansen's (2005) modified test statistic, $\mathcal{T}_H \equiv \max\left(\max\left(\sqrt{T}(\delta_{q,T}^2 - \delta_T^2), \sqrt{T}(\delta_{q,T}^2 - \delta_{FF,T}^2)\right), 0\right)$. Define $\mathcal{T}_W^b$ and $\mathcal{T}_H^b$ as the White and the Hansen statistics computed in the b^{th} bootstrap sample, respectively. With B bootstrap samples, we calculate the White p-value as $(1/B)\sum_{b=1}^{B} \mathcal{I}_{\{\mathcal{T}_W^b > \mathcal{T}_W\}}$ and the Hansen p-value as $(1/B)\sum_{b=1}^{B} \mathcal{I}_{\{\mathcal{T}_H^b > \mathcal{T}_H\}}$, in which $\mathcal{I}_{\{\cdot\}}$ is the indicator function that takes the value of one if the event described in $\{\cdot\}$ is true and zero otherwise. At the 5% significance level, the tests reject the null hypothesis if the p-values are less than 5%, but fail to reject otherwise. The tests that the CAPM (or the Fama-French model) has the smallest HJ distance are designed analogously.

δ_T	$\delta_{FF,T}$	$\delta_{q,T}$	δ_T	$\delta_{FF,T}$	$\delta_{q,T}$	δ_T	$\delta_{FF,T}$	$\delta_{q,T}$
Size and momentum			*SUE*			*IVOL*		
0.496	0.481	0.416	0.263	0.177	0.136	0.298	0.167	0.157
(3.8)	(0.3)	(99.7)	(0.7)	(70.8)	(97.5)	(0.8)	(91.0)	(94.0)
[3.8]	[0.3]	[96.0]	[0.7]	[70.8]	[93.4]	[0.8]	[91.0]	[92.6]
Failure probability			*O*-score			Net stock issues		
0.253	0.204	0.186	0.183	0.071	0.071	0.295	0.258	0.218
(12.2)	(56.8)	(85.4)	(2.8)	(89.4)	(89.9)	(11.1)	(11.0)	(95.3)
[12.2]	[56.8]	[78.3]	[2.8]	[89.4]	[89.9]	[11.1]	[11.0]	[85.9]
Asset growth			Size and book-to-market			Industries		
0.256	0.175	0.172	0.469	0.428	0.399	0.152	0.132	0.137
(3.0)	(86.0)	(85.8)	(3.8)	(38.5)	(97.5)	(63.1)	(65.0)	(45.9)
[3.0]	[86.0]	[84.8]	[3.8]	[38.5]	[92.4]	[63.1]	[61.0]	[45.9]
Beta			Size					
0.151	0.117	0.106	0.108	0.090	0.098			
(23.8)	(54.4)	(79.9)	(77.3)	(65.0)	(39.3)			
[23.8]	[54.4]	[74.1]	[77.3]	[58.6]	[39.3]			

Figure 1. Investment-to-assets in annual percent (I/A, contemporaneous and lagged) for the 25 size and momentum portfolios, 1972:Q1 to 2010:Q4 (156 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). 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). The monthly size breakpoints are based on NYSE quintiles. For each portfolio formation month t, we calculate annual I/A for $t + m, m = -60, \ldots, 60$. The I/A for month $t + m$ is averaged across the portfolio formation months. Panel A plots the median I/A across firms in the four extreme portfolios. Panel B plots I/A as the current year-end I/A relative to month t. Panel C plots the lagged I/A as the I/A on which an annual I/A sort in each June is based.

Panel A: Event-time I/A | Panel B: Calendar-time I/A | Panel C: Calendar-time I/A (lagged)