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Neoclassical Factors

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Abstract

We propose a new multifactor model that consists of the market factor and factor mimicking portfolios based on investment and productivity motivated from neoclassical reasoning. The neoclassical three-factor model goes a long way in explaining the average returns across testing portfolios formed on momentum, financial distress, investment, profitability, net stock issues, and valuation ratios. In particular, winners have higher loadings than losers on both the low-minus-high investment factor and the high-minus-low productivity factor. We suggest that the neoclassical model is a good start to understanding the cross-sectional variations of average stock returns.

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1 Introduction

The Sharpe (1964) and Lintner (1965) capital asset pricing model (CAPM) cannot explain asset pricing anomalies. For example, DeBondt and Thaler (1985), Fama and French (1992), and Lakonishok, Shleifer, and Vishny (1994) show that average returns covary with book-to-market, earnings-to-price, and long-term prior returns. Jegadeesh and Titman (1993) show that stocks with higher short-term prior returns earn higher average returns. Fama and French (1993, 1996) show that their three-factor model, which includes the market excess return (MKT), a mimicking portfolio based on market equity (SMB), and a mimicking portfolio based on book-to-market (HML), can explain many CAPM anomalies. These include average returns across portfolios formed on size and book-to-market, earnings-to-price, cash flow-to-price, and long-term prior returns. Notably, these portfolios display strong HML-loading variations in the same direction as their average returns.

However, the influential Fama-French (1993) model leaves many important anomalies unexplained. Most glaringly, Fama and French (1996) show that their model cannot explain Jegadeesh and Titman's (1993) momentum profits. Winners load positively on HML and losers load negatively on HML. This pattern goes in the opposite direction as the average returns, driving the Fama-French model to exacerbate the momentum anomaly.

The distress-return relation also eludes the Fama-French (1993) model. Fama and French (1996) conjecture that the average HML return might be a risk premium for the relative distress of value firms. The returns of distressed firms tend to move together, meaning that their distress risk cannot be diversified and needs to be compensated with a risk premium. However, recent studies show that distress is associated with lower average returns (e.g., Dichev 1998, Griffin and Lemmon 2002, Campbell, Hilscher, and Szilagyi 2007). Using a comprehensive measure of distress, Campbell et al. report that more distressed stocks earn lower average returns despite their higher total volatilities, market betas, and SMB- and HML-loadings. They suggest that: "This result is a significant challenge to the conjecture that the value and size effects are proxies for a financial distress premium. More generally, it 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. 29)."

We show that the momentum and the distress anomalies are related, and are captured by a new multifactor model motivated from neoclassical reasoning. The model says that the expected return on a portfolio in excess of the risk-free rate, $E[R_j] - R_f$, is described by the sensitivity of its return to three factors: MKT, the difference between the return on a portfolio of low investment-to-assets stocks and the return on a portfolio of high investment-to-assets stocks (INV), and the difference between the return on a portfolio of high earnings-to-assets stocks and the return on a portfolio of low earnings-to-assets stocks ($PROD$). Specifically, the expected excess return on portfolio j is:

$$E[R_j] - R_f = b_j\, E[MKT] + i_j\, E[INV] + p_j\, E[PROD] \tag{1}$$

in which $E[MKT], E[INV]$, and $E[PROD]$ are expected premiums, and the factor loadings, b_j, i_j, and p_j are the slopes in the time series regression:

$$R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j \tag{2}$$

In our 1972–2006 sample, INV and $PROD$ earn average returns of 0.43% ($t = 4.75$) and 0.96% per month ($t = 5.10$), respectively. These average returns subsist after adjusting for their exposures to traditional factors such as the Fama-French (1993) factors and the Carhart (1997) factors. More important, the neoclassical model does a good job in explaining the average returns of 25 size and momentum portfolios. We find that none of the winner-minus-loser portfolios across five size quintiles have significant alphas. The alphas, ranging from 0.08% to 0.54% per month, are all within 1.70 standard errors of zero. For comparison, the five winner-minus-loser alphas vary from 0.92% ($t = 3.10$) to 1.33% per month ($t = 5.78$) in the CAPM and from 0.92% ($t = 2.68$) to 1.44% ($t = 5.54$) in the Fama-French model. However, our model is still rejected by the Gibbons, Ross, and Shanken (1989, GRS) test, as are the CAPM and the Fama-French model.

One reason for the relative success of the neoclassical model is that winners have higher $PROD$-loadings than losers, meaning that winners are more profitable than losers. More intriguingly, winners also have higher INV-loadings than losers. The crux is timing. We show that winners (with high valuation ratios) indeed invest more than losers (with low valuation ratios) at the portfolio formation month t. But more important, winners invest less than losers in the event time before month $t-8$ or $t-12$, depending on the specific size quintile. Because INV is rebalanced annually, the higher INV-loadings for winners accurately reflect their lower investment than losers several quarters prior to the monthly portfolio formation.

The neoclassical model fully captures the negative relation between financial distress and average returns. For example, using Campbell, Hilscher, and Szilagyi's (2007) failure probability measure, we find that the high-minus-low distress decile earns a neoclassical alpha of -0.32% per month ($t = -1.09$). The model cannot be rejected across the distress deciles by the GRS test (p

= 0.06). In contrast, the corresponding alpha is -1.87% ($t = -5.08$) in the CAPM and -2.14% ($t = -6.43$) in the Fama-French (1993) model. Both are rejected by the GRS test at the 1% level. Using Ohlson's (1980) O-score as the distress measure yields similar results. The $PROD$-loading is the main driver of our model performance: More distressed firms are less profitable and have lower $PROD$-loadings than less distressed firms. Previous studies overlook the positive productivity-return relation, and, not surprisingly, find the distress-return relation anomalous.

Several other anomaly variables have recently received much attention such as investment, profitability, and net stock issues. (We provide detailed references later in this section.) We show that the neoclassical model outperforms traditional factor models in explaining these anomalies, sometimes by a big margin. For example, in the universe of 25 investment and profitability portfolios, all but one of the neoclassical alphas for the five low-minus-high investment portfolios are within 1.5 standard errors of zero. In contrast, four out of five CAPM alphas and four out of five Fama-French alphas are significant. The average magnitude of the low-minus-high investment alphas is also lower in our model: 0.26% per month versus 0.79% in the CAPM and 0.59% in the Fama-French model. Further, the average magnitude of alpha for the high-minus-low profitability portfolios is also lower in our model: 0.39% per month versus 1.15% in the CAPM and 1.27% in the Fama-French model.

Our neoclassical model also performs roughly as well as the Fama-French (1993) model in explaining portfolios formed on valuation ratios such as book-to-market. While the Fama-French model explains these portfolio returns through their HML factor, the main driver in our model is the INV factor. Stocks with lower market valuation ratios invest less, load more on the low-minus-high INV factor, and earn higher average returns. Empirically, the explanatory power of INV for valuation-sorted portfolio returns is comparable to that of HML. This evidence lends support to Xing (2007), who shows that a similarly constructed investment factor helps explain the value effect. We add to Xing by examining the effects of $PROD$. Most important, the small-growth portfolio only earns a tiny neoclassical alpha of 0.08% per month ($t = 0.27$) in contrast to the CAPM alpha of -0.63% ($t = -2.61$) and the Fama-French alpha of -0.52% ($t = -4.48$). We show that this neoclassical alpha is linked to the abysmally low profitability of the small-growth firms in the 1990s.

At a minimum, our evidence shows that the neoclassical three-factor model is a good start to describing the cross-sectional variations of average stock returns. This evidence, coupled with the motivation of our factors from equilibrium asset pricing theory, suggests that the neoclassical model can be used in many applications that require estimates of expected stock returns. The list includes evaluating mutual fund performance, measuring abnormal returns in event studies, and estimating expected returns for portfolio choice and costs of capital for capital budgeting.

Our work adds to a large finance and accounting literature that studies how investment and profitability relate to average returns. Lettau and Ludvigson (2002), Fairfield, Whisenant, and Yohn (2003), Richardson and Sloan (2003), Titman, Wei, and Xie (2004), Anderson and Garcia-Feijóo (2006), Cooper, Gulen, and Schill (2007), Polk and Sapienza (2007), Lyandres, Sun, and Zhang (2007), and Xing (2007) show that investment and average returns are negatively correlated. Ball and Brown (1968), Bernard and Thomas (1989, 1990), Ball, Kothari, and Watts (1993), and Chan, Jagadeesh, and Lakonishok (1996) show that firms with higher earnings surprises earn higher average returns. Haugen and Baker (1996), Abarbanell and Bushee (1998), Frankel and Lee (1998), Dechow, Hutton, and Sloan (1999), Piotroski (2000), Cohen, Gompers, and Vuolteenaho (2002), and Fama and French (2006, 2007) show that more profitable firms earn higher average returns.

Our work adds to the literature in two ways. First, we show that the combined effect of profitability and, more surprisingly, investment substantially reduces abnormal momentum profits. We also show that the distress anomaly simply reflects the positive earnings-return relation. Second, perhaps more important, we provide a unifying perspective based on neoclassical investment theory for many anomalies that are often treated in isolation. To the extent that there is no over- or under-reaction in our theory, we reinforce Fama and French's (2006) conclusion that, despite common claims to the contrary, empirical tests in the anomalies literature cannot by themselves tell us whether the anomalies are driven by rational or irrational forces.

Section 2 motivates our neoclassical factors and discusses our empirical strategy. The following three sections report our empirical results. Section 3 constructs the explanatory factors. We use the neoclassical three-factor model to explain average returns for a wide range of testing portfolios, including two-way sorted (Section 4) and one-way sorted (Section 5). We conclude in Section 6.

2 Economic Hypotheses and Empirical Strategy

Section 2.1 develops testable hypotheses, and Section 2.2 discusses our empirical strategy.

2.1 Testable Hypotheses

We start from the q-theoretical framework à la Cochrane (1991, 1996). Within this framework, we derive a characteristics-based expected-return equation, which is the two-period simplification of

Cochrane's infinite-horizon model (see equation A.8 in Appendix A):

$$\text{Expected return} = \frac{\text{Expected profitability} + 1}{\text{Marginal cost of investment}} \tag{3}$$

Thus, the q-theory in its simplest form says that the expected return is the expected profitability divided by marginal cost of investment (which increases with investment). Equation (3) sheds light on anomalies because expected returns are directly tied with firm characteristics. Specifically, investment and expected profitability emerge as the two central drivers of expected returns.

2.1.1 The Investment Hypothesis

Equation (3) says that expected returns decrease with investment-to-assets, given expected profitability. The intuition is perhaps most transparent in the capital budgeting language of Brealey, Myers, and Allen (2006). Given expected cash flows, higher costs of capital imply lower net present values of new capital, which in turn mean lower investment-to-assets. More important, investment is the common driver of anomalies such as value and net stock issues:

> The Investment Hypothesis: The negative investment-return relation drives the positive relation of average returns with valuation ratios such as book-to-market and earnings-to-price as well as the negative relation of average returns with net stock issues.

The q-theory gives rise to a direct link between book-to-market and investment-to-assets. Optimal investment implies that investment-to-assets is an increasing function of marginal q, which is closely related to average q or market-to-book. More precisely, the marginal q equals the average q under constant returns to scale (e.g., Hayashi 1982). Further, the average q and market-to-book equity are closely correlated, and are identical in models with all equity financing. Reflecting the negative investment-return relation, value firms earn higher average returns than growth firms. Other valuation ratios such as earnings-to-price also can capture cross-sectional differences in investment opportunity set, and are connected to investment policies. In general, firms with higher valuation ratios have more growth opportunities, invest more, and earn lower expected returns.

The negative investment-return relation also manifests itself as the net stock issues anomaly. Ritter (1991), Loughran and Ritter (1995), and Spiess and Affleck-Graves (1995) show that equity issuers underperform matching nonissuers in post-issue years. Ikenberry, Lakonishok, and Vermaelen (1995) show that firms conducting open market share repurchases outperform matching firms in post-event years. Pulling together the earlier evidence, Daniel and Titman (2006) and Pontiff and

Woodgate (2006) report a negative relation between net stock issues and average returns. Fama and French (2007) show that the net stock issues effect is pervasive and shows up in all size groups.

The net issues anomaly is often interpreted as investors underreacting to managerial market timing. But the balance-sheet constraint of firms requires that the uses of funds must equal the sources of funds, meaning that issuers should invest more and earn lower average returns than nonissuers (e.g., Lyandres, Sun, and Zhang 2007). Lyandres et al. show that adding an investment factor into the CAPM and the Fama-French (1993) model substantially reduces the magnitude of the underperformance following initial public offerings, seasoned equity offerings, and convertible debt offerings. We add to their work in two ways: We use a more comprehensive net stock issues measure that takes into account share repurchases. And besides INV, we also study the role of $PROD$ in driving the net issues anomaly.

The negative investment-return relation is conditional on expected profitability. This point is important because expected profitability is not disconnected from investment-to-assets: More profitable firms invest more in the data. The conditional nature of the investment-return relation offers the following portfolio interpretation of the investment hypothesis. Sorting on net stock issues, book-to-market, earnings-to-price, and other valuation ratios is closer to sorting on investment-to-assets than sorting on expected profitability. These sorts tend to generate higher magnitudes of spread in investment-to-assets than in expected profitability. Thus, we can interpret the average return variations generated from these diverse sorts using their common implied sort on investment.

2.1.2 The Productivity Hypothesis

Complementing the investment hypothesis, equation (3) also says that given investment-to-assets, firms with higher expected profitability should earn higher expected returns.

> The Productivity Hypothesis: The positive profitability-return relation drives the positive relations of average returns with short-term prior returns as well as the negative relation between average returns and financial distress.

As noted, marginal cost of investment equals marginal q, which is basically average q or market-to-book. Equation (3) then says that the expected return equals the expected profitability divided by market-to-book. The intuition is exactly analogous to that from the Gordon (1962) Growth Model. Consider its two-period version: Price equals expected cash flow divided by the discount rate. High expected cash flow (or expected profitability) relative to low price (or market valuation ratios) means high discount rates.

Going beyond the discounting intuition from valuation theory, neoclassical investment theory provides additional capital budgeting intuition for the positive productivity-return relation. Recall the original formulation of equation (3) says that the expected return is the expected profitability divided by an increasing function of investment-to-assets. It follows that high expected profitability relative to low investment must mean high discount rates: Otherwise firms would observe high net present values of new capital and invest more. Conversely, low expected profitability relative to high investment (such as the small-growth firms in the 1990s) must mean low discount rates: Otherwise these firms would observe low net present values of new capital and invest less.

The positive productivity-return relation has important portfolio implications. For any sorts that generate higher magnitudes of spread in expected profitability than in investment-to-assets, their average return patterns can be explained using the productivity hypothesis. We explore two such sorts, which are sorts on short-term prior returns and on financial distress.

Sorting on momentum should generate a sizable spread in profitability. The intuition is that shocks to earnings are positively correlated with shocks to stock returns contemporaneously. Firms that just beat earnings expectations are likely to experience stock price increases, whereas firms that fall below earnings expectations are likely to experience stock price decreases. The distress anomaly of Dichev (1998) and Campbell, Hilscher, and Szilagyi (2007) also reflects the positive productivity-return relation. Intuitively, less distressed firms are more profitable and should earn higher average returns, even though they are less leveraged. More distressed firms are less profitable and should earn lower average returns, even though they are more leveraged.

2.2 Empirical Strategy

We primarily use the Fama-French (1993) portfolio approach to explore our economic hypotheses. We are attracted to the portfolio approach because of its powerful simplicity. The widespread use of this approach also allows us to easily compare our empirical results to those from the prior literature.

2.2.1 The Portfolio Approach

We construct factor mimicking portfolios based on investment-to-assets and earnings-to-assets, which are pivotal determinants of expected returns (see equation 3). Because these two factors are derived from partial equilibrium q-theory that studies the optimal investment of firms, we also include the market factor, MKT, which can be derived from partial equilibrium consumption theory (e.g., Cochrane 2005, p. 155–156). The resulting three-factor specification ($MKT+INV+PROD$), dubbed the neoclassical three-factor model, can be interpreted as the portfolio implementation of the Arrow-Debreu general equilibrium theory.

We use the neoclassical three-factor model as a parsimonious and practical model for estimating expected returns. In the same way that Fama and French (1996) test their three-factor model, we regress excess returns of a wide range of testing portfolios on the neoclassical factor returns as in equation (2). If the neoclassical model adequately describes the cross section of average returns, the intercepts should be statistically indistinguishable from zero.

The portfolio approach differs from the structural estimation approach of Liu, Whited, and Zhang (2007). Liu et al. parameterize the production and investment technologies of firms in the right-hand-side of equation (3), and use GMM to minimize the average differences between both sides of the equation. This approach is closely linked to the underlying theory, and it also provides an empirical expected-return model. Our portfolio approach can be viewed as a linearized implementation of the nonlinear structural estimation. As noted, although the link between theory and tests is not as close, we adopt the portfolio approach because of its powerful simplicity.

2.2.2 Interpreting Neoclassical Factors

We interpret our neoclassical factors as common factors of returns. While Fama and French (1993) interpret more aggressively their similarly constructed SMB and HML are risk factors in the context of ICAPM or APT, we do not take a strong stance on the risk interpretation of our factors.

First, the economic arguments we use to motivate the two factors are based on recent developments in equilibrium asset pricing theory, which does not allow any form of mispricing. The crux is that, just like consumption-based asset pricing predicts that aggregate expected returns covary with business cycles, investment-based asset pricing predicts that expected returns in the cross section covary with firm characteristics, corporate policies, and events. These endogenous relations cannot be captured by consumption-based frameworks because characteristics are not modeled. Thus, rejecting the CAPM (a canonical consumption-based model) does not mean rejecting Efficient Market Hypothesis because of the bad-model problem (e.g., Fama 1998). Further, perhaps because of the lack of readily available measures, behavioralists often use valuation ratios to proxy for mispricing. Interpreting the Fama and French (1993) factors is controversial because size and B/M directly involve market equity. However, our factors are constructed on economic fundamentals that are less likely to be affected by mispricing, at least directly.

However, Polk and Sapienza (2006) show that investor sentiment can affect investment and thus future profitability through shareholder discount rates. Managerial overconfidence also can distort corporate investment because hubristic managers tend to overestimate the returns to their pet projects (e.g., Malmendier and Tate 2005). Our tests do not rule out these interpretations.

More important, risk-based and characteristics-based interpretations on any common factor are not mutually exclusive: They are the two sides of the same coin. Criticizing the Fama and French (1993) risk interpretation of their SMB and HML factors, Daniel and Titman (1997) argue that it is the size and B/M characteristics rather than the covariance structure of returns that explain the cross section of average returns. However, emerging from investment-based asset pricing is the fresh insight that characteristics are sufficient statistics of expected returns: The right-hand-side of equation (3) only involves characteristics.

Further, covariances and characteristics can be linked analytically (see equation A.10 in Appendix A), meaning that covariances and characteristics are equivalent predictors of returns, at least in theory. But in practice, characteristics-based models are likely to dominate covariances-based models. The reason is that in a time-varying dynamic world, characteristics are more precisely measured than covariances. And a horse race often declares characteristics as the winner. Thus, it is conceivable that the relative success of characteristics-based models in asset pricing tests is driven by measurement errors in betas rather than systematic mispricing. After all, neoclassical investment theory predicts that characteristics should covary with expected returns to begin with.

3 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 2006. The starting date of the sample is restricted by the availability of quarterly earnings data. We exclude financial firms (SIC codes between 6000 and 6999) and firms with negative book value of equity in year $t-1$.

3.1 The Investment Factor, INV

We construct INV from a double (two by three) sort on size and investment-to-assets. We define investment-to-assets (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 value of assets (item 6). 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 capital investment in short-lived assets used in a normal operating cycle such as merchandise, raw materials, supplies, and work in progress.

In June of each year t, all NYSE stocks on CRSP are sorted on market equity (stock price times shares outstanding). We use the median NYSE size to split NYSE, Amex, and NASDAQ stocks into two groups. We also break NYSE, Amex, and NASDAQ stocks into three investment-to-assets (I/A) groups based on the breakpoints for the low 30%, middle 40%, and high 30% of the ranked values. 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 $t+1$. We calculate returns beginning in July of year t to ensure that investment for year $t-1$ is known. The INV factor is designed to mimic the common variations in returns related to investment-to-assets: INV is the difference (low-minus-high investment), 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 1, the average INV return in our sample is 0.43% per month ($t = 4.75$). Regressing INV on MKT generates an alpha of 0.51% per month ($t = 6.12$) and a R^2 of 16%. Regressing INV on the Fama and French (1993) model and the Carhart (1997) model reduces the alpha to 0.33% and 0.22% per month ($t = 4.23$ and 2.87), and increases the R^2 to 31% and 36%, respectively. (The data for the Fama-French factors and the momentum factor are from Kenneth French's Web site.) Thus, INV captures average return variations not subsumed by the other common factors.

INV has a high correlation of 0.51 with HML ($p = 0$). This evidence is consistent with Xing (2006), who shows that an investment growth factor contains information similar to HML and can explain the value effect roughly as well as HML. Xing constructs her factor by sorting on the growth rate of capital expenditure. The average return of her factor is only 0.20% per month, albeit significant. We use a more comprehensive measure of investment that includes both long-term and short-term investments. As a result, our investment factor earns a higher average return.

Panel C of Table 1 provides more details on the six size-I/A portfolios underlying the INV factor. Sorting on I/A generates a large spread in I/A: Portfolio SL^I (small-size and low-investment) has an average I/A of -4.27% per annum, whereas portfolio SH^I (small-size and high-investment) has an average of 30.15%. Portfolio SH^I is also more profitable than portfolio SL^I: The earnings-to-assets (ROA) of portfolio SH^I is 1.04% per quarter versus 0.54% for portfolio SL^I. Portfolio SL^I also has a higher average prior 2–12 month return (from July of year t–1 to May of year t) than portfolio SH^I, 22.15% versus 14.22%. This evidence partially reflects the fact that low-investment firms have higher average future returns than high-investment firms (we sort stocks in June on accounting information at the last fiscal year-end to guard against the look-ahead bias). The evidence does not mean that low-investment firms have higher average contemporaneous returns. In untabulated results, we measure returns over the calendar year $t-1$ and verify that portfolio SL^I has lower average contemporaneous returns than portfolio SH^I.

3.2 The Productivity Factor, $PROD$

We construct $PROD$ based on earnings-to-assets, ROA. Using cash-flow-to-assets to measure productivity does not materially affect our results (not reported). We sort on current profitability (as opposed to expected profitability) because profitability is highly persistent in the data. Fama and French (2006) show that current profitability is the strongest predictor of future profitability, meaning that current profitability is a major part of expected profitability, to which equation (3) applies.

Because $PROD$ is most relevant for explaining momentum profits that are constructed monthly, we use a similar approach to construct $PROD$. ROA is the quarterly earnings (Compustat quarterly item 8) divided by last quarter's assets (item 44). Each month from January 1972 to December 2006, 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 at least four months ago. The choice of the four-month lag is conservative: Using shorter lags only serves to strengthen our results (not reported). We use this lag to ensure that the required accounting information is known before we form the portfolios. 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. The $PROD$ factor is meant to mimic the common variations in returns related to firm-level productivity: $PROD$ is the difference (high-minus-low productivity), 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 1, $PROD$ earns an average return of 0.96% per month ($t = 5.10$) from January 1972 to December 2006. Regressing the $PROD$ return on the market factor, the Fama and French (1993) three factors, and the Carhart (1997) four factors yields large alphas of 1.05%, 1.01%, and 0.74% per month ($t = 5.61$, 5.60, and 4.16), and R^2s of 4%, 31%, and 24%, respectively. This evidence means that, like INV, $PROD$ also captures average return variations not subsumed by well-known common factors. Panel B also reports that $PROD$ and WML have a correlation of 0.26 ($p = 0$), lending support to the notion that shocks to earnings are positively correlated with contemporaneous shocks to returns. Finally, the correlation between INV and $PROD$ is only 0.10 ($p = 0.05$), meaning no need to neutralize the two factors against each other.

Panel D provides more details on the six size-ROA portfolios underlying $PROD$. Sorting on ROA generates a large spread in ROA: Portfolio SL^P (small-size and low-productivity) has an average ROA of -3.33% per quarter, whereas portfolio SH^P (small-size and high-productivity) has an average ROA of 3.37%. The large ROA spread only corresponds to a modest spread in annual I/A: 11.49% versus 12.56%. The evidence helps explain the low correlation between INV and $PROD$ reported earlier. The ROA spread in small firms corresponds to a large spread in prior 2–12 month returns: 9.55% versus 34.44%, helping explain the high correlation between $PROD$ and WML.

4 Tests on Two-Way Sorted Portfolios

We report time series regressions of two-way sorted testing portfolios formed on size and momentum, on size and book-to-market, and on investment and profitability. We study momentum and value portfolios because they are arguably most important anomalies in the cross section. We also study investment and profitability portfolios because our factors are constructed on these characteristics.

4.1 The Size-Momentum Portfolios

Following Jegadeesh and Titman (1993), we construct the 25 size and momentum portfolios using the "6/1/6" convention of momentum. For each month t, we sort stocks on their prior returns from month $t{-}2$ to $t{-}7$ (skipping month $t{-}1$), and calculate the subsequent portfolio returns from month t to $t{+}5$. We also use NYSE market equity quintiles to sort all stocks independently each month into five size portfolios. The 25 size and momentum portfolios are formed monthly as the intersection of the five size quintiles and the five quintiles based on prior 2–7 month returns.

Table 2 reports large momentum profits, especially in small firms. From Panel A, the winner-minus-loser (W-L) average return varies from 0.85% per month (t = 3.01) to 1.25% (t = 5.49). In total, 15 out of 25 size and momentum portfolios have significant CAPM alphas. The null hypothesis that the 25 CAPM alphas are jointly zero is strongly rejected by the GRS test: The test statistic (F_{GRS}) is 3.28 ($p = 0$). More important, 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 1.33% per month (t = 5.78). Consistent with Fama and French (1996), their three-factor model exacerbates the momentum anomaly: The Fama-French alphas for the W-L portfolios are all larger than or equal to their corresponding CAPM alphas. For example, the small-stock W-L portfolio earns a Fama-French alpha of 1.44% per month (t = 5.54). The reason is that losers have higher HML-loadings than winners: Losers behave more like value stocks, and the Fama-French model predicts counterfactually that losers should earn higher average returns. The GRS test rejects the Fama-French model with a F_{GRS} of 3.40 ($p = 0$).

Panel B of Table 2 reports the neoclassical regressions of the size and momentum portfolios. The W-L strategies across all five size quintiles earn insignificant alphas. In particular, the small-stock W-L strategy has an alpha of 0.54% per month (t = 1.70). This performance is noteworthy: This small-stock W-L alpha represents a reduction of 59% in magnitude from its CAPM alpha (1.33%) and a reduction of 63% from its Fama-French alpha (1.44%). The average magnitude of the W-L alphas in the neoclassical model is 0.37% per month. In contrast, the corresponding magnitude is 1.08% in the CAPM and 1.17% per month in the Fama-French model. Further, nine out of the 25 individual alphas are significant, giving rise to an overall rejection of the neoclassical model by the GRS test ($p = 0$). However, the number of significant neoclassical alphas is much lower than that in the CAPM (15) and that in the Fama-French model (14).

4.1.1 Sources of Explanatory Power

The relative success of the neoclassical model in explaining momentum derives from two sources. First, the $PROD$-loadings of momentum portfolios go in the right direction in explaining their average returns. From Table 2, that winners have higher $PROD$-loadings than losers across all size groups. The magnitude of the loading spreads ranges from 0.22 to 0.45, which, given an average $PROD$ return of 0.96% per month, explain 0.21% to 0.43% per month of momentum profits.

Second, intriguingly, the INV-loadings also go in the right direction in explaining momentum profits: Winners have higher INV-loadings than losers. The magnitude of the loading spreads, significant across all size groups, ranges from 0.57 to 0.83. Given an average INV return of 0.43% per month, the INV-loadings explain 0.25% to 0.36% of momentum profits. The INV-loading pattern is counterintuitive: We would expect that winners with high valuation ratios should invest more and have lower loadings on the low-minus-high INV factor than losers with low valuation ratios.

To understand the driving forces behind these loading patterns, we use the event-study approach to examine how ROA and I/A vary across momentum portfolios. To preview the results: 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 INV is rebalanced annually, the higher INV-loadings for winners accurately reflect their lower I/A several quarters prior to the portfolio formation.

For each portfolio formation month t = January 1972 to December 2006, we calculate quarterly ROAs and annual I/As for $t+m, m = -60, \ldots, 60$. The ROA and I/A for $t+m$ are then averaged across portfolio formation months t. ROA is the most recent ROA relative to portfolio formation month t. For a given portfolio, we plot the median ROAs and I/As among the firms in the portfolio. Figure 1 reports the details. From Panel A, although winners have higher I/As at the portfolio formation month t, winners have lower I/As than losers from month t–60 to month t–8. Consistent with this event-time evidence, Panel B shows that winners have higher contemporaneous I/As than losers in the calendar time in the smallest-size quintile. We define the contemporaneous I/A as the I/A at the current fiscal year-end. For example, if the current month is March or September 2003, the contemporaneous I/A is the I/A at the fiscal year-end of 2003.

More important, Panel C shows that winners also have lower lagged or sorting-effective I/As than losers in the smallest-size quintile. We define the sorting-effective I/A as the I/A on which an annual sort on I/A in each June (as in our construction of INV) is based. For example, if the current month is March 2003, the sorting-effective I/A is the I/A at the fiscal year-end of 2001 because the annual sort on I/A is in June 2002. If the current month is September 2003, the sorting-effective I/A is the I/A at the fiscal year-end of 2002 because the applicable sort on I/A is in June 2003. Because INV is rebalanced annually, the lower sorting-effective I/As of winners explain their higher INV-loadings than losers.

To verify that the annual rebalancing of INV is indeed the driving force of the INV-loading pattern across momentum portfolios, we experiment with an alternative investment factor, denoted INV^Q, constructed on quarterly investment data. We measure quarterly I/A as the change in gross property, plant, and equipment (Compustat quarterly item 42) plus the change in inventory (item 38) divided by lagged total assets (item 44). This definition is the exact quarterly counterpart of our definition based on annual data. Each month from January 1975 to December 2006, we categorize NYSE, Amex, and NASDAQ stocks into three groups based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of quarterly I/A from at least four months ago. (The starting point of the sample is restricted by the availability of quarterly investment data.) We also use the NYSE median market equity each month to split all stocks into two size groups. We form six portfolios from the intersections of the two size and three I/A portfolios and calculate monthly value-weighted returns on the six portfolios for the current month. INV^Q is the difference (low-minus-high investment), 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.

Untabulated results show that the INV^Q factor earns an average return of 0.49% per month (t = 3.77). More important, once we replace INV with INV^Q in neoclassical regressions, the W-L portfolios have insignificantly negative INV^Q-loadings. This evidence contrasts with the significantly positive INV-loadings reported in Table 2. (The $PROD$-loadings are not materially affected.) As a result, the magnitude of the neoclassical alphas is in general higher than that in Table 2. For example, the small-stock W-L momentum portfolio has an alpha of 0.88% per month (t = 2.28), which is about 63% higher than the alpha of 0.54% in Table 2.

Finally, untabulated results also show that winners have higher ROAs than losers for about five quarters before and 20 quarters after the portfolio formation month. In the calendar time, winners have consistently higher ROAs than losers, especially in smallest-size quintile. This evidence explains the higher $PROD$-loadings for the winners documented in Table 2.

4.2 The 25 Size-B/M Portfolios

We obtain the 25 Size-B/M portfolios from Kenneth French's Web site. Table 3 shows that value stocks earn higher average returns than growth stocks. The average high-minus-low (H-L) return is 1.09% per month (t = 5.08) in the smallest-size quintile versus 0.25% (t = 1.20) in the biggest-size quintile. The CAPM cannot explain the value premium: 15 out of 25 portfolios have significant alphas and the GRS statistic is 4.25 (p = 0). Three out of five H-L strategies have significant alphas. In particular, the small-stock H-L portfolio earns a positive alpha of 1.32% per month (t = 7.10). The Fama and French (1993) model greatly improves upon the CAPM in capturing the average returns across the 25 size-B/M portfolios. The number of significant alphas reduces from

15 to only six. The small-stock H-L alpha is reduced to 0.68% per month (albeit still significant with $t = 5.50$), which is 48% lower than its CAPM alpha. The reason is that the Fama-French model generates systematic variations in factor loadings: Small stocks have higher SMB loadings than big stocks, and value stocks have higher HML loadings than growth stocks. The average R^2 across the 25 portfolios is about 90%, so even small intercepts are often distinguishable from zero.

The neoclassical model performs about as well as the Fama-French (1993) model in explaining the average returns of the 25 size-B/M portfolios. Panel A of Table 3 shows that, while the Fama-French (1993) model produces six significant alphas out of 25 size-B/M portfolios, the neoclassical model produces seven. But only one out of five H-L alphas is significant in our model versus two out of five in the Fama-French model. The average magnitude of the H-L alphas is lower in our model: 0.20% versus 0.28% per month. In particular, the small-stock H-L earns a neoclassical alpha of 0.57% per month ($t = 2.72$), which is lower than its Fama-French alpha of 0.68% ($t = 5.50$). However, the average R^2 across the 25 portfolios is lower in our model: 75% versus 91%.

More intriguingly, the neoclassical model does exceptionally well in explaining the low average returns of the small-growth portfolio that consists of firms in the smallest-size quintile and the lowest-B/M quintile. The small-growth portfolio earns a CAPM alpha of −0.63% per month ($t = -2.61$), a Fama-French (1993) alpha of −0.52% ($t = -4.48$), but only a tiny neoclassical alpha of 0.08% ($t = 0.27$). This evidence is noteworthy because the small-growth anomaly is notoriously difficult to explain for traditional asset pricing models. For example, Campbell and Vuolteenaho (2004, Table 4) show that the small-growth portfolio is particularly risky in their two-beta model with both cash-flow and discount-rate betas exceeding those of the small-value portfolio. As a result, their two-beta model fails to explain the small-growth anomaly. The existing literature has attributed the abnormally low return for small-growth firms to short-sale constraints and other limits to arbitrage (e.g., Lamont and Thaler 2003, Mitchell, Pulvino, and Stafford 2002).

The INV- and $PROD$-loadings shed light on the explanatory power of the neoclassical model for the 25 size-B/M portfolios. From Panel B of Table 3, value stocks have higher INV-loadings than growth stocks. The loading spreads, ranging from 0.68 to 0.93, are all at least five standard errors from zero. The $PROD$-loading pattern is more complicated. In the smallest-size quintile, the H-L portfolio has a significantly positive $PROD$-loading of 0.39 ($t = 4.53$) because the small-growth portfolio has a large negative $PROD$-loading of −0.62 ($t = -5.65$). However, in the biggest-size quintile, the H-L portfolio has a negative $PROD$-loading of −0.11 ($t = -1.23$).

It is somewhat surprising that the small-growth portfolio has a lower $PROD$-loading than the small-value portfolio. In untabulated results, we find that growth firms have persistently higher ROAs than value firms in the biggest-size quintile for 11 years surrounding the portfolio formation year. But in the smallest-size quintile, growth firms have higher ROAs than value firms before, and have lower $ROAs$ after the portfolio formation. In the calendar time, a striking downward spike of ROA appears for the small-growth portfolio over the past decade. The ROA starts at about 0.50% per quarter in 1997, drops rapidly to about -7% in 2003, before rising back to 0.50% in 2004. The dramatic ROA deterioration of the small-growth firms over the past decade gives rise to their abnormally low $PROD$-loadings. We also verify that the small-stock H-L portfolio has a negative $PROD$-loading in the 1972–1995 sample before the downward spike occurs (not reported).

4.3 The 25 Investment-Profitability Portfolios

We sort all NYSE, Amex, and NASDAQ stocks into five profitability quintiles each month based on quarterly ROA from at least four months ago. Also, we sort all stocks independently in June of each year into five quintiles based on I/A at the last fiscal year-end. Taking intersections yields 25 investment and profitability portfolios. Their value-weighted returns are calculated for the current month, and the portfolios are rebalanced monthly. Table 4 reports that high ROA stocks earn higher average returns than low ROA stocks, especially among high investment firms, and that high investment stocks earn lower average returns than low investment stocks, especially among low ROA firms. The average high-minus-low ROA portfolio return varies from 0.80% per month ($t = 2.20$) in the lowest-I/A quintile to 1.65% ($t = 4.97$) in the highest-I/A quintile. The average low-minus-high I/A portfolio return varies from an insignificant 0.26% per month ($t = 1.23$) in the highest-ROA quintile to 1.11% ($t = 3.41$) in the lowest-ROA quintile.

Traditional factor models cannot explain the 25 investment-profitability portfolio returns. Ten out of 25 portfolios have significant CAPM alphas. The alpha for the high-minus-low ROA portfolio ranges from 0.58% to 1.82% per month and are mostly significant across the five I/A quintiles. And the CAPM alpha for the low-minus-high I/A portfolio ranges from 0.34% to 1.25% per month and are mostly significant across the five ROA quintiles. Despite their higher average returns, high ROA firms have mostly lower SMB and HML loadings than low ROA firms. As a result, 11 out of 25 portfolios have significant Fama-French alphas. In particular, the alpha for the high-minus-low ROA portfolio ranges from 0.63% to 2.04% per month and are all significant across the five I/A quintiles.

The neoclassical model does a much better job in explaining the average returns across the 25 investment-profitability portfolios. From Panel B of Table 4, although the neoclassical model is rejected overall with a GRS statistic of 2.42 ($p = 0$), only three out of 25 alphas are significant. Further, two out of five high-minus-low ROA portfolios have significant alphas. In contrast, four out of five alphas are significant in the CAPM, and all five of them are significant in the Fama-French (1993) model. More important, the average magnitude of the high-minus-low ROA alphas is also lower in our model: 0.39% per month versus 1.15% in the CAPM and 1.27% in the Fama-French model. Further, only one out of the five low-minus-high I/A alphas is significant, whereas four out of five are significant in both the CAPM and the Fama-French model. The average magnitude of the low-minus-high I/A alphas is also lower in our model: 0.26% per month versus 0.79% in the CAPM and 0.59% in the Fama-French model.

As expected, high ROA firms have significantly higher $PROD$-loadings than low ROA firms, and low-investment firms have significantly higher INV-loadings than high-investment firms. The systematic variations in the neoclassical factor loadings across the investment-profitability portfolios (in the same direction as their average returns variation) explain the better empirical performance of our model relative to the CAPM and the Fama-French (1993) model.

5 Tests on One-Way Sorted Portfolios

This section tests the neoclassical factor model using deciles formed on financial distress, net stock issues, and earnings-to-price. The earnings-to-price portfolios represent portfolios sorted on valuation ratios. The other anomaly variables have recently received much attention in empirical finance.

5.1 The Distress Deciles

The neoclassical model explains the distress anomaly. We form ten deciles based on Ohlson's (1980) O-score and on Campbell, Hilscher, and Szilagyi's (2007) failure probability measures. Appendix B contains detailed variable definitions. We have used portfolios formed on Altman's (1968) Z-score, but the CAPM explains well the average Z-score portfolio returns in our sample (not reported).

Each month from June 1975 to December 2006, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles on the failure probability measure from at least four months ago. (The starting point of the sample is restricted by the availability of the data items required to construct the measure.) Monthly value-weighted portfolio returns are calculated for the current month. Panel A of Table 5 reports that, consistent with Campbell, Hilscher, and Szilagyi (2007), more distressed firms earn lower average returns than less distressed firms. The high-minus-low (H-L) distress portfolio has an average return of -1.38% per month ($t = -3.53$).

Controlling for traditional risk measures makes matters worse: More distressed firms are riskier according to traditional factor models. The market beta of the H-L failure probability portfolio is significantly positive, 0.73 ($t = 5.93$), meaning that its CAPM alpha of -1.87% per month ($t = -5.08$) has a higher magnitude than its average return. In total, seven out of ten alphas are significant, leading to an overall rejection of the CAPM ($p = 0$). The results from the Fama-French (1993) model are largely similar. The H-L portfolio has a SMB-loading of 1.10 ($t = 7.46$) and a market beta of 0.57 ($t = 4.57$). As a result, the Fama-French alpha is -2.14% per month ($t = -6.43$). Eight out of ten deciles have significant Fama-French alphas, and the GRS test rejects the model ($p = 0$).

More important, the neoclassical model reduces the H-L alpha to an insignificant level of -0.32% per month ($t = -1.09$). Although two out of ten deciles have significant alphas, the model cannot be rejected by the GRS test at the 5% significance level ($p = 0.06$). The $PROD$-loading goes in the right direction in explaining the anomaly. More distressed firms have lower $PROD$-loadings than less distressed firms: The loading spread is -1.40 ($t = -14.64$). This evidence makes sense because failure probability has a strong negative relation with profitability (see equation B.1), meaning that more distressed firms are less profitable than less distressed firms.

Panel B of Table 5 reports similar results for the O-score portfolios. The highest O-score portfolio underperforms the lowest O-score portfolio by an average of -0.92% per month ($t = -2.84$). Paradoxically, the highest O-score portfolio has a higher market beta than the lowest O-score portfolio, 1.38 versus 1.02. Adjusting for the market beta thus exacerbates the puzzle: The H-L O-score alpha is -1.10% per month ($t = -3.56$). Adjusting for the Fama and French (1993) factors makes things worse. The highest O-score portfolio has significantly higher SMB- and HML-loadings than the lowest O-score portfolio, giving rise to a H-L alpha of -1.44% per month ($t = -6.49$). More important, the neoclassical model eliminates the abnormal return: The alpha is reduced to a tiny -0.09% per month ($t = -0.32$). The driving force is again the large negative $PROD$-loading for the H-L O-score portfolio: -1.07 ($t = -11.03$).

Overall, our evidence suggests that the distress anomaly is another manifestation of the positive ROA-return relation; once productivity is controlled for, the distress anomaly largely disappears.

5.2 The Net Stock Issues Deciles

Following Fama and French (2007), we measure net stock issues as the the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year-end in $t-1$ divided by the split-adjusted shares outstanding at the fiscal year-end in t–2. The split-adjusted shares outstanding is Compustat shares outstanding (25) times the Compustat adjustment factor (item 27).

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 year-end. Monthly value-weighted portfolio returns are calculated from July of year t to June of year t+1. From Panel A of Table 6, firms with high net issues earn lower average returns than firms with low net issues: The H-L net issues portfolio earns an average return of -0.84% per month ($t = -4.64$). The CAPM alpha of the H-L portfolio is -1.06% per month ($t = -5.07$). And seven out of ten deciles have significant alphas. The Fama-French (1993) model reduces the magnitude of the H-L alpha to -0.82% per month ($t = -4.33$). The reason is that the H-L portfolio has a negative HML-loading of -0.39 ($t = -3.91$). The evidence means that, sensibly, high net issues firms tend to be growth firms and low net issues firms tend to be value firms. But the Fama-French model still leaves five out of ten alphas significant and is rejected by the GRS test.

The neoclassical model outperforms traditional factor models in explaining the net issues anomaly. Although the model is rejected by the GRS test, the H-L net issues portfolio earns an insignificant neoclassical alpha of -0.28% per month ($t = -1.39$). The INV-loading goes in the right direction in explaining the anomaly: The H-L portfolio has an INV-loading of -0.55 ($t = -4.25$). This loading pattern is consistent with the underlying investment pattern. In untabulated results, we find that the average portfolio I/A increases monotonically from the lowest net issues decile to the highest net issues decile, and that the I/A-spread is more than ten standard errors from zero.

The $PROD$-loading also goes in the right direction in explaining the new issues anomaly: The H-L portfolio has a $PROD$-loading of -0.39 ($t = -6.53$). In untabulated results, we find that at the portfolio formation in June of each year, the highest net issues decile has a lower average ROA than the lowest decile, and that the ROA spread is highly significant. Our evidence differs from Loughran and Ritter (1995) and Lyandres, Sun, and Zhang (2007), who report that equity issuers are more profitable than matching nonissuers. The reason is that our net issues measure also includes share repurchases. Our evidence makes sense in light of Lie (2005), who shows that firms announcing repurchases exhibit superior operating performance relative to industry peers.

5.3 The Earnings-to-Price Deciles

Fama and French (1996) show that their model can explain average returns of portfolios sorted on valuation ratios such as earnings-to-price, cash flow-to-assets, and dividend-to-price. We report the results for ten earnings-to-price (E/P) deciles. The data for the E/P portfolio returns are from Kenneth French's Web site. The results for portfolios formed on other valuation ratios and for DeBondt and Thaler's (1985) long-term reversal portfolios are similar (not reported).

From Panel B of Table 6, the highest E/P decile earns a higher average return than the lowest E/P decile: 1.00% versus 0.31% per month, meaning that the H-L E/P portfolio earns an average return of 0.69% per month (t = 2.92). The CAPM cannot explain the E/P anomaly: The H-L alpha is 0.82% per month (t = 3.55), six out of ten alphas are significant, and the CAPM is rejected by the GRS test (p-value = 0.01). Remarkably, none of the ten alphas are significant in the Fama-French (1993) model, which cannot be rejected by the GRS test (p-value = 0.57). The H-L E/P portfolio earns a Fama-French alpha of only −0.13% per month (t = −0.90). The main source of the success for the Fama-French model is that high E/P stocks have higher HML-loadings than low E/P stocks: The H-L portfolio has an HML-loading of 1.41 (t = 23.06).

The performance of the neoclassical model is reasonable. One out of ten E/P deciles has a significant alpha, but the GRS test cannot reject the model at the conventional significant levels (p = 0.07). The H-L E/P portfolio earns an alpha of 0.31% per month (t = 1.30). The model gains its explanatory power for the E/P portfolios through their INV loadings. The H-L E/P portfolio has an INV-loading of 0.69 (t = 4.47). In untabulated results, we confirm that the highest E/P decile invests less than the lowest E/P decile on average.

In untabulated results, we also find that the neoclassical model explains average returns across deciles formed on market leverage (e.g., Bhandari 1988). Following Fama and French (1992), we measure market leverage, A/ME, as the ratio of the year-end book assets (COMPUSTAT annual item 6) to the year-end market equity. The highest A/ME stocks earn higher average excess returns than lowest A/ME stocks: 0.85% vs. 0.24% per month, and the average-return spread is 0.62% (t = 2.56). The H-L A/ME portfolio earns a CAPM alpha of 0.75% per month (t = 3.21). The Fama-French model reduces this alpha to an insignificant level of −0.21% through the HML-loading (1.42, t = 17.05) of the zero-cost portfolio. The neoclassical model reduces the alpha to an insignificant 0.18% (t = 0.75) through the INV-loading (1.18, t = 8.27) of the zero-cost portfolio.

Our evidence suggests that high market leverage signals low growth opportunities, low investment-to-assets, and thus high expected returns. This investment story differs from the leverage hypothesis in standard corporate finance textbooks. The leverage story argues that high market leverage means high proportion of assets risk shared by equity holders, and high expected equity returns. This story assumes that investment policy is fixed, meaning that the assets risk does not vary with investment. In contrast, the investment story allows investment and leverage to be jointly determined, giving rise to a negative relation between market leverage and investment, which in turns implies a positive relation between market average and expected returns.

6 Conclusion

We propose a new multifactor model that includes the market factor, the low-minus-high investment factor, and the high-minus-low productivity factor. The model goes a long way in explaining the average returns across portfolios formed on momentum, financial distress, investment, profitability, net stock issues, and valuation ratios. Our evidence shows that, at a minimum, the neoclassical model is a good start to describing the cross-section variation of average stock returns.

Our pragmatic approach means that, in principle, our neoclassical model can be used in many applications that require estimates of expected returns. Examples include portfolio choice, portfolio performance evaluation, measurement of abnormal returns in event studies, and the cost of capital estimates. These applications primarily depend on the empirical performance of our model. The motivation of our factors from equilibrium asset pricing theory also raises the likelihood that the performance of the neoclassical model can persist in the future.

The voluminous literatures in empirical corporate finance and capital markets research in accounting have used factor models to measure abnormal performance following corporate events. The intercepts from the market regression and the Fama-French (1993) three-factor regression are used to measure average abnormal returns. Our evidence suggests that the intercepts from the neoclassical three-factor regressions also can do a reasonable job identifying abnormal performance. For example, using the CAPM alpha as the measure of abnormal performance, Agrawal, Jaffe, and Mandelker (1992) document that stockholders of acquiring firms suffer a significant loss of about 10% over the five post-merger years. Because mergers and acquisitions are a form of capital investment from the perspective of bidders, we conjecture that the post-merger underperformance reflects the negative relation between investment and expected returns. Using the neoclassical model is likely to yield more precise estimates of abnormal performance.

We take the pragmatic approach in constructing common factors motivated from neoclassical economics. While useful in providing a parsimonious factor model for practical purposes, this approach leaves a more fundamental question unanswered. The neoclassical factors are constructed directly on firm characteristics. Although we show formally that these characteristics are linked to risk, our investment-based asset pricing approach does not directly characterize the nature of or quantify the amount of the underlying risk. Our approach is that, rather than determining unobservable expected returns from equally unobservable risk as in traditional asset pricing literature, we infer unobservable expected returns from observable firm characteristics and corporate policies.

A promising direction for future research can link investment-based asset pricing to the long run risk literature (e.g., Bansal and Yaron 2004; Bansal, Dittmar, and Lundblad 2005). The long run risk literature characterizes the risk that investors are afraid of, whereas investment-based asset pricing connects the risk to firm characteristics and corporate policies. General equilibrium models, in which investors and firms are jointly modeled, hold the promise of understanding more fundamental driving forces of risk. However, because of their complex structures, general equilibrium models that can be implemented empirically remains elusive.

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A A Two-Period q-Theory Model of Expected Returns

We derive the q-theory expected-returns model à la Cochrane (1991, 1996). We use a two-period simplification of the dynamic model derived by Liu, Whited, and Zhang (2007). See their paper for a more detailed exposition including the derivation and estimation in the infinite-horizon framework.

Firms use capital and a vector of costlessly adjustable inputs to produce a perishable output good. Firms choose the levels of these inputs each period to maximize their operating profits, defined as revenues minus the expenditures on these inputs. Taking the operating profits as given, firms then choose optimal investment to maximize their market value.

There are only two periods, t and $t+1$. Firm j starts with capital stock k_{jt}, invests in period t, and produces in both t and $t+1$. The firm exits at the end of period $t+1$ with a liquidation value of $(1-\delta_j)k_{jt+1}$, in which δ_j is the firm-specific rate of capital depreciation. Operating profits, $\pi_{jt} = \pi(k_{jt}, x_{jt})$, depend upon capital, k_{jt}, and a vector of exogenous aggregate and firm-specific productivity shocks, denoted x_{jt}. Operating profits exhibit constant returns to scale, that is, $\pi(k_{jt}, x_{jt}) = \pi_1(k_{jt}, x_{jt})k_{jt}$, in which numerical subscripts denote partial derivatives. The expression $\pi_1(k_{jt}, x_{jt})$ is therefore the marginal product of capital.

The law of motion for capital is $k_{jt+1} = i_{jt} + (1-\delta_j)k_{jt}$, in which i_{jt} denotes capital investment. We use the one-period time-to-build convention: Capital goods invested today only become productive at the beginning of the next period. Investment incurs quadratic adjustment costs given by $(a/2)(i_{jt}/k_{jt})^2 k_{jt}$, in which $a > 0$ is a constant parameter. The adjustment-cost function is increasing and convex in i_{jt}, decreasing in k_{jt}, and exhibits constant returns to scale.

Let m_{t+1} be the stochastic discount factor from time t to $t+1$, which is correlated with the aggregate component of x_{jt+1}. Firm j chooses i_{jt} to maximize the market value of equity:

$$\underbrace{\max_{\{i_{jt}\}} \left\{ \overbrace{\pi(k_{jt}, x_{jt}) - i_{jt} - \frac{a}{2}\left(\frac{i_{jt}}{k_{jt}}\right)^2 k_{jt}}^{\textbf{Cash flow at period } t} + E_t \left[m_{t+1} \left[\overbrace{\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}}^{\textbf{Cash flow at period } t+1} \right]\right]\right\}}_{\textbf{Cum dividend market value of equity at period } t}. \tag{A.1}$$

The first part of this expression, denoted by $\pi(k_{jt}, x_{jt}) - i_{jt} - (a/2)(i_{jt}/k_{jt})^2 k_{jt}$, is net cash flow during period t. Firms use operating profits $\pi(k_{jt}, x_{jt})$ to invest, which incurs both purchase costs, i_{jt}, and adjustment costs, $(a/2)\left(i_{jt}/k_{jt}\right)^2 k_{jt}$. The price of capital is normalized to be one. If net cash flow is positive, firms distribute it to shareholders, and if net cash flow is negative, firms collect external equity financing from shareholders. The second part of equation (A.1) contains the expected discounted value of cash flow during period $t+1$, which is given by the sum of operating profits and the liquidation value of the capital stock at the end of $t+1$.

Taking the partial derivative of equation (A.1) with respect to i_{jt} yields the first-order condition:

$$\overbrace{1 + a\left(\frac{i_{jt}}{k_{jt}}\right)}^{\textbf{Marginal cost of investment at period } t} = E_t\left[m_{t+1}\left[\overbrace{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}^{\textbf{Marginal benefit of investment at period } t+1}\right]\right] \equiv q_{jt}. \tag{A.2}$$

The left side of the equality is the marginal cost of investment, and the right side is the marginal benefit commonly dubbed marginal q, denoted q_{jt}. To generate one additional unit of capital at the beginning of next period, k_{jt+1}, firms must pay the price of capital and the marginal adjustment cost, $a(i_{jt}/k_{jt})$. The next-period marginal benefit of this additional unit of capital includes the marginal product of capital, $\pi_1(k_{jt+1}, x_{jt+1})$, and the liquidation value of capital net of depreciation, $1-\delta_j$. Discounting this next-period benefit using the pricing kernel m_{t+1} yields the marginal q.

To derive asset pricing implications from this two-period q-theoretic model, we first define the investment return as the ratio of the marginal benefit of investment at period $t+1$ divided by the marginal cost of investment at period t:

$$\underbrace{r^I_{jt+1}}_{\textbf{Investment return from period } t \textbf{ to } t+1} \equiv \frac{\overbrace{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}^{\textbf{Marginal benefit of investment at period } t+1}}{\underbrace{1 + a\left(i_{jt}/k_{jt}\right)}_{\textbf{Marginal cost of investment at period } t}} \tag{A.3}$$

Following Cochrane (1991), we divide equation (A.2) by the marginal cost of investment:

$$E_t\left[m_{t+1} r^I_{jt+1}\right] = 1. \tag{A.4}$$

We now show that under constant returns to scale, stock returns equal investment returns. From equation (A.1) we define the ex-dividend equity value at period t, denoted p_{jt}, as:

$$\underbrace{p_{jt}}_{\textbf{Ex dividend equity value at period } t} = E_t\left[m_{t+1}\left[\overbrace{\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}}^{\textbf{Cash flow at period } t+1}\right]\right], \tag{A.5}$$

The ex-dividend equity value, p_{jt}, equals the cum-dividend equity value—the maximum in equation (A.1)—minus the net cash flow over period t. We can define the stock return, r^S_{jt+1}, as

$$\underbrace{r^S_{jt+1}}_{\textbf{Stock return from period } t \textbf{ to } t+1} = \frac{\overbrace{\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}}^{\textbf{Cash flow at period } t+1}}{\underbrace{E_t[m_{t+1}[\pi(k_{jt+1}, x_{jt+1}) + (1-\delta_j)k_{jt+1}]]}_{\textbf{Ex dividend equity value at period } t}}, \tag{A.6}$$

in which the ex-dividend market value of equity in the numerator is zero in this two-period setting.

Dividing both the numerator and the denominator of equation (A.6) by k_{jt+1}, and invoking the constant returns assumption yields:

$$r^S_{jt+1} = \frac{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}{E_t[m_{t+1}[\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)]]} = \frac{\pi_1(k_{jt+1}, x_{jt+1}) + (1-\delta_j)}{1 + a(i_{jt}/k_{jt})} = r^I_{jt+1}.$$

The second equality follows from the first-order condition given by equation (A.2). Because of this equivalence, in what follows we use r_{jt+1} to denote both stock and investment returns.

The marginal product of capital in the numerator of the investment-return equation (A.3) is closely related to earnings, so expected returns increase with earnings. Specifically, earnings equals operating cash flows minus capital depreciation, which is the only accrual in our model. Let e_{jt}

denote earnings, then:

$$\underbrace{e_{jt}}_{\textbf{Earnings}} \equiv \overbrace{\pi(k_{jt}, x_{jt})}^{\textbf{Operating cash flows}} - \underbrace{\delta_j k_{jt}}_{\textbf{Capital depreciation}}. \tag{A.7}$$

Using equation (A.7) to rewrite equation (A.3) yields:

$$\underbrace{E_t[r_{jt+1}]}_{\textbf{Expected return}} = \frac{\overbrace{E_t\left[\pi_{jt+1}/k_{jt+1}\right]}^{\textbf{Average product of capital}} + 1 - \delta_j}{\underbrace{1 + a(i_{jt}/k_{jt})}_{\textbf{Marginal cost of investment}}} = \frac{\overbrace{E_t[e_{jt+1}/k_{jt+1}]}^{\textbf{Expected profitability}} + 1}{\underbrace{1 + a(i_{jt}/k_{jt})}_{\textbf{Marginal cost of investment}}} \tag{A.8}$$

Given the market-to-book ratio in the denominator, equation (A.8) predicts that the expected return increases with the expected profitability. Haugen and Baker (1996) and Fama and French (2006) show that, controlling for market valuation ratios, firms with high expected profitability earn higher average returns than firms with low expected profitability. Further, the magnitude of the profitability-return relation equals $1/(1 + a(i_{jt}/k_{jt})) = k_{jt+1}/p_{jt}$, which is inversely related to market capitalization, p_{jt}.

As emphasized in Liu, Whited, and Zhang (2007), equation (A.8) expresses expected returns purely in terms of characteristics. In other words, characteristics are sufficient statistics of expected returns. To show that characteristics and covariances are the two sides of the same coin, we follow Cochrane (2005, p. 14–16) to rewrite equation (A.4) as the beta-pricing form:

$$E_t[r_{jt+1}] = r_{ft} + \beta_{jt}\lambda_{mt} \tag{A.9}$$

where r_{ft} is the risk-free rate, $\beta_{jt} \equiv -\text{Cov}_t[r_{jt+1}, m_{t+1}]/\text{Var}_t[m_{t+1}]$ is the amount of risk, and $\lambda_{mt} \equiv \text{Var}_t[m_{t+1}]/E_t[m_{t+1}]$ is the price of risk. Combining equations (A.8) and (A.9) yields:

$$\beta_{jt} = \left(\frac{E_t[e_{jt+1}/k_{jt+1}] + 1}{1 + a(i_{jt}/k_{jt})} - r_{ft}\right)/\lambda_{mt} \tag{A.10}$$

which provides an analytical link between covariances and characteristics.

B The Distress Measures

We construct the distress measure following Campbell, Hilscher, and Szilagyi (2007, the third column in Table 4):

$$\begin{aligned}\text{Distress}(t) \;\equiv\; & -9.164 - 20.264\, NIMTAAVG_t + 1.416\, TLMTA_t - 7.129\, EXRETAVG_t \\ & + 1.411\, SIGMA_t - 0.045\, RSIZE_t - 2.132\, CASHMTA_t + 0.075\, MB_t - 0.058\, PRICE_t\end{aligned} \tag{B.1}$$

in which

$$NIMTAAVG_{t-1,t-12} \equiv \frac{1-\phi^2}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}\right) \tag{B.2}$$

$$EXRETAVG_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12}\right) \tag{B.3}$$

The coefficient $\phi = 2^{-1/3}$, meaning that the weight is halved each quarter. $NIMTA$ is net income (COMPUSTAT quarterly item 69) divided by the sum of market equity and total liabilities (item 54). 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 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 500 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 Olson (1980, model one of Table 4) to construct O-score:

$$\begin{aligned} &-1.32 - 0.407 \log(MKTASSET/CPI) + 6.03\,TLTA - 1.43\,WCTA + 0.076\,CLCA \\ &\quad - 1.72\,OENEG - 2.37\,NITA - 1.83\,FUTL + 0.285\,INTWO - 0.521\,CHIN \end{aligned} \tag{B.4}$$

where $MKTASSET$ is market assets defined as book asset with book equity replaced by market equity. We calculate $MKTASSET$ as total liabilities + Market Equity + 0.1×(Market Equity − Book Equity), where total liabilities are given by COMPUSTAT quarterly item 54. The adjustment of $MKTASSET$ using ten percent of the difference between market equity and book equity follows Campbell, Hilscher, and Szilagyi (2007) to ensure that assets are not close to zero. The construction of book equity follows Fama and French (1993). CPI is the consumer price index. $TLTA$ is the leverage ratio defined as the book value of debt divided by $MKTASSET$. $WCTA$ is working capital divided by market assets, (COMPUSTAT quarterly item 40 − item 49)/$MKTASSET$. $CLCA$ is current liability (item 40) divided by current assets (item 49). $OENEG$ is one if total liabilities exceeds total assets and is zero otherwise. $NITA$ is net income (item 69) divided by assets, $MKTASSET$. $FUTL$ is the fund provided by operations (item 23) divided by liability (item 54). $INTWO$ is equal to one if net income (item 69) 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 69) for the most recent quarter.

Table 1 : Properties of INV and $PROD$, 1/1972–12/2006, 420 Months

Investment-to-assets, I/A, is 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 value of assets (item 6). In each June from 1972 to 2006, all NYSE stocks on CRSP are sorted on market equity (stock price times shares outstanding), and the median NYSE size is used to split NYSE, Amex, and NASDAQ stocks into two groups, small and big. We also break NYSE, Amex, and NASDAQ stocks into three investment-to-assets groups using the breakpoints for the low 30%, middle 40%, and high 30% of the ranked investment-to-assets. From the intersections of the two size and the three investment-to-assets groups, we construct six size-I/A portfolios, denoted SL^I, SM^I, SH^I, BL^I, BM^I, and BH^I. 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 $t+1$. INV is the difference (low-minus-high investment), each month, between the simple average of the returns on the two low-I/A portfolios (SL^I and BL^I) and the simple average of the returns on the two high-I/A portfolios (SH^I and BH^I). Earnings-to-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 at least four months ago. 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 the three ROA groups. Monthly value-weighted returns on the six portfolios are calculated for the current month, and the portfolios are rebalanced monthly. $PROD$ is the difference (high-minus-low productivity), each month, between the simple average of the returns on the two high-ROA portfolios (SH^P and BH^P) and the simple average of the returns on the two low-ROA portfolios (SL^P and BL^P). The Fama-French (1993) factors MKT, SMB, HML, and the momentum factor WML are from Kenneth French's Web site. For each portfolio from the two double sorts, we report the mean monthly percent excess returns and their t-statistics, average number of firms, average market equity in millions, average book-to-market equity, average prior 2–12 month percent returns (r^{11}, from July of year $t-1$ to May of year t), average annual percent I/A, and average quarterly percent ROA. The t-statistics (in parentheses) are adjusted for heteroscedasticity and autocorrelations in Panel A.

Panel A: Means and factor regressions of INV and $PROD$

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2
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)	
$PROD$	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)

	$PROD$	MKT	SMB	HML	WML
INV	0.10	−0.40	−0.09	0.51	0.20
	(0.05)	(0.00)	(0.07)	(0.00)	(0.00)
$PROD$		−0.19	−0.38	0.22	0.26
		(0.00)	(0.00)	(0.00)	(0.00)
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)

Panel C: Details of the six size-I/A portfolios

	Mean	t(Mean)	# Firms	Size	B/M	r^{11}	I/A	ROA
SL^I	0.94	3.13	902	257	1.43	22.65	−4.27	0.54
SM^I	0.88	3.13	1,075	287	1.09	17.46	7.05	0.90
SH^I	0.45	1.37	856	288	1.00	14.22	30.15	1.04
BL^I	0.76	3.31	137	8,277	0.83	18.76	−2.48	1.56
BM^I	0.56	2.61	353	9,108	0.67	15.81	7.18	1.94
BH^I	0.39	1.44	217	7,646	0.57	16.42	25.71	2.01

Panel D: Details of the six size-$PROD$ portfolios

	Mean	t(Mean)	# Firms	Size	B/M	r^{11}	I/A	ROA
SL^P	−0.22	−0.59	842	253	1.03	9.55	11.49	−3.33
SM^P	0.73	2.67	975	297	1.17	16.33	11.35	1.07
SH^P	1.29	4.25	677	302	0.70	34.44	12.56	3.37
BL^P	0.09	0.29	74	6,629	0.89	14.83	9.96	−1.73
BM^P	0.43	1.99	334	9,391	0.83	15.36	9.40	1.16
BH^P	0.50	2.17	281	11,546	0.40	23.69	11.07	3.34

Table 2 : 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 (1993) 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) monthly return. The monthly size breakpoints are the NYSE market equity quintiles, and the monthly prior return breakpoints are NYSE quintiles. For each portfolio formation month t, we sort stocks on their prior returns from month $t-2$ to $t-7$ based on NYSE breakpoints (skipping month $t-1$), and calculate the subsequent portfolio returns from month t to t+5. All portfolio returns are value-weighted. For all testing portfolios, Panel A reports mean percent excess returns and their t-statistics, CAPM alphas (α) and their t-statistics, and Fama-French (1993) three-factor regressions: $R_j - R_f = \alpha_j^{FF} + b_j^{FF}\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$. Panel B reports the neoclassical three-factor regressions: $R_j - R_f = \alpha_j^{NEO} + b_j^{NEO}\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. 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.

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

	L	2	3	4	W	W-L	L	2	3	4	W	W-L
	Mean						t(Mean)					
S	−0.04	0.60	0.80	0.95	1.21	1.25	−0.09	1.89	2.78	3.29	3.54	5.49
2	−0.11	0.47	0.71	0.81	1.06	1.17	−0.27	1.54	2.60	2.94	3.07	4.75
3	0.03	0.39	0.58	0.71	0.98	0.95	0.08	1.39	2.29	2.80	3.03	3.63
4	0.05	0.36	0.47	0.63	0.90	0.85	0.13	1.31	1.93	2.62	2.97	3.01
B	−0.22	0.21	0.29	0.41	0.68	0.90	−0.65	0.86	1.37	1.95	2.46	3.17
	α						$t(\alpha)$ ($F_{GRS} = 3.28$, $p_{GRS} = 0$)					
S	−0.59	0.15	0.40	0.53	0.73	1.33	−2.01	0.77	2.22	3.00	3.39	5.78
2	−0.69	0.01	0.29	0.38	0.55	1.23	−2.82	0.07	2.06	2.68	2.81	4.89
3	−0.51	−0.05	0.18	0.30	0.48	1.00	−2.21	−0.35	1.56	2.71	2.88	3.67
4	−0.49	−0.07	0.07	0.24	0.43	0.92	−2.02	−0.52	0.72	2.65	2.88	3.10
B	−0.69	−0.17	−0.07	0.05	0.25	0.94	−3.08	−1.40	−0.91	0.78	1.86	3.15
	α^{FF}						$t(\alpha^{FF})$ ($F_{GRS} = 3.40$, $p_{GRS} = 0$)					
S	−0.93	−0.30	−0.05	0.15	0.51	1.44	−3.67	−2.37	−0.54	1.88	4.89	5.54
2	−0.87	−0.34	−0.08	0.06	0.47	1.34	−3.82	−3.05	−1.05	0.84	4.15	4.72
3	−0.62	−0.35	−0.17	0.03	0.47	1.09	−2.58	−2.62	−1.91	0.45	4.26	3.57
4	−0.47	−0.31	−0.22	0.02	0.46	0.92	−1.64	−2.12	−2.47	0.30	3.65	2.68
B	−0.60	−0.13	−0.05	0.07	0.46	1.06	−2.41	−0.97	−0.74	1.01	3.31	3.19
	b^{FF}						s					
S	1.23	1.06	0.98	0.96	1.03	−0.20	1.27	1.03	0.96	0.99	1.15	−0.12
2	1.33	1.13	1.04	1.02	1.09	−0.24	0.90	0.79	0.72	0.77	0.98	0.08
3	1.28	1.11	1.06	1.02	1.07	−0.21	0.63	0.49	0.45	0.50	0.76	0.14
4	1.31	1.15	1.09	1.04	1.07	−0.24	0.25	0.19	0.19	0.25	0.51	0.26
B	1.19	1.00	0.95	0.94	1.01	−0.18	−0.08	−0.18	−0.21	−0.17	0.02	0.10
	h						R^2_{FF}					
S	0.22	0.43	0.44	0.35	0.10	−0.13	0.74	0.89	0.92	0.94	0.92	0.04
2	0.08	0.34	0.38	0.30	−0.07	−0.16	0.78	0.91	0.94	0.95	0.91	0.03
3	0.04	0.32	0.40	0.28	−0.11	−0.15	0.72	0.85	0.91	0.93	0.90	0.02
4	−0.07	0.30	0.36	0.25	−0.13	−0.05	0.66	0.81	0.90	0.92	0.86	0.03
B	−0.11	−0.03	0.02	0.01	−0.29	−0.18	0.62	0.79	0.92	0.92	0.80	0.01

Panel B: $R_j - R_f = \alpha_j^{NEO} + b_j^{NEO}\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$

	L	2	3	4	W	W-L	L	2	3	4	W	W-L
	α^{NEO}						$t(\alpha^{NEO})$ ($F_{GRS} = 2.20$, $p_{GRS} = 0$)					
S	0.38	0.45	0.49	0.60	0.92	0.54	1.04	1.96	2.40	2.99	3.75	1.70
2	0.22	0.25	0.30	0.35	0.75	0.53	0.76	1.43	1.90	2.17	3.27	1.62
3	0.35	0.18	0.12	0.20	0.63	0.28	1.23	1.11	0.94	1.65	3.12	0.77
4	0.40	0.10	0.00	0.07	0.48	0.08	1.29	0.65	−0.03	0.76	2.57	0.19
B	−0.10	−0.01	−0.10	−0.11	0.31	0.41	−0.38	−0.07	−1.15	−1.50	1.99	1.13
	b^{NEO}						$t(b^{NEO})$					
S	1.22	1.09	1.04	1.06	1.21	−0.01	17.04	17.66	17.09	17.28	19.08	−0.12
2	1.28	1.14	1.08	1.10	1.27	−0.01	23.28	23.98	22.20	21.52	23.48	−0.14
3	1.20	1.06	1.04	1.07	1.23	0.03	22.27	23.31	24.50	25.55	25.99	0.48
4	1.17	1.05	1.03	1.06	1.20	0.03	15.46	22.87	33.12	39.11	29.41	0.30
B	1.05	0.93	0.90	0.94	1.08	0.03	15.13	19.06	44.70	59.03	31.23	0.31
	i						$t(i)$					
S	−0.31	0.13	0.25	0.31	0.29	0.60	−1.70	1.02	2.21	2.71	2.25	4.66
2	−0.56	−0.05	0.11	0.17	0.07	0.62	−3.85	−0.44	1.18	1.90	0.57	4.60
3	−0.58	−0.16	0.05	0.12	0.00	0.58	−3.90	−1.76	0.59	1.61	−0.04	3.75
4	−0.80	−0.19	0.03	0.11	0.03	0.83	−4.84	−2.29	0.39	1.95	0.30	4.57
B	−0.67	−0.22	−0.11	0.07	−0.10	0.57	−5.16	−3.02	−2.56	1.84	−1.38	3.35
	p						$t(p)$					
S	−0.80	−0.37	−0.24	−0.24	−0.35	0.45	−6.62	−4.95	−3.56	−3.75	−4.01	3.48
2	−0.59	−0.22	−0.07	−0.07	−0.24	0.35	−5.98	−3.58	−1.30	−1.25	−2.72	2.50
3	−0.53	−0.14	0.03	0.04	−0.14	0.39	−5.36	−2.39	0.67	0.91	−1.75	2.62
4	−0.44	−0.07	0.06	0.10	−0.06	0.38	−3.97	−1.06	1.29	3.07	−0.86	2.29
B	−0.21	−0.04	0.09	0.13	0.00	0.22	−2.41	−0.68	2.89	4.82	0.07	1.72
	R^2_{NEO}											
S	0.67	0.68	0.67	0.69	0.68	0.23						
2	0.75	0.76	0.76	0.77	0.72	0.14						
3	0.75	0.78	0.81	0.83	0.76	0.13						
4	0.73	0.79	0.85	0.89	0.78	0.14						
B	0.66	0.78	0.90	0.92	0.78	0.05						

Table 3 : 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 (1993) 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 Fama-French (1993) three-factor regressions: $R_j - R_f = \alpha_j^{FF} + b_j^{FF}\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$. Panel B reports the neoclassical three-factor regressions: $R_j - R_f = \alpha_j^{NEO} + b_j^{NEO}\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. 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.

	L	2	3	4	H	H-L	L	2	3	4	H	H-L	L	2	3	4	H	H-L	L	2	3	4	H	H-L
	Panel A: Means, CAPM alphas, and Fama-French regressions												Panel B: $R_j - R_f = \alpha_j^{NEO} + b_j^{NEO}\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$											
	Mean						t(Mean)						α^{NEO}						$t(\alpha^{NEO})$ ($F_{GRS} = 2.72$, $p_{GRS} = 0$)					
S	0.10	0.81	0.88	1.07	1.19	1.09	0.25	2.40	3.10	4.05	4.21	5.08	0.08	0.64	0.46	0.59	0.64	0.57	0.27	2.49	2.23	3.10	3.31	2.72
2	0.34	0.66	0.90	1.00	1.04	0.69	0.93	2.27	3.51	4.06	3.77	3.27	0.14	0.19	0.32	0.40	0.38	0.24	0.63	1.09	2.18	2.75	2.19	1.21
3	0.41	0.72	0.74	0.84	1.07	0.66	1.22	2.70	3.14	3.67	4.12	2.86	0.19	0.14	0.07	0.15	0.31	0.13	1.05	1.05	0.60	1.17	1.86	0.57
4	0.51	0.58	0.79	0.84	0.92	0.42	1.68	2.28	3.30	3.72	3.65	1.93	0.19	−0.12	0.05	0.15	0.08	−0.11	1.23	−1.18	0.40	1.32	0.52	−0.45
B	0.40	0.61	0.59	0.65	0.65	0.25	1.67	2.68	2.75	3.13	2.80	1.20	−0.11	−0.13	−0.04	−0.03	0.03	0.14	−1.17	−1.51	−0.39	−0.26	0.16	0.61
	α						$t(\alpha)$ ($F_{GRS} = 4.25$, $p_{GRS} = 0$)						b^{NEO}						$t(b^{NEO})$					
S	−0.63	0.21	0.37	0.60	0.70	1.32	−2.61	1.03	2.15	3.64	3.82	7.10	1.31	1.14	1.04	0.98	1.03	−0.28	21.44	18.92	19.07	17.75	16.96	−5.85
2	−0.38	0.09	0.40	0.53	0.53	0.91	−2.07	0.57	2.96	3.78	3.18	4.83	1.32	1.13	1.03	0.98	1.07	−0.25	27.77	24.34	21.48	21.41	19.06	−4.63
3	−0.27	0.17	0.27	0.40	0.59	0.86	−1.74	1.45	2.32	3.16	3.71	3.96	1.24	1.10	0.99	0.94	1.03	−0.20	33.07	28.58	26.01	25.34	20.69	−3.92
4	−0.13	0.04	0.30	0.39	0.45	0.58	−1.14	0.37	2.68	3.33	3.06	2.82	1.19	1.10	1.03	0.95	1.04	−0.15	42.53	35.32	31.10	28.69	23.68	−2.63
B	−0.11	0.13	0.16	0.26	0.25	0.36	−1.29	1.48	1.54	2.18	1.61	1.81	0.99	1.01	0.90	0.83	0.85	−0.14	38.10	47.07	35.22	24.67	20.89	−2.44
	α^{FF}						$t(\alpha^{FF})$ ($F_{GRS} = 3.08$, $p_{GRS} = 0$)						i						$t(i)$					
S	−0.52	0.08	0.09	0.23	0.16	0.68	−4.48	0.88	1.35	3.31	2.16	5.50	−0.11	0.15	0.35	0.45	0.58	0.69	−0.76	1.20	3.22	4.18	4.68	5.63
2	−0.21	−0.12	0.05	0.09	−0.07	0.15	−2.63	−1.55	0.67	1.23	−0.93	1.42	−0.36	0.05	0.25	0.32	0.51	0.87	−3.26	0.54	2.98	3.67	4.43	6.97
3	−0.03	−0.05	−0.12	−0.09	−0.02	0.01	−0.37	−0.58	−1.50	−1.13	−0.22	0.08	−0.43	0.03	0.24	0.33	0.50	0.93	−4.43	0.46	3.39	4.06	4.20	7.03
4	0.11	−0.17	−0.07	−0.05	−0.11	−0.22	1.33	−1.87	−0.83	−0.56	−1.06	−1.84	−0.36	0.08	0.26	0.39	0.52	0.87	−5.75	1.24	3.88	5.14	5.41	7.30
B	0.17	0.04	−0.02	−0.13	−0.26	−0.43	2.75	0.55	−0.28	−1.75	−2.34	−3.34	−0.26	0.12	0.14	0.26	0.42	0.68	−5.17	2.51	2.19	3.54	3.76	5.05
	b^{FF}						s						p						$t(p)$					
S	1.08	0.95	0.91	0.88	0.99	−0.09	1.32	1.29	1.06	0.99	1.05	−0.27	−0.62	−0.47	−0.26	−0.21	−0.23	0.39	−5.65	−4.21	−3.00	−2.91	−3.50	4.53
2	1.13	1.04	0.99	0.97	1.09	−0.04	0.98	0.86	0.74	0.71	0.85	−0.12	−0.31	−0.12	−0.04	−0.03	−0.11	0.21	−3.71	−1.82	−0.70	−0.58	−1.63	2.64
3	1.06	1.08	1.02	1.01	1.12	0.05	0.73	0.51	0.41	0.38	0.51	−0.22	−0.23	0.02	0.07	0.07	0.02	0.24	−2.95	0.36	1.55	1.27	0.25	2.10
4	1.06	1.11	1.10	1.04	1.16	0.10	0.40	0.22	0.18	0.19	0.18	−0.21	−0.13	0.12	0.12	0.04	0.10	0.23	−2.03	2.74	2.10	0.68	1.49	2.10
B	0.95	1.05	1.00	1.00	1.05	0.10	−0.29	−0.22	−0.23	−0.21	−0.11	0.18	0.12	0.19	0.12	0.16	0.01	−0.11	4.75	5.63	2.61	2.58	0.11	−1.23
	h						R^2_{FF}						R^2_{NEO}											
S	−0.34	0.04	0.28	0.44	0.68	1.02	0.92	0.94	0.95	0.94	0.94	0.70	0.70	0.66	0.67	0.65	0.63	0.40						
2	−0.39	0.19	0.45	0.58	0.79	1.18	0.95	0.94	0.93	0.93	0.94	0.78	0.77	0.75	0.73	0.70	0.67	0.34						
3	−0.47	0.27	0.53	0.69	0.86	1.32	0.95	0.90	0.89	0.89	0.88	0.79	0.81	0.81	0.77	0.72	0.67	0.29						
4	−0.43	0.29	0.55	0.64	0.83	1.25	0.94	0.88	0.87	0.88	0.86	0.76	0.87	0.86	0.80	0.76	0.71	0.26						
B	−0.39	0.16	0.31	0.63	0.80	1.19	0.94	0.89	0.85	0.88	0.78	0.62	0.89	0.88	0.79	0.69	0.57	0.14						

Table 4 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on 25 Investment and Profitability Portfolios, 1/1972–12/2006, 420 Months

The data for the one-month Treasury bill rate (R_f) and the Fama-French (1993) factors are from Kenneth French's Web site. We sort all stocks into five quintiles each month based on NYSE breakpoints of quarterly ROA from at least four months ago, and all stocks independently in June of each year into five quintiles based on NYSE breakpoints of investment-to-assets at the last fiscal yearend. Taking intersections yields 25 investment and profitability portfolios. We calculate value-weighted returns for the current month. Panel A reports mean percent excess returns and their t-statistics, CAPM alphas (α) and their t-statistics, and Fama-French regressions: $R_j - R_f = \alpha_j^{FF} + b_j^{FF}\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$. Panel B reports the neoclassical regressions: $R_j - R_f = \alpha_j^{NEO} + b_j^{NEO}\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$. 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 the p-value.

	L^P	2	3	4	H^P	H-L^P	L^P	2	3	4	H^P	H-L^P
Panel A: Means, CAPM alphas, and Fama-French regressions												
	Mean						t(Mean)					
L^I	0.13	0.67	0.71	1.03	0.93	0.80	0.30	2.05	2.52	3.84	3.02	2.20
2	0.44	0.62	0.83	0.57	0.84	0.40	1.06	2.03	3.46	2.43	3.30	1.24
3	−0.26	0.29	0.45	0.71	0.68	0.95	−0.64	0.97	1.73	3.02	2.91	3.13
4	−0.58	0.31	0.48	0.43	0.58	1.16	−1.37	0.99	1.72	1.79	2.07	3.62
H^I	−0.98	−0.42	0.22	0.41	0.67	1.65	−2.06	−1.19	0.74	1.43	2.08	4.97
L-H^I	1.11	1.09	0.49	0.62	0.26		3.41	4.63	2.39	3.10	1.23	
	α						$t(\alpha)$ ($F_{GRS} = 4.20$, $p_{GRS} = 0$)					
L^I	−0.56	0.07	0.19	0.52	0.35	0.91	−1.76	0.36	1.12	3.47	1.98	2.51
2	−0.25	0.05	0.37	0.10	0.33	0.58	−0.90	0.30	2.92	0.91	2.57	1.85
3	−0.97	−0.26	−0.04	0.24	0.21	1.18	−3.71	−1.44	−0.25	2.09	1.89	4.11
4	−1.26	−0.27	−0.06	−0.07	0.00	1.26	−4.28	−1.44	−0.43	−0.67	−0.02	4.12
H^I	−1.81	−1.07	−0.35	−0.15	0.01	1.82	−5.98	−4.94	−1.99	−1.01	0.08	5.70
L-H^I	1.25	1.14	0.53	0.67	0.34		4.00	4.72	2.56	3.36	1.61	
	α^{FF}						$t(\alpha^{FF})$ ($F_{GRS} = 4.36$, $p_{GRS} = 0$)					
L^I	−0.67	−0.24	−0.16	0.27	0.25	0.93	−2.44	−1.23	−1.04	1.81	1.42	2.83
2	−0.32	−0.12	0.11	−0.08	0.31	0.63	−1.32	−0.63	0.86	−0.74	2.24	2.15
3	−0.93	−0.37	−0.33	0.11	0.33	1.26	−3.69	−2.01	−2.17	0.95	3.11	4.69
4	−1.24	−0.35	−0.27	−0.14	0.28	1.51	−4.36	−1.79	−1.84	−1.29	2.37	5.00
H^I	−1.82	−1.09	−0.58	−0.21	0.22	2.04	−6.40	−5.15	−3.27	−1.30	1.66	6.61
L-H^I	1.15	0.85	0.43	0.49	0.04		3.45	3.56	1.99	2.28	0.17	
	b^{FF}						s					
L^I	1.15	1.21	1.12	1.11	1.14	−0.01	1.17	0.49	0.32	0.09	0.23	−0.94
2	1.15	1.14	1.01	0.98	1.02	−0.13	1.09	0.31	0.12	0.15	0.04	−1.04
3	1.24	1.08	1.09	1.00	0.90	−0.34	0.62	0.26	0.07	0.00	−0.10	−0.72
4	1.17	1.12	1.14	1.03	1.04	−0.13	0.77	0.26	0.14	−0.02	−0.09	−0.86
H^I	1.47	1.20	1.16	1.13	1.17	−0.30	0.81	0.38	0.31	0.09	0.20	−0.61
L-H^I	−0.32	0.01	−0.04	−0.01	−0.02		0.36	0.11	0.01	0.01	0.03	
	h						R^2_{FF}					
L^I	0.01	0.41	0.48	0.37	0.12	0.10	0.63	0.69	0.72	0.72	0.69	0.18
2	−0.03	0.22	0.39	0.27	0.03	0.06	0.69	0.69	0.75	0.79	0.77	0.31
3	−0.14	0.12	0.43	0.19	−0.17	−0.03	0.64	0.66	0.72	0.78	0.78	0.24
4	−0.14	0.08	0.29	0.11	−0.41	−0.27	0.59	0.66	0.74	0.83	0.85	0.18
H^I	−0.09	−0.01	0.32	0.09	−0.34	−0.25	0.65	0.66	0.72	0.73	0.84	0.12
L-H^I	0.11	0.43	0.16	0.28	0.46		−0.06	−0.06	−0.01	−0.04	−0.10	

	L^P	2	3	4	H^P	H-L^P	L^P	2	3	4	H^P	H-L^P
Panel B: $R_j - R_f = \alpha_j^{NEO} + b_j^{NEO}\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$												
	α^{NEO}						$t(\alpha^{NEO})$ ($F_{GRS} = 2.42$, $p_{GRS} = 0$)					
L^I	0.25	0.15	−0.12	0.00	0.04	−0.21	0.79	0.67	−0.69	0.00	0.20	−0.63
2	0.67	0.52	0.23	−0.16	0.05	−0.62	2.54	2.46	1.54	−1.39	0.37	−2.23
3	0.19	0.20	−0.15	0.09	0.08	−0.12	0.87	1.00	−0.86	0.67	0.66	−0.52
4	−0.10	0.47	0.04	−0.08	0.20	0.30	−0.38	2.48	0.25	−0.76	1.63	1.06
H^I	−0.46	−0.18	−0.15	0.05	0.23	0.68	−1.58	−0.86	−0.79	0.30	1.62	2.28
L-H^I	0.71	0.33	0.03	−0.05	−0.19		1.97	1.48	0.16	−0.23	−0.87	
	b^{NEO}						$t(b^{NEO})$					
L^I	1.29	1.20	1.12	1.14	1.22	−0.06	20.41	25.47	23.66	28.66	25.25	−1.01
2	1.24	1.05	0.97	1.00	1.07	−0.18	19.25	20.84	25.80	32.42	23.32	−2.72
3	1.18	1.01	0.99	0.97	0.95	−0.23	23.31	20.99	15.87	31.32	33.67	−4.74
4	1.14	1.00	1.05	0.98	1.08	−0.07	15.25	24.35	22.16	33.38	26.41	−0.73
H^I	1.37	1.09	1.06	1.03	1.21	−0.16	19.15	24.01	17.04	19.32	39.23	−2.09
L-H^I	−0.08	0.11	0.06	0.11	0.01		−0.95	2.03	1.08	1.81	0.21	
	i						$t(i)$					
L^I	0.56	0.45	0.47	0.54	0.28	−0.29	3.28	4.37	4.28	5.72	2.32	−1.48
2	0.27	−0.09	0.37	0.40	0.13	−0.15	2.12	−0.79	4.20	5.57	1.92	−1.12
3	−0.46	−0.08	0.06	0.07	−0.05	0.40	−3.71	−0.72	0.74	0.86	−0.82	3.20
4	−0.39	−0.34	−0.18	−0.21	−0.52	−0.13	−2.43	−3.53	−1.82	−3.70	−7.75	−0.75
H^I	−0.83	−0.60	−0.33	−0.66	−0.75	0.08	−5.41	−5.58	−2.93	−7.24	−8.91	0.51
L-H^I	1.39	1.06	0.80	1.20	1.03		7.67	8.69	6.63	9.48	7.69	
	p						$t(p)$					
L^I	−1.05	−0.30	0.06	0.23	0.16	1.21	−9.12	−3.93	1.04	5.18	3.40	11.40
2	−1.01	−0.40	−0.04	0.06	0.20	1.21	−8.15	−4.69	−0.75	1.46	4.48	9.59
3	−0.89	−0.41	0.08	0.11	0.16	1.05	−13.69	−6.01	1.17	1.92	4.60	14.19
4	−0.92	−0.54	−0.01	0.11	0.06	0.98	−11.61	−7.65	−0.18	2.71	1.31	10.31
H^I	−0.89	−0.56	−0.03	0.14	0.16	1.05	−9.08	−6.39	−0.40	2.47	3.38	9.11
L-H^I	−0.16	0.26	0.09	0.10	−0.00		−1.16	3.33	1.35	1.79	0.04	
	R^2_{NEO}											
L^I	0.67	0.67	0.67	0.75	0.69	0.40						
2	0.74	0.72	0.73	0.78	0.79	0.54						
3	0.76	0.71	0.67	0.78	0.78	0.54						
4	0.67	0.76	0.73	0.84	0.84	0.34						
H^I	0.72	0.74	0.69	0.77	0.85	0.39						
L-H^I	−0.16	−0.19	−0.11	−0.26	−0.18							

Table 5 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Campbell, Hilscher, and Szilagyi's (2007) Failure Probability (F-Prob) Measure and Deciles Formed on Ohlson's (1980) O-Score

The data on the one-month Treasury bill rate, the Fama-French (1993) three factors are from Kenneth French's Web site. See Table 1 for the description of the investment INV factor and the productivity $PROD$ factor. The distress measure is defined in Appendix B. We sort all NYSE, Amex, and NASDAQ stocks at the beginning of each month into deciles based on failure probability and on O-score four months ago. Appendix B contains detailed definitions of F-prob and O-score. Monthly value-weighted returns on the F-prob and O-score portfolios are calculated for the current month, and the portfolios are rebalanced monthly. 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).

	Low	2	3	4	5	6	7	8	9	High	H-L	F_{GRS}
	Panel A: The F-prob deciles, 6/1975–12/2006, 379 months											
Mean	1.03	0.82	0.72	0.63	0.72	0.45	0.58	0.28	0.16	−0.35	−1.38	
t(Mean)	4.07	3.69	3.33	2.79	2.93	1.57	1.80	0.80	0.39	−0.72	−3.53	
α	0.39	0.21	0.10	−0.01	0.01	−0.33	−0.30	−0.61	−0.86	−1.48	−1.87	3.01 (0)
β	0.95	0.90	0.93	0.95	1.06	1.17	1.30	1.32	1.51	1.69	0.73	
$t(\alpha)$	2.60	1.99	1.13	−0.14	0.13	−2.50	−1.68	−2.75	−3.31	−4.57	−5.08	
α^{FF}	0.39	0.36	0.19	0.10	−0.01	−0.49	−0.27	−0.71	−1.06	−1.75	−2.14	4.75 (0)
b^{FF}	0.91	0.87	0.93	0.94	1.06	1.21	1.24	1.24	1.38	1.48	0.57	
s	0.17	−0.14	−0.18	−0.16	0.01	0.12	0.20	0.48	0.85	1.27	1.10	
h	−0.04	−0.19	−0.10	−0.13	0.03	0.20	−0.09	0.02	0.09	0.09	0.13	
$t(\alpha^{FF})$	2.46	3.30	2.18	0.95	−0.07	−3.15	−1.65	−3.24	−4.66	−6.39	−6.43	
α^{NEO}	0.19	−0.01	−0.11	−0.01	0.13	−0.07	0.33	0.34	0.24	−0.13	−0.32	1.78 (0.06)
b^{NEO}	0.99	0.95	0.97	0.95	1.03	1.10	1.16	1.11	1.27	1.42	0.43	
i	0.00	0.07	0.03	−0.08	−0.01	−0.19	−0.27	−0.34	−0.34	0.02	0.03	
p	0.18	0.17	0.17	0.04	−0.10	−0.14	−0.43	−0.69	−0.82	−1.22	−1.40	
$t(\alpha^{NEO})$	1.09	−0.12	−1.29	−0.08	1.14	−0.44	2.23	2.00	1.03	−0.49	−1.09	
$t(b^{NEO})$	25.21	26.98	37.60	24.40	36.96	20.84	30.46	26.98	21.85	18.17	5.78	
$t(i)$	−0.04	1.06	0.65	−1.48	−0.15	−2.38	−2.40	−3.22	−2.21	0.16	0.18	
$t(p)$	2.46	3.52	5.07	0.81	−2.46	−2.32	−6.77	−9.92	−11.54	−13.42	−14.64	
	Panel B: The O-score deciles, 1/1972–12/2006, 420 months											
Mean	0.48	0.62	0.48	0.53	0.50	0.48	0.43	0.26	0.19	−0.44	−0.92	
t(Mean)	2.04	2.54	1.91	2.24	2.03	1.97	1.64	0.92	0.59	−1.04	−2.84	
α	−0.04	0.09	−0.05	0.04	0.00	0.00	−0.07	−0.27	−0.40	−1.14	−1.10	2.49 (0.01)
β	1.02	1.05	1.05	0.98	1.00	0.95	0.99	1.06	1.18	1.38	0.36	
$t(\alpha)$	−0.51	1.15	−0.50	0.42	−0.01	0.03	−0.51	−1.70	−2.06	−3.96	−3.56	
α^{FF}	0.12	0.09	−0.23	−0.21	−0.24	−0.22	−0.43	−0.52	−0.74	−1.32	−1.44	6.33 (0)
b^{FF}	0.99	1.02	1.09	1.03	1.03	0.95	1.03	1.02	1.12	1.16	0.17	
s	−0.15	0.11	0.21	0.30	0.33	0.45	0.55	0.66	0.92	1.35	1.50	
h	−0.21	−0.01	0.25	0.35	0.32	0.28	0.47	0.29	0.40	0.10	0.32	
$t(\alpha^{FF})$	1.68	0.98	−2.41	−2.49	−2.36	−2.11	−3.61	−3.86	−5.04	−6.39	−6.49	
α^{NEO}	0.02	0.14	−0.07	−0.01	0.02	0.19	0.14	0.10	0.17	−0.07	−0.09	1.10 (0.36)
b^{NEO}	1.00	1.03	1.06	1.00	1.00	0.93	0.97	1.00	1.09	1.21	0.22	
i	−0.21	−0.10	0.02	0.14	0.07	0.04	0.15	0.00	0.00	−0.01	0.20	
p	0.05	0.00	0.02	−0.02	−0.06	−0.20	−0.28	−0.36	−0.55	−1.02	−1.07	
$t(\alpha^{NEO})$	0.20	1.50	−0.61	−0.05	0.19	1.40	0.97	0.63	0.91	−0.29	−0.32	
$t(b^{NEO})$	50.55	31.89	27.74	33.31	31.23	25.87	22.19	20.58	20.29	17.43	2.93	
$t(i)$	−4.29	−1.84	0.29	2.04	0.93	0.53	1.63	−0.04	0.02	−0.07	1.18	
$t(p)$	2.74	0.10	0.38	−0.52	−1.55	−4.31	−5.86	−7.58	−9.04	−10.48	−11.03	

Table 6 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on the Net Stock Issues Deciles and the Earnings-to-Price Deciles, 1/1972–12/2006, 420 Months

The data on the one-month Treasury bill rate, the Fama-French (1993) three factors, and the earnings-to-price deciles returns are from Kenneth French's Web site. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. We measure net stock issues as the the natural log of the ratio of the split-adjusted shares outstanding at the fiscal yearend in $t-1$ (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 $t+1$. The earnings-to-price deciles are formed on earnings-to-price ratios at the end of each June using NYSE breakpoints. The earnings used in June of year t are total earnings before extraordinary items (Compustat annual item 18) for the last fiscal yearend in $t-1$. Market equity is price times shares outstanding at the end of December of $t-1$. We also report the Gibbons, Ross, and Shanken (1989) F-statistic (F_{GRS}) testing that the intercepts of all testing portfolios are jointly zero and its associated p-value in parenthesis.

	Low	2	3	4	5	6	7	8	9	High	H-L	F_{GRS}
					Panel A: The net stock issues deciles							
Mean	1.00	0.77	0.39	0.85	0.82	0.88	0.72	0.68	0.27	0.16	−0.84	
t(Mean)	4.73	3.65	1.53	3.88	3.61	3.59	2.68	2.35	0.89	0.55	−4.64	
α	0.42	0.17	−0.30	0.25	0.17	0.18	−0.04	−0.13	−0.55	−0.64	−1.06	3.97 (0)
β	0.88	0.90	1.05	0.92	0.99	1.06	1.16	1.23	1.24	1.21	0.33	
$t(\alpha)$	3.68	1.84	−2.13	2.25	1.98	1.73	−0.36	−0.94	−3.21	−4.34	−5.07	
α^{FF}	0.22	0.08	−0.28	0.15	0.13	0.16	0.00	−0.01	−0.41	−0.59	−0.82	3.10 (0)
b^{FF}	0.99	0.96	1.03	0.99	1.01	1.04	1.12	1.14	1.13	1.14	0.15	
s	0.01	−0.01	0.03	−0.06	0.00	0.18	0.08	0.12	0.16	0.26	0.25	
h	0.32	0.15	−0.03	0.17	0.08	0.04	−0.06	−0.19	−0.23	−0.07	−0.39	
$t(\alpha^{FF})$	2.39	0.88	−2.12	1.37	1.36	1.55	−0.01	−0.07	−2.45	−3.89	−4.33	
α^{NEO}	0.09	0.00	0.01	0.12	0.24	0.35	0.24	0.43	0.16	−0.19	−0.28	2.67 (0)
b^{NEO}	0.96	0.95	0.97	0.94	0.96	1.01	1.07	1.06	1.05	1.08	0.12	
i	0.11	0.07	−0.22	−0.10	−0.17	−0.12	−0.40	−0.51	−0.50	−0.43	−0.55	
p	0.21	0.10	−0.15	0.14	0.02	−0.08	−0.06	−0.23	−0.36	−0.18	−0.39	
$t(\alpha^{NEO})$	0.90	0.05	0.06	1.07	2.49	2.90	1.96	3.14	1.10	−1.10	−1.39	
$t(b^{NEO})$	45.73	43.08	29.22	35.43	42.35	34.29	37.39	35.95	33.72	29.85	2.67	
$t(i)$	1.66	1.47	−3.17	−1.69	−3.47	−1.77	−5.36	−5.80	−6.00	−4.74	−4.25	
$t(p)$	5.06	3.01	−2.47	3.29	0.53	−1.61	−1.58	−6.78	−7.23	−4.09	−6.53	
					Panel B: The earnings-to-price deciles							
Mean	0.31	0.40	0.59	0.57	0.55	0.64	0.83	0.80	0.83	1.00	0.69	
t(Mean)	1.06	1.68	2.58	2.64	2.48	2.98	3.93	3.72	3.63	3.84	2.92	
α	−0.31	−0.11	0.11	0.11	0.08	0.21	0.40	0.37	0.39	0.51	0.82	2.48 (0.01)
β	1.23	1.02	0.95	0.91	0.92	0.86	0.84	0.85	0.87	0.97	−0.25	
$t(\alpha)$	−2.73	−1.39	1.14	1.29	0.90	2.00	4.03	3.54	3.24	3.36	3.55	
α^{FF}	0.06	0.01	0.09	0.07	−0.07	−0.04	0.12	0.04	−0.04	−0.07	−0.13	0.86 (0.57)
b^{FF}	1.06	0.99	0.99	0.96	1.02	0.99	1.00	1.00	1.06	1.19	0.13	
s	−0.02	−0.14	−0.16	−0.14	−0.13	−0.04	−0.10	0.03	0.06	0.23	0.25	
h	−0.57	−0.16	0.05	0.08	0.25	0.38	0.45	0.51	0.65	0.84	1.41	
$t(\alpha^{FF})$	0.71	0.11	0.93	0.89	−0.79	−0.42	1.47	0.44	−0.35	−0.63	−0.90	
α^{NEO}	−0.02	−0.27	−0.15	−0.10	−0.13	−0.08	0.02	0.10	0.21	0.28	0.31	1.76 (0.07)
b^{NEO}	1.14	1.04	0.99	0.95	0.95	0.92	0.93	0.91	0.92	1.03	−0.12	
i	−0.46	−0.06	−0.01	0.05	0.06	0.20	0.33	0.28	0.24	0.23	0.69	
p	−0.05	0.18	0.25	0.17	0.17	0.18	0.21	0.12	0.06	0.10	0.15	
$t(\alpha^{NEO})$	−0.19	−3.28	−1.47	−1.24	−1.24	−0.73	0.17	0.96	1.52	1.87	1.30	
$t(b^{NEO})$	35.18	52.33	43.09	46.31	37.26	35.04	34.92	24.05	19.83	21.65	−1.63	
$t(i)$	−6.87	−1.24	−0.23	1.16	1.08	3.26	6.91	4.79	2.73	2.11	4.47	
$t(p)$	−1.48	7.17	6.40	6.03	3.94	3.77	4.94	2.88	1.09	1.39	1.58	

Figure 1 : Investment-to-Assets (I/A, Contemporaneous and Lagged) for the 25 Size and Momentum Portfolios, 1972:Q1 to 2006:Q4, 140 Quarters

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 for $t+m, m = -60, \ldots, 60$. The I/A for $t+m$ are then averaged across portfolio formation months t. I/A is 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 value of assets (item 6). In Panel B, I/A is the current year-end I/A relative to month t. For example, if the current month is March 2003, then I/A is measured at the fiscal year-end of 2003. In Panel C, the lagged I/A is the I/A on which an annual sorting on I/A in each June is based. For example, if the current month is March 2003, then the lagged I/A is the I/A at the fiscal year-end of 2001. If the current month is September 2003, the lagged I/A is the I/A at the fiscal year-end of 2002. For a given portfolio, we plot the median I/A among the firms in that portfolio.