NBER WORKING PAPER SERIES

NEOCLASSICAL FACTORS

Long Chen
Lu Zhang

Working Paper 13282
http://www.nber.org/papers/w13282

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2007

For helpful discussions, we thank Sreedhar Bharath, Gerald Garvey (BGI discussant), Tyler Shumway, Motohiro Yogo (UBC discussant), Richard Sloan, Scott Richardson, and seminar participants at Barclays Global Investors, Hong Kong University of Science and Technology, UBC PH&N Summer Finance Conference in 2007, and University of Michigan. Cynthia Jin provided valuable assistance in early stages of this project. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

Neoclassical Factors
Long Chen and Lu Zhang
NBER Working Paper No. 13282
July 2007
JEL No. G11,G12,G14,G24,G31,G32

ABSTRACT

Building on neoclassical reasoning, we propose a new multi-factor model that consists of the market factor and factor mimicking portfolios based on investment and productivity. The neo- classical three-factor model outperforms traditional factor models in explaining the average returns across testing portfolios formed on momentum, financial distress, investment, profitability, accruals, net stock issues, earnings surprises, and asset growth. Most intriguingly, winners have higher loadings than losers on both the low-minus-high investment factor and the high- minus-low productivity factor, which in turn help explain momentum profits.

Long Chen
321 Eppley
Department of Finance
The Eli Broad Graduate School of Management
Michigan State University
East Lansing
MI 48824
chen@bus.msu.edu

Lu Zhang
Finance Department
Stephen M. Ross School of Business
University of Michigan
701 Tappan Street, ER 7605 Bus Ad
Ann Arbor MI, 48109-1234
and NBER
zhanglu@bus.umich.edu

1 Introduction

The Sharpe (1964) and Lintner (1965) capital asset pricing model (CAPM) cannot explain many 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) three-factor model leaves 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, leading the Fama-French model to exacerbate the momentum anomaly.

The relation between financial distress and average returns 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 the distress risk is associated with lower average returns (e.g., Dichev 1998, Griffin and Lemmon 2002, Campbell, Hilscher, and Szilagyi 2007). Using a comprehensive measure of financial 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.[1]

We show that the momentum and the distress anomalies are related, and are captured by a new multi-factor 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

[1] Campbell, Hilscher, and Szilagyi (2007) conclude 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)."

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 0.34% ($t = 4.15$) and 0.73% per month ($t = 5.67$), 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. We find that the neoclassical three-factor model goes a long way in describing the cross section of average returns on NYSE, Amex, and NASDAQ stocks.

Most important, the neoclassical model outperforms the Fama-French (1993) model in explaining the average returns of 25 size and momentum portfolios. Using the six-month momentum definition of Jegadeesh and Titman (1993), we find that none of the winner-minus-loser portfolios across five size quintiles have significant alphas. The alphas, ranging from -0.02% to 0.34% per month, are all within 1.6 standard errors of zero. For comparison, the five winner-minus-loser alphas vary from 0.64% ($t = 2.77$) to 1.02% per month ($t = 6.04$) in the CAPM and from 0.75% ($t = 2.92$) to 1.14% per month ($t = 6.07$) in the Fama-French model. In total, seven out of the 25 size and momentum portfolios have significant neoclassical alphas, and our model is rejected by the Gibbons, Ross, and Shanken (1989, GRS) test. However, the number of significant alphas is about half of that in the CAPM (13) and that in the Fama-French model (13).

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. The high-minus-low distress decile earns a neoclassical alpha of 0.18% per month ($t =$ 0.83). And the model cannot be rejected using distress deciles by the GRS test (p-value = 0.08). In contrast, the corresponding alpha is -1.23% ($t = -4.15$) in the CAPM and -1.34% ($t = -5.22$) in the Fama-French (1993) model. And both models are rejected by the GRS test at the 1% level. 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 productivity-return relation, and, not surprisingly, find the distress-return relation anomalous.

Since Fama and French (1996), several other anomaly variables have received much attention, including earnings surprises, investment, profitability, accruals, net stock issues, and asset growth. (We provide detailed references later in this section and in Section 2.) 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, the neoclassical alphas for the five high-minus-low investment portfolios are all within 1.5 standard errors of zero. The alpha with the highest magnitude is -0.30% per month ($t = -1.45$) in the lowest-profitability quintile. In contrast, the corresponding alpha is -1.01% ($t = -4.67$) in the CAPM and -0.70% ($t = -3.45$) in the Fama-French model. Further, the high-minus-low profitability portfolio in the highest-investment quintile earns a neoclassical alpha of 0.27% ($t = 1.34$), whereas the corresponding alpha is 1.22% ($t = 4.96$) in the CAPM and 1.43% ($t = 6.08$) in the Fama-French model.

However, our neoclassical model underperforms the Fama-French (1993) model in explaining the anomalies formed on valuation ratios such as book-to-market (B/M). While the Fama-French model explains these anomalies through their HML factor, the main driver in our model is the INV factor. Stocks with higher valuation ratios invest less, load more on the low-minus-high INV factor, and earn higher average returns. But empirically, the explanatory power of INV for valuation-sorted portfolio returns is not as high as that of HML. This evidence lends support to Fama and French (2007), who show that including net stock issues and asset growth in cross-sectional regressions has little impact on the book-to-market effect. However, the small-growth portfolio only earns a tiny neoclassical alpha of -0.03% per month ($t = -0.10$) 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 the tiny 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 provides a reasonable description of the cross section 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. Fairfield, Whisenant, and Yohn (2003), Richardson and Sloan (2003), Titman, Wei, and Xie (2004), Anderson and Garcia-Feijóo (2006), Fama and French (2006, 2007), Cooper, Gulen, and Schill (2007), Polk and Sapienza (2007), Lyandres, Sun, and Zhang (2007), and Xing (2007) show that firms that invest more earn lower average returns. 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, we complement Fama and French's (2006) effort in providing a unifying perspective for many anomalies that are often treated in isolation. While Fama and French derive their testable predictions from valuation theory, we derive our hypotheses from neoclassical investment theory. To the extent that there is no over- or under-reaction in our theory, we reinforce Fama and French's 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. In fact, our theory and tests suggest that the anomalies can be consistent with Efficient Market Hypothesis.

Our story proceeds as follows. Section 2 motivates our neoclassical factors and discusses our empirical strategy. Section 3 uses time series tests to show that the neoclassical model helps explain anomalies. Section 4 reports cross-sectional tests. We conclude in Section 5.

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 (see equation A.8 in Appendix A) — the two-period simplification of the infinite-horizon equation in Liu, Whited, and Zhang (2007):

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

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 many anomalies, including value, net stock issues, accruals, and asset growth:

> *The Investment Hypothesis*: The negative investment-return relation drives the positive relations of average returns with book-to-market and earnings-to-price as well as the negative relations of average returns with accruals, net stock issues, and asset growth.

2.1.1.1 Intuition 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.[2] 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,

[2] More precisely, the marginal q equals the average q under constant returns to scale, as shown in Hayashi (1982) and Abel and Eberly (1994). But the average q and market-to-book equity are closely correlated, and are identical in models with all equity financing. See Liu, Whited, and Zhang (2007) for detailed derivations.

the accrual anomaly, and the asset growth 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 Lyandres, Sun, and Zhang (2007) argue that 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. 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 follow Fama and French (2007) in using a more comprehensive net issues measure that takes into account share repurchases. And besides INV, we also study the role of $PROD$ in driving the net issues anomaly.

Sloan (1996) shows that firms with high accruals earn abnormally low average returns than firms with low accruals (see also Xie 2001; Fairfield, Whisenant, and Yohn 2003; Richardson, Sloan, Soliman, and Tuna 2004; Hirshleifer, Hou, Teoh, and Zhang 2004). Sloan interprets the evidence as investors overestimating the persistence of the accrual component of earnings only to be systematically surprised later on. But interpreting accruals as working capital investment, Wu, Zhang, and Zhang (2007) hypothesize that firms rationally adjust their working capital investment to respond to discount rate changes. Wu et al. show that adding the investment factor into the CAPM and the Fama-French (1993) model substantially reduces the magnitude of the accrual anomaly. We complement their work by using the accruals measure from Fama and French (2007) that adjusts for the effect of changes in the scale of firms caused by share issues and repurchases. We verify that investment is important in driving the accrual anomaly, but productivity is not.

Cooper, Gulen, and Schill (2007) show that asset growth, defined as the annual changes in total assets divided by lagged total assets, strongly predicts future returns with a negative sign. Following Titman, Wei, and Xie (2004), Cooper et al. interprets the evidence as investors underreacting to managerial overinvestment. Our view is that asset growth is arguably the most comprehensive measure of investment-to-assets, in which investment is simply the changes in total assets.

2.1.1.2 Discussion Noteworthy, 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 both in the data (e.g., Fama and French 1995) and in theory (e.g., Zhang 2005). The conditional nature of the investment-return relation offers the following portfolio interpretation of the investment hypothesis. Sorting on book-to-market, earnings-to-price, accruals, net stock issues, and asset growth 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 earnings surprises and short-term prior returns as well as the negative relation between average returns and financial distress.

2.1.2.1 Intuition 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. Imagine a two-period version of that model: Price equals expected cash flow divided by the discount rate. So high expected cash flow (or expected profitability) relative to low price (or market valuation ratios) means high discount rates. And to the extent that there is no over- or under-reaction (all the expectations are rational) in our neoclassical model, high discount rates correspond to high risk (see equation A.10 for the formal link between risk and characteristics).

Going beyond the discounting intuition from valuation theory, our investment-based 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. So 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 three such sorts, sorts on earnings surprises, on short-term prior returns, and on financial distress.

Sorting on earnings surprises can generate a profitability spread between extreme portfolios. The intuition is that firms that have experienced large, positive earnings surprises are more profitable than firms that have experienced large, negative earnings surprises. Sorting on momentum also should generate an important spread in profitability.[3] 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 Campbell, Hilscher, and Szilagyi (2007) can be another reflection of the positive productivity-return relation. The intuition is that less distressed firms are more profitable and should earn higher average returns, even though they are less levered. And more distressed firms are less profitable and should earn lower average returns, even though they are more levered.

2.2 Empirical Strategy: Strengths and Weaknesses

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 From Theory to Practice

We construct factor mimicking portfolios based on investment-to-assets and earnings-to-assets, which, according to equation (3), are pivotal economic determinants of expected returns. Because these two factors are derived from the partial equilibrium q-theory that studies the optimal investment of firms, we also include the market factor, MKT, which can be derived from the partial equilibrium theory of consumption (see, for example, Cochrane 2005, p. 155–156). The resulting

[3] Liu and Zhang (2007) show that winners have temporarily higher expected profitability and expected growth rates than losers. The duration of the expected-growth spread also matches roughly the duration of momentum profits.

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 alternative methods that have been used to explore the empirical foundation of investment-based asset pricing. Zhang (2005), Cooper (2006), and Gala (2006) build full-fledged equilibrium models and examine if model-implied moments match key facts in the data. This quantitative theory approach à la Kydland and Prescott (1982) is useful to understand underlying economic mechanisms, but it does not provide an easy-to-use model for calculating expected returns in practice. Liu, Whited, and Zhang (2007) 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 structural estimation approach à la Hansen and Singleton (1982) is closely linked to the underlying theory, and it also provides an empirical expected-return model. But the model is more complicated to implement than most models in empirical finance. Our portfolio approach can be viewed as a linearized implementation of Liu et al.'s nonlinear estimation. As noted, although the link between theory and tests is not as close, we adore the portfolio approach because of its powerful simplicity.

We also supplement time series tests on sorted portfolios with Fama and MacBeth (1973) cross-sectional regressions on characteristics. We do so for several reasons. First, our empirical analysis builds on prior studies that use variables such as investment and profitability in cross-sectional tests (e.g., Fama and French 2006, 2007). Replicating their tests with our sample and variable definitions is useful for comparison. Second, more important, we motivate INV and $PROD$ from the q-theory, which directly ties expected returns to investment and profitability characteristics. Thus, using characteristics in cross-sectional regressions can be a more direct test of the theory. Third, cross-sectional regressions can be more powerful that time series tests in some circumstances because they provide an easier way to control for all the characteristics simultaneously.

While sensitive to the differences between time series and cross-sectional tests (see, e.g., Fama and French 2007, p. 2–3), we view these two methods as closely related. If a variable shows up significantly in cross-sectional tests, its factor mimicking portfolio is likely to have important explanatory power in time series tests. We find time series tests easy to interpret because they provide a simple measure of abnormal returns as the regression intercept. Fortunately, although our test results from the two approaches sometimes differ in nuances, they provide the same general inferences.

2.2.2 Interpreting Neoclassical Factors

Following Fama and French (1993, 1996), we interpret our neoclassical factors as common factors in the cross section of returns. While Fama and French pursue a more aggressive interpretation that their similarly constructed SMB and HML are risk factors in the context of ICAPM or APT, we shy away from taking a strong stance on the risk interpretation of our factors.

On the one hand, the theoretical 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. The latter set of endogenous relations cannot possibly be captured by consumption-based frameworks because characteristics are not even 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). And perhaps because of the lack of readily available measures, behavioralists often use valuation ratios to proxy for mispricing. Interpreting Fama and French's (1993) factors is controversial because size and B/M directly involve market equity. But our neoclassical factors are constructed on economic fundamentals that are less likely to be affected by mispricing, at least directly.

On the other hand, Polk and Sapienza (2006) show that investor sentiment can affect investment and hence 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 cannot rule out these interpretations.

More important, risk-based and characteristics-based interpretations on any common factor are not mutually exclusive: In fact, they are the two sides of the same coin. Challenging 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, an analytical link exists between covariances and characteristics (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 simple: In a time-varying, dynamic world, characteristics are more precisely measured than covariances. And a horse race often declares characteristics as the winner. This is the case even in simulated data generated from dynamic single-factor models (e.g., Gomes, Kogan, and Zhang 2003). 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 Time Series Regressions

We report our main results from time series tests. We first construct the explanatory factors in Section 3.1. We then use the neoclassical three-factor model to explain average returns for a wide range of testing portfolios, including both two-way sorted (Section 3.2) and one-way sorted (Section 3.3).

3.1 The Explanatory Factors

This subsection constructs and reports the properties of the investment and productivity factors.

3.1.1 The Investment Factor, INV

Following the Fama and French (1993) portfolio approach, we construct INV from a double (two by three) sort on size and investment-to-assets. (Appendix B describes our sample construction and variable definitions in details.) 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 for stocks traded on NYSE. We use NYSE breakpoints in constructing factors and testing portfolios throughout the paper to help ensure that none of the portfolios are excessively dominated by micro-caps and small stocks (e.g., Fama and French 2007).

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 0.34% per month ($t = 4.15$). Regressing INV on MKT generates an alpha of 0.41% per month ($t = 5.54$) and a R^2 of 17%. Regressing INV on the Fama and French (1993) model and the Carhart (1997) model reduces the alpha to 0.26% and 0.17% per month ($t = 3.66$ and 2.39), and increases the R^2 to 31% and 35%, 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 relatively high correlation of 0.51 with HML (p-value = 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 follow Lyandres, Sun, and Zhang (2007) in using 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 -3.44% per annum, whereas portfolio SH^I (small-size and high-investment) has an average of 28%. Portfolio SH^I is also more profitable than portfolio SL^I: The earnings-to-assets (ROA) of portfolio SH^I is 1.17% per quarter versus 0.66% 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% versus 15%. This evidence partially reflects the fact that low-investment firms have higher average future returns than high-investment firms. (We follow Fama and French (1993) in sorting 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 find that portfolio SL^I has lower average contemporaneous returns than portfolio SH^I, 18% versus 27%.

3.1.2 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. The reason is that profitability is highly persistent (e.g., Fama and French 1995, 2000, 2006). In particular, Fama and French (2006) show that current profitability is the strongest predictor of future profitability, meaning that current profitability is highly correlated with the 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 $PROD$. In particular, we use quarterly data to measure ROA. Indeed, using annual sorts on annual earnings-to-assets at the last fiscal year-end yields an insignificant average return of only five basis points per annum for the productivity factor. This evidence is consistent with that reported by Fama and French (2007, Table II).

However, we also find that the original earnings and momentum anomalies do not survive the frequency change from monthly to annual rebalancing either. Specifically, in June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the NYSE breakpoints of the Standardized Unexpected Earnings (SUE) measured at the fiscal year-end of $t-1$, the average SUE over the last fiscal year, the annual return over the calendar year $t-1$, and the 12-month return from June of year $t-1$ to May of year t. Monthly value-weighted returns of these portfolios are calculated from July of year t to June of year $t+1$. Untabulated results show that none of these strategies generate mean excess returns or CAPM alphas that are significantly different from zero. Because the SUE and momentum anomalies only exist in monthly rebalancing, it seems reasonable to construct the explanatory $PROD$ factor in the same frequency.

Nevertheless, we emphasize that using quarterly earnings to construct $PROD$, while using annual investment to construct INV, is largely driven by data, not by theory. The growing literature on investment-based asset pricing does predict that earnings and prior returns can be related to time-varying expected returns.[4] However, to the best of our knowledge, the theoretical literature has so far not addressed the question why earnings and momentum anomalies are more short-lived than others such as value and investment anomalies. This caveat also applies to our work.

[4]See Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007) for recent examples that relate prior short-term returns to expected returns. Liu and Zhang (2007) document that recent winners have temporarily higher loadings than recent losers on the growth rate of industrial production. Liu, Whited, and Zhang (2007) show that an investment-based expected return model can partially explain the earnings anomaly.

To construct $PROD$, each month from January 1972 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 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 the four-month lag to ensure that the required accounting information is known before we form the portfolios. We also use the NYSE median market equity 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 0.73% per month ($t = 5.67$) 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 0.76%, 0.89%, and 0.66% per month (t = 5.84, 7.04, and 5.43), and R^2s of 1%, 10%, and 22%, respectively. This evidence means that, like INV, $PROD$ also captures average return variations not subsumed by well-known common factors. Panel B reports that $PROD$ and WML have a high correlation of 0.36 (p-value = 0). Intuitively, shocks to earnings are positively correlated with contemporaneous shocks to returns. Thus, we expect $PROD$ to have certain explanatory power for momentum profits.

Intriguingly, the correlation between INV and $PROD$ is only -0.06 (p-value = 0.19), meaning no need to neutralize the two factors against each other. The low correlation is counterintuitive because one would expect that more profitable firms should invest more and that the two factors should be negatively correlated. The low correlation results from our use of quarterly earnings to construct $PROD$ but annual investment to construct INV. If we instead use annual earnings data to construct the productivity factor, we find its correlation with INV to be -0.20 (p-value = 0). And if we use quarterly investment data to construct the investment factor, we find its correlation with $PROD$ to be -0.33 (p-value = 0). Thus, matching rebalancing frequency increases the positive correlation between investment and earnings, thereby increasing the magnitude of the negative correlation between their factor mimicking portfolio returns.

Panel D of Table 1 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 -1.78% per quarter, whereas portfolio SH^P (small-size and high-productivity) has an average ROA of 3.41%. The large ROA spread only corresponds to a modest spread in annual I/A: 11.4% versus 12.6%. The evidence helps explain the low correlation between INV and $PROD$ reported earlier. And the ROA spread in small firms corresponds to a large spread in prior 2–12 month returns: 9.4% versus 34.8%, helping explain the high correlation between $PROD$ and WML.

3.2 Tests on Two-Way Sorted Portfolios

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

3.2.1 Preliminaries

We start by describing the construction and the basic properties of testing portfolios.

3.2.1.1 The Size-Momentum Portfolios The 25 size-momentum portfolios are from Kenneth French's Web site. Fama and French (1996) use the "11/1/1" convention to measure momentum. For each month t, stocks are sorted on their prior returns from month $t-2$ to $t-12$ (skipping month t–1), and the subsequent portfolio returns are calculated for the current month t. The 25 size and 11/1/1-momentum portfolios are formed monthly as the intersection of five portfolios sorted on size and five portfolios sorted on prior 2–12 month returns. The monthly breakpoints are the NYSE market equity quintiles, and the monthly prior 2–12 month returns breakpoints are NYSE quintiles.

Following Jegadeesh and Titman (1993), we also construct an alternative set of 25 size and momentum portfolios using the "6/1/6" convention of momentum. For each month t, we use NYSE breakpoints to 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 6/1/1-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. Panel A uses the "11/1/1" convention of momentum. The winner-minus-loser (W-L) average return varies from 0.64% per month ($t = 2.16$) in the biggest-size quintile to 1.72% ($t = 7.63$) in the smallest-size quintile. In total, 16 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 6.22 (p-value = 0). More important, the CAPM alphas for the winner-minus-loser portfolios are significant positive across all five size quintiles. The small-stock W-L strategy, in particular, earns a CAPM alpha of 1.78% per month ($t = 8.23$). Consistent with Fama and French (1996), their three-factor model exacerbates the momentum anomaly: 18 out of 25 Fama-French alphas are significant. And the Fama-French alphas for the W-L portfolios are all larger than their corresponding CAPM alphas. In particular, the small-stock W-L strategy earns a Fama-French alpha of 1.96% per month ($t = 7.97$). The reason is that losers have higher HML-loadings than winners: Losers behave more like value stocks, and the Fama-French model predicts that losers should earn higher average returns, instead of lower average returns as we see in the data.

The results from the 25 size and 6/1/6-momentum portfolios are similar, but the magnitude of momentum profits is smaller than that with the 11/1/1-momentum. The mean excess return of the W-L portfolio ranges from 0.64% per month ($t = 2.82$) in the biggest-size quintile to 0.97% ($t = 5.48$) in the smallest-size quintile. The CAPM fails to explain the average returns of these testing portfolios: 13 out of 25 individual alphas are significant. And the GRS test rejects the model at the 1% level. In particular, the small-stock W-L strategy earns an alpha of 1.02% per month ($t = 6.04$). The Fama-French (1993) model again generates larger pricing errors than the CAPM. The W-L alpha from the Fama-French model ranges from 0.75% ($t = 2.92$) to 1.14% per month ($t = 6.07$).

3.2.1.2 The 25 Investment-Profitability Portfolios We sort all NYSE, Amex, and NASDAQ stocks into five profitability quintiles each month based on NYSE breakpoints of quarterly ROA from at least four months ago. Also, we sort all stocks independently in June of each year into five quintiles based on NYSE breakpoints of investment-to-assets 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.

Panel A of Table 3 reports descriptive statistics for the 25 investment-profitability portfolios. High ROA stocks earn higher average returns than low ROA stocks, especially among high investment firms. And 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 0.40% per month ($t = 1.64$) in the lowest-I/A quintile to 1.17% ($t = 4.81$) in the highest-I/A quintile. The average low-minus-high I/A portfolio return varies from an insignificant 0.16% per month in the highest-ROA quintile to 0.93% (t = 4.30) in the lowest-ROA quintile. The null hypothesis that all the CAPM alphas are jointly zero is rejected at the 1% level. Despite their higher average returns, high ROA firms have lower SMB and HML loadings than low ROA firms. Consequently, 12 out of 25 portfolios have significant alphas in the Fama-French (1993) model, in contrast to only five significant alphas out of 25 in the CAPM.

3.2.1.3 The 25 Size-B/M Portfolios We obtain the 25 Size-B/M portfolios from Kenneth French's Web site. These portfolios are the intersections of five size portfolios and five B/M portfolios at the end of each June. The size breakpoints for year t are the NYSE market equity quintiles at the end of June of t. B/M for year t is the book equity for the last fiscal year-end in $t-1$ divided by market equity for December of $t-1$. The B/M breakpoints are also NYSE quintiles.

Confirming many previous studies, Panel B of 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-value = 0). Further, 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 represents an impressive improvement over 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, t = 5.50), which is 48% lower than its CAPM alpha. The reason is that, as highlighted in Fama and French (1996), their three-factor 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 89%, so even small intercepts are often distinguishable from zero.

3.2.2 Neoclassical Regressions: The Size-Momentum Portfolios

The neoclassical model outperforms traditional models in pricing the size-momentum portfolios.

3.2.2.1 Benchmark Estimation Table 4 reports the neoclassical regressions of the size and momentum portfolios. Panel A shows that the W-L 11/1/1-momentum strategy has a significant alpha of 0.89% per month ($t = 3.25$) in the smallest size quintile and 0.61% ($t = 2.36$) in the second size quintile. But the alphas are insignificant in the three other size quintiles. In contrast, the W-L alpha is significant across all five size quintiles in both the CAPM and the Fama and French (1993) model (see Table 2). This performance improvement is noteworthy. For example, although still significant ($t = 3.25$), the small-stock W-L alpha of 0.89% per month in the neoclassical model represents a reduction of 50% in magnitude from its CAPM alpha (1.78%) and a reduction of 55% from its Fama-French alpha (1.96%). Further, the average magnitude of the W-L alphas in the neoclassical model is 0.37% per month. In contrast, the magnitude is 1.21% in the CAPM and 1.38% per month in the Fama-French model. Finally, eight out of the 25 individual alphas are significant, giving rise to an overall rejection of the neoclassical model by the GRS test at the 1% level. However, the number of significant alphas in the neoclassical model (8) is much lower than that in the CAPM (16) and that in the Fama-French model (18).

The results using the 6/1/6-momentum portfolios are largely similar. Although the neoclassical model is rejected using the 25 portfolios, the number of significant alphas (7) is lower than that in the CAPM (13) and that in the Fama-French (1993) model (13). More important, none of the five W-L alphas in our model are significant. In particular, the small-stock W-L alpha is 0.34% per month ($t = 1.53$). This neoclassical alpha represents a reduction in magnitude of 67% from the CAPM alpha (1.02% per month, $t = 6.04$) and a reduction of 70% from the Fama-French alpha (1.14%, $t = 6.07$).

3.2.2.2 Sources of Explanatory Power for the Neoclassical Model The relative success of the neoclassical model in explaining momentum profits derives from two sources. First, the $PROD$-loadings of momentum portfolios go in the right direction in explaining their average returns. Table 4 shows that winners have higher $PROD$-loadings than losers across all five size groups. The magnitude of the loading spreads, significant in all cases, ranges from 0.64 to 0.88 in Panel A for the 11/1/1-momentum and from 0.45 to 0.61 in Panel B for the 6/1/6-momentum. This evidence suggests that, not surprisingly, winners are more profitable than losers.

Second, remarkably, 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, again significant across all size groups, ranges from 0.68 to 0.96 for the 11/1/1-momentum and from 0.47 to 0.71 for the 11/1/1-momentum. 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 follow the event-study approach of Fama and French (1995) to examine how ROA and I/A vary across the testing portfolios. To preview the results: Winners indeed have higher contemporaneous investment-to-assets than losers at the portfolio formation month. But more important, winners also have lower investment-to-assets 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 investment-to-assets several quarters prior to the portfolio formation.

Specifically, 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. Figure 1 reports the details for the 25 size and 11/1/1-momentum portfolios. The results for the 25 size and 6/1/6-momentum portfolios are similar (not reported). For a given portfolio, we plot the median ROAs and I/As among the firms in the portfolio.

From Panel A of Figure 1, 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 further 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.

As expected, Figure 1 also shows that winners have higher ROAs than losers for about five quarters before and 20 quarters after the portfolio formation month (Panel D). In the calendar time, winners have consistently higher ROAs than losers, especially in smallest-size quintile (Panels E and F). This evidence explains the higher $PROD$-loadings for the winners documented in Table 4.

3.2.2.3 Quarterly Investment Factor 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. To preview the results, the loading pattern is reversed once we replace INV with INV^Q.

We measure quarterly investment-to-assets 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 (see Appendix B). 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.

The INV^Q factor earns an average return of 0.49% per month (t = 3.56). Table 5 reports neoclassical factor regressions with INV replaced by INV^Q. Most important, the W-L portfolios now have negative, albeit mostly insignificant, loadings on INV^Q. This finding contrasts with the evidence in Table 4 that the W-L portfolios have significant positive loadings on the annual investment factor, INV. The $PROD$-loadings are similar across the two tables. As a result of the negative INV^Q-loadings of the W-L portfolios, the magnitude of the alphas in Table 5 is in general higher than that in Table 4. In particular, the small-stock W-L 11/1/1-momentum portfolio has an alpha of 1.28% per month (t = 3.83), which is about 30% higher than the alpha of 0.89% in Table 4. And the small-stock W-L 6/1/6-momentum portfolio has an alpha of 0.65% per month (t = 2.54), which is about 48% higher than the alpha of 0.34% in Table 4.

3.2.2.4 Alternative Neoclassical Factor Specifications To evaluate the relative role of the neoclassical factors in driving momentum profits, we explore two alternative two-factor specifications: $MKT+INV$ and $MKT+PROD$. Both INV and $PROD$ help reduce the overall magnitude of the alphas, but $PROD$ seems more important. For example, Panel A of Table 6 shows that four out of five W-L 11/1/1-momentum alphas are significant and the average magnitude of these alphas is 0.96% per month in the two-factor model with MKT and INV. In contrast, only two out of five W-L alphas are significant in the two-factor model with MKT and $PROD$, although the average magnitude of these alphas is 0.67% per month. Thus, adding INV further reduces the average magnitude of the W-L alphas from 0.67% to 0.37% per month in the benchmark neoclassical model. From Panel B, using the 6/1/6-momentum portfolios yields largely similar results.

3.2.3 Neoclassical Regressions: The Investment-Profitability Portfolios

The neoclassical model outperforms traditional factor models in explaining the average returns across the 25 investment-profitability portfolios.

Panel A of Table 7 reports the neoclassical three-factor regressions. Although the model is rejected overall with a GRS statistic of 1.68 (p-value = 0.02), only two out of 25 alphas are individually significant. The number of significant alphas is low relative to that in the CAPM (five) and to that in the Fama-French (1993) model (12). Further, only one out of five high-minus-low ROA portfolios (H-L^P) has a significant alpha: The alpha is actually negative, -0.67% per moth ($t = -3.05$), so our model appears to overfit. In contrast, three out of five H-L^P alphas are significant in the CAPM, and all five of them are significant in the Fama-French model. More important, the average magnitude of the H-L^P alphas is also lower in our model: 0.34% per month versus 0.71% in the CAPM and 0.98% in the Fama-French model. Our model also does a good job in describing the five high-minus-low I/A portfolio (H-L^I) returns. From Panel A, none of the five H-L^I alphas are significant, whereas three out of five are significant in the CAPM and in the Fama-French model. More important, the average magnitude of the H-L^I alphas is also lower in our model: 0.17% per month versus 0.55% in the CAPM and 0.39% 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.

In the benchmark specification (Panel A of Table 7), the INV-loadings do not differ significantly across extreme ROA portfolios, and the $PROD$-loadings do not differ significantly across extreme investment portfolios. The evidence is consistent with the low correlation between INV and $PROD$ (-0.06, see Table 1). Consequently, dropping $PROD$ from the factor specification makes the high-minus-low ROA alphas significantly positive, but does not materially affect the high-minus-low investment alphas (Panel B). And dropping INV makes the high-minus-low investment alphas significantly negative, but does not materially affect the high-minus-low ROA alphas (Panel C).

3.2.4 Neoclassical Regressions: The Size-B/M Portfolios

The neoclassical model outperforms the CAPM but underperforms the Fama-French (1993) model in explaining the average returns of the 25 size-B/M portfolios. But our model does exceptionally well in explaining the low average return of the small-growth portfolio that consists of firms in the smallest-size quintile and lowest-B/M quintile.

Panel A of Table 8 shows that, while the Fama-French (1993) model produces six significant alphas out of 25 size-B/M portfolios, the neoclassical model produces 11. Further, three out of five H-L alphas are significant in our model versus only two out of five in the Fama-French model. The average magnitude of the H-L alphas is also higher in our model: 0.45% versus 0.30% per month. And the average R^2 is lower in our model: 73% versus 91%. But the average magnitude of the 25 alphas is 0.27% per month, which is identical to that from the Fama-French model.

More intriguingly, the small-growth portfolio earns a CAPM alpha of -0.63% per month ($t = -2.61$), a Fama-French alpha of -0.52% ($t = -4.48$), but only a tiny neoclassical alpha of -0.03% ($t = -0.10$). This evidence is impressive because the small-growth anomaly is notoriously difficult to explain for consumption-based asset pricing. 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. And the 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 neoclassical model clearly dominates the CAPM in explaining the average 25 size-B/M portfolio returns. In total, 15 out of the 25 CAPM alphas are significant. The small-stock H-L alpha in the CAPM is 1.32% per month ($t = 7.10$). Our model reduces this alpha by about 40% to 0.78% per month, albeit still significant ($t = 3.67$). The average magnitude of the H-L alphas is 0.81% per month in the CAPM, and our model reduces this magnitude by about 45% to 0.45% per month.

The INV- and $PROD$-loadings shed light on the explanatory power of the neoclassical model for the 25 size-B/M portfolios. From Panel A of Table 8, value stocks have higher INV-loadings than growth stocks. The loading spreads, ranging from 0.69 to 1.00, are all at least 4.5 standard errors from zero. The $PROD$-loading pattern is more complicated. The H-L spread in the $PROD$-loading is close to zero across the three middle size quintiles. In the smallest-size quintile, the H-L portfolio has a significant positive $PROD$-loading of 0.27 (t = 2.53) because the small-growth portfolio has a large negative $PROD$-loading of −0.65 (t = −5.16). However, in the biggest-size quintile, the H-L portfolio has a large negative $PROD$-loading of −0.43 (t = −4.21). In particular, the big-growth portfolio has a positive $PROD$-loading of 0.24 (t = 6.49).

The two-factor neoclassical specifications in Panels B and C in Table 8 further illustrate the relative roles of $PROD$ and INV. The alpha of the small-growth portfolio is −0.57% per month (t = −2.22) in the two-factor $MKT + INV$ model, meaning that INV does not help explain the portfolio's low average returns. But the alpha is only −0.15% (t = −0.56) in the two-factor $MKT + PROD$ model, meaning that $PROD$ helps a lot. However, INV helps reduce the overall magnitude of the alphas for other portfolios in the 25 size-B/M universe. The average magnitude of the H-L alphas across the size quintiles is 0.44% per month in the $MKT + INV$ model (close to that in the benchmark specification), but is 0.86% in the $MKT + PROD$ model.

Somewhat surprisingly, the small-growth portfolio has a lower $PROD$-loading than the small-value portfolio. The evidence seems inconsistent with Fama and French (1995), who document that growth firms are more profitable than value firms in the 1963–1992 sample. In untabulated results, we apply their empirical methods to our 1972–2006 sample. 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, but 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. (See also related evidence in Fama and French 2001, 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.

3.3 Tests on One-Way Sorted Portfolios

In this subsection, we test the neoclassical factor model using deciles formed on financial distress, earnings surprises, accruals, net issues, earnings-to-price, and asset growth. We use earnings-to-price portfolios as a representative of the array of one-way sorted value and growth portfolios studied by, for example, Fama and French (1996). All the other anomaly variables have recently received much attention in the empirical finance and accounting literature.

3.3.1 The Distress Deciles

The neoclassical model is successful in explaining the financial distress anomaly. We form ten deciles on Campbell, Hilscher, and Szilagyi's (2007) distress measure. We largely follow their procedure in constructing the measure (see Appendix B).[5] Each month from June 1975 to December 2006, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles using the NYSE breakpoints of distress 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 distress measure.) Monthly value-weighted portfolio returns are calculated for the current month.

Panel A of Table 9 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 -0.89% per month ($t = -3.04$). Controlling for traditional risk measures only makes matters worse: More distressed firms are riskier than less distressed firms according to traditional factor models. The market beta of the H-L portfolio is significantly positive, 0.53 ($t = 5.79$), meaning that its CAPM alpha of -1.23% per month ($t = -4.15$) has an even higher magnitude than its average return. In total, five out of ten alphas are significant, leading to an overall rejection of the model (p-value = 0). The results from the Fama-French (1993) model are largely similar. The H-L portfolio has a SMB-loading of 0.65 ($t = 5.24$) and a market beta of 0.43 ($t = 5.09$). The Fama-French alpha is -1.34% per month ($t = -5.22$). Further, six out of ten deciles have significant alphas, and the GRS test rejects the model ($F_{GRS} = 3.76$, p-value = 0).

More important, the neoclassical model generates an insignificant alpha of 0.18% per month ($t = 0.83$) for the H-L portfolio. Although two out of ten deciles have significant neoclassical alphas, the model cannot be rejected using the GRS test ($F_{GRS} = 1.68$ and p-value = 0.08). The $PROD$-loading goes in the right direction in explaining the distress anomaly. More distressed firms have lower $PROD$-loadings than less distressed firms: The loading spread is -1.48 ($t = -14.59$). This evidence makes sense because the distress measure has a strong negative relation with profitability (see equation B.1), meaning that more distressed firms are less profitable than less distressed firms.

In untabulated results, we directly calculate time series averages of portfolio ROA for the ten

[5] We have used portfolios formed on Ohlson's (1980) O-Score and obtained similar results. We also have used Altman's (1968) Z-score, but the CAPM explains well the average Z-score portfolio returns in our sample (not reported).

distress deciles. We measure portfolio ROA as the value-weighted average ROAs across all the stocks in a given portfolio, in which the weights are given by the market equity to be consistent with the calculations of portfolio returns. The portfolio average ROA decreases monotonically from 3.43% per quarter for the lowest-distress decile, to 1.74% for the fifth decile, and further to −2.15% per quarter for the highest-distress decile. The average ROA spread of 5.58% per quarter between the two extremes is more than 25 standard errors from zero.

From Panel A of Table 9, the highest-distress decile also has a lower INV-loading than the lowest-distress decile: The loading spread is −0.53 ($t = -3.10$). In untabulated results, we calculate time series averages of portfolio I/A for the distress deciles. We measure portfolio I/A as the value-weighted average I/As across all the stocks in a given portfolio, in which the weights are given by the market equity. We find that the average I/A is 11.83% per annum in the highest-decile and 8.88% in the lowest-distress decile. The I/A-spread of 2.95% per annum is significant ($t = 2.55$). Thus, the INV-loading is consistent with the underlying investment pattern. One possible reason for the investment pattern is that the distress measure has a positive loading on the market-to-book (see equation B.1), meaning that more distressed firms can be high-investing growth firms.

3.3.2 The Earnings Surprises Deciles

The neoclassical factor model outperforms traditional factor models in explaining the earnings anomaly, the "granddaddy" of underreaction events in the language of Fama (1998, p. 286). To construct the testing portfolios, we rank all NYSE, Amex, and NASDAQ stocks each month based on the NYSE breakpoints of their most recent past SUE. Monthly value-weighted returns on the SUE portfolios are calculated for the current month, and the portfolios are rebalanced monthly.

From Panel B of Table 9, sorting on SUE produces an average-return spread of 1.17% per month ($t = 8.05$) between the two extreme deciles. The CAPM alpha of the H-L SUE portfolio is 1.22% per month ($t = 8.50$). Eight out of ten portfolios have significant alphas, and the CAPM is strongly rejected by the GRS test. The Fama-French (1993) model cannot explain the earnings anomaly either: Eight out of ten alphas are significant and the model is also rejected by the GRS test ($F_{GRS} = 9.64$, p-value = 0). And the H-L SUE portfolio alpha remains at 1.22% per month ($t = 8.00$). The neoclassical model reduces the alpha from 1.22% per month to 0.89%, which represents a reduction of 27%. But the alpha remains significant ($t = 6.24$). The overall performance of the model is also improved: The number of significant alphas across the deciles is reduced to four, although the model is still rejected by the GRS test ($F_{GRS} = 4.57$, p-value = 0).

Our model improves on the traditional factor models because the H-L SUE portfolio has a positive $PROD$ loading of 0.33 ($t = 5.07$). In untabulated results, we find that the average portfolio ROA increases from 1.12% per quarter for the lowest-SUE decile to 1.68% for the fifth SUE decile and further to 2.60% for the highest-SUE decile. The average ROA spread between the two extreme deciles is only 1.48% per quarter, albeit significant ($t = 12.16$). This low magnitude of the ROA spread helps explain why our model is only partially successful in explaining the earnings anomaly.

3.3.3 The Accrual Deciles

In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the NYSE breakpoints of accruals at the last fiscal year-end of $t-1$. Monthly value-weighted portfolio returns are calculated from July of year t to June of year $t+1$. Panel A of Table 10 shows that, consistent with Sloan (1996), high accrual firms earn lower average returns than low accrual firms and the average H-L accrual portfolio earns an average return of -0.52% per month ($t = -4.13$). The CAPM and the Fama-French (1993) model cannot explain the accrual anomaly: The average H-L accrual portfolio earns a CAPM alpha of -0.55% per month ($t = -4.41$) and a Fama-French alpha of -0.57% ($t = -4.35$). The zero-cost portfolio has traditional factor loadings all close to zero.

In the neoclassical model, the H-L accrual portfolio has near zero loadings on MKT and $PROD$ but a negative INV-loading of -0.51 ($t = -5.33$). As a result, the zero-cost portfolio earns an alpha of -0.38% per month ($t = -2.97$) in our model, which represents a reduction in magnitude of about 33% from its Fama-French alpha. The GRS test still rejects our model, however. In untabulated results, we find that the average portfolio I/A increases monotonically from 4.86% per annum for the lowest-accrual decile to 9.47% for the fifth decile and further to 20.06% for the highest-accrual decile. The significant I/A-spread of 15.21% per annum between the two extremes ($t = 6.61$) explains the INV-loading pattern across the accrual deciles.

3.3.4 The Net Stock Issues Deciles

In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the NYSE breakpoints of 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 B of Table 10, 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 -0.96% per month ($t = -5.23$). The CAPM cannot explain this anomaly: The H-L alpha is -1.11% per month ($t = -4.68$), seven out of ten deciles have significant alphas, and the GRS test rejects the model. The Fama-French (1993) model reduces the magnitude of the alpha to -0.83% per month ($t = -4.01$). The reason is that the H-L portfolio has a negative HML-loading of -0.53 ($t = -5.06$), meaning that, sensibly, high net issues firms are likely to be growth firms and low net issues firms are likely to be value firms. But the Fama-French model still leaves three 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, only one out of ten alphas is significant. Noteworthy, the H-L net issues portfolio earns an insignificant neoclassical alpha of -0.29% per month ($t = -1.31$). The INV-loading goes in the right direction in explaining the anomaly: The H-L portfolio has an INV-loading of -0.75 ($t = -4.97$). The INV-loading pattern is consistent with the underlying investment pattern. In untabulated results, we find that the average portfolio I/A increases monotonically from 6.35% per annum for the lowest net issues decile to 9.15% for the fifth decile and further to 27.43% for the highest net issues decile. And the I/A-spread of 21.08% per annum is more than ten standard errors from zero.

Somewhat surprisingly, the $PROD$-loading also goes in the right direction in explaining the new issues anomaly: The H-L portfolio has a $PROD$-loading of -0.57 ($t = -6.69$). 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: 0.97% versus 2.02% per quarter. The ROA spread of -1.06% is highly significant ($t = 15.11$). Timing does not seem to be the culprit: At the last fiscal year-end $t-1$ when net issues are measured, the highest decile also has a lower average ROA than the lowest decile: 0.83% versus 1.96% per quarter. 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 (although the magnitude of the profitability spread is much smaller than that of the investment spread). Our evidence differs because our net issues measure also includes share repurchases. And our evidence makes sense in light of Lie (2005), who shows that firms announcing repurchases exhibit superior operating performance relative to industry peers.

3.3.5 The Asset Growth Deciles

In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the NYSE breakpoints of asset growth at the last fiscal year-end $t-1$. Consistent with Cooper, Gulen, and Schill (2007), Panel A of Table 11 reports that the highest asset growth decile earns a lower average return than the lowest decile with an average return spread of -0.79% per month (t

$= -4.63$). This average return spread is lower than the level of 1.05% reported by Cooper et al. because we use follow the prescription of Fama and French (2007) in using the NYSE breakpoints of asset growth to avoid excessive influence of micro-caps.

The CAPM cannot explain the asset growth anomaly: Seven out of ten asset growth deciles have significant alphas and the GRS test rejects the model. And the H-L asset growth portfolio has a CAPM alpha of -0.92% per month ($t = -5.52$). Except for the highest asset growth decile, the Fama-French (1993) model makes all the alphas insignificant. The main source of success in their model is that high asset growth firms have lower HML-loadings than low asset growth firms. But the H-L portfolio still has an alpha of -0.46% per month ($t = -3.16$).

The neoclassical model further reduces in magnitude the H-L alpha to -0.37% per month, albeit significant ($t = -2.46$). But the model is still rejected by the GRS test. The main source of our explanatory power is the lower INV-loadings of high asset growth firms than those of low asset growth firms. In particular, the H-L portfolio has an INV-loading of -1.39 ($t = -14.06$). The INV-loading pattern reflects the underlying investment pattern. In untabulated results, we find that the average portfolio I/A increases monotonically from -5.22% per annum for the lowest asset growth decile to 6.36% for the fifth decile and further to 32.97% per annum for the highest decile. The spread of 38.19% per annum between the two extremes is more than nine standard errors from zero. It seems safe to say that both asset growth and our I/A measure capture fundamental firm-level investment. INV fails to fully explain the asset growth anomaly because asset growth is a more comprehensive measure of investment than our I/A measure.

3.3.6 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 E/P portfolio data are from Kenneth French's Web site. The results for portfolios formed on other valuation ratios are similar (not reported).

From Panel B of Table 11, the highest E/P decile earns a higher average return than the lowest E/P decile: 0.31% versus 1.00% 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). And 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 extreme 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 ($t = 23.06$).

In contrast, the performance of our neoclassical model leaves much to be desired. Three out of ten E/P deciles have significant alphas and the GRS test rejects the model at the 1% level. In particular, the H-L E/P portfolio earns an alpha of 0.60% per month ($t = 2.46$). Our model gains some explanatory power for the E/P portfolios through their INV loadings. The H-L E/P portfolio has an INV-loading of 0.71 ($t = 3.97$). In untabulated results, we confirm that the highest E/P decile invests less than the lowest E/P decile on average only by 2.67% per annum. The magnitudes of the I/A spread and the subsequent INV-loading spread are not large enough to bring our model performance up to a level comparable to the Fama-French (1993) model.

4 Cross-Sectional Regressions

We supplement our time series tests with Fama-MacBeth (1973) cross-sectional tests. To facilitate comparison with Fama and French (2007), we follow their test design. With a few exceptions, the general inferences from the cross-sectional tests are similar to those from our earlier time series tests.

At the end of each June from 1972 to 2006, we allocate NYSE, Amex, and NASDAQ stocks to three size groups, micro-caps, small stocks, and big stocks. The breakpoints are the 20^{th} and 50^{th} percentiles of the June market cap for NYSE stocks. Panel A of Table 12 shows averages and standard deviations of returns for the value-weighted and equal-weighted micro, small, and big portfolios from July 1972 to December 2006. We also report time series averages of the number of stocks and the percent of aggregate market cap in each portfolio. On average, micro-caps include 59% of all stocks, but the micro-caps account for only about 2.83% of the market value of all sample stocks. For comparison, big stocks include 21% of all stocks but account for 91% of the total market cap. Consequently, the micro-caps dominate the equal-weighted market returns, whereas the big stocks dominate the value-weighted market returns.

Table 12 also reports averages of the standard deviations of the annual cross section of returns and the anomaly variables. Fama and French (2007) observe that, for returns and all anomaly variables, the micro-cap group has the largest cross-sectional dispersion, followed by the small-stock group, and then by the big-stock group. While replicating their evidence in our 1972–2006 sample, we show that their observation also applies to our annual I/A and quarterly ROA measures. The evidence means that micro-caps have enormous influence in cross-sectional regressions. But their influence is more limited in time series tests because we value-weight portfolio returns.

Following Fama and French (2007), we explain the cross section of monthly returns from July of year t to June of $t+1$ using anomaly variables observed in June of t or the fiscal year-end of $t-1$. The exceptions are momentum and quarterly ROA, which are both updated monthly (as in sorts). We include the market cap and book-to-market (ln(MC) and ln(B/M), respectively, both in logs) in the regressions to proxy for the SMB- and HML-loadings. The idea is that current size and book-to-market are more timely proxies for the loadings than unconditional regression slopes (see Fama and French 1997). Panel A of Table 13 replicates Fama and French's (2007, Table IV) cross-sectional tests in our sample. In Panel B, we perform the tests after replacing their asset growth and profitability with our I/A and quarterly ROA measures, respectively.

Table 13 shows that the value effect is reliable across all size groups in our 1972–2006 sample, even after we include other anomaly variables such as share issuance, asset growth in cross-sectional regressions. With Fama and French's (2007) variable definitions (Panel A), the average slopes for ln(B/M) are 0.26 (t = 3.14) and 0.21 (t = 2.38) for small and big stocks, respectively. The average slope for micro-caps is smaller, 0.14 (t = 2.00). With our I/A and ROA measures (Panel B), the average slopes for ln(B/M) are about 0.47, all of which are more than 4.2 standard errors from zero.

The average momentum slopes in Panel A are similar to those from Fama and French (2007). The average slope for micro-caps (0.32, t = 1.89) is about half the size and more than 3.6 standard errors below the slope for small stocks (0.77, t = 3.81) and more than 1.8 standard errors below the slope for big stocks (0.65, t = 2.66). However, once we control for I/A and quarterly ROA, the average momentum slope is only reliable in small stocks (0.50, t = 2.13). The slope in big stocks is close (0.48, t = 1.80), but the slope in micro-caps is not impressive (0.18, t = 0.93).

The net stock issues show strong marginal explanatory power in all size groups in both panels of Table 13. From Panel A, the average slopes range from −1.47 to −1.64, all of which are more than −4.4 standard errors from zero. And the slopes differ by less than 0.6 standard errors. The slopes vary more in Panel B from −0.64 (t = −1.46) in micro-caps to −1.96 (t = −3.30) in small stocks. And the two are more than 1.8 standard errors apart. The dummy variable for zero net stock issues shows more explanatory power in our tests than in those of Fama and French (2007). In Panel A, the average slope only shows up significant in micro-caps (−0.24, t = −3.23). But the slope is also reliable (-0.34, $t = -2.30$) for small stocks in our tests.

Consistent with Fama and French (2007), we find that the relation between accruals and average returns is not pervasive. In Panel A, the average slope for positive accruals is only reliable in small stocks (-1.05, $t = -3.47$), which is more than 2.7 standard errors from the slope in micro-caps (-0.22, $t = -1.09$). Once we use our I/A and ROA in Panel B, even the strong slope in small stocks is reduced to -0.50, which is less than 1.2 standard errors from zero. The average slopes for negative accruals are all within 1.2 standard errors of zero in Panel A. In Panel B, the slope is -1.00 ($t = -3.37$) in micro-caps but is within 0.4 standard errors of zero in small and big stocks.

We also confirm that the negative relation between asset growth and average returns is not pervasive in cross-sectional regressions. The relation is strong in micro-caps (-1.23, $t = 8.38$), substantially weaker but statistically reliable in small stocks (-0.48, $t = -2.33$), and probably non-existent in big stocks (-0.43, $t = -1.89$). And the average slope for big stocks is -3.6 standard errors from the average slope for micro-caps. Consistent with our earlier time series tests, I/A has a weaker explanatory power for future returns than asset growth. The average slope of I/A is only reliable in micro-caps (-0.89, $t = -3.75$) and is close to zero in small and big stocks. In untabulated results, the I/A slope for micro-caps moves up to -1.07 ($t = -5.89$) if we use profitability to replace quarterly ROA in the regression. But the slopes for small and big stocks, both around -0.15, are within 0.8 standard errors of zero. As noted, asset growth can probably be interpreted as the most comprehensive measure of fundamental investment. Our earlier time series results are likely to be enhanced if we use asset growth to construct the INV factor. Our investment measure is from our earlier work in Lyandres, Sun, and Zhang (2007). And we have not searched around for the investment measure that yields the strongest results possible.

The positive relation between (annual) profitability and average returns in the 1972–2006 sample is in line with (but somewhat weaker than) the relation in the 1963–2006 sample estimated by Fama and French (2007). From Panel A, the average slope estimated from all stocks is reliable (0.69, $t = 2.39$). But the slopes, ranging from 0.22 to 0.68 for micro-caps, small stocks, and big stocks, are all within 1.5 standard errors of zero. In contrast, Panel B shows a much more powerful relation between the positive quarterly ROA and average returns. The average slopes, ranging from 5.19 in big stocks to 49.96 in micro-caps, are all more than 4.5 standard errors from zero. And the average slope estimated from all stocks is 35.76 ($t = 15.20$). We also find some evidence that negative quarterly ROA is associated with lower average returns, at least in micro-caps.

5 Conclusion

Motivated from neoclassical reasoning, we propose a new multi-factor model that includes the market factor, the low-minus-high investment factor, and the high-minus-low productivity factor. We show that the neoclassical three-factor model outperforms traditional factor models in explaining the average returns across portfolios formed on momentum, financial distress, investment, profitability, accruals, net stock issues, earnings surprises, and asset growth. At a minimum, the neoclassical model seems to provide a reasonable description of the cross section of average stock returns.

5.1 Applications

Our pragmatic approach à la Fama and French (1996) 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.

Regressing the excess returns of a target portfolio on the neoclassical factors can provide the exposures of the portfolio to the factors. The expected return estimate on the portfolio can be obtained by summing the products of the regression slopes and their historical average premiums for their corresponding factors. The estimate then can be used to guide portfolio choice and capital budgeting decisions. A similar procedure also can be used to evaluate the performance of a managed portfolio. The intercept from regressing the excess return of the managed portfolio on the neoclassical factors is the estimated average abnormal return of the portfolio. This abnormal return can be used to judge whether the manager has done a good job in generating average returns greater than the average returns from the passive management of combining the neoclassical factors that we have identified.

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.

5.2 Open Questions

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. (And as noted, investment-based asset pricing has so far not addressed the question why earnings and momentum anomalies are more short-lived than, for example, value and investment anomalies.) Our basic philosophy 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.

We can link risk to the real economy even in investment-based partial equilibrium models. Carlson, Fisher, and Giammarino (2004) relate the risk of value-minus-growth strategies to operating leverage. The higher operating leverage of value firms than that of growth firms makes the cash flows of value firms covary more with economic downturns than the cash flows of growth firms. Zhang (2005) argues that it is more costly for firms to downsize than to expand their productive capacity. Because value firms are stuck with more unproductive capital than growth firms in recessions, the cash flows of value firms covary more with economic downturns than the cash flows of growth firms. Johnson (2002) shows that the curvature of log price-dividend ratio with respect to expected growth is convex, meaning that the log price-dividend ratio is more sensitive to changes in expected growth when expected growth is high. Sagi and Seasholes (2006) relate this expected-growth risk to revenue growth volatility, costs, and growth options. However, because investors are not explicitly modeled, these papers fall short of quantifying the underlying risk related to the investor behavior.

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, constructing general equilibrium models that can be implemented empirically remains elusive.

References

Abel, Andrew B. and Janice C. Eberly, 1994, A unified model of investment under uncertainty, *American Economic Review* 84 (1), 1369–1384.

Abarbanell, Jeffrey S. and Brian J. Bushee, 1998, Abnormal returns to a fundamental analysis strategy, *The Accounting Review* 73 (1), 19–45.

Agrawal, Anup, Jeffrey F. Jaffe, and Gershon N. Mandelker, 1992, The post-merger performance of acquiring firms: A re-examination of an anomaly, *Journal of Finance* XLVII (4), 1605–1621.

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23, 589–609.

Anderson, Christopher W., and Luis Garcia-Feijóo, 2006, Empirical evidence on capital investment, growth options, and security *Journal of Finance* 61 (1), 171–194.

Ball, Ray and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of Accounting Research* 6, 159–178.

Ball, Ray, S. P. Kothari, and Ross L. Watts, 1993, Economic determinants of the relation between earnings changes and stock returns, *The Accounting Review* 68 (3), 622–638.

Bansal, Ravi and Amir Yaron, 2004, Risks for the long run: A potential resolution of asset pricing puzzles, *Journal of Finance* 59, 1481–1509.

Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad, 2005, Consumption, dividends, and the cross-section of equity returns, *Journal of Finance* 60, 1639–1672.

Berk, Jonathan B, Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance*, 54, 1153–1607.

Bernard, Victor L. and Jacob K. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* Supplement 27, 1–48.

Bernard, Victor L. and Jacob K. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305–340.

Brealey, Richard A., Stewart C. Myers, and Franklin Allen, 2006, Principles of corporate finance, 8th edition, Irwin McGraw-Hill.

Campbell, John Y. and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94 (5), 1249–1275.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2007, In search of distress risk, working paper, Harvard University.

Carhart, Mark M. 1997, On persistence in mutual fund performance, *Journal of Finance* 52 (1), 57–82.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross section of returns, *Journal of Finance* 59 (6), 2577–2603.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2006, Corporate investment and asset price dynamics: Implications for SEO event studies and long-run performance, *Journal of Finance* 61 (3), 1009–1034.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51 (5), 1681–1713.

Cochrane, John H., 1991, Production-based asset pricing and the link between stock returns and economic fluctuations, *Journal of Finance* 46, 209–237.

Cochrane, John H., 1996, A cross-sectional test of an investment-based asset pricing model, *Journal of Political Economy* 104, 572–621.

Cochrane, John H., 2005, Asset pricing, revised edition, Princeton University Press, Princeton, New Jersey.

Cohen, Randolph B., Paul A. Gompers, and Tuomo Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, *Journal of Financial Economics* 66, 409–462.

Cooper, Ilan, 2006, Asset pricing implications of non-convex adjustment costs and irreversibility of investment, *Journal of Finance* 61 (1), 139–170.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2007, Asset growth and the cross-section of stock returns, forthcoming, *Journal of Finance.*

Daniel, Kent and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52 (1), 1–33.

Daniel, Kent and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605–1643.

DeBondt, Werner F. M. and Richard Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40 (3), 793–805.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 1999, An empirical assessment of the residual income valuation model, *Journal of Accounting and Economics* 26, 1–34.

Dichev, Ilia, 1998, Is the risk of bankruptcy a systematic risk? *Journal of Finance* 53, 1141–1148.

Fairfield, Patricia M., Scott Whisenant, and Terry Lombardi Yohn, 2003, Accrued earnings and growth: Implications for future profitability and market mispricing, *The Accounting Review* 78, 353–371.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

Fama, Eugene F. and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F. and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, *Journal of Finance* L (1), 131–155.

Fama, Eugene F. and Kenneth R. French, 1996, Multifactor explanation of asset pricing anomalies, *Journal of Finance* LI (1), 55–84.

Fama, Eugene F. and Kenneth R. French, 1997, Industry cost of equity, *Journal of Financial Economics* 43, 153–193.

Fama, Eugene F. and Kenneth R. French, 2000, Forecasting profitability and earnings, *Journal of Business* 73 (2), 161–175.

Fama, Eugene F. and Kenneth R. French, 2001, Disappearing dividends: Changing firm characteristics or lower propensity to pay? *Journal of Financial Economics* 60, 3–43.

Fama, Eugene F. and Kenneth R. French, 2004, New lists: Fundamentals and survival rates, *Journal of Financial Economics* 73, 229–269.

Fama, Eugene F. and Kenneth R. French, 2006, Profitability, investment, and average returns, *Journal of Financial Economics* 82, 491–518.

Fama, Eugene F. and Kenneth R. French, 2007, Dissecting anomalies, forthcoming, *Journal of Finance.*

Frankel, Richard and Charles M. C. Lee, 1998, Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283–319.

Gala, Vito D., 2006, Investment and returns, working paper, London Business School.

Gibbons, Michael R., Stephen A. Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica* 57 (5), 1121–1152.

Gomes, Joao F., Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111 (4), 693–732.

Gordon, Myron J., 1962, *The Investment, Financing, and Valuation of the Corporation*, The Irwin Series in Economics, Homewood, Illinois.

Griffin, John M. and Michael L. Lemmon, 2002, Book-to-market equity, distress risk, and stock returns, *Journal of Finance* LVII (2), 2317–2336.

Hansen, Lars Peter and Kenneth J. Singleton, 1982, Generalized instrumental variables estimation of nonlinear rational expectations models, *Econometrica* 50, 1269–1288.

Haugen, Robert A. and Nardin L. Baker, 1996, Commonality in the determinants of expected stock returns, *Journal of Financial Economics* 41, 401–439.

Hayashi, Fumio, 1982, Tobin's marginal and average q: A neoclassical interpretation, *Econometrica* 50 (1), 213–224.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets? *Journal of Accounting and Economics* 38, 297–331.

Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

Johnson, Timothy C., 2002, Rational momentum effects, *Journal of Finance* LVII (2), 585–608.

Kydland, Finn E. and Edward C. Prescott, 1982, Time to build and aggregate fluctuations, *Econometrica* 50 (6), 1345–1370.

Lakonishok, Josef, Andrei Shleifer, Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *Journal of Finance* 49 (5), 1541–1578.

Lamont, Owen A. and Richard H. Thaler, 2003, Can the market add and subtract? Mispricing in tech stock carve-outs? *Journal of Political Economy* 111 (2), 227–268.

Lie, Erik, 2005, Operating performance following open market share repurchase announcements, *Journal of Accounting and Economics* 39, 411–436.

Lintner, John, 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economics and Statistics* 47, 13–37.

Liu, Laura Xiaolei and Lu Zhang, 2007, Momentum profits, factor pricing, and macroeconomic risk, forthcoming, *Review of Financial Studies.*

Liu, Laura Xiaolei, Toni M. Whited, and Lu Zhang, 2007, Investment-based expected stock returns, working paper, University of Michigan.

Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *Journal of Finance* 50, 23–51.

Lyandres, Evgeny, Le Sun, and Lu Zhang, 2007, The new issues puzzle: Testing the investment-based explanation, forthcoming, *Review of Financial Studies.*

Malmendier, Ulrike and Geoffrey Tate, 2005, CEO overconfidence and corporate investment, *Journal of Finance* 60 (6), 2661–2700.

Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2002, Limited arbitrage in equity markets, *Journal of Finance* 57 (2), 551–584.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18 (1), 109–131.

Piostroski, Joseph D., 2000, Value investing: The use of historical financial statement information to separate winners from losers, *Journal of Accounting Research* 38, Supplement: Studies on accounting information and the economics of the firm, 1–41.

Polk, Christopher and Paola Sapienza, 2006, The stock market and corporate investment: A test of catering theory, forthcoming, *Review of Financial Studies.*

Pontiff, Jeffrey and Artemiza Woodgate, 2006, Share issuance and cross-sectional returns, forthcoming, *Journal of Finance.*

Richardson, Scott A. and Richard G. Sloan, 2003, External financing and future stock returns, working paper, University of Pennsylvania.

Richardson, Scott A., Richard G. Sloan, Mark T. Soliman, and Irem Tuna, 2005, Accrual reliability, earnings persistence, and stock prices, *Journal of Accounting and Economics* 39, 437–485.

Ritter, Jay R., 1991, The long-run performance of initial public offerings, *Journal of Finance* 46, 3–27.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

Sagi, Jacob S. and Mark S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum, *Journal of Financial Economics* 84, 389–434.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Sloan, Richard G., 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (3), 289–315.

Spiess, Katherine D. and John Affleck-Graves, 1995, Underperformance in long-run stock returns following seasoned equity offerings, *Journal of Financial Economics* 38, 243–267.

Wu, Jin G., X. Frank Zhang, and Lu Zhang, 2007, The accrual anomaly: Exploring the optimal investment hypothesis, working paper, University of Georgia, University of Michigan, and Yale School of Management.

Xie, Hong, 2001, The mispricing of abnormal accruals, *The Accounting Review* 76 (3), 357–373.

Xing, Yuhang, 2007, Interpreting the value effect through the Q-theory: An empirical investigation, forthcoming, *Review of Financial Studies*.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60 (1), 67–103.

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:

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

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, $\beta_{jt} \equiv -\mathrm{Cov}_t[r_{jt+1}, m_{t+1}]/\mathrm{Var}_t[m_{t+1}]$ is the amount of risk, and $\lambda_{mt} \equiv \mathrm{Var}_t[m_{t+1}]/E_t[m_{t+1}]$ 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 Sample Construction and Variable Definitions

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. Following Fama and French (1993, 2007), we exclude financial firms (SIC codes between 6000 and 6999) and firms with negative book value of equity in year $t-1$.

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. We define earnings-to-assets (ROA) as the quarterly earnings (Compustat quarterly item 8) divided by last quarter's assets (item 44).

Book equity is the shareholder equity plus balance sheet deferred taxes (item 74) and investment tax credit (item 208 if available) minus the book value of preferred stock. The shareholder equity is common equity (item 60), or if not available, its liquidation value (item 235). Depending on data availability, redemption (item 56), liquidation (item10), or par value (item 130), in this order, is used to represent the book value of preferred stock.

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

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

in which

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

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

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.

Following Fama and French (2007), we measure accruals as the change of operating working capital per split-adjusted share from year $t-1$ to t divided by book equity per split-adjusted share at year t. Operating working capital is current assets (Compustat annual item 4) minus cash and short-term investment (item 1) minus current liabilities (item 5) plus debt in current liabilities (item 34). And 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). Profitability is earnings (income before extraordinary, item 18) minus dividends on preferred stocks (item 19), if available, plus income statement deferred taxes (item 50), if available, in $t-1$, divided by book equity for $t-1$.

In time series tests with sorts, we follow Cooper, Gulen, and Schill (2007) and measure asset growth of year t as the change of total assets (Compustat annual item 6) from $t-1$ to t divided by the total assets from year $t-1$. To facilitate comparison with Fama and French (2007), we use their definition of asset growth in cross-sectional regressions. Specifically, we measure asset growth of year t as the natural log of the ratio of assets per split-adjusted share at the fiscal year-end in $t-1$ divided by assets per split-adjusted share at the fiscal year-end in $t-2$.

Following Chan, Jegadeesh, and Lakonishok (1996), we define SUE as the unexpected earnings (the change in quarterly earnings per share from its value four quarters before) divided by the standard deviation of unexpected earnings over the prior eight quarters.

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 NYSE 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 NYSE 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: Factor Regressions of INV and $PROD$

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{WML}	R^2
INV	0.34	0.41	−0.15				0.17
	(4.15)	(5.54)	(−9.20)				
		0.26	−0.09	0.05	0.23		0.31
		(3.66)	(−5.24)	(2.18)	(9.09)		
		0.17	−0.08	0.05	0.25	0.09	0.35
		(2.39)	(−4.61)	(2.19)	(10.12)	(5.37)	
$PROD$	0.73	0.76	−0.05				0.01
	(5.67)	(5.84)	(−1.73)				
		0.89	−0.06	−0.24	−0.18		0.10
		(7.04)	(−1.92)	(−6.02)	(−3.93)		
		0.66	−0.03	−0.24	−0.13	0.22	0.22
		(5.43)	(−0.93)	(−6.56)	(−2.91)	(7.96)	

Panel B: Correlation Matrix (p-value in Parenthesis)

	$PROD$	MKT	SMB	HML	WML
INV	−0.06	−0.41	−0.09	0.51	0.18
	(0.19)	(0.00)	(0.06)	(0.00)	(0.00)
$PROD$		−0.08	−0.26	−0.08	0.36
		(0.08)	(0.00)	(0.12)	(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	0.91	3.08	909	261	1.45	22.43	−3.44	0.66
SM^I	0.81	2.90	850	290	1.09	17.63	6.86	0.97
SH^I	0.52	1.61	892	290	1.05	14.97	27.97	1.17
BL^I	0.69	3.07	152	8,948	0.81	17.90	−1.62	1.59
BM^I	0.56	2.61	299	9,592	0.67	15.94	6.96	1.98
BH^I	0.40	1.52	240	8,143	0.59	16.38	23.57	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	0.02	0.06	1081	267	1.16	9.44	11.35	−1.78
SM^P	0.75	2.79	655	301	1.13	18.48	11.37	1.30
SH^P	1.24	4.06	631	302	0.69	34.78	12.58	3.41
BL^P	0.23	0.88	143	8,278	0.95	13.13	9.68	−0.35
BM^P	0.42	2.01	265	10,018	0.81	15.78	9.31	1.33
BH^P	0.47	2.05	266	12,308	0.41	23.73	10.99	3.36

Table 2 : Summary Statistics and Traditional Factor Regressions for Monthly Percent Excess Returns on 25 Size and 11/1/1-Momentum Portfolios and on 25 Size and 6/1/6-Momentum 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 11/1/1-momentum portfolios are obtained from Kenneth French's Web site. Fama and French use the "11/1/1" convention to measure momentum: The monthly constructed portfolios are the intersections of five portfolios formed on market equity and five portfolios formed on prior (2–12) return. The monthly size breakpoints are the NYSE market equity quintiles, and the monthly prior (2–12) return breakpoints are NYSE quintiles. We also use an alternative set of 25 size and momentum portfolios, in which momentum is measured using the "6/1/6" convention. 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 $t+5$. 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: 25 Size and 11/1/1-Momentum Portfolios

	L	2	3	4	W	W-L	L	2	3	4	W	W-L
	Mean						t(Mean)					
S	−0.19	0.65	0.91	1.08	1.52	1.72	−0.49	2.40	3.61	4.16	4.68	7.63
2	−0.07	0.55	0.82	1.02	1.32	1.40	−0.19	2.00	3.28	3.96	3.96	5.99
3	0.12	0.46	0.66	0.79	1.23	1.11	0.34	1.76	2.78	3.34	3.94	4.17
4	0.14	0.54	0.57	0.79	1.07	0.93	0.40	2.03	2.42	3.37	3.69	3.19
B	0.17	0.45	0.31	0.55	0.81	0.64	0.53	1.90	1.45	2.56	3.07	2.16
	α						$t(\alpha)$ ($F_{GRS}=6.22$, $p_{GRS}=0$)					
S	−0.84	0.16	0.46	0.61	0.94	1.78	−3.43	0.99	2.95	3.82	4.61	8.23
2	−0.76	0.02	0.33	0.51	0.68	1.45	−3.76	0.16	2.47	3.75	3.77	6.30
3	−0.54	−0.06	0.18	0.31	0.61	1.15	−2.71	−0.49	1.59	2.64	3.83	4.34
4	−0.50	0.01	0.09	0.30	0.50	1.00	−2.38	0.06	0.86	3.10	3.51	3.43
B	−0.41	0.00	−0.13	0.11	0.28	0.69	−2.06	0.00	−1.49	1.17	2.17	2.33
	Fama-French (1993) three-factor regressions: $R_j - R_f = a_j + b_j\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$											
	a						$t(a)$ ($F_{GRS}=5.75$, $p_{GRS}=0$)					
S	−1.18	−0.26	0.06	0.26	0.78	1.96	−5.74	−2.42	0.64	3.22	6.98	7.97
2	−0.97	−0.33	−0.01	0.21	0.64	1.61	−5.43	−3.04	−0.10	2.74	5.86	6.30
3	−0.71	−0.38	−0.15	0.02	0.60	1.31	−3.35	−3.52	−1.74	0.23	5.05	4.42
4	−0.66	−0.27	−0.21	0.06	0.51	1.17	−2.78	−2.09	−2.30	0.76	3.95	3.55
B	−0.44	−0.10	−0.21	0.08	0.41	0.85	−2.00	−0.74	−2.40	0.91	2.97	2.58
	b						s					
S	1.18	0.94	0.89	0.90	0.98	−0.20	1.19	0.91	0.84	0.89	1.10	−0.09
2	1.26	1.05	0.98	0.98	1.07	−0.19	0.90	0.73	0.66	0.72	0.95	0.05
3	1.26	1.08	1.00	0.99	1.07	−0.19	0.54	0.45	0.43	0.40	0.69	0.15
4	1.29	1.16	1.07	1.06	1.04	−0.25	0.27	0.14	0.13	0.12	0.44	0.17
B	1.20	0.99	0.97	0.96	1.00	−0.20	−0.15	−0.21	−0.23	−0.28	−0.06	0.09
	h						R^2					
S	0.35	0.52	0.50	0.41	0.09	−0.26	0.76	0.88	0.90	0.91	0.88	0.03
2	0.19	0.45	0.43	0.35	−0.06	−0.26	0.81	0.87	0.90	0.92	0.90	0.03
3	0.17	0.42	0.45	0.38	−0.08	−0.25	0.72	0.85	0.88	0.87	0.87	0.03
4	0.21	0.41	0.44	0.34	−0.08	−0.29	0.66	0.81	0.86	0.88	0.82	0.03
B	0.07	0.18	0.15	0.08	−0.18	−0.25	0.63	0.73	0.86	0.86	0.76	0.02

Panel B: 25 Size and 6/1/6-Momentum Portfolios

	L	2	3	4	W	W-L	L	2	3	4	W	W-L
	Mean						t(Mean)					
S	0.33	0.74	0.85	0.95	1.30	0.97	0.86	2.52	3.07	3.40	3.93	5.48
2	0.19	0.63	0.74	0.82	1.09	0.91	0.53	2.24	2.80	3.08	3.29	4.71
3	0.26	0.54	0.66	0.74	0.99	0.73	0.77	2.05	2.69	3.01	3.21	3.46
4	0.29	0.50	0.60	0.67	0.99	0.71	0.89	1.96	2.53	2.87	3.43	3.10
B	0.13	0.43	0.39	0.50	0.77	0.64	0.46	1.91	1.91	2.41	2.94	2.82
	α						$t(\alpha)$ ($F_{GRS}=3.56$, $p_{GRS}=0$)					
S	−0.34	0.20	0.34	0.43	0.68	1.02	−1.43	1.21	2.07	2.63	3.48	6.04
2	−0.50	0.07	0.21	0.29	0.44	0.95	−2.63	0.49	1.61	2.22	2.59	5.01
3	−0.39	0.00	0.15	0.23	0.37	0.76	−2.22	0.00	1.41	2.21	2.52	3.61
4	−0.34	−0.03	0.10	0.17	0.40	0.74	−1.91	−0.25	1.06	2.04	3.19	3.20
B	−0.41	−0.04	−0.05	0.05	0.23	0.64	−2.53	−0.43	−0.80	0.69	2.05	2.77
	Fama-French (1993) three-factor regressions: $R_j - R_f = a_j + b_j\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$											
	a						$t(a)$ ($F_{GRS}=3.62$, $p_{GRS}=0$)					
S	−0.63	−0.16	−0.02	0.11	0.51	1.14	−3.43	−1.67	−0.26	1.45	5.40	6.07
2	−0.68	−0.24	−0.09	0.02	0.38	1.05	−4.09	−2.74	−1.30	0.34	4.05	5.00
3	−0.53	−0.28	−0.14	−0.01	0.35	0.87	−2.93	−2.83	−1.58	−0.19	3.72	3.72
4	−0.43	−0.26	−0.16	−0.03	0.41	0.84	−2.05	−2.42	−1.94	−0.43	3.86	3.18
B	−0.36	−0.04	−0.06	0.06	0.39	0.75	−2.03	−0.44	−1.04	0.91	3.35	2.92
	b						s					
S	1.18	1.02	0.96	0.96	1.04	−0.15	1.20	0.98	0.94	0.96	1.12	−0.08
2	1.25	1.08	1.03	1.02	1.10	−0.15	0.87	0.75	0.70	0.72	0.93	0.06
3	1.22	1.10	1.05	1.03	1.08	−0.15	0.58	0.46	0.42	0.47	0.72	0.14
4	1.24	1.13	1.07	1.04	1.07	−0.17	0.24	0.15	0.17	0.21	0.44	0.21
B	1.08	0.97	0.93	0.94	1.01	−0.07	−0.12	−0.20	−0.21	−0.20	−0.03	0.09
	h						R^2					
S	0.28	0.43	0.42	0.36	0.10	−0.18	0.80	0.91	0.92	0.93	0.92	0.03
2	0.15	0.36	0.37	0.30	−0.03	−0.17	0.83	0.92	0.93	0.94	0.93	0.02
3	0.13	0.37	0.38	0.31	−0.06	−0.19	0.79	0.88	0.90	0.93	0.91	0.03
4	0.10	0.34	0.37	0.28	−0.08	−0.18	0.72	0.85	0.89	0.92	0.87	0.03
B	−0.06	0.03	0.04	0.01	−0.24	−0.18	0.70	0.84	0.93	0.92	0.84	0.01

Table 3 : Summary Statistics and Traditional Factor Regressions for Monthly Percent Excess Returns on 25 Investment and Profitability Portfolios and 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) three factors, and the 25 size and book-to-market portfolios are from Kenneth French's Web site. We sort all NYSE, Amex, and NASDAQ stocks into five quintiles each month based on NYSE breakpoints of quarterly ROA from at least four months ago. Also, we sort all stocks independently in June of each year into five quintiles based on NYSE breakpoints of investment-to-assets at the last fiscal yearend. From taking intersections, we form 25 investment and profitability portfolios, whose value-weighted returns are calculated for the current month. 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: 25 Investment and Profitability Portfolios

	L^P	2	3	4	H^P	H-L^P	L^P	2	3	4	H^P	H-L^P
	Mean						t(Mean)					
L^I	0.42	0.82	0.55	0.93	0.82	0.40	1.26	2.96	1.92	3.57	2.79	1.64
2	0.54	0.66	0.76	0.38	0.74	0.20	1.60	2.39	3.12	1.58	2.97	0.83
3	0.08	0.47	0.42	0.74	0.62	0.54	0.24	1.72	1.43	2.97	2.62	2.29
4	−0.22	0.32	0.58	0.59	0.60	0.82	−0.64	1.20	2.05	2.31	2.24	3.37
H^I	−0.51	0.32	0.21	0.42	0.66	1.17	−1.39	1.01	0.67	1.46	2.15	4.81
H-L^I	−0.93	−0.49	−0.34	−0.51	−0.16		−4.30	−2.24	−1.38	−2.84	−0.87	
	α						$t(\alpha)$ ($F_{GRS} = 3.17$, $p_{GRS} = 0$)					
L^I	−0.18	0.30	0.04	0.43	0.25	0.43	−0.89	1.90	0.25	2.95	1.60	1.75
2	−0.08	0.16	0.30	−0.09	0.24	0.32	−0.38	1.03	2.17	−0.76	1.80	1.33
3	−0.55	0.01	−0.09	0.26	0.14	0.69	−2.71	0.06	−0.46	1.99	1.31	3.00
4	−0.85	−0.16	0.07	0.07	0.04	0.89	−4.19	−1.01	0.41	0.55	0.36	3.87
H^I	−1.19	−0.24	−0.35	−0.17	0.02	1.22	−5.53	−1.25	−1.86	−1.21	0.19	4.96
H-L^I	−1.01	−0.54	−0.39	−0.59	−0.23		−4.67	−2.47	−1.68	−3.26	−1.22	
	Fama-French (1993) three-factor regressions: $R_j - R_f = a_j + b_j\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$											
	a						$t(a)$ ($F_{GRS} = 3.32$, $p_{GRS} = 0$)					
L^I	−0.53	−0.08	−0.30	0.22	0.16	0.69	−2.97	−0.55	−1.64	1.64	1.01	3.01
2	−0.31	−0.16	0.05	−0.26	0.22	0.52	−1.56	−0.97	0.35	−2.03	1.50	2.10
3	−0.70	−0.42	−0.44	0.13	0.24	0.94	−3.59	−2.45	−2.28	0.95	2.17	4.36
4	−1.02	−0.37	−0.19	0.05	0.30	1.32	−4.97	−2.22	−1.19	0.39	2.84	5.74
H^I	−1.24	−0.54	−0.67	−0.16	0.19	1.43	−6.15	−2.78	−3.26	−1.14	1.57	6.08
H-L^I	−0.70	−0.46	−0.37	−0.39	0.03		−3.45	−2.06	−1.44	−2.16	0.19	
	b						s					
L^I	1.21	1.15	1.12	1.06	1.14	−0.08	0.64	0.29	0.21	0.14	0.19	−0.45
2	1.21	1.11	1.00	0.99	0.98	−0.23	0.49	0.16	0.13	0.10	0.04	−0.45
3	1.21	1.06	1.14	1.02	0.92	−0.29	0.44	0.25	0.10	−0.01	−0.06	−0.50
4	1.22	1.02	1.09	1.05	1.00	−0.21	0.48	0.15	0.20	−0.09	−0.08	−0.56
H^I	1.26	1.19	1.16	1.16	1.15	−0.11	0.51	0.33	0.40	0.02	0.17	−0.35
H-L^I	0.05	0.04	0.04	0.10	0.01		−0.13	0.04	0.19	−0.13	−0.02	
	h						R^2					
L^I	0.46	0.54	0.50	0.29	0.11	−0.34	0.72	0.75	0.64	0.73	0.73	0.09
2	0.29	0.47	0.37	0.25	0.03	−0.25	0.68	0.67	0.72	0.74	0.75	0.13
3	0.18	0.63	0.52	0.20	−0.13	−0.31	0.68	0.64	0.61	0.72	0.78	0.18
4	0.19	0.29	0.37	0.04	−0.39	−0.57	0.68	0.65	0.66	0.78	0.86	0.19
H^I	0.00	0.41	0.45	0.00	−0.28	−0.28	0.71	0.65	0.65	0.79	0.84	0.06
H-L^I	−0.46	−0.12	−0.05	−0.30	−0.39		0.10	0.01	0.02	0.09	0.09	

Panel B: 25 Size and Book-to-Market Portfolios

	L	2	3	4	H	H-L	L	2	3	4	H	H-L
	Mean						t(Mean)					
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
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
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
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
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
	α						$t(\alpha)$ ($F_{GRS} = 4.25$, $p_{GRS} = 0$)					
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
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
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
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
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
	Fama-French (1993) three-factor regressions: $R_j - R_f = a_j + b_j\, MKT + s_j\, SMB + h_j\, HML + \varepsilon_j$											
	a						$t(a)$ ($F_{GRS} = 3.08$, $p_{GRS} = 0$)					
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
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
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
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
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
	b						s					
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
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
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
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
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
	h						R^2					
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
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
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
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
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

Table 4 : Neoclassical Factor Regressions ($R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$) for Monthly Percent Excess Returns on 25 Size and 11/1/1-Momentum Portfolios and on 25 Size and 6/1/6-Momentum Portfolios, 1/1972–12/2006, 420 Months

The data for the one-month Treasury bill rate (R_f), the market factor, and the 25 size and 11/1/1-momentum portfolios are from Kenneth French's Web site. To form the 25 size and 6/1/6-momentum portfolios, we sort all NYSE, Amex, and NASDAQ stocks into five quintiles each month t based on NYSE breakpoints of prior 2–7 months returns (month $t-2$ to $t-7$), and calculate the subsequent portfolio returns from month t to $t+5$. Also, we sort all stocks independently each month into five market equity quintiles based on NYSE breakpoints. We form 25 portfolios from taking intersections. All portfolio returns are value-weighted. We report the neoclassical factor regressions: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. 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	W	W-L	L	2	3	4	W	W-L	L	2	3	4	W	W-L	L	2	3	4	W	W-L
Panel A: 25 Size and 11/1/1-Momentum Portfolios																								
	a						$t(a)$ ($F_{GRS} = 3.74$, $p_{GRS} = 0$)						b						R^2					
S	0.12	0.38	0.50	0.57	1.01	0.89	0.37	1.86	2.72	3.06	4.10	3.25	1.18	0.97	0.94	1.00	1.20	0.01	0.67	0.64	0.64	0.66	0.63	0.24
2	0.09	0.21	0.27	0.42	0.70	0.61	0.38	1.21	1.81	2.71	3.25	2.36	1.25	1.04	1.00	1.04	1.29	0.04	0.76	0.71	0.73	0.74	0.70	0.19
3	0.28	0.03	0.09	0.11	0.51	0.23	1.27	0.21	0.70	0.81	2.77	0.73	1.17	1.04	0.98	0.99	1.24	0.07	0.75	0.76	0.77	0.79	0.74	0.18
4	0.32	0.07	−0.04	0.05	0.26	−0.06	1.36	0.46	−0.37	0.46	1.52	−0.18	1.13	1.06	0.99	1.03	1.19	0.06	0.72	0.77	0.81	0.85	0.77	0.19
B	0.03	0.01	−0.29	−0.24	−0.04	−0.07	0.12	0.05	−2.81	−2.60	−0.27	−0.19	1.06	0.89	0.90	0.94	1.09	0.03	0.65	0.70	0.83	0.85	0.78	0.09
	i						$t(i)$						p						$t(p)$					
S	−0.42	0.24	0.33	0.41	0.31	0.73	−2.18	1.87	2.98	3.50	2.15	5.09	−1.04	−0.41	−0.24	−0.18	−0.26	0.78	−7.28	−4.07	−2.76	−2.36	−2.52	5.38
2	−0.59	0.02	0.24	0.26	0.12	0.71	−4.18	0.20	2.41	2.57	0.99	4.88	−0.80	−0.26	−0.05	−0.03	−0.08	0.72	−8.28	−2.87	−0.64	−0.46	−0.88	5.40
3	−0.65	0.04	0.18	0.23	0.08	0.73	−4.62	0.39	2.21	2.88	0.76	4.12	−0.74	−0.14	0.02	0.14	0.08	0.82	−7.47	−1.85	0.25	2.61	1.03	5.38
4	−0.76	0.06	0.18	0.28	0.20	0.96	−5.20	0.70	2.62	4.27	2.12	4.72	−0.67	−0.11	0.08	0.18	0.21	0.88	−5.90	−1.29	1.12	3.48	2.44	4.91
B	−0.50	−0.04	0.09	0.26	0.18	0.68	−3.47	−0.47	1.50	4.89	1.98	3.19	−0.31	0.01	0.16	0.31	0.33	0.64	−2.78	0.14	3.18	7.04	3.84	3.54
Panel B: 25 Size and 6/1/6-Momentum Portfolios																								
	a						$t(a)$ ($F_{GRS} = 2.03$, $p_{GRS} = 0$)						b						R^2					
S	0.53	0.50	0.50	0.56	0.87	0.34	1.72	2.42	2.59	2.88	3.72	1.53	1.22	1.07	1.03	1.05	1.23	0.00	0.68	0.68	0.68	0.68	0.67	0.23
2	0.27	0.26	0.26	0.30	0.54	0.27	1.15	1.62	1.76	1.96	2.71	1.19	1.25	1.10	1.06	1.08	1.28	0.03	0.77	0.77	0.77	0.77	0.74	0.18
3	0.32	0.17	0.14	0.16	0.40	0.07	1.48	1.23	1.08	1.40	2.35	0.28	1.18	1.05	1.02	1.04	1.23	0.05	0.78	0.80	0.81	0.83	0.77	0.16
4	0.36	0.12	0.06	0.06	0.34	−0.02	1.66	1.02	0.58	0.61	2.29	−0.07	1.12	1.03	1.01	1.02	1.19	0.07	0.77	0.83	0.85	0.88	0.81	0.15
B	0.05	0.04	−0.11	−0.11	0.16	0.10	0.29	0.32	−1.51	−1.56	1.28	0.38	0.98	0.90	0.88	0.91	1.07	0.10	0.73	0.82	0.90	0.91	0.83	0.07
	i						$t(i)$						p						$t(p)$					
S	−0.37	0.12	0.21	0.23	0.17	0.55	−1.95	0.93	1.69	1.88	1.23	4.59	−0.94	−0.45	−0.34	−0.30	−0.34	0.60	−6.85	−4.59	−3.79	−3.57	−3.63	5.11
2	−0.57	0.00	0.11	0.13	−0.01	0.56	−3.86	0.05	1.15	1.28	−0.06	4.60	−0.71	−0.25	−0.13	−0.08	−0.13	0.59	−6.77	−3.12	−1.75	−1.21	−1.57	5.00
3	−0.58	−0.07	0.07	0.13	−0.04	0.54	−4.08	−0.87	0.89	1.58	−0.39	3.75	−0.63	−0.18	−0.02	0.02	−0.02	0.61	−6.43	−2.47	−0.31	0.33	−0.22	4.83
4	−0.70	−0.11	0.09	0.15	0.01	0.71	−5.09	−1.53	1.28	2.31	0.15	4.83	−0.55	−0.14	0.00	0.07	0.06	0.61	−5.49	−1.91	0.01	1.42	1.01	4.48
B	−0.55	−0.17	−0.02	0.06	−0.08	0.47	−5.15	−2.45	−0.62	1.29	−1.11	3.25	−0.31	−0.02	0.10	0.17	0.14	0.45	−3.99	−0.28	2.48	5.75	2.17	3.63

Table 5 : Neoclassical Factor Regressions with the Quarterly Investment Factor ($R_j - R_f = a_j + b_j\, MKT + i_j\, INV^Q + p_j\, PROD + \varepsilon_j$) for Monthly Percent Excess Returns on 25 Size and 11/1/1-Momentum Portfolios and on 25 Size and 6/1/6-Momentum Portfolios, 1/1975–12/2006, 420 Months

The data for the one-month Treasury bill rate (R_f), the market factor, and the 25 size and 11/1/1-momentum portfolios are from Kenneth French's Web site. See Table 5 for the description of the 25 size and 11/1/1-momentum portfolios. We construct the quarterly investment factor, denoted INV^Q, using quarterly investment data. The quarterly investment-to-assets is 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). The sample is from January 1975 to December 2006. The starting point of the sample is restricted by the availability of quarterly investment data. We categorize NYSE, Amex, and NASDAQ stocks into three groups each month 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. We also use the NYSE median each month to split all stocks into two size groups, and form six portfolios from the intersections of the two size and three I/A portfolios. Monthly value-weighted returns on the six portfolios are calculated for the current month. The INV^Q factor is the difference (low-minus-high investment), each month, between the average of the returns on the two low-I/A portfolios and the average of the returns on the two high-I/A portfolios. See Table 1 for the description of the productivity factor $PROD$. 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	W	W-L	L	2	3	4	W	W-L	L	2	3	4	W	W-L	L	2	3	4	W	W-L
Panel A: 25 Size and 11/1/1-Momentum Portfolios																								
	a						$t(a)$ ($F_{GRS} = 4.61$, $p_{GRS} = 0$)						b						R^2					
S	0.09	0.40	0.56	0.76	1.36	1.28	0.27	2.11	3.05	3.64	4.74	3.83	1.20	0.94	0.90	0.94	1.13	−0.08	0.67	0.66	0.65	0.65	0.63	0.21
2	0.00	0.16	0.26	0.50	1.01	1.01	0.01	0.94	1.71	2.94	3.77	3.06	1.30	1.03	1.00	1.03	1.24	−0.06	0.75	0.72	0.74	0.74	0.71	0.17
3	0.17	−0.07	0.04	0.07	0.69	0.51	0.71	−0.48	0.29	0.49	3.14	1.37	1.23	1.04	0.97	1.00	1.23	0.01	0.73	0.78	0.79	0.80	0.75	0.15
4	0.14	−0.07	−0.12	−0.08	0.45	0.31	0.51	−0.46	−1.06	−0.81	2.27	0.75	1.21	1.06	0.99	1.03	1.16	−0.05	0.69	0.78	0.83	0.87	0.77	0.15
B	−0.08	−0.09	−0.35	−0.22	0.06	0.14	−0.29	−0.57	−3.25	−2.10	0.38	0.35	1.08	0.87	0.89	0.91	1.08	0.00	0.61	0.69	0.83	0.84	0.78	0.09
	i						$t(i)$						p						$t(p)$					
S	−0.01	0.35	0.32	0.16	−0.25	−0.24	−0.06	1.85	2.16	1.34	−1.51	−1.07	−1.05	−0.35	−0.18	−0.16	−0.31	0.74	−7.16	−4.37	−2.45	−1.92	−2.48	4.51
2	−0.09	0.26	0.28	0.16	−0.40	−0.31	−0.53	1.84	2.40	1.55	−2.34	−1.53	−0.82	−0.20	0.03	0.02	−0.15	0.67	−7.67	−2.64	0.46	0.30	−1.27	4.13
3	−0.11	0.30	0.33	0.23	−0.31	−0.21	−0.77	2.87	3.42	3.34	−2.31	−1.03	−0.73	−0.07	0.10	0.22	0.04	0.77	−6.22	−1.07	1.79	4.28	0.45	4.13
4	−0.03	0.36	0.37	0.35	−0.24	−0.21	−0.17	3.93	5.22	5.84	−2.03	−0.85	−0.67	−0.03	0.17	0.28	0.18	0.85	−4.80	−0.34	2.90	6.07	1.73	3.86
B	0.14	0.27	0.12	0.10	−0.17	−0.31	0.90	2.85	2.15	1.23	−1.54	−1.28	−0.32	0.05	0.19	0.34	0.31	0.62	−2.39	0.64	3.70	6.97	3.25	3.05
Panel B: 25 Size and 6/1/6-Momentum Portfolios																								
	a						$t(a)$ ($F_{GRS} = 3.40$, $p_{GRS} = 0$)						b						R^2					
S	0.50	0.51	0.54	0.65	1.14	0.65	1.59	2.46	2.68	3.06	4.33	2.54	1.25	1.05	1.01	1.03	1.19	−0.06	0.68	0.70	0.68	0.68	0.68	0.22
2	0.15	0.18	0.20	0.28	0.73	0.57	0.63	1.17	1.31	1.75	3.07	2.01	1.30	1.11	1.06	1.09	1.28	−0.02	0.76	0.78	0.77	0.78	0.75	0.17
3	0.21	0.03	0.03	0.10	0.55	0.34	0.92	0.24	0.21	0.83	2.76	1.10	1.23	1.07	1.04	1.05	1.23	0.00	0.77	0.81	0.83	0.84	0.78	0.14
4	0.22	−0.02	−0.09	−0.03	0.49	0.27	0.88	−0.18	−0.86	−0.33	2.85	0.79	1.18	1.04	1.02	1.03	1.18	0.00	0.74	0.83	0.87	0.89	0.82	0.12
B	−0.09	−0.06	−0.18	−0.15	0.26	0.35	−0.40	−0.46	−2.20	−2.02	2.17	1.21	1.00	0.89	0.88	0.92	1.08	0.08	0.70	0.82	0.90	0.90	0.85	0.09
	i						$t(i)$						p						$t(p)$					
S	−0.01	0.24	0.22	0.14	−0.24	−0.23	−0.05	1.24	1.46	0.99	−1.53	−1.11	−0.95	−0.42	−0.30	−0.28	−0.38	0.57	−6.80	−4.79	−3.51	−3.10	−3.29	4.53
2	−0.10	0.21	0.21	0.14	−0.33	−0.23	−0.55	1.52	1.59	1.15	−2.09	−1.25	−0.72	−0.20	−0.07	−0.03	−0.15	0.56	−6.19	−2.89	−1.06	−0.43	−1.51	3.95
3	−0.07	0.24	0.29	0.19	−0.32	−0.24	−0.52	1.91	2.88	2.09	−2.27	−1.46	−0.62	−0.11	0.06	0.08	−0.05	0.57	−5.53	−1.87	1.14	1.62	−0.61	3.69
4	−0.08	0.24	0.32	0.24	−0.27	−0.19	−0.59	2.61	3.91	4.02	−2.73	−1.01	−0.56	−0.08	0.09	0.14	0.03	0.59	−4.53	−1.14	1.68	3.25	0.39	3.52
B	0.01	0.11	0.12	0.05	−0.33	−0.34	0.08	1.29	2.90	1.46	−5.32	−2.13	−0.31	−0.01	0.11	0.19	0.07	0.38	−3.12	−0.12	2.67	5.63	1.34	2.87

Table 6 : Alternative Two-Factor Specifications of Neoclassical Regressions ($R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$ and $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$) for Monthly Percent Excess Returns on 25 Size and 11/1/1-Momentum and 25 Size and 6/1/6-Momentum, 1/1972–12/2006, 420 Months

The data for the one-month Treasury bill rate (R_f), the market factor, the 25 size and 11/1/1-momentum, and the 25 size and book-to-market portfolios are from Kenneth French's Web site. See Table 1 for the description of the investment INV factor and the productivity $PROD$ factor, and Table 2 for the description of the 25 size and 6/1/6-momentum portfolios. 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.

	$R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$											
	L	2	3	4	W	W-L	L	2	3	4	W	W-L
Panel A: 25 Size and 11/1/1-Momentum Portfolios												
	a						$t(a)$ ($F_{GRS} = 4.81$, $p_{GRS} = 0$)					
S	−0.75	0.03	0.30	0.42	0.79	1.54	−2.69	0.20	1.93	2.60	3.79	6.60
2	−0.58	−0.01	0.23	0.40	0.63	1.21	−2.62	−0.04	1.70	2.84	3.38	4.98
3	−0.33	−0.09	0.11	0.22	0.58	0.91	−1.49	−0.69	0.93	1.84	3.54	3.11
4	−0.24	−0.03	0.02	0.20	0.43	0.67	−1.04	−0.20	0.21	2.07	2.83	2.08
B	−0.23	0.02	−0.16	0.02	0.23	0.46	−1.05	0.12	−1.75	0.23	1.68	1.42
Panel B: 25 Size and 6/1/6-Momentum Portfolios												
	a						$t(a)$ ($F_{GRS} = 2.73$, $p_{GRS} = 0$)					
S	−0.26	0.12	0.22	0.31	0.58	0.84	−0.97	0.68	1.33	1.84	2.87	4.55
2	−0.32	0.05	0.15	0.23	0.44	0.76	−1.54	0.32	1.17	1.69	2.47	3.79
3	−0.20	0.02	0.12	0.18	0.39	0.58	−1.00	0.14	1.09	1.70	2.56	2.52
4	−0.10	0.01	0.06	0.11	0.40	0.49	−0.47	0.07	0.67	1.35	3.07	1.96
B	−0.21	0.03	−0.03	0.03	0.27	0.48	−1.18	0.26	−0.51	0.49	2.39	1.93

	$R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$											
	L	2	3	4	W	W-L	L	2	3	4	W	W-L
Panel A: 25 Size and 11/1/1-Momentum Portfolios												
	a						$t(a)$ ($F_{GRS} = 5.03$, $p_{GRS} = 0$)					
S	−0.08	0.48	0.65	0.76	1.15	1.23	−0.29	2.51	3.65	4.28	4.91	4.69
2	−0.19	0.22	0.38	0.54	0.75	0.94	−0.89	1.30	2.60	3.65	3.59	3.68
3	−0.02	0.05	0.18	0.21	0.55	0.57	−0.09	0.34	1.39	1.69	3.07	1.93
4	−0.03	0.10	0.04	0.17	0.35	0.38	−0.14	0.68	0.35	1.70	2.20	1.19
B	−0.20	−0.01	−0.25	−0.12	0.04	0.25	−0.90	−0.07	−2.42	−1.26	0.33	0.75
Panel B: 25 Size and 6/1/6-Momentum Portfolios												
	a						$t(a)$ ($F_{GRS} = 2.65$, $p_{GRS} = 0$)					
S	0.35	0.55	0.60	0.67	0.95	0.59	1.30	2.82	3.26	3.62	4.29	2.86
2	0.01	0.26	0.31	0.36	0.54	0.53	0.03	1.67	2.15	2.47	2.80	2.39
3	0.06	0.13	0.17	0.22	0.38	0.32	0.29	0.99	1.41	1.97	2.31	1.32
4	0.04	0.07	0.10	0.13	0.35	0.31	0.19	0.62	0.97	1.43	2.45	1.16
B	−0.20	−0.04	−0.13	−0.08	0.12	0.32	−1.14	−0.34	−1.71	−1.27	1.02	1.27

Table 7 : Neoclassical Factor Regressions (The Benchmark Specification $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$ and Two Alternative Two-Factor Specifications $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$ and $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$) 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 market factor are from Kenneth French's Web site. We sort all NYSE, Amex, and NASDAQ stocks into five quintiles each month based on NYSE breakpoints of quarterly ROA from at least four months ago. Also, we sort all stocks independently in June of each year into five quintiles based on NYSE breakpoints of investment-to-assets at the last fiscal year-end. From taking intersections, we form 25 investment and profitability portfolios, whose value-weighted returns are calculated for the current month. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. 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^P	2	3	4	H^P	H-L^P	L^P	2	3	4	H^P	H-L^P	L^P	2	3	4	H^P	H-L^P	L^P	2	3	4	H^P	H-L^P
Panel A: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$																								
	a						$t(a)$ ($F_{GRS} = 1.68$, $p_{GRS} = 0.02$)						b						R^2					
L^I	0.14	0.19	−0.17	0.04	−0.12	−0.25	0.61	1.10	−1.00	0.25	−0.68	−1.02	1.24	1.11	1.08	1.09	1.21	−0.03	0.71	0.71	0.60	0.74	0.74	0.28
2	0.56	0.27	0.17	−0.34	−0.11	−0.67	2.64	1.35	1.23	−2.37	−0.72	−3.05	1.18	1.01	0.98	1.01	1.04	−0.14	0.73	0.63	0.70	0.75	0.79	0.43
3	0.30	0.28	−0.13	0.10	−0.05	−0.35	1.48	1.19	−0.53	0.68	−0.43	−1.69	1.14	0.91	1.01	0.97	0.96	−0.17	0.76	0.57	0.55	0.72	0.79	0.46
4	−0.03	0.16	0.11	0.07	0.11	0.14	−0.16	0.86	0.56	0.50	0.86	0.60	1.15	0.93	1.01	1.00	1.05	−0.10	0.74	0.67	0.62	0.78	0.84	0.30
H^I	−0.17	0.26	−0.03	−0.08	0.10	0.27	−0.87	1.35	−0.11	−0.55	0.81	1.34	1.18	1.02	1.02	1.09	1.16	−0.02	0.77	0.64	0.60	0.82	0.87	0.39
H-L^I	−0.30	0.08	0.15	−0.12	0.21		−1.45	0.38	0.59	−0.67	1.16		−0.06	−0.09	−0.06	0.00	−0.04		0.25	0.15	0.08	0.25	0.21	
	i						$t(i)$						p						$t(p)$					
L^I	0.51	0.56	0.50	0.55	0.34	−0.17	4.31	5.96	4.42	4.94	3.16	−1.19	−0.70	−0.16	0.01	0.21	0.30	0.99	−6.02	−1.88	0.11	2.89	4.30	8.92
2	0.03	0.17	0.50	0.50	0.25	0.23	0.21	1.79	5.24	5.71	3.48	1.63	−0.85	−0.23	−0.11	0.06	0.33	1.18	−8.85	−1.71	−1.49	0.84	4.83	12.60
3	−0.41	0.08	0.08	0.06	0.01	0.41	−3.47	0.69	0.81	0.67	0.08	3.60	−0.89	−0.40	0.01	0.18	0.26	1.15	−9.81	−2.98	0.09	2.43	4.22	12.27
4	−0.38	−0.06	−0.03	−0.17	−0.41	−0.03	−3.01	−0.52	−0.33	−2.12	−5.86	−0.24	−0.88	−0.39	−0.03	0.09	0.14	1.01	−9.72	−4.53	−0.34	1.32	2.36	9.74
H^I	−0.87	−0.56	−0.43	−0.56	−0.74	0.12	−7.13	−4.44	−3.14	−6.56	−9.80	0.96	−0.88	−0.36	−0.18	0.20	0.31	1.19	−9.59	−3.12	−1.32	2.93	5.39	12.00
H-L^I	−1.37	−1.12	−0.94	−1.12	−1.08		−11.50	−8.20	−5.53	−10.72	−8.71		−0.18	−0.20	−0.20	−0.01	0.01		−1.65	−1.99	−1.35	−0.17	0.16	
	Panel B: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$												Panel C: $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$											
	a						$t(a)$ ($F_{GRS} = 2.23$, $p_{GRS} = 0$)						a						$t(a)$ ($F_{GRS} = 2.67$, $p_{GRS} = 0$)					
L^I	−0.44	0.05	−0.16	0.21	0.13	0.58	−2.27	0.34	−0.89	1.57	0.82	2.31	0.37	0.45	0.06	0.29	0.04	−0.33	1.62	2.59	0.34	1.98	0.26	−1.34
2	−0.15	0.08	0.08	−0.30	0.16	0.31	−0.72	0.46	0.64	−2.37	1.19	1.26	0.57	0.34	0.40	−0.11	0.00	−0.57	2.85	1.80	2.79	−0.80	0.02	−2.64
3	−0.45	−0.05	−0.12	0.25	0.16	0.61	−2.15	−0.30	−0.63	1.88	1.46	2.65	0.11	0.31	−0.09	0.13	−0.05	−0.16	0.53	1.38	−0.38	0.90	−0.41	−0.72
4	−0.76	−0.17	0.08	0.15	0.22	0.98	−3.59	−1.05	0.47	1.15	1.97	3.98	−0.21	0.13	0.09	−0.01	−0.08	0.13	−1.07	0.71	0.47	−0.05	−0.63	0.56
H^I	−0.90	−0.04	−0.18	0.08	0.36	1.26	−4.21	−0.19	−0.90	0.64	3.04	5.04	−0.57	0.01	−0.23	−0.34	−0.24	0.32	−2.88	0.03	−0.95	−2.18	−1.82	1.68
H-L^I	−0.46	−0.09	−0.02	−0.13	0.23		−2.35	−0.43	−0.07	−0.80	1.32		−0.94	−0.44	−0.29	−0.63	−0.29		−4.06	−2.04	−1.23	−3.24	−1.44	

Table 8 : Neoclassical Factor Regressions (The Benchmark Specification $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$ and Two Alternative Two-Factor Specifications $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$ and $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$) for Monthly Percent Excess Returns on 25 Size-B/M Portfolios, 1/1972–12/2006, 420 Months

The data for the one-month Treasury bill rate (R_f), the market factor, and the 25 size-B/M portfolios are from Kenneth French's Web site. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. 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: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + p_j\, PROD + \varepsilon_j$

	a						$t(a)$ ($F_{GRS} = 3.00$, $p_{GRS} = 0$)					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
S	−0.03	0.58	0.46	0.64	0.75	0.78	−0.10	2.29	2.30	3.37	3.70	3.67
2	0.02	0.20	0.38	0.48	0.50	0.48	0.09	1.15	2.52	3.26	2.84	2.36
3	0.06	0.16	0.17	0.29	0.48	0.43	0.31	1.22	1.37	2.19	2.81	1.96
4	0.08	−0.07	0.17	0.29	0.26	0.18	0.57	−0.64	1.49	2.47	1.65	0.77
B	−0.20	−0.09	0.05	0.14	0.20	0.40	−2.22	−0.99	0.47	1.09	1.16	1.90

	b						R^2					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
S	1.36	1.18	1.06	0.99	1.04	−0.32	0.66	0.64	0.66	0.65	0.63	0.31
2	1.35	1.14	1.03	0.97	1.07	−0.28	0.76	0.75	0.73	0.70	0.68	0.30
3	1.26	1.10	0.97	0.93	1.02	−0.24	0.79	0.81	0.77	0.72	0.67	0.24
4	1.21	1.09	1.01	0.94	1.02	−0.18	0.86	0.85	0.79	0.76	0.70	0.21
B	0.99	1.00	0.89	0.81	0.85	−0.15	0.89	0.87	0.78	0.67	0.58	0.20

	i						$t(i)$					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
S	−0.26	0.09	0.33	0.44	0.54	0.80	−1.57	0.63	2.65	3.62	3.96	5.68
2	−0.45	0.02	0.25	0.33	0.50	0.95	−3.56	0.18	2.69	3.21	3.84	6.81
3	−0.50	0.06	0.26	0.36	0.50	1.00	−4.39	0.71	3.24	3.84	3.62	6.45
4	−0.40	0.13	0.29	0.42	0.56	0.96	−5.72	1.76	3.83	4.83	5.20	7.04
B	−0.22	0.19	0.18	0.29	0.47	0.69	−3.98	3.13	2.45	3.45	3.65	4.51

	p						$t(p)$					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
S	−0.65	−0.53	−0.31	−0.29	−0.37	0.27	−5.16	−4.53	−3.28	−3.42	−3.91	2.53
2	−0.28	−0.16	−0.10	−0.12	−0.24	0.04	−3.13	−2.01	−1.37	−1.51	−2.67	0.37
3	−0.16	−0.02	−0.01	−0.06	−0.14	0.02	−1.90	−0.28	−0.11	−0.71	−1.33	0.13
4	−0.06	0.07	0.02	−0.09	−0.05	0.01	−1.07	1.15	0.23	−1.19	−0.58	0.07
B	0.24	0.18	0.05	0.01	−0.19	−0.43	6.49	4.48	0.83	0.12	−2.12	−4.21

Panel B: $R_j - R_f = a_j + b_j\, MKT + i_j\, INV + \varepsilon_j$

	a						$t(a)$ ($F_{GRS} = 3.11$, $p_{GRS} = 0$)					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
S	−0.57	0.14	0.21	0.40	0.44	1.01	−2.22	0.61	1.18	2.40	2.49	5.50
2	−0.21	0.06	0.29	0.38	0.30	0.51	−1.09	0.42	2.09	2.85	1.85	2.83
3	−0.07	0.14	0.16	0.24	0.37	0.44	−0.45	1.22	1.41	2.00	2.42	2.12
4	0.03	−0.01	0.18	0.21	0.21	0.18	0.23	−0.09	1.67	1.89	1.49	0.92
B	0.00	0.06	0.09	0.15	0.04	0.05	−0.04	0.76	0.86	1.24	0.27	0.23

Panel C: $R_j - R_f = a_j + b_j\, MKT + p_j\, PROD + \varepsilon_j$

	a						$t(a)$ ($F_{GRS} = 4.34$, $p_{GRS} = 0$)					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
S	−0.15	0.62	0.62	0.84	1.00	1.15	−0.56	2.61	3.18	4.50	4.92	5.42
2	−0.19	0.21	0.50	0.63	0.73	0.92	−0.96	1.26	3.41	4.24	4.18	4.44
3	−0.18	0.19	0.29	0.46	0.71	0.89	−1.05	1.48	2.34	3.46	4.31	4.02
4	−0.10	−0.01	0.30	0.48	0.52	0.62	−0.75	−0.10	2.63	4.06	3.30	2.67
B	−0.30	0.00	0.13	0.27	0.42	0.72	−3.48	−0.02	1.21	2.07	2.55	3.46

Table 9 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Deciles Formed on Campbell, Hilscher, and Szilagyi's (2007) Distress Measure and Deciles Formed on Standardized Unexpected Earnings (SUE)

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 ten deciles based on the NYSE breakpoints of failure probability four months ago. For the SUE portfolios, we rank all NYSE, Amex, and NASDAQ stocks into ten deciles at the beginning of each month by their most recent past SUE based on the NYSE breakpoints. SUE is defined as unexpected earnings (the change in quarterly earnings per share from its value announced four quarters ago) divided by the standard deviation of unexpected earnings over the prior eight quarters. Monthly value-weighted returns on the failure probability and SUE 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 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 Distress Deciles, 6/1975–12/2006, 379 Months											
Mean	0.93	0.86	0.74	0.58	0.58	0.72	0.70	0.48	0.34	0.04	−0.89	
t(Mean)	3.83	3.70	3.31	2.64	2.56	3.01	2.80	1.88	1.06	0.10	−3.04	
α	0.32	0.27	0.13	−0.02	−0.04	0.08	0.03	−0.20	−0.50	−0.91	−1.23	2.73 (0)
β	0.96	0.92	0.95	0.94	0.98	1.01	1.05	1.07	1.31	1.49	0.53	
$t(\alpha)$	2.31	2.15	1.22	−0.19	−0.43	0.73	0.27	−1.73	−2.84	−4.00	−4.15	
a	0.32	0.37	0.13	0.00	−0.05	0.00	0.02	−0.30	−0.60	−1.03	−1.34	3.76 (0)
b	0.93	0.90	0.98	0.96	1.02	1.04	1.04	1.11	1.28	1.36	0.43	
s	0.13	−0.09	−0.13	−0.13	−0.13	0.00	0.04	0.04	0.31	0.79	0.65	
h	−0.03	−0.13	0.03	0.00	0.05	0.12	0.01	0.14	0.08	−0.02	0.01	
$t(a)$	2.37	3.25	1.26	0.01	−0.54	0.02	0.16	−2.30	−3.56	−5.65	−5.22	
a	0.00	0.02	−0.20	−0.22	−0.09	0.09	0.30	0.12	0.21	0.18	0.18	1.68 (0.08)
b	1.00	0.95	1.00	0.97	0.98	1.01	1.02	1.03	1.23	1.35	0.35	
i	0.07	0.10	0.20	0.09	0.00	0.03	−0.07	−0.16	−0.22	−0.46	−0.53	
p	0.36	0.26	0.30	0.20	0.06	−0.03	−0.30	−0.31	−0.76	−1.12	−1.48	
$t(a)$	0.00	0.15	−1.73	−2.21	−0.89	0.73	2.49	0.92	1.47	1.06	0.83	
$t(b)$	30.36	26.61	32.49	40.57	39.10	24.77	32.26	31.97	34.83	29.19	6.54	
$t(i)$	0.68	1.08	3.28	1.24	0.04	0.34	−0.92	−1.82	−2.16	−3.66	−3.10	
$t(p)$	4.93	3.32	5.87	3.74	0.99	−0.51	−5.18	−5.35	−10.27	−15.30	−14.59	
	Panel B: The SUE Deciles, 1/1972–12/2006, 420 Months											
Mean	−0.10	0.16	0.15	0.15	0.24	0.61	0.60	0.88	0.89	1.07	1.17	
t(Mean)	−0.41	0.67	0.59	0.61	1.01	2.62	2.64	3.82	3.75	4.78	8.05	
α	−0.62	−0.34	−0.38	−0.36	−0.26	0.11	0.11	0.39	0.39	0.60	1.22	9.74 (0)
β	1.02	1.00	1.06	1.02	1.00	0.99	0.96	0.97	0.99	0.93	−0.09	
$t(\alpha)$	−6.58	−3.62	−3.82	−3.60	−2.94	1.33	1.38	4.41	3.96	6.79	8.50	
a	−0.59	−0.31	−0.36	−0.31	−0.31	0.12	0.11	0.42	0.41	0.63	1.22	9.64 (0)
b	1.02	0.99	1.03	0.96	1.00	0.99	0.99	0.97	1.00	0.94	−0.08	
s	−0.06	−0.02	0.09	0.12	0.07	−0.05	−0.10	−0.06	−0.07	−0.11	−0.05	
h	−0.04	−0.04	−0.05	−0.09	0.06	−0.01	0.02	−0.04	−0.01	−0.03	0.01	
$t(a)$	−6.13	−3.01	−3.36	−2.94	−3.21	1.34	1.39	4.95	4.37	6.74	8.00	
a	−0.45	−0.25	−0.06	−0.16	−0.14	0.11	−0.05	0.16	0.26	0.43	0.89	4.57 (0)
b	0.99	0.96	1.00	0.98	0.99	0.99	0.98	1.01	1.00	0.95	−0.04	
i	−0.17	−0.24	−0.30	−0.17	−0.04	0.02	0.08	0.17	0.02	0.02	0.19	
p	−0.12	0.01	−0.26	−0.18	−0.13	−0.01	0.17	0.21	0.16	0.21	0.33	
$t(a)$	−4.58	−2.30	−0.56	−1.41	−1.36	1.10	−0.52	1.87	2.71	4.89	6.24	
$t(b)$	41.94	31.84	33.99	40.74	40.44	48.26	46.68	46.74	40.86	36.92	−1.07	
$t(i)$	−2.55	−3.21	−4.50	−2.99	−0.51	0.40	1.22	2.84	0.35	0.36	1.88	
$t(p)$	−2.79	0.23	−4.82	−3.15	−2.55	−0.19	3.98	4.13	3.24	5.22	5.07	

Table 10 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on Ten Accruals Deciles and Ten Net Stock Issues Deciles, 1/1972–12/2006, 420 Months

The data on the one-month Treasury bill rate, the Fama-French (1993) three factors are from Kenneth French's Web site. See the caption of Table 1 for the description of the investment INV factor and the productivity $PROD$ factor. Accruals are measured as the change of operating working capital per split-adjusted share from year $t-1$ to t divided by book equity per split-adjusted share at t. Operating working capital is current assets (Compustat annual item 4) minus cash and short term investment (item 1) minus current liabilities (item 5) plus debt in current liabilities (item 34). 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 NYSE breakpoints of accruals and 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 $t+1$. 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 Accrual Deciles							
Mean	0.73	0.61	0.50	0.53	0.57	0.56	0.53	0.53	0.47	0.22	−0.52	
t(Mean)	2.59	2.35	2.14	2.44	2.68	2.51	2.23	2.11	1.74	0.74	−4.13	
α	0.14	0.05	0.00	0.05	0.11	0.07	0.01	−0.02	−0.11	−0.41	−0.55	3.00 (0)
β	1.17	1.11	1.01	0.94	0.90	0.97	1.03	1.08	1.15	1.25	0.07	
$t(\alpha)$	1.27	0.61	−0.06	0.78	1.47	1.11	0.15	−0.19	−1.17	−3.46	−4.41	
a	0.10	0.14	0.01	0.00	0.05	0.02	−0.02	−0.03	−0.10	−0.47	−0.57	3.22 (0)
b	1.12	1.06	1.01	0.98	0.95	1.01	1.05	1.07	1.11	1.19	0.07	
s	0.29	0.07	−0.06	−0.06	−0.05	−0.07	−0.01	0.10	0.14	0.33	0.04	
h	0.02	−0.14	−0.01	0.09	0.11	0.09	0.05	0.01	−0.03	0.04	0.02	
$t(a)$	0.91	1.62	0.11	0.03	0.55	0.26	−0.28	−0.34	−1.06	−3.95	−4.35	
a	0.17	0.22	0.13	0.14	0.22	0.13	0.08	0.14	0.09	−0.21	−0.38	2.96 (0)
b	1.18	1.08	0.98	0.93	0.88	0.95	1.01	1.03	1.08	1.17	0.00	
i	0.05	−0.16	−0.14	−0.05	−0.14	−0.09	−0.14	−0.32	−0.41	−0.47	−0.51	
p	−0.06	−0.13	−0.11	−0.09	−0.06	−0.02	−0.01	−0.03	−0.03	−0.01	0.06	
$t(a)$	1.24	2.15	1.61	1.79	2.34	1.68	1.06	1.44	0.80	−1.57	−2.97	
$t(b)$	39.51	53.32	46.24	44.23	42.49	49.00	51.84	49.60	38.13	38.41	−0.14	
$t(i)$	0.51	−2.37	−2.38	−1.02	−2.04	−1.84	−2.52	−4.17	−5.95	−5.10	−5.33	
$t(p)$	−1.20	−2.77	−2.51	−2.14	−1.38	−0.49	−0.27	−0.56	−0.63	−0.13	0.96	
					Panel B: The Net Stock Issues Deciles							
Mean	1.00	0.82	0.77	0.57	0.27	0.70	0.72	0.78	0.24	0.04	−0.96	
t(Mean)	4.36	3.65	3.34	2.45	1.01	2.99	2.94	2.95	0.81	0.13	−5.23	
α	0.54	0.37	0.32	0.11	−0.28	0.21	0.20	0.22	−0.36	−0.57	−1.11	3.97 (0)
β	0.91	0.89	0.88	0.90	1.07	0.96	1.02	1.10	1.18	1.20	0.29	
$t(\alpha)$	4.02	2.72	2.16	0.69	−1.82	1.85	2.03	2.08	−2.11	−3.73	−4.68	
a	0.32	0.24	0.24	−0.02	−0.19	0.13	0.17	0.22	−0.27	−0.51	−0.83	3.18 (0)
b	1.06	1.00	0.94	0.98	1.03	1.02	1.04	1.08	1.10	1.12	0.06	
s	0.05	−0.08	−0.01	0.05	−0.05	−0.01	0.01	0.10	0.08	0.17	0.12	
h	0.40	0.26	0.15	0.23	−0.15	0.15	0.06	0.00	−0.17	−0.13	−0.53	
$t(a)$	2.94	1.91	1.60	−0.13	−1.41	1.18	1.67	1.97	−1.57	−3.32	−4.01	
a	0.25	0.12	0.15	−0.06	0.07	0.05	0.20	0.41	0.27	−0.04	−0.29	2.26 (0.02)
b	0.98	0.94	0.92	0.95	0.99	0.97	1.00	1.04	1.02	1.06	0.09	
i	0.24	0.14	0.15	0.18	−0.31	0.00	−0.14	−0.27	−0.64	−0.52	−0.75	
p	0.21	0.20	0.12	0.11	−0.24	0.16	0.05	−0.10	−0.42	−0.36	−0.57	
$t(a)$	1.86	0.91	0.87	−0.46	0.52	0.45	1.80	3.44	1.75	−0.27	−1.31	
$t(b)$	35.55	32.41	23.46	23.27	29.09	35.74	38.81	37.30	27.53	35.66	1.95	
$t(i)$	2.50	1.32	1.84	2.36	−3.35	−0.03	−2.05	−3.39	−5.36	−5.25	−4.97	
$t(p)$	3.11	2.67	1.82	1.32	−3.78	2.77	1.18	−1.88	−7.43	−6.90	−6.69	

Table 11 : Summary Statistics and Factor Regressions for Monthly Percent Excess Returns on the Asset Growth 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 portfolio returns are from Kenneth French's Web site. See Table 1 for the description of the investment factor INV and the productivity factor $PROD$. In June of each year t, we sort all NYSE, Amex, and NASDAQ stocks into ten deciles based on the NYSE breakpoints of asset growth measured at the end of last fiscal year $t-1$. Asset growth of year t is the change of total assets (item 6) from $t-1$ to t divided by total assets from year $t-1$. 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 Asset Growth Deciles							
Mean	0.95	0.76	0.77	0.61	0.62	0.62	0.61	0.52	0.47	0.16	−0.79	
t(Mean)	3.46	3.24	3.54	3.03	2.99	2.93	2.75	2.19	1.70	0.50	−4.63	
α	0.39	0.27	0.31	0.18	0.17	0.17	0.13	0.00	−0.12	−0.53	−0.92	4.33 (0)
β	1.11	0.97	0.90	0.85	0.89	0.90	0.96	1.03	1.18	1.35	0.25	
$t(\alpha)$	3.08	2.88	3.39	2.33	2.41	2.18	1.95	−0.02	−1.34	−4.51	−5.52	
a	0.10	0.05	0.06	0.00	0.05	0.02	0.09	0.06	0.06	−0.35	−0.46	2.45 (0.01)
b	1.15	1.05	1.02	0.94	0.95	0.98	1.00	1.00	1.08	1.21	0.06	
s	0.37	0.12	0.00	−0.03	−0.04	−0.04	−0.08	0.01	0.06	0.25	−0.12	
h	0.39	0.32	0.38	0.28	0.19	0.23	0.06	−0.09	−0.28	−0.30	−0.69	
$t(a)$	0.93	0.57	0.76	0.04	0.68	0.31	1.47	0.83	0.68	−3.32	−3.16	
a	0.28	0.18	0.13	0.04	0.08	0.08	0.10	0.07	0.21	−0.08	−0.37	2.02 (0.03)
b	1.18	1.04	0.96	0.89	0.92	0.91	0.96	1.00	1.07	1.22	0.04	
i	0.57	0.47	0.38	0.31	0.19	0.06	−0.06	−0.27	−0.73	−0.82	−1.39	
p	−0.17	−0.14	0.03	0.02	0.02	0.09	0.07	0.05	−0.04	−0.14	0.03	
$t(a)$	2.15	1.79	1.38	0.50	1.08	0.99	1.38	0.95	2.54	−0.69	−2.46	
$t(b)$	35.66	47.44	40.09	46.60	40.18	50.57	50.88	58.93	60.52	50.21	1.09	
$t(i)$	7.08	7.05	5.56	5.32	3.35	0.98	−1.63	−5.61	−12.53	−9.69	−14.06	
$t(p)$	−2.93	−3.00	0.41	0.36	0.62	1.75	1.92	1.33	−1.27	−3.08	0.47	
					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	
a	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	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	
$t(a)$	0.71	0.11	0.93	0.89	−0.79	−0.42	1.47	0.44	−0.35	−0.63	−0.90	
a	−0.14	−0.32	−0.15	−0.08	−0.06	0.01	0.11	0.18	0.36	0.46	0.60	2.63 (0)
b	1.15	1.03	0.97	0.94	0.94	0.91	0.91	0.90	0.90	1.00	−0.15	
i	−0.50	0.02	0.06	0.12	0.13	0.28	0.41	0.36	0.23	0.20	0.71	
p	0.05	0.27	0.31	0.19	0.13	0.11	0.16	0.05	−0.08	−0.05	−0.10	
$t(a)$	−1.14	−4.04	−1.46	−1.01	−0.62	0.10	1.08	1.66	2.64	2.97	2.46	
$t(b)$	35.40	51.53	40.59	44.17	35.88	32.27	33.56	25.82	19.96	21.41	−2.11	
$t(i)$	−6.62	0.47	0.87	2.27	1.93	3.58	7.31	5.36	2.26	1.64	3.97	
$t(p)$	0.95	7.69	5.50	4.75	2.22	1.68	2.76	0.86	−1.03	−0.50	−0.72	

Table 12 : Value- and Equal-Weighted Average Monthly Returns, and Averages and Cross-Section Standard Deviations of Anomaly Variables, 1/1972–12/2006, 420 Months

The table shows averages of monthly value-weighted (VW) and equal-weighted (EW) average stock returns, and monthly cross-section standard deviations of returns for all stocks (Market) and for Micro, Small, Big, and All but Micro stocks. The table also shows the average number of stocks and the average percent of the total market capitalization (market cap) in each size group each month. Finally, we report the averages of annual EW average values and annual cross-section standard deviations of the anomaly variables used as independent variables in cross-sectional regressions (Table 13). We assign stocks to size groups at the end of June each year. Micro-cap stocks (Micro) are below the 20$^{\text{th}}$ percentile of NYSE market cap at the end of June, Small stocks are between the 20$^{\text{th}}$ and 50$^{\text{th}}$ percentiles, and Big stocks are above the NYSE median. All but Micro combines Small and Big stocks. The firm characteristics, which are used to predict the monthly returns for July of year t to June of year t+1 in cross-sectional regressions are: ln(MC), the natural log of market cap (in millions) in June of t; ln(B/M), the natural log of the ratio of the book equity for the last fiscal year-end in $t-1$ divided by the market equity in December of $t-1$; NS (net stock issues), the change in the natural log of the split-adjusted shares outstanding from the fiscal year-end in t−2 to t−1; Ac/B (accruals), the change in operating working capital per split-adjusted share from $t-2$ to $t-1$ divided by book equity per split-adjusted share in $t-1$; Mom (momentum), the cumulative stock return from month $m-12$ to $m-2$; dA/A (asset growth), the change in the natural log of assets per split-adjusted share from $t-2$ to $t-1$; and Y/B (profitability), equity income in $t-1$ divided by book equity for $t-1$. Zero NS is a dummy variable that is one if NS is zero and zero otherwise. Neg Y is one if equity income is negative and zero otherwise. Neg Ac/B is Ac/B for firms with negative accruals (zero otherwise) and Pos Ac/B is Ac/B for firms with positive accruals (zero otherwise). I/A is the annual change in gross property, plant, and equipment plus the annual change in inventories divided by the lagged book assets. ROA is the quarterly earnings divided by last quarter's assets. Except for ln(MC), ln(B/M), Zero NS, and Neg Y, all the other variables are in percent. Appendix B provides more detailed variable definitions.

Panel A: Average Monthly Values, January 1972–December 2006

		% of Total	VW Return		EW Return		Cross-section Std
	Firms	Market Cap	Ave	Std Dev	Ave	Std Dev	Dev of Returns
Market	3286	100.00	0.98	4.58	1.45	5.93	15.43
Micro	1946	2.83	1.33	6.59	1.69	6.69	17.92
Small	662	6.35	1.17	5.97	1.18	6.04	11.44
Big	677	90.82	0.97	4.51	1.09	5.02	8.86
All but Micro	1340	97.17	0.97	4.56	1.13	5.43	10.28

Panel B: Average of Annual EW Average Values, 1972–2006

	ln(MC)	ln(B/M)	Mom	Zero NS	NS	Neg Ac/B	Pos Ac/B	dA/A	Neg Y	Y/B	I/A	ROA
Market	4.39	−0.34	14.08	0.16	4.74	−6.85	8.00	6.99	0.24	−0.74	10.40	0.57
Micro	3.06	−0.18	12.20	0.22	4.97	−8.75	9.53	4.50	0.33	−7.91	9.48	−0.14
Small	5.38	−0.49	17.67	0.10	4.89	−4.60	6.86	11.19	0.14	7.71	12.28	1.18
Big	7.32	−0.63	16.00	0.06	3.69	−3.38	4.50	10.24	0.08	12.54	11.08	1.77
All but Micro	6.36	−0.56	16.83	0.08	4.32	−3.98	5.67	10.70	0.11	10.09	11.70	1.47

Panel C: Average of Annual Cross-Section Standard Deviations, 1972–2006

	ln(MC)	ln(B/M)	Mom	Zero NS	NS	Neg Ac/B	Pos Ac/B	dA/A	Neg Y	Y/B	I/A	ROA
Market	1.98	0.94	51.40	0.35	13.45	18.72	14.49	24.69	0.41	38.42	18.79	3.63
Micro	1.08	0.97	56.20	0.39	14.31	21.83	16.48	26.83	0.45	44.81	19.85	4.14
Small	0.38	0.83	46.42	0.28	12.52	13.73	11.79	22.20	0.32	24.50	18.14	2.89
Big	0.93	0.77	35.11	0.23	10.57	9.58	8.06	17.81	0.24	15.97	15.17	2.05
All but Micro	1.21	0.81	41.50	0.26	11.72	11.94	10.21	20.19	0.29	21.09	16.77	2.54

Table 13 : Average Slopes and t-Statistics from Monthly Cross-Sectional Regressions, 1/1972–12/2006, 420 Months

This table shows average slopes and their t-statistics from monthly cross-sectional regressions to predict stock returns. The anomaly variables at the last fiscal year-end of $t-1$ (except for momentum and ROA) are used to predict returns from July of year t to June of $t+1$. Momentum (Mom) for month m is the cumulative return from month $m-12$ to $m-2$. ROA is the quarterly earnings divided by last quarter's assets. The ROA used in the current month's regression is from at least four months ago. Table 12 contains other variable definitions. Int is the average intercept and R^2 is the average adjusted R^2. The t-statistics (t) for the average regression slopes use the time series standard deviations of the monthly slopes. In Panel A, we replicate the cross-sectional regressions in Fama and French (2007, Table IV) on our sample. In Panel B, we report the cross-sectional regressions after replacing dA/A with I/A and Y/B with ROA.

Panel A: Replicating the Cross-Sectional Regressions in Fama and French (2007)

		Int	ln(MC)	ln(B/M)	Mom	Zero NS	NS	Neg Ac/B	Pos Ac/B	dA/A	Neg Y	Pos Y/B	R^2
Market	Average	2.42	−0.20	0.19	0.40	−0.15	−1.66	−0.19	−0.35	−1.14	0.12	0.69	0.03
	t	6.83	−4.67	2.96	2.37	−2.31	−6.99	−1.11	−1.89	−8.98	1.04	2.39	
Micro	Average	3.39	−0.51	0.14	0.32	−0.24	−1.64	−0.21	−0.22	−1.23	0.07	0.22	0.02
	t	9.11	−7.49	2.00	1.89	−3.23	−5.78	−1.02	−1.09	−8.38	0.62	0.61	
Small	Average	1.71	−0.06	0.26	0.77	−0.18	−1.47	0.33	−1.05	−0.48	−0.03	0.52	0.04
	t	3.29	−0.78	3.14	3.81	−1.81	−4.46	1.19	−3.47	−2.33	−0.19	1.07	
Big	Average	1.51	−0.06	0.21	0.65	−0.10	−1.64	−0.12	−0.67	−0.43	−0.20	0.68	0.08
	t	3.37	−1.35	2.38	2.66	−0.98	−4.72	−0.35	−1.89	−1.89	−1.00	1.33	
All but Micro	Average	1.50	−0.05	0.24	0.74	−0.16	−1.57	0.03	−0.89	−0.45	−0.07	0.62	0.06
	t	3.55	−1.24	3.09	3.53	−1.97	−5.85	0.11	−3.32	−2.53	−0.44	1.49	
Micro−Small	Average	1.68	−0.45	−0.12	−0.45	−0.06	−0.17	−0.53	0.83	−0.75	0.11	−0.30	
	t	3.79	−5.10	−1.99	−3.68	−0.50	−0.51	−1.63	2.74	−3.11	0.65	−0.51	
Micro−Big	Average	1.88	−0.45	−0.07	−0.33	−0.14	0.01	−0.08	0.45	−0.80	0.27	−0.46	
	t	4.21	−5.47	−0.85	−1.86	−1.10	0.01	−0.22	1.20	−3.02	1.41	−0.77	
Micro−All but Micro	Average	1.90	−0.46	−0.10	−0.42	−0.08	−0.07	−0.23	0.67	−0.78	0.14	−0.40	
	t	4.92	−5.87	−1.64	−3.24	−0.69	−0.20	−0.80	2.43	−3.61	0.98	−0.77	
Small−Big	Average	0.20	0.00	0.05	0.12	−0.08	0.18	0.45	−0.38	−0.05	0.17	−0.16	
	t	0.44	0.03	0.75	0.84	−0.65	0.43	1.12	−1.01	−0.17	0.78	−0.30	

Panel B: Cross-Sectional Regressions Using Our I/A and ROA Measures

		Int	ln(MC)	ln(B/M)	Mom	Zero NS	NS	Neg Ac/B	Pos Ac/B	I/A	Neg ROA	Pos ROA	R^2
Market	Average	1.75	−0.15	0.51	0.31	−0.21	−0.90	−0.77	−0.09	−0.59	−0.56	35.76	0.04
	t	4.91	−3.47	7.21	1.78	−2.77	−3.03	−3.36	−0.38	−3.31	−4.27	15.20	
Micro	Average	1.95	−0.25	0.47	0.18	−0.19	−0.64	−1.00	0.00	−0.89	−0.60	49.96	0.03
	t	5.30	−3.43	5.36	0.93	−2.28	−1.46	−3.37	0.00	−3.75	−4.42	13.74	
Small	Average	1.63	−0.12	0.46	0.50	−0.34	−1.96	−0.17	−0.50	−0.04	−0.14	23.08	0.05
	t	2.71	−1.16	4.24	2.13	−2.30	−3.30	−0.38	−1.15	−0.13	−0.67	5.19	
Big	Average	0.93	−0.01	0.48	0.48	−0.18	−1.41	−0.15	−0.16	0.09	−0.20	20.39	0.08
	t	1.93	−0.17	4.89	1.80	−1.28	−2.68	−0.23	−0.32	0.29	−1.09	4.80	
All but Micro	Average	1.11	−0.03	0.48	0.52	−0.28	−1.60	−0.10	−0.35	−0.05	−0.13	20.10	0.06
	t	2.52	−0.57	5.78	2.39	−2.77	−3.59	−0.28	−0.89	−0.20	−0.76	7.05	
Micro−Small	Average	0.32	−0.13	0.01	−0.33	0.15	1.31	−0.84	0.50	−0.85	−0.47	26.88	
	t	0.62	−1.23	0.08	−1.78	0.94	1.84	−1.71	1.07	−2.51	−2.42	5.25	
Micro−Big	Average	1.03	−0.24	−0.01	−0.30	−0.01	0.76	−0.86	0.16	−0.98	−0.40	29.57	
	t	2.16	−2.61	−0.09	−1.25	−0.05	1.12	−1.30	0.31	−2.42	−2.14	5.22	
Micro−All but Micro	Average	0.84	−0.22	−0.01	−0.34	0.09	0.96	−0.90	0.35	−0.84	−0.48	29.86	
	t	2.12	−2.62	−0.09	−1.93	0.71	1.55	−2.13	0.84	−2.68	−2.98	7.01	
Small−Big	Average	0.71	−0.11	−0.02	0.02	−0.16	−0.55	−0.02	−0.33	−0.13	0.06	2.69	
	t	1.21	−1.03	−0.17	0.10	−0.82	−0.87	−0.03	−0.61	−0.33	0.27	0.41	

Figure 1 : Earnings-to-Assets and Investment-to-Assets (Contemporaneous and Lagged) for the 25 Size and 11/1/1-Momentum Portfolios, 1972:Q1 to 2006:Q4, 140 Quarters

The 25 size and 11/1/1-momentum portfolios from Kenneth French's Web site are constructed monthly as the intersections of five quintiles formed on market equity and five quintiles formed on prior 2–12 month returns (skipping one month). The monthly size breakpoints and the monthly momentum breakpoints are NYSE quintiles. 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 and I/A are defined in Table 1. ROA is the most recent ROA relative to portfolio formation month t. 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 ROAs and I/As among the firms in the portfolio.