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Digesting Anomalies: An Investment Approach

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An empirical q-factor model consisting of the market factor, a size factor, an investment factor, and a profitability factor largely summarizes the cross section of average stock returns. A comprehensive examination of nearly 80 anomalies reveals that about one-half of the anomalies are insignificant in the broad cross section. More importantly, with a few exceptions, the q-factor model's performance is at least comparable to, and in many cases better than that of the Fama-French (1993) 3-factor model and the Carhart (1997) 4-factor model in capturing the remaining significant anomalies. (*JEL* G12, G14)

In a highly influential article, Fama and French (1996) show that, except for momentum, their 3-factor model, which consists of the market factor, a factor based on market equity (small-minus-big, SMB), and a factor based on book-to-market equity (high-minus-low, HML), summarizes the cross section of average stock returns as of the mid-1990s. Over the past 2 decades, however, it has become clear that the Fama-French model fails to account for a wide array of asset pricing anomalies.[1]

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[1] See, for example, Ball and Brown (1968); Bernard and Thomas (1990); Ritter (1991); Jegadeesh and Titman (1993); Ikenberry, Lakonishok, and Vermaelen (1995); Loughran and Ritter (1995);

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Our contribution is to construct a new empirical model that largely summarizes the cross section of average stock returns. In particular, many (but not all) of the anomalies that prove challenging for the Fama-French model can be captured.[2] Our model is in part inspired by investment-based asset pricing, which is in turn built on the neoclassical q-theory of investment. In our model (dubbed the q-factor model), the expected return of an asset in excess of the risk-free rate, denoted $E[r^i]-r^f$, is described by the sensitivities of its returns to 4 factors: the market excess return (MKT), the difference between the return on a portfolio of small size stocks and the return on a portfolio of big size stocks (r_{ME}), the difference between the return on a portfolio of low investment stocks and the return on a portfolio of high investment stocks ($r_{\mathrm{I/A}}$), and the difference between the return on a portfolio of high profitability (return on equity, ROE) stocks and the return on a portfolio of low profitability stocks (r_{ROE}). Formally,

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

in which $E[\mathrm{MKT}]$, $E[r_{\mathrm{ME}}]$, $E[r_{\mathrm{I/A}}]$, and $E[r_{\mathrm{ROE}}]$ are expected factor premiums, and β^i_{MKT}, β^i_{ME}, $\beta^i_{\mathrm{I/A}}$, and β^i_{ROE} are the factor loadings on MKT, r_{ME}, $r_{\mathrm{I/A}}$, and r_{ROE}, respectively.

We construct the q-factors from a triple 2-by-3-by-3 sort on size, investment-to-assets, and ROE. From January 1972 to December 2012, the size factor earns an average return of 0.31% per month ($t=2.12$); the investment factor 0.45% ($t=4.95$); and the ROE factor 0.58% ($t=4.81$). The investment factor has a high correlation of 0.69 with HML, and the ROE factor has a high correlation of 0.50 with the Carhart (1997) momentum factor (up-minus-down, UMD). The alphas of HML and UMD in the q-factor model are small and insignificant, but the alphas of the investment and ROE factors in the Carhart model (that augments the Fama-French model with UMD) are large and significant. As such, HML and UMD might be noisy versions of the q-factors.

To evaluate the empirical performance of the q-factor model, we start with a wide array of nearly 80 variables that cover all major categories of anomalies. Following Fama and French (1996), we construct testing deciles based on the breakpoints from the New York Stock Exchange (NYSE), and calculate value-weighted decile returns. Surprisingly, the high-minus-low deciles formed on

Chan, Jegadeesh, and Lakonishok (1996); Sloan (1996); Ang, Hodrick, Xing, and Zhang (2006); Daniel and Titman (2006); Campbell, Hilscher, and Szilagyi (2008); Cooper, Gulen, and Schill (2008); and Hafzalla, Lundholm, and Van Winkle (2011).

2 The need for a new factor model is evident in Cochrane (2011, p. 1060–61, original emphasis): "We are going to have to repeat Fama and French's anomaly digestion, but with many more dimensions. We have a lot of questions to answer: First, which characteristics really provide *independent* information about average returns? Which are subsumed by others? Second, does each new anomaly variable also correspond to a new factor formed on those same anomalies?... Third, how many of these new factors are really important? Can we again account for N independent dimensions of expected returns with $K<N$ factor exposures?... [T]he world would be much simpler if betas on only a few factors, important in the covariance matrix of returns, accounted for a larger number of mean characteristics."

about one-half of the anomaly variables, including the vast majority of variables related to trading frictions, have average returns that are insignificant at the 5% level. As such, echoing Schwert (2003) and Harvey, Liu, and Zhu (2013), we suggest that many claims in the anomalies literature seem exaggerated.

More importantly, in the playing field consisting of 35 anomalies that are significant in the broad cross section, the q-factor model performs well, compared to the Fama-French and Carhart models. Across the 35 high-minus-low deciles, the average magnitude of the alphas is 0.20% per month in the q-factor model, in contrast to 0.33% in the Carhart model and 0.55% in the Fama-French model. Five high-minus-low alphas are significant at the 5% level in the q-factor model, in contrast to 19 in the Carhart model and 27 in the Fama-French model. In addition, the q-factor model is rejected by the Gibbons, Ross, and Shanken (1989, GRS) test in 20 sets of deciles. In contrast, the Carhart model is rejected in 24, and the Fama-French model in 28 sets of deciles.

In particular, the q-factor model outperforms the Fama-French and Carhart models in capturing momentum. The high-minus-low earnings momentum decile has a Fama-French alpha of 0.55% per month and a Carhart alpha of 0.34%, both of which are significant. The alpha in the q-factor model (the q-alpha) is 0.16% ($t=1.12$). The high-minus-low price momentum decile has a Fama-French alpha of 1.12% ($t=4.47$) and a Carhart alpha of 0.06% ($t=0.51$). The q-alpha is 0.24% ($t=0.71$). The q-factor model performs similarly as the other 2 models in fitting the 25 size and book-to-market portfolios. The average magnitude of the alphas across the 25 portfolios is 0.11% in the q-factor model, which is close to 0.10% in the Fama-French model and 0.11% in the Carhart model. However, the q-factor model underperforms the Fama-French and Carhart models in capturing the operating accrual anomaly and the R&D-to-market anomaly.

Intuitively, investment predicts returns because given expected cash flows, high costs of capital imply low net present values of new capital and low investment, and low costs of capital imply high net present values of new capital and high investment. ROE predicts returns because high expected ROE relative to low investment must imply high discount rates. The high discount rates are necessary to offset the high expected ROE to induce low net present values of new capital and low investment. If the discount rates were not high enough, firms would instead observe high net present values of new capital and invest more. Conversely, low expected ROE relative to high investment must imply low discount rates. If the discount rates were not low enough to counteract the low expected ROE, firms would instead observe low net present values of new capital and invest less.

The traditional approach in asset pricing is to look for common factors from the consumption side of the economy (e.g., Breeden, Gibbons, and Litzenberger 1989). We instead exploit a direct link between stock returns and firm characteristics from the production side, following Cochrane (1991). Berk, Green, and Naik (1999); Carlson, Fisher, and Giammarino (2004);

and Zhang (2005) construct fully specified dynamic models for the cross section of expected stock returns. Liu, Whited, and Zhang (2009) estimate the characteristics-expected return relation derived from q-theory via generalized method of moments. Kogan and Papanikolaou (2013) relate the investment and profitability effects to embodied technology shocks. We differ by using the Black, Jensen, and Scholes (1972) portfolio approach to build a new factor model. A factor model is more flexible in practice because of its simplicity and the availability of high frequency returns data. Finally, the investment and profitability effects are not new to our work.[3] However, recognizing their fundamental importance in investment-based asset pricing, we build a new workhorse model on these effects for the cross section of expected stock returns.[4]

1. Conceptual Framework

The q-factor model is in part inspired from investment-based asset pricing. In this section, we use a simple economic model to illustrate the key intuitions behind the q-factor model.

1.1 An economic model

Consider a 2-period stochastic general equilibrium model as in Lin and Zhang (2013). There are 2 dates, 0 and 1. The economy is populated by a representative household and heterogeneous firms, indexed by $i = 1,2,...,N$. The representative household maximizes its expected utility, $U(C_0)+\rho E_0[U(C_1)]$, in which ρ is time preference, and C_0 and C_1 are consumption in dates 0 and 1, respectively. Firms produce a single commodity to be consumed or invested. Firm i starts with productive assets, A_{i0}, and produces in both dates. Firms exit at the end of date 1, with a liquidation value of zero, meaning that the depreciation rate of assets is 100%.

Firms differ in date-0 assets, A_{i0}, and date-0 profitability, Π_{i0}, which is known at the beginning of date 0. The operating cash flow of firm i is $\Pi_{it}A_{it}$, for $t=0,1$, in which the firm's stochastic date-1 profitability, Π_{i1}, is subject to a vector of aggregate shocks affecting all firms simultaneously, as well as a vector of firm-specific shocks affecting only firm i. Let I_{i0} denote investment for date 0, then $A_{i1}=I_{i0}$, because A_{i0} depreciates fully at the beginning of date 1. Investment entails quadratic adjustment costs, $(a/2)(I_{i0}/A_{i0})^2A_{i0}$, in which $a>0$ is a constant parameter.

[3] See Fairfield, Whisenant, and Yohn (2003); Titman, Wei, and Xie (2004); Cooper, Gulen, and Schill (2008); Xing (2008); and Polk and Sapienza (2009) for the investment effect, and Ball and Brown (1968); Bernard and Thomas (1990); Chan, Jegadeesh, and Lakonishok (1996); Haugen and Baker (1996); Piotroski (2000); Fama and French (2006); and Novy-Marx (2013) for the earnings (profitability) effect.

[4] Fama and French (2013, 2014), circulated after the first draft of our work dated October 2012, have recently incorporated variables that resemble our 2 q-factors into their 3-factor model to form a 5-factor asset pricing model. Their 2013 draft adds only a profitability factor, and the 2014 draft subsequently adds an investment factor.

The household side is standard. Let P_{it} and D_{it} denote the ex-dividend equity and dividend for firm i, respectively. The first principle for consumption says that $P_{i0} = E_0[M_1(P_{i1} + D_{i1})]$ or $E_0[M_1 r_{i1}^S] = 1$, in which $r_{i1}^S \equiv (P_{i1} + D_{i1})/P_{i0}$ is the stock return, and $M_1 \equiv \rho U'(C_1)/U'(C_0)$ is the stochastic discount factor. On the production side, firm i uses the date-0 operating cash flow to pay investment and adjustment costs. If the free cash flow, $D_{i0} \equiv \Pi_{i0} A_{i0} - I_{i0} - (a/2)(I_{i0}/A_{i0})^2 A_{i0}$, is positive, the firm distributes it back to the household. A negative D_{i0} means external equity. At date 1, the firm uses assets, A_{i1}, to obtain the operating cash flow, $\Pi_{i1} A_{i1}$, which is in turn distributed as dividends, D_{i1}. With only 2 dates, the firm does not invest in date 1, $I_{i1} = 0$, and the ex-dividend equity value, P_{i1}, is zero. Taking the household's stochastic discount factor, M_1, as given, firm i chooses I_{i0} to maximize the cum-dividend equity value at the beginning of date 0:

$$P_{i0} + D_{i0} \equiv \max_{\{I_{i0}\}} \quad \Pi_{i0} A_{i0} - I_{i0} - \frac{a}{2}\left(\frac{I_{i0}}{A_{i0}}\right)^2 A_{i0} + E_0[M_1 \Pi_{i1} A_{i1}]. \qquad (2)$$

The first principle for investment is given by:

$$1 + a\frac{I_{i0}}{A_{i0}} = E_0[M_1 \Pi_{i1}]. \qquad (3)$$

Intuitively, to obtain an extra unit of assets at the beginning of date 1, firm i must pay the purchasing price of unity and the marginal adjustment costs. The marginal benefit of this extra unit of assets over period 1 is the marginal product of assets (profitability), Π_{i1}. Discounting this marginal benefit back to date 0 using M_1 yields marginal q, which equals the marginal costs of investment.

Using the definition of D_{i0}, we can derive the ex-dividend equity value from Equation (2) as $P_{i0} = E_0[M_1 \Pi_{i1} A_{i1}]$ at the optimum. As such, we can rewrite the stock return as $r_{i1}^S = (P_{i1} + D_{i1})/P_{i0} = \Pi_{i1} A_{i1}/E_0[M_1 \Pi_{i1} A_{i1}] = \Pi_{i1}/E_0[M_1 \Pi_{i1}]$. Equation (3) then implies $r_{i1}^S = \Pi_{i1}/(1 + a(I_{i0}/A_{i0}))$. Intuitively, firm i will keep investing until the marginal costs of investment at date 0, $1 + a(I_{i0}/A_{i0})$, equal the marginal benefit of investment at date 1, Π_{i1}, discounted to date 0 with the stock return, r_{i1}^S, as the discount rate. Equivalently, the ratio of the date-1 marginal benefit of investment over the date-0 marginal costs of investment should equal the discount rate.[5]

[5] We opt to derive the characteristics-return relation in the simplest setting possible. However, the relation holds under substantially more general conditions. Cochrane (1991) derives this relation in a dynamic setting. Incorporating taxes and debt, Liu, Whited, and Zhang (2009) show that the investment return (the ratio of the next period marginal benefit of investment over the current period marginal costs of investment) equals the weighted average cost of capital (WACC), $w_{it} r_{it+1}^{Ba} + (1 - w_{it}) r_{it+1}^S$, in which w_{it} is the market leverage at the beginning of period t, and r_{it+1}^{Ba} is the after-tax corporate bond return over period t. This equivalence in effect provides the microfoundation for the standard WACC approach to capital budgeting in corporate finance. With the notations in our 2-period setup, the present value of the marginal project is $\Pi_{i1}/[w_{i0} r_{i1}^{Ba} + (1 - w_{i0}) r_{i1}^S]$, which uses the WACC as the discount rate. The costs of the marginal project remain $1 + a(I_{i0}/A_{i0})$. The first principle requires the marginal costs to equal the present value of the marginal project, meaning that its net present value is zero.

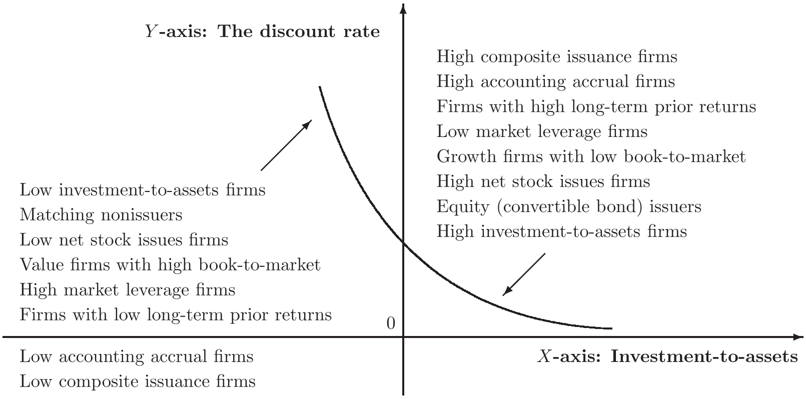

Figure 1
The investment channel

1.2 Implications

Taking the expectation on both sides of $r^S_{i1} = \Pi_{i1}/(1+a(I_{i0}/A_{i0}))$ yields:

$$E_0[r^S_{i1}] = \frac{E_0[\Pi_{i1}]}{1+a(I_{i0}/A_{i0})}. \tag{4}$$

This equation predicts that, all else equal, high investment stocks should earn lower expected returns than low investment stocks earn, and that, all else equal, high expected profitability stocks should earn higher expected returns than low expected profitability stocks earn. When expected returns vary over time and across firms, stock prices would adjust in a way that connects expected returns to investment and profitability per Equation (4). In particular, stock prices would not adjust to give rise to a cross-sectionally constant discount rate, which would mean that investment and profitability do not predict returns in the cross section. A cross-sectionally constant discount rate can only arise if all firms are equally risky, and stock prices follow a random walk.

1.2.1 The investment channel. Equation (4) predicts that given the expected profitability, expected returns decrease with investment-to-assets. This investment channel is consistent with many cross-sectional patterns including the negative relations of average returns with net stock issues, composite issuance, accruals, valuation ratios, and long-term prior returns (reversal). Figure 1 illustrates this insight.

The negative investment-expected return relation is intuitive. Firms invest more when their marginal q (the net present value of future cash flows generated from an additional unit of assets) is high. Given expected profitability or cash flows, low discount rates imply high marginal q and high investment, and high discount rates imply low marginal q and low investment. This intuition is probably most transparent in the capital budgeting context. In our setting, assets are homogeneous, meaning no difference between project costs of capital and firm costs of capital. Given expected cash flows, high costs of capital imply low net present values of new projects and low investment, and low costs of capital imply high net present values of new projects and high investment.[6]

The negative investment-return relation is conditional on expected profitability. Investment is linked to profitability because firms that are more profitable tend to invest more than less profitable firms. This conditional relation provides a natural portfolio interpretation for the investment channel. Sorting on net stock issues, composite issuance, book-to-market, and other valuation ratios is closer to sorting on investment than on expected profitability. These sorts produce wider cross-sectional expected return spreads associated with investment than those associated with expected profitability. As such, we can interpret these diverse sorts using their common implied sort on investment.

The negative relation between average returns and equity issues is consistent with the negative investment-expected return relation. The balance-sheet constraint of firms implies that a firm's uses of funds must equal its sources of funds, meaning that, all else equal, issuers must invest more and earn lower average returns than nonissuers.[7] Cooper, Gulen, and Schill (2008) show that asset growth predicts future returns with a negative slope. However, asset growth is the most comprehensive measure of investment-to-assets, in which investment is measured as the change in total assets. As such, the asset growth effect seems to be the premier manifestation of the investment channel.

The value premium is also consistent with the negative investment-return relation. Investment increases in marginal q (the denominator of Equation (4)), and the marginal q equals the average q under constant returns to scale. The average q and market-to-book are highly correlated and are identical without debt. Consequently, value firms with high book-to-market (low market-to-book) should invest less and earn higher expected returns than growth firms with low book-to-market (high market-to-book). In general, compared to firms

[6] The negative investment-expected return relation (a downward-sloping investment demand curve) has a long tradition in financial economics. Fisher (1930) and Fama and Miller (1972, Figure 2.4) show that the interest rate and investment are negatively correlated. As noted, Cochrane (1991) and Liu, Whited, and Zhang (2009) extend this insight into a dynamic world with uncertainty. In our simple economic model, project-level discount rates equal firm-level expected returns. This equivalence no longer holds in more general settings with project heterogeneity as in real options models such as Berk, Green, and Naik (1999); Carlson, Fisher, and Giammarino (2004); and Kogan and Papanikolaou (2013). However, these real options models also predict the negative investment-expected return relation. Intuitively, expansion options are riskier than assets in place. Investment converts riskier expansion options into less risky assets in place, causing high investment firms to be less risky and earn lower expected returns than low investment firms. A notable exception is Gomes, Kogan, and Zhang (2003), in which projects are assumed to be distributed randomly across firms, implying a flat investment-expected return relation. However, as pointed out in Zhang (2005), this flat relation gives rise to a counterfactual prediction that value stocks have higher cash flow durations than growth stocks, inconsistent with the evidence in Dechow, Sloan, and Soliman (2004).

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

with low valuation ratios, firms with high valuation ratios should have more growth opportunities, invest more, and earn lower expected returns.

High valuation ratios often result from a stream of positive shocks on fundamentals, and low valuation ratios from a stream of negative shocks on fundamentals. High valuation ratios of growth firms can manifest as high long-term prior returns, and low valuation ratios of value firms as low long-term prior returns. As such, firms with high long-term prior returns should invest more and earn lower expected returns than firms with low long-term prior returns, meaning that the investment channel also helps interpret the De Bondt and Thaler (1985) long-term reversal effect.

1.2.2 The profitability channel. Equation (4) also gives rise to the profitability channel that works in parallel with the investment channel. Given investment-to-assets, firms with high expected profitability should earn higher expected returns than firms with low expected profitability. The profitability-expected return relation is consistent with momentum, post-earnings-announcement drift, and the financial distress effect.

Why should high expected profitability firms earn higher expected returns than low expected profitability firms? Equation (4) says that the expected return equals the expected profitability divided by an increasing function of investment-to-assets. From the capital budgeting perspective, high expected profitability relative to low investment must mean high discount rates, which are necessary to offset the high expected profitability to induce low net present values of new capital and low investment. If the discount rates were not high enough to counteract the high expected profitability, firms would instead observe high net present values of new capital and invest more. Similarly, low expected profitability relative to high investments must mean low discount rates (as in small-growth firms in the 1990s). If the discount rates were not low enough to counteract the low expected profitability, these firms would instead observe low net present values of new capital and invest less.

The profitability-expected return relation is also consistent with the standard discounting model. The marginal costs of investment in the denominator of the right-hand side of Equation (4) equal marginal q, which in turn equals average q or market-to-book. As such, the expected return equals the expected profitability divided by market-to-book. Multiplying the numerator and the denominator with book equity equates the expected return with the ratio of the expected cash flows over the market equity. This relation is analogous to the Gordon Growth model. In a 2-period world, the equity value equals the expected cash flows divided by the discount rate. High expected cash flows relative to low market equity (high expected profitability relative to low market-to-book) imply high discount rates. Analogously, low expected cash flows relative to high market equity (low expected profitability relative to high market-to-book) imply low discount rates (e.g., Berk 1995).

The profitability-expected return relation has important implications. For any sorts that produce wider cross-sectional expected return spreads associated with expected profitability than with investment, their average returns can be interpreted with the common implied sort on expected profitability. Examples include momentum, distress, and earning surprises. In particular, momentum winners have higher expected profitability and should earn higher expected returns than momentum losers. Intuitively, shocks to profitability are positively correlated with stock returns. Firms with positive profitability shocks tend to experience immediate stock price increases, whereas firms with negative profitability shocks tend to experience immediate stock price decreases.

In addition, less financially distressed firms are more profitable, meaning higher expected profitability, and, all else equal, should earn higher expected returns than more financially distressed firms. As such, the distress effect is consistent with the positive profitability-expected return relation. Finally, sorting on earnings surprises should produce an expected profitability spread between extreme portfolios. Intuitively, all else equal, firms that have experienced large positive shocks to earnings tend to be more profitable than firms that have experienced large negative shocks to earnings.[8]

1.3 Limitations

We implement the economic model in Equation (4) with factor regressions. We construct factor mimicking portfolios on investment and profitability (as a proxy for expected profitability) in a way that is analogous to the size and book-to-market factors in Fama and French (1993, 1996). We then use the investment and profitability factors as right-hand side variables in factor regressions. The factor approach often delivers better empirical performance than the economic model itself. One reason is that stock returns data are available at high frequencies and are less subject to measurement errors than accounting variables. More important, implementing the economic model directly via structural estimation involves specification errors in the production and capital adjustment technologies that are absent in the factor model.

However, although in part inspired by Equation (4) derived from q-theory, the q-factor model is largely a reduced form, empirical model. In particular, the factor model requires that returns of stocks with similar investment (and returns of stocks with similar profitability) comove together, a prediction that Equation (4) does not make, at least not directly. To ground the q-factor model more rigorously in theories of investment-based asset pricing, one would need

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[8] We have so far only described anomaly variables that are directly related to investment and profitability. In our empirical tests, we confront the q-factor model with a substantially broader set of anomalies. As argued in Lin and Zhang (2013), the consumption model and the investment model of asset pricing are equivalent in general equilibrium, delivering identical expected returns. While the consumption model says that consumption risks are sufficient for accounting for expected returns, the investment model says that characteristics are sufficient. We take the latter prediction seriously and confront the q-factor model with a wide array of anomaly variables that are not directly related to investment and profitability.

to go beyond the first principle in Equation (4). To this end, one would need to specify fully a dynamic investment model to quantify the comovement behind the q-factors, as well as the sources of the cross-sectional heterogeneity in investment, profitability, and their factor loadings. While offering some useful guidance, our empirical work makes little theoretical contribution in this direction.

2. Factors

Monthly returns, dividends, and prices are from the Center for Research in Security Prices (CRSP), and accounting information is from the Compustat Annual and Quarterly Fundamental Files. The sample is from January 1972 to December 2012. The starting date is restricted by the availability of quarterly earnings announcement dates, as well as quarterly book equity data. Financial firms and firms with negative book equity are excluded.

2.1 Factor construction

We measure investment-to-assets, I/A, as the annual change in total assets (Compustat annual item AT) divided by 1-year-lagged total assets. We measure profitability as ROE, which is income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged book equity.[9] We construct the q-factors from a triple 2-by-3-by-3 sort on size, I/A, and ROE. Because both the investment and earnings effects in the data are stronger in small firms than in big firms (e.g., Bernard and Thomas 1990; Fama and French 2008), we control for size when constructing the investment and ROE factors. Sorting jointly with size is also standard in constructing the value factor, HML, and the momentum factor, UMD. HML is from a double 2-by-3 sort on size and book-to-market, and UMD is from a double 2-by-3 sort on size and prior 2–12 month returns. Finally, sorting on investment and ROE independently helps orthogonalize the 2 new factors.

Specifically, at the end of June of each year t, we use the median NYSE size (stock price per share times shares outstanding from CRSP) to split NYSE, Amex, and NASDAQ stocks into 2 groups, small and big. Independently, at the end of June of year t, we break all stocks into 3 I/A groups, using the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of I/A for the fiscal year ending in calendar year $t-1$.

[9] Our measure of the book equity is the quarterly version of the annual book equity measure in Davis, Fama, and French (2000). In particular, book equity is shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock. Fama and French (2006) measure shareholders' equity as total assets minus total liabilities. We follow Davis et al. because Compustat quarterly items SEQQ (stockholders' equity) and CEQQ (common equity) have a broader coverage than items ATQ (total assets) and LTQ (total liabilities) before 1980.

In addition, independently, at the beginning of each month, we sort all stocks into 3 groups based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of ROE. Earnings data in Compustat quarterly files are used in the months immediately after the most recent public quarterly earnings announcement dates (Compustat quarterly item RDQ). For example, if the earnings for the fourth fiscal quarter of year $t-1$ are publicly announced on March 5 (or March 25) of year t, we use the announced earnings (divided by the book equity from the third quarter of year $t-1$) to form portfolios at the beginning of April of year t. In addition, for a firm to enter the factor construction, we require the end of the fiscal quarter that corresponds to its most recently announced quarterly earnings to be within 6 months prior to the portfolio formation. We impose this restriction to exclude stale earnings.

Taking the intersections of the 2 size, 3 I/A, and 3 ROE groups, we form 18 portfolios. Monthly value-weighted portfolio returns are calculated for the current month, and the portfolios are rebalanced monthly. (The ROE portfolios are rebalanced monthly at the beginning of each month, and the size and I/A portfolios are rebalanced annually at the end of each June.) The size factor, r_{ME}, is the difference (small-minus-big), each month, between the simple average of the returns on the 9 small size portfolios and the simple average of the returns on the 9 big size portfolios. Designed to mimic the common variation in returns related to I/A, the investment factor, $r_{\mathrm{I/A}}$, is the difference (low-minus-high), each month, between the simple average of the returns on the 6 low I/A portfolios and the simple average of the returns on the 6 high I/A portfolios. Finally, designed to mimic the common variation in returns related to ROE, the ROE factor is the difference (high-minus-low), each month, between the simple average of the returns on the 6 high ROE portfolios and the simple average of the returns on the 6 low ROE portfolios.

2.2 Empirical properties

From Panel A of Table 1, the size factor earns an average return of 0.31% per month from January 1972 to December 2012 ($t=2.12$). The average return of SMB is 0.19% ($t=1.35$). From Panel B, our size factor and SMB have an almost perfect correlation of 0.95. The data for SMB, HML, and UMD are from Kenneth French's Web site. We construct MKT as the value-weighted market return minus the 1-month Treasury bill rate from CRSP.

The investment factor, $r_{\mathrm{I/A}}$, earns an average return of 0.45% per month ($t=4.95$). Its CAPM alpha is 0.52% ($t=5.93$). The Fama-French alpha is 0.33% ($t=4.85$), and the Carhart alpha 0.28% ($t=3.85$). The investment factor and HML have a significant correlation of 0.69, suggesting that the investment factor would play a similar role as HML in factor regressions.

The ROE factor, r_{ROE}, earns an average return of 0.58% per month ($t=4.81$). The Fama-French alpha of 0.77% ($t=6.94$) and the R^2 of only 20% suggest

Table 1
Empirical properties of the q-factors

Panel A: Descriptive statistics

	Mean	α	β_{MKT}	β_{SMB}	β_{HML}	β_{UMD}	R^2
r_{ME}	0.31	0.23	0.17				0.06
	(2.12)	(1.62)	(4.33)				
		0.04	0.02	0.99	0.17		0.93
		(1.09)	(1.59)	(57.37)	(7.05)		
		0.01	0.02	0.99	0.19	0.03	0.94
		(0.15)	(2.40)	(61.51)	(7.34)	(2.16)	
$r_{I/A}$	0.45	0.52	−0.15				0.13
	(4.95)	(5.93)	(−5.58)				
		0.33	−0.06	−0.02	0.39		0.50
		(4.85)	(−3.66)	(−0.81)	(11.98)		
		0.28	−0.05	−0.02	0.41	0.05	0.52
		(3.85)	(−3.24)	(−0.87)	(11.94)	(1.97)	
r_{ROE}	0.58	0.63	−0.11				0.04
	(4.81)	(5.62)	(−2.38)				
		0.77	−0.09	−0.33	−0.20		0.20
		(6.94)	(−2.08)	(−5.75)	(−2.38)		
		0.50	−0.03	−0.33	−0.10	0.28	0.40
		(4.75)	(−0.98)	(−4.38)	(−1.48)	(6.27)	

Panel B: Correlation matrix (p-values)

	$r_{I/A}$	r_{ROE}	MKT	SMB	HML	UMD
r_{ME}	−0.11	−0.31	0.25	0.95	−0.07	0.01
	(0.02)	(0.00)	(0.00)	(0.00)	(0.13)	(0.90)
$r_{I/A}$		0.06	−0.36	−0.22	0.69	0.05
		(0.20)	(0.00)	(0.00)	(0.00)	(0.31)
r_{ROE}			−0.19	−0.38	−0.09	0.50
			(0.00)	(0.00)	(0.06)	(0.00)
MKT				0.28	−0.32	−0.15
				(0.00)	(0.00)	(0.00)
SMB					−0.23	−0.01
					(0.00)	(0.79)
HML						−0.15
						(0.00)

Size (ME) is price per share times shares outstanding. Investment-to-assets (I/A) is the annual change in total assets (Compustat annual item AT) divided by lagged total assets. ROE is income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged book equity. Book equity is the shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use the stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of the preferred stock (item PSTKQ), or total assets (item ATQ) minus liabilities (item LTQ) in that order as the shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of the preferred stock. At the end of June of each year t, we use the median NYSE size at the end of June to split NYSE, Amex, and NASDAQ stocks into 2 groups, small and big. Independently, at the end of June of each year t, we also sort stocks into 3 I/A groups, using the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked I/A for the fiscal year ending in calendar year $t-1$. In addition, independently, at the beginning of each month, we sort stocks into 3 groups based on NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked ROE. Earnings data in Compustat quarterly files are used in the sorts in the months immediately after the most recent public quarterly earnings announcement dates (item RDQ). Taking the intersections of the 2 size, 3 I/A, and 3 ROE groups, we form 18 portfolios. Monthly value-weighted returns on the 18 portfolios are calculated for the current month, and the portfolios are rebalanced monthly. The size factor, r_{ME}, is the difference (small-minus-big), each month, between the average returns on the 9 small portfolios and the average returns on the 9 big portfolios. The investment factor, $r_{I/A}$, is the difference (low-minus-high), each month, between the average returns on the 6 low I/A portfolios and the average returns on the 6 high I/A portfolios. The ROE factor, r_{ROE}, is the difference (high-minus-low), each month, between the average returns on the 6 high ROE portfolios and the average returns on the 6 low ROE portfolios. The data for SMB, HML, and UMD are from Kenneth French's Web site. MKT is the value-weighted market return minus the 1-month Treasury bill rate from CRSP. The t-statistics (in parentheses) in Panel A are adjusted for heteroscedasticity and autocorrelations, and the p-values (in parentheses) in Panel B test that a given correlation is zero.

that r_{ROE} represents an important source of common return variation missing from the Fama-French model. The Carhart model cannot capture the average ROE factor return either, with an alpha of 0.50% ($t = 4.75$). From Panel B, r_{ROE} has a high correlation of 0.50 with UMD, suggesting that r_{ROE} would play a similar role as UMD in factor regressions. Finally, the investment and the ROE factors have a small, insignificant correlation of 0.06, meaning that the triple sort succeeds in orthogonalizing the 2 q-factors.

Raising an important concern on data mining in empirical finance, Harvey, Liu, and Zhu (2013) argue that the standard significance criterion with a t-statistic (testing that the average return is zero) greater than 2 is inappropriate for newly discovered factors. Instead, new factors must clear a much higher hurdle, with t-statistics greater than 3. Harvey et al. also argue that factors based on first principles should have a lower hurdle of significance than empirically motivated factors. The investment and ROE factors, with at least some connection to investment-based asset pricing and t-statistics of 4.95 and 4.81, respectively, seem to clear their high hurdle.

The average returns of HML and UMD are 0.40% per month ($t = 2.60$) and 0.72% ($t = 3.41$), respectively, in our sample. More importantly, the alphas of HML and UMD in the q-factor model are only 0.06% and 0.13%, respectively; both of which are within 1 standard error from zero. As such, the q-factor model captures the average returns of HML and UMD, but the Fama-French and Carhart models cannot capture the average returns of the 2 q-factors. The evidence suggests that HML and UMD might be noisy versions of the investment and ROE factors, respectively.

2.3 Methodological issues

A few clarifications are in order. First, we design the q-factors to account for anomalies in the broad cross section of returns, as opposed to anomalies that exist only in extremely small and highly illiquid stocks. This design is reflected in our use of NYSE breakpoints and value-weighted portfolio returns in forming the q-factors. Consequently, the stocks that reside in the q-factors represent the broad cross section. The percentages of the total market capitalization for stocks in the size, investment, and ROE factors are 92.76%, 50.42%, and 58.07% of our entire sample, respectively. The percentage for the size factor is not 100% because we require stocks to have valid investment and ROE data. These percentages are largely in line with those for SMB, HML, and UMD, which are 97.20%, 66.92%, and 54.48%, respectively, in our sample.

Second, sorting on investment and ROE jointly is consistent with the economic model in Equation (4), which shows that the investment and ROE effects are conditional in nature. Firms will invest a lot if either the ROE of their investment is high or the cost of capital is low or both. As such, the negative relation between investment and the cost of capital is conditional on a given level of ROE. Investment and the cost of capital could be positively correlated unconditionally, if large investment delivers disproportionately high

ROE. Analogously, the positive relation between ROE and the cost of capital is conditional on a given level of investment. ROE and the cost of capital could be negatively correlated unconditionally, if high ROE comes with disproportionately large investment. Sorting on investment and ROE jointly controls for these conditional relations.

Third, when constructing the q-factors, we form the investment portfolios annually but the ROE portfolios monthly. This design is also consistent with Equation (4). The equation implies, for the most part, contemporaneous correlations between investment and anomaly variables, such as equity issues, accruals, and book-to-market, which the investment factor is hypothesized to capture. Because these anomaly portfolios are all constructed annually, it seems natural to use the same frequency to construct the investment factor. Analogously, Equation (4) implies contemporaneous correlations between ROE and anomaly variables, such as price momentum, earnings surprise, and financial distress, which the ROE factor is hypothesized to capture. Because these anomaly portfolios are all constructed monthly, it seems natural to adopt the same frequency to construct the ROE factor. In addition, Equation (4) says that ROE predicts future stock returns to the extent that it predicts future ROE. Because the most recent ROE contains the most up-to-date information about future ROE, we use the latest ROE in our monthly sorts.

3. Empirical Results

To evaluate the performance of the q-factor model, we use factor regressions:

$$r_t^i - r_t^f = \alpha_q^i + \beta_{\text{MKT}}^i \text{MKT}_\text{t} + \beta_{\text{ME}}^i r_{\text{ME},t} + \beta_{\text{I/A}}^i r_{\text{I/A},t} + \beta_{\text{ROE}}^i r_{\text{ROE},t} + \epsilon^i. \quad (5)$$

If the model is well specified, α_q^i should be economically small and statistically insignificant from zero. Because we neutralize the 2 q-factors against size, we include the size factor in the q-factor model. Including the size factor also brings the q-factor model to the same footing, in terms of the number of factors, as the Carhart model. Finally, Equation (4) is primarily a cross-sectional model. As such, we include the market factor to capture the common variation in returns over time, while accounting for the cross-sectional variation with the q-factors.

3.1 Testing portfolios and overall performance

We report our key empirical results in this subsection.

3.1.1 The playing field. Table 2 lists the 74 primary anomalies that we study. Adding 6 momentum-reversal variables (momentum strategies for holding periods longer than 6 months, see Section 3.2.1), we examine in total 80 anomaly variables. Our goal is to be conceptually comprehensive yet empirically parsimonious. To be comprehensive, we cover all the major

Table 2
List of anomalies

	Panel A: Momentum		
SUE-1	Earnings surprise (1-month holding period), Foster, Olsen, and Shevlin (1984)	SUE-6	Earnings surprise (6-month holding period), Foster, Olsen, and Shevlin (1984)
Abr-1	Cumulative abnormal stock returns around earnings announcements (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)	Abr-6	Cumulative abnormal stock returns around earnings announcements (6-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
RE-1	Revisions in analysts' earnings forecasts (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)	RE-6	Revisions in analysts' earnings forecasts (6-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
R6-1	Price momentum (6-month prior returns, 1-month holding period), Jegadeesh and Titman (1993)	R6-6	Price momentum (6-month prior returns, 6-month holding period), Jegadeesh and Titman (1993)
R11-1	Price momentum (11-month prior returns, 1-month holding period), Fama and French (1996)	I-Mom	Industry momentum, Moskowitz and Grinblatt (1999)
	Panel B: Value-versus-growth		
B/M	Book-to-market equity, Rosenberg, Reid, and Lanstein (1985)	A/ME	Market leverage, Bhandari (1988)
Rev	Reversal, De Bondt and Thaler (1985)	E/P	Earnings-to-price, Basu (1983)
EF/P	Analysts' earnings forecasts-to-price, Elgers, Lo, and Pfeiffer (2001)	CF/P	Cash flow-to-price, Lakonishok, Shleifer, and Vishny (1994)
D/P	Dividend yield, Litzenberger and Ramaswamy (1979)	O/P	Payout yield, Boudoukh et al. (2007)
NO/P	Net payout yield, Boudoukh et al. (2007)	SG	Sales growth, Lakonishok, Shleifer, and Vishny (1994)
LTG	Long-term growth forecasts of analysts, La Porta (1996)	Dur	Equity duration, Dechow, Sloan, and Soliman (2004)
	Panel C: Investment		
ACI	Abnormal corporate investment, Titman, Wei, and Xie (2004)	I/A	Investment-to-assets, Cooper, Gulen, and Schill (2008)
NOA	Net operating assets, Hirshleifer et al. (2004)	$\triangle$PI/A	Changes in property, plant, and equipment plus changes in inventory scaled by assets, Lyandres, Sun, and Zhang (2008)
IG	Investment growth, Xing (2008)	NSI	Net stock issues, Pontiff and Woodgate (2008)
CEI	Composite issuance, Daniel and Titman (2006)	NXF	Net external financing, Bradshaw, Richardson, and Sloan (2006)
IvG	Inventory growth, Belo and Lin (2011)	IvC	Inventory changes, Thomas and Zhang (2002)
OA	Operating accruals, Sloan (1996)	TA	Total accruals, Richardson et al. (2005)
POA	Percent operating accruals, Hafzalla, Lundholm, and Van Winkle (2011)	PTA	Percent total accruals, Hafzalla, Lundholm, and Van Winkle (2011)
	Panel D: Profitability		
ROE	Return on equity, Haugen and Baker (1996)	ROA	Return on assets, Balakrishnan, Bartov, and Faurel (2010)
RNA	Return on net operating assets, Soliman (2008)	PM	Profit margin, Soliman (2008)
ATO	Asset turnover, Soliman (2008)	CTO	Capital turnover, Haugen and Baker (1996)
GP/A	Gross profits-to-assets, Novy-Marx (2013)	F	F-score, Piotroski (2000)
TES	Tax expense surprise, Thomas and Zhang (2011)	TI/BI	Taxable income-to-book income, Green, Hand, and Zhang (2013)
RS	Revenue surprise, Jegadeesh and Livnat (2006)	NEI	Number of consecutive quarters with earnings increases, Barth, Elliott, and Finn (1999)
FP	Failure probability, Campbell, Hilscher, and Szilagyi (2008)	O	O-score, Dichev (1998)

(*continued*)

Table 2
Continued

Panel E: Intangibles

OC/A	Organizational capital-to-assets, Eisfeldt and Papanikolaou (2013)	BC/A	Brand capital-to-assets, Belo, Lin, and Vitorino (2014)
Ad/M	Advertisement expense-to-market, Chan, Lakonishok, and Sougiannis (2001)	RD/S	R&D-to-sales, Chan, Lakonishok, and Sougiannis (2001)
RD/M	R&D-to-market, Chan, Lakonishok, and Sougiannis (2001)	RC/A	R&D capital-to-assets, Li (2011)
H/N	Hiring rate, Belo, Lin, and Bazdresch (2014)	OL	Operating leverage, Novy-Marx (2011)
G	Corporate governance, Gompers, Ishii, and Metrick (2003)	AccQ	Accrual quality, Francis et al. (2005)
Ind	Industries, Fama and French (1997)		

Panel F: Trading frictions

ME	The market equity, Banz (1981)	Ivol	Idiosyncratic volatility, Ang et al. (2006)
Tvol	Total volatility, Ang et al. (2006)	Svol	Systematic volatility, Ang et al. (2006)
MDR	Maximum daily return, Bali, Cakici, and Whitelaw (2011)	β	Market beta, Frazzini and Pedersen (2014)
D-β	Dimson's beta, Dimson (1979)	S-Rev	Short-term reversal, Jegadeesh (1990)
Disp	Dispersion of analysts' earnings forecasts, Diether, Malloy, and Scherbina (2002)	Turn	Share turnover, Datar, Naik, and Radcliffe (1998)
1/P	1/share price, Miller and Scholes (1982)	Dvol	Dollar trading volume, Brennan, Chordia, and Subrahmanyam (1998)
Illiq	Illiquidity as absolute return-to-volume, Amihud (2002)		

This table lists the anomalies that we study. The anomalies are grouped into 6 categories: (i) momentum; (ii) value-versus-growth; (iii) investment; (iv) profitability; (v) intangibles; and (vi) trading frictions. For each anomaly variable, we list its symbol, brief description, and source in the academic literature. Appendix A details variable definition and portfolio construction.

anomaly categories, including momentum, value-versus-growth, investment, profitability, intangibles, as well as trading frictions.

To be parsimonious, we select the most important variables in each category to avoid (excessive) redundancy. For example, we use the Daniel and Titman (2006) composite issuance and the Pontiff and Woodgate (2008) net stock issues as representative examples of equity financing anomalies, but do not separately study the Loughran and Ritter (1995) underperformance anomaly following seasoned equity offerings or the Ikenberry, Lakonishok, and Vermaelen (1995) overperformance anomaly following open market share repurchases. In addition, we have examined 2 different holding periods (1-month and 6-month) for many anomaly portfolios that are monthly rebalanced, such as the Ang et al. (2006) total, idiosyncratic, and systematic volatilities; the Campbell, Hilscher, and Szilagyi (2008) failure probability; and the Balakrishnan, Bartov, and Faurel (2010) return on assets. However, we only report for a given variable the holding period that delivers the higher average return spread across the deciles. Doing so raises the hurdle on the q-factor model.

Our scope of nearly 80 anomalies is comparable to that of McLean and Pontiff (2013), who use 82 variables (but do not provide the detailed list). Green, Hand, and Zhang (2013) identify more than 330 return predictive signals but use only 60 in their tests. Harvey, Liu, and Zhu (2013) identify 314 factors, but many are macro factors, such as Treasury bill return and aggregate consumption growth. In contrast, we examine firm-level anomalies. Moreover, our universe covers most (if not all) of the major categories of anomalies in Harvey et al.'s work.

We detail the variable definition and the construction of testing portfolios in Appendix A. As the benchmark procedure in constructing these portfolios, we use NYSE breakpoints and value-weighted portfolio returns. Doing so is consistent with the construction of the q-factors and SMB, HML, and UMD. Another important reason for the benchmark practice is to alleviate the impact of microcaps, which are stocks with market capitalization below the 20th NYSE percentile. As shown in Fama and French (2008), despite accounting for about 60% of the total number of stocks, microcaps are on average only about 3% of the market capitalization of the NYSE-Amex-NASDAQ universe. Because of transaction costs and lack of liquidity, the portion of anomalies in microcaps is unlikely to be exploitable in practice.[10]

When constructing annually sorted testing portfolios, such as the book-to-market deciles, we follow the Fama and French (1993) timing. At the end of June of each year t, we sort all stocks into deciles, using NYSE breakpoints for book-to-market measured at the fiscal year ending in calendar year $t-1$, and calculate value-weighted decile returns from July of year t to June of $t+1$. To construct monthly sorted testing portfolios involving latest earnings data, such as the ROE deciles, we follow our timing in constructing the ROE factor. In particular, earnings data in Compustat quarterly files are used in the months immediately after the quarterly earnings announcement dates. Finally, to construct monthly sorted testing portfolios involving quarterly accounting data other than earnings, such as the failure probability deciles, we follow the accounting literature in imposing a 4-month lag between the sorting variable and holding period returns (e.g., Hirshleifer et al. 2004). Unlike earnings, other quarterly data items might not be available upon earnings announcement dates. As such, we impose the 4-month lag to guard against look-ahead bias.

3.1.2 Insignificant anomalies in the broad cross section. Out of our list of anomalies, 38 are insignificant in the broad cross section. Table 3 reports their average high-minus-low decile returns and t-statistics.

Most importantly, 12 out of 13 anomalies in the trading frictions category are insignificant at the 5% level. The only significant anomaly is the Ang et al. (2006) systematic volatility. However, their idiosyncratic volatility anomaly is not. The high-minus-low decile earns on average -0.54% per month ($t=-1.56$). Even the Jegadeesh (1990) short-term reversal anomaly earns an

[10] We document that extreme deciles under the benchmark procedure assign only modest portfolio weights to microcaps, but those under an alternative procedure with NYSE-Amex-NASDAQ breakpoints and equal-weighted returns assign excessively large weights (see the Online Appendix). For example, across the momentum variables, the loser deciles allocate on average 10.85% of the portfolio weights to microcaps under the benchmark procedure, but 63.58% under the alternative procedure. For the winner deciles, the comparison is between 5.17% and 52.50%.

Table 3
Insignificant anomalies in the broad cross section

	R6-1	A/ME	Rev	EF/P	D/P	O/P	SG	LTG	ACI	NXF
m	0.48	0.43	−0.39	0.45	0.27	0.35	−0.27	0.01	−0.27	−0.30
t_m	1.43	1.82	−1.57	1.73	0.94	1.53	−1.34	0.02	−1.70	−1.55
	TA	RNA	PM	ATO	CTO	F	TES	TI/BI	RS	O
m	−0.19	0.13	0.10	0.22	0.20	0.37	0.32	0.13	0.29	−0.08
t_m	−1.31	0.61	0.40	1.11	1.11	1.28	1.92	0.86	1.82	−0.37
	BC/A	RD/S	RC/A	H/N	G	AccQ	ME	Ivol	Tvol	MDR
m	0.18	0.01	0.32	−0.25	0.03	−0.18	−0.24	−0.54	−0.37	−0.31
t_m	0.73	0.06	1.27	−1.47	0.09	−0.79	−0.90	−1.56	−0.95	−0.94
	β	D-β	S-Rev	Disp	Turn	1/P	Dvol	Illiq		
m	−0.13	0.07	−0.31	−0.33	−0.12	−0.00	−0.26	0.27		
t_m	−0.36	0.30	−1.39	−1.24	−0.43	−0.01	−1.30	1.14		

For each anomaly variable, we report the average return (m) of the high-minus-low decile and its t-statistic (t_m) adjusted for heteroscedasticity and autocorrelations. Table 2 provides a brief description of the symbols. We form all of the deciles using NYSE breakpoints, and calculate value-weighted portfolio returns. Appendix A details variable definition and portfolio construction.

insignificant −0.31% (t=−1.39). Other notable examples are the Diether, Malloy, and Scherbina (2002) dispersion of analysts' earnings forecasts and the Amihud (2002) illiquidity. The evidence suggests that trading frictions play a limited role in the broad cross section.

Outside trading frictions, the Titman, Wei, and Xie (2004) abnormal investment anomaly yields −0.27% per month, the Richardson et al. (2005) total accrual anomaly yields −0.19%, and the Piotroski (2000) F-score earns 0.37%. All 3 are insignificant. The Gompers, Ishii, and Metrick (2003) corporate governance index earns a tiny 0.03% (t=0.09), and the Francis et al. (2005) accrual quality measure earns −0.18% (t=−0.79).

It is surprising that 38 anomalies (about one-half across all categories), including 12 out of 13 anomalies in the trading frictions category, are insignificant in the broad cross section. Lending support to Harvey, Liu, and Zhu (2013), we suggest that many claims in the anomalies literature are likely exaggerated. While Harvey et al. adopt a sophisticated multiple testing framework to raise the statistical hurdle for significance, we use simple NYSE breakpoints and value-weighted portfolio returns to ensure that the anomalies we study are relevant for the broad cross section.

3.1.3 Significant anomalies: Pricing errors and tests of overall performance. Table 4 reports the overall performance of various factor models in fitting the 35 significant anomalies in the broad cross section. The q-factor model performs well relative to the Carhart model and even more so relative to the Fama-French model. In particular, across the 35 high-minus-low deciles, the average magnitude of the q-alphas is 0.20% per month, which is lower than 0.33% in the Carhart model and 0.55% in the Fama-French model. Moreover, only 5 out of 35 high-minus-low deciles have q-alphas that are significant at

Table 4
Significant anomalies in the broad cross section: Pricing errors and tests of overall performance

	SUE-1	SUE-6	Abr-1	Abr-6	RE-1	RE-6	R6-6	R11-1	I-Mom	B/M	E/P	CF/P	NO/P	Dur	I/A	NOA	△PI/A	IG
m	0.45	0.24	0.73	0.30	0.89	0.60	0.85	1.18	0.51	0.70	0.59	0.52	0.66	−0.54	−0.42	−0.38	−0.51	−0.41
α	0.50	0.27	0.76	0.31	1.02	0.71	0.92	1.29	0.58	0.75	0.69	0.63	0.84	−0.62	−0.50	−0.38	−0.57	−0.45
α_{FF}	0.55	0.39	0.84	0.38	1.20	0.94	1.12	1.52	0.68	0.01	0.05	0.01	0.52	−0.06	−0.15	−0.52	−0.41	−0.26
α_C	0.34	0.18	0.62	0.19	0.56	0.37	0.06	0.09	−0.18	−0.01	0.01	−0.06	0.49	−0.08	−0.09	−0.41	−0.36	−0.20
α_q	0.16	0.02	0.64	0.26	0.12	0.03	0.24	0.24	0.00	0.21	0.17	0.22	0.36	−0.27	0.14	−0.38	−0.26	0.05
t_m	3.59	2.17	5.50	3.11	3.43	2.58	3.17	3.52	2.33	2.88	2.63	2.44	3.23	−2.59	−2.45	−2.55	−3.43	−2.93
t	4.26	2.68	5.84	3.33	4.13	3.28	3.63	4.18	2.68	3.05	3.12	3.01	4.45	−2.98	−2.94	−2.52	−3.91	−3.16
t_{FF}	4.50	3.62	5.93	3.89	4.81	4.52	4.47	4.99	3.25	0.04	0.34	0.08	3.51	−0.44	−1.09	−3.30	−2.93	−1.99
t_C	2.62	1.69	4.37	2.06	2.56	2.15	0.51	0.67	−1.11	−0.06	0.03	−0.40	3.33	−0.56	−0.61	−2.69	−2.48	−1.51
t_q	1.12	0.18	4.07	2.18	0.43	0.14	0.71	0.54	0.01	1.15	0.76	1.04	2.38	−1.32	1.08	−1.90	−1.85	0.39
$\overline{\|\alpha\|}$	0.16	0.11	0.13	0.08	0.19	0.14	0.17	0.21	0.16	0.22	0.23	0.20	0.23	0.24	0.17	0.15	0.15	0.13
$\overline{\|\alpha_{FF}\|}$	0.17	0.13	0.16	0.11	0.27	0.23	0.19	0.26	0.15	0.07	0.10	0.08	0.17	0.11	0.12	0.17	0.13	0.13
$\overline{\|\alpha_C\|}$	0.11	0.09	0.12	0.08	0.11	0.09	0.10	0.13	0.06	0.06	0.09	0.07	0.15	0.08	0.10	0.14	0.12	0.11
$\overline{\|\alpha_q\|}$	0.05	0.07	0.13	0.07	0.10	0.11	0.08	0.13	0.13	0.08	0.10	0.14	0.12	0.08	0.09	0.12	0.14	0.09
p	0.00	0.00	0.00	0.01	0.04	0.21	0.00	0.00	0.09	0.04	0.01	0.05	0.00	0.00	0.00	0.00	0.00	0.00
p_{FF}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.19	0.18	0.43	0.00	0.15	0.01	0.00	0.00	0.00
p_C	0.00	0.00	0.00	0.01	0.16	0.12	0.00	0.00	0.45	0.29	0.38	0.37	0.00	0.41	0.02	0.00	0.01	0.00
p_q	0.42	0.04	0.00	0.02	0.46	0.08	0.00	0.01	0.03	0.35	0.13	0.02	0.00	0.72	0.01	0.00	0.00	0.01

(*continued*)

Table 4
Continued

	NSI	CEI	IvG	IvC	OA	POA	PTA	ROE	ROA	GP/A	NEI	FP	OC/A	Ad/M	RD/M	OL	Svol
m	−0.68	−0.57	−0.41	−0.45	−0.30	−0.46	−0.40	0.80	0.62	0.34	0.39	−0.67	0.56	0.79	0.63	0.39	−0.60
α	−0.78	−0.79	−0.47	−0.51	−0.33	−0.53	−0.50	0.96	0.78	0.32	0.40	−1.06	0.65	0.82	0.47	0.44	−0.72
α_{FF}	−0.64	−0.50	−0.29	−0.38	−0.37	−0.32	−0.29	1.17	1.00	0.50	0.63	−1.44	0.61	0.15	0.22	0.37	−0.66
α_C	−0.54	−0.40	−0.19	−0.30	−0.33	−0.25	−0.27	0.85	0.67	0.45	0.43	−0.67	0.40	0.32	0.31	0.33	−0.62
α_q	−0.26	−0.22	−0.03	−0.28	−0.56	−0.12	−0.10	0.05	0.09	0.11	0.18	−0.17	0.09	0.11	0.60	−0.05	−0.37
t_m	−4.13	−2.96	−2.77	−3.05	−2.32	−3.02	−2.57	3.11	2.70	2.18	3.31	−1.98	4.07	2.96	2.31	2.06	−2.57
t	−4.86	−4.79	−3.29	−3.35	−2.47	−3.64	−3.50	4.02	3.67	2.02	3.45	−3.80	4.69	3.08	1.81	2.22	−3.12
t_{FF}	−4.28	−3.72	−2.10	−2.61	−2.84	−2.42	−2.06	5.43	5.40	3.25	6.03	−6.44	4.52	0.79	0.93	1.91	−2.88
t_C	−3.58	−2.93	−1.34	−1.97	−2.32	−1.88	−1.82	4.03	3.59	2.85	3.73	−3.79	2.97	1.37	1.40	1.76	−2.59
t_q	−1.75	−1.50	−0.20	−1.84	−3.90	−0.87	−0.67	0.37	0.72	0.71	1.68	−0.57	0.66	0.39	2.40	−0.27	−1.42
$\overline{\lvert\alpha\rvert}$	0.18	0.19	0.14	0.16	0.15	0.12	0.12	0.18	0.15	0.06	0.19	0.16	0.14	0.23	0.13	0.11	0.18
$\overline{\lvert\alpha_{FF}\rvert}$	0.18	0.15	0.11	0.12	0.13	0.11	0.11	0.24	0.23	0.14	0.23	0.23	0.15	0.13	0.17	0.11	0.19
$\overline{\lvert\alpha_C\rvert}$	0.15	0.15	0.10	0.10	0.12	0.11	0.10	0.15	0.14	0.14	0.15	0.12	0.13	0.18	0.21	0.12	0.16
$\overline{\lvert\alpha_q\rvert}$	0.11	0.12	0.11	0.08	0.15	0.12	0.08	0.09	0.07	0.11	0.09	0.13	0.11	0.11	0.27	0.12	0.11
p	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.07	0.25	0.00	0.00	0.00	0.04	0.24	0.54	0.01
p_{FF}	0.00	0.00	0.03	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.18	0.02	0.07	0.01
p_C	0.00	0.00	0.11	0.04	0.00	0.01	0.02	0.00	0.04	0.01	0.00	0.00	0.00	0.07	0.01	0.06	0.06
p_q	0.02	0.01	0.08	0.56	0.00	0.00	0.11	0.05	0.75	0.38	0.05	0.00	0.02	0.07	0.00	0.09	0.20

For each anomaly variable, $m, \alpha, \alpha_{FF}, \alpha_C$, and α_q are the average return, the CAPM alpha, the Fama-French alpha, the Carhart alpha, and the q-alpha for the high-minus-low decile, and t_m, t, t_{FF}, t_C, and t_q are their t-statistics adjusted for heteroscedasticity and autocorrelations, respectively. $\overline{|\alpha|}$, $\overline{|\alpha_{FF}|}$, $\overline{|\alpha_C|}$, and $\overline{|\alpha_q|}$ are the average magnitude of the alphas, and p, p_{FF}, p_C, and p_q are the p-values of the GRS test on the null hypothesis that all of the alphas are jointly zero across the deciles formed on the variable. Table 2 provides a brief description of the symbols.

the 5% level. In contrast, 19 high-minus-low deciles have significant Carhart alphas, and 27 have significant Fama-French alphas.

To measure a model's overall performance, we also use the mean absolute value of alphas across the deciles formed on a given anomaly variable, as well as the p-value associated with the GRS test (on the null that the alphas are jointly zero across a given set of deciles). Table 4 shows that the q-factor model has the lowest average magnitude of alphas across all 35 sets of deciles, 0.11% per month. The average magnitude is 0.12% in the Carhart model and 0.16% in the Fama-French model. In addition, the GRS test rejects the q-factor model at the 5% level in 20 out of 35 sets of deciles, the Carhart model in 24 sets of deciles, and the Fama-French model in 28 sets of deciles.

Looking at different categories of anomalies, we observe that the q-factor model outperforms the Fama-French and Carhart models in all except for the value-versus-growth category, in which the 3 models are largely comparable. Across the 9 anomalies in the momentum category, the average magnitude of the high-minus-low alphas is 0.19% per month in the q-factor model, 0.29% in the Carhart model, and 0.85% in the Fama-French model. Out of 9 high-minus-low deciles, 2 have significant alphas in the q-factor model, in contrast to 5 in the Carhart model and all 9 in the Fama-French model. Across the 9 sets of momentum deciles, the average magnitude of the alphas is 0.10% in both the q-factor model and the Carhart model but 0.19% in the Fama-French model. The GRS test rejects the q-factor model and the Carhart model in 6 out of 9 sets of deciles, but rejects the Fama-French model in all 9.

Across the 5 value-versus-growth anomalies, the high-minus-low net payout yield decile has significant alphas in all 3 models. However, the high-minus-low q-alpha is 0.36% per month, which is lower than the Carhart alpha, 0.49%, and the Fama-French alpha, 0.52%. All 3 models are rejected by the GRS test across the net payout yield deciles. In addition, none of the high-minus-low alphas for the book-to-market, earnings-to-price, cash flow-to-price, and duration deciles are significant in the q-factor model, the Carhart model, or the Fama-French model. The GRS statistics are mostly insignificant. However, while the q-factor model is rejected across the cash flow-to-price deciles, the Carhart and Fama-French models are not.

In the investment category, only 1 out of 11 high-minus-low q-alpha is significant, compared to 6 Carhart alphas and 10 Fama-French alphas. The average magnitude of the high-minus-low alphas is 0.22% per month in the q-factor model, which is lower than 0.30% in the Carhart model and 0.38% in the Fama-French model. However, all 3 models are rejected by the GRS test in most sets of deciles in the investment category. The q-factor model performs the best in the profitability category. None of the 5 high-minus-low alphas are significant in the q-factor model, but all 5 are significant in the Carhart and Fama-French models. The average magnitude of the high-minus-low alphas is 0.12% in the q-factor model, which is substantially lower than 0.61% in the Carhart model and 0.95% in the Fama-French model. The q-factor model is rejected by the GRS test in only 1 out of 5 sets of deciles, but the Carhart and Fama-French models are rejected in all 5.

However, the q-factor model underperforms the Fama-French and Carhart models in fitting Sloan (1996) operating accrual anomaly (see Section 3.2.2) and Chan, Lakonishok, and Sougiannis (2001) R&D-to-market anomaly. In particular, the high-minus-low R&D-to-market decile earns an average return of 0.63% per month ($t=2.31$). The Fama-French alpha is 0.22% ($t=0.93$), the Carhart alpha is 0.31% ($t=1.40$), but the q-alpha is 0.60% ($t=2.40$).

Finally, as noted, we include the size factor in the q-factor model to bring it to the same footing as the Carhart model in terms of the number of factors. Including the size factor helps the q-factor model fit the average returns across the size deciles. The small-minus-big decile earns an average return of 0.24% per month ($t=0.90$). The Fama-French and Carhart alphas are small and insignificant. The q-alpha is tiny, 0.03% ($t=0.29$), but would be 0.66% ($t=2.16$) without the size factor.

More importantly, however, the incremental effect of the size factor in capturing the 35 significant anomalies is rather limited, probably because the anomaly variables are not directly related to size. Table 5 replicates Table 4, but for an alternative 3-factor q-model without the size factor. As noted, the magnitude of the high-minus-low alphas averaged across the 35 anomalies is 0.20% per month in the 4-factor q-model. Dropping the size factor raises it to 0.23%, which still beats 0.33% in the Carhart model and 0.55% in the Fama-French model. The mean absolute alpha averaged across the deciles is 0.11% in the 4-factor q-model. Dropping the size factor raises it to only 0.12%, compared to 0.12% in the Carhart model and 0.16% in the Fama-French model.

Overall, except for the operating accrual and R&D-to-market anomalies, the q-factor model performs as well as, and often outperforms the Fama-French and Carhart models across major categories of anomalies. The q-factor model beats the Carhart model and by a bigger margin the Fama-French model in the momentum category. The q-factor model also outperforms in the investment category and dominates the 2 competing models in the profitability category. The 3 models are largely comparable in the value-versus-growth category. Finally, the size factor plays only a limited role in the q-factor model's success.

3.1.4 Q-factor loadings and economic fundamentals. To shed light on the sources of the superior performance of the q-factor model, we examine the q-factor loadings and their underlying characteristics, including size, investment-to-assets, and ROE for the high-minus-low deciles. We align the timing of characteristics with the timing of portfolio returns as in the construction of the q-factors. In particular, for size and investment-to-assets, we align returns from July of year t to June of $t+1$ with size at the end of June of year t and investment-to-assets for the fiscal year ending in calendar year

Table 5
Significant anomalies in the broad cross section: An alternative q-factor model without the size factor

	SUE-1	SUE-6	Abr-1	Abr-6	RE-1	RE-6	R6-6	R11-1	I-Mom	B/M	E/P	CF/P	NO/P	Dur	I/A	NOA	△PI/A	IG
α_3^q	0.21	0.07	0.67	0.30	0.05	−0.05	0.37	0.42	0.15	0.42	0.29	0.30	0.21	−0.38	0.09	−0.35	−0.28	0.00
t_3^q	1.43	0.42	3.95	2.48	0.18	−0.22	0.96	0.85	0.48	2.13	1.21	1.42	1.26	−1.72	0.68	−1.71	−2.00	0.00
$\overline{\lvert\alpha_3^q\rvert}$	0.05	0.07	0.12	0.08	0.14	0.15	0.10	0.16	0.09	0.11	0.12	0.15	0.12	0.11	0.09	0.12	0.11	0.13
p_3^q	0.62	0.13	0.00	0.00	0.20	0.02	0.00	0.00	0.10	0.15	0.04	0.01	0.01	0.31	0.01	0.01	0.03	0.00
	NSI	CEI	IvG	IvC	OA	POA	PTA	ROE	ROA	GP/A	NEI	FP	OC/A	Ad/M	RD/M	OL	Svol	
α_3^q	−0.18	−0.10	0.03	−0.28	−0.44	−0.06	−0.01	−0.14	−0.09	0.12	0.14	0.03	0.21	0.37	0.89	0.07	−0.25	
t_3^q	−1.18	−0.65	0.23	−1.86	−2.83	−0.38	−0.05	−0.84	−0.60	0.79	1.26	0.09	1.31	1.24	2.86	0.37	−0.91	
$\overline{\lvert\alpha_3^q\rvert}$	0.10	0.12	0.15	0.11	0.13	0.09	0.11	0.10	0.09	0.12	0.10	0.17	0.13	0.12	0.30	0.12	0.11	
p_3^q	0.04	0.01	0.01	0.26	0.02	0.07	0.04	0.03	0.55	0.36	0.05	0.00	0.01	0.06	0.00	0.11	0.12	

For each anomaly variable, α_3^q is the high-minus-low alpha from an alternative 3-factor q-model without the size factor, and t_3^q is the t-statistics adjusted for heteroscedasticity and autocorrelations. $\overline{|\alpha_3^q|}$ is the average magnitude of the alphas across a given set of deciles, and p_3^q is the p-value of the GRS test on the null hypothesis that all of the alphas are jointly zero across a given set of deciles. Table 2 provides a brief description of the symbols.

$t-1$. For ROE, we align returns for month t with the ROE calculated with the most recently announced quarterly earnings.

Firm-level characteristics are aggregated to the portfolio level as in Fama and French (1995). Size is the average market capitalization (in billions of dollars) across all firms in a given decile. Investment-to-assets (in percent) is the sum of changes in total assets across all firms in a given decile divided by the sum of 1-year-lagged assets across the same set of firms. ROE (in percent) is the sum of the most recently announced quarterly earnings across all firms in a given decile divided by the sum of their 1-quarter-lagged book equity.

Table 6 shows that many significant anomalies in Table 4 are basically different combinations of the investment and ROE effects. The first 9 columns in the upper panel suggest that price and earnings momentum are mainly linked to the ROE factor. Across the 9 high-minus-low deciles, the ROE factor loadings vary from 0.18 to 1.48, all of which are significant. Consistent with the pattern in ROE factor loadings, the spreads in ROE characteristic between winners and losers are economically large, ranging from 1.49% to 6.58% per quarter. In contrast, the investment factor loadings are mostly insignificant for the high-minus-low deciles.

The next 5 columns (from "B/M" to "Dur") in the upper panel of Table 6 show that the value-versus-growth anomalies are mainly linked to the investment factor. The loadings vary from -0.85 to 1.45 across the high-minus-low deciles, all of which are more than 5 standard errors from zero. Accordingly, the corresponding spreads in investment-to-assets vary from -14.43% to 3.95% per annum. In contrast, the ROE factor loadings for the high-minus-low deciles are mostly insignificant.

The last 4 columns in the upper panel and the first 7 columns in the lower panel show that the investment, equity financing, inventory, and accrual anomalies are primarily linked to the investment factor. The net operating assets (NOA) anomaly is one exception, for which none of the factor loadings are significant for the high-minus-low decile. Leaving aside NOA and operating accruals (OA, which we examine in depth in Section 3.2.2), the investment factor loadings vary from -0.65 to -1.37 across the high-minus-low deciles, all of which are more than 5 standard errors from zero. The corresponding spreads in investment-to-assets are also economically large, varying from 11.12% to 83.89% per annum. In addition, similar to the value-versus-growth deciles, the ROE factor loadings for the high-minus-low deciles in the investment category are mostly insignificant.

The next 5 columns (from "ROE" to "FP") show that the profitability and distress anomalies are captured by the ROE factor. The ROE factor loadings of the high-minus-low deciles vary from -1.62 to 1.50, all of which are more than 7 standard errors from zero. The corresponding ROE spreads are large, ranging from -8.74% per quarter to 16.95%. In contrast, the investment factor loadings are all small and often insignificant.

Table 6
Q-factor loadings and underlying characteristics for significant anomalies in the broad cross section

	SUE-1	SUE-6	Abr-1	Abr-6	RE-1	RE-6	R6-6	R11-1	I-Mom	B/M	E/P	CF/P	NO/P	Dur	I/A	NOA	ΔPI/A	IG
β_{MKT}	−0.08	−0.06	−0.06	−0.03	−0.05	−0.07	−0.09	−0.14	−0.11	−0.03	−0.12	−0.15	−0.18	0.11	0.02	−0.02	0.05	−0.02
β_{ME}	0.10	0.09	0.07	0.09	−0.15	−0.19	0.27	0.40	0.31	0.46	0.25	0.19	−0.32	−0.23	−0.11	0.06	−0.05	−0.11
$\beta_{\mathrm{I/A}}$	0.02	−0.11	−0.13	−0.16	0.04	−0.12	−0.07	0.04	−0.03	1.45	0.99	1.01	1.03	−0.85	−1.37	−0.01	−0.77	−0.82
β_{ROE}	0.48	0.45	0.28	0.18	1.33	1.12	1.02	1.48	0.82	−0.51	−0.09	−0.24	0.02	0.24	0.15	−0.01	0.16	−0.07
$t_{\beta_{\mathrm{MKT}}}$	−1.82	−1.53	−1.31	−1.20	−0.76	−1.24	−1.17	−1.43	−1.72	−0.59	−2.02	−2.41	−3.86	1.67	0.62	−0.55	1.33	−0.71
$t_{\beta_{\mathrm{ME}}}$	1.94	1.27	0.67	1.82	−1.42	−1.98	1.43	1.74	1.86	5.37	1.90	1.66	−4.40	−1.61	−1.81	0.54	−0.94	−1.95
$t_{\beta_{\mathrm{I/A}}}$	0.18	−0.97	−1.25	−2.24	0.25	−0.82	−0.27	0.12	−0.13	12.74	5.76	6.79	10.25	−5.69	−15.50	−0.04	−6.98	−10.91
$t_{\beta_{\mathrm{ROE}}}$	5.75	5.95	3.26	2.94	10.09	9.96	5.31	5.67	4.90	−5.98	−0.66	−1.78	0.19	1.87	2.29	−0.12	1.93	−1.06
ME	0.69	0.75	−0.01	0.03	0.77	0.87	0.40	0.52	0.62	−2.46	−0.73	−0.89	1.23	0.41	0.88	0.07	0.63	0.22
I/A	−1.46	−0.96	−1.37	−1.13	−0.80	0.72	−4.07	−3.83	−1.18	−9.70	−1.11	−5.63	−14.43	3.95	83.89	55.72	61.16	34.03
ROE	5.80	3.38	1.59	1.49	6.58	6.47	4.14	5.34	1.61	−5.68	0.21	−0.72	1.18	0.49	1.63	−1.24	0.84	0.50
t_{ME}	4.91	5.38	−0.29	1.31	8.75	9.65	4.92	4.95	3.67	−10.31	−4.09	−4.57	7.74	5.23	7.75	1.71	7.56	6.16
$t_{\mathrm{I/A}}$	−3.30	−2.57	−2.36	−2.58	−1.22	1.13	−5.54	−4.66	−1.79	−17.06	−1.20	−5.47	−13.81	2.73	32.74	18.28	30.77	22.38
t_{ROE}	16.46	19.07	13.38	15.47	29.77	27.86	16.00	17.06	10.24	−29.57	1.30	−4.83	7.27	2.22	10.00	−7.89	5.10	3.24

	NSI	CEI	IvG	IvC	OA	POA	PTA	ROE	ROA	GP/A	NEI	FP	OC/A	Ad/M	RD/M	OL	Svol
β_{MKT}	0.04	0.24	−0.03	0.04	0.03	−0.01	0.06	−0.10	−0.14	0.05	0.02	0.44	−0.13	0.04	0.16	−0.06	0.04
β_{ME}	0.17	0.26	0.12	0.00	0.28	0.15	0.21	−0.41	−0.38	0.03	−0.10	0.43	0.25	0.50	0.66	0.26	0.31
$\beta_{\mathrm{I/A}}$	−0.68	−1.06	−0.96	−0.65	−0.02	−0.90	−0.90	0.10	−0.10	−0.24	−0.30	0.17	0.35	1.42	0.21	0.16	−0.21
β_{ROE}	−0.32	−0.12	0.05	0.18	0.29	0.05	0.04	1.50	1.31	0.52	0.63	−1.61	0.51	−0.27	−0.58	0.54	−0.43
$t_{\beta_{\mathrm{MKT}}}$	0.99	6.27	−0.77	1.01	0.80	−0.19	1.50	−2.57	−4.48	1.20	0.88	6.46	−3.74	0.50	2.51	−1.22	0.53
$t_{\beta_{\mathrm{ME}}}$	2.24	3.79	2.85	−0.07	4.41	3.20	3.28	−6.56	−6.41	0.51	−2.53	2.45	5.69	2.85	6.75	2.63	2.30
$t_{\beta_{\mathrm{I/A}}}$	−6.14	−13.11	−11.81	−5.49	−0.21	−9.61	−8.72	1.05	−1.23	−2.35	−3.78	0.63	3.52	6.03	1.21	1.34	−1.30
$t_{\beta_{\mathrm{ROE}}}$	−4.07	−1.42	0.56	1.95	4.59	1.04	0.55	20.71	16.86	7.08	10.83	−8.79	7.12	−1.37	−4.10	4.85	−3.54
ME	−1.37	−1.79	0.26	0.19	−0.24	−0.36	−0.36	2.81	2.66	0.39	2.34	−3.09	−1.31	−1.34	−4.39	−1.31	−0.19
I/A	27.04	14.80	37.85	44.80	10.15	11.12	16.14	3.56	5.32	−1.29	5.35	−3.91	−13.77	−10.71	−3.22	−5.71	0.66
ROE	−1.71	−1.41	0.42	1.07	0.88	1.02	0.36	16.95	14.71	3.94	4.32	−8.74	1.52	−3.33	−2.80	1.86	−0.64
t_{ME}	−6.44	−7.77	4.27	4.86	−5.13	−9.39	−6.76	10.56	10.50	10.84	11.58	−10.76	−9.44	−9.83	−9.47	−8.43	−3.95
$t_{\mathrm{I/A}}$	13.85	14.37	23.42	34.89	5.19	7.90	12.93	4.16	6.88	−2.05	11.45	−4.18	−11.38	−12.17	−2.54	−4.70	1.37
t_{ROE}	−11.87	−9.07	3.31	8.13	5.06	7.42	2.56	29.02	27.97	23.88	27.36	−25.56	7.97	−12.60	−9.21	11.42	−4.03

For the high-minus-low decile formed on each anomaly variable, $\beta_{\mathrm{MKT}}, \beta_{\mathrm{ME}}, \beta_{\mathrm{I/A}}$, and β_{ROE} are the loadings on the market, size, investment, and ROE factors in the q-factor model, and $t_{\beta_{\mathrm{MKT}}}, t_{\beta_{\mathrm{ME}}}, t_{\beta_{\mathrm{I/A}}}$, and $t_{\beta_{\mathrm{ROE}}}$ are their t-statistics, respectively. ME is the average market capitalization (in billions of dollars) across all firms in the high decile, minus that in the low decile. I/A (in percent) is the sum of changes in assets across all firms in the high decile divided by the sum of their 1-year-lagged assets, minus the sum of changes in assets across all firms in the low decile divided by the sum of their 1-year-lagged assets. ROE (in percent) is the sum of the latest announced quarterly earnings across all firms in the high decile divided by the sum of their 1-quarter-lagged book equity, minus the sum of the latest announced quarterly earnings across all firms in the low decile divided by the sum of their 1-quarter-lagged book equity. t_{ME}, $t_{\mathrm{I/A}}$, and t_{ROE} are the corresponding t-statistics. All t-statistics are adjusted for heteroscedasticity and autocorrelations. Table 2 provides a brief description of the symbols.

We comment on 3 results from the remaining columns in the lower panel. First, the organizational capital (OC) effect can be captured by the q-factor model. The high-minus-low decile has an investment factor loading of 0.35 ($t=3.52$) and an ROE factor loading of 0.51 ($t=7.12$). Consistent with the loadings, despite being more profitable by 1.52% per quarter, high OC firms invest less than low OC firms by 13.77% per annum. As a result, the q-factor model does a good job in fitting the average return spread of 0.56% per month ($t=4.07$), leaving an alpha of 0.09% ($t=0.66$, Table 4). In contrast, the Carhart alpha is 0.40% ($t=2.97$), and the Fama-French alpha is 0.61% ($t=4.52$).

Second, column "R&D/M" in Table 6 sheds light on why the q-factor model fails to capture the R&D-to-market anomaly. High R&D firms have lower ROE than low R&D firms, with a spread of 2.80% per quarter. Intuitively, because R&D is expensed per standard accounting practice, high R&D expenses give rise to artificially low ROE. As a result, the ROE factor loading of the high-minus-low R&D/M decile is −0.58 ($t=-4.10$), which goes in the wrong direction in fitting the average returns. Adjusting the earnings data for R&D firms by capitalizing instead of expensing R&D might improve the q-factor model's performance in fitting this anomaly.

Third, the ROE factor largely captures the Ang et al. (2006) systematic volatility (Svol) effect. As shown in Table 4, the high-minus-low Svol decile earns a significant average return of −0.60% per month. Whereas the Carhart model leaves a significant alpha of −0.62%, the q-factor model delivers an insignificant alpha of −0.37% ($t=-1.42$). From the last column in Table 6, the high-minus-low decile has an ROE factor loading of −0.43 ($t=-3.54$) and an ROE spread of −0.64% per quarter. In contrast, both the investment factor loading and the investment-to-assets spread are insignificant.[11]

Overall, many anomalies are basically different manifestations of the investment and ROE effects. The ROE factor is the main source of the q-factor model's empirical power to capture anomalies in the momentum and profitability categories. The investment factor is the main source for capturing anomalies in the value-versus-growth and investment categories. Finally, a combination of the 2 factors helps the q-factor model fit the other anomalies.

3.2 Detailed results for selected anomalies

In this subsection, we report more detailed results for earnings and price momentum, which are classic anomalies to the Fama-French model. We also present detailed results for the accrual anomaly, which the q-factor model fails

[11] The Ang et al. (2006) idiosyncratic volatility (Ivol) anomaly has received more attention in the literature than their Svol effect. As shown in Table 3, the high-minus-low Ivol decile earns an average return of −0.54% per month ($t=-1.56$). In the Online Appendix, we show that the high-minus-low Ivol decile has a Fama-French alpha of −0.92% ($t=-4.66$) and a Carhart alpha of −0.59% ($t=-2.75$). The q-alpha is only −0.08% ($t=-0.39$). Differing from the Svol effect, both q-factors help capture the Ivol anomaly. The investment and ROE factor loadings of the high-minus-low Ivol decile are both −0.94 and are more than 5 standard errors from zero.

to capture, as well as the 25 size and book-to-market portfolios, which are the key testing portfolios for Fama and French (1993, 1996).[12]

3.2.1 Earnings momentum (SUE-1) and price momentum (R6-6). Table 7 reports factor regressions for individual SUE-1 and R6-6 deciles. Across the SUE-1 deciles, 5 have significant alphas in the Fama-French model versus 3 in the Carhart model and 1 in the q-factor model. Across the R6-6 deciles, 4 alphas are significant in the Fama-French model versus 3 in the Carhart model and zero in the q-factor model.

The q-factor model captures momentum via the ROE factor. Moving from SUE-1 decile 1 to 10, the ROE factor loadings increase from -0.22 to 0.26, and moving from R6-6 decile 1 to 10, the loadings increase from -0.74 to 0.28. Accordingly, moving from SUE-1 decile 1 to 10, ROE increases from -0.80% to 5.00% per quarter, and moving from R6-6 decile 1 to 10, it increases from -0.71% to 3.43%. Intuitively, earnings and price momentum winners are more profitable and load more heavily on the ROE factor than earnings and price momentum losers, respectively.

Chan, Jegadeesh, and Lakonishok (1996) show that momentum profits are short-lived. To examine this issue, we calculate the returns of earnings and price momentum deciles for holding periods longer than 6 months. At the beginning of month t, we sort all stocks on their most recent SUE and calculate value-weighted decile returns for the holding periods from month t to $t+11$, from $t+12$ to $t+35$, and from $t+36$ to $t+59$. In addition, at the beginning of month t, we sort all stocks on their prior 6-month returns from $t-7$ to $t-2$, skipping month $t-1$, and calculate value-weighted decile returns for the holding periods from month t to $t+11$, from $t+12$ to $t+35$, and from $t+36$ to $t+59$. We call these portfolios designed to capture the reversal of momentum profits momentum-reversal deciles.

Confirming the short-lived nature of momentum, Table 8 shows that none of the earnings momentum-reversal high-minus-low deciles earn significant average returns. Except for the 12-month holding period, the price momentum-reversal high-minus-low deciles do not earn significant average returns either. More importantly, the q-factor model succeeds in capturing the short-lived nature of momentum. In particular, the q-factor model does not produce significant alphas for any of the momentum-reversal high-minus-low deciles.

3.2.2 Operating accruals (OA) and percent operating accruals (POA). Sloan (1996) shows that firms with high operating accruals earn lower average returns than firms with low operating accruals. Accruals are often scaled by lagged assets or average assets over the prior 2 years. Hafzalla, Lundholm, and

[12] The q-factor model's performance across the Fama-French (1997) 10 industry portfolios is largely comparable to that of the Fama-French model and that of the Carhart model (see the Online Appendix).

Table 7
Earnings momentum (SUE-1) and price momentum (R6-6) deciles

	Panel A: SUE-1										Panel B: R6-6									
	Low	2	3	4	5	6	7	8	9	High	Low	2	3	4	5	6	7	8	9	High
m	0.36	0.34	0.35	0.28	0.44	0.43	0.64	0.64	0.64	0.80	0.02	0.28	0.45	0.52	0.46	0.47	0.50	0.55	0.66	0.87
α	−0.13	−0.15	−0.15	−0.20	−0.01	−0.03	0.20	0.18	0.19	0.38	−0.61	−0.24	−0.02	0.07	0.03	0.04	0.07	0.11	0.18	0.31
α_{FF}	−0.12	−0.15	−0.15	−0.18	−0.01	−0.02	0.21	0.24	0.21	0.43	−0.68	−0.29	−0.07	0.03	−0.01	0.01	0.05	0.10	0.21	0.44
α_C	0.00	−0.06	−0.07	−0.10	0.01	0.02	0.21	0.16	0.13	0.34	−0.03	0.16	0.25	0.24	0.11	0.03	−0.02	−0.05	−0.04	0.03
t_m	1.47	1.41	1.36	1.17	2.00	1.86	3.01	3.06	2.96	3.89	0.06	1.02	1.89	2.38	2.24	2.37	2.49	2.58	2.85	2.83
t	−1.39	−1.92	−1.88	−2.38	−0.18	−0.35	2.58	2.54	2.64	5.14	−3.60	−2.07	−0.28	1.00	0.47	0.84	1.61	1.78	2.40	2.13
t_{FF}	−1.29	−1.73	−1.75	−2.30	−0.08	−0.28	2.81	3.43	2.87	5.86	−4.34	−2.49	−0.89	0.40	−0.23	0.18	0.92	1.64	2.76	3.38
t_C	0.01	−0.69	−0.80	−1.18	0.07	0.29	2.63	2.13	1.69	4.55	−0.29	2.18	4.24	4.27	1.77	0.55	−0.27	−0.88	−0.63	0.34
	The q-factor model regressions										The q-factor model regressions									
α_q	0.05	0.00	0.04	0.05	0.00	−0.03	0.09	0.02	0.04	0.21	0.00	0.04	0.11	0.11	−0.01	−0.07	−0.10	−0.11	−0.04	0.24
β_{MKT}	1.03	1.00	1.02	0.94	0.96	0.98	0.98	1.01	0.97	0.95	1.19	1.05	1.00	0.96	0.94	0.94	0.95	0.97	1.03	1.10
β_{ME}	−0.16	0.04	0.00	0.02	0.00	−0.04	−0.05	−0.03	0.01	−0.05	0.16	−0.04	−0.08	−0.08	−0.06	−0.05	−0.02	0.04	0.13	0.43
$\beta_{\mathrm{I/A}}$	0.00	−0.16	−0.12	−0.25	0.06	0.03	0.06	0.07	0.06	0.02	−0.34	−0.08	0.02	0.07	0.09	0.14	0.16	0.12	0.02	−0.40
β_{ROE}	−0.22	−0.12	−0.20	−0.19	−0.06	−0.01	0.13	0.21	0.20	0.26	−0.74	−0.36	−0.20	−0.09	0.00	0.09	0.15	0.23	0.28	0.28
t_q	0.42	−0.04	0.37	0.53	−0.04	−0.32	1.21	0.31	0.44	2.63	−0.02	0.24	0.92	1.21	−0.09	−1.32	−1.73	−1.71	−0.45	1.34
$t_{\beta_{\mathrm{MKT}}}$	32.75	39.64	39.24	34.70	43.64	41.42	51.90	55.30	42.68	37.45	24.15	25.44	35.35	40.62	42.64	49.23	55.21	55.07	38.75	27.49
$t_{\beta_{\mathrm{ME}}}$	−3.61	0.97	0.09	0.55	0.09	−0.85	−1.37	−1.22	0.18	−1.50	1.42	−0.48	−1.23	−1.76	−1.22	−1.25	−0.53	1.50	3.25	4.71
$t_{\beta_{\mathrm{I/A}}}$	−0.01	−2.39	−1.99	−3.30	1.04	0.48	1.12	1.23	0.99	0.36	−2.39	−0.69	0.21	0.95	1.65	3.22	3.93	2.80	0.32	−3.27
$t_{\beta_{\mathrm{ROE}}}$	−3.19	−2.56	−3.62	−3.48	−1.53	−0.20	2.81	5.77	4.15	7.30	−5.87	−3.93	−2.86	−1.53	0.05	2.50	4.42	6.62	5.26	3.26
	Characteristics in the q-factor model										Characteristics in the q-factor model									
ME	1.51	1.53	1.38	1.41	1.39	1.64	1.93	1.85	1.77	2.20	0.46	1.15	1.61	1.90	2.07	2.18	2.16	2.07	1.73	0.86
I/A	11.60	11.42	10.26	8.54	6.59	7.33	7.96	8.26	9.00	10.14	12.62	10.46	9.48	8.83	8.79	8.62	8.71	8.63	8.44	8.56
ROE	−0.80	1.94	2.05	2.34	2.72	3.24	3.59	3.75	3.95	5.00	−0.71	1.73	2.45	2.74	2.94	3.11	3.24	3.34	3.43	3.43

$m, \alpha, \alpha_{FF}, \alpha_C$, and α_q are the average excess return, the CAPM alpha, the Fama-French alpha, the Carhart alpha, and the q-alpha, and t_m, t, t_{FF}, t_C, and t_q are their t-statistics, respectively. $\beta_{\mathrm{MKT}}, \beta_{\mathrm{ME}}, \beta_{\mathrm{I/A}}$, and β_{ROE} are the loadings on the market, size, investment, and ROE factors in the q-factor model, and $t_{\beta_{\mathrm{MKT}}}, t_{\beta_{\mathrm{ME}}}, t_{\beta_{\mathrm{I/A}}}$, and $t_{\beta_{\mathrm{ROE}}}$ are their t-statistics, respectively. ME is the average market capitalization (in billions of dollars) across all of the firms in a given decile. I/A (in percent) is the sum of changes in assets across all of the firms in a given decile divided by the sum of their 1-year-lagged assets. ROE (in percent) is the sum of the most recently announced quarterly earnings across all of the firms in a given decile divided by the sum of their 1-quarter-lagged book equity. All t-statistics are adjusted for heteroscedasticity and autocorrelations.

Table 8
Momentum-reversal deciles

	Panel A: Earnings momentum			Panel B: Price momentum		
	SUE-12	SUE-13-36	SUE-37-60	R6-12	R6-13-36	R6-37-60
m	0.16	−0.11	0.13	0.57	−0.24	−0.03
α	0.19	−0.08	0.16	0.60	−0.25	−0.05
α_{FF}	0.31	−0.04	0.14	0.86	−0.04	0.07
α_C	0.10	0.01	0.14	0.09	−0.02	0.06
α_q	−0.01	0.04	0.07	0.17	−0.09	0.08
t_m	1.57	−1.58	1.69	2.67	−1.84	−0.29
t	2.09	−1.09	2.09	2.86	−1.91	−0.56
t_{FF}	3.31	−0.56	1.90	4.41	−0.37	0.85
t_C	1.17	0.11	1.83	0.83	−0.18	0.76
t_q	−0.06	0.51	0.80	0.71	−0.70	0.86
$\overline{\lvert\alpha\rvert}$	0.09	0.07	0.07	0.13	0.11	0.08
$\overline{\lvert\alpha_{FF}\rvert}$	0.11	0.09	0.09	0.17	0.09	0.08
$\overline{\lvert\alpha_C\rvert}$	0.08	0.09	0.09	0.07	0.09	0.09
$\overline{\lvert\alpha_q\rvert}$	0.07	0.07	0.07	0.06	0.08	0.08
p	0.01	0.10	0.10	0.01	0.00	0.08
p_{FF}	0.00	0.01	0.01	0.00	0.00	0.05
p_C	0.01	0.02	0.05	0.04	0.04	0.02
p_q	0.03	0.00	0.03	0.08	0.00	0.00

At the beginning of each month t, we use NYSE breakpoints to sort all stocks based on their latest earnings surprises. Monthly value-weighted decile returns are calculated, separately, for the holding periods from month t to $t+11$ (SUE-12); from month $t+12$ to $t+35$ (SUE-13-36); and from month $t+36$ to $t+59$ (SUE-37-60). In addition, at the beginning of each month t, we use NYSE breakpoints to sort all stocks based on their prior 6-month returns from month $t-7$ to $t-2$. Skipping month $t-1$, we calculate monthly value-weighted decile returns, separately, for the holding periods from month t to $t+11$ (R6-12); from month $t+12$ to $t+35$ (R6-13-36); and from month $t+36$ to $t+59$ (R6-37-60). $m, \alpha, \alpha_{FF}, \alpha_C$, and α_q are the average return, the CAPM alpha, the Fama-French alpha, the Carhart alpha, and the q-alpha for the high-minus-low decile, and t_m, t, t_{FF}, t_C, and t_q are their t-statistics adjusted for heteroscedasticity and autocorrelations, respectively. $\overline{\lvert\alpha\rvert}$, $\overline{\lvert\alpha_{FF}\rvert}$, $\overline{\lvert\alpha_C\rvert}$, and $\overline{\lvert\alpha_q\rvert}$ are the average magnitude of the alphas, and p, p_{FF}, p_C, and p_q are the p-values of the GRS test on the null that all the alphas are jointly zero across a given set of the deciles.

Van Winkle (2011) show that scaling accruals by the absolute value of earnings (percent accruals) is more effective in selecting firms for which the differences between sophisticated and naive earnings forecasts are the most extreme.

Panel A of Table 9 shows why the q-factor model fails to fit the OA anomaly. The low OA decile, despite having lower investment-to-assets (13.87% per annum) than the high OA decile (24.02%), has a large, negative investment factor loading (−0.56), which is close to that of the high OA decile (−0.58). More important, the ROE factor loading is −0.26 for the low decile and 0.03 for the high decile, and the spread is more than 4 standard errors from zero (Table 6). Intuitively, because earnings equal operating cash flows plus accruals, high OA firms tend to be more profitable and load more heavily on the ROE factor than low OA firms. This pattern in ROE factor loadings goes in the wrong direction in capturing the OA anomaly.

Panel B shows why the q-factor model performs better for the POA anomaly. The ROE factor loadings are largely flat across the deciles. Intuitively, because POA scales accruals with earnings, the earnings in the denominator work against the positive correlation between accruals and earnings in the numerator. In addition, the investment factor loadings fall from 0.35 for the low POA

Table 9
Operating accrual (OA) and percent operating accrual (POA) deciles

	Panel A: OA										Panel B: POA									
	Low	2	3	4	5	6	7	8	9	High	Low	2	3	4	5	6	7	8	9	High
m	0.50	0.56	0.66	0.60	0.57	0.60	0.52	0.40	0.40	0.20	0.64	0.56	0.60	0.61	0.46	0.52	0.55	0.43	0.39	0.18
α	−0.06	0.08	0.22	0.18	0.16	0.20	0.07	−0.03	−0.08	−0.39	0.12	0.07	0.16	0.14	0.00	0.09	0.09	−0.03	−0.10	−0.41
α_{FF}	0.10	0.14	0.22	0.13	0.11	0.16	0.10	−0.04	−0.05	−0.27	−0.01	0.03	0.13	0.12	0.01	0.11	0.22	0.08	−0.06	−0.32
α_C	0.11	0.19	0.20	0.08	0.13	0.13	0.10	0.00	−0.02	−0.22	−0.03	0.05	0.07	0.15	0.00	0.12	0.22	0.12	−0.02	−0.28
t_m	1.71	2.38	3.15	2.97	2.77	3.07	2.40	1.76	1.67	0.65	2.39	2.35	2.82	2.60	2.04	2.49	2.53	1.87	1.62	0.58
t	−0.50	0.81	2.96	2.38	2.01	2.51	1.10	−0.39	−0.96	−3.65	1.04	0.77	1.92	1.75	0.05	1.32	1.27	−0.28	−1.09	−3.26
t_{FF}	0.86	1.47	3.11	1.77	1.40	2.05	1.53	−0.47	−0.65	−3.22	−0.05	0.33	1.48	1.40	0.19	1.53	3.13	0.86	−0.73	−3.32
t_C	0.98	1.74	2.58	1.08	1.54	1.56	1.46	0.02	−0.21	−2.49	−0.30	0.50	0.75	1.68	0.06	1.85	3.20	1.15	−0.22	−2.95
	The q-factor model regressions										The q-factor model regressions									
α_q	0.39	0.22	0.24	−0.06	0.06	−0.02	0.00	−0.12	−0.21	−0.17	−0.04	0.07	0.12	0.26	0.06	−0.04	0.19	0.10	−0.20	−0.16
β_{MKT}	1.08	1.02	0.96	0.95	0.93	0.91	0.98	0.93	1.04	1.11	1.11	1.05	0.96	1.00	0.98	0.95	0.97	0.93	1.03	1.10
β_{ME}	0.02	−0.09	−0.12	−0.03	−0.09	−0.04	−0.09	0.05	0.03	0.30	0.23	−0.04	−0.06	−0.10	−0.07	−0.04	−0.12	−0.03	0.09	0.37
$\beta_{\mathrm{I/A}}$	−0.56	−0.09	0.06	0.27	0.22	0.22	0.01	0.01	−0.03	−0.58	0.35	0.26	0.14	0.05	−0.05	0.06	−0.25	−0.30	−0.11	−0.55
β_{ROE}	−0.26	−0.12	−0.05	0.16	0.00	0.17	0.14	0.11	0.22	0.03	−0.12	−0.20	−0.04	−0.19	−0.02	0.17	0.09	0.07	0.22	−0.06
t_q	3.13	1.62	3.02	−0.78	0.66	−0.19	0.00	−1.23	−2.23	−1.86	−0.40	0.75	1.41	2.89	0.71	−0.55	2.54	0.95	−1.91	−1.34
$t_{\beta_{\mathrm{MKT}}}$	32.16	35.50	56.68	48.78	38.87	42.85	44.43	41.06	35.50	39.68	43.24	37.37	30.61	43.73	47.87	40.75	41.32	35.95	50.05	34.83
$t_{\beta_{\mathrm{ME}}}$	0.46	−2.09	−4.28	−1.17	−2.16	−1.19	−2.55	1.19	0.82	6.79	6.54	−0.91	−1.34	−3.12	−2.22	−1.54	−3.55	−0.85	1.94	7.96
$t_{\beta_{\mathrm{I/A}}}$	−6.04	−0.80	1.05	5.83	2.75	3.14	0.12	0.08	−0.42	−9.86	6.29	3.76	2.36	0.95	−0.67	1.13	−4.84	−5.17	−1.25	−6.41
$t_{\beta_{\mathrm{ROE}}}$	−3.55	−1.79	−1.08	4.17	0.05	4.06	3.21	2.13	3.83	0.69	−2.42	−2.70	−0.70	−4.44	−0.46	4.34	2.02	1.23	3.57	−1.24
	Characteristics in the q-factor model										Characteristics in the q-factor model									
ME	0.81	1.48	1.93	2.21	2.37	2.14	2.37	1.78	1.46	0.58	0.90	1.10	1.41	1.69	1.73	1.97	2.47	2.35	1.49	0.54
I/A	13.87	9.06	7.72	7.37	7.45	7.78	8.63	7.13	11.49	24.02	5.16	6.97	6.48	8.85	8.52	8.38	10.81	11.41	14.22	16.28
ROE	1.88	2.61	2.90	2.91	2.86	2.90	3.09	2.94	2.89	2.75	1.22	1.82	2.24	2.47	2.69	3.21	3.75	3.96	3.51	2.24

$m, \alpha, \alpha_{FF}, \alpha_C$, and α_q are the average excess return, the CAPM alpha, the Fama-French alpha, the Carhart alpha, and the q-alpha, and t_m, t, t_{FF}, t_C, and t_q are their t-statistics, respectively. $\beta_{\mathrm{MKT}}, \beta_{\mathrm{ME}}, \beta_{\mathrm{I/A}}$, and β_{ROE} are the loadings on the market, size, investment, and ROE factors in the q-factor model, and $t_{\beta_{\mathrm{MKT}}}, t_{\beta_{\mathrm{ME}}}, t_{\beta_{\mathrm{I/A}}}$, and $t_{\beta_{\mathrm{ROE}}}$ are their t-statistics, respectively. ME is the average market capitalization (in billions of dollars) across all of the firms in a given decile. I/A (in percent) is the sum of changes in assets across all of the firms in a given decile divided by the sum of their 1-year-lagged assets. ROE (in percent) is the sum of the most recently announced quarterly earnings across all of the firms in a given decile divided by the sum of their 1-quarter-lagged book equity. All t-statistics are adjusted for heteroscedasticity and autocorrelations.

decile to −0.55 for the high POA decile, going in the right direction in fitting the average returns.

3.2.3 25 size (ME) and book-to-market (B/M) portfolios. Table 10 reports that the high-minus-low B/M quintile earns an average return of 1.02% per month (t=4.59) in small stocks but only 0.16% (t=0.79) in big stocks. The Fama-French model does a good job in fitting the average returns of the 25 portfolios. The average magnitude of the alphas is only 0.10%, but their model is still rejected by the GRS test. Only 5 out of 25 portfolios have significant alphas. In particular, the small-growth portfolio has an alpha of −0.54% (t=−4.84).[13] The performance of the Carhart model is largely comparable.

The q-factor model's performance is also similar. The average magnitude of the alphas is 0.11% per month, which is close to 0.10% in the Fama-French model and 0.11% in the Carhart model. Out of 25, 4 portfolios have significant alphas in the q-factor model, compared with 5 in the Fama-French model and 5 in the Carhart model. More importantly, only 1 out of 5 high-minus-low B/M quantiles has a significant alpha in the q-factor model, compared with 3 in the Fama-French model and 2 in the Carhart model. The small-growth portfolio has an insignificant q-alpha of only −0.25% (t=−1.48), but the small-value q-alpha is 0.32% (t=2.72).

The q-factor model's performance is mostly from the investment factor. From the panel denoted "$\beta_{\mathrm{I/A}}$," value stocks have significantly higher investment factor loadings than growth stocks. The loadings spreads range from 1.19 to 1.56 across the size quintiles. The panel denoted "I/A" shows that value stocks invest less than growth stocks, and the investment-to-assets spreads vary from 6.14% per annum to 13.94% across the size quintiles. In contrast, the value-minus-growth loadings on the other factors are mostly small and insignificant.

3.3 Sharpe ratios

In the mean-variance framework, a factor model can account for all the anomalies if and only if the efficient portfolio from combining all the anomaly portfolios lies in the span of the factors. As such, the efficient combination of the factors should have a Sharpe ratio that is greater than or equal to the maximum Sharpe ratio from combining all the anomaly portfolios. Complementing the results from factor regressions, Table 11 reports Sharpe ratios for different (combinations of) factors and anomaly portfolios.

Panel A reports the monthly Sharpe ratio for each individual factor, calculated as the mean return divided by its volatility. The investment and ROE factors have the highest Sharpe ratios, 0.24 and 0.22, compared with the Sharpe ratios of 0.13 and 0.16, respectively, for HML and UMD. Following MacKinlay (1995),

[13] The small-growth anomaly is notoriously difficult to capture (e.g., Fama and French 1993, 1996; Davis, Fama, and French 2000; and Campbell and Vuolteenaho 2004).

Table 10
Twenty-five size and book-to-market portfolios

	Low	2	3	4	High	H-L	Low	2	3	4	High	H–L	Low	2	3	4	High	H–L
	m						α ($\overline{\lvert\alpha\rvert}$=0.29)						α_{FF} ($\overline{\lvert\alpha_{FF}\rvert}$=0.10)					
Small	0.08	0.72	0.84	0.95	1.11	1.02	−0.60	0.13	0.30	0.45	0.59	1.19	−0.54	0.02	0.13	0.18	0.16	0.70
2	0.32	0.69	0.86	0.87	0.99	0.67	−0.34	0.12	0.33	0.39	0.48	0.82	−0.21	0.00	0.09	0.07	0.04	0.25
3	0.38	0.71	0.77	0.77	1.02	0.65	−0.25	0.16	0.28	0.32	0.56	0.81	−0.09	0.04	0.03	0.00	0.13	0.22
4	0.52	0.59	0.73	0.74	0.84	0.32	−0.07	0.08	0.24	0.29	0.40	0.47	0.14	−0.02	0.03	0.00	0.02	−0.12
Big	0.40	0.54	0.54	0.61	0.56	0.16	−0.07	0.10	0.14	0.25	0.19	0.26	0.16	0.11	0.09	0.00	−0.16	−0.32
	t_m						t (p=0.00)						t_{FF} (p_{FF}=0.00)					
Small	0.20	2.02	2.57	3.07	3.30	4.59	−2.55	0.64	1.66	2.54	2.98	5.62	−4.84	0.23	1.58	2.53	1.97	5.66
2	0.90	2.20	3.03	3.29	3.31	2.93	−1.94	0.77	2.34	2.77	2.60	3.70	−2.59	0.01	1.36	0.92	0.45	2.19
3	1.15	2.49	3.03	3.05	3.93	2.76	−1.77	1.40	2.27	2.52	3.37	3.63	−1.21	0.52	0.35	0.02	1.28	1.70
4	1.73	2.35	2.91	3.08	3.24	1.43	−0.57	0.76	2.11	2.33	2.53	2.09	1.74	−0.23	0.27	0.03	0.17	−0.87
Big	1.70	2.53	2.71	3.04	2.43	0.79	−0.79	1.27	1.42	2.10	1.17	1.24	2.66	1.29	0.92	−0.02	−1.31	−2.32
	α_C ($\overline{\lvert\alpha_C\rvert}$=0.11)						α_q ($\overline{\lvert\alpha_q\rvert}$=0.11)						β_{MKT}					
Small	−0.48	0.03	0.12	0.18	0.22	0.70	−0.25	0.27	0.31	0.30	0.32	0.57	1.11	0.96	0.92	0.88	0.96	−0.15
2	−0.18	0.03	0.09	0.10	0.04	0.22	−0.14	0.02	0.03	0.07	0.10	0.24	1.14	1.02	1.01	0.94	1.01	−0.13
3	−0.04	0.04	0.09	0.03	0.16	0.20	−0.01	−0.03	−0.04	−0.01	0.14	0.15	1.10	1.05	1.01	0.95	1.01	−0.09
4	0.15	−0.01	0.07	0.03	0.09	−0.06	0.18	−0.14	−0.01	0.02	0.06	−0.12	1.09	1.07	1.06	0.98	1.02	−0.08
Big	0.17	0.07	0.07	−0.03	−0.13	−0.31	0.10	−0.04	0.06	−0.01	−0.04	−0.13	0.98	0.98	0.93	0.86	0.90	−0.09
	t_C (p_C=0.00)						t_q (p_q=0.00)						$t_{\beta_{\mathrm{MKT}}}$					
Small	−4.00	0.36	1.58	2.59	2.53	5.72	−1.48	2.24	3.09	3.68	2.72	2.91	25.50	29.26	36.30	39.11	27.04	−2.63
2	−2.28	0.37	1.34	1.40	0.44	1.88	−1.21	0.29	0.37	0.67	0.89	1.25	33.73	51.06	53.11	42.18	34.08	−2.43
3	−0.50	0.53	0.93	0.28	1.40	1.43	−0.09	−0.30	−0.37	−0.05	1.16	0.92	39.22	53.02	28.69	37.92	26.87	−1.60
4	1.87	−0.16	0.74	0.24	0.75	−0.42	1.50	−1.58	−0.06	0.21	0.44	−0.61	34.34	42.24	31.78	31.00	25.98	−1.30
Big	2.89	0.91	0.70	−0.36	−1.02	−2.12	1.32	−0.49	0.65	−0.06	−0.23	−0.70	52.33	40.01	30.63	30.86	25.72	−2.09

(continued)

Table 10
Continued

	Low	2	3	4	High	H–L	Low	2	3	4	High	H–L	Low	2	3	4	High	H–L
			β_{ME}						$\beta_{\mathrm{I/A}}$						β_{ROE}			
Small	1.14	1.18	1.08	1.01	0.99	−0.15	−0.66	−0.32	−0.11	0.17	0.53	1.19	−0.40	−0.39	−0.31	−0.26	−0.35	0.05
2	0.93	0.94	0.83	0.72	0.85	−0.07	−0.72	−0.13	0.25	0.42	0.59	1.31	−0.05	−0.08	−0.02	−0.09	−0.20	−0.14
3	0.72	0.63	0.49	0.43	0.47	−0.24	−0.77	0.03	0.37	0.54	0.78	1.56	0.00	0.05	0.04	−0.09	−0.16	−0.16
4	0.40	0.33	0.24	0.20	0.18	−0.21	−0.70	0.18	0.39	0.60	0.77	1.47	0.04	0.09	−0.01	−0.14	−0.16	−0.21
Big	−0.22	−0.09	−0.21	−0.10	−0.14	0.08	−0.39	0.12	0.30	0.61	0.80	1.20	0.14	0.16	−0.05	−0.06	−0.25	−0.39
			$t_{\beta_{\mathrm{ME}}}$						$t_{\beta_{\mathrm{I/A}}}$						$t_{\beta_{\mathrm{ROE}}}$			
Small	16.49	18.22	23.29	33.68	14.79	−1.31	−5.09	−3.64	−1.46	3.06	5.90	8.59	−3.34	−4.73	−5.43	−7.53	−6.82	0.40
2	16.68	32.58	19.26	12.82	13.78	−0.70	−9.48	−2.32	3.93	6.26	8.97	10.46	−0.68	−1.84	−0.56	−1.76	−3.24	−1.25
3	14.60	16.16	5.21	7.05	4.85	−1.80	−11.40	0.43	3.35	6.24	9.13	12.41	0.02	0.93	0.54	−1.23	−2.08	−1.50
4	6.26	6.97	3.22	3.63	2.14	−1.54	−8.47	2.51	4.05	5.50	7.28	9.57	0.68	1.62	−0.19	−1.82	−1.98	−1.65
Big	−7.59	−2.67	−5.22	−1.63	−2.15	1.06	−9.47	2.19	4.98	4.87	6.25	8.00	4.37	3.89	−0.89	−0.68	−2.93	−3.99
			ME						I/A						ROE			
Small	0.07	0.07	0.07	0.06	0.05	−0.03	10.90	12.67	9.00	7.02	1.77	−9.13	−1.38	0.65	0.79	0.56	−0.91	0.46
2	0.33	0.33	0.33	0.33	0.32	−0.01	17.87	14.63	11.22	7.57	3.92	−13.94	2.10	2.34	2.01	1.47	0.05	−2.05
3	0.76	0.76	0.76	0.76	0.76	0.00	18.30	13.64	9.95	8.14	4.47	−13.82	3.35	2.86	2.20	1.63	0.65	−2.70
4	1.86	1.83	1.78	1.77	1.82	−0.04	15.28	11.31	8.86	7.06	5.18	−10.09	4.24	3.14	2.28	1.58	0.74	−3.50
Big	15.98	13.55	11.19	9.94	8.45	−7.53	12.59	11.36	7.49	8.22	6.44	−6.14	5.44	3.71	2.64	2.24	1.05	−4.38

$m, \alpha, \alpha_{FF}, \alpha_C$, and α_q are the average excess return, the CAPM alpha, the Fama-French alpha, the Carhart alpha, and the q-alpha, and t_m, t, t_{FF}, t_C, and t_q are their t-statistics, respectively. $\overline{|\alpha|}$, $\overline{|\alpha_{FF}|}$, $\overline{|\alpha_C|}$, and $\overline{|\alpha_q|}$ are the average magnitude of the alphas, and p, p_{FF}, p_C, and p_q are the p-values of the GRS test across the 25 portfolios. $\beta_{\mathrm{MKT}}, \beta_{\mathrm{ME}}, \beta_{\mathrm{I/A}}$, and β_{ROE} are the market, size, investment, and ROE factor loadings in the q-factor model, and $t_{\beta_{\mathrm{MKT}}}, t_{\beta_{\mathrm{ME}}}, t_{\beta_{\mathrm{I/A}}}$, and $t_{\beta_{\mathrm{ROE}}}$ are their t-statistics, respectively. ME is the average market capitalization (in billions of dollars) across all of the firms in a given portfolio. I/A (in percent) is the sum of changes in assets across all of the firms in a given portfolio divided by the sum of their 1-year-lagged assets. ROE (in percent) is the sum of the most recently announced quarterly earnings across all of the firms in a given portfolio divided by the sum of their 1-quarter-lagged book equity. The t-statistics are adjusted for heteroscedasticity and autocorrelations.

Table 11
Maximum Sharpe ratios

Panel A: Sharpe ratios

MKT	SMB	HML	UMD	r_{ME}	$r_{\mathrm{I/A}}$	r_{ROE}
0.10	0.06	0.13	0.16	0.10	0.24	0.22

Panel B: Maximum Sharpe ratios

CAPM	FF	Carhart	q
0.10	0.21	0.30	0.43

Panel C: Anomaly portfolios

	SUE-1	SUE-6	Abr-1	Abr-6	RE-1	RE-6	R6-6	R11-1	I-Mom	B/M	E/P	CF/P	NO/P	Dur	I/A	NOA	△PI/A	IG
$S_{\mathrm{H-L}}$	0.14	0.09	0.23	0.15	0.16	0.13	0.15	0.16	0.10	0.14	0.12	0.11	0.16	0.12	0.11	0.12	0.17	0.14
S_m	0.27	0.26	0.28	0.23	0.25	0.21	0.31	0.28	0.20	0.21	0.24	0.21	0.30	0.24	0.24	0.29	0.25	0.26
	NSI	CEI	IvG	IvC	OA	POA	PTA	ROE	ROA	GP/A	NEI	FP	OC/A	Ad/M	RD/M	OL	Svol	All
$S_{\mathrm{H-L}}$	0.21	0.14	0.13	0.14	0.10	0.15	0.12	0.15	0.13	0.10	0.14	0.10	0.18	0.14	0.12	0.10	0.14	0.48
S_m	0.30	0.32	0.23	0.25	0.25	0.23	0.23	0.24	0.21	0.18	0.26	0.28	0.26	0.23	0.21	0.17	0.29	1.60

Panel A reports the monthly Sharpe ratio for each individual factor, calculated as the ratio of the mean factor return to its standard deviation. Panel B reports the maximum monthly Sharpe ratio achievable from each factor model, including the CAPM, the Fama-French (FF) model, the Carhart model, and the q-factor model. The maximum Sharpe ratio is calculated as $\sqrt{\mu'_f V_f^{-1} \mu_f}$, in which μ_f is the vector of mean factor returns for a given factor model, and V_f is the variance-covariance matrix for the vector of factor returns. In Panel C, $S_{\mathrm{H-L}}$ is the monthly Sharpe ratio for the high-minus-low decile formed on each anomaly variable, calculated as the mean high-minus-low return divided by its standard deviation. S_m is the maximum monthly Sharpe ratio achievable from a given set of deciles, calculated as $\sqrt{\mu' V^{-1} \mu}$, in which μ is the vector of average returns in excess of the 1-month Treasury bill rate for a given set of deciles, and V is the variance-covariance matrix for the vector of decile excess returns. In column "All," $S_{\mathrm{H-L}}$ is the maximum Sharpe ratio achievable from pooling together 28 out of the 35 high-minus-low deciles that have valid data from January 1972 to December 2012, and it is calculated as $\sqrt{\mu'_f V_f^{-1} \mu_f}$, with each high-minus-low decile treated as a different portfolio. S_m is the maximum Sharpe ratio achievable from pooling together 28 out of the 35 sets of deciles that have valid data from January 1972 to December 2012. Table 2 provides a brief description of the symbols. Appendix A details variable definition and portfolio construction.

we also calculate the maximum Sharpe ratio achievable from a given factor model as $\sqrt{\mu_f' V_f^{-1} \mu_f}$, in which μ_f is the vector of mean factor returns, and V_f is the variance-covariance matrix of the factor returns. Panel B shows that the Fama-French model produces a maximum Sharpe ratio of 0.21, the Carhart model 0.30, and the q-factor model 0.43.

Panel C reports the Sharpe ratios for the high-minus-low deciles and the maximum Sharpe ratios from combining deciles formed on a given anomaly variable. In general, these Sharpe ratios are lower than the maximum Sharpe ratio of 0.43 for the q-factor model. However, once we pool together 28 out of the 35 high-minus-low deciles that cover the entire sample from January 1972 to December 2012, we obtain a maximum Sharpe ratio of 0.48. We also obtain a maximum Sharpe ratio of 1.60 from pooling together all 28 sets of deciles that have valid data for the entire sample.[14]

Overall, the Sharpe ratios in Table 11 suggest that the q-factor model is more effective than the Carhart and Fama-French models, but that the q-factor model is by no means perfect in capturing all the anomalies.

The Sharpe ratios also help in interpreting the q-factor model, which we view as a parsimonious empirical model for estimating expected stock returns. In particular, we emphasize that the q-factor model is silent about the debate between rational asset pricing and mispricing. This interpretation is weaker than the risk factors interpretation per Fama and French (1993, 1996).

Consistent with Fama and French (1993, 1996), our factor regressions provide direct evidence that the q-factors capture shared variation in returns across a wide array of anomaly portfolios. To the extent that the q-factors, constructed on economic fundamentals, represent common variation in returns, their loadings represent covariances between an asset's returns with the factor returns. The Sharpe ratios in Table 11 lend further support to the common variation captured by the q-factors. If stocks with similar investment or stocks with similar profitability do not comove together, it would be possible to diversify away the variances of the q-factors, giving rise to extremely high Sharpe ratios. Table 11 shows otherwise. The Sharpe ratios for the q-factors are high, but not excessively high, indicating comovement in returns.

However, our evidence is not inconsistent with mispricing. If waves of investor sentiment affect stocks with similar investment or stocks with similar profitability simultaneously, the q-factor model would work in the data as well. Moreover, under the mispricing hypothesis, trading opportunities with mild

[14] Calculating the maximum Sharpe ratio achievable from pooling together all the 35 sets of deciles on their common sample starting in February 1986 (the starting date of the sample for the Svol deciles) is infeasible. The reason is that the number of observations is not large enough to estimate the large number of parameters in the variance-covariance matrix. Instead, we calculate the maximum Sharpe ratios from pooling together all the deciles in each category of anomalies. The estimates are 0.67 across the 9 sets of momentum deciles (from "SUE-1" to "I-Mom") on their common sample starting in January 1977; 0.49 across the 5 sets of value-versus-growth deciles on the sample starting in July 1972; 0.65 across the 11 sets of investment deciles on the full sample; 0.49 over the 5 sets of profitability deciles on the sample starting in January 1976; and 0.59 across the remaining 5 sets of deciles on the sample starting in February 1986.

Sharpe ratios can persist, even though opportunities with extreme Sharpe ratios are arbitraged away. MacKinlay (1995), in particular, argues that the maximum Sharpe ratio for the Fama-French model is too high to be consistent with rational asset pricing. As shown in Table 11, the maximum Sharpe ratio for the q-factor model is even higher. Finally, our work is silent about the structural sources behind the common variation in the q-factors and the heterogeneity in their loadings across the diverse anomaly portfolios (Section 1.3).

4. Conclusion

Our examination of nearly 80 anomalies yields 2 major findings. About one-half of the anomalies earn insignificant average returns for the high-minus-low deciles formed with NYSE breakpoints and value-weighted returns. The evidence suggests that many claims in the anomalies literature seem exaggerated, likely by excessively weighting on microcaps. More importantly, an empirical q-factor model consisting of the market factor, a size factor, an investment factor, and a profitability factor outperforms the Fama-French and Carhart models in capturing many (but not all) of the significant anomalies. Many seemingly unrelated anomalies turn out to be different manifestations of the investment and profitability effects. These empirical results highlight the importance of understanding the driving forces behind the q-factors and their broad empirical power in the cross section.

Appendix A

A.1 Variable Definition and Portfolio Construction

For each anomaly variable, we describe its detailed definition and portfolio construction.

A.1.1 Momentum. This category includes 10 momentum variables, including SUE-1, SUE-6, Abr-1, Abr-6, RE-1, RE-6, R6-1, R6-6, R11-1, and I-Mom, as well as 6 momentum-reversal variables: SUE-12, SUE-13-36, SUE-37-60, R6-12, R6-13-36, and R6-37-60.

A.1.1.1 SUE-1, SUE-6, SUE-12, SUE-13-36, and SUE-37-60. Following Foster, Olsen, and Shevlin (1984), we measure earnings surprise as standardized unexpected earnings (SUE). We calculate SUE as the change in the most recently announced quarterly earnings per share (Compustat quarterly item EPSPXQ) from its value 4 quarters ago, divided by the standard deviation of this change in quarterly earnings over the prior 8 quarters (6 quarters minimum).

For a firm to enter our portfolio formation, we require the end of the fiscal quarter that corresponds to the most recently announced earnings to be within 6 months prior to the portfolio formation. We do so to exclude stale information on earnings. We impose this restriction when constructing the ROE factor and portfolios that use quarterly earnings data. To avoid potentially erroneous records, we also require the earnings announcement date (Compustat quarterly item RDQ) to be after the corresponding fiscal quarter end.

At the beginning of each month t, we split all NYSE, Amex, and NASDAQ stocks into deciles based on their most recent past SUE using NYSE breakpoints. Monthly value-weighted portfolio returns are calculated, separately, for the current month t (SUE-1), from month t to $t+5$ (SUE-6), from month t to $t+11$ (SUE-12), from month $t+12$ to $t+35$ (SUE-13-36), and from month $t+36$ to $t+59$ (SUE-37-60). The deciles are rebalanced monthly. The holding period that is longer than

1 month as in, for instance, SUE-6, means that for a given SUE-6 decile in each month there exist 6 subdeciles, each of which is initiated in a different month in the prior 6-month period. We take the simple average of the subdecile returns as the monthly return of the SUE-6 decile.

A.1.1.2 R6-1, R6-6, R6-12, R6-13-36, R6-37-60, and R11-1. At the beginning of each month t, we split all stocks into deciles based on their prior 6-month returns from month $t-7$ to $t-2$ using NYSE breakpoints. Skipping month $t-1$, we calculate monthly value-weighted decile returns, separately, for month t (R6-1), from month t to $t+5$ (R6-6), from month t to $t+11$ (R6-12), from month $t+12$ to $t+35$ (R6-13-36), and from month $t+36$ to $t+59$ (R6-37-60). All the deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than 1 month as in, for instance, R6-6, means that for a given R6-6 decile in each month there exist 6 subdeciles, each of which is initiated in a different month in the prior 6-month period. We take the simple average of the subdeciles returns as the monthly return of the R6-6 decile.

To construct the R11-1 deciles as in Fama and French (1996), we split all stocks into deciles at the beginning of each month t based on their prior 11-month returns from month $t-12$ to $t-2$ using NYSE breakpoints. Skipping month $t-1$, we calculate monthly value-weighted decile returns for month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.1.3 Abr-1 and Abr-6. Following Chan, Jegadeesh, and Lakonishok (1996), we measure cumulative abnormal stock return (Abr) around the latest quarterly earnings announcement date:

$$\text{Abr}_i = \sum_{d=-2}^{+1} r_{id} - r_{md}, \tag{A1}$$

in which r_{id} is stock i's return on day d (with the earnings announced on day 0), and r_{md} is the return on the market index. We cumulate returns until 1 (trading) day after the announcement date to account for the possibility of 1-day-delayed stock price reaction to earnings news. r_{md} is the value-weighted return on the market index. For a firm to enter our portfolio formation, we require the end of the fiscal quarter that corresponds to the most recently announced earnings to be within 6 months prior to the portfolio formation month.

At the beginning of each month t, we split all stocks into deciles based on their most recent past Abr using NYSE breakpoints. Monthly value-weighted decile returns are calculated for the current month t (Abr-1), and, separately, from month t to $t+5$ (Abr-6). The deciles are rebalanced monthly. The 6-month holding period for Abr-6 means that for a given decile in each month there exist 6 subdeciles, each of which is initiated in a different month in the prior 6-month period. We take the simple average of the subdecile returns as the monthly return of the Abr-6 decile.

A.1.1.4 RE-1 and RE-6. Following Chan, Jegadeesh, and Lakonishok (1996), we also measure earnings surprise as changes in analysts' forecasts of earnings. The earnings forecast data are from the Institutional Brokers' Estimate System (IBES). Because analysts' forecasts are not necessarily revised each month, we construct a 6-month moving average of past changes in analysts' forecasts:

$$\text{RE}_{it} = \sum_{j=1}^{6} \frac{f_{it-j} - f_{it-j-1}}{p_{it-j-1}}, \tag{A2}$$

in which f_{it-j} is the consensus mean forecast (IBES unadjusted file, item MEANEST) issued in month $t-j$ for firm i's current fiscal year earnings (fiscal period indicator = 1), and p_{it-j-1} is the prior month's share price (unadjusted file, item PRICE). We adjust for any stock splits and require a minimum of 4 monthly forecast changes when constructing RE.

At the beginning of each month t, we split all stocks into deciles, based on their RE using NYSE breakpoints. Monthly value-weighted decile returns are calculated for the current month t (RE-1), and, separately, from month t to $t+5$ (RE-6). The deciles are rebalanced monthly. The 6-month holding period for RE-6 means that for a given decile in each month there exist 6 subdeciles, each of which is initiated in a different month in the prior 6-month period. We take the simple average of the subdecile returns as the monthly return of the RE-6 decile. Because of the availability of analysts' forecasts data, the sample for RE-1 and RE-6 decile returns starts in January 1977.

A.1.1.5 I-Mom. Moskowitz and Grinblatt (1999) document profitable industry momentum strategies that buy stocks in past winning industries and sell stocks in past losing industries. We use the Fama-French 49-industry classifications. Excluding financial firms from the sample leaves 45 industries. At the beginning of each month t, we sort industries based on their prior six-month value-weighted returns from $t-6$ to $t-1$. Following Moskowitz and Grinblatt, we do not skip month $t-1$ when measuring industry momentum. We form 9 portfolios ($9\times 5=45$), each of which contains 5 different industries. We define the return of a given portfolio as the equal-weighted average of the 5 industry returns within the portfolio. We hold the 9 portfolios for 6 months from t to $t+5$, and rebalance the portfolios at the beginning of $t+1$. For a given I-Mom portfolio in each month there exist 6 subportfolios, each of which is initiated in a different month in the prior 6-month period. We take their simple average as the monthly return of the I-Mom portfolio.

A.1.2 Value-versus-growth. We start by describing the construction of the 25 size (ME) and book-to-market (B/M) portfolios. In addition, Table 2 lists 12 anomaly variables in this category including B/M, A/ME, Rev, E/P, EF/P, CF/P, D/P, O/P, NO/P, SG, LTG, and Dur.

A.1.2.1 The 25 ME and B/M Portfolios. At the end of June of each year t, we split stocks into quintiles based on the June-end ME (price times shares outstanding from CRSP). Independently, we split stocks into quintiles based on B/M, which is the book equity for the fiscal year ending in calendar year $t-1$ divided by the ME at the end of December of $t-1$. We use NYSE breakpoints for both ME and B/M. Taking intersections, we form 25 ME and B/M portfolios and calculate monthly value-weighted portfolio returns from July of year t to June of $t+1$.

As in Davis, Fama, and French (2000), book equity is stockholders' book equity, plus balance-sheet deferred taxes and investment tax credit (Compustat annual item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if available. If not, stockholders' equity is the book value of common equity (item CEQ) plus the par value of preferred stock (item PSTK), or the book value of assets (item AT) minus total liabilities (item LT). Depending on availability, we use redemption (item PSTKRV), liquidating (item PSTKL), or par value (item PSTK) for the book value of preferred stock.

A.1.2.2 B/M. At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on B/M, which is the book equity for the fiscal year ending in calendar year $t-1$ divided by the ME at the end of December of $t-1$. We calculate monthly value-weighted decile returns from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. We measure book equity as in Davis, Fama, and French (2000, see Section A.1.2.1).

A.1.2.3 A/ME. We measure A/ME as the ratio of total book assets to ME. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on A/ME. Total assets (Compustat annual item AT) are from the fiscal year ending in calendar year $t-1$ and the ME (price per share times shares outstanding from Compustat or CRSP) is at the end of December of $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.2.4 Rev. To capture the long-term reversal (Rev) effect, at the beginning of each month t, we use NYSE breakpoints to split stocks into deciles based on the prior returns from month $t-60$ to $t-13$. Monthly value-weighted decile returns are computed for month t, and the deciles are rebalanced at the beginning of $t+1$. To be included in a portfolio for month t, a stock must have a valid price at the end of $t-61$ and a valid return for $t-13$. In addition, any missing returns from month $t-60$ to $t-14$ must be -99.0, which is the CRSP code for a missing price.

A.1.2.5 E/P. To construct the Basu (1983) earnings-to-price (E/P) deciles, we use NYSE breakpoints to split stocks into deciles based on E/P at the end of June of each year t. E/P is calculated as income before extraordinary items (Compustat annual item IB) for the fiscal year ending in calendar year $t-1$ divided by the ME (from Compustat or CRSP) at the end of December of $t-1$. Stocks with negative earnings are excluded. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.2.6 EF/P. Following Elgers, Lo, and Pfeiffer (2001), we measure analysts' earnings forecasts-to-price (EF/P) as the consensus median forecasts (IBES unadjusted file, item MEDEST) for the current fiscal year (fiscal period indicator = 1) divided by share price (unadjusted file, item PRICE). At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on EF/P estimated with forecasts in month $t-1$. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of $t+1$. Because the earnings forecast data start in January 1976, the EF/P decile returns start in February 1976.

A.1.2.7 CF/P. We measure cash flows (CF) as income before extraordinary items (Compustat annual item IB), plus equity's share of depreciation (item DP), plus deferred taxes (if available, item TXDI). The equity's share is defined as ME divided by total assets (item AT) minus book equity plus ME. ME is share price times shares outstanding from Compustat or CRSP. We measure book equity as in Davis, Fama, and French (2000, see Section A.1.2.1).

At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles, based on CF for the fiscal year ending in calendar year $t-1$ divided by the ME at the end of December of $t-1$. We exclude firms with negative CFs. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.2.8 D/P. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on their dividend yields, which are the total dividends paid out from July of year $t-1$ to June of t divided by the ME (from CRSP) at the end of June of t. We calculate monthly dividends as the begin-of-month ME times the difference between cum- and ex-dividend returns. Monthly dividends are then accumulated from July of $t-1$ to June of t. We exclude firms that do not pay dividends. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.2.9 O/P and NO/P. As in Boudoukh et al. (2007), total payouts are dividends on common stock (Compustat annual item DVC) plus repurchases. Repurchases are the total expenditure on the purchase of common and preferred stocks (item PRSTKC) plus any reduction (negative change over the prior year) in the value of the net number of preferred stocks outstanding (item PSTKRV). Net payouts equal total payouts minus equity issuances, which are the sale of common and preferred stock (item SSTK) minus any increase (positive change over the prior year) in the value of the net number of preferred stocks outstanding.

At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on total payouts (O/P) (net payouts, NO/P) for the fiscal year ending in calendar year $t-1$ divided by the ME at the end of December of $t-1$. We exclude firms with non-positive total payouts (zero net payouts). Monthly value-weighted decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Because the data on total expenditure and the sale of common and preferred stocks start in 1971, the O/P (NO/P) decile returns start in July 1972.

A.1.2.10 SG. Following Lakonishok, Shleifer, and Vishny (1994), we measure sales growth (SG) in June of year t as the weighted average of the annual SG ranks for the prior 5 years, $\sum_{j=1}^{5}(6-j)\times\text{Rank}(t-j)$. The SG for year $t-j$ is the growth rate in sales (COMPUSTAT annual item SALE) from fiscal year ending in $t-j-1$ to fiscal year ending in $t-j$. Only firms with data for all 5 prior years are used to determine the annual SG ranks. For each year from $t-5$ to $t-1$, we rank stocks into deciles based on their annual SG, and then assign rank i ($i=1,\ldots,10$) to a firm if its annual SG falls into the i^{th} decile. At the end of June of each year t, we use NYSE breakpoints to assign stocks into deciles based on SG, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.2.11 LTG. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on analysts' consensus median forecast of the long-term earnings growth rate (IBES item MEDEST, fiscal period indictor = 0). Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced monthly. Because the long-term growth forecast data start in December 1981, the LTG decile returns start in January 1982.

A.1.2.12 Dur. Per Dechow, Sloan, and Soliman (2004), we calculate equity duration as:

$$\text{Dur}=\frac{\sum_{t=1}^{T} t\times \text{CD}_t/(1+r)^t}{\text{ME}}+\left(T+\frac{1+r}{r}\right)\frac{P-\sum_{t=1}^{T}\text{CD}_t/(1+r)^t}{\text{ME}}, \tag{A3}$$

in which CD_t is the net cash distribution in year t, ME is market equity, T is the length of forecasting period, and r is the cost of equity. ME is price per share times shares outstanding (Compustat annual item PRCC_F times item CSHO). Net cash distribution, $\text{CD}_t=\text{BE}_{t-1}(\text{ROE}_t-g_t)$, in which BE_{t-1} is the book equity at the end of year $t-1$, ROE_t is return on equity in year t, and g_t is the book equity growth in t. We model ROE as a first-order autoregressive process with an autocorrelation coefficient of 0.57 and a long-run mean of 0.12, and the growth in book equity as a first-order autoregressive process with an autocorrelation coefficient of 0.24 and a long-run mean of 0.06. For the starting year ($t=0$), we measure ROE as income before extraordinary items (item IB) divided by 1-year-lagged book equity (item CEQ), and the book equity growth rate as the annual change in sales (item SALE). Finally, we use a forecasting period of $T=10$ years and a cost of equity of $r=0.12$.

At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on Dur for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.3 Investment. Table 2 lists 14 anomaly variables in this category, including ACI, I/A, NOA, △PI/A, IG, NSI, CEI, NXF, IvG, IvC, OA, TA, POA, and PTA.

A.1.3.1 ACI. Following Titman, Wei, and Xie (2004), we measure ACI at the end of June of year t as $\text{CE}_{t-1}/[(\text{CE}_{t-2}+\text{CE}_{t-3}+\text{CE}_{t-4})/3]-1$, in which CE_{t-j} is capital expenditure (Compustat annual item CAPX) scaled by sales (item SALE) for the fiscal year ending in calendar year $t-j$. The last 3-year average capital expenditure is designed to project the benchmark investment at the portfolio formation year. We exclude firms with sales less than 10 million dollars. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on their ACI. Monthly value-weighted decile returns are computed from July of year t to June of $t+1$.

A.1.3.2 I/A. Following Cooper, Gulen, and Schill (2008), we measure investment-to-assets, I/A, for the portfolio formation year t as total assets (Compustat annual item AT) for the fiscal year ending in calendar year $t-1$ divided by total assets for the fiscal year ending in $t-2$ minus 1. At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on I/A, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.3.3 NOA. Following Hirshleifer et al. (2004), we define net operating assets (NOA) as operating assets minus operating liabilities. Operating assets are total assets (COMPUSTAT annual item AT) minus cash and short-term investment (item CHE). Operating liabilities are total assets minus debt included in current liabilities (item DLC, zero if missing), minus long-term debt (item DLTT, zero if missing), minus minority interests (item MIB, zero if missing), minus preferred stocks (item PSTK, zero if missing), and minus common equity (item CEQ). At the end of June of each year t, we use NYSE breakpoints to assign stocks into deciles based on NOA for the fiscal year ending in calendar year $t-1$ scaled by total assets for the fiscal year ending in $t-2$, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.3.4 △PI/A. Following Lyandres, Sun, and Zhang (2008), we measure △PI/A as changes in gross property, plant, and equipment (Compustat annual item PPEGT) plus changes in inventory (item INVT) scaled by lagged total assets (item AT). At the end of June of each year t, we use NYSE breakpoints to assign stocks into deciles based on △PI/A for the fiscal year ending in calendar year $t-1$, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.3.5 IG. Following Xing (2008), we measure investment growth (IG) for the portfolio formation year t as the growth rate in capital expenditure (Compustat annual item CAPX) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on IG, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.3.6 NSI. Following Fama and French (2008), at the end of June of year t, we measure net stock issues (NSI) as the natural log of the ratio of the split-adjusted shares outstanding at the fiscal year ending in calendar year $t-1$ to the split-adjusted shares outstanding at the fiscal year ending in $t-2$. We measure the split-adjusted shares outstanding as shares outstanding (Compustat annual item CSHO) times the adjustment factor (item AJEX). At the end of June of each year t, we use NYSE breakpoints to sort all stocks into deciles based on NSI. We exclude firms with zero NSI. Monthly value-weighted decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.3.7 CEI. We measure CEI as the growth rate in the ME not attributable to the stock return, $\log(\mathrm{ME_t}/\mathrm{ME_{t-5}})-r(t-5,t)$. For the portfolio formation at the end of June of year t, $r(t-5,t)$ is the cumulative log return on the stock from the last trading day of June in year $t-5$ to the last trading day of June in year t, and ME_t is the ME on the last trading day of June in year t from CRSP. Equity issuance such as seasoned equity issues, employee stock option plans, and share-based acquisitions increase the composite issuance, whereas repurchase activities such as share repurchases and cash dividends reduce the composite issuance. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles on CEI, and calculate monthly value-weighted decile returns from July of year t to June of year $t+1$.

A.1.3.8 NXF. Following Bradshaw, Richardson, and Sloan (2006), we measure net external financing (NXF) as the sum of net equity financing and net debt financing. Net equity financing is the proceeds from the sale of common and preferred stocks (Compustat annual item SSTK) less cash payments for the repurchases of common and preferred stocks (item PRSTKC) less cash payments for dividends (item DV). Net debt financing is the cash proceeds from the issuance of long-term debt (item DLTIS) less cash payments for long-term debt reductions (item DLTR) plus the net changes in current debt (item DLCCH, zero if missing). At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on NXF for the fiscal year ending in calendar year $t-1$ scaled by the average of total assets for fiscal years ending in $t-2$ and $t-1$. We exclude firms with zero NXF. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Because the coverage of the financing data starts in 1971, the NXF decile returns start in July 1972.

A.1.3.9 IvG. We define inventory growth (IvG) for the portfolio formation year t as the growth rate in inventory (Compustat annual item INVT) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on IvG. We exclude firms with zero IvC (most of these firms carry no inventory). Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the decile returns are rebalanced in June of $t+1$.

A.1.3.10 IvC. Following Thomas and Zhang (2002), we define inventory changes (IvC) for the portfolio formation year t as the change in inventory (Compustat annual item INVT) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$, scaled by the average of total assets for fiscal years ending in $t-2$ and $t-1$. At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on IvC. We exclude firms with zero IvC (most of these firms carry no inventory). Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.3.11 OA. Prior to 1988, we use the balance-sheet approach of Sloan (1996) to measure operating accruals (OA) as changes in noncash working capital minus depreciation, in which the noncash working capital is changes in noncash current assets minus changes in current liabilities less short-term debt and taxes payable. In particular, OA equals $(\triangle CA-\triangle CASH)-(\triangle CL-\triangle STD-\triangle TP)-\text{DP}$, in which $\triangle CA$ is the change in current assets (Compustat annual item ACT), $\triangle CASH$ is the change in cash or cash equivalents (item CHE), $\triangle CL$ is the change in current liabilities (item LCT), $\triangle STD$ is the change in debt included in current liabilities (item DLC, zero if missing), $\triangle TP$ is the change in income taxes payable (item TXP, zero if missing), and DP is depreciation and amortization (item DP, zero if missing). Starting from 1988, we follow Hribar and Collins (2002) to measure OA using the statement of cash flows as net income (item NI) minus net cash flow from operations (item OANCF). Doing so helps mitigate measurement errors that can arise from nonoperating activities such as acquisitions and divestitures. Data from the statement of cash flows are only available since 1988. To construct the OA deciles, at the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on OA for the fiscal year ending in calendar year $t-1$ scaled by total assets (item AT) for the fiscal year ending in $t-2$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.3.12 TA. Prior to 1988, we use the balance-sheet approach in Richardson et al. (2005) to measure total accruals (TA) as $\triangle WC+\triangle NCO+\triangle FIN$. $\triangle WC$ is the change in net non-cash working capital. Net non-cash working capital is current operating asset (COA) minus current operating liabilities (COL), with COA = current assets (Compustat annual item ACT) minus cash and short-term investments (item CHE) and COL = current liabilities (item LCT) minus debt in current liabilities (item DLC, zero if missing). $\triangle NCO$ is the change in net non-current operating assets. Net non-current operating assets is non-current operating assets ($NCOA$) minus non-current operating liabilities ($NCOL$), with $NCOA$ = total assets (item AT) minus current assets (item ACT) minus investments and advances (item IVAO, zero if missing), and $NCOL$ = total liabilities (item LT) minus current liabilities (item LCT) minus long-term debt (item DLTT, zero if missing). $\triangle FIN$ is the change in net financial assets. Net financial assets is financial assets ($FINA$) minus financial liabilities ($FINL$), with $FINA$= short-term investments (item IVST, zero if missing) plus long-term investments (item IVAO, zero if missing), and $FINL$= long-term debt (item DLTT, zero if missing) plus debt in current liabilities (item DLC, zero if missing) plus preferred stock (item PSTK, zero if missing).

Starting from 1988, we use the cash flow approach to measure TA as net income (Compustat annual item NI) minus total operating, investing, and financing cash flows (items OANCF, IVNCF, and FINCF) plus sales of stocks (item SSTK, zero if missing) minus stock repurchases and dividends (items PRSTKC and DV, zero if missing). Data from the statement of cash flows are only available since 1988. We use NYSE breakpoints to sort stocks at the end of June of each year t into deciles based on TA for the fiscal year ending in calendar year $t-1$ scaled by total assets (Compustat annual item AT) for the fiscal year ending in $t-2$. We calculate monthly value-weighted decile returns from July of year t to June of $t+1$, and rebalance the deciles in June of $t+1$.

A.1.3.13 POA. Accruals are traditionally scaled by total assets. Hafzalla, Lundholm, and Van Winkle (2011) show that scaling accruals by the absolute value of earnings (percent accruals) is more effective in selecting firms for which the differences between sophisticated and naive forecasts of earnings are the most extreme. To construct the percent operating accruals (POA) deciles, at the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on OA scaled by the absolute value of net income (Compustat annual item NI) for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.3.14 PTA. We use NYSE breakpoints to sort stocks at the end of June of each year t into deciles based on total accurals (TA) scaled by the absolute value of net income (Compustat annual item NI) for the fiscal year ending in calendar year $t-1$. We calculate value-weighted decile returns from July of year t to June of $t+1$, and rebalance the deciles in June of $t+1$.

A.1.4 Profitability. Table 2 lists 14 anomaly variables in this category, including ROE, ROA, RNA, PM, ATO, CTO, GP/A, F, TES, TI/BI, RS, NEI, FP, and O.

A.1.4.1 ROE. ROE is income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged book equity. Book equity is shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (item TXDITCQ) if available, minus the book value of preferred stock. Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ), in that order, as shareholders' equity. We use redemption value (item PSTKRQ) if available, or carrying value for the book value of preferred stock.

At the beginning of each month t, we use NYSE breakpoints to sort all stocks into deciles based on ROE computed with the most recently announced quarterly earnings. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced monthly. Earnings data in Compustat quarterly files are used in the monthly sorts in the months immediately after the most recent public earnings announcement dates (item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to the most recently announced earnings to be within 6 months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information.

A.1.4.2 ROA. We measure ROA as income before extraordinary items (Compustat quarterly item IBQ) divided by 1-quarter-lagged total assets (item ATQ). At the beginning of each month t, we use NYSE breakpoints to sort all stocks into deciles based on ROA computed with the most recently announced quarterly earnings. Monthly value-weighted decile returns are calculated for month t, and the deciles are rebalanced at the beginning of $t+1$. For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to the most recently announced earnings to be within 6 months prior to the portfolio formation to exclude stale earnings information.

A.1.4.3 RNA, PM, and ATO. Following Soliman (2008), we use DuPont analysis to decompose ROE as RNA + FLEV × SPREAD, in which ROE is return on equity, RNA is return on net operating assets, FLEV is financial leverage, and SPREAD is the difference between return on net operating assets and borrowing costs. We further decompose RNA = PM × ATO, in which PM is profit margin (operating income/sales) and ATO is asset turnover (sales/net operating assets).

We use annual sorts to form RNA, PM, and ATO deciles. At the end of June of year t, we measure RNA as operating income after depreciation (Compustat annual item OIADP) for the fiscal year ending in calendar year $t-1$ divided by net operating assets (NOA) for the fiscal year ending in $t-2$. NOA is operating assets minus operating liabilities. Operating assets are total assets (item AT) less cash and short-term investments (CHE) less other investment and advances (item IVAO, zero if missing). Operating liabilities are total assets (item AT), less the long- and short-term portions of debt (items DLTT and DLC, zero if missing), less minority interest (item MIB, zero if missing), less book value of preferred equity (items PSTK, zero if missing), less book value of common equity (items CEQ). PM is operating income after depreciation (item OIADP) divided by sales (item SALE) for the fiscal year ending in calendar year $t-1$. ATO is sales (item SALE) for the fiscal year ending in calendar year $t-1$ divided by NOA for the fiscal year ending in $t-2$. At the end of June of each year t, we use NYSE breakpoints to sort stocks into 3 sets of deciles based on RNA, PM, and ATO. We exclude firms with nonpositive NOA for the fiscal year ending in calendar year $t-2$ when forming the RNA and the ATO deciles. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.4.4 CTO. To construct the Haugen and Baker (1996) capital turnover (CTO) deciles, at the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on sales (Compustat annual item SALE) divided by 1-year-lagged total assets (item AT) for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.4.5 GP/A. Following Novy-Marx (2013), we measure gross profits-to-assets (GP/A) as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS) divided by total assets (item AT, the denominator is current, not lagged, total assets). At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on GP/A for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.4.6 *F*. Piotroski (2000) classifies each firm's fundamental signal as either good or bad depending on the signal's implication for future stock prices and profitability. An indicator variable for a particular signal is 1 if its realization is good and zero if it is bad. The aggregate signal, denoted F, is the sum of the 9 binary signals. F is designed to measure the overall quality, or strength, of the firm's financial position. Nine fundamental signals are chosen to measure 3 areas of a firm's financial condition, profitability, liquidity, and operating efficiency.

Four variables are selected to measure profitability-related factors:

- ROA is income before extraordinary items (Compustat annual item IB) scaled by 1-year-lagged total assets (item AT). If the firm's ROA is positive, the indicator variable F_{ROA} equals 1, and zero otherwise.
- CFO is cash flow from operation scaled by 1-year-lagged total assets (Compustat annual item AT). Cash flow from operation is item OANCF, available after 1988. Prior to that, we use funds from operation (item FOPT) minus the annual change in working capital (item WCAP). If the firm's CFO is positive, the indicator variable F_{CFO} equals 1, and zero otherwise.

- ΔROA is the current year's ROA less the prior year's ROA. If ΔROA is positive, the indicator variable $F_{\Delta\text{ROA}}$ is 1, and zero otherwise.
- Sloan (1996) shows that earnings driven by positive accrual adjustments are a bad signal about future earnings. As such, the indicator F_{ACC} equals 1, if CFO is greater than ROA, and zero otherwise.

Three variables are selected to measure changes in capital structure and a firm's ability to meet future debt obligations. Piotroski (2000) assumes that an increase in leverage, a deterioration of liquidity, or the use of external financing is a bad signal about financial risk.

- ΔLEVER is the change in the ratio of total long-term debt (Compustat annual item DLTT) to average total assets over the prior 2 years. $F_{\Delta\text{LEVER}}$ is 1 if the firm's leverage ratio falls (i.e., $\Delta\text{LEVER} < 0$) in the year preceding portfolio formation, and zero otherwise.
- ΔLIQUID measures the change in a firm's current ratio between the current and prior years, in which the current ratio is the ratio of current assets (Compustat annual item ACT) to current liabilities (item LCT). An improvement in liquidity ($\Delta\text{LIQUID} > 0$) is a good signal about the firm's ability to service current debt obligations. The indicator $F_{\Delta\text{LIQUID}}$ equals 1 if the firm's liquidity improves, and zero otherwise.
- The indicator, EQ, equals 1 if the firm does not issue common equity in the year prior to portfolio formation, and zero otherwise. The issuance of common equity is sales of common and preferred stocks (Compustat annual item SSTK) minus any increase in preferred stock (item PSTK). Issuing equity is interpreted as a bad signal (inability to generate sufficient internal funds to service future obligations).

The remaining 2 signals are designed to measure changes in the efficiency of the firm's operations that reflect 2 key constructs underlying the decomposition of return on assets.

- ΔMARGIN is the firm's current gross margin ratio, measured as gross margin (Compustat annual item SALE minus item COGS) scaled by sales (item SALE), less the prior year's gross margin ratio. An improvement in margins signifies a potential improvement in factor costs, a reduction in inventory costs, or a rise in the price of the firm's product. The indictor $F_{\Delta\text{MARGIN}}$ equals 1 if $\Delta\text{MARGIN} > 0$ and zero otherwise.
- ΔTURN is the firm's current year asset turnover ratio, measured as total sales (Compustat annual item SALE) scaled by 1-year-lagged total assets (item AT), minus the prior year's asset-turnover ratio. An improvement in this ratio signifies greater asset productivity. The indicator, $F_{\Delta\text{TURN}}$, equals 1 if ΔTURN is positive, and zero otherwise.

Piotroski (2000) forms a composite score, F, as the sum of the individual binary signals:

$$F = F_{\text{ROA}} + F_{\Delta\text{ROA}} + F_{\text{CFO}} + F_{\text{ACC}} + F_{\Delta\text{MARGIN}} + F_{\Delta\text{TURN}} + F_{\Delta\text{LEVER}} + F_{\Delta\text{LIQUID}} + EQ. \quad \text{(A4)}$$

At the end of June of each year t, we sort stocks based on F for the fiscal year ending in calender year $t-1$ to form 7 portfolios: low ($F = 0,1,2$), 3, 4, 5, 6, 7, and high ($F = 8,9$). Because extreme F scores are rare, we combine scores 0, 1, and 2 into the low portfolio, and scores 8 and 9 into the high portfolio. Monthly value-weighted portfolio returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June of $t+1$. Because the data on equity offering start in 1971, the F portfolio returns start in July 1972.

A.1.4.7 TES. Following Thomas and Zhang (2011), we measure tax expense surprise (TES) as changes in tax expense, which is tax expense per share (Compustat quarterly item TXTQ/(item CSHPRQ times item AJEXQ)) in quarter q minus tax expense per share in quarter $q-4$, scaled by assets per share (item ATQ/(item CSHPRQ times item AJEXQ)) in quarter $q-4$. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on their TES calculated with Compustat quarterly data items from at least 4 months ago. We exclude firms with zero TES (most of these firms pay no taxes). We calculate deciles returns for the subsequent 3 months from t to $t+2$, and the portfolios are rebalanced at the beginning of month $t+1$. The 3-month holding period means that in each month for any given TES decile there exist 3 subdeciles. We take the simple average of the value-weighted subdecile returns as the monthly return of the TES decile. For sufficient data coverage, we start the TES deciles in January 1976.

A.1.4.8 TI/BI. Following Green, Hand, and Zhang (2013), we measure taxable income-to-book income (TI/BI) as pretax income (Compustat annual item PI) divided by net income (item NI). At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles, based on TI/BI for the fiscal year ending in calendar year $t-1$. We exclude firms with negative or zero net income. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$.

A.1.4.9 RS. Following Jegadeesh and Livnat (2006), we measure revenue surprise (RS) as the change in revenue per share (Compustat quarterly item SALEQ/(item CSHPRQ times item AJEXQ)) from its value 4 quarters ago divided by the standard deviation of this change in quarterly revenue per share over the prior 8 quarters (6 quarters minimum). Jegadeesh and Livnat argue that quarterly revenue data are available when earnings are announced. As such, we use the same timing convention as for the SUE-1 deciles. At the beginning of each month t, we use NYSE breakpoints to split stocks into deciles, based on RS at the most recent quarterly earnings announcement date (item RDQ). Monthly value-weighted deciles returns are calculated for the current month t. To avoid stale information, we require the end of the fiscal quarter that corresponds to the most recent quarterly earnings announcement to be within 6 months prior to the portfolio formation.

A.1.4.10 NEI. We follow Barth, Elliott, and Finn (1999) and Green, Hand, and Zhang (2013) in measuring NEI as the number of consecutive quarters (up to 8 quarters) with an increase in earnings (Compustat quarterly item IBQ) over the same quarter in the prior year. At the beginning of each month t, we sort stocks into 9 portfolios (with NEI $= 0, 1, 2, \ldots, 7$, and 8, respectively) based on NEI calculated at the most recent earnings announcement date (item RDQ). To avoid stale information, we require the end of the fiscal quarter that corresponds to the most recent earnings announcement to be within 6 months prior to the portfolio formation. We calculate monthly value-weighted portfolio returns for the current month t and rebalance the portfolios at the beginning of $t+1$.

A.1.4.11 FP. We construct failure probability (FP) following Campbell, Hilscher, and Szilagyi (2008, the third column in Table IV):

$$\begin{aligned} \mathrm{FP}_t \equiv & -9.164 - 20.264 NIMTAAVG_t + 1.416 TLMTA_t - 7.129 EXRETAVG_t \\ & + 1.411 SIGMA_t - 0.045 RSIZE_t - 2.132 CASHMTA_t + 0.075 MB_t - 0.058 PRICE_t \end{aligned} \tag{A5}$$

in which

$$NIMTAAVG_{t-1,t-12} \equiv \frac{1-\phi^3}{1-\phi^{12}} \left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12} \right) \tag{A6}$$

$$EXRETAVG_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}} \left(EXRET_{t-1} + \cdots + \phi^{11} EXRET_{t-12} \right), \tag{A7}$$

and $\phi = 2^{-1/3}$. $NIMTA$ is net income (Compustat quarterly item NIQ) divided by the sum of market equity (share price times the number of shares outstanding from CRSP) and total liabilities (item LTQ). The moving average *NIMTAAVG* captures the idea that a long history of losses is a better predictor of bankruptcy than 1 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 $EXRETAVG$ captures 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 annualized 3-month rolling sample standard deviation: $\sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$, in which k is the index of trading days in months $t-1$, $t-2$, and $t-3$, r_k is the firm-level daily return, and N is the total number of trading days in the 3-month period. $SIGMA$ is treated as missing if there are less than five nonzero observations over the three months in the rolling window. $RSIZE$ is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index. $CASHMTA$, used to capture the liquidity position of the firm, is the ratio of cash and short-term investments (Compustat quarterly item CHEQ) divided by the sum of market equity and total liabilities (item LTQ).

MB is the market-to-book equity, in which book equity is measured in the same way as the denominator of ROE. Following Campbell et al., we add 10% of the difference between the market equity and the book equity to the book equity to alleviate measurement issues for extremely small book equity values. For firm-month observations that still have negative book equity after this adjustment, we replace these negative values with \$1, to ensure that the market-to-book ratios for these firms are in the right tail of the distribution. $PRICE$ is each firm's log price per share, truncated above at \$15. We further eliminate stocks with prices less than \$1 at the portfolio formation date. We winsorize the variables on the right-hand side of Equation (A5) at the 5th and 95th percentiles of their pooled distribution across all firm-month observations.

To construct the FP deciles, at the beginning of each month t, we use NYSE breakpoints to split stocks into deciles based on FP calculated with accounting data from the fiscal quarter ending at least 4 months ago. Because unlike earnings, other quarterly data items in the definition of FP might not be available upon earnings announcement, we impose a 4-month gap between the fiscal quarter end and portfolio formation to guard against look-ahead bias. We calculate decile returns for the subsequent 6 months after the portfolio formation from month t to $t+5$ and rebalance the deciles at the beginning of $t+1$. (Holding the decile returns for only the current month t yields an insignificant average return of -0.47% per month ($t=-1.25$) for the high-minus-low FP decile.) Because of the 6-month holding period, there exist 6 subdeciles for a given FP decile in each month. We take the simple average of the value-weighted subdecile returns as the monthly return of the FP decile. Because of the limited data coverage, we start the FP deciles in January 1976.

A.1.4.12 *O*. We follow Ohlson (1980, Model 1 in Table 4) to construct O-score:

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

in which TA is total assets (Compustat annual item AT). $TLTA$ is the leverage ratio defined as the book value of debt (item DLC plus item DLTT) divided by total assets. $WCTA$ is working capital divided by total assets, (item ACT minus item LCT)/item AT. $CLCA$ is current liability (item LCT) divided by current assets (item ACT). $OENEG$ is 1 if total liabilities (item LT) exceeds total assets (item AT) and is zero otherwise. $NITA$ is net income (item NI) divided by total assets. $FUTL$ is the fund provided by operations (item PI) divided by total liabilities (item LT). $INTWO$ is equal to 1 if net income (item NI) is negative for the last 2 years, and zero otherwise. $CHIN$ is $(NI_t - NI_{t-1})/(|NI_t|+|NI_{t-1}|)$, in which NI_t is net income (item NI).

At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on O-score for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.5 Intangibles. Table 2 lists 11 anomaly variables in this category, including OC/A, BC/A, Ad/M, RD/S, RD/M, RC/A, H/N, OL, G, AccQ, and Ind.

A.1.5.1 OC/A. Following Eisfeldt and Papanikolaou (2013), we construct the stock of organization capital (OC) using Selling, General, and Administrative (SG&A) expenses (Compustat annual item XSGA). OC is constructed with the perpetual inventory method:

$$\mathrm{OC}_{it} = (1-\delta)\mathrm{OC}_{it-1} + \mathrm{SG\&A}_{it}/CPI_t, \tag{A8}$$

in which CPI_t is the consumer price index during year t and δ is the annual depreciation rate of OC. The initial stock of OC is $\mathrm{OC}_{i0} = \mathrm{SG\&A}_{i0}/(g+\delta)$, in which $\mathrm{SG\&A}_{i0}$ is the first valid SG&A observation (zero or positive) for firm i, and g is the long-term growth rate of SG&A. Following Eisfeldt and Papanikolaou, we assume a depreciation rate of 15% for OC, and a long-term growth rate of 10% for SG&A. Missing SG&A values after the starting date are treated as zero. For portfolio formation at the end of June of year t, we require SG&A to be nonmissing for the fiscal year ending in calendar year $t-1$ because this SG&A value receives the highest weight in OC. In addition, we exclude firms with zero OC. We form organization capital-to-assets (OC/A) by scaling OC with total assets (item AT) from the same fiscal year.

We industry-standardize OC/A using the Fama-French (1997) 17-industry classification. We demean a firm's OC/A by its industry mean and then divide the demeaned OC/A by the standard deviation of OC/A within its industry. When computing industry mean and standard deviation, we winsorize OC/A at the 1 and 99 percentiles of all firms each year. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on OC/A for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.5.2 BC/A. Following Belo, Lin, and Vitorino (2014), we construct brand capital (BC) by accumulating advertising expenses (Compustat annual item XAD):

$$\mathrm{BC}_{it} = (1-\delta)\mathrm{BC}_{it-1} + \mathrm{XAD}_{it}, \tag{A9}$$

in which δ is the annual depreciation rate of BC. The initial stock of BC is $\mathrm{BC}_{i0} = \mathrm{XAD}_{i0}/(g+\delta)$, in which XAD_{i0} is first valid XAD (zero or positive) for firm i, and g is the long-term growth rate of XAD. We assume a depreciation rate of 50% for BC, and a long-term growth rate of 10% for XAD. Missing values of XAD after the starting date are treated as zero. For the portfolio formation at the end of June of year t, we exclude firms with zero BC and require XAD to be nonmissing for the fiscal year ending in calendar year $t-1$. We form brand capital-to-assets (BC/A) by scaling BC with total assets (item AT) from the same fiscal year.

At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on BC/A for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Because sufficient XAD data start in 1972, the BC/A decile returns start in July 1973.

A.1.5.3 Ad/M. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on advertising expenses-to-market (Ad/M), which is advertising expenses (Compustat annual item XAD) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from Compustat or CRSP) at the end of December of $t-1$. We keep only firms with positive advertising expenses. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$. Because sufficient XAD data start in 1972, the BC/A decile returns start in July 1973.

A.1.5.4 RD/S. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on R&D-to-sales, which is R&D expenses (Compustat annual item XRD) divided by sales (item SALE) for the fiscal year ending in calendar year $t-1$. We keep only firms with positive R&D expenses. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$. Because the accounting treatment of R&D expenses was standardized in 1975 (by Financial Accounting Standards Board Statement No. 2), the sample starts in July 1976.

A.1.5.5 RD/M. At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on R&D-to-market (RD/M), which is R&D expenses (Compustat annual item XRD) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from Compustat or CRSP) at the end of December of $t-1$. We keep only firms with positive R&D expenses. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Because the accounting treatment of R&D expenses was standardized in 1975, the RD/M decile returns start in July 1976.

A.1.5.6 RC/A. Per Li (2011), we measure R&D capital (RC) as a weighted average of R&D expenses (Compustat annual item XRD) over the last 5 years with a depreciation rate of 20%:

$$\mathrm{RC}_{it} = \mathrm{XRD}_{it} + 0.8\mathrm{XRD}_{it-1} + 0.6\mathrm{XRD}_{it-2} + 0.4\mathrm{XRD}_{it-3} + 0.2\mathrm{XRD}_{it-4}. \tag{A10}$$

We scale RC with total assets (item AT) to form R&D capital-to-assets (RC/A). At the end of June of each year t, we use NYSE breakpoints to split stocks into deciles based on RC/A for the fiscal year ending in calendar year $t-1$. We keep only firms with positive RC. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. For portfolio formation at the end of June of year t, we require R&D expenses to be nonmissing for the fiscal year ending in calendar year $t-1$, because this value of R&D expenses receives the highest weight in RC. Because RC requires past 5 years of R&D expenses and the accounting treatment of R&D expenses was standardized in 1975, the sample starts in July 1980.

A.1.5.7 H/N. Following Belo, Lin, and Bazdresch (2014), at the end of June of year t, we measure the firm-level hiring rate (H/N) as $(N_{t-1} - N_{t-2})/(0.5N_{t-1} + 0.5N_{t-2})$, in which N_{t-1} is the number of employees (Compustat annual item EMP) from the fiscal year ending in calendar year $t-1$. At the end of June of year t, we use NYSE breakpoints to sort stocks into deciles based on H/N. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$.

A.1.5.8 OL. Following Novy-Marx (2011), we measure operating leverage (OL) as operating costs scaled by total assets (Compustat annual item AT, the denominator is current, not lagged, total assets). Operating costs are the cost of goods sold (item COGS) plus selling, general, and administrative expenses (item XSGA). At the end of June of year t, we use NYSE breakpoints to sort stocks into deciles based on OL for the fiscal year ending in calendar year $t-1$, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.5.9 G. The data for Gompers, Ishii, and Metrick (2003) corporate governance index (G, from September 1990 to December 2006) are from Andrew Metrick's Web site. To form the G portfolios, we use the following breakpoints: $G \leq 5, 6, 7, 8, 9, 10, 11, 12, 13$, and ≥ 14 (see Table VI, Gompers et al.). We rebalance the portfolios in the months immediately following each publication of the G-index, and calculate monthly value-weighted portfolio returns between 2 adjacent publication dates. The first months following the publication dates are September 1990, July 1993, July 1995, February 1998, November 1999, January 2002, January 2004, and January 2006.

A.1.5.10 AccQ. Following Francis et al. (2005), we estimate accrual quality (AccQ) with the following cross-sectional regression (all variables are scaled by lagged total assets):

$$TCA_{it} = \phi_{0,i} + \phi_{1,i} CFO_{it-1} + \phi_{2,i} CFO_{it} + \phi_{3,i} CFO_{it+1} + \phi_{4,i} \triangle REV_{it} + \phi_{5,i} PPE_{it} + v_{it}, \tag{A11}$$

in which TCA_{it} is firm i's total current accruals in year t, CFO_{it} is cash flow from operations in t, $\triangle REV_{it}$ is change in revenues (Compustat annual item SALE) between $t-1$ and t, and PPE_{it} is gross property, plant, and equipment (item PPEGT) in t. $TCA_{it} = \triangle CA_{it} - \triangle CL_{it} - \triangle CASH_{it} + \triangle STDEBT_{it}$, in which $\triangle CA_{it}$ is firm i's change in current assets (item ACT) between year $t-1$ and t, $\triangle CL_{it}$ is change in current liabilities (item LCT), $\triangle CASH_{it}$ is change in cash (item CHE), and $\triangle STDEBT_{it}$ is change in debt in current liabilities (item DLC, zero if missing). $CFO_{it} = NIBE_{it} - TA_{it}$, in which $NIBE_{it}$ is income before extraordinary items (item IB). $TA_{it} = \triangle CA_{it} - \triangle CL_{it} - \triangle CASH_{it} + \triangle STDEBT_{it} - DEPN_{it}$, in which $DEPN_{it}$ is depreciation and amortization expense (item DP, zero if missing).

We estimate annual cross-sectional regressions in Equation (A11) for each of Fama-French (1997) 48 industries (excluding 4 financial industries), with at least 20 firms in year t. We winsorize the regressors at the 1 and 99 percentiles of all firms each year. The annual cross-sectional regressions yield firm- and year-specific residuals, v_{it}. We measure accrual quality, $\text{AccQ}_{it} = \sigma(v_i)_t$, as the standard deviation of firm i's residuals, v_{it}, calculated over years $t-4$ through t.

At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on AccQ for the fiscal year ending in calendar year $t-2$. To avoid look-ahead bias, we do not sort on AccQ for the fiscal year ending in $t-1$, because the regression in Equation (A11) requires the next year's CFO. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

A.1.5.11 Ind. At the end of June of each year t, we use the industry classifications from Kenneth French's Web site to assign stocks into 10 industry portfolios based on SIC codes (Compustat annual item SICH) for the fiscal year ending in calendar year $t-1$. When Compustat SIC codes are unavailable, we use CRSP SIC codes (CRSP item SICCD) for June of year t. Monthly value-weighted portfolio returns are computed from July of year t to June of year $t+1$, and the portfolios are rebalanced in June of $t+1$. We exclude financial firms from the last industry portfolio ("Other").

A.1.6 Trading Frictions. Table 2 lists 13 anomaly variables in this category, including ME, Ivol, Tvol, Svol, MDR, β, D-β, S-Rev, Disp, Turn, 1/P, Dvol, and Illiq.

A.1.6.1 ME. ME is price times shares outstanding from CRSP. At the end of June of each year t, we use NYSE breakpoints to sort stocks into deciles based on the June-end ME, and calculate monthly value-weighted decile returns from July of year t to June of $t+1$.

A.1.6.2 Ivol. Following Ang et al. (2006), we measure a stock's idiosyncratic volatility (Ivol) as the standard deviation of the residuals from regressing the stock's returns in excess of the one-month Treasury bill rate on the Fama-French (1993) 3 factors. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on the Ivol estimated with daily returns from month $t-1$. We require a minimum of 15 daily returns. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.6.3 Tvol. Following Ang et al. (2006), we measure a stock's total volatility (Tvol) as the standard deviation of its daily returns. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on the Tvol estimated with the daily returns from month $t-1$. We require a minimum of 15 daily returns. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.6.4 Svol. Following Ang et al. (2006), we measure systematic volatility (Svol) as $\beta^i_{\triangle \text{VXO}}$ from the bivariate regression:

$$r^i_d = \beta^i_0 + \beta^i_{MKT} MKT_d + \beta^i_{\triangle \text{VXO}} \triangle \text{VXO}_d + \epsilon^i_d, \qquad \text{(A12)}$$

in which r^i_d is stock i's return in excess of the one-month Treasury bill rate on day d, MKT_d is the market factor return, and $\triangle \text{VXO}_d$ is the aggregate volatility shock measured as the daily change in the Chicago Board Options Exchange S&P 100 volatility index (VXO). At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on $\beta^i_{\triangle \mathrm{VXO}}$ estimated with the daily returns from month $t-1$. We require a minimum of 15 daily returns. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$. Because the VXO data start in January 1986, the Svol decile returns start in February 1986.

A.1.6.5 MDR. Following Bali, Cakici, and Whitelaw (2011), at the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on the maximal daily return (MDR) in month $t-1$. We require a minimum of 15 daily returns. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.6.6 β. Following Frazzini and Pedersen (2014), we estimate β for firm i as:

$$\hat{\beta}_i = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}, \tag{A13}$$

in which $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for stock i and the market, and $\hat{\rho}$ is their correlation. To estimate the volatilities, we compute the standard deviation of daily log returns over a 1-year rolling window (with at least 120 daily returns). To estimate correlations, we use overlapping 3-day log returns, $r^{3d}_{it} = \sum_{k=0}^{2}\log(1+r^i_{t+k})$, over a 5-year rolling window (with at least 750 daily returns). At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on $\hat{\beta}_i$ estimated at the end of month $t-1$. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.6.7 D-β. Following Dimson (1979), we use the lead and the lag of the market return, along with the current market return, when estimating beta (D-β):

$$r_{id} - r_{fd} = \alpha_i + \beta_{i1}(r_{md-1} - r_{fd-1}) + \beta_{i2}(r_{md} - r_{fd}) + \beta_{i3}(r_{md+1} - r_{fd+1}) + \epsilon_{id}, \tag{A14}$$

in which r_{id} is the return on stock i on day d, r_{md} is the market return, and r_{fd} is the risk-free rate. We estimate the regression for each stock using daily returns from the prior month. We require a minimum of 15 daily returns. The market beta of stock i is calculated as D-$\beta_i \equiv \hat{\beta}_{i1} + \hat{\beta}_{i2} + \hat{\beta}_{i3}$. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on D-β_i estimated with the daily returns from month $t-1$, and calculate monthly value-weighted decile returns for month t. The deciles are rebalanced at the beginning of month $t+1$.

A.1.6.8 S-Rev. To construct the Jegadeesh (1990) short-term reversal (S-Rev) deciles, at the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on the return in month $t-1$. To be included in month t, a stock must have a valid price at the end of month $t-2$ and a valid return for month $t-1$. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.6.9 Disp. Following Diether, Malloy, and Scherbina (2002), we measure analyst earnings forecasts dispersion (Disp) as the ratio of the standard deviation of earnings forecast (IBES unadjusted file, item STDEV) to the absolute value of the consensus mean forecast (unadjusted file, item MEANEST). We use the earnings forecast for the current fiscal year (fiscal period indicator = 1). Stocks with a mean forecast of zero are assigned to the highest dispersion group. We exclude stocks with a price less than \$5. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on Disp in month $t-1$. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$. Because the forecast data start in January 1976, the Disp decile returns start in February 1976.

A.1.6.10 Turn. Following Datar, Naik, and Radcliffe (1998), at the beginning of each month t, we calculate the share turnover (Turn) of a stock as its average daily share turnover over the prior 6 months from $t-6$ to $t-1$. We require a minimum of 50 daily observations. Daily turnover is the number of shares traded on a given day divided by the number of shares outstanding on that day.[15] At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on Turn and calculate value-weighted decile returns for month t.

A.1.6.11 1/P. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on the reciprocal of the share price (1/P) at the end of month $t-1$. We calculate value-weighted decile returns for the current month t and rebalance the deciles monthly.

A.1.6.12 Dvol. At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on their average daily dollar trading volume (Dvol) over the prior 6 months from $t-6$ to $t-1$. We require a minimum of 50 daily observations. Dollar trading volume is share price times the number of shares traded. We adjust the trading volume of NASDAQ stocks per Gao and Ritter (2010). Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

A.1.6.13 Illiq. We calculate the Amihud (2002) illiquidity measure (Illiq) as the ratio of absolute daily stock return to daily dollar trading volume, averaged over the prior 6 months. We require a minimum of 50 daily observations. Dollar trading volume is share price times the number of shares traded. We adjust the trading volume of NASDAQ stocks per Gao and Ritter (2010). At the beginning of each month t, we use NYSE breakpoints to sort stocks into deciles based on Illiq over the prior 6 months from $t-6$ to $t-1$. We calculate value-weighted decile returns for month t and rebalance the deciles at the beginning of month $t+1$.

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[15] Following Gao and Ritter (2010), we adjust the trading volume for NASDAQ stocks to account for the institutional features of the way that NASDAQ and NYSE-Amex volume are reported. Prior to February 1, 2001, we divide NASDAQ volume by 2.0. This adjustment accounts for the practice of counting as trades both trades with market makers and trades among market makers. On February 1, 2001, according to the director of research of NASDAQ and Frank Hathaway (the chief economist of NASDAQ), a "riskless principal" rule goes into effect and results in a reduction of approximately 10% in reported volume. As such, from February 1, 2001 to December 31, 2001, we divide NASDAQ volume by 1.8. During 2002, securities firms began to charge institutional investors commissions on NASDAQ trades, rather than the prior practice of marking up or down the net price. This practice results in a further reduction in reported volume of approximately 10%. As such, for 2002 and 2003, we divide NASDAQ volume by 1.6. For 2004 and later years, in which the volume of NASDAQ (and NYSE) stocks has mostly been occurring on crossing networks and other venues, we use a divisor of 1.0. This practice reflects the fact that there are no longer important differences in the NASDAQ and NYSE volume.

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