q^5

Kewei Hou[*]
The Ohio State University
and CAFR

Haitao Mo[†]
Louisiana State University

Chen Xue[‡]
University of Cincinnati

Lu Zhang[§]
The Ohio State University
and NBER

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Abstract

In a multiperiod investment framework, firms with high expected growth earn higher expected returns than firms with low expected growth, holding investment and expected profitability constant. This paper forms cross-sectional growth forecasts and constructs an expected growth factor that yields an average premium of 0.82% per month ($t = 9.81$). The q^5 model, which adds the expected growth factor to the Hou-Xue-Zhang (2015) q-factor model, shows strong explanatory power in the cross section, and outperforms the recently proposed Fama-French (2018) 6-factor model.

[*]Fisher College of Business, The Ohio State University, 820 Fisher Hall, 2100 Neil Avenue, Columbus OH 43210; and China Academy of Financial Research (CAFR). Tel: (614) 292-0552. E-mail: hou.28@osu.edu.

[†]E. J. Ourso College of Business, Louisiana State University, 2931 Business Education Complex, Baton Rouge, LA 70803. Tel: (225) 578-0648. E-mail: haitaomo@lsu.edu.

[‡]Lindner College of Business, University of Cincinnati, 405 Lindner Hall, Cincinnati, OH 45221. Tel: (513) 556-7078. E-mail: xuecx@ucmail.uc.edu.

[§]Fisher College of Business, The Ohio State University, 760A Fisher Hall, 2100 Neil Avenue, Columbus OH 43210; and NBER. Tel: (614) 292-8644. E-mail: zhanglu@fisher.osu.edu.

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1 Introduction

Cochrane (1991) shows that in a multiperiod investment framework, firms with high expected investment growth should earn higher expected returns than firms with low expected investment growth, holding current investment and expected profitability constant. Intuitively, the extra productive assets next period produced from current investment, net of depreciation, are worth of the market value (marginal q) that mostly derives from exploiting growth opportunities in subsequent periods. The next period marginal q is then part of the expected marginal benefit of current investment. Per the first principle of investment, the marginal q in turn equals the marginal cost of investment, which increases with investment. High investment next period then signals high marginal q next period. Consequently, to counteract the high expected marginal benefit of current investment, high expected investment (relative to current investment) must imply high current discount rates.

Motivated by this economic insight, we perform cross-sectional forecasting regressions of future investment-to-assets changes on current Tobin's q, operating cash flows, and the change in return on equity. Conceptually, we motivate the instruments from the investment literature (Fazzari, Hubbard, and Petersen 1988; Erickson and Whited 2000; Liu, Whited, and Zhang 2009). Empirically, we show that cash flows and the change in return on equity are reliable predictors of investment-to-assets changes, but not Tobin's q. An independent 2×3 sort on size and the expected 1-year-ahead investment-to-assets change yields an expected investment growth factor, with an average premium of 0.82% per month ($t = 9.81$) from January 1967 to December 2016. The q-factor model cannot explain the factor premium, with an alpha of 0.63% ($t = 9.11$). As such, the expected growth factor represents a new dimension of the expected return variation that is missed by the q-factor model.

We augment the q-factor model with the expected growth factor to form the q^5 model, and then stress-test it along with other recently proposed factor models. As testing deciles, we use a large set of 158 significant anomalies with NYSE breakpoints and value-weighted returns compiled by Hou, Xue, and Zhang (2018). As competing factor models, we examine the q-factor model; the Fama-

French (2015) 5-factor model; the Stambaugh-Yuan (2017) 4-factor model; the Fama-French (2018) 6-factor model; the Fama-French alternative 6-factor model with the operating profitability factor, RMW, replaced by a cash-based profitability factor, RMWc; the Barillas-Shanken (2018) 6-factor model; as well as the Daniel-Hirshleifer-Sun (2018) 3-factor model. The Barillas-Shanken specification includes the market factor, SMB, the investment and return on equity factors from the q-factor model, the Asness-Frazzini (2013) monthly formed HML factor, and the momentum factor, UMD.

Improving on the q-factor model substantially, the q^5 model is the best performing model among all the factor models. Across the 158 anomalies, the average magnitude of the high-minus-low alphas is 0.18% per month, dropping from 0.25% in the q-factor model. The number of significant ($|t| \geq 1.96$) high-minus-low alphas is 19 in the q^5 model (4 with $|t| \geq 3$), dropping from 46 in the q-factor model (17 with $|t| \geq 3$). The number of rejections by the Gibbons, Ross, and Shanken (1989) test is also smaller, 58 versus 98. The q^5 model improves on the q-factor model across all anomaly categories, including momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions, but especially in the investment and profitability categories.

The q-factor model already compares favorably with the Fama-French 6-factor model. The average magnitude of the high-minus-low alphas is 0.28% per month in the 6-factor model (0.25% in the q-factor model). The numbers of significant high-minus-low 6-factor alphas are 67 with $|t| \geq 1.96$ and 33 with $|t| \geq 3$, which are higher than 46 and 17 in the q-factor model, respectively. However, the number of rejections by the Gibbons-Ross-Shanken test is 95, which is slightly lower than 98 in the q-factor model. Replacing RMW with RMWc improves the 6-factor model's performance. The average magnitude of the high-minus-low alphas is the same as in the q-factor model, 0.25%. The numbers of significant high-minus-low alphas are 55 with $|t| \geq 1.96$ and 21 with $|t| \geq 3$, which are still higher than those from the q-factor model. However, the number of rejections by the Gibbons-Ross-Shanken test is only 68, which is substantially lower than 98 in the q-factor model.

The Stambaugh-Yuan model also performs well. The numbers of significant high-minus-low alphas are 57 with $|t| \geq 1.96$ and 25 with $|t| \geq 3$, which are higher than 46 and 17 in the q-factor model, respectively. However, the number of rejections by the Gibbons-Ross-Shanken test is 87, which is somewhat lower than 98 in the q-factor model. The Barillas-Shanken model performs poorly. The numbers of significant high-minus-low alphas are 61 with $|t| \geq 1.96$ and 34 with $|t| \geq 3$, and the number of rejections by the Gibbons-Ross-Shanken test is 147 (out of 158 sets of deciles). Exacerbating the value-versus-growth anomalies, the Daniel-Hirshleifer-Sun model also performs poorly, with the highest average magnitude of high-minus-low alphas, 0.42% per month, and the second highest numbers of significant high-minus-low alphas, 83, and GRS rejections, 108. However, we should emphasize that while the Fama-French 5-factor model performs poorly overall, with no explanatory power for momentum, it is the best performer in the value-versus-growth category.

Our work makes two contributions. First, we bring the expected growth to the front and center of asset pricing research. Prior work has examined investment and profitability (Fama and French 2015; Hou, Xue, and Zhang 2015). However, the role of the expected growth has been largely ignored. Guided by the investment theory, we incorporate an expected growth factor into the q-factor model. Empirically, we show that this extension helps resolve many empirical difficulties of the q-factor model, such as the anomalies based on R&D-to-market as well as operating and discretionary accruals. Intuitively, R&D expenses depress current earnings, but induce future growth. Also, given the level of earnings, high accruals imply low cash flows (internal funds available for investments), and, consequently, low expected growth going forward. By more than halving the number of anomalies unexplained by the q-factor model from 46 to 19, with only one extra factor, the q^5 model makes further progress toward the important goal of dimension reduction (Cochrane 2011).

Second, we conduct a large-scale empirical horse race of recently proposed factor models. Prior studies use only relatively small sets of testing portfolios (Fama and French 2015, 2018; Hou, Xue, and Zhang 2015; Stambaugh and Yuan 2017). To provide a broad perspective on relative performance, we increase the number of testing anomalies drastically to 158. Barillas and Shanken (2018) conduct Bayesian asset pricing tests with only 11 factors, while downplaying the importance of testing assets. We show that inferences on relative performance clearly depend on testing assets. In particular, the monthly formed HML factor causes difficulties in capturing the annually formed value-versus-growth anomalies for the Barillas-Shanken model, difficulties that are entirely absent from the Fama-French 5-factor model and the q-factor model. As such, it is crucial to use a large set of testing assets to draw reliable inferences. Our extensive evidence on how a given anomaly can be explained by different factor models is also important in its own right. Finally, our work stands out in that while we attempt to tie our factors to the first principle of real investment in economic theory, other recently proposed factor models are all purely statistical in nature.

Our work is related to Ball, Gerakos, Linnainmaa, and Nikolaev (2016), who show that cash-based profitability outperforms earnings-based profitability in forecasting returns. We offer an economic explanation by linking cash flows and accruals to the expected growth. George, Hwang, and Li (2018) show that the ratio of current price to 52-week high price contains information about future investment growth, and this information helps explain the accrual and R&D-to-market anomalies. We also build on Watts (2003a, b), Penman and Zhu (2014), and Lev and Gu (2016), who argue that accounting conservatism, such as expensing R&D and other intangible investments, makes earnings a poor indicator of future growth. Penman and Zhu show that several anomaly variables forecast earnings growth, in the same direction of forecasting returns. While earnings growth has received much attention from equity analysts and academics alike, guided by the investment theory, we instead focus on investment growth. Forward-looking in nature, investment growth is broader than earnings growth, as investment reflects expectations of future earnings and discount rates.

The rest of the paper is organized as follows. Section 2 motivates the expected growth factor. Section 3 forms cross-sectional growth forecasts and constructs the expected growth factor. Section 4 stress-tests the factor models. Finally, Section 5 concludes. A separate Internet Appendix details derivations, variable definitions, portfolio construction, and supplementary results.

2 Economic Motivation

We motivate the expected growth factor from the multiperiod investment framework (Cochrane 1991). Time is discrete, and the horizon infinite. Heterogeneous firms, indexed by $i = 1, 2, \ldots, N$, use capital and costlessly adjustable inputs to produce a homogeneous output. These inputs are chosen each period to maximize operating profits (defined as revenue minus the costs of these inputs). Taking operating profits as given, firms choose investment to maximize their market value of equity.

Let $\Pi_{it} = X_{it}A_{it}$ be time-t operating profits of firm i, in which A_{it} is productive assets, and X_{it} return on assets (profitability). The next period profitability, X_{it+1}, is stochastic, subject to aggregate and firm-specific shocks. Let I_{it} denote investment and δ the depreciation rate of assets, $A_{it+1} = I_{it} + (1-\delta)A_{it}$. To adjust assets, firms incur costs, which are quadratic, $(a/2)(I_{it}/A_{it})^2 A_{it}$, with $a > 0$. We assume that firms finance investments only with internal funds and equity (no debt), and pay no taxes. The net payout of firm i is $D_{it} = X_{it}A_{it} - (a/2)(I_{it}/A_{it})^2 A_{it} - I_{it}$. If $D_{it} \geq 0$, the firm distributes it to the household. A negative D_{it} means the external equity.

Let M_{t+1} be the stochastic discount factor, which is correlated with the aggregate component of X_{it+1}. Firm i chooses optimal streams of investment, $\{I_{it+s}\}_{s=0}^{\infty}$, to maximize the cum-dividend market equity, $V_{it} \equiv E_t\left[\sum_{s=0}^{\infty} M_{t+s}D_{it+s}\right]$. The first principle of investment implies that $E_t[M_{t+1}r^I_{it+1}] = 1$, in which the investment return is defined as:

$$r^I_{it+1} \equiv \frac{X_{it+1} + (a/2)\left(I_{it+1}/A_{it+1}\right)^2 + (1-\delta)\left[1 + a\left(I_{it+1}/A_{it+1}\right)\right]}{1 + a\left(I_{it}/A_{it}\right)}. \quad (1)$$

Intuitively, the investment return is the marginal benefits of investment at time $t+1$ divided by the marginal costs of investment at t. The first principle, $E_t[M_{t+1}r^I_{it+1}] = 1$, says that the marginal costs equal the next period marginal benefits discounted to time t with the stochastic discount factor. In the numerator of the investment return, X_{it+1} is the marginal profits produced by an extra unit of assets, $(a/2)(I_{it+1}/A_{it+1})^2$ is the marginal reduction in adjustment costs, and the last term in the numerator is the marginal continuation value of the extra unit of assets, net of depreciation.

Let $P_{it} = V_{it} - D_{it}$ denote the ex-dividend equity value, and $r^S_{it+1} = (P_{it+1} + D_{it+1})/P_{it}$ the stock return. Cochrane (1991) uses no-arbitrage argument to argue, and Restroy and Rockinger (1994) prove under constant returns to scale that the stock return equals the investment return period by period and state by state (the Internet Appendix). As such, equation (1) implies that the stock return equals the next period marginal benefits of investment divided by the current marginal costs of investment. Intuitively, firms will keep investing until the marginal costs of investment, which rise with investment, equal the present value of additional investment, which is the next period marginal benefits of investment discounted by the discount rate (the stock return).

In a two-period model, in which the next period investment is zero, equation (1) collapses to $r^S_{it+1} = (X_{it+1} + 1 - \delta)/(1 + aI_{it}/A_{it})$. *Ceteris paribus*, low investment stocks should earn higher expected returns than high investment stocks, and high expected profitability stocks should earn higher expected returns than low expected profitability stocks. Intuitively, given expected profitability, high costs of capital are associated with low net present values of new projects and low investment. Given investment, high expected profitability must be associated with high discount rates, which are necessary to counteract the high expected profitability to induce low net present values of new projects to keep investment constant. Hou, Xue, and Zhang (2015) build on these insights to construct the investment and return on equity (Roe) factors in the q-factor model.

In the multiperiod framework, equation (1) says that keeping investment and expected profitability constant, the expected return is also linked to the expected investment-to-assets growth. The return in equation (1) can be decomposed into a "dividend yield" and a "capital gain." The "dividend yield" is $[X_{it+1} + (a/2)(I_{it+1}/A_{it+1})^2]/(1 + aI_{it}/A_{it})$, which largely conforms to the two-period model, as the squared term, $(I_{it+1}/A_{it+1})^2$, is economically small. The "capital gain," $(1 - \delta)(1 + aI_{it+1}/A_{it+1})/(1 + aI_{it}/A_{it})$, is the growth of marginal q (the market value of an extra unit of assets). Although the "capital gain" involves the unobservable parameter, a, it is roughly proportional to the investment-to-assets growth, $(I_{it+1}/A_{it+1})/(I_{it}/A_{it})$ (Cochrane 1991). As such, the expected investment-to-assets growth is the third "determinant" of the expected return.

The intuition is analogous to the intuition of the positive relation between the expected return and the expected profitability. The term, $1 + aI_{it+1}/A_{it+1}$, is the marginal costs of investment next period, which, per the first principle of investment, equal the marginal q next period (the present value of cash flows in all future periods generated from one extra unit of assets next period). The expected marginal q is then part of the expected marginal benefits of current investment. This term is absent from the two-period model, which abstracts from growth in subsequent periods. As such, in the multiperiod framework, high expected investment (relative to current investment) must imply a high discount rate to counteract the high expected marginal benefits of current investment.

3 The Expected Investment Growth Factor

Motivated by equation (1), we cross-sectionally forecast investment-to-assets growth in Section 3.1, construct the expected investment growth factor in Section 3.2, and form the q^5 model in Section 3.3.

3.1 Cross-sectional Forecasts

A technical issue arises in that firm-level investment is frequently negative, making the growth rate of investment-to-assets not well defined. As such, we forecast future investment-to-assets changes. Forecasting changes captures the essence of the economic insight that *ceteris paribus*, high expected investment-to-assets relative to current investment-to-assets must imply a high discount rate.

Our forecasting framework is based on monthly Fama-MacBeth (1973) cross-sectional (predictive) regressions. At the beginning of each month t, we measure current investment-to-assets as total assets (Compustat annual item AT) from the most recent fiscal year ending at least four months ago minus the total assets from one year prior, scaled by the 1-year-prior total assets. The left-hand side variables in the cross-sectional regressions are investment-to-assets changes, denoted $\mathrm{d}^{\tau}\mathrm{I/A}$, in which $\tau = 1, 2$, and 3. We measure $\mathrm{d}^1\mathrm{I/A}$, $\mathrm{d}^2\mathrm{I/A}$, and $\mathrm{d}^3\mathrm{I/A}$ as investment-to-assets from the first, second, and third fiscal year after the most recent fiscal year end minus the current investment-to-assets, respectively. The sample is from July 1963 to December 2016.

3.1.1 Predictors Based on A Priori Conceptual Arguments

Which variables should one use to forecast investment-to-assets changes? Our goal is a conceptually motivated yet empirically validated specification for the expected investment-to-assets changes. To this end, we turn to the investment literature in macroeconomics and corporate finance for guidance.

Keynes (1936) and Tobin (1969) argue that a firm should invest if the ratio of its market value to the replacement costs of its assets (Tobin's q) exceeds one. Lucas and Prescott (1971) and Mussa (1977) show that optimal investment requires the marginal costs of investment to equal marginal q. With quadratic adjustment costs, this first-order condition of investment can be rewritten as a linear regression of investment-to-assets on marginal q, which is unobservable, Hayashi (1982) shows that under constant returns to scale, marginal q equals average q, which is observable.

Although marginal q should theoretically summarize the impact of all other variables on investment, firms' internal cash flows typically have economically large and statistically significant slopes once included in the investment-q regression. In particular, Fazzari, Hubbard, and Petersen (1988) and Gilchrist and Himmelberg (1995) show that the cash flows effect on investment is especially strong for firms that are more financially constrained. However, the economic interpretation of the cash flows effect is controversial.[1] We remain agnostic about the exact interpretation of the investment-cash flows relation, which is not directly related to our asset pricing question. As such, we include both Tobin's q and cash flows on the right-hand side of our forecasting regressions.

Both Tobin's q and cash flows are slow-moving. To help capture the short-term dynamics of investment-to-assets changes, we also include the change in return on equity over the past four quarters, denoted dRoe, on the right-hand side of our forecasting regressions. Intuitively, firms that experience recent increases in profitability tend to raise future investments in the short term, and

[1]Using measurement error-consistent generalized methods of moments, Erickson and Whited (2000) find that cash flows do not matter in the investment-q regression even for financially constrained firms, and interpret the cash flows effect as indicative of measurement errors in Tobin's q. In addition, the investment-cash flows relation can arise theoretically even without financial constraints (Gomes 2001; Alti 2003; Abel and Eberly 2011). Finally, in a model with financial constraints, cash flows matter only if one ignores marginal q (Gomes 2001).

firms that experience recent decreases in profitability tend to reduce future investments.[2] Finally, we use only three instruments to keep our empirical specification parsimonious. The parsimony is necessary to guard against in-sample overfitting at the expense of out-of-sample forecasting performance (Hastie, Tibshirani, and Friedman 2009, Chapter 7).

3.1.2 Measurement

Monthly returns are from the Center for Research in Security Prices (CRSP) and accounting information from the Compustat Annual and Quarterly Fundamental Files. We require CRSP share codes to be 10 or 11. Financial firms and firms with negative book equity are excluded.

Our measure of Tobin's q is standard (Kaplan and Zingales 1997). At the beginning of each month t, current Tobin's q is the market equity (price per share times the number of shares outstanding from CRSP) plus long-term debt (Compustat annual item DLTT) and short-term debt (item DLC) scaled by book assets (item AT), all from the most recent fiscal year ending at least four months ago. For firms with multiple share classes, we merge the market equity for all classes.

We follow Ball, Gerakos, Linnainmaa, and Nikolaev (2016) in measuring operating cash flows, denoted Cop. At the beginning of each month t, we measure current Cop as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), scaled by book assets, all from the fiscal year ending at least four months ago. All changes are annual changes, and the missing changes are set to zero.

[2]Novy-Marx (2015) argues that the investment framework cannot explain momentum. However, Liu, Whited, and Zhang (2009) show that firms that experience recent, positive earnings shocks have higher average future investment growth than firms that experience recent, negative earnings shocks. Liu and Zhang (2014) show that this future investment growth spread is temporary, converging within 12 months, and helps explain the short duration of price and earnings momentum. The prior evidence is based on structural estimation at the portfolio level. We instead form firm-level cross-sectional forecasts, on which we further construct an expected growth factor.

We adopt the Cop measure because it is likely the most accurate measure of cash flows. A more popular measure of cash flows in the investment literature is earnings before extraordinary items but after interest, depreciation, and taxes (Compustat annual item IB) plus depreciation. For instance, Li and Wang (2017) use this measure, along with Tobin's q and prior 11-month returns to forecast capital expenditure growth. However, as argued in Ball, Gerakos, Linnainmaa, and Nikolaev (2016), because this measure includes accruals such as changes in accounts payable, accounts receivable, and inventory, it does not accurately capture internal funds available for investments. In particular, given earnings, accruals tend to reduce internal funds and dampen future investment growth. In addition, Cop explicitly recognizes R&D expenditures as a form of investments that induce future growth. In contrast, the more popular measure of cash flows does not.

We measure the change in return on equity, dRoe, as Roe minus the 4-quarter-lagged Roe. Roe is income before extraordinary items (Compustat quarterly item IBQ) scaled by the 1-quarter-lagged book equity. We compute dRoe with earnings from the most recent announcement dates (item RDQ), and if not available, from the fiscal quarter ending at least four months ago. Finally, missing dRoe values are set to zero in the cross-sectional forecasting regressions.

3.1.3 Forecasting Results

Panel A of Table 1 shows monthly cross-sectional regressions of future investment-to-assets changes on the log of Tobin's q, $\log(q)$, cash flows, Cop, and the change in return on equity, dRoe. We winsorize both the left- and right-hand side variables each month at the 1–99% level. To control for the impact of microcaps, we use weighted least squares with the market equity as the weights.

To gauge the out-of-sample performance of the cross-sectional forecasts, at the beginning of each month t, we construct the expected τ-year-ahead investment-to-assets changes, denoted $E_t[\mathrm{d}^\tau \mathrm{I/A}]$, in which $\tau = 1, 2$, and 3 years, by combining the most recent winsorized predictors with the average slopes estimated from the prior 120-month rolling window (30 months minimum). The most recent predictors, $\log(q)$ and Cop, in calculating $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ are from the most recent fiscal year ending at least four months ago as of month t, and dRoe is computed using the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago.

The average slopes in calculating $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ are estimated from the prior rolling window regressions, in which $\mathrm{d}^\tau\mathrm{I/A}$ is from the most recent fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly. For instance, for $\tau = 1$, the regressors in the latest monthly cross-sectional regression are further lagged by 12 months relative to the most recent predictors that we combine with the slopes in calculating $E_t[\mathrm{d}^1\mathrm{I/A}]$. Finally, we report the time series averages of cross-sectional Pearson and rank correlations between $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ calculated at the beginning of month t and the subsequent τ-year-ahead investment-to-assets changes after month t.

Panel A shows that when used alone, Tobin's q is a weak predictor of investment-to-assets changes. At the 1-year horizon, the slope, 0.02, is economically small, albeit statistically significant. The R^2 is only 1.03%, which is perhaps not surprising in forecasting changes.[3] The out-of-sample correlations between the expected and subsequently realized investment changes are tiny.

Cash flows perform better than Tobin's q in forecasting investment-to-assets changes. When used alone, Cop has significant slopes that range from 0.43 to 0.47 (t-values all above 10). The in-sample R^2 varies from 3.13% to 4.1%. More important, the out-of-sample correlations are substantially higher than those with Tobin's q. At the 1-year horizon, for example, the Pearson and rank correlations are 0.15 and 0.18, respectively, both of which are significant at the 1% level. At the 3-year horizon, the Pearson and rank correlations remain large at 0.12 and 0.13, respectively.

The change in return on equity, dRoe, also performs better than Tobin's q, but not as well as cash flows. When used alone, the dRoe slopes range from 0.77 to 0.97, with t-values all above seven. The in-sample R^2 starts at 2.23% at the 1-year horizon, and drops to 1.57% at the 3-year horizon. The out-of-sample correlations are also substantially higher than those with Tobin's q. At the 1-year horizon, the Pearson and rank correlations are 0.07 and 0.14, and both are significant at the 1% level.

[3]For example, Chan, Karceski, and Lakonishok (2003) document a low amount of predictability for earnings growth, even with a myriad of predictors, including valuation ratios.

At the 3-year horizon, the correlations remain largely unchanged at 0.06 and 0.13, respectively.

In our benchmark specification with $\log(q)$, Cop, and dRoe altogether, the slopes are similar to those from univariate regressions. At the 1-year horizon, for instance, the Cop slope remains large and significant, 0.53, the $\log(q)$ slope becomes weakly negative, -0.03, and the dRoe slope remains significant at 0.80. The in-sample R^2 increases to 6.64%. The out-of-sample Pearson and rank correlations, which are important for constructing the expected growth factor, are 0.14 and 0.21, respectively, and both are highly significant. At the 3-year horizon, the $\log(q)$ and Cop slopes both increase in magnitude to -0.09 and 0.76, respectively, but the dRoe slope falls to 0.74. The in-sample R^2 rises to 9.18%, and the out-of-sample correlations rise slightly to 0.16 and 0.22, respectively.

3.2 The Expected Growth Premium

Armed with the cross-sectional forecasts of investment-to-assets changes, we study the expected growth premium via portfolio sorts. We form the expected growth deciles, construct an expected growth factor, and then add it to the q-factor model to form the q^5 model.

3.2.1 Deciles

At the beginning of each month t, we form deciles based on the expected investment-to-assets changes, $E_t[\mathrm{d}^\tau\mathrm{I/A}]$, with $\tau = 1, 2$, and 3. As in Table 1, we calculate $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ by combining the most recent winsorized predictors with the average slopes from the prior 120-month rolling window (30 months minimum). We sort all stocks into deciles based on the NYSE breakpoints of the ranked $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ values, and calculate the value-weighted decile returns for the current month t. The deciles are rebalanced at the beginning of month $t + 1$.

Panel A of Table 2 shows that the expected growth premium is reliable in portfolio sorts. The high-minus-low $E_t[\mathrm{d}^1\mathrm{I/A}]$ decile earns on average 1.06% per month ($t = 6.25$), and the high-minus-low $E_t[\mathrm{d}^2\mathrm{I/A}]$ and $E_t[\mathrm{d}^3\mathrm{I/A}]$ deciles both earn on average 1.18%, with t-values close to seven. From Panel B, the expected growth premium cannot be explained by the q-factor model. The high-minus-low alphas are 0.83%, 0.92%, and 0.99% ($t = 5.85, 5.31$, and 5.73) over the 1-, 2-, and 3-year horizons, respectively. The mean absolute alphas across the deciles are 0.21%, 0.2%, and 0.24%, respectively, and the q-factor model is strongly rejected by the Gibbons, Ross, and Shanken (1989, GRS) test on the null that the alphas are jointly zero across a given set of deciles (untabulated).

Panel C reports the expected investment-to-assets changes, and Panel D the average subsequently realized changes across the $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ deciles. Both the expected and realized changes are value-weighted at the portfolio level, with the market equity as the weights. Reassuringly, the expected changes track the subsequently realized changes closely. In particular, at the 1-year horizon, the expected changes rise monotonically from -15.21% per annum for decile one to 7.79% for decile ten, and the average realized changes from -17.43% for decile one to 6.09% for decile ten. Except for decile seven, the increase in the average realized changes is strictly monotonic. The time series average of cross-sectional correlations between the expected and realized changes is 0.66, which is highly significant. The evidence for the 2- and 3-year horizons is largely similar, with average cross-sectional correlations of 0.72 and 0.68, respectively. The evidence indicates that our empirical specification for the expected investment-to-assets changes seems to be effective.

3.2.2 A Common Factor

In view of the expected growth premium largely unexplained by the q-factor model, we set out to construct an expected growth factor, denoted R_{Eg}. We form R_{Eg} from an independent 2×3 sort on the market equity and the expected 1-year-ahead investment-to-assets change, $E_t[\mathrm{d}^1\mathrm{I/A}]$.

At the beginning of each month t, we use the beginning-of-month median NYSE market equity to split stocks into two groups, small and big. Independently, we split all stocks into three groups, low, median, and high, based on the NYSE breakpoints for the low 30%, median 40%, and high 30% of the ranked $E_t[\mathrm{d}^1\mathrm{I/A}]$ values. Taking the intersection of the two size and three $E_t[\mathrm{d}^1\mathrm{I/A}]$ groups, we form six benchmark portfolios. Monthly value-weighted portfolio returns are calculated for the current month t, and the portfolios are rebalanced at the beginning of month $t + 1$. Designed to mimic the common variation related to $E_t[\mathrm{d}^1\mathrm{I/A}]$, the expected growth factor, R_{Eg}, is the difference (high-minus-low), each month, between the simple average of the returns on the two high $E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios and the simple average of the returns on the two low $E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios.

Panel A of Table 3 reports properties for the six size-$E_t[\mathrm{d}^1\mathrm{I/A}]$ benchmark portfolios. The small-high portfolio earns the highest average return of 1.34% per month ($t = 4.92$), and the big-low portfolio earns the lowest, 0.21% ($t = 0.88$). The average market equity is the smallest, 0.14 $billion, for the small-low portfolio, which also has the highest number of stocks on average, 974. The average market equity is the highest, 9.03 $billion, for the big-high portfolio. The lowest number of stocks on average, 142, belongs to the big-low portfolio. The total market equity aggregated across all firms within a portfolio as a fraction of the entire market equity is the lowest for the small-high portfolio, 2.11%, and the highest for the big-high portfolio, 33.3%.

The expected 1-year-ahead investment-to-assets changes, $E_t[\mathrm{d}^1\mathrm{I/A}]$, is the lowest, −11.43% per annum, for the small-low portfolio, and the highest, 4.46%, for the small-high portfolio. Similarly, the average realized 1-year changes, $\mathrm{d}^1\mathrm{I/A}$, is the lowest, −11.61%, for the small-low portfolio, and the highest, 5.38%, for the small-high portfolio. The dispersions in $E_t[\mathrm{d}^1\mathrm{I/A}]$ and $\mathrm{d}^1\mathrm{I/A}$ are smaller, but remain large, 12.47% and 13.21%, respectively, among big firms. Finally, $E_t[\mathrm{d}^1\mathrm{I/A}]$ is only weakly related to Tobin's q, but its relations with Cop and dRoe are strongly positive.

Panel B reports properties of the expected growth factor, R_{Eg}. From January 1967 to December 2016, its average return is 0.82% per month ($t = 9.81$). The q-factor regression of R_{Eg} yields an economically large alpha of 0.63% ($t = 9.11$). As such, the expected growth factor captures a new dimension of the expected return variation that is missed by the q-factor model.

The subsequent five regressions in Panel B attempt to identify the sources behind the expected growth premium from its components. To this end, we form factors on $\log(q)$, Cop, and dRoe, by interacting each of them separately with the market equity in 2×3 sorts. Cop is the most important component of the expected growth premium. Augmenting the Cop factor into the q-factor model reduces the alpha of R_{Eg} from 0.63% per month ($t = 9.11$) to 0.36% ($t = 6.09$). dRoe plays a more limited role. Adding the dRoe factor into the q-factor model reduces the alpha only slightly to 0.59% ($t = 8.06$). Tobin's q is negligible on its own, but more visible when used together with Cop and dRoe. Adding the $\log(q)$, Cop, and dRoe factors into the q-factor model yields an alpha of 0.24% ($t = 3.73$), which is lower than 0.32% ($t = 4.99$) when adding only the Cop and dRoe factors.[4]

Finally, Panel C shows that the expected growth factor has positive correlations of 0.38 and 0.52 with the investment and Roe factors, but negative correlations of -0.47 and -0.37 with the market and size factors in the q-factor model. The correlations are 0.7 with the Cop factor and 0.44 with the dRoe factor. All the correlations are significantly different from zero.

3.2.3 Alternative Specifications

We have also experimented two alternative specifications of the expected growth factor. Both yield higher expected growth factor premiums (the Internet Appendix). First, we use the percentile rankings of the log of Tobin's q, Cop, and dRoe to forecast the percentile rankings of investment-to-assets changes and to form the expected growth factor. The alternative factor premium is 0.91% per month ($t = 10.3$), which is higher than 0.82% ($t = 9.81$) for the benchmark R_{Eg} factor. The q-factor alpha of the alternative factor is 0.6% ($t = 8.74$). The correlation between the alternative and benchmark factors is 0.87. However, in head-to-head spanning tests, the benchmark factor cannot subsume the alternative factor, with a significant alpha of 0.14% ($t = 2.64$), but the alternative factor can subsume the benchmark factor, with an insignificant alpha of 0.08% ($t = 1.27$).

Second, instead of the expected 1-year-ahead investment-to-assets changes, we form the expected growth factor on the composite score that equal-weights a stock's percentile rankings of the log of Tobin's q, Cop, and dRoe (each realigned to yield a positive slope in forecasting returns).

[4] We form the $\log(q)$ and Cop factors with annual sorts to facilitate comparison with the existing literature (Ball, Gerakos, Linnainmaa, and Nikolaev 2016). In untabulated results, we have also examined the $\log(q)$ and Cop factors with monthly sorts that are analogous to our construction of the expected growth factor, R_{Eg}. Tobin's q continues to play a negligible role, when used alone. Adding the monthly sorted Cop factor into the q-factor model yields an alpha of 0.26% ($t = 4.9$) for R_{Eg}, and adding all three monthly formed factors reduces the alpha further to 0.14% ($t = 2.56$).

The alternative expected growth factor formed on the composite score earns on average 0.89% per month ($t = 9.51$), and its q-factor alpha is 0.46% ($t = 6.27$). The correlation between the alternative and benchmark expected growth factors is 0.66. In head-to-head spanning tests, the benchmark factor cannot subsume the alternative factor, with an alpha of 0.28% ($t = 3.27$), and the alternative factor cannot subsume the benchmark factor, with an alpha of 0.31% ($t = 4.25$).

3.3 The q^5 Model

We augment the q-factor model with the benchmark expected growth factor to form the q^5 model. The expected excess return of an asset, denoted $E[R^i - R^f]$, is described by the loadings of its returns to five factors, including the market factor, R_{Mkt}, the size factor, R_{Me}, the investment factor, $R_{\mathrm{I/A}}$, the return on equity factor, R_{Roe}, and the expected growth factor, R_{Eg}. The first four factors are identical to those in the q-factor model. Formally, the q^5 model says that:

$$E[R^i - R^f] = \beta^i_{\mathrm{Mkt}}\, E[R_{\mathrm{Mkt}}] + \beta^i_{\mathrm{Me}}\, E[R_{\mathrm{Me}}] + \beta^i_{\mathrm{I/A}}\, E[R_{\mathrm{I/A}}] + \beta^i_{\mathrm{Roe}}\, E[R_{\mathrm{Roe}}] + \beta^i_{\mathrm{Eg}}\, E[R_{\mathrm{Eg}}], \tag{2}$$

in which $E[R_{\mathrm{Mkt}}], E[R_{\mathrm{Me}}], E[R_{\mathrm{I/A}}]$, $E[R_{\mathrm{Roe}}]$, and $E[R_{\mathrm{Eg}}]$ are the expected factor premiums, and β^i_{Mkt}, β^i_{Me}, $\beta^i_{\mathrm{I/A}}$, β^i_{Roe}, and β^i_{Eg} are their factor loadings, respectively.

As its first test, we use the q^5 model to explain the expected growth deciles from Table 2. Not surprisingly, the expected growth factor helps explain deciles formed on the expected 1-year-ahead investment-to-assets changes, $E_t[\mathrm{d}^1\mathrm{I/A}]$, on which the expected growth factor is based (the Internet Appendix). The high-minus-low decile earns a q^5 alpha of only -0.13% per month ($t = -1.28$), due to a large R_{Eg}-loading of 1.52 ($t = 23.97$). More important, reassuringly, the expected growth factor also largely explains the $E_t[\mathrm{d}^2\mathrm{I/A}]$ and $E_t[\mathrm{d}^3\mathrm{I/A}]$ deciles. The q^5 alphas of the high-minus-low $E_t[\mathrm{d}^2\mathrm{I/A}]$ and $E_t[\mathrm{d}^3\mathrm{I/A}]$ deciles are only -0.02% ($t = -0.18$) and 0.04 ($t = 0.31$), respectively.

4 Stress-testing Factor Models

The most stringent test of the q^5 model is to confront it with a vast set of testing anomaly portfolios. We use the 158 anomalies that are significant with NYSE breakpoints and value-weighted returns in the 1967–2016 sample from Hou, Xue, and Zhang (2018). We also conduct a large-scale empirical horse race with other recently proposed factor models such as the Fama-French (2018) 6-factor model. We setup the playing field in Section 4.1, discuss the overall performance of different factor models in Section 4.2, and detail individual factor regressions in Section 4.3.

4.1 The Playing Field

We describe testing portfolios as well as all the factor models in the empirical horse race.

4.1.1 Testing Portfolios

For testing portfolios, we use deciles formed on each of the 158 significant anomalies. Table 4 provides the detailed list, which includes 36, 29, 28, 35, 26, and 4 across the momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions categories, respectively. The Internet Appendix details the variable definitions and portfolio construction.

The list includes 46 anomalies that cannot be explained by the q-factor model. Prominent examples include cumulative abnormal stock returns around quarterly earnings announcement dates (Chan, Jegadeesh, and Lakonishok 1996), customer momentum (Cohen and Frazzini 2008), and segment momentum (Cohen and Lou 2012) in the momentum category; cash flow-to-price (Desai, Rajgopal, and Venkatachalam 2004) and net payout yield (Boudoukh, Michaely, Richardson, and Roberts 2007) in the value-versus-growth category; operating accruals (Sloan 1996), discretionary accruals (Xie 2001), net operating assets (Hirshleifer, Hou, Teoh, and Zhang 2004), and net stock issues (Pontiff and Woodgate 2008) in the investment category; operating profits-to-assets (Ball, Gerakos, Linnainmaa, and Nikolaev 2015) and operating cash flows-to-assets (Ball, Gerakos, Linnainmaa, and Nikolaev 2016) in the profitability category; R&D-to-market (Chan, Lakonishok, and

Sougiannis 2001) and seasonalities (Heston and Sadka 2006) in the intangibles category; as well as systematic volatility (Ang, Hodrick, Xing, and Zhang 2006) in the trading frictions category.

4.1.2 Factor Models

In addition to the q and q^5 models, we examine six other models, including (i) the Fama-French (2015) 5-factor model; (ii) the Fama-French (2018) 6-factor model with RMW; (iii) the Fama-French alternative 6-factor model with RMWc; (iv) the Barillas-Shanken (2018) 6-factor model; (v) the Stambaugh-Yuan (2017) 4-factor model; and (vi) the Daniel-Hirshleifer-Sun (2018) 3-factor model.

Fama and French (2015) incorporate two factors that are similar to our investment and Roe factors into their original 3-factor model to form their 5-factor model. RMW is the high-minus-low operating profitability factor, in which operating profitability is total revenue minus cost of goods sold, minus selling, general, and administrative expenses, and minus interest expense, all scaled by the book equity. CMA is the low-minus-high investment factor. RMW and CMA are formed via independent 2×3 sorts by interacting operating profitability, and separately, investment-to-assets, with size. Fama and French (2018) further add the momentum factor, UMD, from Jegadeesh and Titman (1993) and Carhart (1997), into their 5-factor model to form their 6-factor model. UMD is formed in each month t by interacting prior 11-month returns (skipping month $t-1$) with size. We obtain the data of the Fama-French five and six factors from Kenneth French's Web site.

Fama and French (2018) also introduce an alternative 6-factor model, in which RMW is replaced by a cash-based profitability factor, denoted RMWc.[5] Their cash profitability measure is a variant of Ball, Gerakos, Linnainmaa, and Nikolaev's (2016), with the book equity (not book assets) as the denominator, but without adding back R&D expenses. The construction of RMWc is analogous to RMW. Since the RMWc data are not provided on Kenneth French's Web site,

[5]Cash-based profitability is revenues (Compustat annual item REVT) minus cost of goods sold (item COGS, zero if missing), minus selling, general, and administrative expenses (item XSGA, zero if missing), minus interest expense (item XINT, zero if missing) minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), scaled by the book equity. At least one of the three items (COGS, XSGA, and XINT) must be nonmissing.

to facilitate comparison, we reproduce RMWc based on the same sample criterion in Fama and French (2015, 2018). In particular, their sample includes financial firms and firms with negative book equity, except that positive book equity is required for HML, RMW, and RMWc.

Barillas and Shanken (2018) also propose a 6-factor model, including the market factor, SMB from the Fama-French (2015) 5-factor model, the investment and Roe factors from the q-factor model, the Asness-Frazzini (2013) monthly sorted HML factor, denoted HML^{m}, and the momentum factor, UMD. Barillas and Shanken argue that their 6-factor model outperforms the q-factor model and the Fama-French 5-factor model in their Bayesian comparison tests. Asness and Frazzini construct HML^{m} from monthly sequential sorts on, first, size, and then book-to-market, in which the market equity is updated monthly, and the book equity is from the fiscal year ending at least six months ago. To facilitate comparison, we obtain the HML^{m} data directly from the AQR Web site.

Stambaugh and Yuan (2017) group 11 anomalies into two clusters based on pairwise cross-sectional correlations. The first cluster, denoted MGMT (management) contains net stock issues, composite issues, accruals, net operating assets, investment-to-assets, and the change in gross property, plant, and equipment plus the change in inventories scaled by lagged book assets. The second cluster, denoted PERF (performance), includes failure probability, O-score, momentum, gross profitability, and return on assets. The variables in each cluster are realigned to yield positive low-minus-high returns. The composite scores, MGMT and PERF, are defined as a stock's equal-weighted rankings across all the variables within a given cluster. Stambaugh and Yuan form their factors from monthly independent 2×3 sorts from interacting size with each of the composite scores.

However, as shown in Hou, Mo, Xue, and Zhang (2018), Stambaugh and Yuan (2017) deviate from the traditional factor construction (Fama and French 1993) in two important aspects. First, the NYSE-Amex-NASDAQ breakpoints of 20th and 80th percentiles are used, as opposed to the common NYSE breakpoints of 30th and 70th, when sorting on the composite scores. Second, the size factor contains stocks only in the middle portfolios of the composite score sorts, as opposed to stocks from all portfolios. Hou et al. show that the Stambaugh-Yuan factors are sensitive to their factor construction, and their nontraditional construction exaggerates their factors' explanatory power. In our sample from January 1967 to December 2016, the replicated MGMT and PERF factors earn on average 0.47% per month ($t = 4.68$) and 0.49% ($t = 3.67$), whereas the original factors earn 0.61% ($t = 4.72$) and 0.68% ($t = 4.2$), respectively. To level the playing field, we opt to use the replicated factors via the traditional approach. The Internet Appendix details our replication procedure.

Daniel, Hirshleifer, and Sun (2018) propose a 3-factor model that includes the market factor, a financing factor (FIN), and a post-earnings-announcement-draft factor (PEAD). FIN is constructed on the Pontiff-Woodgate (2008) 1-year net issuance and the Daniel-Titman (2006) 5-year composite issuance. PEAD is formed on cumulative abnormal returns around the most recent earnings announcement, Abr. FIN is from annual sorts, and PEAD monthly sorts, both 2×3 with size.

However, as shown in Hou, Mo, Xue, and Zhang (2018), Daniel, Hirshleifer, and Sun (2018) also deviate from the traditional approach. First, only Abr is used, even though standardized unexpected earnings (Sue) and revisions in analysts earnings forecasts (Re) are also common measures of post-earnings-announcement-draft (Chan, Jegadeesh, and Lakonishok 1996). Second, the NYSE breakpoints of the 20th and 80th percentiles are adopted on Abr and the composite issuance, instead of the common 30th and 70th percentiles. Finally, the net issuance sort and its combination with the composite issuance sort are ad hoc.[6] Hou et al. show that the Daniel et al. factors are sensitive to the factor construction, and their nontraditional construction exaggerates the factors' explanatory power.

To ensure that we compare apples with apples, we replicate the Daniel-Hirshleifer-Sun factors via the traditional approach. We form the replicated PEAD factor by sorting on the simple average of a stock's percentile rankings on Sue, Abr, and Re (if available). We use the same composite score

[6] Daniel, Hirshleifer, and Sun (2018) first split all repurchasing firms (with negative net issuance) into two groups based on the NYSE median. Second, all equity issuing firms (with positive net issuance) are split into three groups based on the NYSE breakpoints of the 30th and 70th percentiles. Third, firms with the most negative net issuance are assigned to the low net issuance portfolio, those with the most positive net issuance to the high portfolio, and all other firms to the middle portfolio. Finally, if a firm belongs to the high portfolios per both issuance measures, or to the high portfolio per one issuance measure, but missing the other, the firm is assigned to the high FIN portfolio. If a firm belongs to the low portfolios per both measures, or to the low portfolio per either one, but missing the other, the firm belongs to the low FIN portfolio. In all the other cases, the firm belongs to the middle FIN portfolio.

approach from Stambaugh and Yuan (2017) to combine the two share issuance measures. We then split stocks on the composite FIN and PEAD scores based on their NYSE breakpoints of the 30th and 70th percentiles. The Internet Appendix details our replication procedure. For comparison, from January 1967 to December 2016, the replicated FIN and PEAD factors earn on average 0.32% per month ($t = 2.53$) and 0.72% ($t = 7.78$), whereas the original factors, which span July 1972 to December 2016, earn 0.83% ($t = 4.55$) and 0.62% ($t = 7.73$), respectively.

4.1.3 Sharpe Ratios

Table 5 reports monthly Sharpe ratios for individual factors and maximum Sharpe ratios for all the factor models. The maximum Sharpe ratio for a given factor model is calculated as $\sqrt{\mu_f' V_f^{-1} \mu_f}$, in which μ_f is the vector of mean factor returns, and V_f the variance-covariance matrix of the factor returns in the model (MacKinlay 1995). From Panel A, the individual Sharpe ratio is the highest, 0.44, for the expected growth factor, R_{Eg}, followed by the PEAD factor, 0.32. The investment factor, $R_{\mathrm{I/A}}$, has a Sharpe ratio of 0.22, which is higher than 0.16 for CMA. The Roe factor, R_{Roe}, has a Sharpe ratio of 0.21, which is higher than 0.12 for RMW and 0.19 for RMWc.

Panel B shows that the q^5 model has the highest maximum Sharpe ratio, 0.63, among all the factor models. The Sharpe ratio for the q-factor model is 0.43, which compares favorably with 0.37 for the Fama-French (2018) 6-factor model, but falls short of 0.45 for their alternative 6-factor model. The Barillas-Shanken (2018) 6-factor model has a higher Sharpe ratio of 0.49 than the q-factor model. Based on this evidence, Barillas and Shanken argue that their 6-factor model is a better model than the q-factor model (and that testing assets are irrelevant). Our extensive evidence below based on 158 anomalies overturns their conclusion (Sections 4.2 and 4.3).[7]

4.2 The Big Picture of the Model Performance

In this subsection we examine the overall performance of the factor models.

[7] Hou, Mo, Xue, and Zhang (2018) perform factor spanning tests and examine the conceptual foundation behind the factor models. Their key finding is that the q-factor model largely subsumes the Fama-French 5- and 6-factor models in spanning tests, and the q^5 model subsumes the Stambaugh-Yuan (2017) 4-factor model.

4.2.1 Overall Performance Across All 158 Anomalies

Panel A of Table 6 shows the overall performance of the factor models in explaining the 158 significant anomalies. The q^5 model is the overall best performer. The q-factor model performs well too, with a lower number of significant high-minus-low alphas, but a higher number of rejections by the GRS test than the Fama-French 6-factor model and the Stambaugh-Yuan model. The Fama-French 5-factor, the Barillas-Shanken, and the Daniel-Hirshleifer-Sun models all perform poorly.

The q-factor model leaves 46 significant high-minus-low alphas with $|t| \geq 1.96$ and 17 with $|t| \geq 3$. The average magnitude of the high-minus-low alphas is 0.25% per month. Across all the 158 sets of deciles, the mean absolute alpha is 0.11%, but the q-factor model is still rejected by the GRS test at the 5% level in 98 sets of deciles. The q^5 model improves on the q-factor model substantially. The average magnitude of the high-minus-low alphas is 0.18% per month. The numbers of significant high-minus-low alphas are 19 with $|t| \geq 1.96$ and 4 with $|t| \geq 3$, dropping from 46 and 17, respectively, in the q-factor model. The mean absolute alpha across all the deciles is 0.1%. Finally, the q^5 model is rejected by the GRS test at the 5% level in only 58 sets of deciles, and this number of GRS rejections represents a reduction of 41% from 98 in the q-factor model.

The Fama-French 5-factor model performs poorly. The model leaves 89 high-minus-low alphas with $|t| \geq 1.96$ and 61 with $|t| \geq 3$, both of which are the highest across all the factor models. The average magnitude of the high-minus-low alphas is 0.38% per month. The model is also rejected by the GRS test at the 5% level in 113 sets of deciles. The Fama-French 6-factor model (which adds UMD) performs better. The numbers of high-minus-low alphas with $|t| \geq 1.96$ and $|t| \geq 3$ fall to 67 and 33, respectively. The average magnitude of the high-minus-low alphas drops to 0.28%, and the number of GRS rejections to 95. However, other than the slightly lower number of GRS rejections (95 versus 98), even the 6-factor model underperforms the q-factor model in the average magnitude of high-minus-low alphas (0.28% versus 0.25%) as well as the number of high-minus-low alphas with $|t| \geq 1.96$ (67 versus 46) and the number with $|t| \geq 3$ (33 versus 17).

Replacing RMW with RMWc in the Fama-French 6-factor model further improves its performance. The average magnitude of high-minus-low alphas falls to 0.25% per month, which is on par with the q-factor model. The numbers of significant high-minus-low alphas with $|t| \geq 1.96$ and $|t| \geq 3$ drop to 55 and 21, which are still higher than 46 and 17 in the q-factor model, respectively. Finally, the number of GRS rejections falls to 68, which is substantially lower than 98 in the q-factor model, but still higher than 58 in the q^5 model. The q^5 model also outperforms the alternative 6-factor model with RMWc in terms of the metrics based on significant high-minus-low alphas.

The Barillas-Shanken 6-factor model performs poorly. The average magnitude of the high-minus-low alphas is 0.28% per month (0.25% in the q-factor model). The numbers of significant high-minus-low alphas with $|t| \geq 1.96$ and $|t| \geq 3$ are 61 and 34, respectively, both of which are higher than 46 and 17 in the q-factor model. The mean absolute alpha across all the deciles is 0.14% (0.11% in the q-factor model), and the number of GRS rejections is 147 (98 in the q-factor model).

The Stambaugh-Yuan 4-factor model performs well. It underperforms the q-factor model in terms of the number of high-minus-low alphas with $|t| \geq 1.96$ (57 versus 46) and the number with $|t| \geq 3$ (25 versus 17), but outperforms in terms of the number of rejections by the GRS test (87 versus 98). However, the q^5 model substantially outperforms their model in virtually all metrics.

Finally, the Daniel-Hirshleifer-Sun 3-factor model performs poorly. The average magnitude of the high-minus-low alphas is 0.42% per month, which is the highest among all the factor models. The numbers of significant high-minus-low alphas with $|t| \geq 1.96$ and $|t| \geq 3$ are 83 and 45, which are the second highest among the models. The mean absolute alpha across all the deciles is 0.15%, which is the highest among the models. Finally, the number of GRS rejections is 108, which is only lower than the Fama-French 5-factor model and the Barillas-Shanken 6-factor model.

4.2.2 Performance Across Each Category of Anomalies

Panels B–G of Table 6 show that the q^5 model improves on the q-factor model across all the six categories of anomalies, especially in the investment and profitability categories.

Momentum From Panel B of Table 6, the improvement in the momentum category is noteworthy. Across the 36 significant momentum anomalies, the average magnitude of the high-minus-low q^5 alphas is 0.19% per month (0.26% in the q-factor model). The q^5 model reduces the number of significant high-minus-low alphas with $|t| \geq 1.96$ from 8 to 6, the mean absolute alpha from 0.1% per month slightly to 0.09%, and the number of rejections by the GRS test from 23 to 12.

The Fama-French 5-factor model shows essentially no explanatory power for momentum, leaving 34 out of 36 high-minus-low alphas with $|t| \geq 1.96$ (27 with $|t| \geq 3$) as well as the GRS rejections in 34 sets of deciles. The average magnitude of the high-minus-low alphas, 0.64% per month, and the mean absolute alpha across all the deciles, 0.16%, are the highest among all the factor models.

Even with UMD, the Fama-French 6-factor model still leaves 18 high-minus-low alphas significant with $|t| \geq 1.96$ and 8 with $|t| \geq 3$. The 6-factor model is also rejected by the GRS test in 25 sets of deciles. Changing RMW to RMWc in the Fama-French 6-factor model improves the metrics to 16, 5, and 18, respectively. However, the alternative 6-factor model underperforms the q^5 model in all metrics, including the number of GRS rejections (18 versus 12) and the number of significant high-minus-low alphas (16 versus 6 with $|t| \geq 1.96$ and 5 versus 1 with $|t| \geq 3$).

Other than the slightly lower average magnitude of the high-minus-low alphas, 0.25% versus 0.26% per month, the Barillas-Shanken 6-factor model underperforms the q-factor model. The numbers of high-minus-low alphas with $|t| \geq 1.96$ and $|t| \geq 3$ are 12 and 5 (8 and 1 in the q-factor model), respectively. The mean absolute alpha is 0.13%, the number of GRS rejections 33, and both are higher than 0.1% and 23 in the q-factor model, respectively. The Stambaugh-Yuan 4-factor model performs poorly, leaving 21 high-minus-low alphas with $|t| \geq 1.96$ and 7 with $|t| \geq 3$. The average magnitude of the high-minus-low alphas is 0.34% (0.26% in the q-factor model). Finally, the Daniel-Hirshleifer-Sun 3-factor model underperforms the q-factor model with higher numbers of significant high-minus-low alphas (12 with $|t| \geq 1.96$ and 2 with $|t| \geq 3$), a higher mean absolute alpha across all the deciles (0.15%), and a higher number of GRS rejections (26).

Value-versus-growth Panel C of of Table 6 shows that the Fama-French 5-factor model is the best performer in the value-versus-growth category. The number of high-minus-low alphas with $|t| \geq 1.96$ is only 1, and that with $|t| \geq 3$ is 0. The mean absolute alpha is 0.08% per month, and the number of GRS rejections 9. This performance benefits from having both CMA and HML, while giving up on momentum. Including UMD per the 6-factor model raises the number of alphas with $|t| \geq 1.96$ to 4 and the number of GRS rejections to 11. The q-factor model leaves 4 high-minus-low alphas with $|t| \geq 1.96$ and 0 with $|t| \geq 3$. However, the average magnitude of the high-minus-low alphas, 0.2%, and the number of GRS rejections, 17, are both higher than 0.16% and 11 in the 6-factor model. Adopting RMWc in the 6-factor model further improves the two metrics to 0.15% and 8, respectively. The performance of the q^5 model is largely similar to that of the q-factor model.

The Barillas-Shanken 6-factor model does not perform well. The average magnitude of high-minus-low alphas is 0.24% per month, the numbers of the alphas with $|t| \geq 1.96$ and $|t| \geq 3$ are 11 and 5, respectively, the mean absolute alpha 0.13%, and the number of GRS rejections 26. The Stambaugh-Yuan 4-factor model yields higher numbers of significant high-minus-low alphas, 6 with $|t| \geq 1.96$ and 2 with $|t| \geq 3$, but a lower number of GRS rejections, 15, than the q-factor model.

Finally, the Daniel-Hirshleifer-Sun 3-factor model performs poorly. The high-minus-low absolute alpha is on average 0.81% per month, which is the highest among all the models. All the 29 high-minus-low alphas are significant with $|t| \geq 1.96$ (26 with $|t| \geq 3$). All the 29 sets of deciles yield rejections in the GRS test. The mean absolute alpha of 0.23% is also the highest among all the models. The value-minus-growth deciles tend to have large and negative PEAD factor loadings, going in the wrong direction in explaining average returns, as well as positive but smaller FIN factor loadings, going in the right direction (untabulated). Because the PEAD premium is larger than the FIN premium, the Daniel et al. model exacerbates the value-versus-growth anomalies.

Investment Panel D of of Table 6 shows that the q^5 model is the best performer in the investment category. None of the 28 high-minus-low alphas have $|t| \geq 1.96$ or $|t| \geq 3$. The number of

GRS rejections is 7. The average magnitude of high-minus-low alphas is 0.1% per month, and the mean absolute alpha 0.08%. This performance improves substantially on the q-factor model, which leaves 9 high-minus-low alphas with $|t| \geq 1.96$ and 4 with $|t| \geq 3$, as well as 17 GRS rejections.

While outperforming the q-factor model, the Fama-French alternative 6-factor model with RMWc underperforms the q^5 model, leaving 7 high-minus-low alphas with $|t| \geq 1.96$ and 1 with $|t| \geq 3$. The average magnitude of high-minus-low alphas is 0.18% (0.1% in the q^5 model). The Fama-French 6-factor model with RMW underperforms the q-factor model slightly.

The Barillas-Shanken 6-factor model is largely comparable with the q-factor model, with a lower number of high-minus-low alphas with $|t| \geq 1.96$ (7 versus 9), but a higher number of GRS rejections (26 versus 17). The Stambaugh-Yuan 4-factor model outperforms the q-factor model, with a lower average magnitude of the high-minus-low alphas (0.17% versus 0.2% per month) and a lower number of high-minus-low alphas with $|t| \geq 1.96$ (5 versus 9). However, their model underperforms the q^5 model substantially. Finally, the Daniel-Hirshleifer-Sun 3-factor model performs the worst, with the highest average magnitude of the high-minus-low alphas (0.33%), the highest number of high-minus-low alphas with $|t| \geq 1.96$ (19), and the second highest number of GRS rejections (21).

Profitability From Panel E of Table 6, the q^5 model is also the best performer in the profitability category. Out of 35, the model leaves only 2 high-minus-low alphas with $|t| \geq 1.96$, and 0 with $|t| \geq 3$. The average magnitude of high-minus-low alphas is 0.14% per month, the mean absolute alpha 0.09%, and the number of GRS rejections 12. This performance improves on the q-factor model, which leaves 12 high-minus-low alphas with $|t| \geq 1.96$, 4 with $|t| \geq 3$, and 19 GRS rejections. The average magnitude of high-minus-low alphas is also higher, 0.23%, in the q-factor model.

All the other factor models substantially underperform the q^5 model. In particular, the Fama-French alternative 6-factor model with RMWc has a higher number of GRS rejections (17 versus 12), a higher average magnitude of high-minus-low alphas (0.26% versus 0.14%), as well as higher numbers of high-minus-low alphas with $|t| \geq 1.96$ (14 versus 2) and $|t| \geq 3$ (6 versus 0) than the

q^5 model. The Barillas-Shanken 6-factor model and the Stambaugh-Yuan 4-factor model both underperform the q-factor model slightly. However, the Daniel-Hirshleifer-Sun model 3-factor outperforms the q-factor model, with a lower magnitude of high-minus-low alphas (0.19% versus 0.23%), a lower number of high-minus-low alphas with $|t| \geq 1.96$ (6 versus 12), and a lower number of GRS rejections (12 versus 19). However, even this performance is weaker than the q^5 model.

Intangibles and Trading Frictions Panel F shows that the q^5 model is the best performer in the intangibles category. Out of 26, the model leaves 7 high-minus-low alphas with $|t| \geq 1.96$ (3 with $|t| \geq 3$). The average magnitude of high-minus-low alphas is 0.31% per month, the mean absolute alpha 0.13%, and the number of GRS rejections 10. The next best performer is the Stambaugh-Yuan model, with only slightly worse metrics than the q^5 model. The q-factor model leaves 11 high-minus-low alphas with $|t| \geq 1.96$, and 8 with $|t| \geq 3$. The average magnitude of high-minus-low alphas is 0.41% per month, the mean absolute alpha 0.17%, and the number of GRS rejections 19. The Fama-French and Barillas-Shanken models deliver largely similar performance as the q-factor model. The Daniel-Hirshleifer-Sun model again performs poorly, with the highest average magnitude of high-minus-low alphas (0.59%) and the highest number of high-minus-low alphas with $|t| \geq 1.96$ (14).

Finally, from Panel G, with only 4 trading frictions anomalies, the performance of the models is largely similar, except for the Daniel-Hirshleifer-Sun model, with the highest average magnitude of high-minus-low alphas, 0.43% per month. The q^5 model stands out by leaving none of the high-minus-low alphas with $|t| \geq 1.96$ or $|t| \geq 3$. The average magnitude of high-minus-low alphas is 0.17% per month, the mean absolute alpha 0.08%, and the number of GRS rejections 2.

4.2.3 Composite Testing Deciles

As an alternative way to represent the overall performance of the factor models, we form 7 composite scores across all the 158 anomalies as well as across each of the 6 categories of anomalies. We then use deciles formed on the composite scores as testing portfolios in factor regressions. Although containing less disaggregated information than Table 6, this approach directly quantifies to what extent a given category (as well as all) of the anomalies can be explained by a given factor model.

For a given set of anomalies, we construct its composite score for a stock by equal-weighting the stock's percentile rankings for the anomalies in question. Because anomalies forecast returns with different signs, we realign the anomalies to yield positive slopes in forecasting returns before forming the composite score. At the beginning of month t, we split stocks into deciles based on the NYSE breakpoints of the composite score that aggregates a given set of anomalies.[8] We calculate value-weighted decile returns for month t, and rebalance the deciles at the beginning of month $t+1$.

Table 7 details the factor regressions. The q^5 model is again the best performer. With the composite score that aggregates all the 158 anomalies, the high-minus-low decile earns on average 1.62% per month ($t = 9.13$). The high-minus-low alpha is the lowest in the q^5 model, only 0.31%, albeit still significant ($t = 2.32$). The high-minus-low decile has economically large and significantly positive loadings on all 4 non-market q^5 factors. The mean absolute alpha across all the deciles is also the lowest in the q^5 model, 0.07%, and the model is not rejected by the GRS test ($p = 0.18$).

For comparison, the Fama-French 6-factor alpha for the high-minus-low decile is 0.83% per month ($t = 6.89$), and its alternative 6-factor alpha with RMWc is 0.71% ($t = 6.05$). The mean absolute alphas are 0.15% and 0.11%, respectively, and both 6-factor models are rejected by the GRS test ($p = 0.00$). The q-factor alpha for the high-minus-low decile is 0.78% ($t = 5.18$). The mean absolute alpha is 0.15%, and the model is rejected by the GRS test ($p = 0.00$).

The high-minus-low composite momentum decile earns on average 1.05% per month ($t = 4$). The q^5 model yields a high-minus-low alpha of -0.21% ($t = -0.7$). Both the Roe and expected growth factors contribute to this performance, with economically large and significantly positive loadings. The mean absolute alpha is 0.1%, and the q^5 model is not rejected by the GRS test ($p = 0.24$). For comparison, the Fama-French 6-factor model yields a high-minus-low alpha of 0.29% ($t = 1.86$) and

[8] As detailed in the Internet Appendix, some individual anomaly deciles are formed monthly, whereas others are formed annually. When calculating the percentile rankings for a given anomaly at the beginning of month t, we adopt the same sorting frequency as in individual anomaly deciles. I.e., the percentile rankings for monthly sorted anomalies are recalculated monthly, but those for annually sorted anomalies are recalculated at the end of each June.

a mean absolute alpha of 0.1%, but their model is rejected by the GRS test ($p = 0.03$). The performance of their alternative 6-factor model is largely similar. The q-factor alpha is 0.29% ($t = 0.84$), the mean absolute alpha 0.1%, and the q-factor model is not rejected by the GRS test ($p = 0.07$).

The Fama-French 6-factor model does somewhat better than the q^5 model in explaining the composite value-minus-growth premium, which is on average 0.74% per month ($t = 3.53$). The q^5 model yields a high-minus-low alpha of 0.33% ($t = 1.83$), a mean absolute alpha of 0.16%, and a GRS p-value of 0.00. The 6-factor model produces a high-minus-low alpha of 0.18% ($t = 1.49$) and a mean absolute alpha of 0.11%, but their model is also rejected by the GRS test ($p = 0.02$). The alternative 6-factor model with RMWc does even better, with a high-minus-low alpha of 0.09% ($t = 0.74$), a mean absolute alpha of 0.1%, and an insignificant GRS p-value of 0.08. The Fama-French 5-factor model is again the best performer in this category, with a small high-minus-low alpha of 0.03% ($t = 0.21$), albeit still rejected by the GRS test ($p = 0.02$).

The high-minus-low composite investment decile earns on average 0.7% per month ($t = 4.89$). The q^5 model is the best performer, yielding a tiny high-minus-low alpha of 0.01% ($t = 0.11$), a mean absolute alpha of 0.06%, and a GRS p-value of 0.26. For comparison, the Fama-French 6-factor model generates a high-minus-low alpha of 0.26% ($t = 2.82$), a mean absolute alpha of 0.08%, and a GRS p-value of 0.01. The results for the alternative 6-factor model are largely similar, except for a GRS p-value of 0.07. Finally, the q-factor model yields a high-minus-low alpha of 0.22% ($t = 2.34$), a mean absolute alpha of 0.09%, and a GRS p-value of 0.00.

The high-minus-low composite profitability decile earns on average 0.83% per month ($t = 4.61$). The q^5 model is again the best performer, delivering a high-minus-low alpha of -0.11% ($t = -0.91$), a mean absolute alpha of 0.07%, and a GRS p-value of 0.17. The Fama-French 6-factor model yields a high-minus-low alpha of 0.5% ($t = 4.31$), a mean absolute alpha of 0.11%, and a GRS p-value of 0.00. The alternative 6-factor model reduces the high-minus-low alpha to 0.32% ($t = 2.24$), but the other metrics are similar. Finally, the q-factor model yields a high-minus-low alpha of 0.27%

($t = 2.24$), a mean absolute alpha of 0.08%, and a GRS p-value of 0.01.

The high-minus-low composite intangibles decile earns on average 1.08% per month ($t = 6.13$). The q^5 model yields a high-minus-low alpha of 0.45% ($t = 3.31$), a mean absolute alpha of 0.16%, and a GRS p-value of 0.00. The Fama-French 6-factor model has a somewhat larger high-minus-low alpha, 0.54% ($t = 4.24$), but its other metrics are largely comparable with the q^5 model. Finally, the high-minus-low composite frictions decile earns on average 0.34% ($t = 2.87$). The q^5 model yields a high-minus-low alpha of 0.21% ($t = 1.52$), a mean absolute alpha of 0.08%, and a GRS p-value of 0.23. The performance of the Fama-French 6-factor model is largely similar.

4.2.4 Subsample Analysis

For the extensive tests in Tables 6 and 7, we have also explored subsample analysis by splitting the sample into two, one from January 1967 to December 1991 and the other from January 1992 to December 2016 (the Internet Appendix). Without going through the details, we can report that the q^5 model remains the best performing model for both subsamples and for most performance metrics.

4.3 Individual Factor Regressions

To dig deeper, we detail individual factor regressions of all the 158 anomalies. Table 8 reports the average return and alphas from different models as well as their t-values adjusted for heteroscedasticity and autocorrelations for each high-minus-low decile. We also tabulate the mean absolute alpha and the GRS p-value testing that the alphas are jointly zero across a given set of deciles for a given factor model. To save space, Table 9 only details the factor loadings for the q^5 model.

4.3.1 Momentum

Columns 1–36 in Table 8 detail the alphas for the 36 momentum anomalies. The high-minus-low deciles on earnings surprises (Sue1), revenue surprises (Rs1), and the number of consecutive quarters with earnings increases (Nei1), all at the 1-month horizon, earn average returns of 0.46%, 0.32%, and 0.33% per month ($t = 3.48$, 2.28, and 3.04), respectively. Their q-factor alphas are 0.06%, 0.24%, and 0.12% ($t = 0.46, 1.71$, and 1.2), and the q^5 alphas $-0.04\%, 0.12\%$, and 0.02% ($t = -0.3$, 0.86, and 0.25), respectively. The q-factor model is rejected by the GRS test across the Sue1 and Rs1 deciles, but not the Nei1 deciles. The q^5 model is not rejected across any set of these deciles.

The Fama-French 6-factor alphas for the high-minus-low Sue1, Rs1, and Nei1 deciles are 0.3%, 0.44%, and 0.27% per month ($t = 2.54, 3.27$, and 2.95), and the alternative 6-factor alphas with RMWc 0.25%, 0.41%, and 0.23% ($t = 2.1$, 3.01, and 2.33), respectively. The Stambaugh-Yuan 4-factor model performs similarly, but the Barillas-Shanken 6-factor model yields somewhat smaller and less significant alphas. However, all these models are rejected by the GRS test.

However, all models including the q and q^5 models fail to explain the Abr anomaly at any of the 1-, 6-, and 12-month horizons, in which Abr stands for cumulative abnormal returns around earnings announcements. In particular, at the 1-month horizon, the high-minus-low decile earns on average 0.7% per month ($t = 5.45$). The q-factor alpha is 0.62% ($t = 4.25$), and the q^5 alpha 0.56% ($t = 4$). Similarly, the Fama-French 6-factor alpha is 0.64% ($t = 4.66$). Because Abr is part of the PEAD factor, the Daniel-Hirshleifer-Sun alpha is the smallest, 0.28%, albeit still significant ($t = 2.2$).

Except for the Fama-French 5-factor model, all the models can explain price momentum formed on prior 6-month returns (R^6), prior 11-month returns (R^{11}), prior industry returns (Im), prior 6-month residual returns (ϵ^6), and prior 11-month residual returns (ϵ^{11}). In particular, the Jegadeesh-Titman (1993) high-minus-low decile on prior 6-month returns at the 6-month horizon ($R^6 6$) earns on average 0.82% per month ($t = 3.5$). The q-factor alpha is 0.25% ($t = 0.83$), and the q^5 alpha -0.16% ($t = -0.6$). Similarly, the 6-factor alpha is 0.18% ($t = 1.77$). However, all the models are still rejected by the GRS test at the 5% level across the $R^6 6$ deciles.

Columns 1–36 in Table 9 detail the factor loadings from the q^5 factor regressions of the 36 winner-minus-loser deciles. The 36 loadings on the expected growth factor, R_{Eg}, are universally positive, and 23 of them are significant with $t \geq 1.96$. Intuitively, winners have higher expected growth rates and earn higher expected returns than losers (Johnson 2001; Liu and Zhang 2014).

4.3.2 Value-versus-growth

Columns 37–65 in Table 8 detail the alphas for the 29 value-minus-growth anomalies. Surprisingly, the Barillas-Shanken 6-factor model fails to explain annually sorted value-minus-growth anomalies, including book-to-market (Bm), earnings-to-price (Ep), cash flow-to-price (Cp), sales-to-price (Sp), intrinsic-to-market value (Vhp), enterprise book-to-price (Ebp), and duration (Dur). The Barillas-Shanken alphas for these high-minus-low deciles are $-0,29\%$, -0.52%, -0.47%, -0.47%, -0.48%, -0.33%, and 0.48% per month ($t = -2.17$, -3.05, -3.02, -3.01, -2.71, -2.65, and 3.07), respectively. In contrast, their Fama-French 6-factor alphas are -0.08%, -0.14%, -0.18%, -0.16%, -0.15%, -0.13%, and 0.12% ($t = -0.7$, -1.04, -1.48, -1.22, -1.06, -1.09, and 0.91), respectively. The Barillas-Shanken model is strongly rejected by the GRS test across these 7 sets of deciles, whereas except for the Cp deciles, the 6-factor model is not rejected at the 5% level.

We find that the UMD loadings in the Barillas-Shanken model are economically large, 0.41, 0.46, 0.4, 0.2, 0.39, 0.29, and -0.43, respectively, all of which are more than 3.5 standard errors from zero (untabulated). In contrast, the UMD loadings in the Fama-French 6-factor model are economically small, -0.03, 0.05, -0.06, -0.13, 0.01, -0.12, and -0.02, respectively, all of which, except for two, are insignificant at the 5% level. We verify that the correlation between the monthly formed HML^{m} and UMD is high, -0.65, but the correlation between the annually formed HML and UMD is low, only -0.19. Intuitively, the high HML^{m}-UMD correlation pushes up the UMD loadings in the presence of HML^{m} in the Barillas-Shanken model, causing it to overshoot the average value-minus-growth returns to yield economically large but negative alphas.

For comparison, the q-factor alphas of the high-minus-low Bm, Ep, Cp, Sp, Vhp, Ebp, and Dur deciles are 0.15%, 0.02%, 0.04%, -0.05%, 0.01%, 0.06%, and -0.03% per month ($t = 0.99, 0.12, 0.2, -0.28, 0.06$, 0.42 and -0.17), and their q^5 alphas 0.08%, -0.07%, 0.02%, 0.05%, -0.11%, 0.08%, and 0.06% ($t = 0.51$, -0.37, 0.1, 0.3, -0.61, 0.49, and 0.3), respectively.

However, we should emphasize that the q-factor model and the q^5 model both fail to explain the monthly formed book-to-market anomaly at the 12-month horizon, $\mathrm{Bm^q12}$, with alphas of 0.37% and 0.38% ($t = 2.18$ and 2.25), respectively. In contrast, most of the other models, including the Barillas-Shanken 6-factor model, capture the $\mathrm{Bm^q12}$ anomaly, with insignificant alphas.

Columns 37–65 in Table 9 report the q^5-factor loadings for the 26 value-minus-growth deciles. The expected growth factor loadings are insignificant in all but two cases, net payout yield (Nop) and enterprise multiple (Em). For the high-minus-low Nop decile, the q-factor alpha is 0.35% per month ($t = 2.42$), and the q^5 model reduces the alpha to 0.2% ($t = 1.33$). The high-minus-low decile has an R_{Eg}-loading of 0.22 ($t = 1.98$), indicating that high net payout yields signal high expected growth going forward. For the high-minus-low Em decile, the q-factor alpha is -0.24% ($t = -1.4$), and the q^5 model reduces the alpha further in magnitude to -0.05% ($t = -0.27$).

Strikingly, the Daniel-Hirshleifer-Sun 6-factor model fails to explain any of the value-minus-growth anomalies. In particular, the high-minus-low Bm decile earns on average 0.54% per month ($t = 2.61$). However, its Daniel et al. alpha is 0.87% ($t = 4.16$). We find that the FIN factor loading for the high-minus-low decile is positive, 0.55 ($t = 4.34$), going in the right direction in explaining the average return (untabulated). However, this loading is dominated by the PEAD factor loading of -0.77 ($t = -7.97$), which goes in the wrong direction. Because the PEAD premium is more than twice as large as the FIN premium, the Daniel et al. model makes the Bm anomaly worse. Monthly sorts further exacerbate the problem. The high-minus-low $\mathrm{Bm^q12}$ decile earns on average 0.48% ($t = 2.21$), but the Daniel et al. model yields an alpha of 1.2% ($t = 6.11$). Its FIN factor loading is 0.46 ($t = 5.68$), which is again dominated by the PEAD loading of -1.27 ($t = -11.31$).

4.3.3 Investment

Columns 66–93 in Table 8 detail the alphas for the 28 investment anomalies. The q^5 model shines in this category, leaving zero high-minus-low alpha with $|t| \geq 1.96$.

The high-minus-low decile on net operating assets (Noa) has a significant q-alpha of -0.45% per month ($t = -2.59$). The q^5 alpha is only -0.13% ($t = -0.88$). In contrast, most of the other models fail to explain the Noa anomaly. For example, the Fama-French 6-factor alpha for the high-minus-low decile is -0.45% ($t = -3.18$), and the Barillas-Shanken alpha -0.61% ($t = -4.02$).

More important, the q^5 model explains the accruals anomaly. The high-minus-low decile on operating accruals (Oa) has a large q-factor alpha of -0.56% per month ($t = -4.1$), and the q^5 model reduces the alpha in magnitude to -0.23% ($t = -1.51$). Another challenging anomaly for the q-factor model is discretionary accruals (Dac). The high-minus-low Dac decile has a large q-factor alpha of -0.67% ($t = -4.73$), and the q^5 model reduces the alpha to -0.28% ($t = -1.91$). In contrast, the other models all fail to explain the Oa and Dac anomalies. In particular, the Fama-French 6-factor alphas for the high-minus-low Oa and Dac deciles are -0.47% ($t = -3.42$) and -0.63% ($t = -4.55$), and the Barillas-Shanken alphas -0.54% ($t = -3.68$) and -0.72% ($t = -4.94$), respectively.

The q^5 model also improves on the q-factor model in explaining the dWc (change in net noncash working capital) and dFin (change in net financial assets) anomalies. The high-minus-low dWc and dFin deciles have significant q-factor alphas of -0.51% per month ($t = -3.8$) and 0.43% ($t = 3$), but insignificant q^5 alphas of -0.22% ($t = -1.62$) and 0.12% ($t = 0.81$), respectively. For comparison, the Fama-French 6-factor alphas are -0.45% ($t = -3.45$) and 0.48% ($t = 3.86$), and the Barillas-Shanken alphas -0.4% ($t = -2.74$) and 0.53% ($t = 3.71$), respectively.

Columns 66–93 in Table 9 report the q^5 factor loadings for the 28 investment anomalies. The high-minus-low Noa decile has a large loading of -0.5 ($t = -4.46$) on the expected growth factor, R_{Eg}, in the q^5 model. The high-minus-low Oa and Dac deciles have large R_{Eg}-loadings of -0.53 ($t = -5.02$) and -0.61 ($t = -5.65$), respectively. As such, high operating and discretionary accruals indicate low expected growth. Intuitively, given the level of earnings, high accruals mean low cash flows available for financing investments, giving rise to low expected growth. Similarly, the high-minus-low dWc decile has a large R_{Eg}-loading of -0.46 ($t = -4.58$). Intuitively, increases in net noncash working capital signal low expected growth. Finally, the high-minus-low dFin decile has a large R_{Eg}-loading of 0.5 ($t = 4.63$). Intuitively, increases in net financial assets provide more internal funds available for investments, stimulating expected growth going forward.

4.3.4 Profitability

Columns 94–128 in Table 8 detail the alphas for the 35 anomalies in the profitability category. The q^5 model again shines, leaving only two high-minus-low alphas with $|t| \geq 1.96$ and zero with $|t| \geq 3$.

The high-minus-low deciles on asset turnover, Ato^{q}, have q-factor alphas of 0.35%, 0.34%, and 0.32% per month, with t-values above 2, across the 1-, 6-, and 12-month horizons, respectively. The q^5 model reduces all the alphas to about 0.11%, with t-values below 0.7. For comparison, the Fama-French 6-factor alphas are 0.42%, 0.4%, and 0.36% ($t = 2.74, 2.85$, and 2.61), and the Barillas-Shanken 6-factor alphas 0.52%, 0.53%, and 0.52% ($t = 3.24, 3.67$, and 3.61), respectively.

The high-minus-low deciles on operating profits-to-lagged assets, Ola^{q}, have q-factor alphas of 0.4%, 0.26%, and 0.32% per month ($t = 2.64, 1.89$, and 2.49), but q^5 alphas of -0.08%, -0.2%, and -0.1% ($t = -0.59, -1.79$, and -0.92) across the 1-, 6-, and 12-month horizons, respectively. All the other models except for the Daniel-Hirshleifer-Sun model fail to explain the Ola^{q} anomaly. The Fama-French alternative 6-factor alphas are 0.5%, 0.32%, and 0.33% ($t = 2.87, 2.1$, and 2.44), and the Barillas-Shanken 6-factor alphas 0.48%, 0.34%, and 0.38% ($t = 3.6, 2.91$, and 3.44), respectively.

However, we should emphasize that in two cases, return on equity (Roe) and operating profits-to-lagged book equity (Ole^{q}), at the 6-month horizon, the q^5 model overshoots, yields significantly negative alphas, and underperforms the q-factor model and most of the other models. The high-minus-low Roe6 and $\text{Ole}^{\text{q}}6$ deciles have q-factor alphas of -0.16% per month ($t = -1.32$) and -0.11% ($t = -0.79$), but q^5 alphas of -0.29% ($t = -2.53$) and -0.31% ($t = -2.23$), respectively. For comparison, the Fama-French 6-factor alphas are 0.16% ($t = 1.33$) and 0.02% ($t = 0.2$), and the Barillas-Shanken 6-factor alphas -0.2% ($t = -1.55$) and -0.3% ($t = -2.08$), respectively.

Columns 94–128 in Table 9 report the q^5 factor loadings for the 35 profitability anomalies. Except for the fundamental score (F^{q}) at the 1, 6-, and 12-month horizons, 32 out of 35 loadings on the expected growth factor indicate that, sensibly, high profitability firms have higher expected growth than low profitability firms. (Failure probability, Fp^{q}, which is a measure of financial distress, is inversely related to profitability.) Out of the 32 loadings, 26 are significant at the 5% level. The high-minus-low F^{q} deciles have negative, but mostly insignificant, loadings on the expected growth factor, R_{Eg}. Despite the negative loadings, the q^5 model explains the F^{q} anomaly. The high-minus-low Ato^{q} deciles have economically large R_{Eg}-loadings of 0.38, 0.35, and 0.33 ($t = 3.18$, 3.09, and 2.9) across the 1-, 6-, and 12-month horizons, and the high-minus-low Ola^{q} deciles also have large R_{Eg}-loadings of 0.81, 0.77, and 0.69 (t = 8.12, 9.12, and 7.73), respectively. These loadings propel the q^5 model as the best performer in the profitability category.

4.3.5 Intangibles and Trading Frictions

Columns 129–154 in Table 8 detail the alphas for the 26 anomalies in the intangibles category, and the same columns in Table 9 report their high-minus-low loadings in the q^5 model. The q^5 model helps explain the R&D-to-market (Rdm) anomaly. The high-minus-low decile earns a q-factor alpha of 0.72% per month ($t = 3.11$). The q^5 model reduces the alpha to 0.25% ($t = 1.13$) via a large R_{Eg}-loading of 0.78 ($t = 4.51$). Similarly, in monthly sorts, at the 1-, 6-, and 12-month horizons, the high-minus-low Rdm^{q} deciles have q-alphas of 1.39%, 0.95%, and 0.81% ($t = 3.06$, 2.87, and 3.01), but smaller q^5 alphas of 1.07%, 0.54%, and 0.37% (t = 2.26, 1.57, and 1.31), respectively. The corresponding R_{Eg}-loadings are 0.53, 0.68, and 0.75 ($t = 2.05, 3.16$, and 4.11), respectively. Intuitively, R&D expenses depress current earnings due to Generally Accepted Accounting Principles, but raise intangible capital that induces future growth opportunities. While the q-factor model misses this economic mechanism, the q^5 model with the expected growth factor incorporates it.

The other models mostly fail to explain the R&D-to-market anomaly. In annual sorts, the high-minus-low Rdm decile has a Fama-French 6-factor alpha of 0.6% per month (t = 2.77), a Barillas-Shanken alpha of 0.73% (t = 3.09), but a Stambaugh-Yuan alpha of 0.3% (t = 1.34). In monthly sorts, the high-minus-low Rdm^{q} deciles have 6-factor alphas of 1.33%, 0.92%, and 0.77% (t = 3.58, 3.05, and 3), Barillas-Shanken alphas of 1.4%, 0.96%, and 0.8% ($t = 3.44, 2.89$, and 2.84), and Stambaugh-Yuan alphas of 1.14%, 0.63%, and 0.47% ($t = 2.87, 2.13$, and 1.84), respectively.

We should acknowledge that the q^5 model, despite improving on the q-factor model substantially, still leaves 7 high-minus-low alphas with $|t| \geq 1.96$, including 3 with $|t| \geq 3$, in the intangibles category. In particular, three Heston-Sadka (2008) seasonality variables, $R_{\mathrm{a}}^{[2,5]}, R_{\mathrm{a}}^{[6,10]}$, and $R_{\mathrm{a}}^{[11,15]}$, have high-minus-low q^5 alphas of 0.85%, 0.95%, and 0.55% per month ($t = 4.02, 4.74$, and 3.16), respectively. The R_{Eg}-loadings of these high-minus-low deciles are all economically small and insignificant. All the other factor models also fail to explain these seasonality anomalies.

Finally, the last 4 columns in Table 8 report the alphas for the 4 anomalies in the trading frictions category, and the same columns in Table 9 show their high-minus-low loadings in the q^5 model. The q^5 model yields insignificant high-minus-low alphas for the two idiosyncratic skewness anomalies (Isff1 and Isq1), whereas all the other models produce significant alphas. The high-minus-low Isff1 and Isq1 deciles have positive and marginally significant expected growth factor loadings.

5 Conclusion

In the multiperiod investment framework, firms with high expected investment growth should earn higher expected returns than firms with low expected investment growth, holding current investment and expected profitability constant. Motivated by this prediction, we form cross-sectional forecasts and construct an expected growth factor, which yields an average return of 0.82% per month ($t = 9.81$). We add the expected growth factor to the q-factor model to form the q^5 model. In a large set of testing deciles formed on 158 significant anomalies, the q^5 model is the overall best performing model, improving on the q-factor model substantially. The q-factor model already compares favorably with the Fama-French 6-factor model. Although the best model in the value-versus-growth category, the Fama-French 5-factor model shows no explanatory power for momentum. Finally, the Barillas-Shanken 6-factor model and the Daniel-Hirshleifer-Sun 3-factor model both perform poorly.

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Table 1 : Monthly Cross-sectional Regressions of Future Investment-to-assets Changes, July 1963–December 2016, 642 Months

For each month, we perform cross-sectional regressions of future τ-year-ahead investment-to-assets changes, $\mathrm{d}^{\tau}\mathrm{I/A}$, in which $\tau = 1, 2, 3$, on the log of Tobin's q, $\log(q)$, cash flows, Cop, the change in return on equity, dRoe, as well as on all the three regressors. Current investment-to-assets is from the most recent fiscal year ending at least four months ago, and $\mathrm{d}^{\tau}\mathrm{I/A}$ is investment-to-assets from the subsequent τ-year-ahead fiscal year end minus the current investment-to-assets. The cross-sectional regressions are estimated via weighted least squares with the market equity as weights. We winsorize each variable each month at the 1–99% level. We report the average slopes, the t-values adjusted for heteroscedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2, in percent). At the beginning of each month t, we calculate the expected I/A changes, $E_t[\mathrm{d}^{\tau}\mathrm{I/A}]$, by combining the most recent winsorized predictors with the average cross-sectional slopes. The most recent predictors, $\log(q)$ and Cop, are from the most recent fiscal year ending at least four months ago as of month t, and dRoe is based on the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[\mathrm{d}^{\tau}\mathrm{I/A}]$ are from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $\mathrm{d}^{\tau}\mathrm{I/A}$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly. For instance, for $\tau = 1$, the regressors used in the latest monthly cross-sectional regression are further lagged by 12 months relative to the most recent predictors used in calculating $E_t[\mathrm{d}^{1}\mathrm{I/A}]$. We report time-series averages of cross-sectional Pearson and rank correlations between $E_t[\mathrm{d}^{\tau}\mathrm{I/A}]$ calculated at the beginning of month t and the realized τ-year-ahead investment-to-assets changes. The p-values testing that a given correlation is zero are in brackets.

	Panel A: $\log(q)$				Panel B: Cop			
τ	$\log(q)$	R^2	Pearson	Rank	Cop	R^2	Pearson	Rank
1	0.021	1.03	0.014	0.002	0.427	3.13	0.146	0.180
	(4.91)		[0.01]	[0.62]	(13.31)		[0.00]	[0.00]
2	−0.006	1.15	0.028	0.042	0.469	4.10	0.134	0.158
	(−1.13)		[0.00]	[0.00]	(12.19)		[0.00]	[0.00]
3	−0.018	1.18	0.089	0.104	0.449	3.97	0.117	0.133
	(−3.56)		[0.00]	[0.00]	(10.66)		[0.00]	[0.00]

	Panel C: dRoe				Panel D: $\log(q)$, Cop, and dRoe					
τ	dRoe	R^2	Pearson	Rank	$\log(q)$	Cop	dRoe	R^2	Pearson	Rank
1	0.824	2.23	0.072	0.135	−0.031	0.530	0.802	6.64	0.142	0.213
	(7.98)		[0.00]	[0.00]	(−5.86)	(12.82)	(7.75)		[0.00]	[0.00]
2	0.973	2.00	0.073	0.158	−0.076	0.722	0.930	8.88	0.156	0.226
	(9.99)		[0.00]	[0.00]	(−10.09)	(12.58)	(10.25)		[0.00]	[0.00]
3	0.772	1.57	0.060	0.133	−0.093	0.760	0.743	9.18	0.158	0.221
	(8.49)		[0.00]	[0.00]	(−12.14)	(12.20)	(8.62)		[0.00]	[0.00]

Table 2 : Properties of the Expected Growth Deciles, January 1967–December 2016, 600 Months

We use the log of Tobin's q, $\log(q)$, cash flow, Cop, and the change in return on equity, dRoe, to form the expected investment-to-assets changes, $E_t[\mathrm{d}^\tau\mathrm{I/A}]$, with τ ranging from 1 to 3 years. At the beginning of each month t, we calculate $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ by combining the three most recent predictors (winsorized at the 1–99% level) with the average slopes. The most recent predictors, $\log(q)$ and Cop, are from the most recent fiscal year ending at least four months ago as of month t, and dRoe uses the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ are from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $\mathrm{d}^\tau\mathrm{I/A}$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly. For instance, for $\tau = 1$, the regressors used in the latest monthly cross-sectional regression are further lagged by 12 months relative to the most recent predictors used in calculating $E_t[\mathrm{d}^1\mathrm{I/A}]$. Cross-sectional regressions are estimated via weighted least squares with the market equity as weights. At the beginning of each month t, we sort all stocks into deciles based on the NYSE breakpoints of the ranked $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ values, and compute value-weighted decile returns for the current month t. The deciles are rebalanced at the beginning of month $t+1$. For each decile and the high-minus-low decile, we report the average excess return, $\overline{R}$, the q-factor alpha, α_q, the expected investment-to-assets changes, $E_t[\mathrm{d}^\tau\mathrm{I/A}]$, and the average future realized changes, $\mathrm{d}^\tau\mathrm{I/A}$, and their heteroscedasticity-and-autocorrelation-adjusted t-statistics (beneath the corresponding estimates). $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ and $\mathrm{d}^\tau\mathrm{I/A}$ are value-weighted.

τ	Low	2	3	4	5	6	7	8	9	High	H−L
					Panel A: Average excess returns, $\overline{R}$						
1	−0.12	0.26	0.33	0.45	0.46	0.51	0.57	0.65	0.75	0.95	1.06
	−0.39	1.05	1.43	2.09	2.31	2.64	3.03	3.41	3.99	4.57	6.25
2	−0.09	0.26	0.22	0.39	0.47	0.63	0.61	0.79	0.67	1.09	1.18
	−0.32	1.06	1.00	1.86	2.41	3.37	3.33	4.05	3.39	5.07	6.98
3	−0.09	0.22	0.31	0.38	0.52	0.52	0.75	0.66	0.85	1.09	1.18
	−0.32	0.94	1.39	1.81	2.70	2.77	3.86	3.16	4.30	5.01	6.96
					Panel B: The q-factor alphas, α_q						
1	−0.40	−0.24	−0.22	−0.08	−0.16	0.01	0.09	0.22	0.24	0.43	0.83
	−3.86	−2.35	−2.55	−0.94	−1.77	0.10	1.28	2.13	2.70	4.07	5.85
2	−0.33	−0.14	−0.13	−0.21	−0.10	0.08	−0.01	0.18	0.24	0.59	0.92
	−3.48	−1.71	−1.32	−3.21	−1.29	0.85	−0.14	1.74	2.59	4.06	5.31
3	−0.39	−0.12	−0.21	−0.22	−0.04	−0.10	0.20	0.15	0.32	0.61	0.99
	−3.90	−1.35	−2.50	−2.83	−0.50	−1.08	2.30	1.56	3.04	4.25	5.73
					Panel C: The expected growth, $E_t[\mathrm{d}^\tau\mathrm{I/A}]$						
1	−15.21	−7.70	−5.61	−4.18	−2.99	−1.92	−0.80	0.55	2.62	7.79	23.00
	−35.58	−30.23	−24.17	−19.68	−15.25	−10.44	−4.63	3.50	17.61	39.62	44.31
2	−19.81	−10.17	−7.33	−5.44	−3.91	−2.53	−1.07	0.70	3.36	9.70	29.52
	−33.10	−25.50	−20.37	−16.18	−12.32	−8.34	−3.65	2.52	12.60	31.70	45.18
3	−20.49	−11.17	−8.22	−6.25	−4.64	−3.17	−1.58	0.25	2.95	9.45	29.94
	−29.78	−22.35	−17.91	−14.41	−11.23	−7.96	−4.14	0.70	8.70	27.59	44.81
					Panel D: Average future realized growth, $\mathrm{d}^\tau\mathrm{I/A}$						
1	−17.43	−12.37	−3.83	−3.51	−1.22	−0.35	−0.42	0.56	1.64	6.09	23.52
	−12.01	−8.33	−6.44	−5.19	−2.36	−0.73	−0.90	1.01	3.72	9.15	15.03
2	−24.50	−12.33	−6.53	−3.87	−2.47	−1.66	−0.09	1.41	1.17	3.22	27.71
	−14.75	−11.87	−8.27	−4.75	−4.19	−2.72	−0.20	2.44	2.12	4.93	16.34
3	−23.56	−12.48	−7.07	−3.53	−2.28	−3.02	−1.70	−0.65	0.40	1.52	25.08
	−14.63	−13.06	−9.47	−4.99	−3.75	−4.76	−3.44	−1.15	0.65	2.11	15.30

Table 3 : Properties of the Expected Growth Factor, R_{Eg}, January 1967–December 2016, 600 Months

The log of Tobin's q, $\log(q)$, cash flows, Cop, and change in return on equity, dRoe, are used to form the expected 1-year-ahead investment-to-assets changes, $E_t[\mathrm{d}^1\mathrm{I/A}]$. At the beginning of month t, $E_t[\mathrm{d}^1\mathrm{I/A}]$ combines the most recent predictors (winsorized at the 1–99% level) with average Fama-MacBeth slopes. The most recent $\log(q)$ and Cop are from the most recent fiscal year ending at least four months ago as of month t, and dRoe uses the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ are from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $\mathrm{d}^1\mathrm{I/A}$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged. The regressions are estimated via weighted least squares with the market equity as weights. At the beginning of each month t, we use the median NYSE market equity to split stocks into two groups, small and big, based on the beginning-of-month market equity. Independently, we sort all stocks into three $E_t[\mathrm{d}^1\mathrm{I/A}]$ groups, low, median, and high, based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of its ranked values at the beginning of month t. Taking the intersections, we form six portfolios. We calculate value-weighted portfolio returns for the current month t, and rebalance the portfolios at the beginning of month $t+1$. The expected growth factor, R_{Eg}, is the difference (high-minus-low), each month, between the simple average of the returns on the two high $E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios and the simple average of the returns on the two low $E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios. Panel A reports properties of the six size-$E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios, including value-weighted average excess returns, $\overline{R}$, their t-values, $t_{\overline{R}}$, the volatilities of portfolio excess returns, σ_R, the simple average of the beginning-of-month market equity in billions of dollars, the average number of stocks, the average beginning-of-month market equity as a percentage of total market equity, as well as the value-weighted averages of the expected 1-year-ahead investment-to-assets change, $E_t[\mathrm{d}^1\mathrm{I/A}]$, the realized 1-year-ahead investment-to-assets change, $\mathrm{d}^1\mathrm{I/A}$, the log of Tobin's q, $\log(q)$, and operating cash flows-to-assets, Cop, from the fiscal year ending at least four months ago as of month t, and the change in return on equity, dRoe, calculated with the latest announced earnings, and if not available, earnings from the fiscal quarter ending at least four months ago. Panel B reports for the expected growth factor, R_{Eg}, its average return, $\overline{R}_{\mathrm{Eg}}$, and alphas, factor loadings, and R^2s from the q-factor model, and the q-factor model augmented with an $\log(q)$ factor, a Cop factor, and a dRoe factor, separately or jointly. The t-values adjusted for heteroscedasticity and autocorrelations are in parentheses. To form the $\log(q)$ and Cop factors, at the end of June of year t, we use the median NYSE market equity to split stocks into two groups, small and big. Independently, we split stocks into three $\log(q)$ groups, low, median, and high, based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of its ranked values from the fiscal year ending in calendar year $t-1$. Taking the intersections, we form six portfolios. We calculate monthly value-weighted portfolio returns from July of year t to June of $t+1$, and rebalance the portfolios at the end of June of year $t+1$. The $\log(q)$ factor, $R_{\log(q)}$, is the difference (low-minus-high), each month, between the simple average of the returns on the two low $\log(q)$ portfolios and the simple average of the returns on the two high $\log(q)$ portfolios. The (high-minus-low) Cop factor, R_{Cop}, is constructed analogously. To form the dRoe factor, at the beginning of each month t, we use the median NYSE market equity to split stocks into two groups, small and big, based on the beginning-of-month market equity. Independently, we sort stocks into three dRoe groups, low, median, and high, based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of its ranked values at the beginning of month t. dRoe is calculated with the latest announced earnings, and if not available, with the earnings from the fiscal quarter ending at least four months ago. Taking the intersections, we form six portfolios. We calculate monthly value-weighted portfolio returns for the current month t, and rebalance the portfolios monthly. The dRoe factor, R_{dRoe}, is the difference (high-minus-low), each month, between the simple average of the returns on the two high dRoe portfolios and the simple average of the returns on the two low dRoe portfolios. Finally, Panel C reports the correlations of the expected growth factor, R_{Eg}, with the q-factors, as well as the $\log(q)$, Cop, and dRoe factors.

Panel A: Properties of the six size-expected growth benchmark portfolios

	Low	Median	High	Low	Median	High	Low	Median	High
	$\overline{R}$			$t_{\overline{R}}$			σ_R		
Small	0.22	0.93	1.34	0.71	3.48	4.92	7.12	6.05	6.22
Big	0.21	0.44	0.73	0.88	2.38	3.99	5.57	4.44	4.52
	Average size			# Stocks on average			% Total market cap		
Small	0.14	0.21	0.21	974	623	580	2.53	2.43	2.11
Big	4.54	6.42	9.03	142	233	202	12.27	28.46	33.30
	$E_t[\mathrm{d}^1\mathrm{I/A}]$			$\mathrm{d}^1\mathrm{I/A}$			$\log(q)$		
Small	−11.43	−2.52	4.46	−11.61	0.08	5.38	0.24	0.07	0.22
Big	−8.54	−2.26	3.93	−10.42	−1.47	2.79	0.35	0.33	0.60
	Cop			dRoe					
Small	4.38	14.65	24.39	−2.26	−0.16	1.15			
Big	9.82	17.44	28.27	−1.82	−0.19	0.65			

Panel B: Properties of the expected growth factor, R_{Eg}

$\overline{R}_{\mathrm{Eg}}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	R^2			
0.82	0.63	−0.10	−0.09	0.25	0.30	0.48			
(9.81)	(9.11)	(−6.17)	(−3.47)	(6.26)	(9.43)				
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	$\beta_{\log(q)}$	R^2		
	0.63	−0.11	−0.09	0.27	0.30	−0.02	0.48		
	(9.15)	(−6.20)	(−3.54)	(6.00)	(9.05)	(−0.50)			
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Cop}	R^2		
	0.36	−0.03	−0.02	0.32	0.15	0.57	0.66		
	(6.09)	(−1.84)	(−0.70)	(10.36)	(5.07)	(10.41)			
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{dRoe}	R^2		
	0.59	−0.11	−0.09	0.22	0.23	0.15	0.49		
	(8.06)	(−6.44)	(−3.86)	(4.81)	(5.20)	(2.43)			
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Cop}	β_{dRoe}	R^2	
	0.32	−0.03	−0.03	0.29	0.08	0.57	0.15	0.67	
	(4.99)	(−2.04)	(−0.86)	(7.48)	(2.13)	(9.79)	(2.44)		
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	$\beta_{\log(q)}$	β_{Cop}	β_{dRoe}	R^2
	0.24	−0.01	−0.01	0.08	0.05	0.22	0.69	0.21	0.71
	(3.73)	(−1.02)	(−0.52)	(1.79)	(1.66)	(8.35)	(13.69)	(3.36)	

Panel C: Correlations of R_{Eg} with other factors

R_{Mkt}	R_{Me}	$R_{\mathrm{I/A}}$	R_{Roe}	$R_{\log(q)}$	R_{Cop}	R_{dRoe}
−0.47	−0.37	0.38	0.52	0.21	0.70	0.44

Table 4 : The List of Significant Anomalies To Be Explained

The 158 anomalies (significant with NYSE breakpoints and value-weighted returns) are grouped into six categories: (i) momentum; (ii) value-versus-growth; (iii) investment; (iv) profitability; (v) intangibles; and (vi) trading frictions. The number in parenthesis in the title of a panel is the number of anomalies in that category. For each anomaly variable, we list its symbol, brief description, and its academic source.

Panel A: Momentum (36)

Sue1	Earnings surprise (1-month holding period), Foster, Olsen, and Shevlin (1984)	Abr1	Cumulative abnormal returns around earnings announcements (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
Abr6	Cumulative abnormal returns around earnings announcements (6-month holding period), Chan, Jegadeesh, and Lakonishok (1996)	Abr12	Cumulative abnormal returns around earnings announcements (12-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
Re1	Revisions in analysts' forecasts (1-month holding period), Chan, Jegadeesh, and Lakonishok (1996)	Re6	Revisions in analysts' forecasts (6-month holding period), Chan, Jegadeesh, and Lakonishok (1996)
$R^6 1$	Price momentum (6-month prior returns, 1-month holding period), Jegadeesh and Titman (1993)	$R^6 6$	Price momentum (6-month prior returns, 6-month holding period), Jegadeesh and Titman (1993)
$R^6 12$	Price momentum (6-month prior returns, 12-month holding period), Jegadeesh and Titman (1993)	$R^{11} 1$	Price momentum (11-month prior returns, 1-month holding period), Fama and French (1996)
$R^{11} 6$	Price momentum, (11-month prior returns, 6-month holding period), Fama and French (1996)	Im1	Industry momentum, (1-month holding period), Moskowitz and Grinblatt (1999)
Im6	Industry momentum (6-month holding period), Moskowitz and Grinblatt (1999)	Im12	Industry momentum (12-month holding period), Moskowitz and Grinblatt (1999)
Rs1	Revenue surprise (1-month holding period), Jegadeesh and Livnat (2006)	dEf1	Analysts' forecast change (1-month hold period), Hawkins, Chamberlin, and Daniel (1984)
dEf6	Analysts' forecast change (6-month hold period), Hawkins, Chamberlin, and Daniel (1984)	dEf12	Analysts' forecast change (12-month hold period), Hawkins, Chamberlin, and Daniel (1984)
Nei1	# of consecutive quarters with earnings increases (1-month holding period), Barth, Elliott, and Finn (1999)	52w6	52-week high (6-month holding period), George and Hwang (2004)
$\epsilon^6 6$	6-month residual momentum (6-month holding period), Blitz, Huij, and Martens (2011)	$\epsilon^6 12$	6-month residual momentum (12-month holding period), Blitz, Huij, and Martens (2011)
$\epsilon^{11} 1$	11-month residual momentum (1-month holding period), Blitz, Huij, and Martens (2011)	$\epsilon^{11} 6$	11-month residual momentum (6-month holding period), Blitz, Huij, and Martens (2011)
$\epsilon^{11} 12$	11-month residual momentum (12-month holding period), Blitz, Huij, and Martens (2011)	Sm1	Segment momentum (1-month holding period), Cohen and Lou (2012)
Ilr1	Industry lead-lag effect in prior returns (1-month holding period), Hou (2007)	Ilr6	Industry lead-lag effect in prior returns (6-month holding period), Hou (2007)
Ilr12	Industry lead-lag effect in prior returns (12-month holding period), Hou (2007)	Ile1	Industry lead-lag effect in earnings news (1-month holding period), Hou (2007)

Cm1	Customer momentum (1-month holding period), Cohen and Frazzini (2008)	Cm12	Customer momentum (12-month holding period), Cohen and Frazzini (2008)
Sim1	Supplier industries momentum (1-month holding period), Menzly and Ozbas (2010)	Cim1	Customer industries momentum (1-month holding period), Menzly and Ozbas (2010)
Cim6	Customer industries momentum (6-month holding period), Menzly and Ozbas (2010)	Cim12	Customer industries momentum (12-month holding period), Menzly and Ozbas (2010)

Panel B: Value-versus-growth (29)

Bm	Book-to-market equity, Rosenberg, Reid, and Lanstein (1985)	Bmj	Book-to-June-end market equity, Asness and Frazzini (2013)
Bm^q12	Quarterly Book-to-market equity (12-month holding period)	Rev6	Reversal (6-month holding period), De Bondt and Thaler (1985)
Rev12	Reversal (12-month holding period) De Bondt and Thaler (1985)	Ep	Earnings-to-price, Basu (1983)
Ep^q1	Quarterly earnings-to-price (1-month holding period)	Ep^q6	Quarterly earnings-to-price (6-month holding period)
Ep^q12	Quarterly earnings-to-price (12-month holding period)	Cp	Cash flow-to-price, Lakonishok, Shleifer, and Vishny (1994)
Cp^q1	Quarterly Cash flow-to-price (1-month holding period)	Cp^q6	Quarterly Cash flow-to-price (6-month holding period)
Cp^q12	Quarterly Cash flow-to-price (12-month holding period)	Nop	Net payout yield, Boudoukh, Michaely, Richardson, and Roberts (2007)
Em	Enterprise multiple, Loughran and Wellman (2011)	Em^q1	Quarterly enterprise multiple (1-month holding period)
Em^q6	Quarterly enterprise multiple (6-month holding period)	Em^q12	Quarterly enterprise multiple (12-month holding period)
Sp	Sales-to-price, Barbee, Mukherji, and Raines (1996)	Sp^q1	Quarterly sales-to-price (1-month holding period)
Sp^q6	Quarterly sales-to-price (6-month holding period)	Sp^q12	Quarterly sales-to-price (12-month holding period)
Ocp	Operating cash flow-to-price, Desai, Rajgopal, and Venkatachalam (2004)	Ocp^q1	Quarterly operating cash flow-to-price (1-month holding period)
Ir	Intangible return, Daniel and Titman (2006)	Vhp	Intrinsic value-to-market, Frankel and Lee (1998)
Vfp	Analysts-based intrinsic value-to-market, Frankel and Lee (1998)	Ebp	Enterprise book-to-price Penman, Richardson, and Tuna (2007)
Dur	Equity duration, Dechow, Sloan, and Soliman (2004)		

Panel C: Investment (28)

Aci	Abnormal corporate investment, Titman, Wei, and Xie (2004)	I/A	Investment-to-assets, Cooper, Gulen, and Schill (2008)
Ia^q6	Quarterly investment-to-assets (6-month holding period)	Ia^q12	Quarterly investment-to-assets (12-month holding period)
dPia	(Changes in PPE and inventory)/assets, Lyandres, Sun, and Zhang (2008)	Noa	Net operating assets, Hirshleifer, Hou, Teoh, and Zhang (2004)
dNoa	Changes in net operating assets, Hirshleifer, Hou, Teoh, and Zhang (2004)	dLno	Change in long-term net operating assets, Fairfield, Whisenant, and Yohn (2003)
Ig	Investment growth, Xing (2008)	2Ig	Two-year investment growth, Anderson and Garcia-Feijoo (2006)

Nsi	Net stock issues, Pontiff and Woodgate (2008)	dIi	% change in investment−% change in industry investment, Abarbanell and Bushee (1998)
Cei	Composite equity issuance, Daniel and Titman (2006)	Ivg	Inventory growth, Belo and Lin (2011)
Ivc	Inventory changes, Thomas and Zhang (2002)	Oa	Operating accruals, Sloan (1996)
dWc	Change in net non-cash working capital, Richardson, Sloan, Soliman, and Tuna (2005)	dCoa	Change in current operating assets, Richardson, Sloan, Soliman, and Tuna (2005)
dNco	Change in net non-current operating assets, Richardson, Sloan, Soliman, and Tuna (2005)	dNca	Change in non-current operating assets, Richardson, Sloan, Soliman, and Tuna (2005)
dFin	Change in net financial assets, Richardson, Sloan, Soliman, and Tuna (2005)	dFnl	Change in financial liabilities, Richardson, Sloan, Soliman, and Tuna (2005)
dBe	Change in common equity, Richardson, Sloan, Soliman, and Tuna (2005)	Dac	Discretionary accruals, Xie (2001)
Poa	Percent operating accruals, Hafzalla, Lundholm, and Van Winkle (2011)	Pta	Percent total accruals, Hafzalla, Lundholm, and Van Winkle (2011)
Pda	Percent discretionary accruals	Ndf	Net debt finance, Bradshaw, Richardson, and Sloan (2006)

Panel D: Profitability (35)

Roe1	Return on equity (1-month holding period), Hou, Xue, and Zhang (2015)	Roe6	Return on equity (6-month holding period), Hou, Xue, and Zhang (2015)
dRoe1	Change in Roe (1-month holding period)	dRoe6	Change in Roe (6-month holding period)
dRoe12	Change in Roe (12-month holding period)	Roa1	Return on assets (1-month holding period), Balakrishnan, Bartov, and Faurel (2010)
dRoa1	Change in Roa (1-month holding period)	dRoa6	Change in Roa (6-month holding period)
Rna^q1	Quarterly return on net operating assets (1-month holding period)	Rna^q6	Quarterly return on net operating assets (6-month holding period)
Ato^q1	Quarterly asset turnover (1-month holding period)	Ato^q6	Quarterly asset turnover (6-month holding period)
Ato^q12	Quarterly asset turnover (12-month holding period)	Cto^q1	Quarterly capital turnover (1-month holding period)
Cto^q6	Quarterly capital turnover (6-month holding period)	Cto^q12	Quarterly capital turnover (12-month holding period)
Gpa	Gross profits-to-assets, Novy-Marx (2013)	Gla^q1	Gross profits-to-lagged assets (1-month holding period)
Gla^q6	Gross profits-to-lagged assets (6-month holding period)	Gla^q12	Gross profits-to-lagged assets (12-month holding period)
Ole^q1	Operating profits-to-lagged equity (1-month holding period)	Ole^q6	Operating profits-to-lagged equity (6-month holding period)
Opa	Operating profits-to-assets, Ball, Gerakos, Linnainmaa, and Nikolaev (2015)	Ola^q1	Operating profits-to-lagged assets (1-month holding period)
Ola^q6	Operating profits-to-lagged assets (6-month holding period)	Ola^q12	Operating profits-to-lagged assets (12-month holding period)
Cop	Cash-based operating profitability, Ball, Gerakos, Linnainmaa, and Nikolaev (2016)	Cla	Cash-based operating profits-to-lagged assets
Cla^q1	Cash-based operating profits-to-lagged assets (1-month holding period)	Cla^q6	Cash-based operating profits-to-lagged assets (6-month holding period)
Cla^q12	Cash-based operating profits-to-lagged assets (12-month holding period)	F^q1	Quarterly F-score (1-month holding period)

$\text{F}^{\text{q}}6$	Quarterly F-score (6-month holding period)	$\text{F}^{\text{q}}12$	Quarterly F-score (12-month holding period)
$\text{Fp}^{\text{q}}6$	Failure probability (6-month holding period), Campbell, Hilscher, and Szilagyi (2008)		
	Panel E: Intangibles (26)		
Oca	Organizational capital/assets, Eisfeldt and Papanikolaou (2013)	Ioca	Industry-adjusted organizational capital /assets, Eisfeldt and Papanikolaou (2013)
Adm	Advertising expense-to-market, Chan, Lakonishok, and Sougiannis (2001)	Rdm	R&D-to-market, Chan, Lakonishok, and Sougiannis (2001)
$\text{Rdm}^{\text{q}}1$	Quarterly R&D-to-market (1-month holding period)	$\text{Rdm}^{\text{q}}6$	Quarterly R&D-to-market (6-month holding period)
$\text{Rdm}^{\text{q}}12$	Quarterly R&D-to-market (12-month holding period)	Ol	Operating leverage, Novy-Marx (2011)
$\text{Ol}^{\text{q}}1$	Quarterly operating leverage (1-month holding period)	$\text{Ol}^{\text{q}}6$	Quarterly operating leverage (6-month holding period)
$\text{Ol}^{\text{q}}12$	Quarterly operating leverage (12-month holding period)	Hs	Industry concentration (sales), Hou and Robinson (2006)
Etr	Effective tax rate, Abarbanell and Bushee (1998)	Rer	Real estate ratio, Tuzel (2010)
Eprd	Earnings predictability, Francis, Lafond, Olsson, and Schipper (2004)	Etl	Earnings timeliness, Francis, Lafond, Olsson, and Schipper (2004)
$\text{Alm}^{\text{q}}1$	Quarterly asset liquidity (market assets) (1-month holding period)	$\text{Alm}^{\text{q}}6$	Quarterly asset liquidity (market assets) (6-month holding period)
$\text{Alm}^{\text{q}}12$	Quarterly asset liquidity (market assets) (12-month holding period)	R_{a}^{1}	12-month-lagged return, Heston and Sadka (2008)
$R_{\text{a}}^{[2,5]}$	Years 2–5 lagged returns, annual Heston and Sadka (2008)	$R_{\text{n}}^{[2,5]}$	Years 2–5 lagged returns, nonannual Heston and Sadka (2008)
$R_{\text{a}}^{[6,10]}$	Years 6–10 lagged returns, annual Heston and Sadka (2008)	$R_{\text{n}}^{[6,10]}$	Years 6–10 lagged returns, nonannual Heston and Sadka (2008)
$R_{\text{a}}^{[11,15]}$	Years 11–15 lagged returns, annual Heston and Sadka (2008)	$R_{\text{a}}^{[16,20]}$	Years 16–20 lagged returns, annual Heston and Sadka (2008)
	Panel F: Trading frictions (4)		
Sv1	Systematic volatility risk (1-month holding period), Ang, Hodrick, Xing, and Zhang (2006)	Dtv12	Dollar trading volume (12-month holding period), Brennan, Chordia, and Subrahmanyam (1998)
Isff1	Idiosyncratic skewness per the 3-factor model, (1-month holding period)	Isq1	Idiosyncratic skewness per the *q*-factor model, (1-month holding period)

Table 5 : Monthly Sharpe Ratios, January 1967–December 2016, 600 Months

Panel A reports Sharpe ratios for the market, size, investment, and Roe factors in the Hou, Xue, and Zhang (2015) q-factor model (q), R_{Mkt}, R_{Me}, $R_{\mathrm{I/A}}$, and R_{Roe}, respectively; the expected growth factor, R_{Eg}, in the q^5 model (q^5); the size, value, investment, and profitability factors in the Fama-French (2015) 5-factor model (FF5), SMB, HML, CMA, and RMW, respectively; the momentum factor, UMD, in the Fama-French (2018) 6-factor model (FF6); the cash-based profitability factor, RMWc, in the Fama-French (2018) alternative 6-factor model; the monthly formed value factor, $\mathrm{HML}^{\mathrm{m}}$, in the Barillas-Shanken (2018) 6-factor model (BS6); the management (MGMT) and performance (PERF) factors in the Stambaugh-Yuan (2017) 4-factor model (SY4); and the financing (FIN) and post-earnings-announcement-drift (PEAD) factors in the Daniel-Hirshleifer-Sun 3-factor model (DHS). Panel B reports the maximum Sharpe ratios for each factor model, calculated as $\sqrt{\mu_f' V_f^{-1} \mu_f}$, in which μ_f is the vector of mean factor returns in the factor model, and V_f is the variance-covariance matrix for the vector of factor returns.

Panel A: Sharpe ratios for individual factors							
R_{Mkt}	R_{Me}	$R_{\mathrm{I/A}}$	R_{Roe}	R_{Eg}	SMB	HML	CMA
0.11	0.10	0.22	0.21	0.44	0.08	0.13	0.16
RMW	RMWc	UMD	$\mathrm{HML}^{\mathrm{m}}$	MGMT	PERF	FIN	PEAD
0.12	0.19	0.15	0.10	0.21	0.16	0.11	0.32
Panel B: Maximum Sharpe ratios for factor models							
q	q^5	FF5	FF6	FF6c	BS6	SY4	DHS
0.43	0.63	0.33	0.37	0.45	0.49	0.42	0.42

Table 6 : Overall Performance of Factor Models, January 1967–December 2016, 600 Months

For each model, $\overline{|\alpha_{\text{H}-\text{L}}|}$ is the average magnitude of the high-minus-low alphas, $\#_{|t|\geq 1.96}$ the number of the high-minus-low alphas with $|t| \geq 1.96$, $\#_{|t|\geq 3}$ the number of the high-minus-low alphas with $|t| \geq 3$, $\overline{|\alpha|}$ the mean absolute alpha across the anomaly deciles in a given category, and $\#_{p<5\%}$ the number of sets of deciles within a given category, with which the factor model is rejected by the GRS test at the 5% level. We report the results for the q-factor model (q), the q^5 model (q^5), the Fama-French (2015) 5-factor model (FF5), the Fama-French (2018) 6-factor model with RMW (FF6), the Fama-French alternative 6-factor model with RMWc (FF6c), the Barillas-Shanken (2018) 6-factor model (BS6), the Stambaugh-Yuan (2017) 4-factor model (SY4), and the Daniel-Hirshleifer-Sun (2018) 3-factor model (DHS).

	$\overline{\lvert\alpha_{\text{H}-\text{L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\text{H}-\text{L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\text{H}-\text{L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\text{H}-\text{L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$
	Panel A: All (158)					Panel B: Momentum (36)					Panel C: Value-versus-growth (29)					Panel D: Investment (28)				
q	0.25	46	17	0.11	98	0.26	8	1	0.10	23	0.20	4	0	0.11	17	0.20	9	4	0.10	17
q^5	0.18	19	4	0.10	58	0.19	6	1	0.09	12	0.19	4	0	0.13	15	0.10	0	0	0.08	7
FF5	0.38	89	61	0.12	113	0.64	34	27	0.16	34	0.14	1	0	0.08	9	0.23	11	6	0.09	17
FF6	0.28	67	33	0.11	95	0.29	18	8	0.10	25	0.16	4	1	0.09	11	0.21	10	5	0.09	17
FF6c	0.25	55	21	0.10	68	0.27	16	5	0.10	18	0.15	4	0	0.09	8	0.18	7	1	0.08	7
BS6	0.28	61	34	0.14	147	0.25	12	5	0.13	33	0.24	11	5	0.13	26	0.20	7	4	0.11	26
SY4	0.27	57	25	0.10	87	0.34	21	7	0.10	22	0.20	6	2	0.11	15	0.17	5	3	0.08	17
DHS	0.42	83	45	0.15	108	0.26	12	2	0.15	26	0.81	29	26	0.23	29	0.33	19	2	0.10	21
						Panel E: Profitability (35)					Panel F: Intangibles (26)					Panel G: Trading frictions (4)				
q						0.23	12	4	0.10	19	0.41	11	8	0.17	19	0.23	2	0	0.09	3
q^5						0.14	2	0	0.09	12	0.31	7	3	0.13	10	0.17	0	0	0.08	2
FF5						0.45	28	21	0.12	30	0.41	13	6	0.15	20	0.22	2	1	0.08	3
FF6						0.32	22	11	0.10	21	0.42	11	8	0.16	18	0.20	2	0	0.08	3
FF6c						0.26	14	6	0.10	17	0.43	12	9	0.16	17	0.19	2	0	0.07	1
BS6						0.28	16	11	0.13	34	0.42	13	7	0.19	25	0.21	2	2	0.10	3
SY4						0.29	15	7	0.09	21	0.33	8	6	0.14	10	0.19	2	0	0.08	2
DHS						0.19	6	1	0.09	12	0.59	14	12	0.19	17	0.43	3	2	0.16	3

Table 7 : Explaining Composite Anomalies, January 1967–December 2016, 600 Months

We form composite scores across all the 158 anomalies (All) and across each category of anomalies, including momentum (Mom), value-versus-growth (VvG), investment (Inv), profitability (Prof), intangibles (Intan), and trading frictions (Fric). For a given set of anomalies, we construct the composite score by equal-weighting a stock's percentile ranking for each anomaly (realigned to yield a positive slope in forecasting returns). At the beginning of each month t, we split stocks into deciles based on the NYSE breakpoints of the composite scores, and calculate value-weighted returns for month t. The deciles are rebalanced at the beginning of month $t+1$. For each model and each set of deciles, we report the high-minus-low alpha (Panel A), its t-value (Panel B), the mean absolute alpha (Panel C), and the GRS p-value (Panel D). We report the results for the q-factor model (q), the q^5 model (q^5), the Fama-French (2015) 5-factor model (FF5), the Fama-French (2018) 6-factor model (FF6), the Fama-French alternative 6-factor model with RMWc (FF6c), the Barillas-Shanken (2018) 6-factor model (BS6), the Stambaugh-Yuan (2017) model (SY4), and the Daniel-Hirshleifer-Sun (2018) model (DHS). For the q^5 model, Panel E shows the loadings on the market, size, investment, Roe, and expected growth factors ($\beta_{\text{Mkt}}, \beta_{\text{Me}}, \beta_{\text{I/A}}, \beta_{\text{Roe}}$, and β_{Eg}, respectively) and their t-values. The t-values are adjusted for heteroscedasticity and autocorrelations.

	All	Mom	VvG	Inv	Prof	Intan	Fric		All	Mom	VvG	Inv	Prof	Intan	Fric
$\overline{R}$	1.62	1.05	0.74	0.70	0.83	1.08	0.34	$t_{\overline{R}}$	9.13	4.00	3.53	4.89	4.61	6.13	2.87
Panel A: The high-minus-low alpha, $\alpha_{\text{H}-\text{L}}$								Panel B: $t_{\text{H}-\text{L}}$							
q	0.78	0.29	0.32	0.22	0.27	0.47	0.21		5.18	0.84	1.67	2.34	2.24	3.22	1.68
q^5	0.31	−0.21	0.33	0.01	−0.11	0.45	0.21		2.32	−0.70	1.83	0.11	−0.91	3.31	1.52
FF5	1.19	1.18	0.03	0.30	0.67	0.56	0.20		7.86	3.57	0.21	3.19	5.61	4.37	1.79
FF6	0.83	0.29	0.18	0.26	0.50	0.54	0.21		6.89	1.86	1.49	2.82	4.31	4.24	1.81
FF6c	0.71	0.25	0.09	0.25	0.32	0.55	0.18		6.05	1.55	0.74	2.50	2.24	3.93	1.64
BS6	0.51	0.19	−0.20	0.14	0.34	0.23	0.17		3.54	1.15	−1.45	1.39	2.70	1.64	1.33
SY4	0.80	0.41	0.32	0.09	0.41	0.46	0.21		6.35	1.78	2.02	0.87	3.05	3.46	1.85
DHS	0.92	−0.39	1.11	0.56	−0.10	0.90	0.50		5.59	−1.59	5.81	3.80	−0.64	5.22	3.70
Panel C: The mean absolute alpha, $\overline{\lvert\alpha\rvert}$								Panel D: The GRS p-value, p_{GRS}							
q	0.15	0.10	0.14	0.09	0.08	0.17	0.09		0.00	0.07	0.01	0.00	0.01	0.00	0.01
q^5	0.07	0.10	0.16	0.06	0.07	0.16	0.08		0.18	0.24	0.00	0.26	0.17	0.00	0.23
FF5	0.24	0.28	0.10	0.09	0.13	0.18	0.08		0.00	0.00	0.02	0.00	0.00	0.00	0.04
FF6	0.15	0.10	0.11	0.08	0.11	0.17	0.08		0.00	0.03	0.02	0.01	0.00	0.00	0.06
FF6c	0.11	0.10	0.10	0.06	0.10	0.17	0.08		0.00	0.02	0.08	0.07	0.03	0.00	0.19
BS6	0.10	0.11	0.13	0.09	0.11	0.14	0.10		0.00	0.04	0.01	0.00	0.00	0.00	0.00
SY4	0.14	0.11	0.14	0.07	0.09	0.15	0.09		0.00	0.01	0.00	0.03	0.00	0.00	0.04
DHS	0.18	0.17	0.30	0.13	0.08	0.26	0.14		0.00	0.00	0.00	0.00	0.13	0.00	0.00
Panel E: The q^5 factor loadings															
β_{Mkt}	−0.07	−0.09	0.04	−0.02	0.01	−0.09	−0.03	t_{Mkt}	−1.65	−1.09	0.63	−0.65	0.42	−2.45	−0.88
β_{Me}	0.37	0.32	0.36	0.01	−0.04	0.46	0.52	t_{Me}	6.85	1.61	2.71	0.16	−0.84	5.18	6.67
$\beta_{\text{I/A}}$	0.81	−0.15	1.31	1.23	−0.35	0.79	0.01	$t_{\text{I/A}}$	7.62	−0.53	9.25	19.02	−4.74	6.31	0.06
β_{Roe}	0.54	1.13	−0.44	−0.15	1.08	0.34	−0.03	t_{Roe}	5.42	5.20	−3.23	−2.36	16.83	3.82	−0.42
β_{Eg}	0.73	0.80	−0.02	0.34	0.60	0.02	0.01	t_{Eg}	7.19	3.66	−0.14	4.74	7.02	0.22	0.07

Table 8 : Explaining the 158 Individual Anomalies, January 1967–December 2016, 600 Months

For each high-minus-low decile, we report the average return, $\overline{R}$, the q-factor alpha, α_q, the q^5 alpha, α_{q^5}, the Fama-French (2015) 5-factor alpha, α_{FF5}, the Fama-French (2018) 6-factor alpha, α_{FF6}, the alpha from the alternative 6-factor model with RMW replaced by RMWc, α_{FF6c}, the Barillas-Shanken (2018) 6-factor alpha, α_{BS6}, the Stambaugh-Yuan (2017) alpha, α_{SY4}, and the Daniel-Hirshleifer-Sun (2018) alpha, α_{DHS}, as well as their heteroscedasticity-and-autocorrelation-consistent t-statistics, denoted by $t_{\overline{R}}$, t_q, t_{q^5}, t_{FF5}, t_{FF6}, t_{FF6c}, t_{BS6}, t_{SY4}, and t_{DHS}, respectively. Also, for all the ten deciles formed on a given anomaly variable, we report the mean absolute alphas from the q-factor model, $\overline{|\alpha_q|}$, the q^5 model, $\overline{|\alpha_{q^5}|}$, the 5-factor model, $\overline{|\alpha_{\mathrm{FF5}}|}$, the 6-factor model, $\overline{|\alpha_{\mathrm{FF6}}|}$, the alternative 6-factor model, $\overline{|\alpha_{\mathrm{FF6c}}|}$, the Barillas-Shanken 6-factor model, $\overline{|\alpha_{\mathrm{BS6}}|}$, the Stambaugh-Yuan model, $\overline{|\alpha_{\mathrm{SY4}}|}$, and the Daniel-Hirshleifer-Sun model, $\overline{|\alpha_{\mathrm{DHS}}|}$, as well as the p-values from the GRS test on the null hypothesis that all the alphas across a given set of deciles are jointly zero. The p-values are denoted by p_q, p_{q^5}, p_{FF5}, p_{FF6}, p_{FF6c}, p_{BS6}, p_{SY4}, and p_{DHS}, respectively. Table 4 describes the anomaly symbols, and the Online Appendix details variable definitions and portfolio construction.

	1 Sue1	2 Abr1	3 Abr6	4 Abr12	5 Re1	6 Re6	7 $R^6 1$	8 $R^6 6$	9 $R^6 12$	10 $R^{11} 1$	11 $R^{11} 6$	12 Im1	13 Im6	14 Im12	15 Rs1	16 dEf1	17 dEf6	18 dEf12	19 Nei1	20 52w6
$\overline{R}$	0.46	0.70	0.33	0.23	0.75	0.47	0.60	0.82	0.55	1.16	0.80	0.68	0.60	0.63	0.32	0.94	0.56	0.33	0.33	0.56
$t_{\overline{R}}$	3.48	5.45	3.41	2.99	3.18	2.24	2.08	3.50	2.91	3.99	3.13	2.86	3.01	3.57	2.28	4.33	3.19	2.37	3.04	2.01
α_q	0.06	0.62	0.30	0.24	0.09	−0.02	−0.03	0.25	0.16	0.31	0.14	0.28	0.07	0.32	0.24	0.55	0.18	0.07	0.12	0.01
α_{q^5}	−0.04	0.56	0.25	0.20	0.08	−0.08	−0.44	−0.16	−0.06	−0.20	−0.17	−0.10	−0.33	0.03	0.12	0.48	0.16	0.06	0.02	−0.34
α_{FF5}	0.52	0.82	0.46	0.40	0.78	0.59	0.74	1.00	0.80	1.29	1.06	0.74	0.66	0.84	0.56	1.08	0.72	0.50	0.41	0.77
α_{FF6}	0.30	0.64	0.30	0.26	0.37	0.21	−0.21	0.18	0.20	0.21	0.20	0.09	−0.01	0.30	0.44	0.74	0.40	0.27	0.27	0.03
α_{FF6c}	0.25	0.65	0.30	0.25	0.38	0.21	−0.18	0.16	0.13	0.20	0.13	0.09	−0.05	0.22	0.41	0.64	0.37	0.22	0.23	0.02
α_{BS6}	0.14	0.67	0.30	0.25	0.08	−0.01	−0.16	0.12	0.12	0.13	0.08	0.20	−0.07	0.23	0.40	0.55	0.20	0.11	0.17	−0.14
α_{SY4}	0.29	0.71	0.36	0.31	0.58	0.35	−0.05	0.28	0.33	0.30	0.33	0.18	0.08	0.37	0.37	0.90	0.49	0.34	0.27	0.07
α_{DHS}	−0.35	0.28	0.06	0.04	−0.41	−0.50	−0.70	−0.25	−0.32	−0.33	−0.45	−0.19	−0.29	−0.07	−0.26	0.17	−0.22	−0.27	−0.30	−0.75
t_q	0.46	4.25	2.61	2.79	0.38	−0.08	−0.08	0.83	0.81	0.81	0.49	0.93	0.30	1.45	1.71	2.49	1.08	0.60	1.20	0.02
t_{q^5}	−0.30	4.00	2.26	2.24	0.31	−0.38	−1.31	−0.60	−0.31	−0.59	−0.63	−0.34	−1.37	0.13	0.86	2.07	0.92	0.49	0.25	−1.47
t_{FF5}	3.92	5.81	4.58	5.37	3.16	2.73	2.20	3.65	4.16	3.73	3.88	2.67	2.81	4.30	4.06	4.68	4.07	3.89	4.28	3.09
t_{FF6}	2.54	4.66	3.30	4.10	1.89	1.26	−1.10	1.77	1.83	1.74	1.57	0.43	−0.10	1.99	3.27	3.75	3.14	2.60	2.95	0.26
t_{FF6c}	2.10	4.50	3.12	3.69	1.96	1.28	−0.90	1.44	1.19	1.63	1.03	0.46	−0.35	1.44	3.01	3.06	2.77	2.13	2.33	0.14
t_{BS6}	1.25	4.48	2.93	3.29	0.43	−0.04	−0.76	1.00	0.86	1.01	0.52	0.91	−0.44	1.32	3.15	2.80	1.51	1.05	1.82	−1.08
t_{SY4}	2.42	5.11	3.61	4.19	2.59	1.92	−0.17	1.38	2.10	1.22	1.55	0.72	0.43	2.08	2.81	4.42	3.31	3.14	2.65	0.42
t_{DHS}	−3.17	2.20	0.76	0.62	−2.14	−2.91	−1.97	−1.02	−2.08	−1.03	−1.85	−0.70	−1.41	−0.39	−1.80	0.92	−1.70	−2.63	−2.17	−3.08
$\overline{\lvert\alpha_q\rvert}$	0.10	0.12	0.07	0.07	0.11	0.11	0.17	0.08	0.06	0.12	0.10	0.12	0.11	0.12	0.07	0.16	0.11	0.11	0.08	0.05
$\overline{\lvert\alpha_{q^5}\rvert}$	0.09	0.12	0.07	0.06	0.10	0.10	0.22	0.13	0.09	0.17	0.14	0.07	0.09	0.07	0.07	0.17	0.13	0.11	0.08	0.13
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.19	0.16	0.08	0.08	0.19	0.16	0.14	0.16	0.15	0.23	0.21	0.21	0.20	0.21	0.14	0.26	0.17	0.15	0.15	0.15
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.13	0.12	0.07	0.06	0.09	0.08	0.20	0.10	0.06	0.14	0.08	0.09	0.09	0.11	0.10	0.18	0.11	0.08	0.10	0.08
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.12	0.12	0.05	0.04	0.08	0.07	0.21	0.11	0.07	0.14	0.10	0.09	0.09	0.10	0.10	0.16	0.10	0.07	0.09	0.07
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.12	0.13	0.09	0.09	0.11	0.11	0.22	0.13	0.09	0.17	0.13	0.15	0.15	0.15	0.10	0.17	0.13	0.13	0.10	0.08
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.12	0.12	0.08	0.07	0.10	0.10	0.19	0.10	0.07	0.12	0.08	0.08	0.08	0.10	0.09	0.21	0.13	0.10	0.11	0.08
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.12	0.12	0.10	0.08	0.23	0.22	0.32	0.19	0.16	0.26	0.22	0.14	0.14	0.14	0.13	0.21	0.18	0.16	0.12	0.24
p_q	0.01	0.00	0.00	0.00	0.08	0.02	0.00	0.00	0.02	0.00	0.01	0.46	0.05	0.11	0.01	0.00	0.00	0.01	0.07	0.33
p_{q^5}	0.13	0.00	0.00	0.02	0.34	0.12	0.00	0.00	0.06	0.01	0.01	0.85	0.21	0.37	0.08	0.01	0.00	0.03	0.23	0.13
p_{FF5}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
p_{FF6}	0.00	0.00	0.00	0.00	0.05	0.03	0.00	0.00	0.00	0.00	0.00	0.38	0.05	0.04	0.00	0.00	0.00	0.00	0.01	0.10
p_{FF6c}	0.00	0.00	0.01	0.01	0.15	0.19	0.00	0.00	0.00	0.00	0.01	0.52	0.23	0.17	0.04	0.01	0.00	0.02	0.10	0.24
p_{BS6}	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.04
p_{SY4}	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00	0.82	0.17	0.09	0.01	0.00	0.00	0.00	0.00	0.17
p_{DHS}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.34	0.02	0.02	0.00	0.00	0.00	0.00	0.02	0.00

	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
	$\epsilon^6 6$	$\epsilon^6 12$	$\epsilon^{11} 1$	$\epsilon^{11} 6$	$\epsilon^{11} 12$	Sm1	Ilr1	Ilr6	Ilr12	Ile1	Cm1	Cm12	Sim1	Cim1	Cim6	Cim12	Bm	Bmj	$\mathrm{Bm}^{\mathrm{q}}12$	Rev6
$\overline{R}$	0.45	0.37	0.61	0.50	0.33	0.53	0.69	0.34	0.35	0.58	0.78	0.15	0.79	0.75	0.29	0.27	0.54	0.46	0.48	−0.42
$t_{\overline{R}}$	3.74	3.85	3.72	3.82	2.88	2.36	3.33	3.35	4.27	3.48	3.85	2.22	3.65	3.35	2.76	3.41	2.61	2.12	2.21	−2.01
α_q	0.26	0.20	0.26	0.22	0.12	0.59	0.73	0.19	0.19	0.32	0.70	0.05	0.57	0.64	0.06	0.08	0.15	0.28	0.37	−0.21
α_{q^5}	0.06	0.05	0.02	0.05	0.01	0.40	0.50	0.01	0.02	0.11	0.68	−0.02	0.25	0.36	−0.17	−0.12	0.08	0.30	0.38	−0.07
α_{FF5}	0.47	0.43	0.57	0.56	0.42	0.66	0.80	0.37	0.39	0.70	0.75	0.13	0.75	0.74	0.25	0.29	−0.10	−0.13	−0.12	−0.01
α_{FF6}	0.20	0.19	0.21	0.23	0.16	0.58	0.66	0.10	0.12	0.49	0.74	0.02	0.60	0.62	−0.01	0.04	−0.08	0.07	0.16	−0.10
α_{FF6c}	0.18	0.17	0.22	0.21	0.14	0.55	0.65	0.09	0.10	0.44	0.72	0.02	0.56	0.54	0.02	0.03	−0.08	0.10	0.18	−0.15
α_{BS6}	0.17	0.18	0.14	0.16	0.12	0.64	0.77	0.15	0.13	0.43	0.74	0.03	0.57	0.66	0.02	0.03	−0.29	−0.11	−0.04	−0.06
α_{SY4}	0.27	0.25	0.28	0.31	0.22	0.64	0.67	0.17	0.17	0.45	0.75	0.03	0.56	0.57	0.01	0.05	0.03	0.08	0.23	0.10
α_{DHS}	0.07	−0.01	0.07	0.02	−0.09	0.56	0.51	0.00	0.00	0.01	0.76	0.02	0.47	0.40	−0.05	−0.04	0.87	1.05	1.20	−0.99
t_q	1.64	1.57	1.25	1.31	0.82	2.15	2.94	1.45	1.80	1.84	2.84	0.55	1.87	2.36	0.35	0.65	0.99	1.59	2.18	−1.20
t_{q^5}	0.38	0.35	0.08	0.29	0.08	1.37	2.03	0.04	0.22	0.59	2.70	−0.23	0.82	1.25	−1.05	−1.03	0.51	1.77	2.25	−0.37
t_{FF5}	3.45	3.78	3.03	3.62	3.16	2.77	3.41	3.11	3.83	4.21	3.38	1.45	2.72	3.02	1.76	2.48	−0.88	−0.95	−0.84	−0.04
t_{FF6}	1.76	2.16	1.32	1.90	1.51	2.43	3.03	1.22	2.06	2.92	3.00	0.23	2.36	2.66	−0.07	0.56	−0.70	0.54	1.35	−0.59
t_{FF6c}	1.54	1.76	1.37	1.73	1.30	2.10	2.74	1.01	1.57	2.53	2.84	0.19	2.11	2.32	0.20	0.38	−0.63	0.79	1.47	−0.85
t_{BS6}	1.36	1.85	0.84	1.23	1.08	2.55	3.30	1.59	2.04	2.38	3.09	0.38	2.11	2.66	0.16	0.32	−2.17	−0.80	−0.37	−0.30
t_{SY4}	1.91	2.27	1.53	2.11	1.84	2.41	2.94	1.62	2.04	2.64	3.05	0.33	2.07	2.35	0.05	0.52	0.20	0.48	1.77	0.59
t_{DHS}	0.47	−0.07	0.35	0.16	−0.72	2.00	2.15	0.02	0.05	0.04	2.92	0.24	1.51	1.59	−0.35	−0.42	4.16	5.09	6.11	−3.88
$\overline{\lvert\alpha_q\rvert}$	0.06	0.06	0.09	0.06	0.06	0.12	0.19	0.09	0.09	0.11	0.21	0.12	0.14	0.18	0.07	0.06	0.09	0.12	0.13	0.07
$\overline{\lvert\alpha_{q^5}\rvert}$	0.06	0.06	0.07	0.05	0.04	0.11	0.11	0.04	0.03	0.06	0.18	0.10	0.08	0.12	0.06	0.05	0.10	0.15	0.15	0.06
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.08	0.08	0.15	0.12	0.09	0.15	0.21	0.14	0.14	0.18	0.23	0.11	0.18	0.20	0.07	0.08	0.05	0.07	0.08	0.04
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.05	0.05	0.08	0.06	0.05	0.13	0.18	0.08	0.08	0.12	0.22	0.12	0.14	0.17	0.06	0.05	0.06	0.09	0.09	0.05
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.04	0.04	0.08	0.04	0.03	0.13	0.18	0.08	0.08	0.12	0.23	0.12	0.15	0.17	0.05	0.05	0.06	0.10	0.11	0.05
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.07	0.07	0.09	0.07	0.07	0.13	0.22	0.14	0.13	0.15	0.27	0.20	0.15	0.19	0.08	0.07	0.11	0.11	0.12	0.09
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.05	0.06	0.09	0.07	0.06	0.13	0.16	0.06	0.06	0.10	0.20	0.08	0.14	0.16	0.07	0.06	0.07	0.11	0.11	0.05
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.05	0.05	0.07	0.05	0.06	0.12	0.16	0.14	0.14	0.14	0.25	0.13	0.13	0.17	0.11	0.09	0.21	0.26	0.27	0.21
p_q	0.00	0.00	0.01	0.01	0.08	0.17	0.04	0.20	0.12	0.18	0.06	0.04	0.49	0.02	0.05	0.01	0.11	0.02	0.00	0.08
p_{q^5}	0.04	0.00	0.32	0.16	0.36	0.48	0.65	0.26	0.50	0.75	0.06	0.15	0.98	0.29	0.18	0.25	0.17	0.00	0.00	0.46
p_{FF5}	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.00	0.03	0.02	0.10	0.01	0.09	0.01	0.42	0.12	0.08	0.40
p_{FF6}	0.00	0.00	0.02	0.02	0.10	0.10	0.03	0.29	0.10	0.03	0.03	0.06	0.39	0.02	0.17	0.18	0.35	0.10	0.03	0.22
p_{FF6c}	0.02	0.00	0.16	0.19	0.35	0.05	0.04	0.49	0.19	0.10	0.03	0.02	0.35	0.06	0.29	0.28	0.50	0.17	0.04	0.30
p_{BS6}	0.00	0.00	0.00	0.00	0.02	0.06	0.00	0.02	0.01	0.02	0.01	0.01	0.40	0.01	0.02	0.01	0.00	0.01	0.00	0.01
p_{SY4}	0.00	0.00	0.01	0.02	0.06	0.24	0.18	0.16	0.12	0.13	0.03	0.22	0.44	0.04	0.09	0.07	0.48	0.03	0.01	0.10
p_{DHS}	0.14	0.01	0.15	0.22	0.21	0.47	0.04	0.13	0.11	0.09	0.01	0.03	0.28	0.01	0.00	0.00	0.00	0.00	0.00	0.00

	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	Rev12	Ep	Ep^{q}1	Ep^{q}6	Ep^{q}12	Cp	Cp^{q}1	Cp^{q}6	Cp^{q}12	Nop	Em	Em^{q}1	Em^{q}6	Em^{q}12	Sp	Sp^{q}1	Sp^{q}6	Sp^{q}12	Ocp	Ocp^{q}1
$\overline{R}$	−0.39	0.44	0.93	0.59	0.43	0.43	0.62	0.48	0.40	0.63	−0.54	−0.71	−0.43	−0.43	0.50	0.59	0.56	0.53	0.70	0.64
$t_{\overline{R}}$	−1.99	2.26	4.94	3.42	2.60	2.14	2.93	2.42	2.12	3.40	−2.86	−3.21	−2.05	−2.15	2.37	2.39	2.43	2.47	3.14	2.28
α_{q}	−0.13	0.02	0.41	0.09	−0.04	0.04	0.42	0.31	0.16	0.35	−0.24	−0.48	−0.21	−0.19	−0.05	0.20	0.14	0.05	0.36	0.48
α_{q^5}	−0.01	−0.07	0.52	0.10	−0.04	0.02	0.53	0.37	0.21	0.20	−0.05	−0.45	−0.15	−0.12	0.05	0.36	0.28	0.18	0.24	0.43
α_{FF5}	−0.02	−0.10	0.41	0.08	−0.07	−0.22	0.05	−0.05	−0.15	0.22	−0.05	−0.33	−0.04	−0.03	−0.26	−0.21	−0.23	−0.24	−0.02	0.12
α_{FF6}	−0.06	−0.14	0.55	0.17	−0.03	−0.18	0.40	0.23	0.02	0.24	−0.01	−0.45	−0.14	−0.08	−0.16	0.13	0.05	−0.04	0.06	0.41
α_{FF6c}	−0.09	−0.21	0.47	0.10	−0.09	−0.25	0.37	0.19	−0.01	0.16	0.13	−0.31	−0.01	0.05	−0.18	0.10	0.03	−0.06	0.01	0.40
α_{BS6}	−0.00	−0.52	−0.04	−0.32	−0.46	−0.47	0.01	−0.09	−0.26	0.12	0.17	−0.17	0.07	0.12	−0.47	−0.25	−0.28	−0.36	−0.15	0.31
α_{SY4}	0.11	0.04	0.70	0.32	0.13	0.07	0.48	0.32	0.18	0.17	−0.16	−0.55	−0.27	−0.23	−0.09	0.16	0.10	0.02	0.30	0.60
α_{DHS}	−0.84	0.56	0.94	0.55	0.41	0.67	1.19	1.00	0.82	0.38	−0.70	−0.86	−0.59	−0.54	0.73	1.15	1.07	0.91	1.01	1.13
t_{q}	−0.78	0.12	1.74	0.46	−0.25	0.20	1.96	1.65	0.95	2.42	−1.40	−2.00	−0.99	−1.03	−0.28	0.70	0.59	0.23	1.98	1.62
t_{q^5}	−0.08	−0.37	2.25	0.58	−0.25	0.10	2.59	2.11	1.36	1.33	−0.27	−1.91	−0.72	−0.65	0.30	1.44	1.33	1.00	1.28	1.66
t_{FF5}	−0.14	−0.81	2.38	0.56	−0.57	−1.74	0.28	−0.31	−1.23	1.83	−0.35	−1.70	−0.20	−0.21	−1.82	−1.04	−1.38	−1.60	−0.12	0.53
t_{FF6}	−0.41	−1.04	3.21	1.23	−0.21	−1.48	2.91	1.81	0.18	1.92	−0.06	−2.55	−0.87	−0.51	−1.22	0.70	0.33	−0.33	0.47	2.59
t_{FF6c}	−0.56	−1.59	2.85	0.69	−0.68	−2.08	2.69	1.51	−0.07	1.22	0.94	−1.77	−0.05	0.34	−1.33	0.55	0.22	−0.48	0.07	2.46
t_{BS6}	−0.01	−3.05	−0.23	−2.27	−3.66	−3.02	0.06	−0.69	−2.13	0.83	1.07	−1.01	0.43	0.75	−3.01	−1.27	−1.73	−2.38	−0.92	1.81
t_{SY4}	0.66	0.19	3.77	1.99	0.90	0.39	2.97	2.18	1.27	1.35	−0.94	−2.79	−1.47	−1.37	−0.57	0.78	0.60	0.13	1.70	3.04
t_{DHS}	−3.40	3.12	4.34	3.06	2.63	3.75	5.92	5.78	5.13	3.16	−4.07	−4.16	−3.38	−3.17	3.53	4.05	4.42	4.25	5.01	4.50
$\overline{\lvert\alpha_{q}\rvert}$	0.05	0.10	0.16	0.13	0.10	0.11	0.18	0.14	0.11	0.11	0.11	0.20	0.12	0.11	0.06	0.07	0.06	0.06	0.11	0.18
$\overline{\lvert\alpha_{q^5}\rvert}$	0.05	0.13	0.20	0.16	0.13	0.14	0.23	0.18	0.16	0.11	0.12	0.22	0.14	0.14	0.06	0.10	0.07	0.06	0.12	0.18
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.03	0.07	0.13	0.09	0.07	0.11	0.10	0.08	0.07	0.10	0.09	0.17	0.10	0.09	0.09	0.08	0.09	0.10	0.06	0.10
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.04	0.07	0.17	0.11	0.08	0.09	0.15	0.10	0.07	0.09	0.09	0.18	0.09	0.09	0.07	0.06	0.05	0.07	0.08	0.16
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.04	0.07	0.16	0.10	0.07	0.11	0.16	0.11	0.09	0.09	0.08	0.17	0.10	0.10	0.09	0.06	0.06	0.07	0.08	0.16
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.08	0.14	0.13	0.14	0.13	0.17	0.13	0.14	0.14	0.14	0.13	0.17	0.13	0.13	0.16	0.10	0.12	0.15	0.13	0.15
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.04	0.10	0.20	0.15	0.11	0.11	0.20	0.14	0.12	0.12	0.11	0.20	0.12	0.11	0.05	0.06	0.05	0.05	0.11	0.22
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.18	0.18	0.29	0.21	0.17	0.18	0.33	0.26	0.23	0.12	0.19	0.27	0.19	0.16	0.23	0.32	0.28	0.24	0.20	0.35
p_{q}	0.33	0.07	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.02	0.02	0.28	0.43	0.39	0.15	0.04	0.23
p_{q^5}	0.58	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.07	0.02	0.00	0.02	0.02	0.59	0.44	0.56	0.44	0.09	0.17
p_{FF5}	0.72	0.22	0.01	0.00	0.08	0.01	0.13	0.14	0.26	0.00	0.02	0.00	0.06	0.03	0.05	0.48	0.24	0.04	0.41	0.62
p_{FF6}	0.59	0.28	0.00	0.00	0.03	0.03	0.00	0.02	0.27	0.00	0.04	0.00	0.10	0.07	0.11	0.59	0.45	0.10	0.33	0.03
p_{FF6c}	0.63	0.58	0.00	0.00	0.19	0.02	0.00	0.03	0.26	0.03	0.08	0.01	0.22	0.20	0.32	0.73	0.72	0.37	0.31	0.10
p_{BS6}	0.05	0.00	0.02	0.00	0.00	0.00	0.05	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.02	0.16
p_{SY4}	0.31	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.00	0.04	0.02	0.55	0.78	0.77	0.27	0.11	0.05
p_{DHS}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	61 Ir	62 Vhp	63 Vfp	64 Ebp	65 Dur	66 Aci	67 I/A	68 Ia^{q}6	69 Ia^{q}12	70 dPia	71 Noa	72 dNoa	73 dLno	74 Ig	75 2Ig	76 Nsi	77 dIi	78 Cei	79 Ivg	80 Ivc
$\overline{R}$	−0.47	0.38	0.47	0.41	−0.42	−0.30	−0.44	−0.50	−0.48	−0.48	−0.44	−0.55	−0.39	−0.46	−0.33	−0.64	−0.29	−0.57	−0.33	−0.44
$t_{\overline{R}}$	−2.22	2.05	2.18	2.00	−2.19	−2.13	−2.89	−3.00	−3.11	−3.64	−3.25	−4.14	−2.99	−3.76	−2.52	−4.46	−2.61	−3.32	−2.44	−3.33
α_q	−0.16	0.01	0.12	0.06	−0.03	−0.16	0.07	−0.11	0.00	−0.18	−0.45	−0.15	0.03	−0.07	0.06	−0.29	0.11	−0.29	0.01	−0.28
α_{q^5}	−0.02	−0.11	0.11	0.08	0.06	−0.16	0.08	0.00	0.09	−0.11	−0.13	−0.10	0.13	−0.12	0.06	−0.12	0.10	−0.04	0.10	0.01
α_{FF5}	0.13	−0.15	0.09	−0.22	0.11	−0.30	0.02	0.01	0.03	−0.30	−0.53	−0.26	−0.09	−0.18	−0.07	−0.30	0.00	−0.30	−0.08	−0.36
α_{FF6}	0.05	−0.15	0.08	−0.13	0.12	−0.21	0.02	−0.06	0.02	−0.26	−0.45	−0.23	−0.04	−0.15	0.01	−0.28	0.09	−0.26	−0.03	−0.30
α_{FF6c}	0.03	−0.22	0.02	−0.11	0.14	−0.20	0.00	−0.12	−0.04	−0.29	−0.44	−0.22	−0.12	−0.19	−0.03	−0.20	0.09	−0.17	−0.01	−0.24
α_{BS6}	0.18	−0.48	−0.25	−0.33	0.48	−0.17	0.14	0.00	0.10	−0.18	−0.61	−0.07	0.01	−0.02	0.09	−0.22	0.27	−0.08	0.09	−0.25
α_{SY4}	0.02	0.05	0.28	−0.03	−0.02	−0.19	0.16	0.14	0.19	−0.05	−0.17	−0.09	0.19	−0.04	0.08	−0.15	0.09	−0.22	0.03	−0.19
α_{DHS}	−1.00	0.55	0.50	0.85	−0.53	−0.20	−0.43	−0.67	−0.53	−0.43	−0.32	−0.42	−0.22	−0.37	−0.31	−0.29	−0.13	−0.30	−0.21	−0.48
t_q	−1.05	0.06	0.55	0.42	−0.17	−1.02	0.62	−1.09	0.03	−1.47	−2.59	−1.04	0.19	−0.59	0.49	−2.32	1.06	−2.25	0.09	−2.08
t_{q^5}	−0.12	−0.61	0.49	0.49	0.30	−1.07	0.63	0.02	0.77	−0.91	−0.88	−0.66	0.79	−0.90	0.44	−0.89	0.83	−0.31	0.75	0.08
t_{FF5}	0.96	−1.06	0.50	−1.70	0.80	−2.05	0.17	0.10	0.36	−2.61	−3.37	−1.81	−0.62	−1.65	−0.59	−2.58	−0.01	−2.92	−0.66	−2.97
t_{FF6}	0.39	−1.06	0.42	−1.09	0.91	−1.37	0.22	−0.56	0.18	−2.26	−3.18	−1.64	−0.28	−1.37	0.08	−2.39	0.89	−2.33	−0.26	−2.44
t_{FF6c}	0.21	−1.48	0.09	−0.86	0.99	−1.29	−0.02	−1.23	−0.46	−2.29	−2.88	−1.64	−0.82	−1.57	−0.23	−1.60	0.86	−1.56	−0.06	−1.89
t_{BS6}	1.20	−2.71	−1.23	−2.65	3.07	−1.00	1.28	0.01	0.92	−1.42	−4.02	−0.53	0.05	−0.13	0.71	−1.65	2.37	−0.55	0.69	−1.78
t_{SY4}	0.14	0.29	1.31	−0.18	−0.09	−1.31	1.30	1.30	1.83	−0.43	−1.21	−0.66	1.36	−0.37	0.69	−1.36	0.79	−1.91	0.27	−1.45
t_{DHS}	−4.25	3.05	2.21	4.32	−2.79	−1.27	−2.49	−3.77	−2.99	−2.76	−2.20	−2.94	−1.23	−3.17	−1.73	−2.52	−1.03	−2.72	−1.53	−2.95
$\overline{\lvert\alpha_q\rvert}$	0.07	0.13	0.14	0.11	0.08	0.12	0.08	0.07	0.06	0.11	0.11	0.08	0.04	0.09	0.08	0.12	0.06	0.12	0.10	0.07
$\overline{\lvert\alpha_{q^5}\rvert}$	0.05	0.15	0.18	0.09	0.09	0.12	0.09	0.05	0.05	0.11	0.09	0.05	0.08	0.11	0.08	0.10	0.06	0.07	0.09	0.09
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.06	0.09	0.12	0.08	0.05	0.14	0.09	0.05	0.04	0.10	0.11	0.09	0.05	0.08	0.06	0.12	0.05	0.11	0.09	0.08
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.05	0.08	0.12	0.08	0.05	0.12	0.08	0.06	0.05	0.10	0.10	0.08	0.06	0.08	0.06	0.12	0.05	0.11	0.08	0.08
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.06	0.09	0.13	0.09	0.05	0.11	0.08	0.06	0.04	0.08	0.09	0.07	0.06	0.07	0.06	0.10	0.04	0.08	0.10	0.08
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.09	0.14	0.15	0.14	0.13	0.13	0.10	0.08	0.07	0.13	0.13	0.08	0.06	0.11	0.10	0.13	0.09	0.13	0.13	0.10
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.04	0.12	0.12	0.07	0.07	0.11	0.09	0.07	0.06	0.10	0.08	0.06	0.06	0.08	0.07	0.12	0.06	0.11	0.10	0.06
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.25	0.20	0.15	0.24	0.20	0.13	0.11	0.18	0.15	0.09	0.11	0.09	0.08	0.11	0.11	0.11	0.08	0.10	0.11	0.09
p_q	0.37	0.01	0.05	0.00	0.18	0.00	0.00	0.08	0.18	0.01	0.00	0.13	0.76	0.00	0.06	0.00	0.41	0.00	0.06	0.28
p_{q^5}	0.80	0.01	0.04	0.15	0.18	0.07	0.01	0.33	0.58	0.00	0.01	0.47	0.40	0.01	0.15	0.09	0.77	0.44	0.02	0.24
p_{FF5}	0.18	0.06	0.11	0.03	0.41	0.00	0.00	0.21	0.24	0.01	0.00	0.02	0.84	0.02	0.21	0.00	0.35	0.00	0.07	0.09
p_{FF6}	0.45	0.14	0.12	0.06	0.58	0.00	0.01	0.14	0.20	0.02	0.00	0.05	0.77	0.02	0.16	0.00	0.48	0.00	0.09	0.09
p_{FF6c}	0.29	0.23	0.19	0.12	0.57	0.03	0.04	0.36	0.53	0.14	0.04	0.28	0.77	0.11	0.42	0.00	0.75	0.08	0.03	0.08
p_{BS6}	0.29	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.03	0.51	0.00	0.00	0.00	0.01	0.00	0.00	0.03
p_{SY4}	0.51	0.04	0.16	0.30	0.45	0.01	0.01	0.03	0.03	0.01	0.01	0.27	0.69	0.01	0.11	0.00	0.63	0.02	0.01	0.50
p_{DHS}	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.01	0.50	0.00	0.00	0.00	0.01	0.00	0.01	0.01

	81 Oa	82 dWc	83 dCoa	84 dNco	85 dNca	86 dFin	87 dFnl	88 dBe	89 Dac	90 Poa	91 Pta	92 Pda	93 Ndf	94 Roe1	95 Roe6	96 dRoe1	97 dRoe6	98 dRoe12	99 Roa1	100 dRoa1
$\overline{R}$	−0.27	−0.42	−0.31	−0.41	−0.42	0.28	−0.32	−0.32	−0.39	−0.39	−0.42	−0.48	−0.30	0.68	0.42	0.75	0.36	0.24	0.57	0.56
$t_{\overline{R}}$	−2.19	−3.25	−2.28	−3.52	−3.47	2.39	−3.09	−2.03	−2.95	−2.89	−3.14	−3.91	−2.45	3.12	1.98	5.53	3.16	2.39	2.63	3.76
α_q	−0.56	−0.51	0.08	−0.06	−0.02	0.43	−0.07	0.12	−0.67	−0.13	−0.19	−0.39	0.01	−0.03	−0.16	0.34	−0.03	−0.10	0.04	0.06
α_{q^5}	−0.23	−0.22	0.20	0.05	0.03	0.12	0.01	0.17	−0.28	−0.01	−0.04	−0.12	0.10	−0.17	−0.29	0.10	−0.21	−0.18	−0.20	−0.13
α_{FF5}	−0.52	−0.50	0.05	−0.20	−0.15	0.50	−0.17	0.13	−0.64	−0.13	−0.16	−0.42	−0.07	0.53	0.32	0.79	0.40	0.26	0.53	0.53
α_{FF6}	−0.47	−0.45	0.06	−0.17	−0.14	0.48	−0.15	0.13	−0.63	−0.10	−0.16	−0.37	−0.06	0.35	0.16	0.56	0.21	0.11	0.30	0.31
α_{FF6c}	−0.31	−0.30	0.09	−0.17	−0.17	0.36	−0.13	0.07	−0.53	0.01	−0.13	−0.34	−0.03	0.23	0.04	0.56	0.19	0.09	0.16	0.28
α_{BS6}	−0.54	−0.40	0.18	−0.08	−0.05	0.53	−0.12	0.19	−0.72	−0.04	−0.08	−0.40	0.01	−0.07	−0.20	0.35	−0.05	−0.11	−0.02	0.11
α_{SY4}	−0.44	−0.43	0.13	0.00	0.01	0.38	−0.06	0.28	−0.50	−0.15	−0.07	−0.26	−0.03	0.35	0.16	0.55	0.18	0.10	0.31	0.35
α_{DHS}	−0.33	−0.28	−0.33	−0.33	−0.35	0.26	−0.24	−0.32	−0.43	−0.28	−0.29	−0.41	−0.16	−0.46	−0.63	0.12	−0.18	−0.21	−0.48	−0.05
t_q	−4.10	−3.80	0.78	−0.50	−0.21	3.00	−0.62	0.97	−4.73	−1.00	−1.42	−2.60	0.11	−0.28	−1.32	2.37	−0.31	−1.11	0.34	0.37
t_{q^5}	−1.51	−1.62	1.66	0.41	0.24	0.81	0.12	1.19	−1.91	−0.05	−0.34	−0.78	0.84	−1.40	−2.53	0.68	−1.76	−1.93	−1.75	−0.72
t_{FF5}	−4.20	−3.90	0.55	−1.62	−1.26	4.17	−1.63	1.17	−4.90	−1.13	−1.32	−3.01	−0.67	3.98	2.49	5.54	3.31	2.58	3.80	3.41
t_{FF6}	−3.42	−3.45	0.56	−1.39	−1.18	3.86	−1.39	1.18	−4.55	−0.88	−1.32	−2.57	−0.58	2.86	1.33	4.36	1.98	1.28	2.51	2.01
t_{FF6c}	−2.04	−2.14	0.76	−1.38	−1.37	2.65	−1.19	0.67	−3.63	0.05	−1.04	−2.28	−0.23	1.45	0.24	4.24	1.77	0.93	1.10	1.84
t_{BS6}	−3.68	−2.74	1.55	−0.71	−0.43	3.71	−1.06	1.44	−4.94	−0.32	−0.54	−2.54	0.11	−0.56	−1.55	2.61	−0.46	−1.25	−0.19	0.62
t_{SY4}	−3.23	−3.33	1.14	−0.02	0.11	2.90	−0.60	2.19	−3.45	−1.19	−0.61	−1.92	−0.27	2.20	0.98	3.93	1.62	1.11	2.01	2.18
t_{DHS}	−2.30	−1.74	−2.08	−2.30	−2.49	2.08	−1.83	−1.69	−2.96	−2.04	−2.25	−2.73	−1.21	−2.47	−3.37	0.93	−1.77	−2.24	−2.61	−0.33
$\overline{\lvert\alpha_q\rvert}$	0.13	0.13	0.08	0.10	0.10	0.08	0.09	0.08	0.15	0.11	0.08	0.17	0.08	0.09	0.08	0.09	0.07	0.08	0.07	0.10
$\overline{\lvert\alpha_{q^5}\rvert}$	0.06	0.09	0.09	0.07	0.04	0.06	0.06	0.07	0.06	0.09	0.10	0.09	0.05	0.10	0.09	0.07	0.09	0.09	0.08	0.07
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.12	0.12	0.07	0.09	0.09	0.10	0.09	0.07	0.14	0.11	0.07	0.16	0.05	0.12	0.09	0.16	0.09	0.06	0.14	0.16
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.11	0.11	0.07	0.09	0.09	0.09	0.09	0.06	0.14	0.11	0.07	0.15	0.06	0.08	0.05	0.10	0.06	0.05	0.07	0.11
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.07	0.08	0.07	0.07	0.07	0.08	0.07	0.07	0.12	0.08	0.07	0.12	0.07	0.06	0.04	0.09	0.05	0.04	0.06	0.11
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.14	0.15	0.11	0.10	0.12	0.10	0.10	0.13	0.17	0.11	0.10	0.18	0.08	0.10	0.10	0.10	0.09	0.09	0.10	0.13
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.11	0.11	0.07	0.08	0.07	0.08	0.07	0.07	0.11	0.10	0.09	0.12	0.04	0.09	0.06	0.10	0.06	0.05	0.07	0.11
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.09	0.08	0.10	0.12	0.11	0.07	0.08	0.11	0.10	0.09	0.11	0.13	0.05	0.18	0.17	0.09	0.09	0.10	0.15	0.10
p_q	0.00	0.00	0.06	0.00	0.01	0.02	0.04	0.09	0.00	0.00	0.04	0.00	0.32	0.00	0.04	0.04	0.06	0.01	0.74	0.39
p_{q^5}	0.49	0.12	0.10	0.46	0.82	0.57	0.42	0.53	0.52	0.05	0.01	0.19	0.92	0.00	0.01	0.37	0.07	0.05	0.64	0.58
p_{FF5}	0.00	0.00	0.13	0.01	0.01	0.00	0.01	0.19	0.00	0.00	0.06	0.00	0.75	0.00	0.01	0.00	0.01	0.04	0.02	0.00
p_{FF6}	0.01	0.00	0.18	0.02	0.02	0.00	0.01	0.33	0.00	0.01	0.06	0.00	0.58	0.04	0.15	0.00	0.11	0.07	0.42	0.11
p_{FF6c}	0.21	0.18	0.13	0.24	0.29	0.12	0.31	0.44	0.01	0.09	0.17	0.01	0.69	0.60	0.60	0.01	0.38	0.46	0.80	0.11
p_{BS6}	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.01	0.01	0.00	0.04	0.04
p_{SY4}	0.01	0.01	0.14	0.07	0.11	0.02	0.13	0.18	0.01	0.01	0.00	0.01	0.83	0.05	0.22	0.01	0.12	0.10	0.37	0.13
p_{DHS}	0.08	0.09	0.01	0.00	0.02	0.07	0.16	0.03	0.03	0.11	0.00	0.00	0.86	0.00	0.00	0.09	0.02	0.00	0.08	0.19

	101 dRoa6	102 Rna$^{\mathrm{q}}$1	103 Rna$^{\mathrm{q}}$6	104 Ato$^{\mathrm{q}}$1	105 Ato$^{\mathrm{q}}$6	106 Ato$^{\mathrm{q}}$12	107 Cto$^{\mathrm{q}}$1	108 Cto$^{\mathrm{q}}$6	109 Cto$^{\mathrm{q}}$12	110 Gpa	111 Gla$^{\mathrm{q}}$1	112 Gla$^{\mathrm{q}}$6	113 Gla$^{\mathrm{q}}$12	114 Ole$^{\mathrm{q}}$1	115 Ole$^{\mathrm{q}}$6	116 Opa	117 Ola$^{\mathrm{q}}$1	118 Ola$^{\mathrm{q}}$6	119 Ola$^{\mathrm{q}}$12	120 Cop
$\overline{R}$	0.27	0.64	0.43	0.62	0.53	0.42	0.44	0.40	0.36	0.37	0.51	0.33	0.28	0.71	0.48	0.41	0.75	0.52	0.46	0.63
$t_{\overline{R}}$	1.99	2.77	2.01	3.44	3.07	2.56	2.44	2.34	2.14	2.63	3.48	2.46	2.18	3.40	2.39	2.09	3.53	2.59	2.46	3.57
α_q	−0.19	0.19	0.10	0.35	0.34	0.32	−0.10	−0.08	−0.06	0.17	0.21	0.11	0.14	0.03	−0.11	0.46	0.40	0.26	0.32	0.69
α_{q^5}	−0.27	−0.04	−0.15	0.11	0.11	0.11	−0.16	−0.14	−0.11	0.04	0.04	−0.04	0.00	−0.17	−0.31	−0.04	−0.08	−0.20	−0.10	0.10
α_{FF5}	0.25	0.57	0.38	0.52	0.50	0.45	0.07	0.07	0.08	0.26	0.41	0.28	0.26	0.32	0.12	0.57	0.74	0.54	0.54	0.82
α_{FF6}	0.05	0.42	0.28	0.42	0.40	0.36	0.03	0.02	0.04	0.24	0.33	0.22	0.22	0.18	0.02	0.52	0.58	0.41	0.43	0.73
α_{FF6c}	0.05	0.30	0.14	0.37	0.34	0.29	−0.09	−0.10	−0.09	0.17	0.25	0.13	0.13	0.04	−0.14	0.41	0.50	0.32	0.33	0.51
α_{BS6}	−0.19	0.19	0.11	0.52	0.53	0.52	−0.04	−0.02	0.03	0.31	0.31	0.20	0.22	−0.20	−0.30	0.58	0.48	0.34	0.38	0.82
α_{SY4}	0.08	0.44	0.30	0.25	0.24	0.20	−0.11	−0.10	−0.08	0.05	0.23	0.14	0.16	0.21	0.06	0.39	0.55	0.41	0.45	0.58
α_{DHS}	−0.24	−0.25	−0.30	0.34	0.25	0.18	−0.10	−0.10	−0.08	0.08	0.08	−0.04	−0.01	−0.28	−0.37	−0.01	0.00	−0.13	−0.08	0.19
t_q	−1.38	1.41	0.79	2.06	2.09	2.03	−0.60	−0.50	−0.35	1.24	1.59	0.93	1.17	0.18	−0.79	2.96	2.64	1.89	2.49	5.04
t_{q^5}	−1.77	−0.29	−1.24	0.62	0.69	0.67	−0.95	−0.81	−0.66	0.29	0.31	−0.28	0.01	−1.17	−2.23	−0.28	−0.59	−1.79	−0.92	0.89
t_{FF5}	1.83	4.08	3.02	3.17	3.41	3.19	0.47	0.50	0.58	2.06	3.01	2.34	2.27	2.35	0.99	3.60	4.47	3.85	4.24	6.53
t_{FF6}	0.42	3.22	2.37	2.74	2.85	2.61	0.21	0.15	0.29	1.86	2.51	1.90	1.97	1.35	0.20	3.67	3.89	3.25	3.75	6.15
t_{FF6c}	0.35	1.96	1.04	2.28	2.23	1.97	−0.50	−0.62	−0.58	1.24	1.80	1.08	1.06	0.23	−0.89	2.55	2.87	2.10	2.44	4.28
t_{BS6}	−1.42	1.39	0.83	3.24	3.67	3.61	−0.25	−0.10	0.16	2.14	2.20	1.63	1.78	−1.33	−2.08	3.57	3.23	2.52	3.01	5.93
t_{SY4}	0.58	2.58	1.90	1.65	1.67	1.42	−0.69	−0.69	−0.51	0.35	1.66	1.12	1.30	1.23	0.40	2.44	3.60	2.91	3.44	4.51
t_{DHS}	−1.71	−1.34	−1.68	1.67	1.33	0.99	−0.53	−0.52	−0.45	0.49	0.54	−0.28	−0.10	−1.62	−2.24	−0.04	0.01	−0.71	−0.47	1.16
$\overline{\lvert\alpha_q\rvert}$	0.08	0.06	0.06	0.11	0.07	0.07	0.08	0.08	0.08	0.12	0.10	0.10	0.09	0.07	0.08	0.13	0.13	0.07	0.07	0.17
$\overline{\lvert\alpha_{q^5}\rvert}$	0.08	0.06	0.05	0.13	0.12	0.12	0.12	0.12	0.11	0.06	0.09	0.09	0.06	0.09	0.11	0.08	0.07	0.07	0.06	0.08
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.09	0.15	0.11	0.14	0.11	0.10	0.07	0.08	0.07	0.12	0.13	0.13	0.12	0.09	0.06	0.16	0.22	0.16	0.14	0.20
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.05	0.11	0.07	0.11	0.08	0.08	0.07	0.07	0.07	0.12	0.12	0.13	0.12	0.08	0.06	0.14	0.17	0.12	0.11	0.18
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.06	0.10	0.08	0.13	0.09	0.09	0.07	0.07	0.06	0.13	0.15	0.15	0.14	0.06	0.06	0.12	0.17	0.11	0.11	0.14
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.10	0.12	0.12	0.12	0.10	0.11	0.10	0.09	0.10	0.19	0.17	0.18	0.17	0.11	0.12	0.17	0.15	0.11	0.11	0.20
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.06	0.10	0.06	0.12	0.09	0.08	0.09	0.10	0.09	0.07	0.08	0.07	0.06	0.09	0.07	0.11	0.15	0.10	0.09	0.14
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.09	0.09	0.08	0.10	0.06	0.05	0.07	0.07	0.07	0.07	0.08	0.07	0.05	0.13	0.14	0.05	0.06	0.07	0.06	0.08
p_q	0.04	0.20	0.46	0.01	0.08	0.07	0.41	0.05	0.02	0.13	0.14	0.16	0.34	0.11	0.02	0.00	0.01	0.05	0.05	0.00
p_{q^5}	0.10	0.53	0.72	0.01	0.02	0.01	0.03	0.01	0.01	0.63	0.19	0.08	0.30	0.40	0.04	0.10	0.51	0.18	0.29	0.32
p_{FF5}	0.03	0.00	0.02	0.00	0.00	0.00	0.52	0.06	0.04	0.02	0.01	0.02	0.07	0.07	0.19	0.00	0.00	0.00	0.00	0.00
p_{FF6}	0.25	0.01	0.07	0.00	0.01	0.01	0.48	0.09	0.08	0.03	0.01	0.02	0.07	0.13	0.09	0.00	0.00	0.00	0.00	0.00
p_{FF6c}	0.15	0.14	0.30	0.00	0.02	0.03	0.59	0.20	0.26	0.08	0.00	0.00	0.02	0.50	0.49	0.00	0.00	0.02	0.03	0.00
p_{BS6}	0.01	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
p_{SY4}	0.19	0.04	0.46	0.00	0.02	0.02	0.15	0.02	0.02	0.14	0.16	0.11	0.30	0.17	0.11	0.00	0.00	0.01	0.01	0.00
p_{DHS}	0.02	0.72	0.37	0.01	0.17	0.50	0.39	0.04	0.07	0.67	0.30	0.47	0.77	0.01	0.00	0.57	0.58	0.46	0.37	0.12

	121 Cla	122 Cla^{q}1	123 Cla^{q}6	124 Cla^{q}12	125 F^{q}1	126 F^{q}6	127 F^{q}12	128 Fp^{q}6	129 Oca	130 Ioca	131 Adm	132 Rdm	133 Rdm^{q}1	134 Rdm^{q}6	135 Rdm^{q}12	136 Ol	137 Ol^{q}1	138 Ol^{q}6	139 Ol^{q}12	140 Hs
$\overline{R}$	0.55	0.52	0.49	0.46	0.52	0.48	0.38	−0.62	0.54	0.53	0.66	0.70	1.11	0.80	0.82	0.44	0.49	0.48	0.48	−0.31
$t_{\overline{R}}$	3.23	3.26	3.60	3.63	2.32	2.39	2.05	−1.99	2.67	4.31	2.71	2.75	2.91	2.18	2.43	2.62	2.60	2.62	2.77	−2.12
α_q	0.75	0.46	0.41	0.45	0.13	0.14	0.05	−0.18	0.13	0.07	0.09	0.72	1.39	0.95	0.81	0.01	0.08	0.10	0.12	−0.30
α_{q^5}	0.17	−0.02	−0.03	0.04	0.24	0.28	0.18	0.33	−0.13	−0.02	0.06	0.25	1.07	0.54	0.37	0.06	0.11	0.04	0.04	−0.12
α_{FF5}	0.85	0.63	0.57	0.60	0.37	0.37	0.26	−0.86	0.36	0.30	−0.09	0.57	0.89	0.63	0.60	0.14	0.26	0.25	0.29	−0.41
α_{FF6}	0.78	0.54	0.47	0.51	0.23	0.26	0.18	−0.35	0.34	0.17	0.04	0.60	1.33	0.92	0.77	0.13	0.26	0.25	0.27	−0.34
α_{FF6c}	0.56	0.45	0.37	0.40	0.25	0.24	0.12	−0.32	0.43	0.16	0.03	0.76	1.36	1.01	0.88	0.13	0.24	0.24	0.26	−0.32
α_{BS6}	0.89	0.53	0.46	0.51	0.05	0.09	0.00	−0.24	0.27	0.03	−0.26	0.73	1.40	0.96	0.80	−0.02	0.10	0.09	0.11	−0.46
α_{SY4}	0.66	0.41	0.40	0.43	0.33	0.38	0.28	−0.28	0.00	0.09	0.08	0.30	1.14	0.63	0.47	0.02	0.15	0.14	0.14	−0.26
α_{DHS}	0.19	0.10	0.11	0.15	0.05	0.04	−0.04	0.56	0.19	0.20	0.93	1.13	1.82	1.48	1.36	0.13	0.15	0.18	0.18	−0.17
t_q	5.23	3.02	2.97	3.63	0.58	0.85	0.36	−0.68	0.69	0.57	0.35	3.11	3.06	2.87	3.01	0.06	0.48	0.61	0.77	−1.56
t_{q^5}	1.40	−0.13	−0.28	0.41	1.21	1.67	1.28	1.39	−0.63	−0.16	0.27	1.13	2.26	1.57	1.31	0.33	0.61	0.21	0.25	−0.55
t_{FF5}	6.82	4.28	4.35	5.07	1.78	2.23	1.94	−3.18	1.80	2.40	−0.50	2.55	2.26	1.98	2.22	0.94	1.51	1.54	1.81	−2.50
t_{FF6}	6.36	3.93	4.10	4.84	1.15	1.53	1.30	−2.17	1.71	1.41	0.21	2.77	3.58	3.05	3.00	0.88	1.56	1.57	1.71	−1.96
t_{FF6c}	4.68	3.16	3.06	3.71	1.20	1.33	0.82	−1.85	1.90	1.21	0.13	3.34	3.65	3.36	3.51	0.81	1.29	1.35	1.52	−1.85
t_{BS6}	6.22	3.69	3.70	4.63	0.27	0.53	0.02	−1.40	1.39	0.25	−1.14	3.09	3.44	2.89	2.84	−0.10	0.59	0.53	0.64	−2.46
t_{SY4}	4.87	2.97	3.44	4.23	1.59	2.24	1.85	−1.93	−0.01	0.72	0.35	1.34	2.87	2.13	1.84	0.17	0.93	0.86	0.96	−1.44
t_{DHS}	1.12	0.67	0.85	1.26	0.23	0.22	−0.24	2.29	0.88	1.40	3.07	4.31	3.91	3.34	3.34	0.76	0.83	0.94	0.98	−1.01
$\overline{\lvert\alpha_q\rvert}$	0.14	0.19	0.10	0.11	0.09	0.14	0.10	0.12	0.12	0.09	0.06	0.27	0.52	0.46	0.45	0.09	0.09	0.09	0.09	0.14
$\overline{\lvert\alpha_{q^5}\rvert}$	0.06	0.08	0.05	0.04	0.09	0.12	0.09	0.17	0.09	0.08	0.09	0.12	0.36	0.27	0.23	0.10	0.11	0.11	0.10	0.13
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.17	0.21	0.14	0.15	0.14	0.12	0.08	0.11	0.14	0.10	0.07	0.24	0.40	0.37	0.38	0.07	0.09	0.09	0.08	0.15
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.14	0.19	0.11	0.12	0.11	0.11	0.08	0.11	0.14	0.09	0.07	0.25	0.49	0.43	0.42	0.07	0.09	0.09	0.08	0.13
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.12	0.17	0.10	0.12	0.10	0.10	0.06	0.11	0.16	0.07	0.06	0.26	0.46	0.41	0.40	0.06	0.10	0.09	0.08	0.13
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.18	0.20	0.12	0.13	0.10	0.15	0.11	0.11	0.18	0.14	0.11	0.35	0.58	0.52	0.51	0.11	0.12	0.12	0.11	0.19
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.11	0.18	0.10	0.11	0.13	0.13	0.10	0.12	0.08	0.07	0.07	0.17	0.44	0.34	0.32	0.06	0.07	0.07	0.08	0.12
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.06	0.12	0.05	0.05	0.06	0.10	0.07	0.25	0.09	0.07	0.18	0.29	0.54	0.47	0.47	0.10	0.10	0.11	0.11	0.10
p_q	0.00	0.00	0.02	0.00	0.08	0.00	0.00	0.00	0.05	0.02	0.72	0.00	0.00	0.00	0.00	0.05	0.11	0.01	0.01	0.03
p_{q^5}	0.51	0.55	0.82	0.39	0.21	0.00	0.00	0.01	0.21	0.53	0.40	0.21	0.01	0.04	0.04	0.10	0.11	0.04	0.03	0.12
p_{FF5}	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.04	0.00	0.82	0.00	0.01	0.01	0.00	0.05	0.10	0.02	0.01	0.00
p_{FF6}	0.00	0.00	0.00	0.00	0.08	0.00	0.01	0.00	0.04	0.02	0.66	0.00	0.00	0.00	0.00	0.04	0.08	0.02	0.02	0.01
p_{FF6c}	0.00	0.00	0.13	0.00	0.17	0.00	0.06	0.00	0.03	0.25	0.74	0.00	0.00	0.00	0.00	0.38	0.05	0.02	0.02	0.04
p_{BS6}	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
p_{SY4}	0.00	0.00	0.02	0.00	0.03	0.00	0.00	0.00	0.23	0.17	0.67	0.04	0.00	0.03	0.03	0.33	0.40	0.06	0.08	0.19
p_{DHS}	0.51	0.04	0.64	0.56	0.44	0.03	0.08	0.00	0.31	0.12	0.02	0.00	0.00	0.00	0.00	0.16	0.06	0.00	0.01	0.14

	141	142	143	144	145	146	147	148	149	150	151	152	153	154	155	156	157	158
	Etr	Rer	Eprd	Etl	Alm$^{\mathrm{q}}$1	Alm$^{\mathrm{q}}$6	Alm$^{\mathrm{q}}$12	R_{a}^{1}	$R_{\mathrm{a}}^{[2,5]}$	$R_{\mathrm{n}}^{[2,5]}$	$R_{\mathrm{a}}^{[6,10]}$	$R_{\mathrm{n}}^{[6,10]}$	$R_{\mathrm{a}}^{[11,15]}$	$R_{\mathrm{a}}^{[16,20]}$	Sv1	Dtv12	Isff1	Isq1
$\overline{R}$	0.24	0.34	−0.53	0.34	0.58	0.60	0.54	0.67	0.69	−0.50	0.83	−0.46	0.62	0.54	−0.49	−0.40	0.28	0.25
$t_{\overline{R}}$	2.29	2.44	−2.96	2.79	2.75	3.05	2.84	3.43	4.11	−2.22	5.06	−2.38	4.46	3.26	−2.23	−2.23	3.11	2.80
α_q	0.09	0.34	−0.55	0.27	0.25	0.24	0.14	0.58	0.81	−0.20	1.11	0.03	0.60	0.62	−0.22	−0.13	0.27	0.29
α_{q^5}	0.11	0.18	−0.43	0.18	0.24	0.22	0.17	0.50	0.85	−0.09	0.95	0.05	0.55	0.61	−0.16	−0.15	0.20	0.19
α_{FF5}	0.20	0.29	−0.91	0.36	0.02	0.09	0.05	0.67	0.73	0.05	1.05	−0.08	0.68	0.60	−0.26	−0.06	0.30	0.28
α_{FF6}	0.17	0.27	−0.81	0.26	0.09	0.10	0.03	0.48	0.74	−0.05	1.11	0.00	0.65	0.60	−0.25	−0.06	0.26	0.24
α_{FF6c}	0.23	0.25	−0.85	0.33	0.09	0.10	0.02	0.41	0.66	−0.05	1.11	−0.03	0.66	0.63	−0.18	−0.09	0.27	0.24
α_{BS6}	0.13	0.35	−0.81	0.35	−0.03	−0.03	−0.12	0.47	0.78	0.12	1.11	0.33	0.58	0.59	−0.21	−0.01	0.31	0.33
α_{SY4}	0.13	0.20	−0.58	0.18	0.15	0.17	0.12	0.59	0.83	0.05	1.01	−0.09	0.59	0.56	−0.24	−0.03	0.24	0.25
α_{DHS}	0.13	0.15	0.00	0.37	0.94	0.89	0.76	0.32	0.58	−0.77	1.13	−0.36	0.52	0.59	−0.11	−0.95	0.27	0.38
t_q	0.75	2.05	−3.02	1.56	1.68	1.78	1.01	2.75	4.06	−1.06	5.05	0.15	3.48	3.22	−0.90	−1.72	2.56	2.84
t_{q^5}	0.82	1.14	−2.49	1.10	1.61	1.62	1.22	2.25	4.02	−0.42	4.74	0.24	3.16	2.83	−0.59	−1.94	1.73	1.76
t_{FF5}	1.83	1.86	−5.56	2.48	0.18	0.76	0.44	3.58	4.03	0.27	5.37	−0.47	3.91	3.72	−1.15	−0.77	3.05	2.89
t_{FF6}	1.51	1.73	−4.97	1.90	0.71	0.93	0.28	2.67	3.80	−0.31	5.69	−0.02	4.13	3.43	−1.08	−0.79	2.76	2.54
t_{FF6c}	2.03	1.59	−5.08	2.41	0.72	0.90	0.21	2.12	3.24	−0.28	5.25	−0.19	3.76	3.30	−0.75	−1.13	2.63	2.35
t_{BS6}	0.97	2.08	−4.64	2.23	−0.20	−0.28	−0.93	2.23	3.73	0.69	4.73	1.70	3.16	3.32	−0.84	−0.11	3.12	3.14
t_{SY4}	1.10	1.23	−3.71	1.30	1.06	1.28	0.90	3.16	4.21	0.29	4.97	−0.50	3.85	3.01	−0.98	−0.35	2.36	2.39
t_{DHS}	1.13	0.82	0.01	2.38	4.77	4.49	3.93	1.31	2.56	−3.24	5.43	−1.72	3.07	3.08	−0.52	−4.41	2.68	3.19
$\overline{\lvert\alpha_q\rvert}$	0.09	0.14	0.16	0.08	0.09	0.09	0.07	0.14	0.16	0.12	0.24	0.15	0.17	0.15	0.09	0.09	0.09	0.10
$\overline{\lvert\alpha_{q^5}\rvert}$	0.09	0.13	0.16	0.08	0.09	0.07	0.06	0.13	0.17	0.11	0.20	0.10	0.17	0.15	0.09	0.09	0.07	0.09
$\overline{\lvert\alpha_{\mathrm{FF5}}\rvert}$	0.08	0.12	0.23	0.08	0.07	0.06	0.05	0.17	0.15	0.09	0.22	0.16	0.18	0.15	0.10	0.06	0.09	0.09
$\overline{\lvert\alpha_{\mathrm{FF6}}\rvert}$	0.08	0.13	0.20	0.07	0.07	0.07	0.05	0.13	0.15	0.11	0.24	0.14	0.18	0.16	0.08	0.06	0.08	0.09
$\overline{\lvert\alpha_{\mathrm{FF6c}}\rvert}$	0.07	0.13	0.22	0.08	0.09	0.07	0.07	0.12	0.14	0.11	0.24	0.15	0.19	0.17	0.07	0.06	0.07	0.08
$\overline{\lvert\alpha_{\mathrm{BS6}}\rvert}$	0.10	0.21	0.23	0.09	0.09	0.08	0.07	0.13	0.16	0.14	0.23	0.15	0.18	0.15	0.10	0.06	0.11	0.13
$\overline{\lvert\alpha_{\mathrm{SY4}}\rvert}$	0.08	0.09	0.15	0.07	0.08	0.09	0.07	0.15	0.16	0.10	0.22	0.13	0.16	0.14	0.08	0.07	0.08	0.10
$\overline{\lvert\alpha_{\mathrm{DHS}}\rvert}$	0.10	0.10	0.07	0.09	0.24	0.25	0.22	0.11	0.11	0.22	0.24	0.15	0.15	0.15	0.07	0.40	0.08	0.09
p_q	0.02	0.02	0.01	0.12	0.06	0.05	0.22	0.07	0.00	0.00	0.00	0.00	0.00	0.01	0.23	0.00	0.00	0.00
p_{q^5}	0.13	0.06	0.02	0.26	0.10	0.13	0.21	0.34	0.00	0.01	0.00	0.29	0.00	0.06	0.41	0.06	0.04	0.04
p_{FF5}	0.06	0.02	0.00	0.05	0.17	0.11	0.23	0.04	0.00	0.00	0.00	0.00	0.00	0.01	0.37	0.01	0.00	0.00
p_{FF6}	0.09	0.01	0.00	0.24	0.08	0.09	0.21	0.15	0.00	0.00	0.00	0.00	0.00	0.01	0.53	0.03	0.01	0.00
p_{FF6c}	0.20	0.01	0.00	0.26	0.13	0.16	0.30	0.30	0.00	0.00	0.00	0.01	0.00	0.01	0.74	0.13	0.06	0.04
p_{BS6}	0.01	0.00	0.00	0.04	0.03	0.03	0.05	0.02	0.00	0.00	0.00	0.00	0.00	0.01	0.13	0.00	0.00	0.00
p_{SY4}	0.12	0.27	0.01	0.36	0.20	0.18	0.17	0.11	0.00	0.00	0.00	0.02	0.00	0.06	0.34	0.19	0.01	0.00
p_{DHS}	0.06	0.32	0.58	0.09	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.01	0.53	0.00	0.00	0.00

Table 9 : The q^5-factor Loadings for the 158 Individual Anomalies, January 1967–December 2016, 600 Months

For each of the 158 high-minus-low deciles, we show the loadings on the market, size, investment-to-assets, Roe, and expected growth factors (β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively) in the q^5 model, as well as their heteroscedasticity-and-autocorrelation-adjusted t-values (denoted t_{Mkt}, t_{Me}, $t_{\mathrm{I/A}}$, t_{Roe}, and t_{Eg}, respectively). Table 4 describes the anomalies, and the Online Appendix details variable definitions and portfolio construction.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Sue1	Abr1	Abr6	Abr12	Re1	Re6	$R^6$1	$R^6$6	$R^6$12	R^{11}1	R^{11}6	Im1	Im6	Im12	Rs1	dEf1	dEf6	dEf12	Nei1	52w6
β_{Mkt}	−0.02	−0.05	−0.03	−0.01	−0.05	−0.05	−0.15	−0.02	0.01	−0.06	−0.01	−0.14	−0.01	0.00	−0.03	0.02	0.07	0.03	0.03	−0.39
β_{Me}	−0.01	0.07	0.09	0.07	−0.17	−0.15	0.29	0.28	0.09	0.38	0.18	0.20	0.29	0.17	−0.11	−0.05	−0.02	−0.08	−0.05	−0.32
$\beta_{\mathrm{I/A}}$	−0.13	−0.15	−0.19	−0.28	0.07	−0.13	−0.12	−0.21	−0.32	−0.16	−0.29	−0.09	−0.10	−0.31	−0.49	−0.18	−0.32	−0.35	−0.34	0.32
β_{Roe}	0.80	0.24	0.16	0.15	1.24	1.02	0.99	0.84	0.75	1.23	1.16	0.60	0.65	0.56	0.53	0.74	0.77	0.67	0.60	1.13
β_{Eg}	0.16	0.09	0.06	0.05	0.03	0.10	0.65	0.64	0.36	0.80	0.49	0.60	0.64	0.45	0.19	0.12	0.04	0.02	0.15	0.54
t_{Mkt}	−0.58	−1.26	−0.96	−0.44	−0.92	−1.02	−1.64	−0.31	0.23	−0.62	−0.09	−1.77	−0.14	0.03	−0.58	0.41	1.47	0.82	1.17	−5.75
t_{Me}	−0.20	0.71	1.87	1.90	−1.96	−1.70	1.43	1.64	0.67	1.84	1.03	1.04	1.90	1.28	−2.06	−0.56	−0.21	−1.19	−1.33	−1.97
$t_{\mathrm{I/A}}$	−1.43	−1.44	−2.72	−4.83	0.41	−0.86	−0.37	−0.95	−1.90	−0.52	−1.35	−0.33	−0.49	−1.70	−5.77	−1.27	−2.68	−3.82	−4.74	1.56
t_{Roe}	10.06	2.50	2.38	3.26	8.72	7.79	3.11	4.01	5.19	4.39	5.57	2.73	3.60	3.65	6.15	6.67	7.57	8.87	9.34	5.37
t_{Eg}	1.57	0.81	0.76	0.85	0.16	0.69	2.49	3.05	2.08	2.96	2.20	2.87	3.55	2.65	1.97	0.73	0.32	0.15	1.98	3.06

	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
	$\epsilon^6$6	$\epsilon^6$12	ϵ^{11}1	ϵ^{11}6	ϵ^{11}12	Sm1	Ilr1	Ilr6	Ilr12	Ile1	Cm1	Cm12	Sim1	Cim1	Cim6	Cim12	Bm	Bmj	Bm^{q}12	Rev6
β_{Mkt}	0.00	0.01	0.05	0.03	0.02	0.01	−0.14	−0.08	−0.03	0.00	0.08	0.03	0.08	0.03	−0.02	0.00	0.02	−0.05	0.03	0.05
β_{Me}	0.12	0.07	0.15	0.13	0.05	−0.19	−0.08	0.09	0.09	0.03	−0.15	0.10	0.10	−0.14	0.16	0.13	0.42	0.32	0.32	−0.60
$\beta_{\mathrm{I/A}}$	0.04	−0.04	0.14	0.04	−0.01	0.10	0.01	−0.07	−0.11	−0.25	0.25	−0.03	0.15	0.06	0.05	−0.06	1.33	1.36	1.25	−1.02
β_{Roe}	0.14	0.21	0.27	0.29	0.29	−0.19	−0.05	0.24	0.25	0.53	−0.07	0.08	−0.02	0.07	0.20	0.20	−0.60	−0.81	−0.95	0.73
β_{Eg}	0.31	0.25	0.39	0.27	0.17	0.33	0.37	0.29	0.27	0.33	0.04	0.12	0.51	0.43	0.36	0.32	0.12	−0.04	−0.02	−0.21
t_{Mkt}	0.10	0.15	0.77	0.52	0.49	0.13	−2.06	−2.44	−1.01	−0.06	1.03	1.00	1.09	0.42	−0.77	0.12	0.41	−1.25	0.60	0.93
t_{Me}	1.88	1.05	2.21	1.58	0.60	−1.96	−0.80	1.26	1.60	0.33	−1.73	1.60	0.78	−1.48	2.19	2.49	5.18	3.36	3.00	−7.73
$t_{\mathrm{I/A}}$	0.43	−0.47	1.06	0.37	−0.09	0.53	0.04	−0.61	−1.33	−1.96	1.42	−0.40	0.62	0.32	0.34	−0.52	12.85	11.01	9.50	−9.76
t_{Roe}	1.40	2.70	2.07	2.74	3.10	−1.09	−0.34	2.65	3.43	4.88	−0.40	1.36	−0.09	0.50	2.03	2.72	−6.45	−8.69	−8.07	7.39
t_{Eg}	2.62	2.43	2.21	1.80	1.36	1.63	2.08	2.91	3.63	2.55	0.22	2.16	2.62	2.48	3.51	4.50	1.02	−0.34	−0.17	−1.50

	41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60
	Rev12	Ep	Ep^{q}1	Ep^{q}6	Ep^{q}12	Cp	Cp^{q}1	Cp^{q}6	Cp^{q}12	Nop	Em	Em^{q}1	Em^{q}6	Em^{q}12	Sp	Sp^{q}1	Sp^{q}6	Sp^{q}12	Ocp	Ocp^{q}1
β_{Mkt}	0.06	−0.07	−0.01	−0.03	−0.05	0.02	0.06	0.00	−0.03	−0.14	0.08	0.05	0.07	0.09	0.07	0.10	0.07	0.05	0.02	0.12
β_{Me}	−0.60	0.29	0.28	0.25	0.27	0.23	0.18	0.17	0.22	−0.32	−0.20	0.04	0.01	−0.04	0.62	0.57	0.61	0.64	0.18	0.13
$\beta_{\mathrm{I/A}}$	−0.93	0.98	0.86	0.84	0.83	1.29	1.05	1.01	1.05	1.00	−0.90	−0.69	−0.68	−0.70	1.17	1.12	1.15	1.13	1.37	1.18
β_{Roe}	0.57	−0.13	0.21	0.18	0.14	−0.42	−0.53	−0.52	−0.43	−0.01	0.27	−0.02	0.00	−0.01	−0.23	−0.45	−0.42	−0.30	−0.60	−0.62
β_{Eg}	−0.18	0.15	−0.17	−0.03	0.00	0.03	−0.17	−0.09	−0.08	0.22	−0.31	−0.05	−0.10	−0.12	−0.17	−0.26	−0.22	−0.22	0.20	0.09
t_{Mkt}	1.12	−1.19	−0.19	−0.50	−1.05	0.39	1.08	0.00	−0.64	−3.04	1.48	0.87	1.44	2.00	1.51	1.55	1.13	0.96	0.35	1.43
t_{Me}	−8.41	2.43	2.12	2.04	2.37	1.92	1.29	1.36	1.96	−3.96	−2.44	0.43	0.06	−0.50	4.48	3.35	3.93	4.49	1.56	0.61
$t_{\mathrm{I/A}}$	−9.02	6.17	5.01	5.92	6.17	8.91	6.29	6.63	7.47	9.64	−6.90	−4.61	−5.60	−6.20	9.02	6.03	7.02	7.83	9.27	5.59
t_{Roe}	5.14	−0.89	1.28	1.33	1.19	−3.05	−3.40	−3.83	−3.47	−0.05	2.07	−0.19	0.03	−0.13	−1.85	−2.29	−2.45	−2.15	−4.56	−2.77
t_{Eg}	−1.30	1.05	−1.13	−0.19	−0.03	0.23	−1.10	−0.60	−0.62	1.98	−2.43	−0.30	−0.71	−0.93	−1.26	−1.57	−1.49	−1.60	1.42	0.42

	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80
	Ir	Vhp	Vfp	Ebp	Dur	Aci	I/A	Ia^{q}6	Ia^{q}12	dPia	Noa	dNoa	dLno	Ig	2Ig	Nsi	dIi	Cei	Ivg	Ivc
β_{Mkt}	−0.06	−0.02	−0.04	0.05	0.04	0.01	0.03	0.05	0.03	0.03	−0.06	−0.01	−0.09	0.00	0.06	0.01	0.03	0.18	−0.03	−0.01
β_{Me}	−0.58	0.25	0.18	0.51	−0.24	−0.29	−0.13	−0.19	−0.21	−0.11	0.07	0.03	−0.17	−0.15	−0.29	0.13	−0.16	0.25	0.06	−0.05
$\beta_{\mathrm{I/A}}$	−1.13	0.85	0.53	1.24	−1.00	0.12	−1.37	−1.31	−1.33	−0.82	0.09	−1.01	−0.76	−0.77	−0.74	−0.59	−0.65	−0.91	−0.90	−0.56
β_{Roe}	0.75	−0.18	0.22	−0.63	0.18	−0.18	0.15	0.40	0.25	0.13	0.15	0.05	0.04	−0.08	−0.05	−0.19	−0.19	0.00	0.10	0.32
β_{Eg}	−0.23	0.20	0.03	−0.03	−0.14	−0.01	−0.01	−0.18	−0.13	−0.11	−0.50	−0.08	−0.15	0.07	0.00	−0.28	0.02	−0.39	−0.14	−0.46
t_{Mkt}	−1.34	−0.26	−0.69	1.11	0.73	0.18	1.16	1.67	0.99	0.77	−1.52	−0.37	−1.81	−0.16	1.84	0.20	1.03	5.19	−0.99	−0.31
t_{Me}	−8.40	2.06	1.74	6.39	−1.79	−4.94	−2.34	−3.60	−4.58	−2.23	0.74	0.54	−2.51	−2.60	−4.56	1.84	−3.55	3.84	1.36	−1.01
$t_{\mathrm{I/A}}$	−10.66	5.18	3.27	12.27	−6.81	0.94	−17.50	−13.14	−14.46	−8.70	0.59	−8.89	−7.11	−10.02	−8.80	−7.33	−7.88	−12.01	−11.87	−5.21
t_{Roe}	7.55	−1.21	1.55	−7.17	1.34	−1.86	2.13	5.13	3.59	1.55	1.49	0.63	0.35	−1.23	−0.74	−2.80	−2.67	−0.06	1.21	3.51
t_{Eg}	−1.75	1.38	0.15	−0.26	−1.10	−0.05	−0.10	−2.15	−1.62	−1.29	−4.46	−1.04	−1.41	0.80	0.05	−3.57	0.24	−4.47	−1.38	−4.64

	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100
	Oa	dWc	dCoa	dNco	dNca	dFin	dFnl	dBe	Dac	Poa	Pta	Pda	Ndf	Roe1	Roe6	dRoe1	dRoe6	dRoe12	Roa1	dRoa1
β_{Mkt}	0.01	−0.03	0.02	−0.04	−0.06	0.02	0.02	0.02	−0.05	−0.03	0.04	−0.03	0.05	−0.06	−0.09	0.06	0.06	0.02	−0.09	0.12
β_{Me}	0.27	0.33	−0.05	−0.09	−0.10	−0.07	−0.08	−0.14	0.13	0.14	0.16	0.02	−0.12	−0.35	−0.41	−0.02	0.00	0.00	−0.35	0.13
$\beta_{\mathrm{I/A}}$	0.12	−0.18	−1.10	−0.73	−0.84	−0.42	−0.38	−1.34	0.42	−0.84	−0.79	−0.15	−0.39	0.09	0.00	0.12	0.13	0.10	−0.15	0.16
β_{Roe}	0.45	0.30	0.18	0.04	0.05	−0.12	−0.11	0.28	0.37	0.16	0.13	0.11	−0.21	1.43	1.30	0.49	0.48	0.47	1.24	0.51
β_{Eg}	−0.53	−0.46	−0.18	−0.17	−0.09	0.50	−0.13	−0.07	−0.61	−0.19	−0.24	−0.43	−0.14	0.21	0.21	0.38	0.28	0.13	0.36	0.31
t_{Mkt}	0.24	−0.59	0.93	−1.06	−1.62	0.61	0.78	0.63	−1.50	−0.82	0.99	−0.81	1.39	−1.59	−2.58	1.42	1.64	0.69	−3.05	2.87
t_{Me}	4.84	3.96	−1.04	−1.73	−2.01	−1.49	−1.87	−2.05	2.53	3.26	2.39	0.35	−2.40	−5.75	−6.32	−0.25	0.07	0.09	−6.12	1.83
$t_{\mathrm{I/A}}$	1.21	−1.76	−17.09	−10.88	−12.40	−3.46	−5.45	−12.49	4.48	−8.53	−7.04	−1.30	−5.38	1.01	0.01	1.46	1.73	1.91	−2.11	1.45
t_{Roe}	6.28	3.95	2.91	0.55	0.69	−1.38	−1.52	3.06	5.49	2.43	1.46	1.30	−2.81	18.46	16.18	5.25	5.40	7.30	15.81	4.57
t_{Eg}	−5.02	−4.58	−2.02	−2.12	−1.05	4.63	−1.50	−0.76	−5.65	−1.93	−2.11	−4.44	−1.45	2.09	2.19	3.30	2.71	1.85	4.10	2.47

	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118	119	120
	dRoa6	Rna^{q}1	Rna^{q}6	Ato^{q}1	Ato^{q}6	Ato^{q}12	Cto^{q}1	Cto^{q}6	Cto^{q}12	Gpa	Gla^{q}1	Gla^{q}6	Gla^{q}12	Ole^{q}1	Ole^{q}6	Opa	Ola^{q}1	Ola^{q}6	Ola^{q}12	Cop
β_{Mkt}	0.09	−0.10	−0.11	0.14	0.12	0.11	0.12	0.12	0.11	0.06	0.02	0.04	0.02	−0.02	−0.03	−0.17	−0.04	−0.04	−0.07	−0.13
β_{Me}	0.13	−0.42	−0.46	0.45	0.40	0.35	0.34	0.33	0.31	0.06	0.13	0.07	0.06	−0.23	−0.28	−0.39	−0.27	−0.32	−0.32	−0.53
$\beta_{\mathrm{I/A}}$	0.13	−0.21	−0.29	−0.61	−0.71	−0.78	−0.17	−0.24	−0.30	−0.36	−0.35	−0.44	−0.51	0.32	0.27	−0.56	−0.42	−0.47	−0.56	−0.30
β_{Roe}	0.56	1.17	1.02	0.45	0.43	0.38	0.80	0.75	0.70	0.49	0.57	0.52	0.45	1.06	0.96	0.42	0.83	0.74	0.66	0.21
β_{Eg}	0.12	0.38	0.42	0.38	0.35	0.33	0.10	0.09	0.09	0.20	0.28	0.25	0.23	0.31	0.30	0.79	0.81	0.77	0.69	0.94
t_{Mkt}	2.11	−2.58	−3.14	2.53	2.33	2.13	2.22	2.40	2.16	1.46	0.43	1.29	0.74	−0.55	−0.86	−4.55	−0.99	−1.32	−2.60	−3.71
t_{Me}	1.78	−8.55	−10.51	5.79	5.84	6.10	3.08	3.41	3.56	1.11	2.64	1.59	1.47	−2.10	−3.16	−4.68	−3.59	−5.59	−5.59	−7.84
$t_{\mathrm{I/A}}$	1.57	−2.29	−3.32	−6.25	−7.42	−8.32	−1.65	−2.47	−3.10	−4.14	−4.12	−5.66	−6.26	2.41	2.32	−6.54	−4.45	−6.03	−7.49	−3.96
t_{Roe}	5.25	15.50	13.39	4.51	5.43	5.04	9.22	9.52	9.15	6.40	8.77	8.20	6.63	9.80	8.81	6.08	10.52	11.32	9.12	3.74
t_{Eg}	1.03	4.45	5.21	3.18	3.09	2.90	0.81	0.75	0.77	1.86	2.85	2.65	2.58	2.53	2.44	7.29	8.12	9.12	7.73	10.77

	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140
	Cla	Cla$^\natural$1	Cla$^\natural$6	Cla$^\natural$12	F$^\natural$1	F$^\natural$6	F$^\natural$12	Fp$^\natural$6	Oca	Ioca	Adm	Rdm	Rdm$^\natural$1	Rdm$^\natural$6	Rdm$^\natural$12	Ol	Ol$^\natural$1	Ol$^\natural$6	Ol$^\natural$12	Hs
β_{Mkt}	−0.11	−0.01	0.03	−0.01	−0.10	−0.07	−0.07	0.34	−0.12	−0.05	0.06	0.23	0.07	0.01	0.02	−0.05	−0.11	−0.13	−0.13	−0.19
β_{Me}	−0.55	−0.27	−0.27	−0.27	−0.37	−0.44	−0.44	0.37	0.26	0.26	0.48	0.68	0.21	0.59	0.69	0.31	0.27	0.34	0.33	−0.09
$\beta_{\mathrm{I/A}}$	−0.55	−0.31	−0.28	−0.32	0.45	0.36	0.35	0.33	0.14	0.33	1.32	−0.03	0.49	0.53	0.66	0.12	0.04	0.00	−0.01	0.36
β_{Roe}	0.13	0.22	0.22	0.18	0.77	0.72	0.70	−1.31	0.47	0.44	−0.30	−0.85	−1.16	−1.07	−0.89	0.59	0.68	0.59	0.56	0.06
β_{Eg}	0.93	0.80	0.73	0.67	−0.19	−0.25	−0.22	−0.84	0.41	0.15	0.04	0.78	0.53	0.68	0.75	−0.07	−0.04	0.10	0.13	−0.30
t_{Mkt}	−3.01	−0.30	1.08	−0.34	−1.63	−1.54	−1.64	5.31	−1.92	−1.44	0.77	3.84	0.58	0.08	0.21	−1.13	−2.06	−2.62	−2.72	−3.73
t_{Me}	−8.94	−4.53	−5.74	−6.07	−3.55	−5.06	−5.48	2.02	3.28	5.54	2.77	7.43	1.05	4.22	5.75	3.21	3.37	3.72	4.13	−1.13
$t_{\mathrm{I/A}}$	−6.64	−3.26	−3.30	−4.33	3.01	3.16	3.62	1.36	1.24	3.55	5.84	−0.22	1.61	2.48	3.71	1.18	0.36	0.04	−0.09	2.32
t_{Roe}	1.96	3.05	4.22	3.68	6.71	7.67	7.31	−6.96	3.84	6.36	−1.31	−5.60	−4.05	−6.03	−6.09	5.42	6.50	5.40	5.29	0.45
t_{Eg}	11.45	6.85	9.25	9.94	−1.30	−1.84	−2.34	−5.04	2.62	1.37	0.22	4.51	2.05	3.16	4.11	−0.55	−0.28	0.76	1.02	−2.56

	141	142	143	144	145	146	147	148	149	150	151	152	153	154	155	156	157	158
	Etr	Rer	Eprd	Etl	Alm$^\natural$1	Alm$^\natural$6	Alm$^\natural$12	R_{a}^{1}	$R_{\mathrm{a}}^{[2,5]}$	$R_{\mathrm{n}}^{[2,5]}$	$R_{\mathrm{a}}^{[6,10]}$	$R_{\mathrm{n}}^{[6,10]}$	$R_{\mathrm{a}}^{[11,15]}$	$R_{\mathrm{a}}^{[16,20]}$	Sv1	Dtv12	Isff1	Isq1
β_{Mkt}	0.01	0.09	0.10	0.03	0.08	0.08	0.08	0.23	0.06	0.16	−0.01	0.16	0.00	−0.06	0.01	0.14	0.00	−0.01
β_{Me}	0.11	−0.10	0.34	0.31	0.67	0.70	0.71	−0.14	−0.18	−0.26	0.05	−0.30	−0.06	−0.08	0.30	−1.13	0.15	0.21
$\beta_{\mathrm{I/A}}$	0.06	−0.13	0.50	−0.18	0.85	0.78	0.73	−0.20	−0.27	−1.28	−0.43	−0.80	−0.04	−0.05	−0.19	−0.36	−0.03	−0.08
β_{Roe}	0.16	−0.03	−0.57	0.00	−0.45	−0.35	−0.23	0.14	0.05	0.47	−0.30	−0.27	0.07	−0.02	−0.50	0.28	−0.08	−0.17
β_{Eg}	−0.04	0.25	−0.18	0.15	0.02	0.03	−0.05	0.12	−0.06	−0.18	0.25	−0.03	0.08	0.01	−0.10	0.03	0.12	0.15
t_{Mkt}	0.35	1.68	1.67	0.69	2.29	2.52	2.43	4.21	1.06	2.41	−0.14	2.82	−0.05	−1.31	0.07	5.51	−0.04	−0.18
t_{Me}	1.97	−0.96	4.36	3.32	7.69	10.60	11.53	−1.28	−1.71	−1.97	0.50	−3.37	−0.66	−1.41	2.41	−31.69	4.03	2.89
$t_{\mathrm{I/A}}$	0.56	−1.06	4.03	−1.10	8.24	9.29	8.77	−1.35	−2.29	−9.00	−2.51	−5.78	−0.25	−0.36	−1.21	−7.20	−0.44	−1.09
t_{Roe}	1.98	−0.30	−4.90	0.00	−5.12	−4.84	−3.00	1.00	0.46	3.17	−2.28	−1.91	0.63	−0.16	−3.73	6.73	−1.32	−2.77
t_{Eg}	−0.38	1.92	−1.41	1.14	0.18	0.30	−0.55	0.79	−0.40	−1.16	1.70	−0.22	0.61	0.12	−0.63	0.57	1.52	1.96

Internet Appendix: "q^5"
(for Online Publication Only)

Kewei Hou*
The Ohio State University
and CAFR

Haitao Mo†
Louisiana State University

Chen Xue‡
University of Cincinnati

Lu Zhang§
The Ohio State University
and NBER

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Abstract

This Online Appendix provides detailed derivation, variable definition, and portfolio construction as well as supplementary results for our manuscript titled "q^5."

*Fisher College of Business, The Ohio State University, 820 Fisher Hall, 2100 Neil Avenue, Columbus OH 43210; and China Academy of Financial Research (CAFR). Tel: (614) 292-0552. E-mail: hou.28@osu.edu.

†E. J. Ourso College of Business, Louisiana State University, 2931 Business Education Complex, Baton Rouge, LA 70803. Tel: (225) 578-0648. E-mail: haitaomo@lsu.edu.

‡Lindner College of Business, University of Cincinnati, 405 Lindner Hall, Cincinnati, OH 45221. Tel: (513) 556-7078. E-mail: xuecx@ucmail.uc.edu.

§Fisher College of Business, The Ohio State University, 760A Fisher Hall, 2100 Neil Avenue, Columbus OH 43210; and NBER. Tel: (614) 292-8644. E-mail: zhanglu@fisher.osu.edu.

A Proof That Stock and Investment Returns Are Equal

This proof follows Liu, Whited, and Zhang (2009), who in turn construct their proof based on Restroy and Rockinger (1994). Let q_{it} be the Lagrangian multiplier associated with the capital accumulation equation $A_{it+1} = (1-\delta)A_{it} + I_{it}$. Form the Lagrangian function for the equity value maximization problem of firm i:

$$\mathcal{L} = \ldots + X_{it}A_{it} - \frac{a}{2}\left(\frac{I_{it}}{A_{it}}\right)^2 A_{it} - I_{it} - q_{it}(A_{it+1} - (1-\delta)A_{it} - I_{it})$$
$$+E_t\left[M_{t+1}\left[X_{it+1}A_{it+1} - \frac{a}{2}\left(\frac{I_{it+1}}{A_{it+1}}\right)^2 A_{it+1} - I_{it+1} - q_{it+1}(A_{it+2} - (1-\delta)A_{it+1} - I_{it+1})\right]\right] + \ldots \quad \text{(A.1)}$$

The first-order conditions with respect to I_{it} and A_{it+1} are, respectively,

$$q_{it} = 1 + a\frac{I_{it}}{A_{it}}; \quad \text{(A.2)}$$
$$q_{it} = E_t\left[M_{t+1}\left[X_{it+1} + \frac{a}{2}\left(\frac{I_{it+1}}{A_{it+1}}\right)^2 + (1-\delta)q_{it+1}\right]\right]. \quad \text{(A.3)}$$

To show the marginal q equals the average q, we start with $P_{it} + D_{it} = V_{it}$ and expand V_{it}:

$$P_{it} + X_{it}A_{it} - \frac{a}{2}\left(\frac{I_{it}}{A_{it}}\right)^2 A_{it} - I_{it} = X_{it}A_{it} - a\frac{I_{it}}{A_{it}}I_{it} + \frac{a}{2}\left(\frac{I_{it}}{A_{it}}\right)^2 A_{it} - I_{it}$$
$$- q_{it}(A_{it+1} - (1-\delta)A_{it} - I_{it}) + E_t\left[M_{t+1}\left(X_{it+1}A_{it+1} - a\frac{I_{it+1}}{A_{it+1}}I_{it+1}\right.\right.$$
$$\left.\left.+\frac{a}{2}\left(\frac{I_{it+1}}{A_{it+1}}\right)^2 A_{it+1} - I_{it+1} - q_{it+1}(A_{it+2} - (1-\delta)A_{it+1} - I_{it+1}) + \ldots\right)\right]. \quad \text{(A.4)}$$

Substituting equations (A.2) and (A.3), and using the linear homogeneity of adjustment costs:

$$P_{it} = \left(1 + a\frac{I_{it}}{A_{it}}\right) I_{it} + q_{it}(1-\delta)A_{it} = q_{it}A_{it+1}. \quad \text{(A.5)}$$

Finally, we are ready to show the equivalence between the stock and the investment returns:

$$r^S_{it+1} = \frac{P_{it+1} + X_{it+1}A_{it+1} - (a/2)\left(I_{it+1}/A_{it+1}\right)^2 A_{it+1} - I_{it+1}}{P_{it}}$$
$$= \frac{q_{it+1}(I_{it+1} + (1-\delta)A_{it+1}) + X_{it+1}A_{it+1} - (a/2)\left(I_{it+1}/A_{it+1}\right)^2 A_{it+1} - I_{it+1}}{q_{it}A_{it+1}}$$
$$= \frac{(1-\delta)q_{it+1} + X_{it+1} + (a/2)\left(I_{it+1}/A_{it+1}\right)^2}{q_{it}} = r^I_{it+1}, \quad \text{(A.6)}$$

in which the second equality follows from equation (A.2), and the third equality follows from the linear homogeneity of the adjustment costs function. Let $\Phi_{it} \equiv (a/2)\left(I_{it}/A_{it}\right)^2 A_{it}$, its linear homogeneity means that $\Phi_{it} = I_{it}\partial\Phi_{it}/\partial I_{it} + K_{it}\partial\Phi_{it}/\partial K_{it}$.

B Supplementary Results

Tables A.1–A.5 report two alternative specifications for the expected growth factor. Table A.1 reports monthly cross-sectional regressions of the percentile rankings of future investment-to-assets changes on the percentile rankings of $\log(q)$, Cop, and dRoe. Table A.2 shows the descriptive statistics of deciles formed on the expected growth constructed with the percentile rankings. Table A.3 reports the properties of the expected growth factor formed with the percentile rankings. Table A.4 shows the properties of deciles on the expected growth formed with the composite score that aggregates $\log(q)$, Cop, and dRoe, and Table A.5 shows the properties of the expected growth factor based on the composite score.

Table A.6 reports the q^5-factor regressions of the expected growth deciles.

Table A.7 reports the overall performance of factor models in subsamples. For the first subsample from January 1967 to December 1991, we require an anomaly to have at least 15 years (180 months) of data. There are 11 anomalies that do not satisfy this requirement because their starting dates are later than January 1967. These anomalies (with starting dates in parentheses) are Sm1 (July 1977); Cm1 and Cm12 (July 1979); Ocp$^{\text{q}}$1 (January 1985); F$^{\text{q}}$1, F$^{\text{q}}$6, and F$^{\text{q}}$12 (January 1989); and Sv1 (February 1986). In contrast, all the 158 anomalies enter the second subsample from January 1992 to December 2016.

Table A.8 shows the factor regressions for the composite testing deciles in subsamples. At each portfolio formation month, we use all available anomaly variables to form the composite scores.

C Variable Definition and Portfolio Construction

We follow the variable definition and portfolio construction in Hou, Xue, and Zhang (2017). When forming testing deciles, we always use NYSE breakpoints and value-weight decile returns.

C.1 Momentum

C.1.1 Sue1, Standardized Unexpected Earnings

Per Foster, Olsen, and Shevlin (1984), Sue denotes Standardized Unexpected Earnings, and is calculated as the change in split-adjusted quarterly earnings per share (Compustat quarterly item EPSPXQ divided by item AJEXQ) from its value four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters (six quarters minimum). At the beginning of each month t, we split all NYSE, Amex, and NASDAQ stocks into deciles based on their most recent past Sue. Before 1972, we use the most recent Sue computed with quarterly earnings from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use Sue computed with quarterly earnings from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter our portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Sue to be within six months prior to the portfolio formation. We do so to exclude stale information on earnings. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly portfolio returns are calculated for the current month t, and the portfolios are rebalanced at the beginning of month $t + 1$.

C.1.2 Abr1, Abr6, and Abr12, Cumulative Abnormal Returns Around Earnings Announcement Dates

We calculate cumulative abnormal stock return (Abr) around the latest quarterly earnings announcement date (Compustat quarterly item RDQ) (Chan, Jegadeesh, and Lakonishok 1996)):

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

in which r_{id} is stock i's return on day d (with the earnings announced on day 0) and r_{md} is the market index return. We cumulate returns until one (trading) day after the announcement date to account for the one-day-delayed reaction to earnings news. r_{md} is the value-weighted market return for the Abr deciles with NYSE breakpoints and value-weighted returns.

At the beginning of each month t, we split all stocks into deciles based on their most recent past Abr. For a firm to enter our portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Abr to be within six months prior to the portfolio formation. We do so to exclude stale information on earnings. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for the current month t (Abr1), and, separately, from month t to $t+5$ (Abr6) and from month t to $t+11$ (Abr12). The deciles are rebalanced monthly. The six-month holding period for Abr6 means that for a given decile in each month there exist six sub-deciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the sub-decile returns as the monthly return of the Abr6 decile. Because quarterly earnings announcement dates are largely unavailable before 1972, the Abr portfolios start in January 1972.

C.1.3 Re1 and Re6, Revisions in Analyst Earnings Forecasts

Following Chan, Jegadeesh, and Lakonishok (1996), we measure earnings surprise as the revisions in analysts' forecasts of earnings obtained from the Institutional Brokers' Estimate System (IBES). Because analysts' forecasts are not necessarily revised each month, we construct a six-month moving average of past changes in analysts' forecasts:

$$\text{RE}_{it} = \sum_{\tau=1}^{6} \frac{f_{it-\tau} - f_{it-\tau-1}}{p_{it-\tau-1}}, \tag{C.2}$$

in which $f_{it-\tau}$ is the consensus mean forecast (IBES unadjusted file, item MEANEST) issued in month $t-\tau$ for firm i's current fiscal year earnings (fiscal period indicator = 1), and $p_{it-\tau-1}$ is the prior month's share price (unadjusted file, item PRICE). We require both earnings forecasts and share prices to be denominated in US dollars (currency code = USD). We also adjust for any stock splits and require a minimum of four monthly forecast changes when constructing Re. At the beginning of each month t, we split all stocks into deciles based on their Re. Monthly decile returns are calculated for the current month t (Re1), and, separately, from month t to $t+5$ (Re6). The deciles are rebalanced monthly. The six-month holding period for Re6 means that for a given decile in each month there exist six sub-deciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the sub-decile returns as the monthly return of the Re6 decile. Because analyst forecast data start in January 1976, the Re portfolios start in July 1976.

C.1.4 $R^6 1$, $R^6 6$, and $R^6 12$, Prior Six-month Returns

At the beginning of each month t, we split all stocks into deciles based on their prior six-month returns from month $t-7$ to $t-2$. Skipping month $t-1$, we calculate monthly decile returns, separately, for month t ($R^6 1$), from month t to $t+5$ ($R^6 6$), and from month t to $t+11$ ($R^6 12$). The deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in, for instance, $R^6 6$, means that for a given decile in each month there exist six sub-deciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the sub-deciles returns as the monthly return of the $R^6 6$ decile. We do not impose a price screen to exclude stocks with prices per share below \$5 as in Jegadeesh and Titman (1993). These stocks are mostly microcaps. Value-weighting returns assigns only tiny weights to these stocks, which in turn do not need to be excluded.

C.1.5 $R^{11} 1$ and $R^{11} 6$, Prior 11-month Returns

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 $t-2$. Skipping month $t-1$, we calculate monthly decile returns for month t ($R^{11} 1$), and separately, from month t to $t+5$ ($R^{11} 6$). All the deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in $R^{11} 6$ means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the $R^{11} 6$ decile. Because we exclude financial firms, these decile returns are different from those posted on Kenneth French's Web site.

C.1.6 Im1, Im6, and Im12, Industry Momentum

We start with the Fama-French (1997) 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 (1999), we do not skip month $t-1$. We form nine portfolios ($9 \times 5 = 45$), each of which contains five different industries. We define the return of a given portfolio as the simple average of the five industry returns within the portfolio. We calculate portfolio returns for the nine portfolios for the current month t (Im1), from month t to $t+5$ (Im6), and from month t to $t+11$ (Im12). The portfolios are rebalanced at the beginning of $t+1$. The holding period that is longer than one month as in, for instance, Im6, means that for a given portfolio in each month there exist six subportfolios, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subportfolio returns as the monthly return of the Im6 portfolio.

C.1.7 Rs1, Revenue Surprises

Following Jegadeesh and Livnat (2006), we measure revenue surprises (Rs) as changes in revenue per share (Compustat quarterly item SALEQ/(item CSHPRQ times item AJEXQ)) from its value four quarters ago divided by the standard deviation of this change in quarterly revenue per share over the prior eight quarters (six quarters minimum). At the beginning of each month t, we split stocks into deciles based on their most recent past Rs. Before 1972, we use the most recent Rs computed with quarterly revenue from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use Rs computed with quarterly revenue from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). Jegadeesh and Livnat find that quarterly revenue data are generally available when earnings are announced. For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Rs to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale revenue information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly deciles returns are calculated for the current month t (Rs1), and the deciles are rebalanced at the beginning of month $t+1$.

C.1.8 dEf1, dEf6, and dEf12, Changes in Analyst Earnings Forecasts

Following Hawkins, Chamberlin, and Daniel (1984), we define dEf $\equiv (f_{it-1} - f_{it-2})/(0.5\,|f_{it-1}| + 0.5\,|f_{it-2}|)$, in which f_{it-1} is the consensus mean forecast (IBES unadjusted file, item MEANEST) issued in month $t-1$ for firm i's current fiscal year earnings (fiscal period indicator = 1). We require earnings forecasts to be denominated in US dollars (currency code = USD). We also adjust for any stock splits between months $t-2$ and $t-1$ when constructing dEf. At the beginning of each month t, we sort stocks into deciles on the prior month dEf, and calculate returns for the current month t (dEf1), from month t to $t+5$ (dEf6), and from month t to $t+11$ (dEf12). The deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, dEf6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the dEf6 decile. Because analyst forecast data start in January 1976, the dEf portfolios start in March 1976.

C.1.9 Nei1, The Number of Quarters with Consecutive Earnings Increase

We follow Barth, Elliott, and Finn (1999) and Green, Hand, and Zhang (2013) in measuring Nei as the number of consecutive quarters (up to eight 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 nine portfolios (with Nei $= 0, 1, 2, \ldots, 7$, and 8, respectively) based on their most recent past Nei. Before 1972, we use Nei computed with quarterly earnings from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use Nei computed with earnings from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Nei to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. We calculate monthly portfolio returns for the current month t (Nei1), and the deciles are rebalanced at the beginning of month $t+1$. For sufficient data coverage, the Nei portfolios start in January 1969.

C.1.10 52w6, 52-week High

At the beginning of each month t, we split stocks into deciles based on 52w, which is the ratio of its split-adjusted price per share at the end of month $t-1$ to its highest (daily) split-adjusted price per share during the 12-month period ending on the last day of month $t-1$. Monthly decile returns are calculated from month t to $t+5$ (52w6), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the 52w6 decile. Because a disproportionately large number of stocks can reach the 52-week high at the same time and have

52w equal to one, we use only 52w smaller than one to form the portfolio breakpoints. Doing so helps avoid missing portfolio observations.

C.1.11 $\epsilon^6 6$ and $\epsilon^6 12$, Six-month Residual Momentum

We split all stocks into deciles at the beginning of each month t based on their prior six-month average residual returns from month $t-7$ to $t-2$ scaled by their standard deviation over the same period. Skipping month $t-1$, we calculate monthly decile returns from month t to $t+5$ ($\epsilon^6 6$) and from month t to $t+11$ ($\epsilon^6 12$). Residual returns are estimated each month for all stocks over the prior 36 months from month $t-36$ to month $t-1$ from regressing stock excess returns on the Fama-French three factors. To reduce the noisiness of the estimation, we require returns to be available for all prior 36 months. All the deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in $\epsilon^6 6$ means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the $\epsilon^6 6$ decile.

C.1.12 $\epsilon^{11} 1$, $\epsilon^{11} 6$, and $\epsilon^{11} 12$, 11-month Residual Momentum

We split all stocks into deciles at the beginning of each month t based on their prior 11-month residual returns from month $t-12$ to $t-2$ scaled by their standard deviation over the same period. Skipping month $t-1$, we calculate monthly decile returns for month t ($\epsilon^{11} 1$), from month t to $t+5$ ($\epsilon^{11} 6$), and from month t to $t+11$ ($\epsilon^{11} 12$). Residual returns are estimated each month for all stocks over the prior 36 months from month $t-36$ to month $t-1$ from regressing stock excess returns on the Fama-French three factors. To reduce the noisiness of the estimation, we require returns to be available for all prior 36 months. All the deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than 1 month as in $\epsilon^{11} 6$ means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the $\epsilon^{11} 6$ decile.

C.1.13 Sm1, Segment Momentum

Following Cohen and Lou (2012), we extract firms' segment accounting and financial information from Compustat segment files. Industries are based on two-digit SIC codes. Standalone firms are those that operate in only one industry with segment sales, reported in Compustat segment files, accounting for more than 80% of total sales reported in Compustat annual files. Conglomerate firms are those that operating in more than one industry with aggregate sales from all reported segments accounting for more than 80% of total sales.

At the end of June of each year, we form a pseudo-conglomerate for each conglomerate firm. The pseudo-conglomerate is a portfolio of the conglomerate's industry segments constructed with solely the standalone firms in each industry. The segment portfolios (value-weighted across standalone firms) are then weighted by the percentage of sales contributed by each industry segment within the conglomerate. At the beginning of each month t (starting in July), using segment information form the previous fiscal year, we sort all conglomerate firms into deciles based on the returns of their pseudo-conglomerate portfolios in month $t-1$. Monthly deciles are calculated for month t (Sm1), and the deciles are rebalanced at the beginning of month $t+1$. Because the segment data start in 1976, the Sm portfolios start in July 1977.

C.1.14 Ilr1, Ilr6, and Ilr12, Industry Lead-lag Effect in Prior Returns

We start with the Fama-French (1997) 49-industry classifications. Excluding financial firms from the sample leaves 45 industries. At the beginning of each month t, we sort industries based on the month $t-1$ value-weighted return of the portfolio consisting of the 30% biggest (market equity) firms within a given industry. We form nine portfolios ($9 \times 5 = 45$), each of which contains five different industries. We define the return of a given portfolio as the simple average of the five value-weighted industry returns within the portfolio. The nine portfolio returns are calculated for the current month t (Ilr1), from month t to $t+5$ (Ilr6), and from month t to $t+11$ (Ilr12), and the portfolios are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in, for instance, Ilr6, means that for a given portfolio in each month there exist six subportfolios, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subportfolio returns as the monthly return of the Ilr6 portfolio.

C.1.15 Ile1, Industry Lead-lag Effect in Earnings Surprises

We start with the Fama-French (1997) 49-industry classifications. Excluding financial firms from the sample leaves 45 industries. We calculate Standardized Unexpected Earnings, Sue, as the change in split-adjusted quarterly earnings per share (Compustat quarterly item EPSPXQ divided by item AJEXQ) from its value four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters (six quarters minimum). At the beginning of each month t, we sort industries based on their most recent Sue averaged across the 30% biggest firms within a given industry.[1] To mitigate the impact of outliers, we winsorize Sue at the 1st and 99th percentiles of its distribution each month. We form nine portfolios ($9 \times 5 = 45$), each of which contains five different industries. We define the return of a given portfolio as the simple average of the five value-weighted industry returns within the portfolio. The nine portfolio returns are calculated for the current month t (Ile1), and the portfolios are rebalanced at the beginning of month $t+1$.

C.1.16 Cm1 and Cm12, Customer Momentum

Following Cohen and Frazzini (2008), we extract firms' principal customers from Compustat segment files. For each firm we determine whether the customer is another company listed on the CRSP/Compustat tape, and we assign it the corresponding CRSP permno number. At the end of June of each year t, we form a customer portfolio for each firm with identifiable firm-customer relations for the fiscal year ending in calendar year $t-1$. For firms with multiple customer firms, we form equal-weighted customer portfolios. The customer portfolio returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced in June.

At the beginning of each month t, we sort all stocks into quintiles based on their customer portfolio returns, Cm, in month $t-1$. We do not form deciles because a disproportionate number of firms can have the same Cm, which leads to fewer than ten portfolios in some months. Monthly quintile returns are calculated for month t (Cm1) and from month t to $t+11$ (Cm12), and the quintiles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month in Cm12 means that for a given quintile in each month there exist 12 subquintiles, each

[1] Before 1972, we use the most recent Sue with earnings from fiscal quarters ending at least four months prior to the portfolio month. Starting from 1972, we use Sue with earnings from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter our portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Sue to be within six months prior to the portfolio month. We also require the earnings announcement date to be after the corresponding fiscal quarter end.

of which is initiated in a different month in the prior 12-month period. We take the simple average of the subquintile returns as the monthly return of the Cm12 quintile. For sufficient data coverage, we start the Cm portfolios in July 1979.

C.1.17 Sim1, Cim1, Cim6, and Cim12, Supplier (Customer) industries Momentum

Following Menzly and Ozbas (2010), we use Benchmark Input-Output Accounts at the Bureau of Economic Analysis (BEA) to identify supplier and customer industries for a given industry. BEA Surveys are conducted roughly once every five years in 1958, 1963, 1967, 1972, 1977, 1982, 1987, 1992, 1997, 2002, and 2007. We delay the use of any data from a given survey until the end of the year in which the survey is publicly released during 1964, 1969, 1974, 1979, 1984, 1991, 1994, 1997, 2002, 2007, and 2013, respectively. The BEA industry classifications are based on SIC codes in the surveys from 1958 to 1992 and based on NAICS codes afterwards. In the surveys from 1997 to 2007, we merge three separate industry accounts, 2301, 2302, and 2303 into a single account. We also merge "Housing" (HS) and "Other Real Estate" (ORE) in the 2007 Survey. In the surveys from 1958 to 1992, we merge industry account pairs 1–2, 5–6, 9–10, 11–12, 20–21, and 33–34. We also merge industry account pairs 22–23 and 44–45 in the 1987 and 1992 surveys. We drop miscellaneous industry accounts related to government, import, and inventory adjustments.

At the end of June of each year t, we assign each stock to an BEA industry based on its reported SIC or NAICS code in Compustat (fiscal year ending in $t-1$) or CRSP (June of t). Monthly value-weighted industry returns are calculated from July of year t to June of $t+1$, and the industry portfolios are rebalanced in June of $t+1$. For each industry, we further form two separate portfolios, the suppliers portfolio and the customers portfolios. The share of an industry's total purchases from other industries is used to calculate the supplier industries portfolio returns, and the share of the industry's total sales to other industries is used to calculate the customer industries portfolio returns.

At the beginning of each month t, we split industries into deciles based on the supplier portfolio returns, Sim, and separately, on the customer portfolio returns, Cim, in month $t-1$. We then assign the decile rankings of each industry to its member stocks. Monthly decile returns are calculated for month t (Sim1 and Cim1), from month t to $t+5$ (Cim6), and from month t to $t+11$ (Cim12), and the deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month as in Cim6 means that for a given decile in each month there exist six subdeciles, each initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Cim6 decile.

C.2 Value-versus-growth

C.2.1 Bm, Book-to-market Equity

At the end of June of each year t, we split stocks into deciles based on Bm, which is the book equity for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Bm. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. Following Davis, Fama, and French (2000), we measure book equity as 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 it is available. If not, we measure stockholders' equity as 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.

C.2.2 Bmj, Book-to-June-end Market Equity

Following Asness and Frazzini (2013), at the end of June of each year t, we sort stocks into deciles based on Bmj, which is book equity per share for the fiscal year ending in calendar year $t-1$ divided by share price (from CRSP) at the end of June of t. We adjust for any stock splits between the fiscal year end and the end of June. Book equity per share is book equity divided by the number of shares outstanding (Compustat annual item CSHO). Following Davis, Fama, and French (2000), we measure book equity as stockholders' book equity, plus balance sheet deferred taxes and investment tax credit (item TXDITC) if available, minus the book value of preferred stock. Stockholders' equity is the value reported by Compustat (item SEQ), if it is available. If not, we measure stockholders' equity as 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. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.2.3 Bm$^{\mathrm{q}}$12, Quarterly Book-to-market Equity

At the beginning of each month t, we split stocks into deciles based on Bm$^{\mathrm{q}}$, which is the book equity for the latest fiscal quarter ending at least four months ago divided by the market equity (from CRSP) at the end of month $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Bm$^{\mathrm{q}}$. We calculate decile returns from month t to $t+11$ (Bm$^{\mathrm{q}}$12), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month means that for a given decile in each month there exist 12 subdeciles, each of which is initiated in a different month in the prior 12 months. We take the simple average of the subdecile returns as the monthly return of the Bm$^{\mathrm{q}}$12 decile. Book equity is shareholders' equity, plus balance sheet deferred taxes and investment tax credit (Compustat quarterly item TXDITCQ) if available, minus the book value of preferred stock (item PSTKQ). Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the book value of preferred stock, or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity.

Before 1972, the sample coverage is limited for quarterly book equity in Compustat quarterly files. We expand the coverage by using book equity from Compustat annual files as well as by imputing quarterly book equity with clean surplus accounting. Specifically, whenever available we first use quarterly book equity from Compustat quarterly files. We then supplement the coverage for fiscal quarter four with annual book equity from Compustat annual files. Following Davis, Fama, and French (2000), we measure annual book equity as 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.

If both approaches are unavailable, we apply the clean surplus relation to impute the book equity. Specifically, we impute the book equity for quarter t forward based on book equity from prior quarters. Let BEQ_{t-j}, $1 \leq j \leq 4$ denote the latest available quarterly book equity as of quarter t, and $\text{IBQ}_{t-j+1,t}$ and $\text{DVQ}_{t-j+1,t}$ be the sum of quarterly earnings and quarterly dividends from quarter $t-j+1$ to t, respectively. BEQ_t can then be imputed as $\text{BEQ}_{t-j}+\text{IBQ}_{t-j+1,t}-\text{DVQ}_{t-j+1,t}$. We do not use prior book equity from more than four quarters ago (i.e., $1 \leq j \leq 4$) to reduce imputation errors. Quarterly earnings are income before extraordinary items (Compustat quarterly item IBQ). Quarterly dividends are zero if dividends per share (item DVPSXQ) are zero. Otherwise, total dividends are dividends per share times beginning-of-quarter shares outstanding adjusted for stock splits during the quarter. Shares outstanding are from Compustat (quarterly item CSHOQ supplemented with annual item CSHO for fiscal quarter four) or CRSP (item SHROUT), and the share adjustment factor is from Compustat (quarterly item AJEXQ supplemented with annual item AJEX for fiscal quarter four) or CRSP (item CFACSHR). Because we use quarterly book equity at least four months after the fiscal quarter end, all the Compustat data used in the imputation are at least four-month lagged prior to the portfolio formation. In addition, we do not impute quarterly book equity backward using future earnings and book equity information to avoid look-ahead bias.

C.2.4 Rev6 and Rev12, Reversal

To capture the De Bondt and Thaler (1985) long-term reversal (Rev) effect, at the beginning of each month t, we split stocks into deciles based on the prior returns from month $t-60$ to $t-13$. Monthly decile returns are computed from month t to $t+5$ (Rev6) and from month t to $t+11$ (Rev12). The deciles are rebalanced at the beginning of $t+1$. The holding period longer than one month as in, for instance, Rev6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdeciles returns as the monthly return of the Rev6 decile. 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 ending price.

C.2.5 Ep, Earnings-to-price

At the end of June of each year t, we split stocks into deciles based on earnings-to-price, Ep, which is income before extraordinary items (Compustat annual item IB) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Ep. Firms with non-positive earnings are excluded. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.2.6 Ep^{q}1, Ep^{q}6, and Ep^{q}12, Quarterly Earnings-to-price

At the beginning of each month t, we split stocks into deciles based on quarterly earnings-to-price, Ep^{q}, which is income before extraordinary items (Compustat quarterly item IBQ) divided by the market equity (from CRSP) at the end of month $t-1$. Before 1972, we use quarterly earnings from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use quarterly earnings from the most recent quarterly earnings announcement dates (item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent quarterly earnings to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Firms with non-positive earnings are excluded. For firms with more than one share class, we merge the market equity for all share classes before computing Ep^{q}. We calculate decile returns for the current month t ($\text{Ep}^{\text{q}}1$), from month t to $t+5$ ($\text{Ep}^{\text{q}}6$), and from month t to $t+11$ ($\text{Ep}^{\text{q}}12$), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, $\text{Ep}^{\text{q}}6$, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the $\text{Ep}^{\text{q}}6$ decile.

C.2.7 Cp, Cash Flow-to-price

At the end of June of each year t, we split stocks into deciles based on cash flow-to-price, Cf, which is cash flows for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. Cash flows are income before extraordinary items (Compustat annual item IB) plus depreciation (item DP)). For firms with more than one share class, we merge the market equity for all share classes before computing Cp. Firms with non-positive cash flows are excluded. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.2.8 $\text{Cp}^{\text{q}}1$, $\text{Cp}^{\text{q}}6$, and $\text{Cp}^{\text{q}}12$, Quarterly Cash Flow-to-price

At the beginning of each month t, we split stocks into deciles based on quarterly cash flow-to-price, Cp^{q}, which is cash flows for the latest fiscal quarter ending at least four months ago divided by the market equity (from CRSP) at the end of month $t-1$. Quarterly cash flows are income before extraordinary items (Compustat quarterly item IBQ) plus depreciation (item DPQ). For firms with more than one share class, we merge the market equity for all share classes before computing Cp^{q}. Firms with non-positive cash flows are excluded. We calculate decile returns for the current month t ($\text{Ep}^{\text{q}}1$), from month t to $t+5$ ($\text{Ep}^{\text{q}}6$), and from month t to $t+11$ ($\text{Ep}^{\text{q}}12$), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, $\text{Ep}^{\text{q}}6$, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the $\text{Ep}^{\text{q}}6$ decile.

C.2.9 Nop, Net Payout Yield

Per Boudoukh, Michaely, Richardson, and Roberts (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 (item PSTKRV).

At the end of June of each year t, we sort stocks into deciles based on net payouts for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Nop. Firms with non-positive total payouts (zero net payouts) are excluded. Monthly 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 data on total expenditure and the sale of common and preferred stocks start in 1971, the Nop portfolios start in July 1972.

C.2.10 Em, Enterprise Multiple

Enterprise multiple, Em, is enterprise value divided by operating income before depreciation (Compustat annual item OIBDP). Enterprise value is the market equity plus the total debt (item DLC plus item DLTT) plus the book value of preferred stocks (item PSTKRV) minus cash and short-term investments (item CHE). At the end of June of each year t, we split stocks into deciles based on Em for the fiscal year ending in calendar year $t-1$. The Market equity (from CRSP) is measured at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Em. Firms with negative enterprise value or operating income before depreciation are excluded. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.2.11 $\text{Em}^{\text{q}}1$, $\text{Em}^{\text{q}}6$, and $\text{Em}^{\text{q}}12$, Quarterly Enterprise Multiple

Em^{q}, is enterprise value scaled by operating income before depreciation (Compustat quarterly item OIBDPQ). Enterprise value is the market equity plus total debt (item DLCQ plus item DLTTQ) plus the book value of preferred stocks (item PSTKQ) minus cash and short-term investments (item CHEQ). At the beginning of each month t, we split stocks into deciles on Em^{q} for the latest fiscal quarter ending at least four months ago. The Market equity (from CRSP) is measured at the end of month $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Em^{q}. Firms with negative enterprise value or operating income before depreciation are excluded. Monthly decile returns are calculated for the current month t ($\text{Em}^{\text{q}}1$), from month t to $t+5$ ($\text{Em}^{\text{q}}6$), and from month t to $t+11$ ($\text{Em}^{\text{q}}12$), and the deciles are rebalanced at the beginning of $t+1$. The holding period longer than one month as in $\text{Em}^{\text{q}}6$ means that for a given decile in each month there exist six subdeciles, each initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the $\text{Em}^{\text{q}}6$ decile. For sufficient data coverage, the EM^{q} portfolios start in January 1975.

C.2.12 Sp, Sales-to-price

At the end of June of each year t, we sort stocks into deciles based on sales-to-price, Sp, which is sales (Compustat annual item SALE) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Sp. Firms with non-positive sales are excluded. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.2.13 $\text{Sp}^{\text{q}}1$, $\text{Sp}^{\text{q}}6$, and $\text{Sp}^{\text{q}}12$, Quarterly Sales-to-price

At the beginning of each month t, we sort stocks into deciles based on quarterly sales-to-price, Sp^{q}, which is sales (Compustat quarterly item SALEQ) divided by the market equity at the end of month $t-1$. Before 1972, we use quarterly sales from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use quarterly sales from the most recent quarterly earnings announcement dates (item RDQ). Sales are generally announced with earnings during quarterly earnings announcements (Jegadeesh and Livnat 2006). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent quarterly sales to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Firms with non-positive sales are excluded. For firms with more than one share class, we merge the market equity for all share classes before computing Sp^{q}. Monthly decile returns are calculated for the current month t ($\text{Sp}^{\text{q}}1$), from month t to $t+5$ ($\text{Sp}^{\text{q}}6$), and from month t to $t+11$ ($\text{Sp}^{\text{q}}12$), and the deciles are rebalanced at the beginning of $t+1$. The holding period longer than one month as in $\text{Sp}^{\text{q}}6$ means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the $\text{Sp}^{\text{q}}6$ decile.

C.2.14 Ocp, Operating Cash Flow-to-price

At the end of June of each year t, we sort stocks into deciles based on operating cash flows-to-price, Ocp, which is operating cash flows for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. Operating cash flows are measured as funds from operation (Compustat annual item FOPT) minus change in working capital (item WCAP) prior to 1988, and then as net cash flows from operating activities (item OANCF) stating from 1988. For firms with more than one share class, we merge the market equity for all share classes before computing Ocp. Firms with non-positive operating cash flows are excluded. Monthly 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 data on funds from operation start in 1971, the Ocp portfolios start in July 1972.

C.2.15 $\text{Ocp}^{\text{q}}1$, Quarterly Operating Cash Flow-to-price

At the beginning of each month t, we split stocks on quarterly operating cash flow-to-price, Ocp^{q}, which is operating cash flows for the latest fiscal quarter ending at least four months ago divided by the market equity at the end of month $t-1$. Operating cash flows are measured as the quarterly change in year-to-date funds from operation (Compustat quarterly item FOPTY) minus change in quarterly working capital (item WCAPQ) prior to 1988, and then as the quarterly change in year-to-date net cash flows from operating activities (item OANCFY) stating from 1988. For firms with more than one share class, we merge the market equity for all share classes before computing Ocp^{q}. Firms with non-positive operating cash flows are excluded. Monthly decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of $t+1$. Because the data on year-to-date funds from operation start in 1984, the Ocp^{q} portfolios start in January 1985.

C.2.16 Ir, Intangible Return

Following Daniel and Titman (2006), at the end of June of each year t, we perform the cross-sectional regression of each firm's past five-year log stock return on its five-year-lagged log book-to-market and five-year log book return:

$$r(t-5,t) = \gamma_0 + \gamma_1 bm_{t-5} + \gamma_2 r^B(t-5,t) + u_t \tag{C.3}$$

in which $r(t-5,t)$ is the past five-year log stock return from the end of year $t-6$ to the end of $t-1$, bm_{t-5} is the five-year-lagged log book-to-market, and $r^B(t-5,t)$ is the five-year log book return. The five-year-lagged log book-to-market is computed as $bm_{t-5} = \log(B_{t-5}/M_{t-5})$, in which B_{t-5}

is the book equity for the fiscal year ending in calendar year $t-6$ and M_{t-5} is the market equity (from CRSP) at the end of December of $t-6$. For firms with more than one share class, we merge the market equity for all share classes before computing bm_{t-5}. The five-year log book return is computed as $r^B(t-5,t) = \log(B_t/B_{t-5}) + \sum_{s=t-5}^{t-1}(r_s - \log(P_s/P_{s-1}))$, in which B_t is the book equity for the fiscal year ending in calendar year $t-1$, r_s is the stock return from the end of year $s-1$ to the end of year s, and P_s is the stock price per share at the end of year s. Following Davis, Fama, and French (2000), we measure book equity as 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 it is available. If not, we measure stockholders' equity as 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 firm's intangible return, Ir, is defined as its residual from the annual cross-sectional regression. At the end of June of each year t, we sort stocks based on Ir for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of year $t+1$.

C.2.17 Vhp and Vfp, (Analyst-based) Intrinsic Value-to-market

Following Frankel and Lee (1998), at the end of June of each year t, we implement the residual income model to estimate the intrinsic value:

$$\mathrm{Vh}_t = \mathrm{B}_t + \frac{(E_t[\mathrm{Roe}_{t+1}] - r)}{(1+r)}\mathrm{B}_t + \frac{(E_t[\mathrm{Roe}_{t+2}] - r)}{(1+r)r}\mathrm{B}_{t+1} \tag{C.4}$$

$$\mathrm{Vf}_t = \mathrm{B}_t + \frac{(E_t[\mathrm{Roe}_{t+1}] - r)}{(1+r)}\mathrm{B}_t + \frac{(E_t[\mathrm{Roe}_{t+2}] - r)}{(1+r)^2}\mathrm{B}_{t+1} + \frac{(E_t[\mathrm{Roe}_{t+3}] - r)}{(1+r)^2 r}\mathrm{B}_{t+2} \tag{C.5}$$

in which Vh_t is the historical Roe-based intrinsic value and Vf_t is the analysts earnings forecast-based intrinsic value. B_t is the book equity (Compustat annual item CEQ) for the fiscal year ending in calendar year $t-1$. Future book equity is computed using the clean surplus accounting: $\mathrm{B}_{t+1} = (1 + (1-k)E_t[\mathrm{Roe}_{t+1}])\mathrm{B}_t$, and $\mathrm{B}_{t+2} = (1 + (1-k)E_t[\mathrm{Roe}_{t+2}])\mathrm{B}_{t+1}$. $E_t[\mathrm{Roe}_{t+1}]$ and $E_t[\mathrm{Roe}_{t+2}]$ are the return on equity expected for the current and next fiscal years. k is the dividend payout ratio, measured as common stock dividends (item DVC) divided by earnings (item IBCOM) for the fiscal year ending in calendar year $t-1$. For firms with negative earnings, we divide dividends by 6% of average total assets (item AT). r is a constant discount rate of 12%. When estimating Vh_t, we replace all Roe expectations with most recent Roe_t: $\mathrm{Roe}_t = \mathrm{Ni}_t/[(\mathrm{B}_t + \mathrm{B}_{t-1})/2]$, in which Ni_t is earnings for the fiscal year ending in $t-1$, and B_t and B_{t-1} are the book equity from the fiscal years ending in $t-1$ and $t-2$.

When estimating Vf_t, we use analyst earnings forecasts from IBES to construct Roe expectations. Let Fy1 and Fy2 be the one-year-ahead and two-year-ahead consensus mean forecasts (IBES unadjusted file, item MEANEST; fiscal period indicator = 1 and 2) reported in June of year t. Let s be the number of shares outstanding from IBES (unadjusted file, item SHOUT). When IBES shares are not available, we use shares from CRSP (daily item SHROUT) on the IBES pricing date (item PRDAYS) that corresponds to the IBES report. Then $E_t[\mathrm{Roe}_{t+1}] = s\mathrm{Fy1}/[(\mathrm{B}_{t+1} + \mathrm{B}_t)/2]$, in which $\mathrm{B}_{t+1} = (1 + s(1-k)\mathrm{Fy1})\mathrm{B}_t$. Analogously, $E_t[\mathrm{Roe}_{t+2}] = s\mathrm{Fy2}/[(\mathrm{B}_{t+2} + \mathrm{B}_{t+1})/2]$, in which $\mathrm{B}_{t+2} = (1+s(1-k)\mathrm{Fy2})\mathrm{B}_{t+1}$. Let Ltg denote the long-term earnings growth rate forecast from IBES (item MEANEST; fiscal period indicator = 0). Then $E_t[\text{Roe}_{t+3}] = s\text{Fy2}(1+\text{Ltg})/[(\text{B}_{t+3}+\text{B}_{t+2})/2]$, in which $\text{B}_{t+3} = (1+s(1-k)\text{Fy2}(1+\text{Ltg}))\text{B}_{t+2}$. If Ltg is missing, we set $E_t[\text{Roe}_{t+3}]$ to be $E_t[\text{Roe}_{t+2}]$. Firms are excluded if their expected Roe or dividend payout ratio is higher than 100%. We also exclude firms with negative book equity.

At the end of June of each year t, we sort stocks into deciles on the ratios of Vh and Vf scaled by the market equity (from CRSP) at the end of December of $t-1$, denoted Vhp and Vfp, respectively. For firms with more than one share class, we merge the market equity for all share classes before computing intrinsic value-to-market. Firms with non-positive intrinsic value are excluded. Monthly 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 analyst forecast data start in 1976, the Vfp deciles start in July 1977.

C.2.18 Ebp, Enterprise Book-to-price

Following Penman, Richardson, and Tuna (2007), we measure enterprise book-to-price, Ebp, as the ratio of the book value of net operating assets (net debt plus book equity) to the market value of net operating assets (net debt plus market equity). Net debt is financial liabilities minus financial assets. We measure financial liabilities as the sum of long-term debt (Compustat annual item DLTT), debt in current liabilities (item DLC), carrying value of preferred stock (item PSTK), and preferred dividends in arrears (item DVPA, zero if missing), less preferred treasury stock (item TSTKP, zero if missing). We measure financial assets as cash and short-term investments (item CHE). Book equity is common equity (item CEQ) plus any preferred treasury stock (item TSTKP, zero if missing) less any preferred dividends in arrears (item DVPA, zero if missing). Market equity is the number of common shares outstanding times share price (from CRSP). At the end of June of each year t, we sort stocks into deciles based on Ebp from the fiscal year ending in calendar year $t-1$. Market equity is measured at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Ebp. We exclude firms with non-positive book or market value of net operating assets. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.2.19 Dur, Equity Duration

Following Dechow, Sloan, and Soliman (2004), we calculate firm-level equity duration, Dur, as:

$$\text{Dur} = \frac{\sum_{t=1}^{T} t \times \text{CD}_t/(1+r)^t}{\text{ME}} + \left(T + \frac{1+r}{r}\right) \frac{\text{ME} - \sum_{t=1}^{T} \text{CD}_t/(1+r)^t}{\text{ME}}, \tag{C.6}$$

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. Market equity 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. Following Dechow et al., we use autoregressive processes to forecast ROE and book equity growth in future years. 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 one-year lagged book equity (item CEQ), and the book equity growth rate as the annual change in sales (item SALE). Nissim and Penman (2001) show that past sales growth is a better indicator of future book equity growth than past book equity growth. Finally, we use a forecasting period of $T = 10$ years and a cost of equity of $r = 0.12$. Firms are excluded if book equity ever becomes negative during the forecasting period. At the end of June of each year t, we sort stocks into deciles based on Dur constructed with data from the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3 Investment

C.3.1 Aci, Abnormal Corporate Investment

At the end of June of year t, we measure abnormal corporate investment, Aci, as $\mathrm{Ce}_{t-1}/[(\mathrm{Ce}_{t-2}+\mathrm{Ce}_{t-3}+\mathrm{Ce}_{t-4})/3]-1$, 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 three-year average capital expenditure is designed to project the benchmark investment in the portfolio formation year. We exclude firms with sales less than ten million dollars. At the end of June of each year t, we sort stocks into deciles based on Aci. Monthly decile returns are computed from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.2 I/A, Investment-to-assets

At the end of June of each year t, we sort stocks into deciles based on investment-to-assets, I/A, which is measured 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 one. Monthly decile returns are computed from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.3 $\mathrm{Ia}^{\mathrm{q}}6$ and $\mathrm{Ia}^{\mathrm{q}}12$, Quarterly Investment-to-assets

Quarterly investment-to-assets, Ia^{q}, is defined as quarterly total assets (Compustat quarterly item ATQ) divided by four-quarter-lagged total assets minus one. At the beginning of each month t, we sort stocks into deciles based on Ia^{q} for the latest fiscal quarter ending at least four months ago. Monthly decile returns are calculated from month t to $t+5$ ($\mathrm{Ia}^{\mathrm{q}}6$) and from month t to $t+11$ ($\mathrm{Ia}^{\mathrm{q}}12$), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, $\mathrm{Ia}^{\mathrm{q}}6$, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the $\mathrm{Ia}^{\mathrm{q}}6$ decile.

C.3.4 dPia, Changes in PPE and Inventory-to-assets

Changes in PPE and Inventory-to-assets, dPia, is defined as the annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus the annual change in inventory (item INVT) scaled by one-year-lagged total assets (item AT). At the end of June of each year t, we sort stocks into deciles based on dPia for the fiscal year ending in calendar year $t-1$. Monthly decile returns are computed from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.5 Noa and dNoa, (Changes in) Net Operating Assets

Following Hirshleifer, Hou, Teoh, and Zhang (2004), we measure net operating assets 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). Noa is net operating assets scalded by one-year-lagged total assets. Changes in net operating assets, dNoa, is the annual change in net operating assets scaled by one-year-lagged total assets. At the end of June of each year t, we sort stocks into deciles based on Noa, and separately, on dNOA, for the fiscal year ending in calendar year $t-1$. Monthly decile returns are computed from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.6 dLno, Changes in Long-term Net Operating Assets

Following Fairfield, Whisenant, and Yohn (2003), we measure changes in long-term net operating assets as the annual change in net property, plant, and equipment (Compustat item PPENT) plus the change in intangibles (item INTAN) plus the change in other long-term assets (item AO) minus the change in other long-term liabilities (item LO) and plus depreciation and amortization expense (item DP). dLno is the change in long-term net operating assets scaled by the average of total assets (item AT) from the current and prior years. At the end of June of each year t, we sort stocks into deciles based on dLno for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.7 Ig, Investment Growth

At the end of June of each year t, we sort stocks into deciles based on investment growth, Ig, which is 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 $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.8 2Ig, Two-year Investment Growth

At the end of June of each year t, we sort stocks into deciles based on two-year investment growth, 2Ig, which is the growth rate in capital expenditure (Compustat annual item CAPX) from the fiscal year ending in calendar year $t-3$ to the fiscal year ending in $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.9 Nsi, Net Stock Issues

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 $t-2$. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item AJEX). At the end of June of each year t, we sort stocks with negative Nsi into two portfolios (1 and 2), stocks with zero Nsi into one portfolio (3), and stocks with positive Nsi into seven portfolios (4 to 10). Monthly decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.10 dIi, % Change in Investment - % Change in Industry Investment

Following Abarbanell and Bushee (1998), we define the %d($\cdot$) operator as the percentage change in the variable in the parentheses from its average over the prior two years, e.g., %d(Investment) = [Investment(t) − E[Investment(t)]]/E[Investment(t)], in which E[Investment(t)] = [Investment($t-1$)

+ Investment($t-2$)]/2. dIi is defined as %d(Investment) − %d(Industry investment), in which investment is capital expenditure in property, plant, and equipment (Compustat annual item CAPXV). Industry investment is the aggregate investment across all firms with the same two-digit SIC code. Firms with non-positive $E[Investment(\mathrm{t})]$ are excluded and we require at least two firms in each industry. At the end of June of each year t, we sort stocks into deciles based on dIi for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.11 Cei, Composite Equity Issuance

At the end of June of each year t, we sort stocks into deciles based on composite equity issuance, Cei, which is the log growth rate in the market equity not attributable to stock return, $\log\left(\mathrm{ME_t}/\mathrm{ME_{t-5}}\right) - r(t-5,t)$. $r(t-5,t)$ is the cumulative log stock return 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 market equity (from CRSP) on the last trading day of June in year t. Monthly decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.12 Ivg, Inventory Growth

At the end of June of each year t, we sort stocks into deciles based on inventory growth, Ivg, which is the annual growth rate in inventory (Compustat annual item INVT) from the fiscal year ending in calendar year $t-2$ to the fiscal year ending in $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.13 Ivc, Inventory Changes

At the end of June of each year t, we sort stocks into deciles based on inventory changes, Ivc, which is the annual change in inventory (Compustat annual item INVT) scaled by the average of total assets (item AT) for the fiscal years ending in $t-2$ and $t-1$. We exclude firms that carry no inventory for the past two fiscal years. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.14 Oa, Operating Accruals

Prior to 1988, we use the balance sheet approach in 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 (dCA−dCASH)−(dCL−dSTD−dTP)−DP, in which dCA is the change in current assets (Compustat annual item ACT), dCASH is the change in cash or cash equivalents (item CHE), dCL is the change in current liabilities (item LCT), dSTD is the change in debt included in current liabilities (item DLC), dTP is the change in income taxes payable (item TXP), and DP is depreciation and amortization (item DP). Missing changes in income taxes payable are set to zero. 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. At the end of June of each year t, we sort stocks into deciles 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 decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.15 dWc and dCoa, Changes in Net Non-cash Working Capital and in Current Operating Assets

Richardson, Sloan, Soliman, and Tuna (2005, Table 10) show that several components of total accruals also forecast returns in the cross section. dWc 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) − cash and short term investments (item CHE) and Col = current liabilities (item LCT) − debt in current liabilities (item DLC). dCoa is the change in current operating asset. Missing changes in debt in current liabilities are set to zero. At the end of June of each year t, we sort stocks into deciles based, separately, on dWc and dCoa for the fiscal year ending in calendar year $t-1$, all scaled by total assets (item AT) for the fiscal year ending in calendar year $t-2$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.16 dNco and dNca, Changes in Net Non-current Operating Assets and in Non-current Operating Assets

dNco is the change in net non-current operating assets. Net non-current operating assets are non-current operating assets (Nca) minus non-current operating liabilities (Ncl), with Nca = total assets (Compustat annual item AT) − current assets (item ACT) − long-term investments (item IVAO), and Ncl = total liabilities (item LT) − current liabilities (item LCT) − long-term debt (item DLTT). dNca is the change in non-current operating assets. Missing changes in long-term investments and long-term debt are set to zero. At the end of June of each year t, we sort stocks into deciles based, separately, on dNco and dNca for the fiscal year ending in calendar year $t-1$, all scaled by total assets for the fiscal year ending in calendar year $t-2$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.17 dFin, dFnl, and dBe, Changes in Net Financial Assets, in Financial Liabilities, and in Book Equity

dFin is the change in net financial assets. Net financial assets are financial assets (Fna) minus financial liabilities (Fnl), with Fna = short-term investments (Compustat annual item IVST) + long-term investments (item IVAO), and Fnl = long-term debt (item DLTT) + debt in current liabilities (item DLC) + preferred stock (item PSTK). dFnl is the change in financial liabilities. dBe is the change in book equity (item CEQ). Missing changes in debt in current liabilities, long-term investments, long-term debt, short-term investments, and preferred stocks are set to zero (at least one change has to be non-missing when constructing any variable). At the end of June of each year t, we sort stocks into deciles based, separately, on dFin, dFnl, and dBe for the fiscal year ending in calendar year $t-1$, all scaled by total assets (item AT) for the fiscal year ending in calendar year $t-2$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.18 Dac, Discretionary Accruals

We measure discretionary accruals, Dac, using the modified Jones model from Dechow, Sloan, and Sweeney (1995):

$$\frac{\mathrm{Oa}_{i,t}}{\mathrm{A}_{i,t-1}} = \alpha_1 \frac{1}{\mathrm{A}_{i,t-1}} + \alpha_2 \frac{\mathrm{dSALE}_{i,t} - \mathrm{dREC}_{i,t}}{\mathrm{A}_{i,t-1}} + \alpha_3 \frac{\mathrm{PPE}_{i,t}}{\mathrm{A}_{i,t-1}} + e_{i,t}, \tag{C.7}$$

in which $\mathrm{Oa}_{i,t}$ is operating accruals for firm i (see Appendix C.3.14), A_{t-1} is total assets (Compustat annual item AT) at the end of year $t-1$, $\mathrm{dSALE}_{i,t}$ is the annual change in sales (item SALE) from year $t-1$ to t, $\mathrm{dREC}_{i,t}$ is the annual change in net receivables (item RECT) from year $t-1$ to t, and $\mathrm{PPE}_{i,t}$ is gross property, plant, and equipment (item PPEGT) at the end of year t. We estimate the cross-sectional regression (C.7) for each two-digit SIC industry and year combination, formed separately for NYSE/AMEX firms and for NASDAQ firms. We require at least six firms for each regression. The discretionary accrual for stock i is defined as the residual from the regression, $e_{i,t}$. At the end of June of each year t, we sort stocks into deciles based on Dac for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.19 Poa, Percent Operating Accruals

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 sort stocks into deciles based on operating accruals scaled by the absolute value of net income (Compustat annual item NI) for the fiscal year ending in calendar year $t-1$. See Appendix C.3.14 for the measurement of operating accruals. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.20 Pta, Percent Total Accruals

At the end of June of each year t, we sort stocks into deciles on percent total accruals, Pta, calculated as total accruals scaled by the absolute value of net income (Compustat annual item NI) for the fiscal year ending in calendar year $t-1$. See Appendix **??** for the measurement of total accruals. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of year $t+1$.

C.3.21 Pda, Percent Discretionary Accruals

At the end of June of each year t, we split stocks into deciles based on percent discretionary accruals, Pda, calculated as the discretionary accruals, Dac, for the fiscal year ending in calendar year $t-1$ multiplied with total assets (Compustat annual item AT) for the fiscal year ending in $t-2$ scaled by the absolute value of net income (item NI) for the fiscal year ending in $t-1$. See Appendix C.3.18 for the measurement of discretionary accruals. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.3.22 Ndf, Net Debt Financing

Ndf is net debt financing, Ndf (Bradshaw, Richardson, and Sloan 2006). Ndf 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 sort stocks into deciles based on Ndf 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 $t-1$. Monthly 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 data on financing activities start in 1971, the portfolios start in July 1972.

C.4 Profitability

C.4.1 Roe1 and Roe6, Return on Equity

Return on equity, Roe, is income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged book equity (Hou, Xue, and Zhang 2015). 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 (item PSTKQ). Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the book value of preferred stock, or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity.

Before 1972, the sample coverage is limited for quarterly book equity in Compustat quarterly files. We expand the coverage by using book equity from Compustat annual files as well as by imputing quarterly book equity with clean surplus accounting. Specifically, whenever available we first use quarterly book equity from Compustat quarterly files. We then supplement the coverage for fiscal quarter four with annual book equity from Compustat annual files. Following Davis, Fama, and French (2000), we measure annual book equity as 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.

If both approaches are unavailable, we apply the clean surplus relation to impute the book equity. First, if available, we backward impute the beginning-of-quarter book equity as the end-of-quarter book equity minus quarterly earnings plus quarterly dividends. Quarterly earnings are income before extraordinary items (Compustat quarterly item IBQ). Quarterly dividends are zero if dividends per share (item DVPSXQ) are zero. Otherwise, total dividends are dividends per share times beginning-of-quarter shares outstanding adjusted for stock splits during the quarter. Shares outstanding are from Compustat (quarterly item CSHOQ supplemented with annual item CSHO for fiscal quarter four) or CRSP (item SHROUT), and the share adjustment factor is from Compustat (quarterly item AJEXQ supplemented with annual item AJEX for fiscal quarter four) or CRSP (item CFACSHR). Because we impose a four-month lag between earnings and the holding period month (and the book equity in the denominator of ROE is one-quarter-lagged relative to earnings), all the Compustat data in the backward imputation are at least four-month lagged prior to the portfolio formation. If data are unavailable for the backward imputation, we impute the book equity for quarter t forward based on book equity from prior quarters. Let BEQ_{t-j}, $1 \leq j \leq 4$ denote the latest available quarterly book equity as of quarter t, and $\mathrm{IBQ}_{t-j+1,t}$ and $\mathrm{DVQ}_{t-j+1,t}$

be the sum of quarterly earnings and quarterly dividends from quarter $t - j + 1$ to t, respectively. BEQ_t can then be imputed as $\text{BEQ}_{t-j} + \text{IBQ}_{t-j+1,t} - \text{DVQ}_{t-j+1,t}$. We do not use prior book equity from more than four quarters ago (i.e., $1 \leq j \leq 4$) to reduce imputation errors.

At the beginning of each month t, we sort all stocks into deciles based on their most recent past Roe. Before 1972, we use the most recent Roe computed with quarterly earnings from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use Roe computed with quarterly earnings from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Roe to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for the current month t (Roe1) and from month t to $t+5$ (Roe6). The deciles are rebalanced monthly. The holding period that is longer than one month as in, for instance, Roe6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdeciles returns as the monthly return of the Roe6 decile.

C.4.2 dRoe1, dRoe6, and dRoe12, Changes in Return on Equity

Change in return on equity, dRoe, is return on equity minus its value from four quarters ago. See Appendix C.4.1 for the measurement of return on equity. At the beginning of each month t, we sort all stocks into deciles on their most recent past dRoe. Before 1972, we use the most recent dRoe with quarterly earnings from fiscal quarters ending at least four months ago. Starting from 1972, we use dRoe computed with quarterly earnings from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent dRoe to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for the current month t (dRoe1), from month t to $t+5$ (dRoe6), and from month t to $t+11$ (dRoe12). The deciles are rebalanced monthly. The holding period that is longer than one month as in, for instance, dRoe6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdeciles returns as the monthly return of the dRoe6 decile.

C.4.3 Roa1, Return on Assets

Return on assets, Roa, is income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged total assets (item ATQ). At the beginning of each month t, we sort all stocks into deciles based on Roa computed with quarterly earnings from the most recent earnings announcement dates (item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Roa to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for month t, and the deciles are rebalanced at the beginning of $t+1$. For sufficient data coverage, the Roa portfolios start in January 1972.

C.4.4 dRoa1 and dRoa6, Changes in Return on Assets

Change in return on assets, dRoa, is return on assets minus its value from four quarters ago. See Appendix C.4.3 for the measurement of return on assets. At the beginning of each month t, we sort all stocks into deciles based on dRoa computed with quarterly earnings from the most recent earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent dRoa to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for month t (dRoa1) and from month t to $t+5$ (dRoa6), and the deciles are rebalanced at the beginning of $t+1$. The holding period that is longer than one month as in, for instance, dRoa6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the dRoa6 decile. For sufficient data coverage, the dRoa portfolios start in January 1973.

C.4.5 Rna^{q}1, Rna^{q}6, Ato^{q}1, Ato^{q}6, and Ato^{q}12, Quarterly Return on Net Operating Assets, Quarterly Asset Turnover

Quarterly return on net operating assets, Rna^q, is quarterly operating income after depreciation (Compustat quarterly item OIADPQ) divided by one-quarter-lagged net operating assets (Noa). Noa is operating assets minus operating liabilities. Operating assets are total assets (item ATQ) minus cash and short-term investments (item CHEQ), and minus other investment and advances (item IVAOQ, zero if missing). Operating liabilities are total assets minus debt in current liabilities (item DLCQ, zero if missing), minus long-term debt (item DLTTQ, zero if missing), minus minority interests (item MIBQ, zero if missing), minus preferred stocks (item PSTKQ, zero if missing), and minus common equity (item CEQQ). Quarterly asset turnover, Ato^q, is quarterly sales divided by one-quarter-lagged Noa. At the beginning of each month t, we sort stocks into deciles based on Rna^q for the latest fiscal quarter ending at least four months ago. Separately, we sort stocks into deciles based on Ato^q computed with quarterly sales from the most recent earnings announcement dates (item RDQ). Sales are generally announced with earnings during quarterly earnings announcements (Jegadeesh and Livnat 2006). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Ato^q to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for month t (Rna^{q}1 and Ato^{q}1), from month t to $t+5$ (Rna^{q}6 and Ato^{q}6), and from month t to $t+11$ (Ato^{q}12). The deciles are rebalanced at the beginning of $t+1$. The holding period that is longer than one month as in, for instance, Ato^{q}6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the Atoq6 decile. For sufficient data coverage, the Rna^q portfolios start in January 1976 and the Ato^q portfolios start in January 1972.

C.4.6 Cto^{q}1, Cto^{q}6, and Cto^{q}12, Quarterly Capital Turnover

Quarterly capital turnover, Cto^q, is quarterly sales (Compustat quarterly item SALEQ) scaled by one-quarter-lagged total assets (item ATQ). At the beginning of each month t, we sort stocks into deciles based on Cto^q computed with quarterly sales from the most recent earnings announcement dates (item RDQ). Sales are generally announced with earnings during quarterly earnings announcements (Jegadeesh and Livnat 2006). For a firm to enter the portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Ato^{q} to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end. Monthly decile returns are calculated for month t ($\text{Cto}^{\text{q}}1$), from month t to $t+5$ ($\text{Cto}^{\text{q}}6$), and from month t to $t+11$ ($\text{Cto}^{\text{q}}12$). The deciles are rebalanced at the beginning of $t+1$. The holding period that is longer than one month as in, for instance, $\text{Cto}^{\text{q}}6$, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the $\text{Cto}^{\text{q}}6$ decile. For sufficient data coverage, the Cto^{q} portfolios start in January 1972.

C.4.7 Gpa, Gross Profits-to-assets

Following Novy-Marx (2013), we measure gross profits-to-assets, Gpa, 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 sort stocks into deciles based on Gpa for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.4.8 $\text{Gla}^{\text{q}}1$, $\text{Gla}^{\text{q}}6$, and $\text{Gla}^{\text{q}}12$, Quarterly Gross Profits-to-lagged Assets

Gla^{q}, is quarterly total revenue (Compustat quarterly item REVTQ) minus cost of goods sold (item COGSQ) divided by one-quarter-lagged total assets (item ATQ). At the beginning of each month t, we sort stocks into deciles based on Gla^{q} for the fiscal quarter ending at least four months ago. Monthly decile returns are calculated for month t ($\text{Gla}^{\text{q}}1$), from month t to $t+5$ ($\text{Gla}^{\text{q}}6$), and from month t to $t+11$ ($\text{Gla}^{\text{q}}12$). The deciles are rebalanced at the beginning of $t+1$. The holding period that is longer than one month as in, for instance, $\text{Gla}^{\text{q}}6$, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdecile returns as the monthly return of the $\text{Gla}^{\text{q}}6$ decile. For sufficient data coverage, the Gla^{q} portfolios start in January 1976.

C.4.9 $\text{Ole}^{\text{q}}1$ and $\text{Ole}^{\text{q}}6$, Quarterly Operating Profits-to-lagged Equity

Quarterly operating profits-to-lagged equity, Ole^{q}, is quarterly total revenue (Compustat quarterly item REVTQ) minus cost of goods sold (item COGSQ, zero if missing), minus selling, general, and administrative expenses (item XSGAQ, zero if missing), and minus interest expense (item XINTQ, zero if missing), scaled by one-quarter-lagged book equity. We require at least one of the three expense items (COGSQ, XSGAQ, and XINTQ) to be non-missing. 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 (item PSTKQ). Depending on availability, we use stockholders' equity (item SEQQ), or common equity (item CEQQ) plus the book value of preferred stock, or total assets (item ATQ) minus total liabilities (item LTQ) in that order as shareholders' equity.

At the beginning of each month t, we split stocks on Ole^{q} for the fiscal quarter ending at least four months ago. Monthly decile returns are calculated for month t ($\text{Ole}^{\text{q}}1$) and from month t to $t+5$ ($\text{Ole}^{\text{q}}6$), and the deciles are rebalanced at the beginning of $t+1$. The holding period longer than one month as in $\text{Ole}^{\text{q}}6$ means that for a given decile in each month there exist six subdeciles, each initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Ole^q6 decile. For sufficient data coverage, the Ole^q portfolios start in January 1972.

C.4.10 Opa, Operating Profits-to-assets

Following Ball, Gerakos, Linnainmaa, and Nikolaev (2015), we measure operating profits-to-assets, Opa, as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), and plus research and development expenditures (item XRD, zero if missing), scaled by book assets (item AT, the denominator is current, not lagged, total assets). At the end of June of each year t, we sort stocks into deciles based on Opa for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.4.11 Ola^q1, Ola^q6, and Ola^q12, Quarterly Operating Profits-to-lagged Assets

Quarterly operating profits-to-lagged assets, Ola^q, is quarterly total revenue (Compustat quarterly item REVTQ) minus cost of goods sold (item COGSQ), minus selling, general, and administrative expenses (item XSGAQ), plus research and development expenditures (item XRDQ, zero if missing), scaled by one-quarter-lagged book assets (item ATQ). At the beginning of each month t, we sort stocks into deciles based on Ola^q for the fiscal quarter ending at least four months ago. Monthly decile returns are calculated for month t (Ola^q1), from month t to $t+5$ (Ola^q6), and from month t to $t+11$ (Ola^q12). The deciles are rebalanced at the beginning of $t+1$. The holding period longer than one month as in Ola^q6 means that for a given decile in each month there exist six subdeciles, each initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Ola^q6 decile. For sufficient data coverage, the Ola^q portfolios start in January 1976.

C.4.12 Cop, Cash-based Operating Profitability

Following Ball, Gerakos, Linnainmaa, and Nikolaev (2016), we measure cash-based operating profitability, Cop, as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), all scaled by book assets (item AT, the denominator is current, not lagged, total assets). All changes are annual changes in balance sheet items and we set missing changes to zero. At the end of June of each year t, we sort stocks into deciles based on Cop for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.4.13 Cla, Cash-based Operating Profits-to-lagged Assets

Cash-based operating profits-to-lagged assets, Cla, is total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), all scaled by one-year-lagged book assets (item AT). All changes are annual changes in balance sheet items and we set missing changes to zero. At the end of June of each year t, we sort stocks into deciles based on Cla for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.4.14 Cla^{q}1, Cla^{q}6, and Cla^{q}12, Quarterly Cash-based Operating Profits-to-lagged Assets

Quarterly cash-based operating profits-to-lagged assets, Cla, is quarterly total revenue (Compustat quarterly item REVTQ) minus cost of goods sold (item COGSQ), minus selling, general, and administrative expenses (item XSGAQ), plus research and development expenditures (item XRDQ, zero if missing), minus change in accounts receivable (item RECTQ), minus change in inventory (item INVTQ), plus change in deferred revenue (item DRCQ plus item DRLTQ), and plus change in trade accounts payable (item APQ), all scaled by one-quarter-lagged book assets (item ATQ). All changes are quarterly changes in balance sheet items and we set missing changes to zero. At the beginning of each month t, we split stocks on Cla^{q} for the fiscal quarter ending at least four months ago. Monthly decile returns are calculated for month t (Cla^{q}1), from month t to $t+5$ (Cla^{q}6), and from month t to $t+11$ (Cla^{q}12). The deciles are rebalanced at the beginning of $t+1$. The holding period longer than one month as in Cla^{q}6 means that for a given decile in each month there exist six subdeciles, each initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Cla^{q}6 decile. For sufficient data coverage, the Cla^{q} portfolios start in January 1976.

C.4.15 F^{q}1, F^{q}6, and F^{q}12, Quarterly Fundamental Score

To construct quarterly F-score, F^{q}, we use quarterly accounting data and the same nine binary signals from Piotroski (2000). Among the four signals related to profitability: (i) Roa is quarterly income before extraordinary items (Compustat quarterly item IBQ) scaled by one-quarter-lagged total assets (item ATQ). If the firm's Roa is positive, the indicator variable $\mathrm{F}_{\mathrm{Roa}}$ equals one and zero otherwise. (ii) Cf/A is quarterly cash flow from operation scaled by one-quarter-lagged total assets. Cash flow from operation is the quarterly change in year-to-date net cash flow from operating activities (item OANCFY) if available, or the quarterly change in year-to-date funds from operation (item FOPTY) minus the quarterly change in working capital (item WCAPQ). If the firm's Cf/A is positive, the indicator variable $\mathrm{F}_{\mathrm{Cf/A}}$ equals one and zero otherwise. (iii) dRoa is the current quarter's Roa less the Roa from four quarters ago. If dRoa is positive, the indicator variable $\mathrm{F}_{\mathrm{dROA}}$ is one and zero otherwise. Finally, (iv) the indicator $\mathrm{F}_{\mathrm{Acc}}$ equals one if Cf/A > Roa and zero otherwise.

Among the three signals related changes in capital structure and a firm's ability to meet future debt obligations: (i) dLever is the change in the ratio of total long-term debt (Compustat quarterly item DLTTQ) to the average of current and one-quarter-lagged total assets. $\mathrm{F}_{\mathrm{dLever}}$ is one if the firm's leverage ratio falls, i.e., dLever < 0, relative to its value four quarters ago, and zero otherwise. (ii) dLiquid measures the change in a firm's current ratio between the current quarter and four quarters ago, in which the current ratio is the ratio of current assets (item ACTQ) to current liabilities (item LCTQ). An improvement in liquidity (dLiquid > 0) is a good signal about the firm's ability to service current debt obligations. The indicator $\mathrm{F}_{\mathrm{dLiquid}}$ equals one if the firm's liquidity improves and zero otherwise. (iii) The indicator, Eq, equals one if the firm does not issue common equity during the past four quarters and zero otherwise. The issuance of common equity is sales of common and preferred stocks minus any increase in preferred stocks (item PSTKQ). To measure sales of common and preferred stocks, we first compute the quarterly change in year-to-date sales of common and preferred stocks (item SSTKY) and then take the total change for the past four quarters. Issuing equity is interpreted as a bad signal (inability to generate sufficient internal funds to service future obligations). For the remaining two signals, (i) dMargin is the firm's current gross margin ratio, measured as gross margin (item SALEQ minus item COGSQ) scaled by sales (item SALEQ), less the gross margin ratio from four quarters ago. The indictor $\mathrm{F}_{\mathrm{dMargin}}$ equals one if dMargin > 0 and zero otherwise. (ii) dTurn is the firm's current asset turnover ratio, measured as (item SALEQ) scaled by one-quarter-lagged total assets (item ATQ), minus the asset turnover ratio from four quarters ago. The indicator, $\mathrm{F}_{\mathrm{dTurn}}$, equals one if dTurn > 0 and zero otherwise.

The composite score, F^{q}, is the sum of the individual binary signals:

$$\mathrm{F}^{\mathrm{q}} \equiv \mathrm{F}_{\mathrm{Roa}} + \mathrm{F}_{\mathrm{dRoa}} + \mathrm{F}_{\mathrm{Cf/A}} + \mathrm{F}_{\mathrm{Acc}} + \mathrm{F}_{\mathrm{dMargin}} + \mathrm{F}_{\mathrm{dTurn}} + \mathrm{F}_{\mathrm{dLever}} + \mathrm{F}_{\mathrm{dLiquid}} + \mathrm{Eq}. \tag{C.8}$$

At the beginning of each month t, we sort stocks based on Fq for the fiscal quarter ending at least four quarters ago to form seven portfolios: low (F^{q} = 0,1,2), 3, 4, 5, 6, 7, and high (F^{q} = 8, 9). Monthly portfolio returns are calculated for month t (F^{q}1), from month t to $t+5$ (F^{q}6), and from month t to $t+11$ (F^{q}12), and the portfolios are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, F^{q}6, means that for a given portfolio in each month there exist six subportfolios, each of which is initiated in a different month in prior six months. We take the simple average of the subportfolio returns as the monthly return of the F^{q}6 portfolio. For sufficient data coverage, the F^{q} portfolios start in January 1985.

C.4.16 Fp^{q}6, Failure Probability

Failure probability (Fp) is from Campbell, Hilscher, and Szilagyi (2008, Table IV, Column 3):

$$\begin{aligned}\mathrm{Fp}_t \equiv & -9.164 - 20.264\mathrm{NIMTAAVG}_t + 1.416\mathrm{TLMTA}_t - 7.129\mathrm{EXRETAVG}_t \\ & + 1.411\mathrm{SIGMA}_t - 0.045\mathrm{RSIZE}_t - 2.132\mathrm{CASHMTA}_t + 0.075\mathrm{MB}_t - 0.058\mathrm{PRICE}_t\end{aligned} \tag{C.9}$$

in which

$$\mathrm{NIMTAAVG}_{t-1,t-12} \equiv \frac{1-\phi^3}{1-\phi^{12}}\left(\mathrm{NIMTA}_{t-1,t-3} + \cdots + \phi^9\mathrm{NIMTA}_{t-10,t-12}\right) \tag{C.10}$$

$$\mathrm{EXRETAVG}_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}\left(\mathrm{EXRET}_{t-1} + \cdots + \phi^{11}\mathrm{EXRET}_{t-12}\right), \tag{C.11}$$

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 one large quarterly loss in a single month. EXRET $\equiv \log(1+R_{it}) - \log(1+R_{\mathrm{S\&P500},t})$ 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 total liabilities divided by the sum of market equity and total liabilities. SIGMA is the annualized three-month rolling sample standard deviation: $\sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$, in which

k is the index of trading days in months $t-1, t-2$, and $t-3$, r_k is the firm-level daily return, and N is the total number of trading days in the three-month period. SIGMA is treated as missing if there are less than five nonzero observations over the three months in the rolling window. RSIZE is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index. CASHMTA, aimed to capture the liquidity position of the firm, is 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 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 (Campbell, Hilscher, and Szilagyi 2008). 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 (C.1) at the 1th and 99th percentiles of their distributions each month.

At the beginning of each month t, we split stocks into deciles based on Fp calculated with accounting data from the fiscal quarter ending at least four months ago. We calculate decile returns from month t to $t+5$ (Fp$^{\text{q}}$6), and the deciles are rebalanced at the beginning of month $t+1$. The holding period that is longer than one month means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six-month period. We take the simple average of the subdeciles returns as the monthly return of the Fp$^{\text{q}}$6 decile. For sufficient data coverage, the quarterly Fp deciles start in January 1976.

C.5 Intangibles

C.5.1 Oca and Ioca, (Industry-adjusted) Organizational Capital-to-assets

Following Eisfeldt and Papanikolaou (2013), we construct the stock of organization capital, Oc, using the perpetual inventory method:

$$\text{Oc}_{it} = (1-\delta)\text{Oc}_{it-1} + \text{SG\&A}_{it}/\text{CPI}_t, \tag{C.12}$$

in which Oc_{it} is the organization capital of firm i at the end of year t, $\text{SG\&A}_{it}$ is selling, general, and administrative (SG&A) expenses (Compustat annual item XSGA) in t, CPI_t is the average consumer price index during year t, and δ is the annual depreciation rate of Oc. The initial stock of Oc is $\text{Oc}_{i0} = \text{SG\&A}_{i0}/(g+\delta)$, in which $\text{SG\&A}_{i0}$ is the first valid SG&A observation (zero or positive) for firm i and g is the long-term growth rate of SG&A. 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 non-missing 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. Organizational Capital-to-assets, Oca, is Oc scaled by total assets (item AT). We also industry-standardize Oca using the FF (1997) 17-industry classification. To calculate the industry-adjusted Oca, Ioca, we demean a firm's Oca by its industry mean and then divide the demeaned Oca by the standard deviation of Oca within its industry. To alleviate the impact of outliers, we winsorize Oca at the 1 and 99 percentiles of all firms each year before the industry standardization. At the end of June of each year t, we sort stocks into deciles based on Oca, and separately, on Ioca, for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.5.2 Adm, Advertising Expense-to-market

At the end of June of each year t, we sort stocks into deciles based on advertising expenses-to-market, Adm, which is advertising expenses (Compustat annual item XAD) for the fiscal year ending in calendar year $t-1$ divided by the market equity (from CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Adm. We keep only firms with positive advertising expenses. Monthly 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 Adm portfolios start in July 1973.

C.5.3 Rdm, R&D Expense-to-market

At the end of June of each year t, we sort stocks into deciles based on R&D-to-market, Rdm, 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 CRSP) at the end of December of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Rdm. We keep only firms with positive R&D expenses. Monthly 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 Rdm portfolios start in July 1976.

C.5.4 Rdm^{q}1, Rdm^{q}6, and Rdm^{q}12, Quarterly R&D Expense-to-market

At the beginning of each month t, we split stocks into deciles based on quarterly R&D-to-market, Rdm^q, which is quarterly R&D expense (Compustat quarterly item XRDQ) for the fiscal quarter ending at least four months ago scaled by the market equity (from CRSP) at the end of $t-1$. For firms with more than one share class, we merge the market equity for all share classes before computing Rdm^q. We keep only firms with positive R&D expenses. We calculate decile returns for the current month t (Rdm^{q}1), from month t to $t+5$ (Rdm^{q}6), and from month t to $t+11$ (Rdm^{q}12), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, Rdm^{q}6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Rdm^{q}6 decile. Because the quarterly R&D data start in late 1989, the Rdm^q portfolios start in January 1990.

C.5.5 Ol, Operating Leverage

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

C.5.6 Ol^{q}1, Ol^{q}6, and Ol^{q}12, Quarterly Operating Leverage

At the beginning of each month t, we split stocks into deciles based on quarterly operating leverage, Ol^q, which is quarterly operating costs divided by assets (Compustat quarterly item ATQ) for the fiscal quarter ending at least four months ago. Operating costs are the cost of goods sold (item COGSQ) plus selling, general, and administrative expenses (item XSGAQ). We calculate decile returns for the current month t (Ol^q1), from month t to $t+5$ (Ol^q6), and from month t to $t+11$ (Ol^q12), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in, for instance, Ol^q6, means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Ol^q6 decile. For sufficient data coverage, the Ol^q portfolios start in January 1972.

C.5.7 Hs, Industry Concentration in Sales

Following Hou and Robinson (2006), we measure a firm's industry concentration with the Herfindahl index, $\sum_{i=1}^{N_j} s_{ij}^2$, in which s_{ij} is the market share of firm i in industry j, and N_j is the total number of firms in the industry. We calculate the market share of a firm using sales (Compustat annual item SALE). Industries are defined by three-digit SIC codes. We exclude financial firms (SIC between 6000 and 6999) and firms in regulated industries. Following Barclay and Smith (1995), the regulated industries include: railroads (SIC=4011) through 1980, trucking (4210 and 4213) through 1980, airlines (4512) through 1978, telecommunication (4812 and 4813) through 1982, and gas and electric utilities (4900 to 4939). To improve the accuracy of the concentration measure, we exclude an industry if the market share data are available for fewer than five firms or 80% of all firms in the industry. We measure industry concentration as the average Herfindahl index during the past three years. Industry concentration calculated with sales is denoted Hs. At the end of June of each year t, we sort stocks into deciles based on Hs for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.5.8 Etr, Effective Tax Rate

Following Abarbanell and Bushee (1998), we measure effective tax rate, Etr, as:

$$\text{Etr}(t) = \left[\frac{\text{TaxExpense}(t)}{\text{EBT}(t)} - \frac{1}{3}\sum_{\tau=1}^{3}\frac{\text{TaxExpense}(t-\tau)}{\text{EBT}(t-\tau)}\right] \times \text{dEPS}(t), \tag{C.13}$$

in which TaxExpense(t) is total income taxes (Compustat annual item TXT) paid in year t, EBT(t) is pretax income (item PI) plus amortization of intangibles (item AM), and dEPS is the change in split-adjusted earnings per share (item EPSPX divided by item AJEX) between years $t-1$ and t, deflated by stock price (item PRCC_F) at the end of $t-1$. At the end of June of each year t, we sort stocks into deciles based on Etr for the fiscal year ending in calendar year $t-1$. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.5.9 Rer, Industry-adjusted Real Estate Ratio

Following Tuzel (2010), we measure the real estate ratio as the sum of buildings (Compustat annual item PPENB) and capital leases (item PPENLS) divided by net property, plant, and equipment (item PPENT) prior to 1983. From 1984 onward, the real estate ratio is the sum of buildings at cost (item FATB) and leases at cost (item FATL) divided by gross property, plant, and equipment (item PPEGT). Industry-adjusted real estate ratio, Rer, is the real estate ratio minus its industry average. Industries are defined by two-digit SIC codes. To alleviate the impact of outliers, we winsorize the real estate ratio at the 1st and 99th percentiles of its distribution each year before computing Rer. Following Tuzel (2010), we exclude industries with fewer than five firms. At the end of June of each year t, we sort stocks into deciles based on Rer for the fiscal year ending in calendar year $t-1$.

Monthly 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 real estate data start in 1969, the Rer portfolios start in July 1970.

C.5.10 Eprd, Earnings Predictability

Following Francis, Lafond, Olsson, and Schipper (2004), we estimate earnings predictability, Eprd, from a first-order autoregressive model for annual split-adjusted earnings per share (Compustat annual item EPSPX divided by item AJEX). At the end of June of each year t, we estimate the autoregressive model in the ten-year rolling window up to the fiscal year ending in calendar year $t-1$. Only firms with a complete ten-year history are included. Eprd is measured as the residual volatility. We sort stocks into deciles based on Eprd. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.5.11 Etl, Earnings Timeliness

Following Francis, Lafond, Olsson, and Schipper (2004), we measure earnings timeliness, Etl, from the following rolling-window regression:

$$\text{EARN}_{it} = \alpha_{i0} + \alpha_{i1}\,\text{NEG}_{it} + \beta_{i1}R_{it} + \beta_{i2}\text{NEG}_{it}R_{it} + e_{it}, \tag{C.14}$$

in which EARN_{it} is earnings (Compustat annual item IB) for the fiscal year ending in calendar year t, scaled by the fiscal year-end market equity. R_{it} is firm i's 15-month stock return ending three months after the end of fiscal year ending in calendar year t. NEG_{it} equals one if $R_{it} < 0$, and zero otherwise. For firms with more than one share class, we merge the market equity for all share classes. We measure Etl as the R^2 from the regression in (C.14). At the end of June of each year t, we sort stocks into deciles based on Etl calculated over the ten-year rolling window up to the fiscal year ending in calendar year $t-1$. Only firms with a complete ten-year history are included. Monthly decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$.

C.5.12 Alm$^{\text{q}}$1, Alm$^{\text{q}}$6, and Alm$^{\text{q}}$12, Quarterly Asset Liquidity

We measure quarterly asset liquidity as cash + 0.75 $\times$ noncash current assets + 0.50 $\times$ tangible fixed assets. Cash is cash and short-term investments (Compustat quarterly item CHEQ). Noncash current assets is current assets (item ACTQ) minus cash. Tangible fixed assets is total assets (item ATQ) minus current assets (item ACTQ), minus goodwill (item GDWLQ, zero if missing), and minus intangibles (item INTANQ, zero if missing). Alm$^{\text{q}}$ is quarterly asset liquidity scaled by one-quarter-lagged market value of assets. Market value of assets is total assets plus market equity (item PRCCQ times item CSHOQ) minus book equity (item CEQQ). At the beginning of each month t, we sort stocks into deciles based on Alm$^{\text{q}}$ for the fiscal quarter ending at least four months ago. Monthly decile returns are calculated for the current month t (Alm$^{\text{q}}$1), from month t to $t+5$ (Alm$^{\text{q}}$6), and from month t to $t+11$ (Alm$^{\text{q}}$12). The deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month as in Alm$^{\text{q}}$6 means that for a given decile in each month there exist six subdeciles, each of which is initiated in a different month in the prior six months. We take the simple average of the subdecile returns as the monthly return of the Alm$^{\text{q}}$6 decile. For sufficient data coverage, the quarterly asset liquidity portfolios start in January 1976.

C.5.13 R_{a}^{1}, $R_{\mathrm{a}}^{[2,5]}$, $R_{\mathrm{n}}^{[2,5]}$, $R_{\mathrm{a}}^{[6,10]}$, $R_{\mathrm{n}}^{[6,10]}$, $R_{\mathrm{a}}^{[11,15]}$, and $R_{\mathrm{a}}^{[16,20]}$, Seasonality

Following Heston and Sadka (2008), at the beginning of each month t, we sort stocks into deciles based on various measures of past performance, including returns in month $t-12$ (R_{a}^{1}), average returns across months $t-24, t-36, t-48$, and $t-60$ ($R_{\mathrm{a}}^{[2,5]}$), average returns from month $t-60$ to $t-13$ except for lags 24, 36, 48, and 60 ($R_{\mathrm{n}}^{[2,5]}$), average returns across months $t-72, t-84, t-96, t-108$, and $t-120$ ($R_{\mathrm{a}}^{[6,10]}$), average returns from month $t-120$ to $t-61$ except for lags 72, 84, 96, 108, and 120 ($R_{\mathrm{n}}^{[6,10]}$), average returns across months $t-132, t-144, t-156, t-168$, and $t-180$ ($R_{\mathrm{a}}^{[11,15]}$), and average returns across months $t-192, t-204, t-216, t-228$, and $t-240$ ($R_{\mathrm{a}}^{[16,20]}$). Monthly decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

C.6 Trading frictions

C.6.1 Sv1, Systematic Volatility Risk

Following Ang, Hodrick, Xing, and Zhang (2006), we measure systematic volatility risk, Sv, as $\beta^{i}_{\mathrm{dVXO}}$ from the bivariate regression:

$$r^{i}_{d} = \beta^{i}_{0} + \beta^{i}_{\mathrm{MKT}}\mathrm{MKT}_{d} + \beta^{i}_{\mathrm{dVXO}}\mathrm{dVXO}_{d} + \epsilon^{i}_{d}, \tag{C.15}$$

in which r^{i}_{d} is stock i's excess return on day d, MKT_{d} is the market factor return, and dVXO_{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 sort stocks into deciles based on $\beta^{i}_{\mathrm{dVXO}}$ estimated with the daily returns from month $t-1$. We require a minimum of 15 daily returns. Monthly 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 Sv portfolios start in February 1986.

C.6.2 Dtv12, Dollar Trading Volume

At the beginning of each month t, we sort stocks into deciles based on their average daily dollar trading volume, Dtv, over the prior six 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).[2] Monthly decile returns are calculated from month t to $t+11$ (Dtv12), and the deciles are rebalanced at the beginning of month $t+1$. The holding period longer than one month for Dtv12, means that for a given decile in each month there exist 12 subdeciles, each of which is initiated in a different month in the prior 12 months. We take the simple average of the subdecile returns as the monthly return of the Dtv12 decile.

[2] We adjust the NASDAQ trading volume to account for the institutional differences between NASDAQ and NYSE-Amex volumes (Gao and Ritter 2010). Prior to February 1, 2001, we divide NASDAQ volume by two. This procedure adjusts 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. From February 1, 2001 to December 31, 2001, we thus 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%. 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.

C.6.3 Isff1, Idiosyncratic Skewness per the Fama-French 3-factor Model

At the beginning of each month t, we sort stocks into deciles based on idiosyncratic skewness, Isff, calculated as the skewness of the residuals from regressing a stock's excess return on the Fama-French three factors using daily observations from month $t-1$. We require a minimum of 15 daily returns. Monthly decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

C.6.4 Isq1, Idiosyncratic Skewness per the q-factor Model

At the beginning of each month t, we sort stocks into deciles based on idiosyncratic skewness, Isq, calculated as the skewness of the residuals from regressing a stock's excess return on the q-factors using daily observations from month $t-1$. We require a minimum of 15 daily returns. Monthly decile returns are calculated for the current month, and the deciles are rebalanced at the beginning of month $t+1$. Because the q-factors start in January 1967, the Ivq portfolios start in February 1967.

D Replicating the Stambaugh-Yuan (2017) Factors

To make the document self-contained, we furnish the details of replicating the Stambaugh-Yuan factors in Hou, Mo, Xue, and Zhang (2018).

D.1 Factor Construction

We describe below the 11 anomaly variables used to construct the Stambaugh-Yuan factors (Appendix D.2). At the beginning of each month, we rank stocks into percentiles (1 to 100) based on each anomaly. The rankings are created such that high rankings are associated with lower future average returns. The first composite measure, MGMT (management), is the average of the six percentile rankings in net stock issues, composite equity issuance, accruals, net operating assets, investment-to-assets, and changes in property, plant, and equipment plus change in inventory scaled by assets. The second composite measure, PERF (performance), is the average of the five percentile rankings in failure probability, O-score, momentum, gross profitability, and return on assets. In any given month, an anomaly variable needs at least 30 stocks with non-missing values in order to be included in the composite measure. In addition, we compute a composite measure for a stock only if it has non-missing values for at least three of the component anomalies.

We replicate the Stambaugh-Yuan factors from two separate, independent 2×3 sorts, with one on size and MGMT, and another on size and PERF. At the beginning of each month t, we sort stocks by the NYSE median size into two groups, small and big. Independently, we split stocks based on MGMT, and separately, on PERF, into three groups, low, median, and high, with the 30th and 70th percentiles of the NYSE breakpoints. Taking intersections yields six size-MGMT and six size-PERF portfolios. Monthly value-weighted portfolio returns are calculated for the current month t, and the portfolios are rebalanced at the beginning of month $t+1$. The MGMT factor is the average of the returns on the two low MGMT portfolios minus the average of the returns on the two high MGMT portfolios. The PERF factor is the average of the returns on the two low PERF portfolios minus the average of the returns on the two high PERF portfolios. Finally, each of the two independent sorts yields a size factor, which is the average of the returns on the three small portfolios minus the average of the returns on the three big portfolios. We take the average of the two size factors as the size factor in the replicated Stambaugh-Yuan model.

D.2 Variable Definitions

Net stock issues is the annual change in the log of the split-adjusted shares outstanding. The split-adjusted shares outstanding is shares outstanding (Compustat annual item CSHO) times the adjustment factor (item AJEX). At the beginning of each month, we use the latest net stock issues from fiscal year ending at least four months ago. Following Stambaugh and Yuan (2017), at the beginning of month t, we measure composite equity issuance as the growth rate in market equity minus the cumulative stock return from month $t-16$ to $t-5$ (skipping month $t-4$ to $t-1$).

Following Sloan (1996), we measure accruals 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, accruals equals $(\mathrm{dCA}-\mathrm{dCASH})-(\mathrm{dCL}-\mathrm{dSTD}-\mathrm{dTP})-\mathrm{DP}$, in which dCA is the change in current assets (Compustat annual item ACT), dCASH is the change in cash or cash equivalents (item CHE), dCL is the change in current liabilities (item LCT), dSTD is the change in debt included in current liabilities (item DLC), dTP is the change in income taxes payable (item TXP), and DP is depreciation and amortization (item DP). Missing changes in income taxes payable are set to zero. We scale accruals by average total assets from the previous and current years. At the beginning of each month, we use the latest accruals from fiscal year ending at least four months ago.

We measure net operating assets 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). We scale net operating assets by one-year-lagged total assets. At the beginning of each month, we use the latest net operating assets from fiscal year ending at least four months ago.

We measure investment-to-assets as the annual change in total assets (Compustat annual item AT) scaled by one-year-lagged total assets. At the beginning of each month, we use the latest asset growth from fiscal year ending at least four months ago. Changes in PPE and inventory-to-assets are measured as the annual change in gross property, plant, and equipment (Compustat annual item PPEGT) plus the annual change in inventory (item INVT) scaled by one-year-lagged total assets (item AT). At the beginning of each month, we use the latest investment-to-assets from fiscal year ending at least four months ago.

At the beginning of month t, we follow Campbell, Hilscher, and Szilagyi (2008, Table IV, Column 3) to construct failure probability:

$$\begin{aligned}\mathrm{Fp}_t \equiv & -9.164-20.264\mathrm{NIMTAAVG}_t+1.416\mathrm{TLMTA}_t-7.129\mathrm{EXRETAVG}_t \\ & +1.411\mathrm{SIGMA}_t-0.045\mathrm{RSIZE}_t-2.132\mathrm{CASHMTA}_t+0.075\mathrm{MB}_t-0.058\mathrm{PRICE}_t \end{aligned} \tag{C.1}$$

in which

$$\mathrm{NIMTAAVG}_{t-1,t-12} \equiv \frac{1-\phi^3}{1-\phi^{12}}\left(\mathrm{NIMTA}_{t-1,t-3}+\cdots+\phi^9\mathrm{NIMTA}_{t-10,t-12}\right) \tag{C.2}$$

$$\mathrm{EXRETAVG}_{t-1,t-12} \equiv \frac{1-\phi}{1-\phi^{12}}\left(\mathrm{EXRET}_{t-1}+\cdots+\phi^{11}\mathrm{EXRET}_{t-12}\right), \tag{C.3}$$

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 one large quarterly loss in a single month. EXRET $\equiv \log(1+R_{it}) - \log(1+R_{\mathrm{S\&P500},t})$ 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 total liabilities divided by the sum of market equity and total liabilities. SIGMA is the annualized three-month rolling sample standard deviation: $\sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$, in which k is the index of trading days in months $t-1, t-2$, and $t-3$, r_k is the firm-level daily return, and N is the total number of trading days in the three-month period. SIGMA is treated as missing if there are less than five nonzero observations over the three months in the rolling window. RSIZE is the relative size of each firm measured as the log ratio of its market equity to that of the S&P 500 index. CASHMTA, aimed to capture the liquidity position of the firm, is 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 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 (Campbell, Hilscher, and Szilagyi 2008). 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. Variables requiring quarterly accounting data are from fiscal quarter ending at least four months ago to ensure the availability of balance sheet items. We winsorize the variables on the right-hand side of equation (C.1) at the 1th and 99th percentiles of their distributions each month.

We follow Ohlson (1980, Model One in Table 4) to construct O-score:

$$\begin{aligned} O \equiv\ & -1.32 - 0.407\log(\mathrm{TA}) + 6.03\mathrm{TLTA} - 1.43\mathrm{WCTA} + 0.076\mathrm{CLCA} \\ & - 1.72\mathrm{OENEG} - 2.37\mathrm{NITA} - 1.83\mathrm{FUTL} + 0.285\mathrm{INTWO} - 0.521\mathrm{CHIN}, \end{aligned} \quad \text{(C.4)}$$

in which TA is total assets (Compustat annual item AT). TLTA is the leverage ratio defined as total debt (item DLC plus item DLTT) divided by total assets. WCTA is working capital (item ACT minus item LCT) divided by total assets. CLCA is current liability (item LCT) divided by current assets (item ACT). OENEG is one if total liabilities (item LT) exceeds total assets and zero otherwise. NITA is net income (item NI) divided by total assets. FUTL is the fund provided by operations (item PI plus item DP) divided by total liabilities. INTWO is equal to one if net income is negative for the last two years and zero otherwise. CHIN is $(\mathrm{NI}_s - \mathrm{NI}_{s-1})/(|\mathrm{NI}_s| + |\mathrm{NI}_{s-1}|)$, in which NI_s and NI_{s-1} are the net income for the current and prior years. We winsorize all non-dummy variables on the right-hand side of equation (C.4) at the 1th and 99th percentiles of their distributions each year. At the beginning of each month, we use the latest O-score from fiscal year ending at least four months ago.

At the beginning of each month t, we measure momentum as the 11-month cumulative return from month $t-12$ to $t-2$ (skipping month $t-1$). Gross profitability is 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 beginning of each month, we use the latest gross profitability from fiscal year ending at least four months ago.

Return on Assets is income before extraordinary items (Compustat quarterly item IBQ) divided by one-quarter-lagged total assets (item ATQ). At the beginning of each month, we use return on assets computed with quarterly earnings from the most recent earnings announcement dates (item RDQ). For a firm to enter our sample, we require the end of the fiscal quarter that corresponds to its most recent return on assets to be within six months prior to the portfolio formation. This restriction is imposed to exclude stale earnings information. To avoid potentially erroneous records, we also require the earnings announcement date to be after the corresponding fiscal quarter end.

E Replicating the Daniel-Hirshleifer-Sun (2018) Factors

We replicate the Daniel-Hirshleifer-Sun factors as in Hou, Mo, Xue, and Zhang (2018). We replicate the post-earnings-announcement-draft factor (PEAD) by combining standardized unexpected earnings (Sue), the 4-day cumulative abnormal return around the most recent quarterly earnings announcement dates (Abr), and revisions in analysts' earnings forecasts (Re).

Sue is the change in split-adjusted quarterly earnings per share (Compustat quarterly item EPSPXQ divided by item AJEXQ) from its value four quarters ago divided by the standard deviation of this change in quarterly earnings over the prior eight quarters (six quarters minimum). Before 1972, we use the most recent Sue with earnings from fiscal quarters ending at least four months prior to the portfolio formation. Starting from 1972, we use Sue with quarterly earnings from the most recent quarterly earnings announcement dates (Compustat quarterly item RDQ). For a firm to enter our portfolio formation, we require the end of the fiscal quarter that corresponds to its most recent Sue to be within six months prior to the portfolio formation. Abr is measured as a stock's daily return minus the value-weighted market's daily return cumulated from two days prior to and one day after the most recent quarterly earnings announcement dates. To measure Re, because analysts' earnings forecasts from the Institutional Brokers' Estimate System (IBES) are not necessarily revised each month, we construct a 6-month moving average of past revisions, $\sum_{\tau=1}^{6}(f_{it-\tau} - f_{it-\tau-1})/p_{it-\tau-1}$, in which $f_{it-\tau}$ is the consensus mean forecast (IBES unadjusted file, item MEANEST) issued in month $t-\tau$ for firm i's current fiscal year earnings (fiscal period indicator = 1), and $p_{it-\tau-1}$ is the prior month's share price (unadjusted file, item PRICE). We require both earnings forecasts and share prices to be denominated in US dollars (currency code = USD). We also adjust for any stock splits and require a minimum of four monthly forecast changes when constructing Re.

At the beginning of each month t, we calculate a stock's NYSE percentiles on each of the three PEAD variables, and then take their simple average as the stock's ranked PEAD value. When taking the simple average, we use the available NYSE percentiles, allowing us to extend the sample backward to January 1967. This approach follows Stambaugh and Yuan (2017).

We use the same approach to replicate the financing factor (FIN) by combining the net share issuance and the composite share issuance in annual sorts. At the end of June of each year t, net share issuance is the natural log of the ratio of split-adjusted shares outstanding for fiscal year ending in calendar year $t-1$ (the common share outstanding, Compustat annual item CSHO, times the adjustment factor, item AJEX) to the split-adjusted shares outstanding for fiscal year ending in $t-2$. The composite share issuance is the log growth rate of the market equity not attributable to stock return, $\log(\mathrm{Me_t}/\mathrm{Me_{t-5}}) - r(t-5,t)$, in which $r(t-5,t)$ is the cumulative log stock return 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 market equity from CRSP on the last trading day of June in year t.

Finally, armed with the composite FIN and PEAD scores, we split stocks based on their NYSE breakpoints of the 30th and 70th percentiles in double 2×3 sorts with size.

Table A.1 : Monthly Cross-sectional Regressions of Percentile Rankings of Future Investment-to-assets Changes on Percentile Rankings of log(q), Cop, and dRoe, July 1963–December 2016, 642 Months

For each month, we perform cross-sectional regressions of percentile rankings of future τ-year-ahead investment-to-assets changes, denoted $\mathrm{d}^\tau\mathrm{I/A}$, in which $\tau = 1, 2, 3$, on the percentile rankings of the log of Tobin's q, $\log(q)$, cash flows, Cop, and the change in return on equity, dRoe. We measure current investment-to-assets from the most recent fiscal year ending at least four months ago, and calculate $\mathrm{d}^\tau\mathrm{I/A}$ as investment-to-assets from the subsequent τ-year-ahead fiscal year end minus the current investment-to-assets. All the cross-sectional regressions are estimated via weighted least squares with the market equity as the weights. We winsorize the cross section of each variable each month at the 1–99% level. We report the average slopes, their t-values adjusted for heteroscedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients (R^2, in percent). In addition, at the beginning of each month t, we calculate the expected I/A changes, $E_t[\mathrm{d}^\tau\mathrm{I/A}]$, by combining the most recent winsorized predictors with the average cross-sectional slopes. The most recent predictors, $\log(q)$ and Cop, are from the most recent fiscal year ending at least four months ago as of month t, and dRoe is based on the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ are estimated from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $\mathrm{d}^\tau\mathrm{I/A}$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly. For instance, for $\tau = 1$, the regressors used in the latest monthly cross-sectional regression are further lagged by 12 months relative to the most recent predictors used in calculating $E_t[\mathrm{d}^1\mathrm{I/A}]$. We report time-series averages of cross-sectional Pearson and rank correlations between percentile ranking-based $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ calculated at the beginning of month t and the realized percentile rankings of τ-year-ahead investment-to-assets changes. The p-values testing that a given correlation is zero are in brackets.

τ	$\log(q)$	Cop	dRoe	R^2	Pearson	Rank
1	−0.059	0.182	0.126	7.78	0.241	0.245
	(−6.38)	(18.28)	(19.57)		[0.00]	[0.00]
2	−0.135	0.228	0.146	10.33	0.243	0.253
	(−12.97)	(19.73)	(22.68)		[0.00]	[0.00]
3	−0.165	0.232	0.119	10.14	0.232	0.244
	(−13.96)	(18.51)	(16.76)		[0.00]	[0.00]

Table A.2 : Properties of Deciles on the Expected Growth Formed with Percentile Rankings, January 1967–December 2016, 600 Months

We use the percentile rankings of the log of Tobin's q, $\log(q)$, cash flow, Cop, and the change in return on equity, dRoe, to form the expected investment-to-assets changes, $E_t[\mathrm{d}^\tau \mathrm{I/A}]$, with τ ranging from 1 to 3 years. At the beginning of each month t, we calculate $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ by combining the three most recent predictors (winsorized at the 1–99% level) with the average cross-sectional regression slopes. The most recent predictors, $\log(q)$ and Cop, are from the most recent fiscal year ending at least four months ago as of month t, and dRoe uses the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ are estimated from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $\mathrm{d}^\tau \mathrm{I/A}$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly. For instance, for $\tau = 1$, the regressors used in the latest monthly cross-sectional regression are further lagged by 12 months relative to the most recent predictors used in calculating $E_t[\mathrm{d}^1 \mathrm{I/A}]$. Cross-sectional regressions are estimated via weighted least squares with the market equity as the weights. At the beginning of each month t, we sort all stocks into deciles based on the NYSE breakpoints of the ranked $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ values, and compute value-weighted decile returns for the current month t. The deciles are rebalanced at the beginning of month $t+1$. For each decile and the high-minus-low decile, we report the average excess return, $\overline{R}$, and the q-factor alpha, α_q, as well as their heteroscedasticity-and-autocorrelation-adjusted t-statistics (beneath the corresponding estimates).

τ	Low	2	3	4	5	6	7	8	9	High	H−L
					Panel A: Average excess returns, $\overline{R}$						
1	−0.20	0.21	0.31	0.45	0.46	0.48	0.55	0.69	0.75	0.92	1.12
	−0.66	0.87	1.39	2.03	2.20	2.53	2.77	3.59	4.12	4.68	6.55
2	−0.20	0.15	0.31	0.41	0.43	0.59	0.58	0.68	0.65	1.11	1.30
	−0.68	0.61	1.43	1.90	2.05	3.04	2.98	3.65	3.37	5.23	7.99
3	−0.17	0.14	0.37	0.33	0.51	0.63	0.56	0.64	0.82	1.13	1.30
	−0.60	0.58	1.66	1.54	2.48	3.16	2.82	3.33	4.12	5.08	7.40
					Panel B: The q-factor alphas, α_q						
1	−0.47	−0.19	−0.09	−0.07	0.06	−0.02	0.12	0.12	0.14	0.35	0.82
	−4.22	−2.00	−1.35	−0.70	0.58	−0.21	1.52	1.71	1.78	3.76	5.84
2	−0.38	−0.09	−0.15	−0.02	0.06	0.11	−0.02	0.07	0.19	0.45	0.82
	−3.82	−0.94	−1.63	−0.17	0.76	1.19	−0.29	0.92	2.15	4.30	5.46
3	−0.31	−0.21	−0.06	−0.01	−0.02	0.11	−0.03	0.08	0.32	0.54	0.85
	−3.16	−2.18	−0.69	−0.19	−0.18	1.43	−0.43	0.91	3.45	4.08	4.99

Table A.3 : Properties of the Expected Growth Factor Formed with Percentile Rankings, R^P_{Eg}, January 1967–December 2016, 600 Months

The percentile rankings of the log of Tobin's q, $\log(q)$, cash flows, Cop, and change in return on equity, dRoe, are used to form the expected 1-year-ahead investment-to-assets changes, $E_t[\mathrm{d}^1\mathrm{I/A}]$. At the beginning of month t, $E_t[\mathrm{d}^1\mathrm{I/A}]$ combines the most recent predictors (winsorized at the 1–99% level) with average Fama-MacBeth slopes. The most recent $\log(q)$ and Cop are from the most recent fiscal year ending at least four months ago as of month t, and dRoe uses the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[\mathrm{d}^\tau\mathrm{I/A}]$ are from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $\mathrm{d}^1\mathrm{I/A}$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged. The regressions are estimated via weighted least squares with the market equity as the weights. At the beginning of each month t, we use the median NYSE market equity to split stocks into two groups, small and big, based on the beginning-of-month market equity. Independently, we sort all stocks into three $E_t[\mathrm{d}^1\mathrm{I/A}]$ groups, low, median, and high, based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of its ranked values at the beginning of month t. Taking the intersections, we form six portfolios. We calculate value-weighted portfolio returns for the current month t, and rebalance the portfolios at the beginning of month $t+1$. The expected growth factor, R^P_{Eg}, is the difference (high-minus-low), each month, between the simple average of the returns on the two high $E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios and the simple average of the returns on the two low $E_t[\mathrm{d}^1\mathrm{I/A}]$ portfolios. Panel A reports for the expected growth factor, R^P_{Eg}, its average return, $\overline{R}^P_{\mathrm{Eg}}$, and alphas, factor loadings, and R^2s from the single factor model with only the benchmark expected growth factor, R_{Eg}, from the q-factor model, and the q-factor model augmented with the benchmark R_{Eg}. The t-values adjusted for heteroscedasticity and autocorrelations are in parentheses. The panel also reports for the benchmark R_{Eg}, its average return, and alphas, factor loadings, and R^2s from the single factor model with only the alternative expected growth factor, R^P_{Eg}, and the q-factor model augmented with R^P_{Eg}. Panel B reports the correlations of R^P_{Eg} with other factors.

Panel A: Properties of the expected growth factors, R^P_{Eg} and R_{Eg}

$\overline{R}^P_{\mathrm{Eg}}$	α	β_{Eg}	R^2			
0.91	0.14	0.94	0.77			
(10.30)	(2.64)	(28.08)				
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	R^2	
	0.60	−0.07	−0.07	0.29	0.46	0.58	
	(8.74)	(−4.22)	(−2.31)	(6.39)	(13.14)		
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
	0.13	0.01	−0.00	0.11	0.23	0.74	0.83
	(3.33)	(0.57)	(−0.26)	(3.45)	(6.60)	(22.52)	
$\overline{R}_{\mathrm{Eg}}$	α	β^P_{Eg}	R^2				
0.82	0.08	0.82	0.77				
(9.81)	(1.27)	(20.08)					
	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β^P_{Eg}	R^2
	0.15	−0.05	−0.03	0.02	−0.06	0.80	0.79
	(2.69)	(−3.85)	(−1.91)	(0.52)	(−2.71)	(17.14)	

Panel B: Correlations of R^P_{Eg} with other factors

R_{Eg}	R_{Mkt}	R_{Me}	$R_{\mathrm{I/A}}$	R_{Roe}
0.87	−0.41	−0.37	0.37	0.65

Table A.4 : Properties of Deciles on the Expected Growth Formed with the Composite Score That Aggregates $\log(q)$, Cop, and dRoe, January 1967–December 2016, 600 Months

We form the composite score that aggregates the log of Tobin's q, $\log(q)$, cash flow, Cop, and the change in return on equity, dRoe. For each portfolio formation month, we form the composite measure by equal-weighting a stock's percentile rankings across the three variables (each of which is realigned to yield a positive slope in forecasting returns). At the beginning of each month t, we sort all stocks into deciles based on the NYSE breakpoints of the composite score, and compute value-weighted decile returns for the current month t. The deciles are rebalanced at the beginning of month $t+1$. For each decile and the high-minus-low decile, we report the average excess return, $\overline{R}$, and the q-factor alpha, α_q, as well as their heteroscedasticity-and-autocorrelation-adjusted t-values (beneath the corresponding estimates).

Low	2	3	4	5	6	7	8	9	High	H−L
				Panel A: Average excess returns, $\overline{R}$						
−0.03	0.32	0.40	0.47	0.56	0.60	0.69	0.79	0.84	1.18	1.21
−0.11	1.42	1.88	2.38	2.72	3.19	3.70	4.11	4.35	5.43	7.22
				Panel B: The q-factor alphas, α_q						
−0.19	−0.08	−0.07	−0.01	0.00	0.04	0.17	0.07	0.10	0.54	0.73
−1.86	−1.08	−0.88	−0.10	0.04	0.49	1.80	0.70	1.03	4.55	4.24

Table A.5 : Properties of the Expected Growth Factor Formed with the Composite Score That Aggregates $\log(q)$, Cop, and dRoe, R^C_{Eg}, January 1967–December 2016, 600 Months

We form the composite score across the log of Tobin's q, $\log(q)$, cash flow, Cop, and the change in return on equity, dRoe. For each portfolio formation month, we form the composite score by equal-weighting a stock's percentile rankings across the three variables (each realigned to yield a positive slope in forecasting returns). At the beginning of each month t, we use the median NYSE market equity to split stocks into two groups, small and big, based on the beginning-of-month market equity. Independently, we sort all stocks into three groups, low, median, and high, based on the NYSE breakpoints for the low 30%, middle 40%, and high 30% of the ranked values of the composite score at the beginning of month t. Taking the intersections, we form six portfolios. We calculate value-weighted portfolio returns for the current month t, and rebalance the portfolios at the beginning of month $t+1$. The expected growth factor, R^C_{Eg}, is the difference (high-minus-low), each month, between the simple average of the returns on the two high composite score portfolios and the simple average of the returns on the two low composite score portfolios. Panel A reports for the expected growth factor, R^C_{Eg}, its average return, $\overline{R}^C_{\text{Eg}}$, and alphas, factor loadings, and R^2s from the single factor model with only the benchmark expected growth factor, R_{Eg}, from the q-factor model, and the q-factor model augmented with the benchmark R_{Eg}. The t-values adjusted for heteroscedasticity and autocorrelations are in parentheses. The panel also reports for the benchmark R_{Eg}, its average return, and alphas, factor loadings, and R^2s from the single factor model with only the alternative expected growth factor, R^C_{Eg}, and the q-factor model augmented with R^C_{Eg}. Panel B reports the correlations of R^C_{Eg} with other factors.

Panel A: Properties of the expected growth factors, R^C_{Eg} and R_{Eg}

$\overline{R}^C_{\text{Eg}}$	α	β_{Eg}	R^2				
0.89	0.28	0.75	0.43				
(9.51)	(3.27)	(11.17)					
	α	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	R^2	
	0.46	−0.03	0.03	0.67	0.30	0.50	
	(6.27)	(−1.64)	(1.13)	(11.90)	(6.63)		
	α	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
	0.13	0.02	0.07	0.54	0.14	0.52	0.61
	(1.98)	(1.25)	(3.35)	(10.93)	(2.65)	(10.66)	
$\overline{R}_{\text{Eg}}$	α	β^C_{Eg}	R^2				
0.82	0.31	0.57	0.43				
(9.81)	(4.25)	(16.98)					
	α	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β^C_{Eg}	R^2
	0.44	−0.09	−0.10	−0.03	0.18	0.42	0.59
	(5.94)	(−5.65)	(−4.52)	(−0.53)	(6.44)	(7.87)	

Panel B: Correlations of R^C_{Eg} with other factors

R_{Eg}	R_{Mkt}	R_{Me}	$R_{\text{I/A}}$	R_{Roe}
0.66	−0.35	−0.17	0.61	0.37

Table A.6 : Explaining the Average Returns Across the Expected Growth Deciles with the q^5 Model, January 1967–December 2016, 600 Months

We use the log of Tobin's q, $\log(q)$, cash flow, Cop, and the change in return on equity, dRoe, to form the expected investment-to-assets changes, $E_t[\mathrm{d}^\tau \mathrm{I/A}]$, with τ ranging from 1 to 3 years. At the beginning of each month t, we calculate $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ by combining the three most recent predictors (winsorized at the 1–99% level) with the average cross-sectional slopes. The most recent predictors, $\log(q)$ and Cop, are from the most recent fiscal year ending at least four months ago as of month t, and dRoe uses the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The slopes in calculating $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ are estimated from the prior 120-month rolling window (30 months minimum), in which $\mathrm{d}^\tau \mathrm{I/A}$ uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged accordingly. For instance, for $\tau = 1$, the regressors used in the latest monthly cross-sectional regression are further lagged by 12 months relative to the most recent predictors used in calculating $E_t[\mathrm{d}^1 \mathrm{I/A}]$. Cross-sectional regressions are estimated via weighted least squares with the market equity as weights. At the beginning of each month t, we sort all stocks into deciles based on the NYSE breakpoints of the ranked $E_t[\mathrm{d}^\tau \mathrm{I/A}]$ values, and compute value-weighted decile returns for the current month t. The deciles are rebalanced at the beginning of month $t+1$. For each decile and the high-minus-low decile, we report the q^5-factor regressions, including the intercept, α_{q^5}, and the loadings on the market, size, investment, Roe, and expected growth factors ($\beta_{\mathrm{Mkt}}, \beta_{\mathrm{Me}}, \beta_{\mathrm{I/A}}, \beta_{\mathrm{Roe}}$, and β_{Eg}, respectively). The t-values are adjusted for heteroscedasticity and autocorrelations. $\overline{|\alpha_{q^5}|}$ is the mean absolute alpha for a given set of deciles, and p_{q^5} the p-value from the GRS test on the null that the alphas across the deciles are jointly zero.

	Low	2	3	4	5	6	7	8	9	High	H−L
	Panel A: $\tau = 1$ ($\overline{|\alpha_{q^5}|} = 0.09$ and $p_{q^5} = 0.04$)										
α_{q^5}	0.06	0.25	0.12	0.07	−0.04	0.07	0.12	0.05	−0.02	−0.06	−0.13
β_{Mkt}	1.10	1.03	1.05	1.04	0.99	0.97	0.96	1.03	1.01	1.05	−0.05
β_{Me}	0.22	0.07	0.04	−0.02	−0.05	−0.09	−0.07	−0.12	−0.01	0.06	−0.17
$\beta_{\mathrm{I/A}}$	−0.36	−0.02	0.08	0.05	0.29	0.06	0.01	−0.10	−0.20	−0.42	−0.07
β_{Roe}	−0.10	0.19	0.12	0.06	0.08	0.05	0.03	−0.11	0.02	−0.01	0.09
β_{Eg}	−0.74	−0.77	−0.53	−0.23	−0.19	−0.10	−0.05	0.26	0.41	0.78	1.52
t_{q^5}	0.69	3.09	1.40	0.75	−0.39	0.82	1.40	0.47	−0.25	−0.73	−1.28
t_{Mkt}	48.12	50.95	45.08	48.58	33.40	42.22	48.38	40.87	57.16	51.98	−1.62
t_{Me}	6.55	1.84	1.41	−0.42	−1.27	−1.65	−2.43	−3.35	−0.47	1.37	−3.14
$t_{\mathrm{I/A}}$	−5.56	−0.34	1.57	1.13	4.11	0.79	0.11	−1.04	−2.98	−6.84	−0.98
t_{Roe}	−2.31	3.40	2.51	1.51	1.28	0.97	0.69	−1.42	0.42	−0.29	2.09
t_{Eg}	−10.73	−11.68	−7.93	−3.83	−2.85	−1.64	−0.72	5.15	7.33	12.39	23.97

	Low	2	3	4	5	6	7	8	9	High	H−L
					Panel B: $\tau = 2$ ($\overline{\lvert\alpha_{q^5}\rvert} = 0.09$ and $p_{q^5} = 0.12$)						
α_{q^5}	0.12	0.18	0.06	−0.12	0.02	0.07	−0.06	−0.08	−0.09	0.10	−0.02
β_{Mkt}	1.12	1.02	1.06	1.04	0.96	0.96	0.98	1.02	0.99	1.06	−0.05
β_{Me}	0.12	0.07	−0.12	0.01	−0.05	−0.03	−0.03	0.04	0.04	0.11	−0.01
$\beta_{\mathrm{I/A}}$	−0.43	−0.22	−0.16	0.12	0.12	0.15	0.16	0.11	−0.24	−0.29	0.14
β_{Roe}	0.00	0.15	0.00	0.15	0.20	0.06	0.14	−0.01	−0.09	−0.10	−0.10
β_{Eg}	−0.71	−0.50	−0.30	−0.14	−0.18	0.01	0.08	0.40	0.51	0.75	1.46
t_{q^5}	1.37	2.33	0.69	−1.60	0.21	0.80	−0.78	−0.75	−0.92	0.90	−0.18
t_{Mkt}	42.58	45.66	31.29	51.93	42.29	45.87	48.50	42.93	39.64	46.79	−1.39
t_{Me}	3.46	2.01	−1.92	0.29	−1.52	−1.12	−0.84	0.75	1.01	1.92	−0.15
$t_{\mathrm{I/A}}$	−7.12	−4.25	−2.29	2.39	1.98	2.06	2.77	1.18	−3.48	−2.61	1.12
t_{Roe}	−0.01	2.87	0.02	4.21	4.58	1.13	2.87	−0.11	−1.38	−1.42	−0.98
t_{Eg}	−10.64	−8.46	−4.05	−2.30	−2.82	0.13	1.42	5.63	7.29	9.37	16.87
					Panel C: $\tau = 3$ ($\overline{\lvert\alpha_{q^5}\rvert} = 0.09$ and $p_{q^5} = 0.09$)						
α_{q^5}	0.05	0.16	−0.05	−0.10	0.00	−0.15	0.13	−0.13	−0.01	0.09	0.04
β_{Mkt}	1.10	1.05	1.05	1.01	0.95	1.00	0.98	1.02	1.02	1.05	−0.05
β_{Me}	0.13	−0.04	−0.05	0.01	−0.02	−0.09	0.04	0.08	0.07	0.14	0.01
$\beta_{\mathrm{I/A}}$	−0.44	−0.26	0.02	0.10	0.10	0.18	0.06	−0.02	−0.09	−0.24	0.21
β_{Roe}	0.13	0.10	0.14	0.23	0.16	0.13	0.06	−0.12	−0.05	−0.20	−0.33
β_{Eg}	−0.68	−0.43	−0.25	−0.19	−0.07	0.09	0.11	0.44	0.51	0.81	1.49
t_{q^5}	0.54	1.89	−0.61	−1.25	0.05	−1.52	1.47	−1.38	−0.09	0.80	0.31
t_{Mkt}	44.10	38.08	40.87	47.02	46.28	49.00	37.41	45.88	37.30	39.82	−1.44
t_{Me}	3.66	−0.86	−0.97	0.39	−0.73	−1.86	0.93	1.55	1.48	2.66	0.21
$t_{\mathrm{I/A}}$	−7.46	−3.98	0.31	1.55	1.81	2.09	0.92	−0.22	−1.07	−1.90	1.47
t_{Roe}	2.12	2.12	2.50	5.57	3.19	2.00	1.54	−2.13	−0.70	−2.73	−3.34
t_{Eg}	−10.10	−6.85	−3.72	−2.90	−0.96	1.39	1.77	4.88	7.48	9.37	15.86

Table A.7 : Overall Performance of Factor Models, Subsample Analysis, January 1967–December 2016, 600 Months

For each model, $\overline{|\alpha_{\mathrm{H-L}}|}$ is the average magnitude of the high-minus-low alphas, $\#_{|t|\geq 1.96}$ the number of the high-minus-low alphas with $|t| \geq 1.96$, $\#_{|t|\geq 3}$ the number of the high-minus-low alphas with $|t| \geq 3$, $\overline{|\alpha|}$ the mean absolute alpha across the anomaly deciles in a given category, and $\#_{p<5\%}$ the number of sets of deciles within a given category, with which the factor model is rejected by the GRS test at the 5% level. We report the results for the q-factor model (q), the q^5 model (q^5), the Fama-French (2015) 5-factor model (FF5), the Fama-French (2018) 6-factor model with RMW (FF6), the Fama-French alternative 6-factor model with RMWc (FF6c), the Barillas-Shanken (2018) 6-factor model (BS6), the Stambaugh-Yuan (2017) model (SY4), and the Daniel-Hirshleifer-Sun (2018) model (DHS).

	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq 1.96}$	$\#_{\lvert t\rvert\geq 3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$
Panel A: January 1967–December 1991																				
	All (147)					Momentum (33)					Value-versus-growth (28)					Investment (28)				
q	0.30	36	10	0.13	59	0.24	5	3	0.12	14	0.49	10	4	0.18	19	0.18	7	1	0.10	13
q^5	0.28	22	2	0.14	62	0.35	6	0	0.16	16	0.30	6	0	0.16	13	0.14	1	0	0.12	14
FF5	0.46	72	39	0.13	61	0.86	31	21	0.20	28	0.24	7	0	0.09	5	0.16	1	0	0.08	3
FF6	0.32	50	23	0.11	35	0.42	16	11	0.13	14	0.20	2	1	0.09	6	0.11	0	0	0.08	1
FF6c	0.29	43	17	0.12	42	0.35	14	6	0.13	15	0.19	3	1	0.10	6	0.10	0	0	0.08	5
BS6	0.30	40	9	0.14	83	0.28	7	3	0.14	19	0.38	13	3	0.14	18	0.15	1	0	0.12	20
SY4	0.30	46	16	0.12	46	0.34	11	5	0.12	13	0.26	5	2	0.13	8	0.13	1	0	0.08	2
DHS	0.54	66	36	0.21	98	0.43	12	3	0.25	29	1.03	25	20	0.30	25	0.30	8	3	0.14	17
						Profitability (32)					Intangibles (23)					Trading frictions (3)				
q						0.20	5	0	0.11	5	0.44	9	2	0.15	7	0.16	0	0	0.10	1
q^5						0.22	5	0	0.13	11	0.42	4	2	0.15	7	0.11	0	0	0.10	1
FF5						0.58	24	14	0.16	18	0.38	9	4	0.13	6	0.14	0	0	0.08	1
FF6						0.44	21	8	0.13	10	0.41	11	3	0.13	4	0.10	0	0	0.09	0
FF6c						0.40	14	6	0.13	12	0.45	12	4	0.14	4	0.12	0	0	0.09	0
BS6						0.34	13	1	0.14	15	0.34	6	2	0.16	10	0.20	0	0	0.09	1
SY4						0.39	19	6	0.15	19	0.39	9	3	0.12	4	0.19	1	0	0.10	0
DHS						0.38	10	2	0.16	15	0.64	8	7	0.20	11	0.62	3	1	0.23	1

	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq1.96}$	$\#_{\lvert t\rvert\geq3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq1.96}$	$\#_{\lvert t\rvert\geq3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq1.96}$	$\#_{\lvert t\rvert\geq3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$	$\overline{\lvert\alpha_{\mathrm{H-L}}\rvert}$	$\#_{\lvert t\rvert\geq1.96}$	$\#_{\lvert t\rvert\geq3}$	$\overline{\lvert\alpha\rvert}$	$\#_{p<5\%}$
	Panel B: January 1992–December 2016																			
	All (158)					Momentum (36)					Value-versus-growth (29)					Investment (28)				
q	0.27	33	8	0.13	63	0.21	2	0	0.12	13	0.19	1	0	0.11	8	0.23	6	0	0.12	10
q^5	0.21	9	1	0.12	25	0.19	3	0	0.11	5	0.25	0	0	0.13	7	0.13	0	0	0.10	4
FF5	0.34	53	16	0.13	52	0.46	14	2	0.14	14	0.12	1	0	0.10	5	0.27	7	2	0.11	3
FF6	0.27	35	14	0.12	43	0.20	4	0	0.12	7	0.18	2	1	0.10	4	0.25	6	2	0.11	5
FF6c	0.26	31	12	0.12	29	0.20	3	0	0.11	3	0.17	1	1	0.09	3	0.24	4	1	0.10	3
BS6	0.27	38	15	0.14	83	0.21	4	0	0.13	18	0.17	1	0	0.10	9	0.24	6	2	0.13	10
SY4	0.26	34	6	0.13	57	0.22	4	0	0.12	13	0.28	6	1	0.13	10	0.20	4	0	0.11	7
DHS	0.38	47	8	0.15	57	0.22	2	0	0.15	15	0.64	21	3	0.20	15	0.32	6	0	0.12	6
						Profitability (35)					Intangibles (26)					Trading frictions (4)				
q						0.29	14	4	0.13	18	0.45	9	4	0.19	12	0.29	1	0	0.11	2
q^5						0.16	1	0	0.11	3	0.36	4	1	0.15	5	0.24	1	0	0.11	1
FF5						0.40	17	10	0.13	19	0.44	12	2	0.18	10	0.30	2	0	0.10	1
FF6						0.30	12	6	0.11	15	0.43	9	5	0.18	11	0.28	2	0	0.09	1
FF6c						0.27	12	5	0.11	11	0.45	10	5	0.18	8	0.26	1	0	0.09	1
BS6						0.31	14	10	0.14	29	0.44	11	3	0.20	14	0.28	2	0	0.11	3
SY4						0.29	11	4	0.12	17	0.35	8	1	0.16	8	0.24	1	0	0.10	2
DHS						0.21	6	0	0.10	8	0.60	10	5	0.20	10	0.41	2	0	0.16	3

Table A.8 : Explaining Composite Anomalies, Subsample Analysis, January 1967–December 2016, 600 Months

We form composite scores across all the 158 anomalies (All) and across each category of anomalies, including momentum (Mom), value-versus-growth (VvG), investment (Inv), profitability (Prof), intangibles (Intan), and trading frictions (Fric). For a given set of anomalies, we construct the composite score by equal-weighting a stock's percentile ranking for each anomaly (realigned to yield a positive slope in forecasting returns). At the beginning of each month t, we split stocks into deciles based on the NYSE breakpoints of the composite scores, and calculate value-weighted returns for month t. The deciles are rebalanced at the beginning of month $t+1$. For each model and each set of deciles, we report the high-minus-low alpha (Panel A), its t-value (Panel B), the mean absolute alpha (Panel C), and the GRS p-value (Panel D). We report the results for the q-factor model (q), the q^5 model (q^5), the Fama-French (2015) 5-factor model (FF5), the Fama-French (2018) 6-factor model (FF6), the Fama-French alternative 6-factor model with RMWc (FF6c), the Barillas-Shanken (2018) 6-factor model (BS6), the Stambaugh-Yuan (2017) model (SY4), and the Daniel-Hirshleifer-Sun (2018) model (DHS). For the q^5 model, Panel E shows the loadings on the market, size, investment, Roe, and expected growth factors ($\beta_{\mathrm{Mkt}}, \beta_{\mathrm{Me}}, \beta_{\mathrm{I/A}}, \beta_{\mathrm{Roe}}$, and β_{Eg}, respectively) and their t-values. The t-values are adjusted for heteroscedasticity and autocorrelations.

Panel A: January 1967–December 1991

	All	Mom	VvG	Inv	Prof	Intan	Fric		All	Mom	VvG	Inv	Prof	Intan	Fric
$\overline{R}$	1.83	1.48	0.68	0.67	0.88	1.18	0.25	$t_{\overline{R}}$	8.71	4.58	2.37	3.52	4.05	5.72	1.58
	The high-minus-low alpha, $\alpha_{\mathrm{H-L}}$								$t_{\mathrm{H-L}}$						
q	0.80	0.27	0.61	0.18	0.21	0.93	0.04		4.02	0.76	2.50	1.30	1.19	3.75	0.30
q^5	0.19	−0.41	0.35	−0.05	−0.02	0.78	0.00		1.04	−1.22	1.30	−0.28	−0.09	3.36	0.01
FF5	1.24	1.65	−0.23	0.26	0.73	0.75	0.10		6.22	4.43	−1.31	2.12	4.32	3.60	0.95
FF6	0.82	0.65	−0.06	0.17	0.54	0.76	0.04		5.01	3.56	−0.36	1.37	3.15	3.60	0.37
FF6c	0.71	0.50	−0.06	0.11	0.51	0.85	0.00		4.27	2.57	−0.31	0.83	2.77	3.91	0.02
BS6	0.27	0.21	−0.45	−0.06	0.43	0.46	0.03		1.52	0.98	−2.53	−0.43	2.63	1.99	0.25
SY4	0.74	0.39	0.30	0.03	0.34	0.80	0.08		4.29	1.31	1.28	0.20	2.16	3.86	0.64
DHS	0.83	−0.69	1.34	0.36	−0.21	1.26	0.65		3.79	−2.40	4.55	2.22	−0.98	4.53	3.25
	The mean absolute alpha, $\overline{\lvert\alpha\rvert}$								The GRS p-value, p_{GRS}						
q	0.17	0.09	0.23	0.07	0.07	0.25	0.11		0.00	0.32	0.00	0.10	0.22	0.00	0.01
q^5	0.13	0.17	0.19	0.10	0.09	0.23	0.12		0.01	0.28	0.00	0.08	0.32	0.01	0.01
FF5	0.26	0.34	0.10	0.08	0.17	0.21	0.09		0.00	0.00	0.02	0.27	0.00	0.00	0.01
FF6	0.16	0.13	0.09	0.07	0.15	0.23	0.10		0.00	0.01	0.06	0.49	0.02	0.00	0.00
FF6c	0.14	0.13	0.11	0.08	0.16	0.24	0.12		0.00	0.01	0.03	0.40	0.02	0.00	0.00
BS6	0.13	0.10	0.13	0.10	0.09	0.14	0.12		0.00	0.05	0.01	0.06	0.10	0.13	0.00
SY4	0.14	0.11	0.16	0.09	0.13	0.23	0.11		0.00	0.05	0.01	0.17	0.03	0.00	0.00
DHS	0.16	0.24	0.39	0.13	0.14	0.32	0.15		0.00	0.00	0.00	0.00	0.09	0.00	0.01
	The q^5 factor loadings														
β_{Mkt}	0.04	0.05	0.08	−0.03	0.02	−0.09	−0.06	t_{Mkt}	0.89	0.64	1.34	−0.90	0.44	−1.94	−1.44
β_{Me}	0.33	−0.06	0.46	0.07	−0.03	0.43	0.77	t_{Me}	4.89	−0.45	4.35	1.13	−0.58	6.24	16.35
$\beta_{\mathrm{I/A}}$	0.78	0.11	0.89	1.00	−0.34	0.10	0.00	$t_{\mathrm{I/A}}$	6.56	0.57	6.17	10.61	−3.82	0.59	−0.05
β_{Roe}	0.13	0.97	−1.06	−0.25	0.99	−0.03	−0.07	t_{Roe}	1.03	5.65	−7.74	−3.49	11.00	−0.20	−0.88
β_{Eg}	1.08	1.21	0.45	0.39	0.40	0.27	0.07	t_{Eg}	7.97	5.36	2.47	3.68	3.39	1.61	0.69

Panel A: January 1992–December 2016															
	All	Mom	VvG	Inv	Prof	Intan	Fric		All	Mom	VvG	Inv	Prof	Intan	Fric
$\overline{R}$	1.41	0.63	0.80	0.74	0.78	0.98	0.44	$t_{\overline{R}}$	4.98	1.49	2.59	3.39	2.64	3.60	2.43
The high-minus-low alpha, $\alpha_{\mathrm{H-L}}$								$t_{\mathrm{H-L}}$							
q	0.78	0.09	0.28	0.37	0.40	0.40	0.35		3.72	0.19	0.99	2.66	2.24	2.14	1.91
q^5	0.48	−0.17	0.45	0.14	−0.07	0.38	0.38		2.46	−0.37	1.69	1.00	−0.45	2.07	1.91
FF5	1.06	0.78	0.12	0.36	0.61	0.44	0.35		4.84	1.65	0.68	2.55	3.27	2.68	2.03
FF6	0.77	0.02	0.26	0.35	0.45	0.41	0.36		4.26	0.10	1.52	2.44	2.52	2.56	2.08
FF6c	0.75	0.04	0.20	0.34	0.41	0.48	0.32		4.15	0.16	1.19	2.26	1.92	2.86	1.90
BS6	0.65	0.01	0.06	0.35	0.44	0.28	0.32		3.16	0.06	0.30	2.51	2.54	1.54	1.76
SY4	0.79	0.06	0.49	0.21	0.49	0.40	0.36		4.33	0.18	2.04	1.34	2.35	2.42	2.05
DHS	1.02	−0.21	0.90	0.62	0.28	0.85	0.51		4.93	−0.70	3.39	2.96	1.32	3.39	2.72
The mean absolute alpha, $\overline{\lvert\alpha\rvert}$								The GRS p-value, p_{GRS}							
q	0.18	0.12	0.08	0.14	0.12	0.19	0.13		0.01	0.53	0.79	0.02	0.08	0.00	0.03
q^5	0.11	0.10	0.11	0.10	0.09	0.16	0.12		0.47	0.65	0.42	0.32	0.52	0.01	0.08
FF5	0.22	0.21	0.07	0.13	0.13	0.17	0.13		0.00	0.32	0.89	0.01	0.05	0.00	0.04
FF6	0.16	0.11	0.06	0.12	0.11	0.17	0.13		0.00	0.60	0.88	0.01	0.15	0.00	0.03
FF6c	0.14	0.12	0.05	0.11	0.10	0.17	0.13		0.02	0.33	0.97	0.02	0.43	0.00	0.11
BS6	0.16	0.11	0.06	0.14	0.13	0.18	0.14		0.02	0.63	0.90	0.01	0.02	0.00	0.01
SY4	0.17	0.12	0.15	0.12	0.13	0.17	0.13		0.00	0.34	0.45	0.04	0.06	0.00	0.04
DHS	0.24	0.15	0.25	0.18	0.10	0.27	0.17		0.00	0.20	0.11	0.01	0.47	0.00	0.00
The q^5 factor loadings															
β_{Mkt}	−0.09	−0.14	0.08	−0.02	0.03	−0.10	−0.02	t_{Mkt}	−1.57	−1.04	0.86	−0.39	0.56	−1.49	−0.43
β_{Me}	0.38	0.62	0.25	−0.05	−0.05	0.45	0.34	t_{Me}	5.22	2.37	1.61	−1.13	−1.05	3.98	3.52
$\beta_{\mathrm{I/A}}$	0.69	−0.41	1.39	1.36	−0.35	1.12	0.01	$t_{\mathrm{I/A}}$	4.69	−1.14	8.08	14.47	−3.56	9.60	0.05
β_{Roe}	0.83	1.37	−0.07	−0.15	1.11	0.38	0.01	t_{Roe}	7.12	4.75	−0.37	−1.58	12.10	3.58	0.06
β_{Eg}	0.48	0.42	−0.27	0.37	0.76	0.03	−0.04	t_{Eg}	3.54	1.46	−1.37	3.88	6.79	0.29	−0.32