q^5

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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.

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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:

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

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, $R_{\text{I/A}}$, 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:

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

in which $E[R_{\text{Mkt}}], E[R_{\text{Me}}], E[R_{\text{I/A}}]$, $E[R_{\text{Roe}}]$, and $E[R_{\text{Eg}}]$ are the expected factor premiums, and β^i_{Mkt}, β^i_{Me}, $\beta^i_{\text{I/A}}$, 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, $E_t[\text{d}^1\text{I/A}]$, 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 $E_t[\text{d}^2\text{I/A}]$ and $E_t[\text{d}^3\text{I/A}]$ deciles. The q^5 alphas of the high-minus-low $E_t[\text{d}^2\text{I/A}]$ and $E_t[\text{d}^3\text{I/A}]$ 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, $\text{Bm}^{\text{q}}12$, 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 $\text{Bm}^{\text{q}}12$ 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 $\text{Bm}^{\text{q}}12$ 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$^{\rm q}$, 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$^{\rm q}$, 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$^{\rm q}$ 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$^{\rm q}$), 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 Ole$^{\rm 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$^{\rm q}$) 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 $\mathrm{Ato}^{\mathrm{q}}$ 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 $\mathrm{Ola}^{\mathrm{q}}$ 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 $\mathrm{Rdm}^{\mathrm{q}}$ 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 $\mathrm{Rdm}^{\mathrm{q}}$ 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: $\log(q)$

τ	$\log(q)$	R^2	Pearson	Rank
1	0.021	1.03	0.014	0.002
	(4.91)		[0.01]	[0.62]
2	−0.006	1.15	0.028	0.042
	(−1.13)		[0.00]	[0.00]
3	−0.018	1.18	0.089	0.104
	(−3.56)		[0.00]	[0.00]

Panel B: Cop

τ	Cop	R^2	Pearson	Rank
1	0.427	3.13	0.146	0.180
	(13.31)		[0.00]	[0.00]
2	0.469	4.10	0.134	0.158
	(12.19)		[0.00]	[0.00]
3	0.449	3.97	0.117	0.133
	(10.66)		[0.00]	[0.00]

Panel C: dRoe

τ	dRoe	R^2	Pearson	Rank
1	0.824	2.23	0.072	0.135
	(7.98)		[0.00]	[0.00]
2	0.973	2.00	0.073	0.158
	(9.99)		[0.00]	[0.00]
3	0.772	1.57	0.060	0.133
	(8.49)		[0.00]	[0.00]

Panel D: $\log(q)$, Cop, and dRoe

τ	$\log(q)$	Cop	dRoe	R^2	Pearson	Rank
1	−0.031	0.530	0.802	6.64	0.142	0.213
	(−5.86)	(12.82)	(7.75)		[0.00]	[0.00]
2	−0.076	0.722	0.930	8.88	0.156	0.226
	(−10.09)	(12.58)	(10.25)		[0.00]	[0.00]
3	−0.093	0.760	0.743	9.18	0.158	0.221
	(−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^{q}12	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^{q}1	Quarterly earnings-to-price (1-month holding period)	Ep^{q}6	Quarterly earnings-to-price (6-month holding period)
Ep^{q}12	Quarterly earnings-to-price (12-month holding period)	Cp	Cash flow-to-price, Lakonishok, Shleifer, and Vishny (1994)
Cp^{q}1	Quarterly Cash flow-to-price (1-month holding period)	Cp^{q}6	Quarterly Cash flow-to-price (6-month holding period)
Cp^{q}12	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^{q}1	Quarterly enterprise multiple (1-month holding period)
Em^{q}6	Quarterly enterprise multiple (6-month holding period)	Em^{q}12	Quarterly enterprise multiple (12-month holding period)
Sp	Sales-to-price, Barbee, Mukherji, and Raines (1996)	Sp^{q}1	Quarterly sales-to-price (1-month holding period)
Sp^{q}6	Quarterly sales-to-price (6-month holding period)	Sp^{q}12	Quarterly sales-to-price (12-month holding period)
Ocp	Operating cash flow-to-price, Desai, Rajgopal, and Venkatachalam (2004)	Ocp^{q}1	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^{q}6	Quarterly investment-to-assets (6-month holding period)	Ia^{q}12	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)

$\mathrm{F}^{\mathrm{q}}6$	Quarterly F-score (6-month holding period)	$\mathrm{F}^{\mathrm{q}}12$	Quarterly F-score (12-month holding period)
$\mathrm{Fp}^{\mathrm{q}}6$	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)
$\mathrm{Rdm}^{\mathrm{q}}1$	Quarterly R&D-to-market (1-month holding period)	$\mathrm{Rdm}^{\mathrm{q}}6$	Quarterly R&D-to-market (6-month holding period)
$\mathrm{Rdm}^{\mathrm{q}}12$	Quarterly R&D-to-market (12-month holding period)	Ol	Operating leverage, Novy-Marx (2011)
$\mathrm{Ol}^{\mathrm{q}}1$	Quarterly operating leverage (1-month holding period)	$\mathrm{Ol}^{\mathrm{q}}6$	Quarterly operating leverage (6-month holding period)
$\mathrm{Ol}^{\mathrm{q}}12$	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)
$\mathrm{Alm}^{\mathrm{q}}1$	Quarterly asset liquidity (market assets) (1-month holding period)	$\mathrm{Alm}^{\mathrm{q}}6$	Quarterly asset liquidity (market assets) (6-month holding period)
$\mathrm{Alm}^{\mathrm{q}}12$	Quarterly asset liquidity (market assets) (12-month holding period)	R_{a}^{1}	12-month-lagged return, Heston and Sadka (2008)
$R_{\mathrm{a}}^{[2,5]}$	Years 2–5 lagged returns, annual Heston and Sadka (2008)	$R_{\mathrm{n}}^{[2,5]}$	Years 2–5 lagged returns, nonannual Heston and Sadka (2008)
$R_{\mathrm{a}}^{[6,10]}$	Years 6–10 lagged returns, annual Heston and Sadka (2008)	$R_{\mathrm{n}}^{[6,10]}$	Years 6–10 lagged returns, nonannual Heston and Sadka (2008)
$R_{\mathrm{a}}^{[11,15]}$	Years 11–15 lagged returns, annual Heston and Sadka (2008)	$R_{\mathrm{a}}^{[16,20]}$	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, $\overline{|\alpha_{\mathrm{H-L}}|}$ 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) 4-factor model (SY4), and the Daniel-Hirshleifer-Sun (2018) 3-factor model (DHS).

	$\overline{\|\alpha_{\mathrm{H-L}}\|}$	$\#_{\|t\|\geq 1.96}$	$\#_{\|t\|\geq 3}$	$\overline{\|\alpha\|}$	$\#_{p<5\%}$	$\overline{\|\alpha_{\mathrm{H-L}}\|}$	$\#_{\|t\|\geq 1.96}$	$\#_{\|t\|\geq 3}$	$\overline{\|\alpha\|}$	$\#_{p<5\%}$	$\overline{\|\alpha_{\mathrm{H-L}}\|}$	$\#_{\|t\|\geq 1.96}$	$\#_{\|t\|\geq 3}$	$\overline{\|\alpha\|}$	$\#_{p<5\%}$	$\overline{\|\alpha_{\mathrm{H-L}}\|}$	$\#_{\|t\|\geq 1.96}$	$\#_{\|t\|\geq 3}$	$\overline{\|\alpha\|}$	$\#_{p<5\%}$
	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 ($\beta_{\mathrm{Mkt}}, \beta_{\mathrm{Me}}, \beta_{\mathrm{I/A}}, \beta_{\mathrm{Roe}}$, and β_{Eg}, respectively) and their t-values. The t-values are adjusted for heteroscedasticity and autocorrelations.

	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, $\alpha_{\mathrm{H-L}}$								Panel B: $t_{\mathrm{H-L}}$						
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
$\beta_{\mathrm{I/A}}$	0.81	−0.15	1.31	1.23	−0.35	0.79	0.01	$t_{\mathrm{I/A}}$	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 $\epsilon^6 6$	22 $\epsilon^6 12$	23 $\epsilon^{11} 1$	24 $\epsilon^{11} 6$	25 $\epsilon^{11} 12$	26 Sm1	27 Ilr1	28 Ilr6	29 Ilr12	30 Ile1	31 Cm1	32 Cm12	33 Sim1	34 Cim1	35 Cim6	36 Cim12	37 Bm	38 Bmj	39 $\mathrm{Bm}^q 12$	40 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 Rev12	42 Ep	43 Ep^{q1}	44 Ep^{q6}	45 Ep^{q12}	46 Cp	47 Cp^{q1}	48 Cp^{q6}	49 Cp^{q12}	50 Nop	51 Em	52 Em^{q1}	53 Em^{q6}	54 Em^{q12}	55 Sp	56 Sp^{q1}	57 Sp^{q6}	58 Sp^{q12}	59 Ocp	60 Ocp^{q1}
$\overline{R}$	−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 $\mathrm{Ia^q6}$	69 $\mathrm{Ia^q12}$	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	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
$\overline{R}$	−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^{q}1	103 Rna^{q}6	104 Ato^{q}1	105 Ato^{q}6	106 Ato^{q}12	107 Cto^{q}1	108 Cto^{q}6	109 Cto^{q}12	110 Gpa	111 Gla^{q}1	112 Gla^{q}6	113 Gla^{q}12	114 Ole^{q}1	115 Ole^{q}6	116 Opa	117 Ola^{q}1	118 Ola^{q}6	119 Ola^{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	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136	137	138	139	140
	Cla	Cla^{q}1	Cla^{q}6	Cla^{q}12	F^{q}1	F^{q}6	F^{q}12	Fp^{q}6	Oca	Ioca	Adm	Rdm	Rdm^{q}1	Rdm^{q}6	Rdm^{q}12	Ol	Ol^{q}1	Ol^{q}6	Ol^{q}12	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
	$\epsilon^6 6$	$\epsilon^6 12$	$\epsilon^{11} 1$	$\epsilon^{11} 6$	$\epsilon^{11} 12$	Sm1	Ilr1	Ilr6	Ilr12	Ile1	Cm1	Cm12	Sim1	Cim1	Cim6	Cim12	Bm	Bmj	$\mathrm{Bm}^q 12$	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	$\mathrm{Ep}^q 1$	$\mathrm{Ep}^q 6$	$\mathrm{Ep}^q 12$	Cp	$\mathrm{Cp}^q 1$	$\mathrm{Cp}^q 6$	$\mathrm{Cp}^q 12$	Nop	Em	$\mathrm{Em}^q 1$	$\mathrm{Em}^q 6$	$\mathrm{Em}^q 12$	Sp	$\mathrm{Sp}^q 1$	$\mathrm{Sp}^q 6$	$\mathrm{Sp}^q 12$	Ocp	$\mathrm{Ocp}^q 1$
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 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
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
$\beta_{\text{I/A}}$	−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
$t_{\text{I/A}}$	−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 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
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
$\beta_{\text{I/A}}$	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
$t_{\text{I/A}}$	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 dRoa6	102 Rna^{q}1	103 Rna^{q}6	104 Ato^{q}1	105 Ato^{q}6	106 Ato^{q}12	107 Cto^{q}1	108 Cto^{q}6	109 Cto^{q}12	110 Gpa	111 Gla^{q}1	112 Gla^{q}6	113 Gla^{q}12	114 Ole^{q}1	115 Ole^{q}6	116 Opa	117 Ola^{q}1	118 Ola^{q}6	119 Ola^{q}12	120 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
$\beta_{\text{I/A}}$	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
$t_{\text{I/A}}$	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 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
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 Etr	142 Rer	143 Eprd	144 Etl	145 Alm^{q}1	146 Alm^{q}6	147 Alm^{q}12	148 R^{1}_{a}	149 $R^{[2,5]}_{\mathrm{a}}$	150 $R^{[2,5]}_{\mathrm{n}}$	151 $R^{[6,10]}_{\mathrm{a}}$	152 $R^{[6,10]}_{\mathrm{n}}$	153 $R^{[11,15]}_{\mathrm{a}}$	154 $R^{[16,20]}_{\mathrm{a}}$	155 Sv1	156 Dtv12	157 Isff1	158 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