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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 q⁵-model, which augments the Hou-Xue-Zhang (2015) q-factor model with the new factor, shows strong explanatory power in the cross section, and outperforms other recently proposed factor models such as the Fama-French (2018) six-factor model.

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An online appendix is available at http://www.nber.org/data-appendix/w24709

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-toassets 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 compiled by Hou, Xue, and Zhang (2017). The competing factor models include the q-factor model, the Fama-French (2015) five-factor model, the Stambaugh-Yuan

(2017) four-factor model, the Fama-French (2018) six-factor model, the alternative six-factor model with the operating profitability factor, RMW, replaced by a cash-based profitability factor, RMWc, as well as the Barillas-Shanken (2018) six-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 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 well with other factor models. The average magnitude of the high-minus-low alphas is 0.28% per month in the Fama-French six-factor model (0.25% in the q-factor model). The numbers of significant high-minus-low six-factor alphas are 67 with $|t| \ge 1.96$ 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 six-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). Finally, we should emphasize that while the Fama-French five-factor model performs poorly overall, with no explanatory power for momentum, it is the best performer in the value-versus-growth category.

Our work contributes to asset pricing research in two important aspects. First, we bring the expected growth to the front and center of inquiry. 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 furthers 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, and downplay 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-minus-growth anomalies for the Barillas-Shanken model, difficulties that are absent from the Fama-French five-factor model and the q-factor model. As such, it is critical 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 within an economicsbased theoretical framework, other recently proposed factor models are purely statistical in nature.¹

Our work is related to Ball, Gerakos, Linnainmaa, and Nikolaev (2016), who show that cashbased profitability outperforms earnings-based profitability (with accruals) in forecasting returns. We offer an economic interpretation by linking cash flows and accruals to future growth. We also build on Penman and Zhu (2014), Lev and Gu (2016), and others, 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 also show that several anomaly variables forecast earnings growth, in the same direction of forecasting returns. While earnings growth has traditionally 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, because 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 q^5 -model along with other recent factor models. Finally, Section 5 concludes. A separate Online Appendix details derivation, variable definition, and portfolio construction.

2 Motivation

We motivate the expected growth factor from the economic model of Cochrane (1991). Time is discrete, and the horizon infinite. The economy is populated by a representative household and heterogeneous firms, indexed by $i = 1, 2, ..., N$. The household side is standard (Cochrane 2005). On the production side, firms produce a single commodity to be consumed or invested. Firms use capital and costlessly adjustable inputs to produce a homogeneous output. These inputs are

¹Hou, Mo, Xue, and Zhang (2018) study the conceptual foundations of factor models, and conduct spanning tests.

chosen each period to maximize operating profits (revenue minus the costs of these inputs). Taking operating profits as given, firms choose investment to maximize the 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, $(a/2)(I_{it}/A_{it})^2A_{it}$, 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 representative household's 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 $E_t[M_{t+1}r_{it+1}^I]=1$, in which the investment return is defined as:

$$
r_{it+1}^I \equiv \frac{X_{it+1} + (a/2) (I_{it+1}/A_{it+1})^2 + (1 - \delta) [1 + a (I_{it+1}/A_{it+1})]}{1 + a (I_{it}/A_{it})}.
$$
 (1)

Intuitively, the investment return is the marginal benefit of investment at time $t + 1$ divided by the marginal cost of investment at t. The first principle, $E_t[M_{t+1}r_{it+1}^I]=1$, says that the marginal cost equals the next period marginal benefit 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 $r_{it+1}^S = (P_{it+1} + D_{it+1})/P_{it}$ 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 Online Appendix). As such, equation (1) implies that the stock return equals the next period marginal benefit of investment divided by the current period marginal cost of investment. Intuitively, firms will keep investing until the marginal cost of investment, which rises with investment, equals the present value of additional investment, which is the next period marginal benefit 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 $r_{it+1}^S = (X_{it+1} + 1 - \delta)/(1 + aI_{it}/A_{it})$. 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. In addition, given investment, high expected profitability is 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.

More generally, 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 two components, 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, Hayashi 1982). 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 cost of investment next period, which, per the first principle of investment, equals 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 benefit 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 high discount rates to counteract the high expected marginal benefit of current investment.

3 An Expected Growth Factor

Motivated by equation (1), we construct cross-sectional forecasts of investment-to-assets growth in Section 3.1, and form an expected growth factor in Section 3.2.

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 high discount rates.

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 one-year-prior total assets. The left-hand side variables in the cross-sectional regressions are investment-to-assets changes, denoted $d^{T}I/A$, in which $\tau = 1, 2$, and 3. We measure $d^{T}I/A$, $d^{T}I/A$, and $d^{3}I/A$ 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 cost of investment to equal the 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.² 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.

Finally, 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 firms that experience recent decreases in profitability tend to reduce future investments.³

²Using 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).

³Novy-Marx (2015) argues that the investment framework cannot explain the dRoe-return relation. 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 form firm-level cross-sectional forecasts, on which we further construct an expected growth factor.

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.

We adopt the Cop measure because it is likely a more 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, 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 follow Hou, Xue, and Zhang (2017) in measuring the change in return on equity, dRoe, which is Roe minus the four-quarter-lagged Roe, and Roe is income before extraordinary items (Compustat quarterly item IBQ) scaled by the one-quarter-lagged book equity (the Online Appendix). 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 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 $E_t[d^{\tau}I/A]$, 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 $E_t[d^T]/A$ 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 $E_t[d^{\tau}I/A]$ are estimated from the prior rolling window regressions, in which $d^{T}I/A$ 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 $E_t[d^1]/A$. Finally, we report the time series averages of cross-sectional Pearson and rank correlations between $E_t[\mathbf{d}^{\tau}\mathbf{I}/\mathbf{A}]$ 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.⁴ The out-of-sample correlations between the expected and subsequently realized investment changes are tiny. At the 2-year horizon, the slope is small, negative, and insignificant, and the R^2 remains slightly above 1%. The out-of-sample correlations remain small, below 0.05, albeit significant. Finally, at the 3-year horizon, the slope is still small and negative, but significant, and the R^2 is 1.18%. However, the outof-sample correlations are larger, 0.09 for Pearson and 0.10 for rank, both of which are significant.

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. 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

⁴For example, Chan, Karceski, and Lakonishok (2003) document a low amount of predictability for earnings growth, even with a wide variety of predictors including valuation ratios.

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 crucial 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 in Portfolio Sorts

Armed with the cross-sectional forecasts of investment-to-assets changes, we study the expected growth premium in portfolio sorts. We form the expected growth deciles, construct an expected growth factor, and then augment the q-factor model with the new factor 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, $E_t[d^{\tau}I/A]$, with $\tau = 1, 2$, and 3. As in Table 1, we calculate $E_t[d^{\tau}I/A]$ 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 $E_t[d^T A]$ 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 $E_t[d^1]/A]$ decile earns on average 1.06% per month $(t = 6.25)$, and the highminus-low $E_t[\mathrm{d}^2 I/A]$ and $E_t[\mathrm{d}^3 I/A]$ 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 highminus-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 $E_t[d^{\tau}I/A]$ deciles. Both the expected and realized changes are value-weighted at the portfolio level, with the market equity as 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 23% for decile ten, and the average realized changes from −17.43% for decile one to 23.52% 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 is reasonable.

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, $E_t[\mathbf{d}^1 I/A]$.

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 $E_t[d^1]/A]$ values. Taking the intersection of the two size and three $E_t[d^1]/A]$ 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 $E_t[d^1]/A$, 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 $E_t[\text{d}^1 I/A]$ portfolios and the simple average of the returns on the two low $E_t[\text{d}^1 I/A]$ portfolios.

Panel A of Table 3 reports properties for the six size- $E_t[d^1]/A$ 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 billions of dollars, 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 billions of dollars, 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, $E_t[d^1]/A$, 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, $d^{1}I/A$, is the lowest, -11.61% , for the small-low portfolio, and the highest, 5.38%, for the small-high portfolio. The dispersions in $E_t[d^1]/A$ and d^1I/A are smaller, but remain large, 12.47% and 13.21% , respectively, among big firms. Finally, $E_t[d^1I/A]$ 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% ($t = 9.11$). The evidence suggests that the expected growth factor is 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.⁵

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 Augmenting the q-factor Model with the Expected Growth Factor

We augment the q-factor model with the 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, $R_{I/A}$, 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:

$$
E[R^{i} - R^{f}] = \beta_{\text{Mkt}}^{i} E[R_{\text{Mkt}}] + \beta_{\text{Me}}^{i} E[R_{\text{Me}}] + \beta_{\text{I/A}}^{i} E[R_{\text{I/A}}] + \beta_{\text{Roe}}^{i} E[R_{\text{Roe}}] + \beta_{\text{Eg}}^{i} E[R_{\text{Eg}}], \quad (2)
$$

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 $\beta_{\rm Mkt}^i$, $\beta_{\rm Me}^i$, $\beta_{\rm I/A}^i$, $\beta_{\rm Re}^i$, and $\beta_{\rm Eg}^i$ are their factor loadings, respectively.

As its first test, in untabulated results, 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, $E_t[\text{d}^1I/A]$, on which the new factor is based. 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 $E_t[d^2I/A]$ and $E_t[d^3I/A]$ deciles. The q^5 -alphas of the high-minus-low

⁵We 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% ($t = 2.56$).

 $E_t[d^2]/A]$ and $E_t[d^3]/A]$ deciles are only -0.02% ($t = -0.18$) and 0.04 ($t = 0.31$), respectively. Finally, the mean absolute alphas are small, 0.07%, 0.09%, and 0.11%, and the p-values of the GRS test are 0.42, 0.19, and 0.01 over the 1-, 2-, and 3-year horizons, 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 in the 1967–2016 sample from Hou, Xue, and Zhang (2017). We also conduct a large-scale horse race with other recently proposed factor models.

4.1 The Playing Field

We describe testing portfolios as well as all the other factor models in the 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, valueversus-growth, investment, profitability, intangibles, and trading frictions categories, respectively. The Online Appendix details the variable definition and portfolio construction.

The list includes 46 anomalies that the q-factor model cannot explain (Hou, Xue, and Zhang 2017). Prominent examples include cumulative abnormal stock returns around earnings announcements (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 et al. 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-class of models, we examine five other models, including (i) the Fama-French (2015) five-factor model; (ii) the Fama-French (2018) six-factor model with an operating profitability factor; (iii) the Fama-French six-factor model with a cash-based profitability factor; (iv) the Barillas-Shanken (2018) six-factor model; and (v) the Stambaugh-Yuan (2017) four-factor model.

Fama and French (2015) incorporate two factors that are similar to our investment and Roe factors into their original three-factor model to form a five-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 five-factor model to form a six-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 six-factor model, in which RMW is replaced by a cash-based profitability factor, denoted RMWc. ⁶ Their measure of cash-based operating profitability is a variant of Ball, Gerakos, Linnainmaa, and Nikolaev's (2016), using the book equity (not book assets) as the denominator, and without adding back R&D expenses. The construction of RMWc is analogous to RMW. Since the RMWc data are not provided on Kenneth

 6 Cash-based operating 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.

French's Web site, to facilitate comparison, we construct 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 the positive book equity is required for HML, RMW, and RMWc.

Barillas and Shanken (2018) also propose a six-factor model, including the market factor, SMB from the Fama-French (2015) five-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 six-factor model outperforms the q-factor model and the Fama-French five-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. We obtain the HML^m data directly from the AQR Web site.⁷

Stambaugh and Yuan (2017) group 11 anomalies into two clusters based on pairwise crosssectional 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 equalweighted 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 standard factor construction (Fama and French 1993, 2015) in several important aspects. First, the breakpoints of 20th and 80th percentiles are used, as opposed to 30th and 70th, when sorting on the composite scores. Second, the NYSE, Amex, and NASDAQ breakpoints are adopted, as opposed to the NYSE breakpoints. Third, the size factor contains stocks only in the middle

⁷ https://www.aqr.com/Insights/Datasets/The-Devil-in-HMLs-Details-Factors-Monthly

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 nonstandard construction exaggerates their factors' explanatory power. To level the playing field, we opt to use the Stambaugh-Yuan factors replicated with the standard construction (the Online Appendix).

4.2 Overall Performance

Panel A of Table 5 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 two Fama-French six-factor models and the Stambaugh-Yuan model. The Fama-French five-factor model yields the highest number of significant high-minus-low alphas, and the Barillas-Shanken model the highest number of the GRS rejections.

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 number of the high-minus-low alphas with $|t| \geq 1.96$ is 19, dropping from 46 in the q-factor model, and the number with $|t| \geq 3$ is only 4, dropping from 17 in the q-factor model. The mean absolute alpha across all the deciles is 0.1% , which is slightly lower than 0.11% in the q-factor model. 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 five-factor model does not perform well. 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 six-factor model with 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 six-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 $|t| \ge 1.96$ (67 versus 46) and the number with $|t| \ge 3$ (33 versus 17).

Replacing RMW with RMWc in the Fama-French six-factor model 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, but 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 Fama-French six-factor model with RMWc in terms of the metrics based on significant high-minus-low alphas.

The Barillas-Shanken model underperforms the q-factor model. 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). Finally, the Stambaugh-Yuan model 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 $q⁵$ -model substantially outperforms the Stambaugh-Yuan model in virtually all metrics.

4.3 Performance Across Categories

The remaining panels, B–G, of Table 5 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.

From Panel B, the improvement in the momentum category is also 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 highminus-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 five-factor model shows essentially no explanatory power for momentum, leaving 34 out of 36 high-minus-low alphas with $|t| \ge 1.96$ (27 with $|t| \ge 3$), 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 six-factor model still leaves 18 high-minus-low alphas significant with $|t| \geq 1.96$ and 8 with $|t| \geq 3$. The six-factor model is also rejected by the GRS test in 25 sets of deciles. Changing RMW to RMWc in the six-factor model improves the metrics to 16, 5, and 18, respectively. However, the alternative six-factor model underperforms the q^5 -model in all metrics, including the number of GRS rejections (18 versus 12), the number of significant high-minus-low alphas (16 versus 6 with $|t| \ge 1.96$ and 5 versus 1 with $|t| \ge 3$).

Other than the slightly lower average magnitude of the high-minus-low alphas, 0.25% versus 0.26% per month, the Barillas-Shanken 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%, and the number of GRS rejections 33, and both are higher than 0.1% and 23 in the q-factor model, respectively. Finally, the Stambaugh-Yuan model does not perform well, 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).

Panel C shows that the Fama-French five-factor model is the best performer in the value-versusgrowth 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 six-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 $|t| \ge 1.96$ 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 six-factor model. Adopting RMWc in the six-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 model does not perform well in the value-minus-growth category. 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. All the metrics are the highest among all the factor models. The Stambaugh-Yuan 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.

Panel D 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. The Fama-French six-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).

From Panel E, 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 $|t| \ge 1.96$, and 0 with $|t| \ge 3$. 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 substantially on the q -factor model, which leaves 12 high-minus-low alphas with $|t| \ge 1.96$, 4 with $|t| \ge 3$, 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 underperform the q^5 -model to a large degree. In particular, the Fama-French six-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 $|t| \ge 1.96$ (14 versus 2) and $|t| \ge 3$ (6 versus 0) than the q^5 -model.

Panel F shows that the q^5 -model is also the best performer in the intangibles category. Out of 26, the model leaves 7 high-minus-low alphas with $|t| \ge 1.96$, and 3 with $|t| \ge 3$. 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.

Finally, Panel G shows the results in the trading frictions category. With only 4 anomalies, the performance of all models is largely similar. However, 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.

4.4 Individual Factor Regressions

To dig deeper into the performance of different factor models, we detail individual factor regressions of all the 158 anomalies. Table 6 reports the average return and alphas from different models as well as their *t*-values 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 7 only details the factor loadings for the q^5 -model.

4.4.1 Momentum

Columns 1–36 in Table 6 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.

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

However, all models including the q -class of 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 six-factor alpha is 0.64% $(t = 4.66)$.

Except for the Fama-French five-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 $(R⁶6)$ 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 six-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 7 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).

4.4.2 Value-versus-growth

Columns 37–65 in Table 6 detail the alphas for the 29 value-minus-growth anomalies. Perhaps surprisingly, the Barillas-Shanken model fails to explain annually sorted value-minus-growth anomalies, including book-to-market (Bm), earnings-to-price (Ep), cash flow-to-price (Cp), salesto-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 six-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 six-factor model is not rejected at the 5% level.

In untabulated results, 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. In contrast, the UMD loadings in the Fama-French six-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 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, leading it to overshoot the average value-minus-growth returns so as to yield economically large but negative alphas.

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), respectively. Similarly, their q^5 -alphas are 0.08% , -0.07% , 0.02% , 0.05% , -0.11% , 0.08%, and 0.06% ($t = 0.51, -0.37, 0.1, 0.3, -0.61, 0.49, \text{ and } 0.3$), 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, Bm^q12 , with alphas of 0.37% and 0.38% $(t = 2.18$ and 2.25), respectively. In contrast, all the other models, including the Barillas-Shanken model, capture the Bm^q12 anomaly, with insignificant high-minus-low alphas.

Columns 37–65 in Table 7 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% $(t = -0.27)$.

4.4.3 Investment

Columns 66–93 in Table 6 detail the alphas for the 28 investment anomalies. The q^5 -model shines in this category, leaving no high-minus-low alpha with $|t| \geq 1.96$ or $|t| \geq 3$. The high-minus-low decile on net operating assets (Noa) has a significant q-factor alpha of -0.45% per month $(t = -2.59)$, but an insignificant q^5 -alpha of -0.13% ($t = -0.88$). Except for the Stambaugh-Yuan model, all the other models fail to explain the Noa anomaly. The Fama-French six-factor alpha for the highminus-low Noa 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% ($t = -1.91$). All the other models fail to explain the Oa and Dac anomalies. In particular, the Fama-French six-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 six-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 7 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 ($t = -4.58$), meaning that 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.

4.4.4 Profitability

Columns 94–128 in Table 6 detail the alphas for the 35 anomalies in the profitability category. The q^5 -model again shines, leaving only 2 high-minus-low alphas with $|t| \ge 1.96$ and 0 with $|t| \ge 3$. For example, the high-minus-low deciles on asset turnover, Ato^q, have q-factor alphas of 0.35% , 0.34% , and 0.32% per month, with t-values above 2, across the 1-, 6-, and 12-month horizons, respectively.

The q^5 -model reduces all the alphas to about 0.11%, with t-values below 0.7. For comparison, except for the Stambaugh-Yuan model, all the other models fail to explain the Ato^q anomaly. In particular, the Fama-French six-factor alphas are 0.42% , 0.4% , and 0.36% ($t = 2.74, 2.85,$ and 2.61), and the Barillas-Shanken alphas 0.52% , 0.53% , and 0.52% ($t = 3.24, 3.67$, and 3.61), respectively.

The high-minus-low deciles on operating profits-to-lagged assets, Ola^q, have q-factor alphas of 0.4%, 0.26%, and 0.32% per month $(t = 2.64, 1.89, \text{ and } 2.49)$, 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. For comparison, all the other models fail to explain the Ola^q anomaly. In particular, the Fama-French six-factor alphas with RMWc are 0.5%, 0.32%, and 0.33% ($t = 2.87, 2.1$, and 2.44), and the Barillas-Shanken alphas 0.48%, 0.34%, and 0.38% $(t = 3.6, 2.91, \text{ and } 3.44)$, respectively.

However, we should emphasize that in two cases, return on equity (Roe) and operating profitsto-lagged book equity (Ole^q), both at the 6-month horizon, the q^5 -model overshoots, yields significantly negative alphas, and underperforms the q-factor model as well as most of the other models. The high-minus-low Roe6 and Ole^q6 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 six-factor alphas are 0.16% ($t = 1.33$) and 0.02% ($t = 0.2$), and the Barillas-Shanken alphas -0.2% ($t = -1.55$) and -0.3% ($t = -2.08$), respectively.

Columns 94–128 in Table 7 report the q^5 -factor loadings for the 35 profitability anomalies. Except for the fundamental score (F^q) at the 1, 6-, and 12-month horizons, 32 out of 35 loadings on the expected growth factor indicate that, sensibly, high profitability firms have higher expected growth than low profitability firms. (Failure probability, Fp^{q} , which is a measure of financial distress, is inversely related to profitability.) Out of the 32 loadings, 26 are significant at the 5% level. The high-minus-low F^q deciles have negative, but mostly insignificant, loadings on R_{Eg} . Despite the negative loadings, the q^5 -model explains the F^q anomaly. The high-minus-low Ato^q deciles have economically large R_{Eg} -loadings of 0.38, 0.35, and 0.33 ($t = 3.18$, 3.09, and 2.9) across the 1-, 6-, and 12-month horizons, and the high-minus-low Ola^q deciles also have large $R_{\rm Eg}$ -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 among all the factor models in the profitability category.

4.4.5 Intangibles and Trading Frictions

Columns 129–154 in Table 6 detail the alphas for the 26 anomalies in the intangibles category, and the same columns in Table 7 report their high-minus-low loadings in the q^5 -model. The q^5 -model helps explain the R&D-to-market (Rdm) anomaly. The high-minus-low decile earns a q-factor alpha of 0.72% per month ($t = 3.11$). The q^5 model reduces the alpha to 0.25% ($t = 1.13$) via a large R_{Eg} -loading of 0.78 ($t = 4.51$). Similarly, in monthly sorts, at the 1-, 6-, and 12-month horizons, the high-minus-low Rdm^q deciles have q-alphas of 1.39%, 0.95%, and 0.81% ($t = 3.06, 2.87,$ and 3.01), but smaller q^5 -alphas of 1.07%, 0.54%, and 0.37% ($t = 2.26, 1.57,$ and 1.31), respectively. The matching 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 accommodates it.

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

We should emphasize 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, $R_{\rm a}^{[2,5]}$, $R_{\rm a}^{[6,10]}$, and $R_{\rm a}^{[11,15]}$, have high-minus-low q^5 -alphas of 0.85%, 0.95%, and 0.55% per month $(t = 4.02, 4.74, \text{ and } 3.16)$,

respectively. The $R_{\rm{Eg}}$ loadings of these high-minus-low deciles are all economically small and insignificant. All the other factor models also fail to explain the seasonality anomalies.

Finally, the last 4 columns in Table 6 report the alphas for the 4 anomalies in the trading frictions category, and the same columns in Table 7 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 R_{Eg} -loadings.

5 Conclusion

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. Motivated by this theoretical prediction, we form crosssectional forecasts, and construct an expected growth factor, which yields an average return of 0.82% per month ($t = 9.81$). We augment the q-factor model with the new factor to form the q^5 -model.

In a large set of testing deciles formed on 158 significant anomalies, the q^5 -model improves on the q-factor model substantially. The q^5 -model is the overall best performing model. The qfactor model also compares well with the Fama-French six-factor model, the alternative six-factor model with the cash-based profitability factor, and the Stambaugh-Yuan four-factor model. The Fama-French five-factor model is the best model in the value-versus-growth category, but shows no explanatory power for momentum. The Barillas-Shanken six-factor model performs poorly, with a high number of significant high-minus-low alphas and a high number of rejections by the GRS test.

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

For each month, we perform cross-sectional regressions of future τ -year-ahead investment-to-assets changes, denoted $d^{\tau}I/A$, in which $\tau = 1, 2, 3$, on the logarithm of Tobin's q, log(q), cash flows, Cop, the change in return on equity, dRoe, as well as on all the three regressors together. We measure current investment-to-assets from the most recent fiscal year ending at least four months ago, andcalculate $d^{\tau}I/A$ as investment-to-assets from the subsequent τ -year-ahead fiscal year end minus the current investment-to-assets. All the cross-sectional regressions are estimated via weighted least squares with the market equity as weights. We winsorize the cross section of each variable each month at the $1-99\%$ level. We report the average slopes, their t-values adjusted for heteroscedasticity and autocorrelations (in parentheses), and goodness-of-fit coefficients $(R^2$, in percent). In addition, at the beginning of each month t, we calculate the expected I/A changes, $E_t[d^{\tau}I/A]$, 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 $E_t[d^{\tau}I/A]$ are estimated from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $d^{\tau}I/A$, 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 $E_t[d^1I/A]$. We report time-series averages of cross-sectional Pearson and rank correlations between $E_t[d^{\tau}I/A]$ 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.

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

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, $E_t[d^{\tau}I/A]$, with τ ranging from 1 to 3 years. At the beginning of each month t, we calculate $E_t[\mathrm{d}^T I/A]$ by combining the three most recent predictors (winsorized at the 1–99% level) with the average cross-sectional regression slopes. The most recent predictors, $log(q)$ and Cop, are from the most recent fiscal year ending at least four months ago as of month t, and dRoe uses the latest announced earnings, and if not available, the earnings from the most recent fiscal quarter ending at least four months ago. The average slopes in calculating $E_t[d^{\tau}I/A]$ are estimated from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $d^{\tau}I/A$, 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 $E_t[d^1]/A$. 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 $E_t[d^{\tau}I/A]$ 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, $E_t[d^{\tau}I/A]$, and the average future realized changes, $d^{T}I/A$, and their heteroscedasticity-and-autocorrelation-adjusted t-statistics (beneath the corresponding estimates). $E_t[d^{\tau}I/A]$ and $d^{\tau}I/A$ are value-weighted.

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

We use the log of Tobin's q, $log(q)$, cash flows, Cop, and change in return on equity, dRoe, to form the expected 1-year-ahead investment-to-assets changes, $E_t[d^1]/A$. At the beginning of month t, we compute $E_t[\text{d}^1 I/A]$ by combining 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 $E_t[d^{\tau}I/A]$ are from the prior 120-month rolling window (30 months minimum), in which the dependent variable, $d^{1}I/A$, uses data from the fiscal year ending at least four months ago as of month t, and the regressors are further lagged. For instance, the regressors in the latest monthly cross-sectional regression as of month t are further lagged by 12 months relative to the most recent predictors in calculating $E_t[d^1]/A]$. 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 all NYSE, Amex, and NASDAQ stocks into two groups, small and big, based on the beginning-of-month market equity. Independently, we sort all stocks into three $E_t[d^1]/A]$ 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 of the two size and three expected growth groups, we form six portfolios. We calculate value-weighted portfolio returns for the current month t, and rebalance the portfolios monthly. 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 $E_t[d^1]/A]$ portfolios and the simple average of the returns on the two low $E_t[d^1]/A]$ portfolios.

Panel A reports properties of the six size- $E_t[d^1]/A]$ portfolios, including value-weighted average excess returns, 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 beginningof-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, $E_t[\text{d}^1 I/A]$, the realized 1-year-ahead investment-to-assets change, d^1I/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}_{Eg} , and alphas, factor loadings, and R^2 s from the q-factor model, and the q-factor model augmented with an $log(q)$ factor, a Cop factor, and a dRoe factor, either 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 of the two size and three $log(q)$ groups, 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 of the two size and three dRoe groups, 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 market, size, investment, and Roe factors in the q-factor model, as well as the $log(q)$, Cop, and dRoe factors.

Table 4 : The List of Anomalies To Be Explained

The 158 significant anomalies are grouped into six categories: (i) momentum; (ii) value-versusgrowth; (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.

Table ⁵ : Overall Performance of Factor Models in Explaining Anomalies

For each model, $|\alpha_{\rm H-L}|$ is the average magnitude of the high-minus-low alphas, $\#_{|t|\geq 1.96}$ the number of the high-minus-low alphas with absolute t-values greater than or equal to 1.96, $\#_{|t|\geq 3}$ the number of the high-minus-low alphas with absolute t-values greater than or equal to three, $|\alpha|$ the mean absolute alpha across the anomaly deciles within a given category, and $#_{p<5\%}$ the number of sets of se 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 q-factor model augmented with the expected growth factor, R_{Eg}), the Fama-French (2015) five-factor model (FF5), the Fama-French (2018) six-factor model with RMW (FF6), the Fama-French alternative six-factor model with RMWc (FF6c), the Barillas-Shanken (2018) six-factor model (BS6), and the Stambaugh-Yuan (2017) model (SY4).

Table ⁶ : Explaining the ¹⁵⁸ Anomalies with Factor Models

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) five-factor alpha, α_{FF5} , the Fama-French (2018) six-factor alpha, α_{FF6} , the alpha from the alternative six-factor model with RMW replaced by RMWc, $\alpha_{\rm FF6c}$, the Barillas-Shanken (2018) six-factor alpha, $\alpha_{\rm BSS6}$, and the Stambaugh-Yuan (2017) alpha, $\alpha_{\rm SY4}$, as well as their heteroscedasticity-and-autocorrelation-consistent t-statistics, denoted by $t_{\overline{R}}$, t_q , t_q , t_{q5} , t_{FF6} , t_{FF6} , t_{BS6} , and t_{SY4} , respectively. Also, for all the ten deciles formed on a given anomaly variable, we report the mean absolute alphas from the q-factor model, $|\alpha_q|$, the q^5 -model, $\overline{|\alpha_{q^5}|}$, the five-factor model, $\overline{|\alpha_{\text{FF5}}|}$, the six-factor model, $\overline{|\alpha_{\text{FF6}}|}$, the alternative six-factor model, $\overline{|\alpha_{\text{FF6c}}|}$, the Barillas-Shanken six-factor model, $\overline{|\alpha_{BS6}|}$, and the Stambaugh-Yuan model, $\overline{|\alpha_{SY4}|}$, 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, and p_{SY4} , respectively. Table ⁴ describes the anomaly symbols, and the Online Appendix details variable definition and portfolio construction.

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Table 7 : The $q^5\text{-model Factor}$ Loadings

For each of the significant ¹⁵⁸ anomalies, we report for the high-minus-low decile the loadings on the market, size, investment-toassets, Roe, and expected growth factors (denoted β_{Mkt} , β_{Me} , $\beta_{I/A}$, β_{Roe} , and β_{Eg} , respectively) in the q^5 -regression, as well as their heteroscedasticity-and-autocorrelation-consistent t-statistics (denoted t_{Mkt} , t_{Me} , $t_{\text{I/A}}$, t_{Roe} , and t_{Eg} , respectively). Table 4 describes the anomaly symbols, and the Online Appendix details variable definition and portfolio construction.

		$\overline{2}$	3	$\overline{4}$	$5\overline{)}$	6	$\overline{7}$	8	9	10	11	12	13	14	15	16	17	18	19	20
				Suel Abr1 Abr6 Abr12								Re1 Re6 R^61 R^66 R^612 $R^{11}1$ $R^{11}6$ 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															$0.17 - 0.11 - 0.05 - 0.02 - 0.08$			$-0.05 - 0.32$	
																			$\beta_{I/A}$ -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}		$0.80 \quad 0.24 \quad 0.16$										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
$\beta_{\rm Eg}$		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	
$t_{\rm I/A}$																$-1.43 - 1.44 - 2.72 - 4.83$ $0.41 - 0.86 - 0.37 - 0.95 - 1.90 - 0.52 - 1.35 - 0.33 - 0.49 - 1.70 - 5.77 - 1.27 - 2.68 - 3.82$			-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
$t_{\rm Eg}$	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
		ϵ^6 6 ϵ^6 12	$\epsilon^{11}1$		$\epsilon^{11}6\;\,\epsilon^{11}12$	Sm1	Ilr1		$Ilrf$ $Ilrf$							Ile1 Cm1 Cm12 Sim1 Cim1 Cim6 Cim12			Bm Bm i $Bmq12$ Rev6	
$\beta_{\rm Mkt}$	$0.00\,$	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
$\beta_{\rm Me}$	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		$0.42 \quad 0.32$		$0.32 - 0.60$
$\beta_{\text{I/A}}$		$0.04 - 0.04$	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}		$0.14 \quad 0.21$	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}		$0.31 \quad 0.25$	0.39	0.27	0.17		$0.33 \quad 0.37$	0.29		0.27 0.33 0.04			$0.12 \quad 0.51$		0.43 0.36		$0.32 \quad 0.12 - 0.04$		$-0.02 - 0.21$	
$t_{\rm Mkt}$	0.10	0.15	0.77	0.52	0.49				$0.13 - 2.06 - 2.44 - 1.01 - 0.06$ 1.03				$1.00 \quad 1.09$	$0.42 - 0.77$		0.12		$0.41 - 1.25$		$0.60 \quad 0.93$
$t_{\rm Me}$	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		$3.00 - 7.73$
$t_{\rm I/A}$		$0.43 - 0.47$	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				$9.50 - 9.76$
$t_{\rm{Roe}}$	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	
$t_{\rm{Eg}}$	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 $1.02 - 0.34 - 0.17 - 1.50$	

