Security Analysis: An Investment Perspective

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Abstract

The investment theory, in which the expected return varies cross-sectionally with investment, expected profitability, and expected growth, is a good start to understanding Graham and Dodd's (1934) *Security Analysis*. Empirically, the q^5 model goes a long way toward explaining prominent equity strategies rooted in security analysis, including Frankel and Lee's (1998) intrinsic-to-market value, Piotroski's (2000) fundamental score, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Buffett's Berkshire, Bartram and Grinblatt's (2018) agnostic analysis, as well as Penman and Zhu's (2014, 2018) and Lewellen's (2015) expected-return strategies.

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1 Introduction

The investment theory, in which the expected return varies cross-sectionally with investment, expected profitability, and expected investment growth, is a good start to understanding Graham and Dodd's (1934) *Security Analysis*. As the theory's empirical implementation, the q^5 model proposed in Hou et al. (2019a) goes a long way toward explaining prominent equity strategies rooted in security analysis, including Frankel and Lee's (1998) intrinsic-to-market value, Piotroski's (2000) fundamental score, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Buffett's Berkshire Hathaway, Bartram and Grinblatt's (2018) agnostic analysis, as well as Penman and Zhu's (2014, 2018) and Lewellen's (2015) expected-return strategies.

These prominent strategies are all different combinations of investment, expected profitability, and expected growth, which are the key expected-return drivers in the investment theory. The investment factor adequately accounts for Frankel and Lee's (1998) intrinsic-to-market anomaly, since the market equity is in the denominator. From January 1967 to December 2018, the high-minus-low quintile earns 0.27%, 0.35%, and 0.36% per month ($t = 2.01$, 2.25, and 2.29), and the q^5 alphas are 0.13%, 0.13%, and 0.11% ($t = 1.05$, 0.88, and 0.68), helped by the large investment factor loadings of 0.5, 0.7, and 0.72 ($t = 4.8$, 5.38, and 5.77) across micro, small, and big stocks, respectively.

Piotroski (2000) combines nine signals that measure firms' profitability, liquidity, and operating efficiency. The return on equity (Roe) factor mostly accounts for his anomaly. The high-minus-low quintile earns 0.5%, 0.36%, and 0.28% per month ($t = 3.25$, 2.5, and 1.78), and the q^5 alphas are 0.33%, 0.1%, and 0.03% ($t = 2.67$, 0.81, and 0.15), helped by the large Roe factor loadings of 0.59, 0.45, and 0.39 ($t = 6.12$, 5.49, and 3.77) across micro, small, and big stocks, respectively.

Greenblatt (2005, 2010) proposes a "magic formula" that buys good companies, with high returns on capital, at bargain prices, with high earnings yield. The Roe factor is the key force behind his formula, with the investment and expected growth factors playing a secondary role. The high-minus-low quintile earns 0.43%, 0.47%, and 0.47% per month ($t = 2.51$, 2.87, and 3.08), and the

q^5 alphas are 0.06%, 0.03%, and −0.11% (t = 0.43, 0.18, and −0.84), helped by the large Roe factor loadings of 0.67, 0.57, and 0.39 (t = 6.1, 5.08, and 4.51) across micro, small, and big stocks, respectively. The investment factor loadings are large and significant in micro and small stocks, and the expected growth factor loadings are large and significant in big stocks.

Asness, Frazzini, and Pedersen (2019) measure quality as a combination of profitability, growth, and safety, for which investors are willing to pay a higher price. In our sample, the quality-minus-junk quintile earns 0.61%, 0.42%, and 0.22% per month (t = 3.92, 3.19, and 1.53), with the q^5 alphas of 0.3%, 0.09%, and 0.07% (t = 2.45, 0.83, and 0.59), respectively. High quality stocks tend to have lower market betas, bigger market equity, and higher investment-to-assets, but also higher Roe and expected growth, than low quality stocks. The latter two factors are sufficiently strong to overcome the other three factors to largely account for the quality-minus-junk premium. Also, when examining the separate quality components, we find that the high-minus-low growth portfolio has a large, negative loading on the investment factor but only a small, albeit positive, loading on the expected growth factor. The evidence suggests that the growth score can potentially be improved. While aiming to capture expected growth, the growth score ends up capturing past growth (investment).

In spanning test, the Frazzini-Pedersen (2014) betting-against-beta (BAB) factor earns on average 0.9% per month (t = 5.73). The q-factor alpha is only 0.32% (t = 1.94), helped by the large loadings of 0.68 (t = 5.51) and 0.45 (t = 4.67) on the investment and Roe factors, respectively. The q^5 alpha is 0.29% (t = 1.73), again helped by similarly large loadings on the investment and Roe factors. The other three factor loadings are weakly positive. As such, BAB tilts toward low investment and high Roe stocks, which should earn high expected returns per the investment theory.

Asness et al. (2018) show that the size premium can be resurrected if controlling for their quality measure, and the quality-minus-junk premium can be strengthened if controlling for size. We document similar evidence based on our own two quality measures, Roe and expected growth. In addition, conceptually, we show that the market equity-quality interaction, which is also stronger than the physical size-quality interaction, accords well with the investment theory.

Bartram and Grinblatt (2018) show that a "mispricing" measure, which is the percentage deviation from a firm's peer-implied intrinsic value (estimated from monthly cross-sectional regressions of the market equity on 28 contemporaneous accounting variables) from its market equity, predicts returns reliably. The high-minus-low "mispricing" quintile earns on average 0.92%, 0.5%, and 0.46% per month ($t = 4.25$, 2.42, and 2.11), but the q^5 model reduces the return spreads to insignificance, with alphas of 0.48%, 0.27%, and 0.42% ($t = 1.82$, 1.23, and 1.7) across micro, small, and big stocks, respectively. Since the market equity is in the denominator of the Bartram-Grinblatt measure, the investment factor again plays the key role, with the loadings of 0.64, 1.0, and 0.7 ($t = 3.43$, 5.7, and 3.73) across micro, small, and big stocks, respectively. In contrast, the Roe and expected growth factor loadings are mostly insignificant, also with mixed signs.

Penman and Zhu (2014, 2018) construct a fundamental analysis strategy on an expected-return proxy from projecting future returns on eight anomaly variables that are a priori connected to future earnings growth. The high-minus-low expected-return quintile earns on average 0.78%, 0.33%, and 0.48% per month ($t = 4.82$, 2.24, and 3.29), and except for microcaps, the q^5 model largely succeeds in explaining the return spreads, with the alphas of 0.55%, 0.01%, and 0.16% ($t = 3.23$, 0.09, and 1.25) across micro, small, and big stocks, respectively. The investment factor loadings are consistently large and significant, while the Roe and expected growth factor loadings have mixed signs. Intuitively, among the eight signals, two are value metrics, three are investment measures, and two are equity issues, all of which are either directly or indirectly related to investment.

Lewellen (2015) shows that cross-sectional return forecasts based on 15 variables predict returns reliably. Although not framed in security analysis, Lewellen's method is simple yet highly effective. The high-minus-low quintile earns on average 1.68%, 0.83%, and 0.56% per month ($t = 9.7$, 5.28, and 2.58), and the q^5 model leaves much to be desired, with alphas of 1.29%, 0.44%, and 0.34% ($t = 7.79$, 2.46, and 1.44) across micro, small, and big stocks, respectively. The investment factor loadings are large and mostly significant, but the Roe and expected growth factor loadings are not.

Collectively, our evidence suggests that the investment theory is a good start to understanding Graham and Dodd's (1934) *Security Analysis*. Efficient markets and security analysis have long been perceived as diametrically opposite (Buffett 1984). This view permeates the contemporary literature (Bartram and Grinblatt 2018; Asness, Frazzini, and Pedersen 2019). By connecting cross-sectionally varying expected returns with accounting variables, the investment theory reconciles security analysis with efficient markets. Traditional academic finance, with the Sharpe-Lintner CAPM as the workhorse theory, dismisses security analysis profits as due to luck and recommends investors to hold only the market portfolio. In sharp contrast, the investment theory systematically validates security analysis on the grounds of equilibrium theory, by pointing investors to key expected return drivers in the cross section, including investment, expected profitability, and expected growth.

The investment theory provides an equilibrium foundation for active management. Even as factor investing becomes increasingly popular, the latest factor models still fail to fully explain Buffett's alpha in Berkshire Hathaway. In the February 1968–December 2018 sample, which is longer than the November 1976–March 2017 sample in Frazzini, Kabiller, and Pedersen (2018), Berkshire earns 1.44% per month ($t = 4.96$) in excess of the riskfree rate. The AQR 6-factor alpha is 0.61% ($t = 2.09$), the q-factor alpha 0.64% ($t = 2.45$), and the q^5 alpha 0.77% ($t = 2.69$). We interpret the evidence as saying that discretionary active management cannot be fully substituted by passive factor investing. Our factor models and their underlying theory are all deliberate abstractions of reality. Identifying the missing sources and evaluating their impact on the expected profitability and expected growth, and ultimately on the expected return, leave ample space for active management.

The rest of the paper is organized as follows. Section 2 briefly reviews the investment theory. Section 3 uses the q-factor and q^5 models to explain prominent security analysis strategies. Section 4 elaborates our economic perspective on security analysis. Finally, Section 5 concludes. A separate Internet Appendix details the security analysis strategies and furnishes supplementary results.

2 The Investment Theory

Firms 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 the market equity. We suppress the firm index for notational simplicity. Let $\Pi_t \equiv \Pi(X_t, A_t) = X_{it}A_t$ be an individual firm's time-t operating profits, in which A_t is productive assets, and X_t return on assets. The next period profitability, X_{t+1}, is stochastic, subject to a vector of exogenous aggregate and firm-specific shocks. Let I_t be investment and δ the depreciation rate of assets, then $A_{t+1} = I_t + (1-\delta)A_t$. Firms incur quadratic costs when adjusting capital, $(a/2)(I_t/A_t)^2 A_t$, in which $a > 0$.

Firms finance investments only with internal funds and equity (no debt) and pay no taxes. The net payout is $D_t = X_t A_t - I_t - (a/2)(I_t/A_t)^2 A_t$. Let M_{t+1} be the stochastic discount factor, which is correlated with the aggregate component of X_{t+1}. Firm choose optimal streams of investment, $\{I_{t+s}\}_{s=0}^{\infty}$, to maximize the cum-dividend market equity, $V_t \equiv E_t\left[\sum_{s=0}^{\infty} M_{t+s} D_{t+s}\right]$. The first-order condition says $E_t[M_{t+1} r_{t+1}^I] = 1$, in which the investment return is given by:

$$r_{t+1}^I \equiv \frac{X_{t+1} + (a/2)\left(I_{t+1}/A_{t+1}\right)^2 + (1-\delta)\left[1 + a\left(I_{t+1}/A_{t+1}\right)\right]}{1 + a\left(I_t/A_t\right)}. \tag{1}$$

Intuitively, the investment return is the marginal benefit of investment at time $t+1$ divided by the marginal cost of investment at t. In the numerator, X_{t+1} is the marginal profits produced by an extra unit of capital, $(a/2)(I_{t+1}/A_{t+1})^2$ the marginal reduction in adjustment costs, and the last term in the numerator the marginal continuation value of the extra unit of capital net of depreciation.

Cochrane (1991) argues via no-arbitrage, and Restroy and Rockinger (1994) prove with constant returns to scale that the stock return equals the investment return, state by state and period by period (detailed in Hou et al. 2019a). Intuitively, equation (1) says that 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). Equivalently, equation (1) says that the expected return varies cross-sectionally, depending on firms' investment, expected profitability, and expected investment growth.

In a two-period setup, equation (1) reduces to $r^I_{t+1} = (X_{t+1} + 1 - \delta)/(1 + aI_t/A_t)$. As such, all else equal, low investment and high profitability stocks should earn higher expected returns than high investment and low profitability stocks, respectively. Intuitively, given profitability, high costs of capital give rise to low net present values of new projects and low investment, and given investment, high profitability imply high discount rates that are necessary to offset the high 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 from independent $2 \times 3 \times 3$ sorts on size, investment-to-assets (I/A), and Roe. Hou et al. (2019b) extend the q-factors backward from January 1972 to January 1967.

More generally, holding investment and expected profitability constant, the expected return also increases with the expected investment-to-assets growth. The "capital gain" component of equation (1), $(1 - \delta)(1 + aI_{t+1}/A_{t+1})/(1 + aI_t/A_t)$, is the growth of marginal q, which is closely related the investment-to-assets growth, $(I_{t+1}/A_{t+1})/(I_t/A_t)$. Intuitively, $1 + aI_{t+1}/A_{t+1}$ is the marginal q next period (the present value of cash flows in all future periods arising from one extra unit of assets). The expected marginal q is then part of the expected marginal benefit of current investment. As such, high expected investment (relative to current investment) must imply high discount rates to offset the high expected marginal benefit of current investment.

Hou et al. (2019a) augment the q-factor model with an expected investment growth factor to form the q^5 model. The expected growth factor is from independent 2×3 sorts on size and the expected 1-year-ahead investment-to-assets change, which is formed from monthly cross-sectional regressions of realized 1-year-ahead investment-to-assets change on Tobin's q, cash flows, and the change in Roe. The Internet Appendix details the measurement of the expected growth.

3 Explaining Prominent Security Analysis Strategies

We use the q-factor and q^5 models to explain Frankel and Lee's (1998) intrinsic-to-market value in Section 3.1, Piotroski's (2000) fundamental score in Section 3.2, Greenblatt's (2005, 2010) "magic formula" in Section 3.3, Asness, Frazzini, and Pedersen's (2019) quality-minus-junk strategies and Warren Buffett's Berkshire Hathaway in Section 3.4, Bartram and Grinblatt's (2018) agnostic fundamental strategies in Section 3.5, Penman and Zhu's (2014, 2018) fundamental strategies in Section 3.6, and Lewellen's (2015) expected-return strategies in Section 3.7.

Monthly returns are from Center for Research in Security Prices (CRSP) (share codes 10 or 11). Accounting variables are from Compustat Annual and Quarterly Fundamental Files. We exclude financials and firms with negative book equity. The sample is from January 1967 to December 2018.

3.1 Frankel and Lee's (1998) Intrinsic-to-market Value Strategies

In a prominent study, Frankel and Lee (1998) estimate the intrinsic value from the residual income model and show that the intrinsic-to-market value forecasts returns. Following Graham and Dodd (1934), they interpret the evidence as mispricing. When the market value is below the intrinsic value, buying the security earns an abnormal return, as the deviant market value eventually rises to converge to the intrinsic value. When the market value is above the intrinsic value, selling the security earns an abnormal return, as the market value ultimately falls to gravitate to the intrinsic value.

We follow exactly the Frankel-Lee (1998) measurement of the intrinsic value based on a two-period version of the residual income model at the end of June of each year t:

$$V_t^h = B_t + \frac{(E_t[\text{Roe}_{t+1}] - r)}{(1+r)} B_t + \frac{(E_t[\text{Roe}_{t+2}] - r)}{(1+r)r} B_{t+1}, \tag{2}$$

in which V_t^h is the intrinsic value, B_t the book equity, and $E_t[\text{Roe}_{t+1}]$ and $E_t[\text{Roe}_{t+2}]$ the expected returns on equity for the current and next fiscal years, respectively. B_t is the book equity (Compustat annual item CEQ) for the fiscal year ending in calendar year $t-1$. Future book equity is computed with the clean surplus accounting, $B_{t+1} = (1+(1-k)E_t[\text{Roe}_{t+1}])B_t$, in which k is the dividend payout ratio, measured as common stock dividends (item DVC) divided by earnings (item IBCOM) for the fiscal year ending in calendar year $t-1$. For firms with negative earnings, we divide dividends by 6% of average total assets (item AT) from the fiscal year ending in calendar years $t-1$ and $t-2$.

The discount rate, r, is a constant, 12%. $E_t[\text{Roe}_{t+1}]$ and $E_t[\text{Roe}_{t+2}]$ are replaced with most recent Roe_t, defined as $Ni_t/[(B_t+B_{t-1})/2]$, in which Ni_t is earnings (Compustat annual item IBCOM) for the fiscal year ending in $t-1$, and B_t and B_{t-1} are the book equity from the fiscal years ending in $t-1$ and $t-2$. We exclude firms if their expected Roe or dividend payout ratio is higher than 100%. We also exclude firms with negative book equity and firms with non-positive intrinsic value.

At the end of June of each year t, we sort stocks into deciles based on the NYSE breakpoints of intrinsic-to-market value, V_t^h/P_t, for the fiscal year ending in calendar year $t-1$, in which P_t is the market equity (from CRSP) at the end of December of year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. To examine how the intrinsic-to-market anomaly varies with size, we also perform double 3×5 sorts on size and V_t^h/P_t. At the end of June of each year t, we sorts stocks into quintiles based on the NYSE breakpoints of V_t^h/P_t for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity at the end of June of year t. Taking intersections yields 15 portfolios. For comparison, we also report one-way sorts on V_t^h/P_t into quintiles.

Table 1 shows that consistent with Frankel and Lee (1998), the intrinsic-to-market value shows some ability to predict returns. The high-minus-low V^h/P decile earns on average 0.28% per month, albeit insignificant ($t = 1.55$). Its q-factor and q^5 alphas are economically small and statistically insignificant. However, both are rejected by the GRS test on the null that the alphas are jointly zero across the ten deciles. The predictability is stronger in quintiles, which yield an average high-minus-low return of 0.43% ($t = 2.79$). The quintile spread does not vary much with size, with 0.27%, 0.35%, and 0.36% ($t = 2.01$, 2.25, and 2.29) across micro, small, and big stocks, respectively.[1]

[1]Frankel and Lee (1998) also calculate an analysts' forecast-based intrinsic value, V_t^f, in which the Roe expectations

The q-factor and q^5 models do a good job in the two-way sorts. The q-factor alphas of the high-minus-low quintile are 0.13%, 0.18%, and 0.17% ($t = 0.94$, 1.13, and 1.07) across micro, small, and big stocks, and their q^5 alphas 0.13%, 0.13%, and 0.11% ($t = 1.05$, 0.88, and 0.68), respectively. Neither model can be rejected by the GRS test on the null that the alphas are jointly zero across the 3×5 testing portfolios. The investment factor is the key driving force behind the explanatory power. In the q^5 regressions, the investment factor loadings of the high-minus-low quintiles are 0.5, 0.7, and 0.72 ($t = 4.8$, 5.38, and 5.77) across micro, small, and big stocks, respectively. In contrast, their Roe and expected growth factor loadings are economically small and statistically insignificant.

In the investment theory, the intrinsic value equals the market value, with no mispricing, and the intrinsic-to-market ratio equals one by construction. Why does the intrinsic-to-market ratio still forecast returns? The crux is that the estimated intrinsic-to-market ratio from equation (2) is a nonlinear function of investment-to-assets, expected profitability, and expected investment growth, which, per the investment theory, should forecast returns. Most important, the book-to-market equity component of the intrinsic-to-market ratio is linked to investment-to-assets. The linkage arises because the marginal cost of investment, which rises with investment, equals the marginal q, which is the inverse of book-to-market equity, without debt. Although the expected profitability and the expected growth (via the book equity dated $t+1$) also appear in equation (2), it turns out that the investment factor is the key force driving the Frankel-Lee intrinsic-to-market anomaly.

3.2 Piotroski's (2000) Fundamental Score Strategies

Piotroski (2000) shows that a fundamental analysis strategy is highly effective when applied to a sample of high book-to-market firms. Nine fundamental signals are chosen to measure a firm's profitability, liquidity, and operating efficiency. Each signal is classified as good or bad (one or zero), depending on its implications for future stock prices and profitability. The fundamental

are computed with analysts earnings forecasts from IBES. In untabulated results, we show that V^f/P shows only weak predictive power of returns. From July 1976 onward (when analysts' forecasts become available), the high-minus-low decile earns on average 0.35% per month ($t = 1.63$), and the high-minus-low quintile 0.13% ($t = 0.72$). Also, the quintile spread is 0.18%, 0.08%, and 0.11% ($t = 0.92$, 0.39, and 0.59) across micro, small, and big stocks, respectively.

score, denoted F, is the sum of the nine binary signals. All the accounting variables in the F-score construction are from Compustat Annual Fundamental Files (the Internet Appendix).

At the end of June of each year t, we sort stocks based on F-score for the fiscal year ending in calender year $t - 1$ to form seven portfolios: low (F = 0,1,2), 3, 4, 5, 6, 7, and high (F = 8, 9). Because extreme F-scores are rare, we combine scores 0, 1, and 2 into the low portfolio and scores 8 and 9 into the high portfolio. Monthly portfolio returns are calculated from July of year t to June of $t + 1$, and the portfolios are rebalanced in June of $t + 1$. For two-way sorts, at the end of June of each year t, we sort stocks on F-score to form quintiles: low (F = 0–3), 4, 5, 6, and high (F = 7–9). Independently, we sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios. For sufficient data coverage, the F-score portfolio returns start in July 1972.

Panel A of Table 2 shows that the F-score predictability is mixed in our extended sample. The high-minus-low portfolio earns on average only 0.28% per month ($t = 1.09$). In untabulated results, we show that restricting the sample to the high book-to-market quintile per Piotroski (2000) yields even weaker evidence, as the high-minus-low portfolio earns only 0.2% ($t = 0.54$). Sampling variations play an important role. If we end the sample in December 1998, which is close to Piotroski's original sample, the average high-minus-low return is 0.76%, albeit still insignificant ($t = 1.7$). From January 1999 onward, the average return is −0.54% ($t = -0.88$). The sampling variations are less extreme in our full sample, which includes all book-to-market quintiles. The average high-minus-low return is 0.51% ($t = 1.69$) and −0.03% ($t = -0.07$) before and after December 1998, respectively.

The F-score predictability is stronger in quintiles, which yield an average high-minus-low return of 0.3% per month ($t = 1.97$). Across micro, small, and big stocks, the quintile spreads are 0.5%, 0.36%, and 0.28% (t = 3.25, 2.5, and 1.78), respectively. The q-factor and q^5 models largely explain this predictability. The q-factor alphas of the high-minus-low quintiles are 0.23%, 0.1%, and 0.12% (t = 1.56, 0.85, and 0.84), and the q^5 alphas 0.33%, 0.1%, and 0.03% (t = 2.67, 0.81, and 0.15) across micro, small, and big stocks, respectively. Although the GRS test rejects the q-factor model with the 15 two-way portfolios ($p = 0.01$), it cannot reject the q^5 model ($p = 0.09$).

The Roe factor is the key driving force behind the explanatory power. In the q^5 regressions, the Roe factor loadings of the high-minus-low quintiles are 0.59, 0.45, and 0.39 ($t = 6.12$, 5.49, and 3.77) across micro, small, and big stocks, respectively. The investment factor also plays a role, with significant loadings for micro and small stocks but not for big stocks. Finally, the expected growth factor loadings are all economically small and statistically insignificant.

Intuitively, F-score contains four fundamental signals that measure a firm's profitability, including return on assets (Roa), cash flow-to-assets (Cf/A), change of Roa, and an indicator on whether Cf/A > Roa. F-score also contains two operating efficiency measures, the change in gross margin and change in asset turnover. All these signals are closely related to return on equity underlying our Roe factor. F-score also contains an equity issuance indicator, which is positively correlated with investment-to-assets. Finally, Piotroski (2000) only works with binary indicators, with two values (zero and one). Doing so likely understates the heterogeneity across firms and dampens the predictive power relative to the Roe factor (built on continuous Roe values).

3.3 Greenblatt's (2005, 2010) "Magic Formula"

In a popular book titled "The little book that beats the market," Greenblatt (2005) proposes a "magic formula" that embodies Warren Buffett and Charlie Munger's interpretation of the Graham-Dodd (1934) philosophy. The basic idea is to buy good companies (ones that have high returns on capital) at bargain prices (prices that give the investor high earnings yields).

We follow the measurement in Greenblatt (2010, Appendix). Return on capital is earnings before interest and taxes (EBIT) over the sum of net working capital and net fixed assets. Earnings yield is EBIT divided by the enterprise value, which is the market equity plus net interest-bearing debt. However, Greenblatt does not specify which Compustat data items are used in his calculations. We measure EBIT as Compustat annual item OIADP per Dichev (1998). Following Richardson et al.

(2005), we measure net working capital as current operating assets (Coa) minus current operating liabilities (Col), in which Coa is current assets (item ACT) minus cash and short-term investments (item CHE), and Col is current liabilities (item LCT) minus debt in current liabilities (item DLC). We measure net fixed assets as net property, plant, and equipment (item PPENT). The enterprise value is the market equity (price per share times shares outstanding, from CRSP), plus the book value of debt (item DLC plus item DLTT), plus the book value of preferred stocks (item PSTKRV, PSTKL, or PSTK, in that order, depending on availability), minus cash and short-term investments.

At the end of June of each year t, we form a composite score by averaging the percentiles of return on capital and earnings yield for the fiscal year ending in calendar year $t-1$ and sort stocks into deciles based on the NYSE breakpoints of the composite score. Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of year $t+1$. For two-way sorts, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of the composite score for the fiscal year ending in calendar year $t-1$. Independently, we sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios.

Table 3 shows that the Greenblatt measure forecasts returns reliably. In one-way sorts, the high-minus-low decile earns on average 0.67% per month ($t = 3.01$). In two-way sorts with size, the high-minus-low quintile earns on average 0.43%, 0.47%, and 0.47% ($t = 2.51$, 2.87, and 3.08) across micro, small, and big stocks, respectively. The q-factor and q^5 models largely explain the Greenblatt formula. The high-minus-low decile has a q-factor alpha of 0.26% ($t = 1.51$) and a q^5 alpha of -0.13% ($t = -0.76$). The high-minus-low quintile has q-factor alphas of 0.05%, 0.08%, and 0.19% ($t = 0.29$, 0.56, and 1.41) and q^5 alphas of 0.06%, 0.03%, and -0.11% ($t = 0.43$, 0.18, and -0.84) across micro, small, and big stocks, respectively. The GRS test cannot reject the q-factor or q^5 model.

The Roe factor is the key driving force behind the explanatory power. In the q^5 regressions of the high-minus-low portfolios, the Roe factor loadings are consistently large and significant both in one-way and two-way sorts. The investment factor loadings are large and significant for micro and small stocks, but not for big stocks or the full sample. The expected growth factor loadings are significantly positive for big stocks and the full sample, but not for micro or small stocks. Intuitively, as a measure of profitability, Greenblatt's (2010) return on capital is closely related to Roe. Also, the earnings yield is a value metric, which gives rise to the role of investment-to-assets due to the investment-q linkage (Section 3.1). Finally, return on capital is also related to the operating cash flow-to-assets ratio, which is a key component in the expected growth measure.

3.4 Asness, Frazzini, and Pedersen's (2019) Quality-minus-junk Strategies

Asness, Frazzini, and Pedersen (2019) define quality as characteristics (such as profitability, growth, and safety) for which investors should be willing to pay a higher price. Empirically, high quality stocks earn significant higher average returns than low quality stocks. The quality-minus-junk strategies are the latest embodiment of the Graham-Dodd (1934) principle of buying high quality stocks at bargain prices. We show that the investment theory is a good start to understanding quality investing, and the q^5 model goes a long way toward explaining the quality-minus-junk strategies.

3.4.1 Explaining the Quality-minus-junk Strategies

Following Asness, Frazzini, and Pedersen (2019), we construct the quality score as the average of the profitability, growth, and safety scores. We measure profitability as gross profitability, return on equity, return on assets, cash flow-to-assets, gross margin, and minus accruals. Each month we convert each variable into cross-sectional ranks, which are then standardized into a z-score. Standardization means that we divide the cross-sectionally demeaned values of the rankings by their cross-sectional standard deviation. The profitability score is the average of the individual z-scores of the six profitability measures. We measure growth as the 5-year growth in residual per-share profitability measures, excluding accruals. The growth score is the average of the individual z-scores of the five growth measures. Finally, we measure safety with the Frazzini-Pedersen (2014) beta, leverage, O-score, Z-score, and the volatility of return on equity. The safety score is the average of the individual z-scores of the five safety measures (the Internet Appendix).

At the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the quality score. To align the timing between component signals and subsequent returns, we follow Asness, Frazzini, and Pedersen (2019) in using the Fama-French (1992) timing, which assumes that accounting variables in fiscal year ending in calendar year $y-1$ are publicly known at the June-end of year y, except for beta and the volatility of return on equity. We treat beta as known at the end of estimation month and the volatility of return on equity as known four months after the fiscal quarter when it is estimated. Monthly value-weighted decile returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t+1$.

In addition, we perform two-way sorts to examine how the quality-minus-junk premium varies with size. At the beginning of each month t, we sort stocks into quintiles based on the NYSE breakpoints of the quality score and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity at the beginning of month t. Taking intersections yields 15 portfolios. Monthly value-weighted portfolio returns are calculated for the current month t, and the portfolios are rebalanced at the beginning of month $t+1$.

Panel A of Table 4 shows that the high-minus-low quality (quality-minus-junk) decile earns on average 0.33% per month but is only marginally significant ($t = 1.66$).[2] The q-factor model fails to explain the quality-minus-junk spread, with an alpha of 0.44% ($t = 3.28$), and the model is rejected by the GRS test on the null that the alphas across the quality deciles are jointly zero ($p = 0.00$). In contrast, the q^5 model yields a tiny alpha of 0.06% ($t = 0.42$), and the GRS test fails to reject the q^5 model ($p = 0.12$). In the q^5 regression, the quality-minus-junk decile has significantly negative market, size, and investment factor loadings, indicating that high quality stocks have lower market betas, bigger market equity, and higher investments than low quality stocks. These three loadings

[2]In untabulated results, we largely reproduce the Asness-Frazzini-Pedersen (2019, Table 3) estimate of 0.42% ($t = 2.56$) in the sample from July 1957 to December 2016. Their sample includes financial stocks, stocks with negative book equity, and stocks on exchanges other than NYSE, Amex, and NASDAQ. All these stocks are excluded from our sample. The estimate in our reproduction with their exact sample selection is 0.41% ($t = 2.1$).

go in the wrong way in explaining the average return. Going in the right direction, the quality-minus-junk decile also has significantly positive Roe and expected growth factor loadings. As such, high quality stocks have higher profitability and higher expected growth than low quality stocks.

Panel B shows that the quality-minus-junk premium varies inversely with size, 0.61%, 0.42%, and 0.22% ($t = 3.92$, 3.19, and 1.53) across micro, small, and big stocks, respectively. The q-factor alphas are all economically large and statistically significant, 0.39%, 0.25%, and 0.33% ($t = 3.13$, 2.19, and 2.75), respectively. Other than the alpha in micro stocks, 0.3% ($t = 2.45$), the q^5 alphas continue to be small, 0.09% ($t = 0.83$) in small stocks and 0.07% ($t = 0.59$) in big stocks. The size and investment factor loadings again go in the wrong direction, especially in big stocks, but the Roe and expected growth factor loadings are sufficiently powerful to yield small q^5 alphas. However, the q^5 model is rejected by the GRS test across the 15 two-way portfolios.

Asness, Frazzini, and Pedersen (2019) also construct an alternative quality score as the average of the profitability, growth, safety, and payout scores. The payout z-score is the average of the z-scores of the rankings of equity net issuance, debt net issuance, and total net payout over profits (the Internet Appendix). Because the quality-minus-junk factor posted on the AQR Web site contains the payout component,[3] we also examine the alternative quality score in detail.

From Table 5, the alternative quality score shows stronger predictive power of returns than the benchmark score. The alternative quality-minus-junk decile earns on average 0.5% per month ($t = 2.68$). The q-factor model leaves a large and significant alpha of 0.5% ($t = 3.77$), and the model is rejected by the GRS test ($p = 0.00$). However, the q^5 model shrinks the alpha to 0.1% ($t = 0.84$), and the model is not rejected by the GRS test ($p = 0.18$). The Roe and expected growth factor loadings, which go in the right direction in explaining the average return, are again powerful enough to overcome the market, size, and investment factor loadings, all of which go in the wrong direction.

From Panel B, the alternative quality-minus-junk premium also varies inversely with size, 0.72%,

[3]See https://www.aqr.com/Insights/Datasets/Quality-Minus-Junk-Factors-Monthly

0.45%, and 0.36% per month ($t = 4.39$, 3.3, and 2.71) across micro, small, and big stocks, respectively. The q-factor model leaves economically large and statistically significant quality-minus-junk alphas across all the three size groups. However, except for micro stocks, in which the alpha is 0.33% ($t = 2.54$), the q^5 alpha is small in the broad cross section, 0.08% ($t = 0.73$) in small stocks and 0.04% ($t = 0.43$) in big stocks. More important, because of the presence of payout, which correlates negatively with investments, the (low-minus-high) investment factor loadings of the quality-minus-junk quintile become significantly positive in micro and small stocks. In big stocks, the investment factor loadings become smaller in magnitude, albeit still negative. However, the q^5 model continues to be rejected by the GRS test across the 15 two-way portfolios ($p = 0.00$).

The Internet Appendix furnishes results on strategies formed separately on the profitability, growth, safety, and payout scores. Without going through all the details, we highlight that the average returns of the high-minus-low deciles on the profitability, growth, safety, and payout scores are 0.37%, 0.18%, 0.2%, and 0.47% ($t = 2.11$, 1.12, 0.96, and 2.79), and their q^5 alphas -0.01%, 0.31%, 0.16%, and -0.09 ($t = -0.1$, 2.17, 1.05, -0.67), respectively. Resembling the overall quality score, the high-minus-low profitability decile has significantly negative market, size, and investment factor loadings, which are in turn dominated by significantly positive Roe and expected growth factor loadings. Intuitively, high profitability signals high expected growth. The loadings pattern for the high-minus-low safety score is largely similar. Intuitively, the safety score contains O- and Z-scores for bankruptcy risk, which is inversely related to profitability.

The high-minus-low growth score decile has a tiny market beta, a negative size factor loading of -0.35 ($t = -6.15$), as well as positive Roe and expected growth factor loadings of 0.37 ($t = 4.18$) and 0.24 ($t = 2.41$), respectively. More important, the investment factor loading is economically large and highly significant, -1.12 ($t = -12.03$), which in turn drives up the q^5 alpha to 0.31% ($t = 2.17$). Intuitively, the growth score measures the past 5-year growth rates in profits, earnings, and cash flows, all of which are positively correlated with past asset growth (investments). As such, the high-minus-low growth decile loads strongly and negatively on our (low-minus-high) investment factor.[4] This evidence suggests that the construction of the Asness-Frazzini-Pedersen (2019) growth score can potentially be improved. Their growth score aims to model expected growth but ends up capturing past growth (investment-to-assets) rather than expected growth.

Finally, the high-minus-low payout decile has significantly negative market and size factor loadings (-0.14 and -0.21) and significantly positive Roe and expected growth factor loadings (0.16 and 0.26), respectively. The investment factor loading is economically large, 1.05, and highly significant ($t = 15.86$). Intuitively, payout and investment are negatively correlated, yielding a positive loading on the low-minus-high investment factor for the high-minus-low payout decile.

3.4.2 Buffett's Alpha

Frazzini, Kabiller, and Pedersen (2018) show that Warren Buffett's Berkshire Hathaway's alpha becomes insignificant once controlling for the betting-against-beta (BAB) and quality-minus-junk (QMJ) factor loadings. Frazzini et al. adopt the AQR 6-factor model, which consists of the market, SMB, and HML from the Fama-French (1993) 3-factor model, UMD, the Frazzini-Pedersen (2014) BAB, and the Asness-Frazzini-Pedersen (2019) alternative QMJ with payout. From November 1976 to March 2017, Frazzini et al. show that Berkshire earns an insignificant alpha of 0.45% per month ($t = 1.55$) in the AQR 6-factor regression. The market, HML, BAB, and QMJ factors all play a role in explaining Buffett's alpha, with loadings of 0.95, 0.4, 0.27, and 0.47 ($t = 12.77$, 3.55, 3.04, and 3.06), respectively. The SMB and UMD loadings are weakly negative and insignificant.

We obtain Berkshire's returns and prices data first from CRSP and then fill in missing observations from Compustat. The sample constructed in this way goes from February 1968 to December 2018. The observations prior to November 1976, in January and February 1977, in March and April 1978, and in May and June 1979 are from Compustat, and the remainder is from CRSP.[5]

[4] More precisely, Asness, Frazzini, and Pedersen (2019) measure the growth score with the growth in residual income, which is net income minus the product of the riskfree rate and the book equity. As such, the growth in residual income increases with the growth in net income but decreases with asset growth (see their footnote 12). Despite the negative relation between the growth in residual income and asset growth (conditional on the growth in net income), the positive relation between the growth in net income and asset growth is strong enough to yield a large negative investment factor loading for the high-minus-low growth score decile.

[5] In CRSP, the Berkshire returns are not technically missing in February 1977, April 1978, and June 1979 but are

The market, SMB, HML, and UMD data are from Kenneth French's Web site. The BAB and alternative QMJ with payout, denoted QMJ*, are from the AQR Web site. Because the benchmark QMJ factor without payout, denoted QMJ, are not available online, we construct QMJ per the exact Asness-Frazzini-Pedersen (2019) procedure in our sample, which excludes financial stocks, stocks with negative book equity, and stocks not traded on NYSE, Amex, or NASDAQ.[6]

The first two rows in Panel A of Table 6 reproduce Frazzini, Kabiller, and Pedersen (2018, Table 4). Our reproduction yields an AQR 6-factor alpha of 0.46% per month ($t = 1.69$) for Berkshire from November 1976 to March 2017. For comparison, Frazzini et al. report an alpha of 0.45% ($t = 1.55$). Our factor loadings are also close to the original estimates. The next two rows show that the alpha increases slightly to 0.5% ($t = 1.89$) once we replace QMJ* with QMJ.

The first two rows in Panel B shows that in the same sample period, the average excess return of Berkshire is very high, 1.51% per month ($t = 4.81$). More important, the performance of the q-factor model is quantitatively similar to that of the AQR 6-factor model. The q-factor alpha is 0.48% ($t = 1.75$), aided by significantly positive investment and Roe factor loadings, 0.73 ($t = 4.4$) and 0.5 ($t = 4.56$), respectively. As such, Buffett tends to buy stocks with high profitability and low investment. Because the investment factor is a substitute for the value factor in the q-factor model, the evidence indicates that Buffett prefers to buy profitable firms at bargain prices, consistent with the long-standing Graham-Dodd (1934) philosophy. The next two rows in Panel B shows that in the q^5 regression Berkshire has a negative loading of -0.3 on the expected growth factor, albeit insignificant ($t = -1.46$). As a result, the q^5 alpha is higher, 0.66% ($t = 2.1$).

In the full sample from February 1968 to December 2018, Berkshire excess returns are on average 1.44% per month ($t = 4.96$). The q-factor model again performs similarly as the AQR 6-factor

2-month returns that span over the missing prior months of January 1977, March 1978, and May 1979, respectively.

[6]Following Asness, Frazzini, and Pedersen (2019), at the beginning of each month t, we perform sequential 2×3 sorts, first on size and then on the quality score, based on the NYSE median market equity at the beginning of the month and the NYSE 30–40–30 breakpoints of the quality score. The timing alignment of quality with subsequent returns is the same in Table 4. Taking intersections yields six portfolios. Monthly value-weighted returns are calculated for the current month t, and the portfolios are rebalanced at the beginning of month $t + 1$. QMJ is the returns of the average high quality portfolios minus the returns of the average low quality portfolios.

model. However, both models fail to reduce Berkshire's performance to insignificance. The q-factor alpha is 0.64% ($t = 2.44$), which is close to the AQR alpha of 0.61% ($t = 2.08$). Both alphas are economically large. The expected growth factor loading, -0.2, again goes in the wrong direction, albeit insignificant ($t = -1.11$), yielding a higher q^5 alpha of 0.77% ($t = 2.67$).[7]

3.4.3 Spanning Tests with the AQR 6-factor Model

Table 7 reports the factor spanning tests between the q-factor and q^5 models and the AQR 6-factor model. We again use two versions of the AQR model, with the alternative QMJ with payout from the AQR Web site (QMJ*) and the QMJ without payout replicated in our sample (QMJ). We find that the AQR 6-factor model cannot explain the q and q^5 factor premiums. Conversely, the q-factor and q^5 models can explain the BAB premium. Neither explains QMJ* due to sample differences. However, the q^5 model subsumes QMJ, with and without payout, reconstructed in our sample.

From Panel A, the AQR model explains the Roe premium but not the investment and expected growth premiums. With QMJ*, the AQR 6-factor alphas of the investment, Roe, and expected growth factors are 0.24%, 0.05%, and 0.62% per month (t = 3.21, 0.66, and 9.09), respectively. The investment factor has a large loading of 0.39 ($t = 13.1$) on HML, but all the other loadings are small in magnitude. The Roe factor has a large loading of 0.64 ($t = 11.54$) on QMJ*, which, along with the smaller loadings of 0.18 and 0.11 on UMD and BAB, respectively, reduces the Roe alpha to 0.05%. The expected growth factor has a loading of 0.34 ($t = 6.27$) on QMJ* as well as smaller loadings of 0.11 on HML and UMD. The GRS test rejects the AQR model on the null that the alphas of nonmarket q-factors, with and without the expected growth factor, are jointly zero (Panel C). Using QMJ yields somewhat higher alphas for the q and q^5 factors and stronger GRS rejections.

Panel B uses the q-factor and q^5 models to explain the AQR factors. SMB is on average 0.19% per month ($t = 1.54$). The q-factor alpha is 0.06% ($t = 1.65$). The q^5 alpha is also small, 0.1%, albeit

[7] Prior to September 1988, monthly Berkshire returns can differ drastically between CRSP and Compustat. The deviations vary from -25.2% to $+20.3\%$, with an average magnitude of 0.36%. From September 1988 onward, the returns from the two sources are exactly identical. For robustness, we have examined the results with Compustat's Berkshire returns prior to September 1988. The results are quantitatively similar (the Internet Appendix).

significant ($t = 2.63$). More important, the BAB factor is on average 0.9% ($t = 5.73$). The q-factor alpha is only 0.32% ($t = 1.94$), helped by the large loadings on the investment and Roe factors, 0.68 ($t = 5.51$) and 0.45 ($t = 4.67$), respectively. The size factor also helps with a loading of 0.15 ($t = 2.19$). The q^5 alpha is similar, 0.29% ($t = 1.73$), as the expected growth factor loading is small, 0.05. Frazzini and Pedersen (2014) interpret the BAB factor as indicating that leverage-constrained investors overweight high-beta assets, causing them to require lower risk-adjusted returns than low-beta assets. Our evidence suggests that BAB tilts toward small, low investment, and high Roe stocks, which should earn high expected returns per the investment theory. Our supply-side interpretation is complementary to Frazzini and Pedersen's demand-side interpretation.

QMJ* with payout from the AQR Web site is on average 0.42% per month ($t = 4.15$). The q-factor alpha is 0.33% ($t = 5.23$). The Roe loading is large, 0.49, but the investment loading is weakly negative, -0.08. The q^5 alpha is smaller, 0.17%, albeit significant ($t = 2.71$), with an expected growth loading of 0.23 ($t = 4.63$). QMJ without payout replicated in our sample is on average 0.3% ($t = 3.02$). The q-factor alpha is 0.27% ($t = 3.69$), but the q^5 model reduces it to insignificance, 0.11% ($t = 1.69$). As noted, two differences separate QMJ* from QMJ. QMJ* contains payout, but QMJ does not. QMJ* is also formed in a somewhat broader sample that includes financial stocks, stocks with negative book equity, and stocks traded on exchanges other than NYSE, Amex, and NASDAQ. In untabulated results, we verify that the sample differences are more important. Replicating the alternative QMJ with payout in our sample yields an average premium of 0.39% ($t = 3.9$), a q-factor alpha of 0.26% ($t = 3.67$), and a q^5 alpha of 0.11% ($t = 1.59$).

Finally, from Panel C, the GRS test rejects both the q-factor and q^5 models based on the null that the alphas of nonmarket AQR-factors, with either QMJ* or QMJ, are jointly zero.

3.4.4 Size Matters, If You Control Your Quality

Asness et al. (2018) show that the size premium can be resurrected if controlling for their quality score, and the quality-minus-junk premium can be strengthened if controlling for size. Table 8 reports similar evidence based on our own two quality measures, Roe and the expected growth.

To set things up, Panel A shows one-way quintiles on the market equity, total assets (Compustat annual item AT, a physical size measure), Roe, and the expected growth (Eg). We use monthly sorts with NYSE breakpoints, value-weighted returns, and 1-month holding period. The market equity is from the beginning of the portfolio formation month, and total assets from the fiscal year ending at least four months ago. The Internet Appendix details the timing alignment of Roe and Eg with subsequent returns. On size, the small-minus-big market equity quintile earns only 0.16% per month ($t = 0.76$), and the small-minus-big total assets quintile 0.13% ($t = 0.62$). On quality, the high-minus-low Roe quintile earns 0.44% ($t = 2.71$), and the high-minus-low Eg quintile 0.82% ($t = 6.56$).

Panel B shows two-way independent sorts on size and quality, again with NYSE breakpoints, value-weighted returns, and 1-month holding period. Consistent with Asness et al. (2018), controlling for quality resurrects the size premium. The small-minus-big market equity quintile averaged across the Roe quintiles earns on average 0.48% per month ($t = 2.53$). Averaging across the expected growth quintiles yields a similar size premium of 0.5% ($t = 2.57$). In addition, controlling for size strengthens the quality premium. The high-minus-low Roe quintile averaged across the market equity quintiles earns on average 0.77% ($t = 5.47$), rising from 0.44% ($t = 2.71$) from the one-way Roe sorts. The high-minus-low Eg quintile averaged across the market equity quintiles earn on average 1.07% ($t = 11.52$), rising from 0.82% ($t = 6.56$) from the one-way Eg sorts.

The investment theory can explain this evidence. As noted, the denominator in equation (1) equals marginal q, which in turn equals Tobin's q with constant returns to scale. As the market equity is in the denominator, equation (1) makes several predictions on the interaction between the size and quality premiums. First, the negative relation between the market equity and the discount rate is stronger in firms with higher quality (expected profitability and expected investment). Second, the positive relation between quality and the discount rate is stronger in firms with smaller market equity. Finally, because more profitable firms with higher market equity tend to invest more both today and tomorrow, the numerator and denominator of equation (1) tend to move in the same direction. As such, unconditional one-way sorts on the market equity and on quality work to counteract against each other. Joint two-way sorts avoid this problem so as to strengthen both the size and quality premiums. These predictions are all borne out in Panel B of Table 8.

Panel B also shows that the interactive effect between total assets and quality is much weaker than the interactive effect between the market equity and quality. The small-minus-big total assets quintile averaged across the Roe quintiles is on average only 0.14% per month (t = 0.76), which is close to that from the one-way sorts, 0.13% (t = 0.62). Averaging across the expected growth quintiles raises the average return of the small-minus-big total assets quintile to 0.33% (t = 1.92).

The investment theory again can explain this evidence. Because of constant returns to scale, the physical size is not a state variable and does not affect the expected return in the economic model. In the data, the physical size matters only to the extent that it correlates positively with the market equity. The Internet Appendix furnishes largely similar evidence with alternative physical size measures, including book equity, sales, net property, plant, and equipment, and the number of employees. We interpret the evidence as according with constant returns to scale.

3.5 Bartram and Grinblatt's (2018) Agnostic Fundamental Analysis Strategies

Bartram and Grinblatt (2018) show that the deviation of a firm's peer-implied intrinsic value from its market value forecasts future returns reliably. Instead of relying on the residual income model as in Frankel and Lee (1998), Bartram and Grinblatt estimate a stock's intrinsic value as the fitted component from monthly cross-sectional regressions via ordinary least squares of the stock's market equity, P, on 28 accounting variables. The variables include 14 from the balance sheet and 14 from the income statement, all of which are from Compustat quarterly files. Because Bartram and Grinblatt use point-in-time data, to which we do not have access, we follow their working paper dated 2015 and use quarterly Compustat data.[8] The 14 income statement variables are annualized

[8]The 28 variables from Compustat quarterly files are: total assets (item ATQ), income before extraordinary items, adjusted for common stock equivalents (item IBADJQ), income before extraordinary items, available for

by summing the quarterly values from the most recent four fiscal quarters. The sample starts in January 1977 because of the low coverage of the right-hand side variables prior to 1977.

The dependent and explanatory variables in the monthly cross-sectional intrinsic value regressions are contemporaneous. At the beginning of each month, we regress the beginning-of-the-month market equity on the most recently available quarterly accounting variables (from the fiscal quarter ending at least four months ago), except for income before extraordinary items (Compustat quarterly item IBQ), net income (loss) (item NIQ), and net sales (item SALEQ). We treat these three variables as known publicly immediately after quarterly earnings announcement dates (item RDQ). To exclude stale accounting information, we require the end of the fiscal quarter that corresponds to the most recent quarterly accounting variables to be within six months prior to the regression month.

Each month we control for the outliers in the accounting variables by winsorizing their ratios to total asset (Compustat quarterly item ATQ) at the 1–99% level of the ratios and then multiplying total assets back to the winsorized ratios. A stock's intrinsic value, V, each month, is given by the fitted component of the month's cross-sectional regression, and the agnostic fundamental measure is defined as the percentage deviation of the intrinsic value from the market value, $(V - P)/P$.

At the beginning of month t, we sort stocks into deciles based on the NYSE breakpoints of the computed agnostic measure, $(V - P)/P$. Monthly value-weighted returns are calculated for the current month t, and the deciles are rebalanced at the beginning of month $t + 1$. We also perform monthly two-way independent sorts on the beginning-of-the-month market equity and the agnostic measure with NYSE breakpoints, value-weighted returns, and 1-month holding period.

Common (item IBCOMQ), income before extraordinary items (item IBQ), total liabilities and stockholders equity (item LSEQ), dividends, preferred/preference (item DVPQ), net income (loss) (item NIQ), stockholders equity (item SEQQ), total revenue (item REVTQ), net sales/turnover (item SALEQ), extraordinary items and discontinued operations (item XIDOQ), common stock equivalents, dollar savings (item CSTKEQ), net property, plant, and equipment (item PPENTQ), total long-term debt (item DLTTQ), total common/ordinary equity (item CEQQ), preferred/preference stock (capital) (item PSTKQ), non-operating income (expense) (item NOPIQ), discontinued operations (item DOQ), extraordinary items (item XIQ), liabilities, total and noncontrolling interest (item LTMIBQ), total liabilities (item LTQ), current liabilities (item LCTQ), current assets (item ACTQ), noncurrent assets (item ANCQ), pretax income (item PIQ), income taxes (item TXTQ), other assets (item AOQ), other liabilities (item LOQ). Among the 28 data items, three are "perfectly" redundant. REVTQ is exactly the same as SALEQ (but with more missing values). LSEQ is exactly identical to ATQ, also with the same coverage. ANCQ equals ATQ − ACTQ. As such, we drop REVTQ, LSEQ, and ANCQ from the 28-variable list.

Panel A of Table 9 reports the one-way sorts. With the portfolio agnostic measure calculated as the value-weighted average of the agnostic measures for all the stocks within a given portfolio, the decile-level agnostic measure ranges from -1.35 to 3.77 from the low to the high decile. In contrast, the variation in book-to-market is more muted, from 0.53 to 1.03. More important, consistent with Bartram and Grinblatt (2018), the agnostic measure predicts return reliably. The high-minus-low decile earns on average 0.48% per month ($t = 2.88$). The q-factor alpha is 0.32% per month ($t = 1.47$), but the q^5 alpha is 0.47% ($t = 2.22$). The GRS test rejects the q-factor model but not the q^5 model. In the q^5 regression, the high-minus-low decile loads positively on the investment factor, 0.61 ($t = 4.24$), going in the right direction, but loads negatively on the expected growth factor, -0.23 ($t = -1.98$), going in the wrong direction in explaining the average return. The size factor also helps with a loading of 0.29 ($t = 2.79$), but the market and Roe factor loadings are tiny.

From Panel B, the q-factor and q^5 models do a better job in the two-way sorted portfolios. The high-minus-low agnostic quintile earns on average 0.92%, 0.5%, and 0.46% per month ($t = 4.25$, 2.42, and 2.11) across micro, small, and big stocks, respectively. The q-factor model mostly reduces the average returns to insignificance, with alphas of 0.54%, 0.21%, and 0.33% ($t = 2.03$, 0.85, and 1.23), and the q^5 model does too, with alphas of 0.48%, 0.27%, and 0.42% ($t = 1.82$, 1.23, and 1.7), respectively. The investment factor loadings are economically large and highly significant, but the Roe and expected growth factor loadings are mostly insignificant, with mixed signs.

Bartram and Grinblatt (2018) impose the \$5 price screen in their sample selection, but to be consistent with our other tests, we do not. The Internet Appendix furnishes the evidence with the \$5 price screen imposed. The results are largely similar. The high-minus-low agnostic decile earns a somewhat higher average return of 0.63% per month ($t = 3.41$), but its q^5 alpha is only 0.38% ($t = 1.99$). The high-minus-low quintile earns on average 0.81%, 0.47%, and 0.37% ($t = 3.7$, 2.26, and 1.7) across micro, small, and big stocks, respectively. The q-factor and q^5 alphas become larger and more significant in microcaps but remain relatively small and insignificant in small and big stocks.

3.6 Penman and Zhu's (2014, 2018) Fundamental Analysis Strategies

The clean surplus relation in financial accounting states that $B_{it+1} = B_{it} + Y_{it+1} - D_{it+1}$, in which B_{it} is firm i's book equity, Y_{it} earnings, and D_{it} net dividends. Penman and Zhu (2014) and Penman et al. (2018) use this relation to rewrite the 1-period-ahead expected return, $E_t[r^S_{it+1}]$, as:

$$E_t[r^S_{it+1}] = E_t\left[\frac{P_{it+1} + D_{it+1} - P_{it}}{P_{it}}\right] = \frac{E_t[Y_{it+1}]}{P_{it}} + E_t\left[\frac{(P_{it+1} - B_{it+1}) - (P_{it} - B_{it})}{P_{it}}\right]. \quad (3)$$

Penman and Zhu argue that the expected change in the market-minus-book equity (the market equity's deviation from the book equity), $E_t[(P_{it+1} - B_{it+1}) - (P_{it} - B_{it})]$, is related to the expected earnings growth. Intuitively, an increase in the deviation means that price rises more than book equity. Because earnings raise book equity via the clean surplus relation, an expected increase in the deviation means that price increases more than earnings. A lower earnings at $t + 1$ relative to price, P_t, must mean higher earnings afterward, as price reflects life-long earnings for the firm. As such, an expected increase in the deviation captures higher expected earnings growth after $t + 1$.

Penman and Zhu (2014) forecast the forward earnings yield, Y_{it+1}/P_{it}, and the 2-year-ahead earnings growth with several anomaly variables, many of which forecast the forward earnings yield and earnings growth in the same direction of forecasting returns. Penman and Zhu (2018) construct a fundamental analysis strategy based on the expected-return proxy from projecting future returns on anomaly variables that are a priori connected to future earnings growth. The expected-return proxy, denoted ER8, is based on eight variables. We work with ER8 because it is the most comprehensive proxy in their study. The eight variables include earnings-to-price, book-to-market, accruals, investment, growth in net operating assets, return on assets, net external financing, and net share issues, all of which are from Compustat annual files (the Internet Appendix).

We largely follow Penman and Zhu (2018) in constructing ER8, except that we adopt the Fama-French (1993) timing for annual sorts (more standard in empirical finance). At the end of June of each year t, using the prior 10-year rolling window, we perform annual cross-sectional regressions of stock returns cumulated from July of a previous year to June of the subsequent year via ordinary least squares. If the July-to-June interval contains fewer than 12 monthly returns, we annualize the cumulative return based on available monthly returns. The last annual regression in the rolling window uses the annual return cumulated from July of year $t-1$ to June of t on the eight accounting variables for the fiscal year ending in calendar year $t-2$. The other nine annual regressions in the rolling window are specified analogously. We winsorize both the left- and right-hand side variables in each regression at the 1–99% level. We combine the average slopes from the 10-year rolling window with the eight winsorized variables for the fiscal year ending in calendar year $t-1$ to calculate ER8.

Finally, we sort stocks into deciles based on the NYSE breakpoints of ER8. Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced at the June-end of $t+1$. To examine how the ER8 premium varies with size, we also perform independent, annual 3×5 sorts on the June-end market equity and ER8 with NYSE breakpoints and value-weighted returns. Because of limited coverage for net external finance prior to 1972, the annual cross-sectional regressions start in June 1972, and the ER8 portfolios start in July 1982.

Table 10 reports the results. From Panel A, the high-minus-low ER8 decile earns on average 0.69% per month ($t = 3.79$). While the q-factor model fails to explain the average return, with an alpha of 0.55% ($t = 3.32$), the q^5 model shrinks the alpha to 0.25% ($t = 1.5$). In the q^5 regression, the investment factor loading is 0.66 ($t = 6.66$), and the expected growth factor loading 0.46 ($t = 4.23$).

Intuitively, ER8 contains two value metrics, earnings-to-price and book-to-market, which correlate negatively with investment-to-assets, due to the investment-value linkage (Section 3.1). In addition, Penman and Zhu (2018) select the eight variables based on their predictive power of earnings growth. Because earnings growth and investment growth tend to be positively correlated, the high-minus-low ER8 decile loads positively on the expected investment growth factor.

From Panel B, the ER8 premium varies inversely with size. The high-minus-low quintile earns on average 0.78%, 0.33%, and 0.48% ($t = 4.82$, 2.24, and 3.29) across micro, small, and big stocks, respectively. While the q^5 alpha is 0.55% ($t = 3.23$) in microcaps, it is insignificant in small stocks, 0.01% ($t = 0.09$), and in big stocks, 0.16% ($t = 1.25$). While the investment factor loadings are consistently large and significant, the expected growth factor loading is significant only in big stocks.

3.7 Lewellen's (2015) Expected-return Strategies

Lewellen (2015) shows that cross-sectional return forecasts predict future realized returns reliably. As noted, Penman and Zhu (2018) adopt a similar methodology when forming their fundamental analysis strategies. However, Lewellen does not restrict the return predictors to also forecast earnings growth per Penman and Zhu and does not tie his cross-sectional forecasts with security analysis. Nevertheless, because Lewellen's methodology is simple yet highly effective, we study in detail to what extent the q-factor and q^5 models can explain his strategies.

We adopt Lewellen's (2015) (most comprehensive) Model 3, with 15 anomaly variables. The lists contains size, book-to-market, prior 11-month returns, prior 36-month and 12-month growth rates in shares outstanding, accruals, return on assets, asset growth, dividend yield, cumulative returns from month -36 to -13, market beta, return volatility, share turnover, debt-to-price, and sales-to-price. All the accounting variables are from Compustat annual files (the Internet Appendix).

At the beginning of each month t, we use the prior 120-month rolling window to perform monthly cross-sectional regressions of returns on the 15 variables. In particular, the last monthly regression uses the returns over month $t-1$ on the accounting variables for the fiscal year ending at least four months prior to the beginning of month $t-1$ (with the market equity at the beginning of month $t-1$). Following Lewellen (2015), we use ordinary least squares. We winsorize the right-hand side variables at the 1–99% level for each regression. We then combine the average slopes from the rolling window with the 15 anomaly variables for the fiscal year ending at least four months prior to the beginning of month t (the market equity at the beginning of month t) to compute expected returns.

Finally, we sort stocks into deciles based on the NYSE breakpoints of the expected returns, calculate value-weighted returns for the current month t, and rebalance the deciles at the beginning of month $t+1$. For two-way 3×5 sorts, we interact the expected returns with the market equity at the beginning of month t, with NYSE breakpoints and value-weighted returns. The cross-sectional regressions start in January 1964, and Lewellen's expected-return portfolios start in January 1974.

Panel A of Table 11 shows that the high-minus-low expected-return decile earns on average 0.99% per month ($t = 3.84$). The q-factor alpha is 0.68% ($t = 2.5$), and the q^5 alpha 0.55% ($t = 2.06$). The GRS test rejects the q-factor model but not the q^5 model ($p = 0.07$). The investment factor loading is large, 0.5 ($t = 2.23$). The size factor loading is also large and significant, 0.88 ($t = 5.87$), but the Roe factor loading is negative and significant, -0.46 ($t = -3$), and the expected growth factor loading is small and insignificant, 0.19 ($t = 0.88$).

From Panel B, the high-minus-low expected-return quintile earns on average 1.68%, 0.83%, and 0.56% ($t = 9.7$, 5.28, and 2.58), the q-factor alphas 1.48%, 0.65%, and 0.33% ($t = 7.9$, 3.62, and 1.31), and q^5 alphas 1.29%, 0.44%, and 0.34% ($t = 7.79$, 2.46, and 1.44), respectively. Both models are strongly rejected by the GRS test. In the q^5 regressions, the investment factor loadings are large and mostly significant, both the Roe and expected growth factor loadings have mixed signs. Intuitively, the 15 anomaly variables include asset growth, accruals, and equity issues, which are directly related to investment-to-assets, as well as several value metrics such as book-to-market, dividend yield, debt-to-price, and sales-to-price, which are indirectly related to investment-to-assets.

4 An Economic Perspective

We interpret our evidence as saying that the investment theory, in which the expected return varies cross-sectionally with investment, expected profitability, and expected growth, is a good start to understanding Graham and Dodd's (1934) *Security Analysis*. The realized return equals the expected return plus the abnormal return. As such, predictability with any anomaly variables has two parallel interpretations. In the first, the anomaly variables forecast the abnormal return, violating efficient markets, as in Graham and Dodd. In the second interpretation, the anomaly variables are connected to the expected return, retaining efficient markets, as in the investment theory.

4.1 Reconciling with the Graham-Dodd (1934) Perspective

Graham and Dodd (1934) lay the intellectual foundation for security analysis, which is "concerned with the intrinsic value of the security and more particularly with the discovery of discrepancies between the intrinsic value and the market price (p. 17)." The basic philosophy is to invest in undervalued securities that are selling well below the intrinsic value, which is "that value which is justified by the facts, e.g., the assets, earnings, dividends, definite prospects, as distinct, let us say, from market quotations established by artificial manipulation or distorted by psychological excesses (p. 17)."

The intrinsic value is not exactly identified, however. "It needs only to establish either that the value is *adequate*—e.g., to protect a bond or to justify a stock purchase—or else that the value is considerably higher or considerably lower than the market price (Graham and Dodd 1934, p. 18, original emphasis)." To be protected from the ambiguity in estimating the intrinsic value, Graham (1949) advocates the "margin of safety," which is an investing principle that an investor only purchases a security when its market price is sufficiently below its intrinsic value.

Efficient markets and security analysis have long been viewed as diametrically opposite. For example, honoring the 50th anniversary of Graham and Dodd (1934), Buffett (1984) reports the successful performance of nine famous investors. After arguing that their success is beyond chance, Buffett writes: "Our Graham & Dodd investors, needless to say, do not discuss beta, the capital asset pricing model or covariance in returns among securities. These are not subjects of any interest to them. In fact, most of them would have difficulty defining those terms (p. 7)."

4.1.1 Cross-sectionally Varying Expected Returns without Mispricing

The investment theory reconciles security analysis with efficient markets. It is well known that time-varying expected returns accord with stock market predictability (Marsh and Merton 1986; Campbell and Cochrane 1999), without mispricing per Shiller (1981). Analogously, the investment theory implies cross-sectionally varying expected returns, which provide an economic foundation for security analysis, without mispricing per Graham and Dodd (1934).

The mispricing perspective is the dominating view in the contemporary literature on security analysis. For instance, Bartram and Grinblatt (2018) start with the basic premise: "A cornerstone of market efficiency is the principle that trading strategies derived from public information should not work (p. 126)." This premise implicitly uses the constant expected return (as in the random walk hypothesis) as the null of efficient markets and rules out the possibility that the "public information" can be indicative of cross-sectionally varying expected returns.

Bartram and Grinblatt (2018) also appeal to the law of one price: "Like fair values obtained from any asset pricing model, the values obtained with [the intrinsic-value regressions] are the market values of synthetic stocks or replicating portfolios; replicating, because each of the portfolios' fundamental characteristics is identical to those from the firm being valued (p. 127)." However, the law of one price states that "if two portfolios have the same payoffs (in every state of nature), then they must have the same price (Cochrane 2005, p. 61)." In particular, the law does not say that firms with the same (historical) accounting data should have the same market value.

In the real options theory, the market value equals assets in place plus growth options (Berk, Green, and Naik 1999). While the Bartram-Grinblatt intrinsic-value regressions might reasonably pin down the value of (backward-looking) assets in place, it is not clear how effective these regressions are to estimate the value of (forward-looking) growth options. This concern is especially acute, as value-creating investments in patents, brand names, information technology, employee training, and other intangible assets are expensed, largely missing from financial statements, even though intangibles account for an increasingly larger portion of the market value (Lev and Gu 2016).

4.1.2 Active Management within Efficient Markets

The traditional view of academic finance, with the Sharpe-Lintner CAPM as the workhorse theory of efficient markets, tends to dismiss any profits of security analysis as resulting purely from luck and recommend investors to passively hold the market portfolio.[9] In addition to departing from the mis-

[9] For instance, in a prominent textbook on investments, Bodie, Kane, and Marcus (2017, p. 356) write: "[T]he efficient market hypothesis predicts that *most* fundamental analysis also is doomed to failure. if the analyst relies

pricing perspective, the investment theory also deviates from the traditional academic view by systematically validating the Graham-Dodd (1934) practice of security analysis on economic grounds. The theory directs equity analysts' attention to key expected-return drivers, such as investment, expected profitability, and expected investment growth, thereby providing an economic foundation for active management long perceived as incompatible with standard economic principles.

The equilibrium foundation for active management also points to the limitations of factor investing. As powerful as the latest factor models are, they all fail to fully explain Buffett's alpha in Berkshire Hathaway. As shown in Table 6, although explaining a large portion of Berkshire's average excess return of 1.44% per month from February 1968 to December 2018, the q-factor model leaves a big alpha of 0.64% ($t = 2.45$), and the q^5 model 0.77% ($t = 2.69$). The AQR 6-factor alpha is similar, 0.61% ($t = 2.09$). Echoing Kok, Ribando, and Sloan (2017), we interpret the evidence as suggesting that discretionary active management cannot be (fully) substituted by passive factor investing.

One interpretation is that Warren Buffett simply has a better expected profitability model than current profitability and a better expected growth model than the one embedded in the q^5 model. A more likely interpretation is that our parametric equation (1) is incomplete. Many forces that affect earnings power and future growth, such as employee training, brand building, research and development, and managerial quality, are hard, if not impossible, to measure. Identifying these forces and evaluating their impact on the expected return leave plenty of room for active management.

4.2 Complementarity with the Penman-Zhu (2014, 2018) Perspective

The academic accounting literature on fundamental analysis, pioneered by Ou and Penman (1989), has traditionally subscribed to the Graham-Dodd perspective: "Rather than taking prices as value benchmarks, 'intrinsic values' discovered from financial statements serve as benchmarks with which prices are compared to identify overpriced and underpriced stocks. Because deviant prices ultimately gravitate to the fundamentals, investment strategies which produce 'abnormal returns' can

on publicly available earnings and industry information, his or her evaluation of the firm's prospects is not likely to be significantly more accurate than those of rival analysts (original emphasis)."

be discovered by the comparison of prices to these fundamental values (p. 296)."

More recently, however, the accounting literature has adopted a more nuanced view. For instance, Penman and Zhu (2014) conclude that "the returns to anomaly variables are consistent with rational pricing in the sense that the returns are those one would expect if the market were efficient in its pricing. That is, the returns are not "anomalous" in the sense that we cannot explain them; rather, they can be logically explained as indicating expected returns for risk borne (p. 1836)."[10]

Conceptually, the Penman-Zhu (2014, 2018) model and the investment theory share many commonalities. Both focus on the 1-period-ahead expected return, unlike other applications of the residual income model (Gebhardt, Lee, and Swaminathan 2001; Fama and French 2006, 2015; Richardson, Tuna, and Wysocki 2010). Both deliver the same insight that the 1-period-ahead expected earnings and the expected growth are the two key drivers of the expected return. However, important differences exist in the underlying reasoning and the specific drivers of the expected return.

Equation (3) decomposes the expected return into the expected earnings yield and the expected change in the market-minus-book equity. Penman and Zhu (2014) then use powerful accounting insights to connect the latter term to the expected earnings growth. By comparison, equation (1) is an economic model derived from the first principle of real investment. The first principle says that the marginal cost of investment, $1 + a(I_t/A_t)$, equals the marginal q, which in turn equals average q, P_t/A_{t+1}. This investment-value linkage allows us to substitute the market equity out of equation (1) both in the numerator and the denominator, with (a function of) investment-to-assets, which is a fundamental variable. In contrast, the market equity remains in the Penman-Zhu model. In this sense, the investment theory is perhaps even more "fundamental" than the Penman-Zhu model.

While the investment theory seems more appealing on economic grounds, it should be empha-

[10]For example, accounting principles connect the expected growth to risk. In Penman and Reggiani (2013), the deferral of earnings recognition raises the expected earnings growth, which might deviate from subsequent realized earnings growth, and this risk might be embedded in the expected return. Penman and Zhu (2018) emphasize that intangible assets are not booked when earnings from investments such as research and development and advertising are uncertain. These investments are expensed against earnings immediately, reducing current earnings but inducing higher expected earnings growth, which is in turn at risk because of the uncertainty.

sized that the theory assumes perfect accounting, which does not exist in reality. In particular, profitability, X_{it}, is economic profitability, which does not capture any negative impact of accruals (earnings management). Also, investment includes all investing activities that increase future earnings, such as research and development, advertising, and employee training. As such, the powerful accounting insights of Penman and Zhu (2014, 2018) are missing from the investment theory. These insights are especially important for our empirical implementation. In fact, the expected growth factor in the q^5 model is partially motivated by these accounting insights (Hou et al. 2019a). As such, we view Penman and Zhu (2014, 2018) and the investment theory as complementary.

5 Conclusion

In the investment theory, the expected return varies cross-sectionally, depending on firms' investment, expected profitability, and expected growth. While the realized return is predictable, the abnormal return is not, retaining efficient markets. Empirically, the q^5 model goes a long way toward accounting for prominent equity strategies rooted in security analysis, including Frankel and Lee's (1998) intrinsic-to-market value, Piotroski's (2000) fundamental score, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Buffett's Berkshire Hathaway, Bartram and Grinblatt's (2018) agnostic analysis, as well as Penman and Zhu's (2014, 2018) and Lewellen's (2015) expected-return strategies. We interpret the evidence as saying that the investment theory is a good start to understanding Graham and Dodd's (1934) *Security Analysis*.

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Table 1 : The Frankel-Lee (1998) Intrinsic-to-Market Value Portfolios, January 1967–December 2018

Intrinsic-to-market is the intrinsic value, V^h, over the market equity, P. Section 3.1 details the measurement of V^h. In Panel A, at the end of June of each year t, we sort stocks into deciles on the NYSE breakpoints of V^h/P for the fiscal year ending in calendar year $t-1$, in which the market equity is at the end of December of year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of V^h/P for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios. The "All" rows report results from one-way V^h/P sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on V^h/P

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.48	0.43	0.60	0.49	0.48	0.59	0.74	0.64	0.92	0.76	0.28	
$t_{\overline{R}}$	1.94	2.14	3.31	2.83	2.61	3.34	4.25	3.40	4.88	3.34	1.55	
α_q	0.21	−0.12	−0.05	−0.11	−0.18	−0.07	0.10	0.02	0.31	0.14	−0.07	0.00
t_q	1.89	−1.72	−0.68	−1.31	−2.06	−0.83	1.11	0.26	2.75	1.06	−0.38	
α_{q^5}	0.19	−0.13	−0.14	−0.15	−0.23	−0.17	0.01	−0.11	0.22	0.06	−0.14	0.01
t_{q^5}	1.87	−1.64	−1.62	−1.77	−2.44	−1.75	0.10	−1.08	1.94	0.48	−0.73	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.02	0.23	0.92	−0.11	0.09		−0.35	2.00	6.06	−0.80	0.64	0.17

Panel B: Quintiles from two-way independent sorts on size and V^h/P

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.44	0.54	0.51	0.68	0.86	0.43		2.00	3.16	2.92	3.86	4.45	2.79
Micro	0.72	0.89	0.86	0.88	1.00	0.27		2.34	3.26	3.34	3.46	3.66	2.01
Small	0.59	0.80	0.86	0.82	0.94	0.35		2.11	3.30	3.89	3.77	3.79	2.25
Big	0.44	0.53	0.49	0.66	0.80	0.36		2.05	3.15	2.82	3.79	4.21	2.29
			α_q ($p_{\mathrm{GRS}} = 0.05$)							t_q			
All	0.04	−0.07	−0.13	0.05	0.27	0.23		0.51	−1.23	−1.73	0.69	2.57	1.50
Micro	0.04	0.15	0.13	0.08	0.17	0.13		0.39	1.53	1.50	0.72	1.60	0.94
Small	−0.11	−0.03	0.04	−0.03	0.07	0.18		−1.24	−0.35	0.50	−0.33	0.66	1.13
Big	0.07	−0.07	−0.15	0.05	0.24	0.17		0.91	−1.15	−1.81	0.65	2.25	1.07
			α_{q^5} ($p_{\mathrm{GRS}} = 0.08$)							t_{q^5}			
All	0.02	−0.15	−0.21	−0.06	0.17	0.15		0.28	−2.09	−2.44	−0.73	1.71	0.99
Micro	0.04	0.20	0.08	0.14	0.18	0.13		0.44	1.89	0.95	1.31	1.78	1.05
Small	−0.08	0.00	0.01	−0.03	0.04	0.13		−0.93	0.01	0.17	−0.39	0.45	0.88
Big	0.05	−0.16	−0.22	−0.06	0.16	0.11		0.59	−2.11	−2.44	−0.75	1.50	0.68
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.08	0.19	0.70	−0.17	0.12		−1.74	2.30	5.95	−1.48	1.13		0.20
Micro	−0.05	−0.16	0.50	0.05	0.00		−1.31	−2.03	4.80	0.48	−0.02		0.18
Small	−0.03	−0.19	0.70	−0.08	0.08		−0.47	−1.37	5.38	−0.61	0.68		0.19
Big	−0.08	0.12	0.72	−0.16	0.09		−1.55	1.45	5.77	−1.30	0.84		0.18

Table 2 : The Piotroski (2000) F-score Portfolios, July 1972–December 2018

The Internet Appendix details the measurement of F-score. In Panel A, at the end of June of each year t, we sort stocks on F for the fiscal year ending in calender year $t-1$ to form seven portfolios: low ($F = 0, 1, 2$), 3, 4, 5, 6, 7, and high ($F = 8, 9$). Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel B, at the end of June of year t, we sort stocks on F for the fiscal year ending in calendar year $t-1$ to form quintiles: low (F = 0–3), 4, 5, 6, and high (F = 7–9). Independently, we sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios. The "All" rows report results from one-way sorts on F into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. For sufficient data coverage, the F portfolio returns start in July 1972. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the seven portfolios are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Portfolios from one-way sorts on F-score

	L	2	3	4	5	6	H	H−L				p_{GRS}
$\overline{R}$	0.44	0.32	0.57	0.55	0.55	0.59	0.71	0.28				
$t_{\overline{R}}$	1.27	1.19	2.83	2.86	2.93	3.17	3.44	1.09				
α_q	0.09	−0.11	0.16	0.10	0.01	0.11	0.08	−0.02				0.02
t_q	0.46	−1.00	2.13	1.81	0.11	1.66	0.74	−0.07				
α_{q^5}	0.24	−0.10	0.05	0.07	0.00	0.06	0.07	−0.17				0.47
t_{q^5}	0.92	−0.85	0.68	1.48	−0.08	0.74	0.57	−0.59				
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.19	−0.33	0.15	0.70	0.23		−2.72	−2.51	1.06	4.50	1.26	0.26

Panel B: Quintiles from two-way independent sorts on size and F-score

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.32	0.57	0.55	0.55	0.62	0.30		1.17	2.83	2.86	2.93	3.32	1.97
Micro	0.53	0.75	0.77	0.90	1.02	0.50		1.48	2.38	2.67	3.25	3.84	3.25
Small	0.48	0.69	0.70	0.82	0.85	0.36		1.49	2.54	2.82	3.40	3.52	2.50
Big	0.32	0.57	0.53	0.53	0.60	0.28		1.19	2.87	2.82	2.83	3.25	1.78
			α_q ($p_{\text{GRS}} = 0.01$)							t_q			
All	−0.07	0.16	0.10	0.01	0.10	0.17		−0.61	2.13	1.81	0.11	1.71	1.26
Micro	0.01	0.17	0.13	0.19	0.24	0.23		0.09	1.53	1.71	2.11	2.65	1.56
Small	−0.11	0.01	−0.03	0.02	−0.01	0.10		−1.04	0.18	−0.52	0.26	−0.08	0.85
Big	−0.02	0.20	0.11	0.00	0.11	0.12		−0.12	2.44	1.84	0.04	1.69	0.84
			α_{q^5} ($p_{\text{GRS}} = 0.09$)							t_{q^5}			
All	−0.04	0.05	0.07	0.00	0.05	0.09		−0.33	0.68	1.48	−0.08	0.71	0.58
Micro	−0.11	0.13	0.12	0.20	0.22	0.33		−0.97	1.20	1.42	2.25	2.58	2.67
Small	−0.12	−0.01	−0.03	0.04	−0.01	0.10		−1.07	−0.19	−0.54	0.53	−0.19	0.81
Big	0.03	0.07	0.08	−0.01	0.05	0.03		0.21	0.91	1.52	−0.15	0.73	0.15
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.15	−0.17	0.01	0.41	0.12		−3.64	−2.63	0.12	4.35	1.09		0.28
Micro	−0.14	−0.22	0.28	0.59	−0.15		−4.23	−2.61	2.53	6.12	−1.74		0.43
Small	−0.17	−0.16	0.38	0.45	0.00		−4.30	−3.16	4.52	5.49	0.01		0.39
Big	−0.14	−0.04	−0.00	0.39	0.14		−3.07	−0.51	−0.05	3.77	1.19		0.18

Table 3 : The Greenblatt (2010) Portfolios, January 1967–December 2018

A composite score is formed on the percentiles of return on capital and earnings yield (detailed in Section 3.3). In Panel A, at the end of June of each year t, we sort stocks into deciles based on the NYSE breakpoints of the composite score for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of the composite score for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the June-end market equity. Taking intersections yields 15 portfolios. The "All" rows report results from one-way sorts on the composite score into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on the Greenblatt measure

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.24	0.39	0.49	0.52	0.51	0.45	0.54	0.66	0.76	0.91	0.67	
$t_{\overline{R}}$	0.78	1.79	2.57	2.84	2.65	2.34	2.93	3.47	4.22	4.61	3.01	
α_q	0.03	−0.07	0.01	0.06	−0.01	−0.05	−0.03	0.14	0.16	0.29	0.26	0.06
t_q	0.22	−0.75	0.18	0.85	−0.08	−0.73	−0.44	2.02	2.13	3.00	1.51	
α_{q^5}	0.15	−0.02	−0.02	0.13	0.09	−0.07	−0.12	0.12	0.05	0.02	−0.13	0.25
t_{q^5}	1.09	−0.15	−0.19	1.64	1.20	−0.98	−1.30	1.63	0.73	0.21	−0.76	
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.15	−0.19	0.23	0.65	0.59		−3.52	−2.34	1.83	6.09	4.68	0.44

Panel B: Quintiles from two-way independent sorts on size and the Greenblatt measure

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.32	0.50	0.47	0.59	0.84	0.52		1.34	2.79	2.53	3.23	4.63	3.56
Micro	0.53	0.73	0.81	0.94	0.96	0.43		1.51	2.60	2.78	3.36	3.60	2.51
Small	0.46	0.75	0.74	0.86	0.93	0.47		1.51	3.06	3.05	3.43	3.86	2.87
Big	0.35	0.49	0.46	0.56	0.82	0.47		1.51	2.78	2.48	3.15	4.60	3.08
			α_q ($p_{\text{GRS}} = 0.06$)							t_q			
All	−0.02	0.04	−0.03	0.02	0.25	0.27		−0.21	0.65	−0.67	0.39	3.70	2.17
Micro	0.10	−0.02	0.05	0.10	0.15	0.05		0.76	−0.18	0.58	1.01	1.59	0.29
Small	0.00	−0.06	−0.01	0.02	0.08	0.08		−0.02	−0.71	−0.13	0.32	0.97	0.56
Big	0.07	0.06	−0.03	0.02	0.26	0.19		0.63	0.94	−0.59	0.34	3.56	1.41
			α_{q^5} ($p_{\text{GRS}} = 0.87$)							t_{q^5}			
All	0.06	0.07	−0.02	−0.04	0.05	−0.01		0.62	1.16	−0.37	−0.54	0.68	−0.10
Micro	0.08	0.04	0.10	0.13	0.14	0.06		0.64	0.43	1.23	1.31	1.49	0.43
Small	0.03	0.01	0.06	0.00	0.06	0.03		0.37	0.11	0.83	0.04	0.74	0.18
Big	0.15	0.08	−0.02	−0.04	0.04	−0.11		1.41	1.34	−0.31	−0.57	0.49	−0.84
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.12	0.06	0.02	0.40	0.42		−3.44	1.02	0.28	4.86	4.48		0.31
Micro	−0.10	−0.26	0.37	0.67	−0.02		−2.23	−2.13	2.88	6.10	−0.19		0.43
Small	−0.13	−0.10	0.42	0.57	0.08		−2.74	−0.78	3.52	5.08	0.82		0.35
Big	−0.12	0.17	0.00	0.39	0.45		−2.85	2.71	0.02	4.51	4.42		0.25

Table 4 : The Asness-Frazzini-Pedersen (2019) Quality Score Portfolios, January 1967–December 2018

The Internet Appendix details the measurement of the quality score. In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the quality score. To align the timing between component signals and subsequent returns, we use the Fama-French (1993) timing, which assumes that accounting variables in fiscal year ending in calendar year $y-1$ are publicly known at the June-end of year y, except for beta and the volatility of return on equity. We treat beta as known at the end of estimation month and the volatility of return on equity as known four months after the fiscal quarter when it is estimated. Monthly value-weighted decile returns are calculated from the current month t, and the deciles are rebalanced at the beginning of month $t+1$. In Panel B, at the beginning of each month t, we sort stocks into quintiles based on the NYSE breakpoints of the quality score and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the beginning of month t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way quality-minus-junk sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on the quality score

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.31	0.42	0.42	0.49	0.43	0.51	0.55	0.58	0.61	0.65	0.33	
$t_{\overline{R}}$	1.04	1.83	2.11	2.48	2.27	2.68	2.93	3.08	3.35	3.31	1.66	
α_q	−0.11	−0.17	−0.12	−0.05	−0.17	0.00	0.01	0.10	0.05	0.34	0.44	0.00
t_q	−0.98	−1.85	−1.73	−0.71	−2.09	0.00	0.14	1.82	0.96	4.32	3.28	
α_{q^5}	0.07	−0.04	−0.08	−0.02	−0.15	0.08	0.02	0.12	0.07	0.13	0.06	0.12
t_{q^5}	0.63	−0.51	−1.02	−0.30	−1.79	1.15	0.30	2.08	1.06	1.67	0.42	
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.24	−0.55	−0.65	0.59	0.57		−5.55	−10.99	−7.68	7.51	6.26	0.64

Panel B: Quintiles from two-way independent sorts on size and the quality score

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.37	0.46	0.47	0.56	0.63	0.26		1.48	2.34	2.58	3.05	3.36	1.79
Micro	0.29	0.78	0.91	0.92	0.90	0.61		0.79	2.60	3.13	3.27	3.36	3.92
Small	0.50	0.72	0.79	0.77	0.92	0.42		1.61	2.93	3.15	3.10	3.65	3.19
Big	0.40	0.43	0.44	0.54	0.62	0.22		1.69	2.25	2.47	2.99	3.31	1.53
			α_q ($p_{\text{GRS}} = 0.00$)							t_q			
All	−0.14	−0.09	−0.07	0.06	0.24	0.38		−1.81	−1.50	−1.19	1.11	4.03	3.53
Micro	−0.10	0.18	0.24	0.29	0.29	0.39		−0.59	1.40	2.15	2.43	2.29	3.13
Small	0.01	0.04	0.02	0.10	0.26	0.25		0.12	0.65	0.33	1.29	2.98	2.19
Big	−0.09	−0.09	−0.07	0.06	0.24	0.33		−0.96	−1.33	−1.18	1.00	3.92	2.75
			α_{q^5} ($p_{\text{GRS}} = 0.00$)							t_{q^5}			
All	−0.01	−0.06	−0.02	0.07	0.11	0.12		−0.12	−0.84	−0.36	1.35	1.85	1.14
Micro	−0.01	0.22	0.23	0.34	0.29	0.30		−0.06	1.73	2.26	2.81	2.32	2.45
Small	0.14	0.08	0.06	0.12	0.23	0.09		1.82	1.08	0.90	1.86	2.77	0.83
Big	0.04	−0.06	−0.02	0.07	0.11	0.07		0.39	−0.75	−0.36	1.24	1.75	0.59
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.17	−0.36	−0.61	0.42	0.39		−5.74	−8.82	−9.04	6.76	5.47		0.60
Micro	−0.18	−0.21	0.00	0.64	0.13		−5.94	−4.09	0.00	8.06	1.83		0.50
Small	−0.18	−0.12	−0.12	0.54	0.23		−4.89	−1.34	−1.41	6.72	3.00		0.44
Big	−0.15	−0.22	−0.66	0.38	0.39		−4.40	−5.12	−8.74	5.60	4.76		0.45

Table 5 : The Asness-Frazzini-Pedersen (2019) Alternative Quality Score (with the Payout Component) Portfolios, January 1967–December 2018

The Internet Appendix details the measurement of the alternative quality score. In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the quality score. To align the timing between component signals and subsequent returns, we use the Fama-French (1993) timing, which assumes that accounting variables in fiscal year ending in calendar year $y-1$ are publicly known at the June-end of year y, except for beta and the volatility of return on equity. We treat beta as known at the end of estimation month and the volatility of return on equity as known four months after the fiscal quarter when it is estimated. Monthly value-weighted decile returns are calculated from the current month t, and the deciles are rebalanced at the beginning of month $t+1$. In Panel B, at the beginning of each month t, we sort stocks into quintiles based on the NYSE breakpoints of the quality score and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the beginning of month t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way quality-minus-junk sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on quality-minus-junk

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.13	0.38	0.41	0.50	0.48	0.63	0.51	0.62	0.66	0.62	0.50	
$t_{\overline{R}}$	0.45	1.57	1.95	2.46	2.54	3.17	2.66	3.33	3.70	3.45	2.68	
α_q	−0.26	−0.07	−0.02	−0.01	−0.02	−0.04	−0.05	0.09	0.19	0.24	0.50	0.00
t_q	−2.48	−1.01	−0.20	−0.14	−0.26	−0.50	−0.70	1.37	3.20	3.31	3.77	
α_{q^5}	−0.06	0.04	0.04	−0.02	0.09	−0.02	−0.05	0.10	0.17	0.04	0.10	0.18
t_{q^5}	−0.62	0.51	0.47	−0.24	1.32	−0.24	−0.71	1.52	2.44	0.58	0.84	
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.23	−0.49	−0.29	0.48	0.59		−7.06	−10.77	−3.13	6.11	7.03	0.63

Panel B: Quintiles from two-way independent sorts on size and quality-minus-junk

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.24	0.47	0.54	0.58	0.63	0.39		0.94	2.32	2.83	3.13	3.60	2.74
Micro	0.20	0.85	0.95	1.02	0.93	0.72		0.55	2.76	3.35	3.72	3.62	4.39
Small	0.47	0.76	0.76	0.88	0.92	0.45		1.48	2.99	3.10	3.58	3.85	3.30
Big	0.25	0.44	0.51	0.55	0.62	0.36		1.03	2.26	2.74	3.03	3.53	2.71
			α_q ($p_{\text{GRS}}=0.00$)							t_q			
All	−0.17	−0.01	−0.03	0.04	0.22	0.39		−2.26	−0.22	−0.60	0.73	4.16	3.95
Micro	−0.16	0.23	0.26	0.34	0.29	0.44		−0.92	1.85	2.04	3.07	2.42	3.46
Small	−0.01	0.12	0.00	0.14	0.21	0.22		−0.12	2.12	−0.01	2.18	2.33	1.98
Big	−0.11	0.00	−0.04	0.03	0.22	0.33		−1.33	−0.06	−0.60	0.55	4.01	3.07
			α_{q^5} ($p_{\text{GRS}}=0.00$)							t_{q^5}			
All	−0.02	0.00	0.04	0.04	0.08	0.10		−0.29	−0.03	0.80	0.75	1.52	1.07
Micro	−0.06	0.27	0.27	0.37	0.26	0.33		−0.35	2.16	2.14	3.62	2.24	2.54
Small	0.13	0.15	0.01	0.15	0.20	0.08		1.55	2.39	0.13	2.42	2.37	0.73
Big	0.03	0.01	0.04	0.03	0.07	0.04		0.32	0.09	0.76	0.59	1.36	0.43
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.17	−0.40	−0.20	0.38	0.43		−6.14	−10.46	−2.98	6.47	6.42		0.64
Micro	−0.24	−0.18	0.17	0.66	0.17		−7.64	−3.82	1.93	7.91	2.34		0.54
Small	−0.23	−0.15	0.17	0.53	0.22		−6.16	−1.76	2.15	5.90	2.80		0.50
Big	−0.14	−0.26	−0.22	0.34	0.43		−4.59	−6.64	−2.88	5.57	5.76		0.49

Table 6 : Buffett's Alpha, February 1968–December 2018

Panel A reports two versions of the AQR 6-factor regressions of Berkshire Hathaway's excess returns. For each sample period, the first two rows use the QMJ factor downloaded from the AQR Web site, and the next two rows use our reproduced QMJ factor (without the payout score) based on Asness, Frazzini, and Pedersen (2019). Panel B shows average excess return, $\overline{R}$, the q-factor alpha, the q^5 alpha, the q-factor and q^5 loadings on the market, size, investment, Roe, and expected growth factors, β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively, and the R-squares of the q-factor and q^5 regressions. All the t-values reported in the rows beneath the corresponding estimates are adjusted for heteroscedasticity and autocorrelations.

Panel A: The AQR 6-factor regressions of Berkshire excess returns

Sample	α	β_{Mkt}	β_{SMB}	β_{HML}	β_{UMD}	β_{BAB}	β_{QMJ}	R^2
11/76–3/17	0.46	0.92	−0.18	0.38	−0.05	0.27	0.39	0.29
	1.69	10.62	−1.45	3.00	−0.93	3.04	2.81	
	0.50	0.89	−0.18	0.40	−0.04	0.29	0.40	0.29
	1.89	11.34	−1.51	3.10	−0.64	3.25	2.81	
2/68–12/18	0.61	0.78	−0.11	0.30	−0.02	0.27	0.29	0.19
	2.08	8.21	−0.70	1.98	−0.24	2.65	1.91	
	0.61	0.76	−0.10	0.35	−0.00	0.27	0.35	0.19
	2.10	8.87	−0.62	2.19	−0.04	2.73	2.33	

Panel B: The q-factor and q^5 regressions of Berkshire excess returns

Sample	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	R^2
11/76–3/17	1.51	0.48	0.87	−0.14	0.73	0.50		0.27
	4.81	1.75	10.30	−1.03	4.40	4.56		
		0.66	0.84	−0.16	0.78	0.60	−0.30	0.27
		2.10	9.70	−1.18	4.58	4.63	−1.46	
2/68–12/18	1.44	0.64	0.75	−0.03	0.58	0.42		0.17
	4.96	2.44	8.40	−0.21	3.61	3.46		
		0.77	0.73	−0.05	0.62	0.48	−0.20	0.18
		2.67	8.14	−0.30	3.79	3.48	−1.11	

Table 7 : Factor Spanning Tests, the q-factor and q^5 Models versus the AQR 6-factor Model, January 1967–December 2018

$\overline{R}$ is a factor's average return, α the intercept from a spanning regression, and R^2 its goodness-of-fit coefficient. $R_{\mathrm{Mkt}}, R_{\mathrm{Me}}, R_{\mathrm{I/A}}$, and R_{Roe} are the market, size, investment, and Roe factors in the q-factor model (q), respectively, and R_{Eg} the expected growth factor in the q^5 model (q^5). MKT, SMB, and HML are the market, size, and value factors in the Fama-French 3-factor model, and UMD the momentum factor. The data on MKT, SMB, HML, and UMD are from Kenneth French's Web site. BAB is the betting-against-beta factor obtained from the AQR Web site. QMJ* is the quality-minus-junk factor from the AQR Web site, and QMJ our reproduced quality-minus-junk factor based on Asness, Frazzini, and Pedersen (2019). In Panel A, for each q and q^5 factor, the first two rows use QMJ*, and the next two rows use our reproduced QMJ in the AQR 6-factor model. The t-values (reported in the rows beneath the corresponding estimates) are adjusted for heteroscedasticity and autocorrelations.

Panel A: Explaining the q and q^5 factors

	$\overline{R}$	α	MKT	SMB	HML	UMD	BAB	QMJ	R^2
R_{Me}	0.29	−0.01	0.03	0.98	0.19	0.03	−0.00	0.04	0.93
	2.31	−0.32	2.65	67.87	8.64	1.72	−0.09	1.59	
		−0.02	0.03	0.99	0.20	0.03	−0.00	0.06	0.94
		−0.49	2.85	70.06	9.61	1.83	−0.20	2.81	
$R_{\mathrm{I/A}}$	0.38	0.24	−0.08	−0.05	0.39	0.04	0.06	−0.02	0.52
	4.59	3.21	−4.71	−1.88	13.10	1.78	2.25	−0.55	
		0.28	−0.10	−0.08	0.35	0.04	0.07	−0.13	0.54
		4.00	−6.74	−3.00	12.05	1.82	2.88	−3.08	
R_{Roe}	0.55	0.05	0.10	−0.12	−0.07	0.18	0.11	0.64	0.62
	5.44	0.66	4.24	−2.89	−1.49	5.71	3.20	11.54	
		0.13	0.05	−0.13	−0.04	0.21	0.13	0.59	0.62
		1.75	2.20	−3.34	−0.71	6.91	4.24	10.24	
R_{Eg}	0.84	0.62	−0.04	−0.10	0.11	0.11	0.01	0.34	0.49
	10.28	9.09	−2.19	−4.09	4.00	4.77	0.41	6.27	
		0.67	−0.08	−0.11	0.13	0.12	0.02	0.29	0.48
		9.64	−4.20	−4.91	3.70	5.55	1.03	5.93	

Panel B: Explaining the AQR factors

	$\overline{R}$	α	R_{Mkt}	R_{Me}	$R_{\mathrm{I/A}}$	R_{Roe}	R_{Eg}	R^2
SMB	0.19	0.06	−0.01	0.92	−0.20	−0.11		0.93
	1.54	1.65	−0.64	54.74	−6.13	−4.03		
		0.10	−0.01	0.92	−0.19	−0.09	−0.05	0.93
		2.63	−1.07	54.39	−5.87	−3.14	−2.06	
BAB	0.90	0.32	0.06	0.15	0.68	0.45		0.22
	5.73	1.94	1.21	2.19	5.51	4.67		
		0.29	0.07	0.16	0.67	0.43	0.05	0.22
		1.73	1.33	2.18	5.35	4.17	0.54	
QMJ*	0.42	0.33	−0.21	−0.15	−0.08	0.49		0.67
	4.15	5.23	−11.92	−6.21	−1.95	13.61		
		0.17	−0.18	−0.13	−0.13	0.42	0.23	0.69
		2.71	−11.40	−5.15	−3.58	13.45	4.63	
QMJ	0.30	0.27	−0.14	−0.15	−0.29	0.47		0.57
	3.02	3.69	−6.75	−4.94	−6.46	11.09		
		0.11	−0.11	−0.13	−0.34	0.40	0.23	0.59
		1.69	−5.87	−3.99	−7.68	8.67	4.46	

Panel C: GRS F-statistics (F_{GRS}) and their p-values (p_{GRS}) testing that the alphas of nonmarket factors are jointly zero

	R_{Me}, $R_{\mathrm{I/A}}, R_{\mathrm{Roe}}$		$R_{\mathrm{Me}}, R_{\mathrm{I/A}}$, $R_{\mathrm{Roe}}, R_{\mathrm{Eg}}$		SMB, HML, UMD, BAB, QMJ*		SMB, HML, UMD, BAB, QMJ	
	AQR*	AQR	AQR*	AQR	q	q^5	q	q^5
F_{GRS}	5.85	9.29	28.63	33.70	8.56	3.96	6.32	3.22
p_{GRS}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01

Table 8 : The Size Premium After Controlling for Quality, January 1967–December 2018

Panel A shows one-way sorts on the market equity (Me), total assets (At), return on equity (Roe), and the expected growth (Eg). The Internet Appendix details the measurement of Roe and Eg. We report average excess returns ($\overline{R}$) and their t-values adjusted for heteroscedasticity and autocorrelations ($t_{\overline{R}}$) beneath the average returns. Panel B shows two-way independent sorts. All sorts are monthly with NYSE breakpoints, value-weighted returns, and 1-month holding period. At each portfolio formation month, the market equity is from the beginning of the month, earnings in Roe from 1972 onward are the recently announced quarterly earnings, and all the other accounting variables are at least 4-month lagged. In Panel B, the "Ave." columns show the results for the portfolio that averages across the five size quintiles, excluding S−B, and the "Ave." rows show the results for the portfolio that averages across the five quality quintiles, excluding H−L.

Panel A: One-way sorts

	S	2	3	4	B	S−B		L	2	3	4	H	H−L
Me	0.64	0.74	0.69	0.64	0.49	0.16	Roe	0.22	0.42	0.51	0.59	0.65	0.44
	2.09	2.70	2.83	2.91	2.83	0.76		0.80	2.20	2.82	3.26	3.43	2.71
At	0.63	0.66	0.64	0.58	0.51	0.13	Eg	0.04	0.35	0.46	0.59	0.85	0.82
	2.05	2.51	2.85	2.74	3.07	0.62		0.15	1.65	2.50	3.34	4.59	6.56

Panel B: Two-way sorts

	$\overline{R}$: S	2	3	4	B	S−B	Ave.	$t_{\overline{R}}$: S	2	3	4	B	S−B	Ave.
The market equity and Roe														
L	0.15	0.24	0.35	0.35	0.23	−0.08	0.26	0.43	0.71	1.17	1.20	0.89	−0.32	0.90
2	0.75	0.77	0.58	0.51	0.39	0.36	0.60	2.67	3.05	2.50	2.48	2.10	1.85	2.73
3	0.94	0.74	0.72	0.60	0.45	0.50	0.69	3.46	2.98	3.32	2.98	2.51	2.58	3.26
4	1.22	0.98	0.81	0.72	0.56	0.66	0.86	4.39	3.85	3.44	3.35	3.17	3.40	3.88
H	1.54	1.21	0.98	0.86	0.57	0.97	1.03	4.87	4.33	3.73	3.62	3.10	4.22	4.24
H−L	1.39	0.97	0.63	0.51	0.35		0.77	9.34	5.36	4.11	2.86	2.00		5.47
Ave.	0.92	0.79	0.69	0.61	0.44	0.48		3.15	2.99	2.87	2.78	2.42	2.53	
The market equity and the expected growth														
L	0.02	0.17	0.12	0.08	0.09	−0.07	0.09	0.05	0.52	0.38	0.27	0.38	−0.33	0.33
2	0.71	0.65	0.57	0.52	0.31	0.40	0.55	2.43	2.41	2.35	2.21	1.48	2.15	2.32
3	1.09	0.95	0.78	0.75	0.36	0.72	0.79	3.83	3.71	3.16	3.44	2.05	3.45	3.52
4	1.26	1.08	0.96	0.87	0.51	0.76	0.93	4.39	4.17	4.06	3.92	2.92	3.60	4.19
H	1.47	1.34	1.19	1.06	0.79	0.67	1.17	4.85	5.01	4.66	4.49	4.34	3.10	4.95
H−L	1.45	1.18	1.07	0.98	0.70		1.07	14.09	8.92	8.61	7.61	5.07		11.52
Ave.	0.91	0.84	0.72	0.65	0.41	0.50		3.07	3.13	2.89	2.83	2.23	2.57	
Total assets and Roe														
L	−0.01	0.27	0.20	0.29	0.37	−0.38	0.23	−0.02	0.82	0.64	1.02	1.52	−1.55	0.77
2	0.53	0.60	0.56	0.51	0.43	0.11	0.52	1.84	2.02	2.34	2.40	2.36	0.53	2.33
3	0.65	0.60	0.57	0.59	0.47	0.18	0.58	2.28	2.46	2.52	2.90	2.67	0.94	2.71
4	0.81	0.71	0.73	0.58	0.59	0.21	0.68	2.88	2.91	3.33	2.69	3.44	1.14	3.19
H	1.15	0.95	0.83	0.71	0.57	0.58	0.84	3.86	3.49	3.56	3.19	3.23	2.83	3.71
H−L	1.16	0.68	0.64	0.42	0.20		0.62	6.92	3.88	3.69	2.28	1.22		4.46
Ave.	0.63	0.63	0.58	0.54	0.49	0.14		2.12	2.39	2.49	2.50	2.77	0.76	
Total assets and the expected growth														
L	−0.03	0.06	0.08	0.34	0.10	−0.12	0.11	−0.08	0.19	0.28	1.15	0.40	−0.55	0.40
2	0.69	0.56	0.42	0.44	0.33	0.36	0.49	2.34	2.18	1.75	1.81	1.60	1.90	2.10
3	0.83	0.79	0.68	0.54	0.40	0.44	0.65	3.04	3.06	3.03	2.51	2.25	2.22	3.01
4	1.03	0.85	0.95	0.65	0.52	0.52	0.80	3.80	3.36	4.34	3.17	3.01	2.79	3.79
H	1.28	1.17	1.00	0.90	0.80	0.48	1.03	4.49	4.47	4.24	4.09	4.47	2.49	4.63
H−L	1.30	1.11	0.92	0.56	0.70		0.92	10.01	6.53	5.92	3.59	4.58		8.71
Ave.	0.76	0.69	0.63	0.57	0.43	0.33		2.67	2.65	2.73	2.57	2.37	1.92	

Table 9 : The Bartram-Grinblatt (2018) Agnostic Fundamental Analysis Portfolios, January 1977–December 2018

The Internet Appendix details the agnostic fundamental measure, $(V - P)/P$, which is the deviation of the estimated intrinsic value from the market equity as a fraction of the market equity. In Panel A, at the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the agnostic measure constructed with firm-level variables from at least four months ago. Monthly value-weighted decile returns are calculated from the current month t, and the deciles are rebalanced at the beginning of month $t + 1$. $(V - P)/P$ is the value-weighted average of the agnostic measure for each portfolio. In Panel B, at the beginning of each month t, we sort stocks into quintiles based on the NYSE breakpoints of the agnostic measure constructed with firm-level variables from at least four months ago and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the beginning of month t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way agnostic sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we also report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way agnostic sorts

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$(V-P)/P$	−1.35	−0.43	−0.19	−0.01	0.17	0.38	0.64	0.98	1.56	3.77	5.12	
Book-to-market	0.53	0.36	0.40	0.51	0.59	0.63	0.69	0.74	0.82	1.03	0.49	
$\overline{R}$	0.58	0.52	0.62	0.51	0.81	0.81	0.86	0.90	1.00	1.06	0.48	
$t_{\overline{R}}$	2.02	2.10	3.10	2.86	3.90	3.95	3.73	3.62	3.68	3.48	2.88	
α_q	0.09	−0.01	0.04	0.07	0.22	0.20	0.19	0.19	0.27	0.41	0.32	0.04
t_q	0.76	−0.09	0.48	0.70	2.72	1.77	1.35	1.18	1.62	2.15	1.47	
α_{q^5}	0.05	−0.05	−0.01	−0.03	0.14	0.19	0.28	0.30	0.36	0.52	0.47	0.05
t_{q^5}	0.42	−0.42	−0.17	−0.24	1.65	1.62	1.99	1.86	2.36	3.07	2.22	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.03	0.29	0.61	−0.10	−0.23		−0.47	2.79	4.24	−0.69	−1.98	0.18

Panel B: Quintiles from two-way independent sorts on size and the agnostic measure												
	L	2	3	4	H	H−L	L	2	3	4	H	H−L
	$(V-P)/P$						Book-to-market					
All	−0.77	−0.11	0.26	0.82	2.76	3.54	0.41	0.45	0.61	0.72	0.93	0.53
Micro	−3.53	−0.10	0.32	0.92	4.01	7.54	0.86	0.62	0.64	0.71	1.03	0.17
Small	−1.29	−0.11	0.30	0.86	2.55	3.84	0.57	0.48	0.58	0.71	0.97	0.40
Big	−0.66	−0.11	0.26	0.81	2.12	2.78	0.39	0.45	0.61	0.73	0.92	0.54
	$\overline{R}$						$t_{\overline{R}}$					
All	0.57	0.57	0.82	0.87	1.02	0.45	2.29	3.11	4.12	3.73	3.65	2.17
Micro	0.20	0.36	0.83	0.82	1.11	0.92	0.48	1.00	2.49	2.73	3.44	4.25
Small	0.58	0.85	0.84	0.98	1.08	0.50	1.73	3.00	3.12	3.63	3.59	2.42
Big	0.58	0.57	0.83	0.87	1.04	0.46	2.37	3.16	4.23	3.79	3.78	2.11
	α_q ($p_{\mathrm{GRS}}=0.00$)						t_q					
All	0.06	0.07	0.22	0.19	0.31	0.25	0.54	1.01	3.17	1.36	1.84	0.95
Micro	−0.10	−0.26	0.08	0.00	0.44	0.54	−0.37	−1.34	0.48	−0.01	2.16	2.03
Small	0.06	0.13	0.03	0.14	0.27	0.21	0.52	1.41	0.34	1.10	1.62	0.85
Big	0.07	0.08	0.25	0.24	0.41	0.33	0.64	1.16	3.40	1.56	2.24	1.23
	α_{q^5} ($p_{\mathrm{GRS}}=0.00$)						t_{q^5}					
All	0.03	−0.03	0.18	0.28	0.41	0.38	0.24	−0.42	2.26	2.04	2.71	1.66
Micro	−0.02	−0.27	−0.05	0.01	0.46	0.48	−0.06	−1.36	−0.27	0.08	2.55	1.82
Small	0.10	0.10	0.03	0.20	0.36	0.27	0.88	1.16	0.28	1.62	2.49	1.23
Big	0.05	−0.02	0.19	0.34	0.47	0.42	0.46	−0.32	2.40	2.19	2.71	1.70
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}	t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	0.07	0.30	0.78	−0.24	−0.21	0.93	1.43	3.95	−1.28	−1.50		0.21
Micro	0.03	−0.22	0.64	0.36	0.09	0.35	−2.21	3.43	1.64	0.49		0.20
Small	0.02	−0.37	1.00	0.11	−0.09	0.32	−2.13	5.70	0.54	−0.61		0.25
Big	0.11	0.07	0.70	−0.28	−0.13	1.58	0.37	3.73	−1.54	−0.84		0.12

Table 10 : The Penman-Zhu (2018) Fundamental Portfolios, Annually Formed, July 1982–December 2018

The Internet Appendix details the Penman-Zhu annually estimated fundamental measure. In Panel A, at the end of June of year t, we sort stocks into deciles based on the NYSE breakpoints of the Penman-Zhu measure for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are calculated from July of year t to June of $t+1$, and the deciles are rebalanced at the end of June of $t+1$. In Panel B, at the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of the Penman-Zhu measure for the fiscal year ending in calendar year $t-1$ and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the June-end of year t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\mathrm{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on the Penman-Zhu measure

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.26	0.68	0.80	0.68	0.82	0.79	0.83	0.85	1.04	0.94	0.69	
$t_{\overline{R}}$	0.90	2.61	3.68	3.20	3.79	4.30	4.06	4.30	4.87	3.78	3.79	
α_q	−0.42	0.14	0.08	0.00	0.06	0.03	0.07	0.07	0.35	0.13	0.55	0.00
t_q	−4.44	1.54	0.83	−0.04	0.59	0.42	0.99	0.80	3.45	0.97	3.32	
α_{q^5}	−0.27	0.19	0.04	−0.09	−0.03	−0.01	−0.05	−0.06	0.28	−0.01	0.25	0.02
t_{q^5}	−2.61	2.10	0.43	−0.91	−0.27	−0.13	−0.59	−0.57	2.95	−0.11	1.50	
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	−0.01	−0.24	0.66	−0.15	0.46		−0.22	−3.07	6.66	−1.85	4.23	0.30

Panel B: Quintiles from two-way independent sorts on size and the Penman-Zhu measure

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
	$\overline{R}$							$t_{\overline{R}}$					
All	0.48	0.73	0.79	0.81	1.01	0.54		1.78	3.49	4.05	4.22	4.61	3.77
Micro	0.35	0.95	0.93	1.05	1.13	0.78		0.93	2.87	2.98	3.48	3.72	4.82
Small	0.52	0.97	0.96	1.01	0.85	0.33		1.61	3.46	3.76	4.02	3.10	2.24
Big	0.51	0.72	0.78	0.80	1.00	0.48		1.99	3.51	4.08	4.19	4.63	3.29
	α_q ($p_{\mathrm{GRS}} = 0.00$)							t_q					
All	−0.12	0.03	0.03	0.06	0.29	0.42		−1.84	0.36	0.44	0.89	3.32	3.45
Micro	−0.11	0.33	0.27	0.36	0.43	0.54		−1.00	3.05	2.62	2.73	3.06	3.52
Small	−0.13	0.12	0.07	0.12	−0.04	0.09		−1.65	1.58	0.83	1.53	−0.40	0.73
Big	−0.09	0.03	0.03	0.05	0.30	0.39		−1.25	0.38	0.45	0.78	2.98	2.85
	α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)							t_{q^5}					
All	−0.02	−0.04	−0.03	−0.07	0.18	0.20		−0.24	−0.56	−0.42	−0.98	2.18	1.77
Micro	−0.14	0.27	0.23	0.30	0.41	0.55		−1.19	2.50	2.12	2.19	2.65	3.23
Small	−0.07	0.05	0.08	0.14	−0.06	0.01		−0.85	0.62	1.20	1.75	−0.64	0.09
Big	0.02	−0.04	−0.03	−0.08	0.18	0.16		0.36	−0.50	−0.42	−1.08	1.91	1.25
	β_{Mkt}	β_{Me}	$\beta_{\mathrm{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\mathrm{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	−0.04	−0.21	0.70	−0.13	0.34		−1.19	−4.85	7.88	−2.20	4.58		0.45
Micro	−0.09	−0.24	0.52	0.33	−0.01		−2.07	−3.49	4.21	3.53	−0.06		0.39
Small	−0.06	−0.20	0.73	0.13	0.12		−1.42	−3.09	8.54	1.32	1.47		0.41
Big	−0.05	−0.16	0.68	−0.19	0.36		−1.24	−3.39	6.62	−2.66	4.33		0.38

Table 11 : The Lewellen (2015) Expected-return Portfolios, January 1974–December 2018

The Internet Appendix details the 15 variables in Lewellen's expected-return strategies. The expected returns are estimated from monthly cross-sectional regressions via ordinary least squares (Section 3.7). In Panel A, at the beginning of each month t, we sort stocks into deciles with the NYSE breakpoints of the expected-return measure. Monthly value-weighted decile returns are calculated from the current month t, and the deciles are rebalanced at the beginning of month $t+1$. In Panel B, at the beginning of each month t, we sort stocks into quintiles based on the NYSE breakpoints of the expected-return measure and, independently, sort stocks into micro, small, and big portfolios based on the NYSE 20th and 50th percentiles of the market equity from the beginning of month t. Taking intersections yields 15 portfolios. The "All" rows report results from one-way sorts into quintiles. For each testing portfolio, we report average excess return, $\overline{R}$, the q-factor alpha, α_q, and the q^5 alpha, α_{q^5}. For each high-minus-low portfolio, we report the q^5 loadings on the market, size, investment, Roe, and expected growth factors, denoted β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, p_{GRS} is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, p_{GRS} is the p-value of the GRS test on the null that the alphas of the 3×5 testing portfolios are jointly zero.

Panel A: Deciles from one-way sorts on the Penman-Zhu measure

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.33	0.59	0.67	0.67	0.70	0.74	0.89	0.76	1.06	1.32	0.99	
$t_{\overline{R}}$	1.44	3.08	3.59	3.25	3.41	3.44	3.96	3.06	3.97	4.06	3.84	
α_q	−0.12	0.07	0.15	0.15	0.10	0.13	0.26	0.12	0.34	0.56	0.68	0.00
t_q	−1.01	0.87	2.17	1.62	1.26	1.59	2.72	1.08	2.78	2.94	2.50	
α_{q^5}	−0.10	0.00	0.07	0.06	0.01	0.03	0.12	0.05	0.32	0.46	0.55	0.07
t_{q^5}	−0.76	−0.01	1.02	0.51	0.08	0.34	1.24	0.47	2.58	2.56	2.06	
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}	R^2
H−L	0.13	0.88	0.50	−0.46	0.19		1.97	5.87	2.23	−3.00	0.88	0.37

Panel B: Quintiles from two-way independent sorts on size and the Penman-Zhu measure

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.45	0.67	0.70	0.83	1.17	0.71		2.22	3.56	3.39	3.59	4.05	3.43
Micro	−0.25	0.52	0.87	0.97	1.43	1.68		−0.64	1.65	3.03	3.48	4.52	9.70
Small	0.34	0.78	1.00	1.07	1.18	0.83		1.07	2.97	4.16	4.38	4.04	5.28
Big	0.48	0.67	0.68	0.77	1.04	0.56		2.39	3.60	3.28	3.31	3.59	2.58
			α_q ($p_{\text{GRS}} = 0.00$)							t_q			
All	−0.01	0.16	0.11	0.20	0.45	0.45		−0.07	2.69	1.76	2.04	3.01	2.11
Micro	−0.77	−0.14	0.12	0.23	0.71	1.48		−3.23	−0.98	0.94	2.07	5.21	7.90
Small	−0.33	−0.01	0.19	0.22	0.32	0.65		−2.36	−0.10	2.08	3.24	3.67	3.62
Big	0.04	0.18	0.10	0.16	0.37	0.33		0.50	2.84	1.45	1.46	1.94	1.31
			α_{q^5} ($p_{\text{GRS}} = 0.00$)							t_{q^5}			
All	−0.04	0.07	0.02	0.08	0.40	0.44		−0.42	1.06	0.24	0.90	2.86	2.12
Micro	−0.64	−0.06	0.12	0.25	0.65	1.29		−2.81	−0.46	0.91	2.28	4.42	7.79
Small	−0.16	−0.01	0.20	0.21	0.28	0.44		−1.14	−0.09	2.18	2.91	3.02	2.46
Big	0.00	0.08	0.00	0.05	0.34	0.34		−0.05	1.12	−0.04	0.46	1.88	1.44
	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}		t_{Mkt}	t_{Me}	$t_{\text{I/A}}$	t_{Roe}	t_{Eg}		R^2
All	0.15	0.68	0.44	−0.36	0.01		2.98	5.21	2.39	−2.94	0.07		0.37
Micro	−0.17	0.12	0.35	0.16	0.28		−3.02	1.26	2.49	0.98	2.10		0.19
Small	−0.05	0.15	0.49	−0.12	0.32		−1.40	1.29	3.11	−1.03	2.18		0.14
Big	0.18	0.49	0.38	−0.29	−0.02		2.93	3.01	1.74	−2.04	−0.11		0.22