The Economics of Security Analysis

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Abstract

The investment CAPM, in which expected returns vary cross-sectionally with investment, profitability, and expected growth, provides an equilibrium foundation for Graham and Dodd (1934). The q^5 model is a good start to explaining prominent quantitative security analysis strategies, such as Abarbanell and Bushee's (1998) fundamental signals, Frankel and Lee's (1998) intrinsic-to-market, Greenblatt's (2005) "magic formula," Asness, Frazzini, and Pedersen's (2019) quality-minus-junk, Bartram and Grinblatt's (2018) agnostic analysis, operating cash flow-to-market inspired by Ball (1978), and Penman and Zhu's (2014, 2020) expected-return strategy, as well as best-performing active, discretionary funds, such as Buffett's Berkshire Hathaway.

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1 Introduction

Graham and Dodd (1934, 1940) pioneer an investment philosophy that buys undervalued securities selling below their intrinsic values. Their teaching has had long-lasting impact on the asset management industry. Many famous investors such as Warren Buffett, Joel Greenblatt, Seth Klarman, Bill Miller, and Charlie Munger follow the Graham-Dodd philosophy. The publication of their 1934 magnus opus has also helped create the financial analysts profession. Unfortunately, perhaps because it is premised on the discrepancy between the intrinsic value and the market value of an asset, security analysis has long been perceived as incompatible with modern finance, the bulk of which builds on efficient markets (Fama 1970). This perspective pervades the contemporary literature in accounting and finance (Frankel and Lee 1998; Bartram and Grinblatt 2018; Greenwald et al. 2021).

We argue that the investment CAPM is a good start to reconciling Graham and Dodd's (1934) security analysis with efficient markets. The basic philosophy is to price securities from the perspective of their issuers, instead of their investors (Zhang 2017), building on an early precursor of Cochrane (1991). Restating the net present value rule in corporate finance, the investment CAPM predicts that a firm's discount rate equals the incremental benefit of its marginal project divided by its incremental cost. The incremental benefit can be measured with quality metrics, such as expected profitability and expected growth, whereas the incremental cost is closely tied to Tobin's q. As such, to earn high expected returns, the investment CAPM recommends investors to buy high quality stocks at bargain prices, a prescription that is exactly in line with Graham and Dodd's.

As the theory's empirical implementation, the Hou et al. (2021) q^5 model largely explains quantitative security analysis strategies. Abarbanell and Bushee (1998) combine 7 fundamental signals. From January 1967 to December 2020, the high-minus-low quintile formed on their composite score earns on average 0.16%, 0.22%, and 0.15% per month ($t = 2.06$, 2.98, and 1.6) across micro, small, and big stocks, and the q^5 alphas are 0.11%, 0.16%, and 0.11% ($t = 1.2$, 1.93, and 1.03), respectively. The return on equity (Roe) and expected growth factors combine to explain their composite score.

The investment factor explains Frankel and Lee's (1998) intrinsic-to-market. The investment CAPM predicts that growth firms with high Tobin's q should invest more and earn lower expected returns than value firms with low Tobin's q. The high-minus-low intrinsic-to-market quintile earns on average 0.27%, 0.33%, and 0.29% per month ($t = 1.99$, 2.16, and 1.9) across micro, small, and big stocks, and the q^5 alphas are 0.2%, 0.19%, and 0.11% ($t = 1.64$, 1.35, and 0.71), helped by the large investment factor loadings of 0.54, 0.73, and 0.72 ($t = 4.95$, 5.37, and 5.96), respectively.

Greenblatt (2005, 2010) proposes a "magic formula" that buys good companies (with high returns on capital) at bargain prices (high earnings yields). The high-minus-low quintile from combining his two signals earns 0.35%, 0.4%, and 0.41% per month ($t = 2.05$, 2.49, and 2.7) across micro, small, and big stocks, and the q^5 alphas are 0.06%, 0.04%, and -0.13% ($t = 0.46$, 0.29, and -0.98), helped by the large Roe factor loadings of 0.67, 0.59, and 0.42 ($t = 6.22$, 5.3, and 4.85), respectively.

Asness, Frazzini, and Pedersen (2019) measure quality as combining profitability, growth, and safety, for which investors are willing to pay a high price. Their quality-minus-junk quintile earns on average 0.55%, 0.37%, and 0.22% per month ($t = 3.61$, 2.88, and 1.51) across micro, small, and big stocks, with the q^5 alphas of 0.27%, 0.08%, and 0.04% ($t = 2.02$, 0.77, and 0.38), respectively. High quality stocks have lower loadings on the market, size, and investment factors but higher loadings on the Roe and expected growth factors than low quality stocks. The latter two factors are sufficiently powerful to overcome the former three to explain the quality premium.

Bartram and Grinblatt (2018) show that a "mispricing" measure, which is the percentage deviation of a firm's peer-implied intrinsic value (estimated from monthly cross-sectional regressions of the market equity on a long list of accounting variables) from its market equity, predicts returns reliably. The high-minus-low quintile earns on average 0.81%, 0.42%, and 0.36% per month ($t = 3.71$, 2.09, and 1.59) across micro, small, and big stocks, but the q^5 alphas are insignificant, 0.42%, 0.27%, and 0.36% ($t = 1.62$, 1.33, and 1.56), respectively. The investment factor again plays the key role.

Inspired by Ball (1978), we show that operating cash flow-to-market is a very strong value indictor. The high-minus-low decile earns on average 0.79% per month ($t = 3.73$). Its q-factor alpha is 0.5% ($t = 2.89$), but the q^5 alpha is only 0.15% ($t = 0.92$). In two-way sorts, the high-minus-low quintile earns on average 0.88%, 0.61%, and 0.37% ($t = 6.22, 3.75$, and 1.99) in micro, small, and big stocks, but the q^5 alphas are 0.51%, 0.12%, and −0.03% ($t = 3.72, 0.85$, and −0.22), helped by the investment factor loadings of 0.79, 1.1, and 1.14 ($t = 7.85, 9.44$, and 10.17), respectively.

Operating cash flow-to-market is a better value metric than book-to-market. With the latter as the standard value metric, the high-minus-low decile earns on average only 0.3% per month, which is insignificant ($t = 1.45$). The high-minus-low quintile earns 0.71%, 0.39%, and 0.08% ($t = 3.71, 2.05$, and 0.52) in micro, small, and big stocks, respectively. We interpret the evidence as suggesting that missing intangibles from the balance sheet might not be necessarily deficient because their value can be ascertained from the flow variables in the income statement (Penman 2009).

Penman and Zhu (2014, 2020) construct a fundamental-based expected-return proxy from projecting future returns on 8 anomaly variables that are a priori connected to future earnings growth. The high-minus-low expected-return quintile earns on average 0.72%, 0.28%, and 0.5% per month ($t = 4.42$, 1.96, and 3.5) across micro, small, and big stocks, and the q^5 model largely succeeds in explaining the return spreads (except for microcaps), with alphas of 0.59%, 0.03%, and 0.21% ($t = 3.74$, 0.25, and 1.69), respectively. The investment factor is again the key driving force.

Perhaps more important, the q^5 model is a good start to explaining top-20 active, discretionary equity funds, which exploit hard-to-quantify, qualitative information. From January 1967 to December 2020, for portfolios consisting of only top-20 active funds, the q^5 model explains 59.3–75.8% of their performance, depending on specific measurement. The equal-weighted top-20 fund portfolio earns an average excess return before fees of 1.08% per month ($t = 6.25$). The q^5 model shrinks it to an alpha of 0.44% ($t = 4.46$), which represents a reduction of 59.3% in magnitude. For the value-weighted top-20 fund portfolio, the q^5 model reduces the average excess return of 1.01% ($t = 5.89$) to an alpha of 0.3% ($t = 2.45$), yielding a reduction of 68.9% in magnitude. Net of fees, the equal-weighted top-20 fund portfolio earns an average excess return of 1% ($t = 5.8$), and the q^5 model shrinks it by 64% to an alpha of 0.36% ($t = 3.65$). The value-weighted top-20 fund portfolio earns 0.95% ($t = 5.51$), net of fees. The q^5 alpha is only 0.23% ($t = 1.92$), yielding a reduction of 75.8%.

The legendary performance of Buffett's Berkshire Hathaway arises partly from its strong loadings on our investment and Roe factors, echoing the well-known Buffett-Munger philosophy of buying profitable firms at bargain prices. From February 1968 to December 2020, Berkshire earns an average excess return of 1.41% per month ($t = 4.98$), which the q-factor model reduces by 58.2% to an alpha of 0.59%, albeit still significant ($t = 2.34$).[1] The investment factor loading is 0.59 ($t = 3.82$), and the Roe factor loading 0.38 ($t = 3.31$). The q^5 model yields a somewhat larger alpha of 0.74% ($t = 2.66$) due to a negative expected growth factor loading of -0.23 ($t = -1.3$).

Penman and Zhang (2020a, b) challenge the accounting underlying the q models, which measure investment as the growth of total assets on the balance sheet. This measure does not include expensed, intangible investment, which tends to forecast returns with a positive sign, in contrast to the negative (tangible) investment-return relation postulated in the investment CAPM. We clarify that the q^5 model handles tangible and intangible investments separately, with the former built in the investment factor and the latter in the expected growth factor. This factor structure accommodates the differential risks of the two types of investments that arise from accounting conservatism.

Our work provides an equilibrium foundation for Graham and Dodd (1934) and the enormous literature on financial statement analysis. Graham and Dodd attribute security analysis entirely to mispricing. In contrast, by connecting expected returns to accounting variables, we show that security analysis *should* work within efficient markets to begin with. Academic finance, with the classic CAPM as the workhorse theory, largely dismisses security analysis as due to luck (Bodie, Kane, and Marcus 2021).[2] The consumption CAPM fails to model accounting variables theoretically and

[1] For comparison, in the same February 1968–December 2020 sample, the AQR 6-factor model yields an alpha of 0.58% per month ($t = 2.07$) for Berkshire (Frazzini, Kabiller, and Pedersen 2018).

[2] "[T]he efficient market hypothesis predicts that *most* fundamental analysis also is doomed to failure. If the analyst relies 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 (p. 339, original emphasis)."

performs often worse than the CAPM empirically. In contrast, by inheriting Graham and Dodd's exclusive focus on firms, the investment CAPM validates security analysis on equilibrium grounds.

Several related articles explore different implications of the investment theory in asset pricing. Gomes and Schmid (2010) study the relation between financial leverage and stock returns in a dynamic model with endogenous investment and financing decisions. Cooper and Priestley (2011) quantify the risk dynamics of the investment factor. Jones and Tuzel (2013) study the relation between inventory investment and cost of equity. Kilic, Yang, and Zhang (2021) examine the time-varying investment-profitability correlation in the cross section. Our work instead attempts to integrate capital markets research in accounting with the investment theory.

The rest of the paper unfolds as follows. In Section 2, we describe traditional views on security analysis and elaborate our new, economics-based perspective. We explain quantitative security analysis strategies in Section 3 and active, discretionary equity funds in Section 4. We clarify the accounting treatment underlying the q and q^5 models in Section 5. Finally, Section 6 concludes. A separate Internet Appendix details derivations, variable definitions, and supplementary results.

2 An Equilibrium Theory of Security Analysis

Section 2.1 reviews the original Graham-Dodd (1934, 1940) perspective. Section 2.2 presents traditional, contradictory academic views in finance and accounting. Finally, Section 2.3 offers our economics-based perspective that potentially reconciles the conflicting views on security analysis.

2.1 The Graham-Dodd Perspective

Graham and Dodd (1934, 1940) 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. 20)."[3] The basic philosophy is to invest in undervalued securities that are selling well below the intrinsic value, "which is justified by the

[3] We refer to page numbers in Graham and Dodd (1940), the second edition, which is viewed as more authoritative.

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. 20–21)." However, the intrinsic value is not exactly defined: "[S]ecurity analysis does not seek to determine exactly what is the intrinsic value of a given security. 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 (p. 22, original emphasis)."

Graham and Dodd (1940) clearly view the intrinsic value as distinct from the market price: "[T]he market is not a *weighting machine*, on which the value of each issue is recorded by an exact and impersonal mechanism, in accordance with its specific qualities. Rather should we say that the market is a *voting machine*, whereon countless individuals register choices which are the product partly of reason and partly of emotion (p. 27, original emphasis)."

In addition, Graham (1949, 1973, *The Intelligent Investor*) writes: "One of your partners, named Mr. Market, is very obliging indeed. Every day he tells you what he thinks your interest is worth and furthermore offers either to buy you out or to sell you an additional interest on that basis. Sometimes his idea of value appears plausible and justified by business developments and prospects as you know them. Often, on the other hand, Mr. Market lets his enthusiasm or his fears run away from him, and the value he proposes seems to you a little short of silly (p. 204–205)."

2.2 Traditional Academic Perspectives

The academic literature has so far provided contradictory perspectives on security analysis. On the one hand, the fundamental analysis literature in accounting has largely subscribed to the Graham-Dodd perspective. For example, Ou and Penman (1989) write: "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 be discovered by the comparison of prices to these fundamental values (p. 296)."

Bartram and Grinblatt (2018) start with the same basic premise: "A cornerstone of market efficiency is the principle that trading strategies derived from public information should not work (p. 126)." "Perhaps the most controversial aspect of our results is the claim that the profits obtained are from fundamental analysis. By using the term 'fundamental analysis,' we are ultimately telling a behavioral story about mispricing and convergence to fair value (p. 143)."

In a prominent textbook on financial statement analysis and security valuation, Penman (2013) states: "Passive investors accept market prices as fair value. Fundamental investors, in contrast, are active investors. They see that *price is what you pay, value is what you get.* They understand that *the primary risk in investing is the risk of paying too much* (or selling for too little). The fundamentalist actively challenges the market price: Is it indeed a fair price (p. 210, original emphasis)?"

On the other hand, the traditional view of academic finance, with the classic Sharpe-Lintner CAPM as the workhorse theory of efficient markets, tends to dismiss any profits from security analysis as purely from luck and recommend investors to passively hold the market portfolio. In particular, in a leading textbook on investments, Bodie, Kane, and Marcus (2021) have largely adopted this dismissive view on security analysis (footnote 2).

2.3 Our Economic Foundation

Because realized returns equal expected returns plus abnormal returns, predictability with any anomaly variables has two parallel interpretations. In the first interpretation, the variables forecast abnormal returns, or forecasting errors are forecastable, violating efficient markets (Graham and Dodd 1934, 1940). In the second, the variables are connected, cross-sectionally, to expected returns, but abnormal returns are unpredictable, thereby retaining efficient markets (Zhang 2017).

2.3.1 The First Principle

The investment CAPM details how expected returns are connected with anomaly variables in the cross section. The first principle of real investment implies that:

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

in which r_{t+1} is a firm's cost of capital, X_{t+1} return on assets, I_t real investment, A_t productive assets, $a > 0$ a constant parameter, and δ the depreciation rate of assets (the Internet Appendix, Section A). Intuitively, the equation says that a firm should keep investing until the marginal cost of investment equals the present value of additional investment, which is the next period marginal benefit of investment discounted by the cost of capital. At the margin, for the last project that the firm takes, its net present value is zero (the net present value rule in corporate finance).

Equation (1) says that the cost of capital should vary cross-sectionally, depending on investment, expected profitability, and expected investment growth.[4] The numerator of equation (1) gives rise to two quality metrics, which are expected profitability and expected growth (expected future investment relative to current investment). The marginal cost of investment, $1+a(I_t/A_t)$, in the denominator equals the marginal q, which in turn equals Tobin's q because of constant returns to scale. As such, to earn high expected returns, investors should buy stocks with high quality at bargain prices (low Tobin's q). This prescription is exactly Graham and Dodd's (1934, 1940).

On the importance of expected profitability and expected growth, Graham and Dodd (1940) write: "A new conception was given central importance—that of *trend of earnings.* The past was important only in so far as it showed the direction in which the future could be expected to move. A continuous increase in profits proved that the company was on the upgrade and promised still better results in the future than had been accomplished to date. Conversely, if the earnings had

[4]With only two periods, equation (1) says that all else equal, low investment and high profitability stocks should earn higher expected returns than high investment and low profitability stocks, respectively (Hou, Xue, and Zhang 2015). With multiple periods, high expected investment relative to current investment must imply high discount rates to offset the high expected marginal benefit of current investment to keep current investment low (Hou et al. 2021).

declined or even remained stationary during a prosperous period, the future must be thought unpromising, and the issue was certainly to be avoided (p. 353, original emphasis)." "The concept of *earnings power* has a definite and important place in investment theory. It combines a statement of actual earnings, shown over a period of years, with a reasonable expectation that these will be approximated in the future, unless extraordinary conditions supervene (p. 506, original emphasis)."

On the importance of bargain prices, Graham and Dodd (1940) write: "Assuming a fair degree of confidence on the part of the investor that the company will expand in the future, what *price* is he justified in paying for this attractive element? Obviously, if he can get a good future for *nothing*, i.e., if the price reflects only the past record, he is making a sound investment. But this is not the case, of course, *if the market itself is counting on future growth*. Characteristically, stocks thought to have good prospects sell at relatively high prices (p. 366–367, original emphasis)."

2.3.2 An Equilibrium Foundation for Security Analysis

Despite similar prescriptions, our equilibrium treatment of security analysis differs fundamentally from Graham and Dodd's (1934). Predating equilibrium theory under uncertainty, Graham and Dodd implicitly assume a constant discount rate and attribute return predictability with accounting information to mispricing. Their extraordinary business astuteness empowers them to discover the enduring investment truth of buying high quality stocks at bargain prices. In contrast, we provide an economic model of cross-sectionally varying expected returns within efficient markets.

While departing from Graham and Dodd (1934), we also deviate from traditional academic finance, which, with the classic CAPM and its extensions as workhorse models, mostly dismisses security analysis. Instead, we embrace and validate security analysis on equilibrium grounds, by zeroing in on key expected-return drivers, i.e., investment, profitability, and expected growth.

In general equilibrium, asset prices are determined jointly by demand and supply of assets. The CAPM arises from the mean-variance investor's problem, while ignoring firms. As long as returns, which are given exogenously, are consistent with the optimal behavior of firms left outside the model, market betas should be sufficient to price assets. The abstraction from investors in the investment CAPM is exactly symmetrical. The investment CAPM arises from a manager's capital budgeting problem, while ignoring investors. As long as returns are consistent with the optimal behavior of some marginal investor left outside the model, equation (1) should be sufficient to price assets.

Clearly, one needs both demand and supply to fully grasp equilibrium asset pricing. Betas play a central role in the CAPM and its extensions, which do not model firm variables. Symmetrically and complementarily, firm variables play a central role in the investment CAPM, which does not model betas. As such, we view the investment CAPM primarily as an expected-return model that can potentially yield more reliable expected-return estimates (to aid, for example, portfolio optimization) than traditional asset pricing models. While the CAPM fails empirically as a general equilibrium model in pricing assets, its partial equilibrium insights, such as diversification, remain intact.

This demand versus supply dichotomy is probably why (supply-focused) security analysis has long been perceived as incommensurable with (demand-focused) modern finance. In particular, honoring the 50th anniversary of Graham and Dodd (1934), Buffett (1984) reports the successful performance of 9 famous value 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)." This dichotomy is unfortunate, as demand and supply are the two sides of the same coin of equilibrium asset pricing.

Graham and Dodd (1934, 1940) write tentatively about the risk of expected growth: "*[O]nce the investor pays a substantial amount for the growth factor*, he is inevitably assuming certain kinds of risk; viz., that the growth will be less than he anticipates, that over the long pull he will have paid too much for what he gets, that for a considerable period the market will value the stock less optimistically than he does (p. 367, original emphasis)." However, precisely because investors are left unmodeled, we emphasize that our evidence does not rule out distorted beliefs on the investor side. Rather, challenging the conventional wisdom that security analysis only works in inefficient markets, we show that security analysis should work in efficient markets to begin with.

3 Explaining Quantitative Security Analysis Strategies

We use the q and q^5 models to explain the most prominent quantitative security analysis strategies, including Abarbanell and Bushee's (1998) fundamental strategy (Section 3.1), Frankel and Lee's (1998) intrinsic-to-market value (Section 3.2), Greenblatt's (2005, 2010) "magic formula" (Section 3.3), Asness, Frazzini, and Pedersen's (2019) quality-minus-junk (Section 3.4), Bartram and Grinblatt's (2018) agnostic strategy (Section 3.5), operating cash flow-to-market inspired by Ball (1978) (Section 3.6), and Penman and Zhu's (2014, 2020) expected-return strategy (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 financial firms and firms with negative book equity. The sample is from January 1967 to December 2020. The q and q^5 factors data are from the q-factor data library (http://global-q.org).

3.1 Abarbanell and Bushee's (1998) Fundamental Strategy

Abarbanell and Bushee (1998) show that a collection of fundamental signals, which contain information about future earnings news, can forecast returns. Their signals include inventory, account receivable, capital expenditure, gross margin, selling and administrative expenses, effective tax rate, and labor force efficiency.[5] We use the 7 signals to form a composite signal, denoted AB,

[5] Following Abarbanell and Bushee (1998), we define the %d(·) operator as the percentage change in the variable in the parentheses from its average over the prior two years, for example, %d(Sales) = [Sales(t) − E[Sales(t)]]/E[Sales(t)], in which E[Sales(t)] = [Sales($t-1$) + Sales($t-2$)]/2. Inventory is calculated as %d(Sales) − %d(Inv), in which sales is net sales (Compustat annual item SALE), and inv is finished goods inventories (item INVFG) if available, or total inventories (item INVT). Firms with nonpositive average sales or inventory during the past two years are excluded. Account receivable is %d(Sales) − %d(RECT), in which RECT is total receivables (item RECT). Firms with nonpositive average sales or receivables during the past two years are excluded. Capital expenditure is %d(Investment) − %d(Industry investment), in which investment is capital expenditure in property, plant, and equipment (item CAPXV). Industry investment is the aggregate investment across all firms with the same 2-digit SIC code. Firms with nonpositive E[Investment(t)] are excluded and we require at least two firms in each industry. Gross margin is %d(Gross margin) − %d(Sales), in which gross margin is sales minus cost of goods sold (item COGS). Firms with nonpositive average gross margin or sales during the past two years are excluded. Selling and administrative expenses are %d(Sales) − %d(SG&A), in which SG&A is item XSGA. Firms with nonpositive average sales or SG&A during the past two

which equal-weights a stock's percentile rankings of the signals (each realigned to yield a positive slope when forecasting returns). At the end of June of each year t, we sort stocks into deciles based on the NYSE breakpoints of AB for the fiscal year ending in calendar year $t-1$. Monthly value-weighted decile returns are from July of year t to June of $t+1$, and the deciles are rebalanced in June of $t+1$. We also perform double 3×5 sorts on size and AB. At the end of June of year t, we sort stocks into quintiles based on the NYSE breakpoints of AB for the fiscal year ending in 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 June-end of t. Taking intersections yields 15 portfolios.

Table 1 shows that consistent with Abarbanell and Bushee (1998), their composite signal, AB, reliably predicts returns. From Panel A, the high-minus-low decile earns on average 0.29% per month ($t = 2.42$). Both the q and q^5 models leave insignificant high-minus-low alphas. In the q^5 regression, the Roe factor loading is 0.26 ($t = 2.93$), the size loading is 0.13 ($t = 2.44$), but the other loadings are insignificant. The Gibbons-Ross-Shanken (1989, GRS) test on the null that the alphas are jointly zero across the deciles fails to reject either q or q^5 model.

In two-way sorts, the high-minus-low AB quintile does not vary much with size, earning on average 0.16%, 0.22%, and 0.15% per month ($t = 2.06, 2.98$, and 1.6) across micro, small, and big stocks, respectively. The q-factor model leaves a significant alpha of 0.24% ($t = 3.18$) for the small-stock high-minus-low quintile, but the q^5 model reduces it to 0.16% ($t = 1.93$). In the q^5 regressions, the investment factor loadings are often significantly negative, but the positive Roe and expected growth loadings combine to explain the AB strategy. With the 15 portfolio as testing assets, the GRS test rejects the q-factor model ($p = 0.00$) but not the q^5 model ($p = 0.13$).[6]

years are excluded. Effective tax rate is $\left[\frac{\text{TaxExpense}(t)}{\text{EBT}(t)} - \frac{1}{3}\sum_{\tau=1}^{3} \frac{\text{TaxExpense}(t-\tau)}{\text{EBT}(t-\tau)}\right] \times \text{dEPS}(t)$, in which TaxExpense($t$) is total income taxes (item TXT) paid in year t, EBT(t) is pretax income (item PI) plus amortization of intangibles (item AM), and dEPS is the change in split-adjusted earnings per share (item EPSPX divided by item AJEX) between years $t-1$ and t, deflated by stock price (item PRCC_F) at the end of $t-1$. Finally, labor force efficiency for year t is $\left[\frac{\text{Sales}(t)}{\text{Employees}(t)} - \frac{\text{Sales}(t-1)}{\text{Employees}(t-1)}\right] / \frac{\text{Sales}(t-1)}{\text{Employees}(t-1)}$, in which Employees($t$) is the number of employees (item EMP). Abarbanell and Bushee also consider two indicators, earnings quality (1 for LIFO and 0 otherwise) and audit qualification (1 for unqualified and 0 otherwise). We drop the two indicators because they are unfit for forming portfolios.

[6]The q and q^5 models also largely explain the anomaly of Piotroski's (2000) fundamental (F) score, which combines 9 signals on profitability, liquidity, and operating efficiency (the Internet Appendix, Section B.1, Table

3.2 Frankel and Lee's (1998) Intrinsic-to-market Ratio

Frankel and Lee (1998) estimate the intrinsic value from the residual income model and show that the intrinsic-to-market ratio forecasts returns. We follow exactly their measurement of the intrinsic value based on a 2-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 year, respectively.[7]

At the end of June of each year t, we sort stocks into deciles based on the NYSE breakpoints of intrinsic-to-market ratio, 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 $t+1$. At the end of June of each year t, we also sort 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 June-end market equity. Taking intersections yields 15 portfolios.

Table 2 shows that consistent with Frankel and Lee (1998), the intrinsic-to-market ratio shows some ability to predict returns. The high-minus-low V^h/P decile earns on average 0.23% per month, albeit insignificant ($t = 1.29$). 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

S1). In particular, the high-minus-low F score quintile earns 0.36%, 0.3%, and 0.2% per month ($t = 2.21$, 2.08, and 1.31) across micro, small, and big stocks, and the q^5 alphas are 0.28%, 0.14%, and 0.04% ($t = 2.19$, 1.04, and 0.22), helped by the large Roe factor loadings of 0.62, 0.47, and 0.4 ($t = 6.37$, 5.68, and 3.98), respectively.

[7] 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 years 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.

across the deciles. The predictability is stronger in quintiles, which yield an average high-minus-low return of 0.36% ($t = 2.38$). The quintile spread does not vary much with size, with 0.27%, 0.33%, and 0.29% ($t = 1.99$, 2.16, and 1.9) across micro, small, and big stocks, respectively.

The q-factor alphas of the high-minus-low quintiles are 0.13%, 0.17%, and 0.13% per month ($t = 0.93$, 1.01, and 0.87) across micro, small, and big stocks, and their q^5 alphas 0.2%, 0.19%, and 0.11% ($t = 1.64$, 1.35, and 0.71), respectively. Neither model can be rejected by the GRS test with the 3×5 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 0.54, 0.73, and 0.72 ($t = 4.95$, 5.37, and 5.96) across micro, small, and big stocks, respectively. In contrast, the Roe and expected growth factor loadings are small and insignificant.

In the investment CAPM, the intrinsic value equals exactly the market value, with no mispricing (the intrinsic-to-market ratio equals one by construction). Why does the intrinsic-to-market ratio still predict returns? The crux is that the estimated intrinsic-to-market ratio from equation (2) is a nonlinear function of investment, profitability, and expected investment growth, which, per the investment CAPM, should forecast returns. Most important, the book-to-market component of intrinsic-to-market is linked to investment. This 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 profitability and expected growth (via the book equity at $t + 1$) also appear in equation (2), the investment factor is the key driving force empirically.

More broadly, even without mispricing, an estimated intrinsic value can deviate from the market value because of errors in cash flow forecasts and in discount rates. Accounting textbooks typically go to great lengths for cash flow forecasts but refer to investment textbooks for discount rates (Penman 2013). However, it is well known that the discount rate estimates from multifactor models are very imprecise, even at the industry level (Fama and French 1997). Alas, intrinsic value estimates can be very sensitive to the assumed discount rates.[8] As such, we view the Frankel-Lee

[8] For example, Penman (2013) writes: "Compound the error in beta and the error in the risk premium and

intrinsic value estimates in equation (2), which assumes a constant discount rate of 12%, mostly as a nonlinear function of investment, profitability, and expected growth.

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

In a popular investment 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 investors 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.[9] 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. The high-minus-low decile earns on average 0.57% per month ($t = 2.54$). In two-way sorts, the high-minus-low quintile earns

you have a considerable problem. The CAPM, even if true, is quite imprecise when applied. Let's be honest with ourselves: No one knows what the market risk premium is. And adopting multifactor pricing models adds more risk premiums and betas to estimate. These models contain a strong element of smoke and mirrors (p. 650)."

[9] Greenblatt (2005, 2010) 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.

on average 0.35%, 0.4%, and 0.41% ($t = 2.05$, 2.49, and 2.7) 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 0.19% ($t = 1.1$) and a q^5 alpha of -0.13% ($t = -0.76$). The high-minus-low quintile has q-factor alphas of 0.0%, 0.03%, and 0.14% ($t = 0.01$, 0.22, and 1.03) and q^5 alphas of 0.06%, 0.04%, and -0.13% ($t = 0.46$, 0.29, and -0.98) across micro, small, and big stocks, respectively. The GRS test cannot reject the q-factor or q^5 model with the two-way portfolios.

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 in both one-way and two-way sorts. The investment factor loadings are large and significant for micro and small stocks, but not for big stocks. The expected growth factor loadings are significantly positive for big stocks but not for micro or small stocks. Intuitively, as a measure of profitability, Greenblatt's (2010) return on capital is closely related to Roe. The earnings yield is a value metric, which connects to investment due to the investment-value linkage.

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

Asness, Frazzini, and Pedersen (2019) define quality as characteristics (profitability, growth, and safety), for which investors should be willing to pay a high price. Empirically, high quality stocks earn higher average returns than low quality stocks. The quality-minus-junk premium is the latest embodiment of the Graham-Dodd (1934) principle of buying high quality stocks at bargain prices.

Following Asness, Frazzini, and Pedersen (2019), we form the quality score as the average of the profitability, growth, and safety scores.[10] At the beginning of each month t, we sort stocks into deciles based on the NYSE breakpoints of the quality score. We assume that accounting variables for

[10]We measure profitability with gross profitability, return on equity, return on assets, cash flow-to-assets, gross margin, and negative accruals. Each month we convert each variable into cross-sectional ranks, which are standardized into a z-score. Standardization means dividing the cross-sectionally demeaned values of the rankings by their cross-sectional standard deviation. The profitability score averages the individual z-scores of the 6 profitability measures. We measure growth as the 5-year growth in residual per-share profitability measures, excluding accruals. The growth score averages the individual z-scores of the 5 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 averages the individual z-scores of the 5 safety measures. The Internet Appendix details the measurement (Section B.2).

the 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 4 months after the fiscal quarter when it is estimated.

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 quality-minus-junk decile earns on average 0.28% per month but is insignificant ($t = 1.43$).[11] The q-factor model produces a significant alpha of 0.38% ($t = 2.82$), and the model is rejected by the GRS test on the null that the alphas across the quality deciles are jointly zero ($p = 0.00$). However, the q^5 model yields a tiny alpha of 0.02% ($t = 0.15$), and the GRS test fails to reject the q^5 model ($p = 0.11$). The quality-minus-junk decile has significantly negative market, size, and investment loadings, going in the wrong direction in explaining average returns, but significantly positive Roe and expected growth loadings, going in the right direction.

Panel B shows that the quality premium varies inversely with size, 0.55%, 0.37%, and 0.22% ($t = 3.61$, 2.88, and 1.51) across micro, small, and big stocks, respectively. The q-factor alphas are all economically large and statistically significant, 0.36%, 0.22%, and 0.31% ($t = 2.91$, 2.05, and 2.62), respectively. Other than the alpha in micro stocks, 0.27% ($t = 2.02$), the q^5 alphas continue to be small, 0.08% ($t = 0.77$) in small stocks and 0.04% ($t = 0.38$) 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,

[11] We largely reproduce the Asness-Frazzini-Pedersen (2019, Table 3) estimate of 0.42% ($t = 2.56$) in their sample from July 1957 to December 2016 (untabulated). 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 (which we view as more standard). The estimate in our reproduction with their sample criteria is 0.41% ($t = 2.1$).

the q^5 model is still rejected by the GRS test across the 15 two-way portfolios ($p = 0.00$).

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 averages the z-scores based on the rankings of equity net issuance, debt net issuance, and total net payout over profits (the Internet Appendix, Section B.2). Because the quality-minus-junk factor posted on the AQR Web site contains the payout component,[12] we also examine this alternative quality score for robustness.

The alternative quality score shows stronger return predictive power than the original score (the Internet Appendix, Table S2). The high-minus-low decile earns on average 0.43% per month ($t = 2.32$). The q^5 alpha is 0.08% ($t = 0.61$), and the GRS test cannot reject the model ($p = 0.2$). The alternative quality premium varies inversely with size, 0.66%, 0.4%, and 0.32% ($t = 4.05$, 2.94, and 2.31) across micro, small, and big stocks, respectively. Except for microcaps, in which the alpha is 0.33% ($t = 2.5$), the q^5 alpha is small, 0.08% ($t = 0.77$) in small stocks and −0.01% ($t = -0.12$) in big stocks. Because of payout, which correlates negatively with investment, the (low-minus-high) investment factor loadings of the quality-minus-junk quintiles become significantly positive in micro and small stocks. In big stocks, the investment factor loading remains negative. However, the q^5 model is still rejected by the GRS test across the 15 two-way portfolios ($p = 0.00$).

The Internet Appendix also shows results on strategies formed separately on the profitability, growth, safety, and payout scores (Table S3–S6). Without going into the details, the average returns of the high-minus-low deciles on the profitability, growth, safety, and payout scores are 0.36%, 0.25%, 0.12%, and 0.41% per month ($t = 2.01$, 1.49, 0.54, and 2.43), respectively. The q^5 alphas are mostly insignificant, −0.04%, 0.33%, 0.09%, and −0.12 ($t = -0.3$, 2.4, 0.58, −0.92), respectively.

Although the high-minus-low growth decile has positive Roe and expected growth factor loadings of 0.37 and 0.23, respectively, its investment factor loading is large in magnitude, −1.08 ($t = -11.93$). Intuitively, the growth score measures the past 5-year growth rates in profits, earnings,

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

and cash flows, all of which are positively correlated with past asset growth (investment), giving rise to a strongly negative loading on the investment factor. As such, 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) more than expected growth.

3.5 Bartram and Grinblatt's (2018) Agnostic Strategy

Bartram and Grinblatt (2018) show that the deviation of a firm's peer-implied intrinsic value from its market value forecasts returns reliably. A stock's intrinsic value is the fitted component from monthly cross-sectional regressions via ordinary least squares of the stock's market equity, P, on a long list of accounting variables. The variables include 14 from the balance sheet and 14 from the income statement, all of which are from Compustat quarterly files.[13] The sample starts in January 1977 because of the low coverage of the right-hand side accounting 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 4 months ago).[14] A stock's intrinsic value, V, each month, is given by the

[13]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. The 14 income statement variables are annualized by summing the quarterly values from the most recent four fiscal quarters. 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 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.

[14]The exceptions to this rule are income before extraordinary items (Compustat quarterly item IBQ), net income (loss) (item NIQ), and net sales (item SALEQ), which we treat as publicly known 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 6 months prior to the regression month. Each month we control for the outliers in the accounting variables by winsorizing their ratios to total asset (item ATQ) at the 1–99% level of the ratios and then multiplying total assets back to the winsorized ratios.

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.

Panel A of Table 5 reports the one-way sorts. The agnostic measure predicts return reliably. The high-minus-low decile earns on average 0.39% per month ($t = 2.22$). The q-factor alpha is 0.22% ($t = 1.03$), and the q^5 alpha is 0.35% ($t = 1.65$). The GRS test cannot reject the q-factor model or the q^5 model. In the q^5 regression, the high-minus-low decile loads positively on the investment factor, 0.57 ($t = 3.76$), going in the right direction, but loads negatively on the expected growth factor, -0.2 ($t = -1.66$), going in the wrong direction in explaining the average return. The size factor also helps with a loading of 0.32 ($t = 3.09$), but the market and Roe factor loadings are tiny.

From Panel B, the high-minus-low quintiles earn on average 0.81%, 0.42%, and 0.36% per month ($t = 3.71$, 2.09, and 1.59) across micro, small, and big stocks, respectively. The q-factor model reduces the average returns to insignificance, with alphas of 0.46%, 0.15%, and 0.2% ($t = 1.78$, 0.61, and 0.73), and the q^5 model does too, with alphas of 0.42%, 0.27%, and 0.36% ($t = 1.62$, 1.33, and 1.56), 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.[15]

[15] 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 $5 price screen imposed (Table S7). The results are largely similar. The high-minus-low agnostic decile earns a somewhat higher average return of 0.53% per month ($t = 2.75$), and its q^5 alpha is 0.31% ($t = 1.66$). The high-minus-low quintiles earn on average 0.71%, 0.43%, and 0.28% ($t = 3.15$, 2.1, and 1.24) across micro, small, and big stocks, respectively. The q^5 alpha becomes significant in microcaps but remain relatively small and insignificant in small and big stocks.

3.6 Operating Cash Flow-to-market

Ball (1978) argues that accounting earnings is connected with expected returns, especially when scaled by price.[16] Ball et al. (2016) argue that operating cash flow is a better proxy for economic profits than earnings and scale the cash flow with book assets (not market equity) to explain the profitability premium. It follows from Ball (1978) that scaling operating cash flow by the market equity could potentially yield even stronger explanatory power for expected returns.

We split stocks at the end of June of year t into deciles based on the NYSE breakpoints of operating cash flow-to-market, denoted Cop/M. The numerator is from the fiscal year ending in calendar year $t-1$ and the market equity is from the December-end of year $t-1$.[17] For two-way sorts, we split stocks into quintiles on Cop/M, and independently, into micro, small, and big stocks with the NYSE 20th and 50th percentiles of the June-end market equity of year t. Taking intersections yields 15 portfolios. Monthly value-weighted returns are calculated from July of year t to June of $t+1$, and the portfolios are rebalanced at the June-end of $t+1$.

Table 6 shows strong predictive power for operating cash flow-to-market. The high-minus-low decile earns on average 0.79% per month ($t = 3.73$). The q-factor model leaves a large alpha of 0.5% ($t = 2.89$), but the q^5 model yields a much smaller alpha of 0.15% ($t = 0.92$). The q^5 model cannot be rejected by the GRS test ($p = 0.59$). In the two-way sorts, the high-minus-low quintile earns on average 0.88%, 0.61%, and 0.37% ($t = 6.22, 3.75$, and 1.99), and the q^5 alphas are 0.51%, 0.12%, and -0.03% ($t = 3.72, 0.85$, and -0.22) across the micro, small, and big stocks, respectively. As such, except for microcaps, the q^5 model largely explains the quintile spreads. The investment factor loadings are economically large and statistically significant. The expected growth factor loadings

[16]Intuitively, price is a function of expected dividends and expected returns. As such, price-scaled accounting variables that are informative about expected dividends should be tied to expected returns. Because dividends are distributions of earnings, current earnings contains information about expected earnings and in turn about expected dividends. In all, scaled by price, earnings reveals information about expected returns.

[17]Following Ball et al. (2016), we measure operating cash flow as total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC). Missing annual changes are set to zero.

are positive but insignificant. However, the model is still rejected by the GRS test ($p = 0.00$).

Operating cash flow-to-market is a better value metric than book-to-market. In the 1967–2020 sample, the high-minus-low book-to-market decile earns on average only 0.3% per month ($t = 1.45$) (the Internet Appendix, Table S8). The insignificance echoes recent discussion on a possibly disappearing value premium.[18] In contrast, the average return of the high-minus-low Cop/M decile is substantially larger, 0.79% ($t = 3.73$). The rise of an intangible economy might have caused the declining book-to-market premium (Lev and Srivastava 2020). However, echoing Penman (2009), our evidence suggests that missing intangibles from the balance sheet is not necessarily deficient because their impact on value could potentially be inferred from the flow variables in the income statement.

3.7 Penman and Zhu's (2014, 2020) Expected-return Strategy

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) use this relation to rewrite the 1-period-ahead expected return, $E_t[r_{it+1}]$, as:

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

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 expected earnings growth.[19]

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 (2020) 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

[18] See, for example, the Bloomberg article by Nir Kaissar, July 21, 2021, titled "What happened to price-to-book ratio in value investing?" available at https://www.bloomberg.com/opinion/articles/2021-07-21/personal-finance-what-happened-to-price-to-book-ratio-in-value-investing?sref=8yFYal8I

[19] Intuitively, an increase in the deviation means that price rises more than book equity. Because earnings raises 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 $t+1$.

proxy, denoted ER8, is based on 8 variables. We work with ER8 because it is the most comprehensive proxy in their study. The list consists of 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, Section B.3).

We follow Penman and Zhu (2020) in constructing ER8, except that we adopt the more standard timing for annual sorts. 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 the previous year to June of the subsequent year via ordinary least squares.[20] 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 8 accounting variables for the fiscal year ending in calendar year $t-2$. The other 9 annual regressions in the rolling window are specified accordingly. 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 8 winsorized variables for the fiscal year ending in calendar year $t-1$ to calculate ER8.

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.

From Panel A of Table 7, the high-minus-low ER8 decile earns on average 0.74% per month ($t = 4.21$). The q^5 alpha is 0.36%, albeit significant ($t = 2.17$). The investment factor loading is 0.56 ($t = 5.55$), and the expected growth factor loading 0.51 ($t = 4.59$). Intuitively, ER8 contains 2 value metrics, earnings-to-price and book-to-market, both of which correlate negatively with investment, due to the investment-value linkage. Also, the 8 variables based on their predictive power of earnings growth. Because earnings growth and investment growth tend to be positively correlated,

[20] If the July-to-June interval has fewer than 12 months, we annualize the cumulative return with available months.

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 0.72%, 0.28%, and 0.5% ($t = 4.42$, 1.96, and 3.5) across micro, small, and big stocks, respectively. The q^5 alpha is 0.59% ($t = 3.74$) in microcaps but insignificant in small stocks, 0.03% ($t = 0.25$), and in big stocks, 0.21% ($t = 1.69$). While the investment factor loadings are consistently large and significant, the expected growth factor loading is significant only in big stocks.

Theoretically, our model differs from the Penman-Zhu model in one crucial aspect. Equation (3) decomposes the expected return into the expected earnings yield and the expected change in market-minus-book. Penman and Zhu then use accounting insights to connect the latter to the expected earnings growth. In contrast, equation (1) is an economic model based on the first principle of 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 market equity out of equation (1) both in the numerator and the denominator, with (a function of) investment, which is a fundamental variable. In this sense, the investment CAPM is even more "fundamental" than the Penman-Zhu model, which still has the market equity in its formulation.

4 Explaining the Performance of Active Equity Funds

Quantitative strategies pick stocks based on potentially distorted accounting numbers and overlook qualitative information that active, discretionary managers exploit. To mitigate this concern, we supplement our empirical tests with best-performing active equity funds (Section 4.1) and Buffett's Berkshire Hathaway (Section 4.2). These funds provide a track record of best active managers.

4.1 Best-performing Active, Discretionary Equity Funds

We obtain mutual fund names, monthly after-cost net returns, and fund characteristics, such as expense ratios, total net assets (TNA), and investing styles, from the CRSP Mutual Fund database. We calculate monthly before-cost gross fund returns by adding 1/12 of the matching annual expense ratio to monthly net returns. We identify domestic equity funds by selecting style codes (item crsp_obj_cd) that start with "ED." We exclude funds that invest on average less than 70% of their total assets in U.S. stocks (item per_com). To select only active funds, we further drop index funds, exchange traded funds or notes (ETF/ETN), inverse and leveraged funds using both CRSP Mutual Fund index/ETF/ETN identifiers (items index_fund_flag and et_flag) and name search.[21]

For funds with multiple share classes, we link the share classes via the MFLINKS table from WRDS and combine them into a single TNA-weighted observation. We exclude months with missing fund names and with TNA below $15 million to mitigate omission bias (Elton, Gruber, and Blake 2001). To compute gross fund returns, we require non-missing net fund returns but impute a given missing monthly expense ratio with its latest value in the past 12 months (if available). Our sample of domestic active equity funds covers 4,173 unique funds from January 1967 to December 2020.

We select top 20 active funds based on their information ratios. The information ratio of a given fund is its alpha divided by its residual volatility, both of which are estimated from the CAPM regression of the fund's gross returns in its full-life sample. With the CAPM as the benchmark for evaluating active funds, the information ratio quantifies the tradeoff between the reward (alpha) and risk (residual volatility) of active management (Bodie, Kane, and Marcus 2021, p. 820–821). Full-life includes months with TNA below $15 million. We exclude funds that do not have complete histories between their first and last months. We require a minimum track record of 10 years. We include both live and dead funds. There exist 2,089 unique funds with an uninterrupted track record of at least 10 years. Top 20 amounts to roughly top 1%. Finally, choosing top funds based on their full-life performance induces hindsight bias, but the bias only raises the hurdle on our models.

Table 8 lists the top-20 active equity funds in the CRSP Mutual Fund database. The best-

[21] Following Dannhauser and Pontiff (2019), we identify index funds if CRSP fund names contain "SP," "DOW," "Dow," or "DJ," or if lowercase fund names contain "index," "idx," "indx," "ind," "composite," "russell," "s&p," "s and p," "s & p," "msci," "bloomberg," "kbw," "nasdaq," "nyse," "stoxx," "ftse," "wilshire," "morningstar," "100," "400," "500," "600," "900," "1000," "1500," "2000," "3000," or "5000." We identify ETFs if CRSP fund names contain "ETF" or if lowercase fund names contain "ishares," "spdr," "holdrs," "streettracks," "exchange traded," or "exchange-traded." We identify ETNs if CRSP fund names contain "ETN" or if lowercase fund names contain "exchange traded note" or "exchange-traded note." Finally, we identify inverse and leveraged funds if lowercase fund names contain "plus," "enhanced," "inverse," "2x," "3x," "ultra," "1.5x," or "2.5x."

performing fund is Pacific Capital Funds: Small Cap Fund, which boasts a monthly information ratio of 0.3 from December 1999 to June 2010. The fund beats the market with a CAPM alpha of 0.92% per month ($t = 3.16$). Its geometric average gross return is 0.87%. Net of expenses, the geometric average net return is 0.75%. Its time series average TNA is $195 million, which is relatively small. Among the 2,089 active funds with an uninterrupted record of at least 10 years, the mean TNA is $1,144.3 million, 25th percentile $107.6 million, median $333.8 million, and 75th percentile $988.8 million. The best fund's TNA resides between the 25th percentile and the median.

The largest top-20 fund is Vanguard Specialized Funds: Vanguard Health Care Fund, with an average TNA of $8,866.2 million, which far exceeds the 95th TNA percentile of $4,483.1 million. Its monthly information ratio of 0.24 from December 1985 to April 2008 ranks 10th on the top-20 list. The fund beats the market with a CAPM alpha of 0.62% ($t = 3.47$). Finally, the smallest fund on the top-20 list is Monetta Trust: Monetta Core Growth Fund, with only a TNA of $69.1 million, which resides between the 10th percentile of $40.6 million and the 25th percentile of $107.6 million. Its information ratio of 0.29 from July 2007 to December 2020 ranks second on the top-20 list. It beats the market with an alpha of 0.33% ($t = 3.13$).

Panel A of Table 9 shows that the equal-weighted aggregate portfolio of all active equity funds earns an average gross return in excess of the riskfree rate of 0.62% per month ($t = 3.17$). However, consistent with Sharpe's (1991) arithmetic of active management, the CAPM alpha is only 0.03% ($t = 0.66$). As such, the average fund barely beats the market before fees. The TNA-weighted aggregate portfolio earns on average 0.56% ($t = 2.91$) before fees. The CAPM alpha is again tiny, −0.03% ($t = -0.79$). From Panel B, net of fees, the equal-weighted aggregate portfolio earns on average 0.54% ($t = 2.73$), with a tiny negative CAPM alpha of −0.06% ($t = -1.29$). The TNA-weighted aggregate portfolio, net of fees, earns on average 0.49% ($t = 2.55$). This portfolio underperforms the market with a significantly negative CAPM alpha of −0.1% ($t = -2.91$).

The top-20 funds represent a very high hurdle for the q^5 model. From Panel A of Table 9, the equal-weighted top-20 fund portfolio earns an average excess return before fees of 1.08% per month ($t = 6.25$), which yields a CAPM alpha of 0.62% ($t = 6.53$). The q^5 model produces an alpha of 0.44% ($t = 4.46$), which amounts to a reduction of 29% in economic magnitude from the CAPM alpha and of 59.3% from the average excess return. The market, size, and expected growth factor loadings are all significant, whereas the investment and Roe factor loadings are not. The TNA-weighted top-20 fund portfolio earns an average excess return before fees of 1.01% ($t = 5.89$), with a CAPM alpha of 0.58% ($t = 5.63$). The q^5 model yields an alpha of 0.3% ($t = 2.45$), which represents a reduction of 48.3% in magnitude from the CAPM alpha and 68.9% from the average excess return.

Panel B shows that, net of fees, the equal-weighted top-20 fund portfolio earns on average 1% per month ($t = 5.8$), with a CAPM alpha of 0.54% ($t = 5.73$). The q^5 model yields an alpha of 0.36% ($t = 3.65$), which amounts to a reduction of 33.3% from the CAPM alpha and of 64% from the average excess return. For the TNA-weighted top-20 fund portfolio, the average excess return is 0.95% ($t = 5.51$), and the CAPM alpha is 0.52% ($t = 5.01$). The q^5 alpha is only 0.23% ($t = 1.92$), which represents a reduction of 55.8% in magnitude from the CAPM alpha and 75.8% from the average excess return. The market, size, and expected growth factor loadings are all positive and significant, but the investment and Roe factor loadings are insignificant, albeit positive.

The remainder of Table 9 shows the q^5 regression for each of the top-20 funds. From Panel A, the average excess returns before fees range from 0.59% ($t = 1.22$) to 1.56% per month ($t = 3.51$) across the top-20 funds.[22] All but two average excess returns are significant at the 5% level. The CAPM alphas vary from 0.15% ($t = 2.79$) to 1.29% ($t = 2.41$), all of which are significant. The q^5 alphas vary from 0.09% ($t = 0.47$) to 1.05% ($t = 2.05$). However, 14 out of 20 q^5 alphas are still significant. Panel B shows that net of fees, the average excess returns range from 0.5% ($t = 1.02$) to 1.49% ($t = 3.35$), the CAPM alphas from 0.05% ($t = 0.97$) to 1.13% ($t = 2.1$), and the q^5 alphas from 0.00% ($t = 0.03$) to 0.9% ($t = 1.74$). Out of the top-20 funds, the CAPM produces 15

[22] The average excess returns in Table 9 are simple returns, which are appropriate for factor regressions. These returns are different from the full-life geometric average raw returns reported in Table 8.

significant alphas, net of fees, whereas the q^5 model yields only 7.

Across the top-20 funds, the market factor loadings are all positive, economically large, and statistically significant. The size and investment factor loadings are mixed. The size factor loadings are significantly positive for 7 funds but significantly negative for 4 funds. The investment factor loadings are significantly positive for 3 funds but significantly negative for 4 funds. As such, the traditional size and value factors are largely uninformative about top fund performance. More important, the Roe and expected growth factor loadings, which are unique to the q models, play a more clear-cut role in explaining the top performance. The loadings for both factors are significantly positive for 6 out of 20 top funds (despite one significantly negative loading for each). As such, top funds earn high average returns partially from their Roe and expected growth factor exposures.

4.2 Buffett's Alpha

We obtain Berkshire's return and price data first from CRSP and then fill in missing observations using data from Compustat. The sample constructed in this way goes from February 1968 to December 2020. 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 from CRSP.[23]

From Panel A of Table 10, in the February 1968–December 2020 sample, Berkshire's excess return is on average 1.41% per month ($t = 4.98$). The q-factor model reduces the average return by 58.2% in economic magnitude to an alpha of 0.59%, albeit still significant ($t = 2.34$). The investment and Roe factor loadings are both large and significant, 0.59 ($t = 3.82$) and 0.38 ($t = 3.31$), respectively. The evidence indicates that Berkshire behaves like high profitability and low investment stocks. Because the investment factor is a substitute for the value factor in the q-factor model, the evidence echoes the Buffett-Munger philosophy of buying profitable firms at bargain prices.

The expected growth factor loading in the q^5 regression is -0.23, albeit insignificant ($t = -1.3$), going in the wrong direction as the average return to yield a higher q^5 alpha of 0.74% ($t = 2.66$).

[23] In CRSP, the Berkshire returns are not technically missing in February 1977, April 1978, and June 1979 but are 2-month returns that span over the missing prior months of January 1977, March 1978, and May 1979, respectively.

The evidence is corroborated by Buffett's reluctance in investing high expected growth stocks, likely because of their relatively high valuation (and uncertainty with future growth).

We emphasize that the q^5 model features two related but different aspects of quality, expected profitability and expected growth. The evidence indicates that Buffett's "circle of competence" encompasses mature industries but not necessarily new industries with new technologies and high growth potential. While Graham and Dodd (1934, 1940) have long recognized expected growth as an important dimension of quality, capturing this dimension in practice remains challenging.[24]

5 Accounting for Asset Pricing Factors

While the investment CAPM is appealing on economic grounds, it assumes perfect accounting, which does not exist in reality. To operationalize the theory, we need to make auxiliary assumptions on how to measure investment, profitability, and expected growth. The real challenge is to evaluate the theory's explanatory power despite a myriad of accounting imperfections.

Penman and Zhang (2020a, b) call into question the accounting treatment underlying the q and q^5 models. Most important, we measure investment as the growth of total assets on the balance sheet, which does not account for expensed investment, such as research and development, advertising expenditures, employee training. In addition, these intangible investments tend to forecast returns with a positive sign, which contradicts the negative investment-return relation derived in equation (1). Rightfully, Penman and Zhang emphasize that, due to accounting conservatism, investment booked to the balance sheet reflects the low risk associated with future payoffs from the underlying tangible assets. In contrast, investment expensed to the income statement reflects the

[24]Frazzini, Kabiller, and Pedersen (2018) show that from November 1976 to March 2017, Berkshire earns an insignificant alpha of 0.45% per month ($t = 1.55$). Panel B of Table 10 largely reproduces their evidence. We obtain an AQR 6-factor alpha of 0.45% ($t = 1.67$) in the same sample period. Our loadings are also close to their original estimates. However, once we extend the sample backward to February 1968 (and forward to December 2020), the AQR 6-factor alpha rises to 0.58% ($t = 2.07$). The q-factor alphas are close to the AQR alphas across the two samples, but the q^5 alphas are somewhat larger due to the negative expected growth loadings. Finally, 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 also examined the evidence with Compustat's Berkshire returns prior to September 1988. The results are quantitatively close (the Internet Appendix, Table S9).

high risk associated with future payoffs from the underlying intangible assets.

Our treatment in the q models is largely congruent with Penman and Zhang (2020a, b). On the debate on whether to capitalize intangibles or not, with Lev (2001) and Lev and Gu (2016) on the one side and Penman (2009) and Barker et al. (2020) on the other, our accounting treatment is more aligned with the latter. Our investment factor is built on tangible investments booked to the balance sheet, for which conservative accounting also gives rise to a negative relation with expected returns.

More important, intangible investments are incorporated into the q^5 model via the expected growth factor, which uses Ball et al.'s (2016) operating cash flow as a key instrument (the Internet Appendix, Section B.6). The cash flow includes R&D expenses, which are the most reliably measured intangible investments at the firm level. The cash flow excludes SG&A, a part of which is likely intangible investments. However, separating the investment from the expense component of SG&A is difficult (Penman and Zhang 2020a, footnote 5). For example, advertising expenses not only produce future revenues (intangible assets) but also yield current revenues (current period expenses). Using cash flow directly to form expected growth sidesteps this intractable measurement problem.

The bottomline is that the q^5 model treats tangible and intangible investments differently, with the former via the investment factor and the latter via the expected growth factor. This treatment accommodates their different risks and relations with expected returns per conservative accounting.[25] We reject the idea that one should aggregate tangible and intangible investments as well as their book values together. Doing so would destroy the accounting information on their differential risks (Penman and Zhang 2020a). Capitalizing intangibles also involves amortization and impairment under uncertainty, which could contaminate the quality of earnings (Barker et al. 2020).[26]

[25] Our treatment is also grounded in the investment theory. For example, in Lin's (2012) equilibrium model, tangible and intangible capital goods are two different inputs in the production function. Expected returns are negatively correlated with tangible investments but positively correlated with intangible investments. Intuitively, intangible investments induce endogenous technological progress, which not only raises the marginal benefit of tangible investments via production innovation, but also decreases the marginal cost of tangible investments via technology improvement. Relatedly, Peters and Taylor (2017) treat tangible and intangible capital goods as perfect substitutes in the production function. While this assumption works for their purpose of studying the investment behavior, we view it as unfit for asset prices because it ignores the heterogeneity between tangible and intangible investments.

[26] Penman and Zhang (2020a) also argue that Roe is a poor measure of economic profitability. Roe misses intangible

6 Conclusion

This paper attempts to provide an equilibrium foundation for Graham and Dodd (1934). In the investment CAPM, expected returns vary cross-sectionally, depending on real investment, expected profitability, and expected growth. While realized returns are predictable, abnormal returns are not, thereby retaining efficient markets. As such, the investment CAPM provides an economics-based, conceptual framework for security analysis. This framework is consistent with the bulk of modern finance and economics but is largely missing from capital markets research in accounting. Empirically, the q^5 model goes a long way in explaining the performance of prominent quantitative security analysis strategies as well as that of best-performing active, discretionary equity funds.

The performance of the q^5 model should *not* be misinterpreted as reducing security analysis to a few quantitative indicators. We have never made or intended to make such a claim. On the contrary, we are inspired by the fundamental analysis literature, which we believe has broad and profound implications for asset pricing. While challenging the traditional mispricing premise of security analysis, we completely agree with Sloan (2019) that active, discretionary management cannot be fully replaced by passive factor investing. The q models are just simple, convenient, and practical tools. Guided by economic theory, identifying the sources of expected profitability, expected growth, and ultimately expected returns, via thorough and systematic financial statement analysis, quantitative and qualitative, with deep understanding of the strengths and weaknesses of accounting principles, is what we envision as the job description of a successful active manager.

assets in the denominator and intangible investments expensed away from earnings in the numerator. Because intangible investments tend to forecast return with a positive sign, conservative accounting causes Roe to predict returns with a negative sign in the data (Penman and Zhang 2020b). This evidence seemingly contradicts the investment CAPM, which predicts a positive profitability-return relation. To respond to this critique, Section B.4 of the Internet Appendix details that the weakly negative Roe-return relation resides only in annual sorts (Table S10). In monthly sorts on quarterly Roe, the positive Roe-return relation postulated by the investment CAPM dominates the negative relation from conservative accounting. More important, because of information advantage of quarterly earnings announcements, quarterly Roe outperforms other quarterly profitability measures (including operating cash flows) in monthly sorts.

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Table 1 : The Abarbanell-Bushee (1998) Security Analysis Portfolios, January 1967–December 2020

Section 3.1 details the measurement of the Abarbanell-Bushee composite signal, denoted AB. In Panel A, at the end of June of each year t, we sort stocks into deciles on the NYSE breakpoints of AB 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 AB 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 AB 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 Abarbanell-Bushee score

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.46	0.54	0.55	0.56	0.66	0.67	0.60	0.68	0.59	0.74	0.29	
$t_{\overline{R}}$	2.10	2.65	2.84	3.10	3.79	3.69	3.55	3.82	3.08	3.50	2.42	
α_q	−0.04	0.03	0.05	−0.02	0.11	0.02	−0.04	0.13	0.11	0.13	0.17	0.15
t_q	−0.44	0.50	0.63	−0.25	1.65	0.29	−0.63	1.73	1.42	1.22	1.17	
α_{q^5}	−0.05	0.02	0.05	0.03	0.06	0.03	−0.06	0.07	0.10	0.08	0.13	0.74
t_{q^5}	−0.53	0.28	0.65	0.38	0.80	0.51	−0.93	0.87	1.13	0.70	0.85	
	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	−0.03	0.13	−0.12	0.26	0.06		−0.66	2.44	−1.06	2.93	0.44	0.06

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

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.50	0.56	0.66	0.65	0.67	0.17		2.43	3.12	3.81	3.86	3.42	1.92
Micro	0.75	0.91	0.88	1.04	0.91	0.16		2.44	3.26	3.17	3.80	3.03	2.06
Small	0.67	0.80	0.87	0.92	0.89	0.22		2.55	3.36	3.71	3.93	3.65	2.98
Big	0.49	0.55	0.65	0.63	0.64	0.15		2.45	3.06	3.79	3.81	3.33	1.60
			α_q ($p_{\text{GRS}}=0.00$)							t_q			
All	0.00	0.02	0.06	0.06	0.14	0.14		0.07	0.43	1.40	1.16	2.08	1.52
Micro	0.08	0.13	0.09	0.29	0.22	0.14		0.77	1.45	1.29	3.44	2.73	1.52
Small	−0.10	0.00	−0.02	0.03	0.14	0.24		−1.54	−0.01	−0.27	0.49	2.58	3.18
Big	0.03	0.03	0.07	0.07	0.15	0.12		0.49	0.49	1.48	1.22	1.95	1.18
			α_{q^5} ($p_{\text{GRS}}=0.13$)							t_{q^5}			
All	−0.02	0.02	0.03	0.02	0.11	0.13		−0.30	0.43	0.69	0.31	1.51	1.27
Micro	0.08	0.17	0.13	0.26	0.19	0.11		0.75	1.80	1.65	3.08	2.50	1.20
Small	−0.04	0.04	−0.01	0.06	0.12	0.16		−0.65	0.72	−0.13	0.92	1.92	1.93
Big	0.00	0.03	0.04	0.02	0.12	0.11		0.05	0.51	0.79	0.40	1.47	1.03
	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	−0.01	0.00	−0.15	0.16	0.01		−0.30	0.06	−2.18	2.51	0.18		0.05
Micro	−0.02	0.09	−0.05	0.03	0.04		−0.72	1.63	−0.67	0.59	0.68		0.02
Small	−0.07	0.06	−0.13	0.07	0.12		−3.09	2.24	−2.50	1.59	2.29		0.07
Big	−0.01	0.00	−0.16	0.17	0.01		−0.19	0.11	−2.18	2.58	0.06		0.05

Table 2 : The Frankel-Lee (1998) Intrinsic-to-Market Value Portfolios, January 1967–December 2020

Intrinsic-to-market is the intrinsic value, V^h, over the market equity, P. Section 3.2 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}, $\beta_{\text{I/A}}$, 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 intrinsic-to-market value

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.56	0.49	0.65	0.54	0.54	0.64	0.83	0.65	0.91	0.79	0.23	
$t_{\overline{R}}$	2.34	2.50	3.67	3.21	2.98	3.58	4.79	3.50	4.96	3.53	1.29	
α_q	0.19	−0.12	−0.04	−0.10	−0.17	−0.09	0.14	−0.02	0.25	0.11	−0.07	0.00
t_q	1.66	−1.77	−0.64	−1.25	−1.99	−0.99	1.58	−0.19	2.30	0.88	−0.39	
α_{q^5}	0.17	−0.14	−0.14	−0.13	−0.19	−0.14	0.05	−0.10	0.18	0.08	−0.09	0.03
t_{q^5}	1.61	−1.79	−1.70	−1.61	−2.07	−1.51	0.58	−1.02	1.65	0.64	−0.49	
	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	−0.03	0.25	0.91	−0.11	0.02		−0.42	2.12	6.02	−0.77	0.14	0.17

Panel B: Quintiles from two-way independent sorts on size and intrinsic-to-market value

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.51	0.59	0.57	0.74	0.88	0.36		2.41	3.55	3.24	4.27	4.60	2.38
Micro	0.76	0.94	0.87	0.93	1.03	0.27		2.50	3.48	3.45	3.68	3.77	1.99
Small	0.65	0.84	0.89	0.86	0.97	0.33		2.36	3.52	4.05	3.98	3.90	2.16
Big	0.52	0.58	0.55	0.72	0.82	0.29		2.45	3.54	3.15	4.20	4.37	1.90
			α_q ($p_{\text{GRS}} = 0.14$)							t_q			
All	0.03	−0.07	−0.13	0.06	0.22	0.19		0.36	−1.21	−1.84	0.85	2.21	1.29
Micro	0.02	0.15	0.11	0.08	0.15	0.13		0.19	1.56	1.25	0.82	1.38	0.93
Small	−0.11	−0.03	0.02	−0.04	0.06	0.17		−1.28	−0.42	0.31	−0.40	0.47	1.01
Big	0.06	−0.06	−0.15	0.06	0.19	0.13		0.74	−1.12	−1.90	0.80	1.89	0.87
			α_{q^5} ($p_{\text{GRS}} = 0.10$)							t_{q^5}			
All	0.01	−0.14	−0.17	−0.03	0.16	0.15		0.08	−2.09	−2.13	−0.34	1.65	1.05
Micro	0.03	0.21	0.07	0.14	0.23	0.20		0.28	2.02	0.88	1.44	2.37	1.64
Small	−0.08	0.00	0.02	0.01	0.11	0.19		−0.89	−0.03	0.25	0.12	1.12	1.35
Big	0.03	−0.14	−0.18	−0.03	0.14	0.11		0.41	−2.07	−2.12	−0.38	1.41	0.71
	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	−0.08	0.20	0.70	−0.16	0.06		−1.75	2.42	6.15	−1.39	0.53		0.20
Micro	−0.03	−0.16	0.54	0.06	−0.11		−0.68	−2.00	4.95	0.56	−0.94		0.15
Small	0.00	−0.17	0.73	−0.06	−0.04		0.04	−1.22	5.37	−0.46	−0.30		0.16
Big	−0.08	0.14	0.72	−0.15	0.04		−1.59	1.57	5.96	−1.23	0.35		0.18

Table 3 : The Greenblatt (2010) Portfolios, January 1967–December 2020

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 $\beta_{\rm Mkt}$, $\beta_{\rm Me}$, $\beta_{\rm I/A}$, $\beta_{\rm Roe}$, and $\beta_{\rm Eg}$, respectively. All the t-values are adjusted for heteroscedasticity and autocorrelations. In Panel A, $p_{\rm GRS}$ is the p-value of the GRS test on the null that the alphas of the ten deciles are jointly zero. In Panel B, $p_{\rm GRS}$ 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	$p_{\rm GRS}$
$\overline{R}$	0.40	0.47	0.53	0.58	0.55	0.53	0.57	0.70	0.83	0.96	0.57	
$t_{\overline{R}}$	1.30	2.21	2.86	3.21	2.94	2.79	3.15	3.79	4.68	4.97	2.54	
α_q	0.10	−0.03	−0.01	0.05	−0.03	−0.04	−0.06	0.12	0.16	0.29	0.19	0.04
t_q	0.68	−0.30	−0.17	0.62	−0.47	−0.58	−0.77	1.88	2.31	3.25	1.10	
α_{q^5}	0.18	0.02	−0.02	0.10	0.07	−0.05	−0.10	0.12	0.06	0.05	−0.13	0.42
t_{q^5}	1.30	0.22	−0.24	1.31	0.94	−0.69	−1.12	1.65	0.83	0.57	−0.76	
	$\beta_{\rm Mkt}$	$\beta_{\rm Me}$	$\beta_{\rm I/A}$	$\beta_{\rm Roe}$	$\beta_{\rm Eg}$		$t_{\rm Mkt}$	$t_{\rm Me}$	$t_{\rm I/A}$	$t_{\rm Roe}$	$t_{\rm Eg}$	R^2
H−L	−0.13	−0.20	0.30	0.67	0.48		−3.00	−2.43	2.37	6.26	3.55	0.42

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	0.44	0.55	0.53	0.63	0.90	0.46	1.84	3.11	2.90	3.57	5.03	3.16
Micro	0.62	0.77	0.86	0.98	0.97	0.35	1.81	2.75	2.97	3.53	3.71	2.05
Small	0.55	0.80	0.79	0.89	0.95	0.40	1.84	3.30	3.26	3.60	3.98	2.49
Big	0.47	0.54	0.52	0.61	0.88	0.41	2.03	3.11	2.86	3.50	5.01	2.70
			α_q ($p_{\rm GRS} = 0.05$)						t_q			
All	0.03	0.01	−0.04	0.01	0.25	0.22	0.32	0.17	−0.81	0.25	4.02	1.76
Micro	0.12	−0.04	0.04	0.09	0.12	0.00	0.85	−0.38	0.47	0.92	1.35	0.01
Small	0.01	−0.05	−0.03	0.00	0.05	0.03	0.15	−0.63	−0.44	0.01	0.58	0.22
Big	0.12	0.03	−0.04	0.01	0.26	0.14	1.08	0.44	−0.71	0.20	3.85	1.03
			α_{q^5} ($p_{\rm GRS} = 0.82$)						t_{q^5}			
All	0.10	0.04	−0.01	−0.03	0.07	−0.03	1.01	0.66	−0.22	−0.48	1.05	−0.24
Micro	0.07	0.06	0.12	0.16	0.14	0.06	0.60	0.64	1.46	1.71	1.58	0.46
Small	0.04	0.04	0.06	0.03	0.08	0.04	0.46	0.51	0.86	0.38	1.03	0.29
Big	0.19	0.06	−0.01	−0.03	0.06	−0.13	1.77	0.83	−0.14	−0.50	0.88	−0.98
	$\beta_{\rm Mkt}$	$\beta_{\rm Me}$	$\beta_{\rm I/A}$	$\beta_{\rm Roe}$	$\beta_{\rm Eg}$	$t_{\rm Mkt}$	$t_{\rm Me}$	$t_{\rm I/A}$	$t_{\rm Roe}$	$t_{\rm Eg}$		R^2
All	−0.11	0.07	0.08	0.42	0.37	−3.12	1.12	0.95	5.21	3.90		0.31
Micro	−0.09	−0.25	0.41	0.67	−0.09	−2.04	−2.06	3.22	6.22	−0.91		0.41
Small	−0.11	−0.09	0.47	0.59	−0.01	−2.21	−0.69	3.92	5.30	−0.08		0.33
Big	−0.10	0.18	0.06	0.42	0.40	−2.61	2.83	0.68	4.85	3.88		0.26

Table 4 : The Asness-Frazzini-Pedersen (2019) Quality Score Portfolios, January 1967–December 2020

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}, $\beta_{\mathrm{I/A}}$, 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 quality score

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.44	0.47	0.54	0.52	0.48	0.55	0.58	0.63	0.68	0.73	0.28	
$t_{\overline{R}}$	1.47	2.06	2.50	2.71	2.58	2.97	3.16	3.38	3.74	3.77	1.43	
α_q	−0.06	−0.17	−0.05	−0.08	−0.17	−0.02	−0.02	0.07	0.07	0.32	0.38	0.00
t_q	−0.56	−1.94	−0.47	−1.02	−2.15	−0.29	−0.30	1.31	1.24	4.42	2.82	
α_{q^5}	0.11	−0.03	0.04	−0.03	−0.14	0.04	−0.01	0.11	0.09	0.13	0.02	0.11
t_{q^5}	0.98	−0.41	0.35	−0.33	−1.63	0.59	−0.10	1.94	1.49	1.86	0.15	
	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	−0.22	−0.55	−0.62	0.62	0.54		−5.24	−10.67	−7.11	7.81	5.97	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	0.45	0.52	0.51	0.60	0.71	0.25	1.80	2.67	2.87	3.35	3.81	1.74
Micro	0.41	0.85	0.93	0.97	0.96	0.55	1.13	2.86	3.26	3.50	3.64	3.61
Small	0.59	0.78	0.83	0.82	0.96	0.37	1.93	3.21	3.32	3.34	3.90	2.88
Big	0.48	0.49	0.49	0.59	0.69	0.22	2.01	2.58	2.77	3.30	3.76	1.51
	α_q ($p_{\mathrm{GRS}} = 0.00$)						t_q					
All	−0.13	−0.08	−0.08	0.03	0.23	0.36	−1.66	−1.11	−1.45	0.66	4.21	3.40
Micro	−0.08	0.18	0.19	0.27	0.28	0.36	−0.49	1.47	1.79	2.43	2.41	2.91
Small	0.00	0.04	0.01	0.09	0.23	0.22	0.06	0.64	0.07	1.11	2.87	2.05
Big	−0.08	−0.07	−0.09	0.03	0.23	0.31	−0.85	−0.98	−1.43	0.56	4.07	2.62
	α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)						t_{q^5}					
All	0.01	−0.01	−0.04	0.06	0.11	0.10	0.18	−0.10	−0.69	1.13	2.09	0.97
Micro	0.03	0.26	0.22	0.32	0.29	0.27	0.15	2.17	2.20	2.84	2.52	2.02
Small	0.13	0.11	0.08	0.14	0.21	0.08	1.68	1.57	1.23	2.13	2.72	0.77
Big	0.07	0.00	−0.04	0.05	0.11	0.04	0.69	−0.05	−0.68	1.03	2.00	0.38

	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	−0.15	−0.36	−0.59	0.43	0.40	−4.99	−8.83	−8.86	7.06	5.73	0.61
Micro	−0.17	−0.21	0.03	0.63	0.14	−5.75	−4.07	0.33	8.00	1.76	0.49
Small	−0.17	−0.12	−0.10	0.56	0.21	−4.95	−1.33	−1.24	7.03	2.84	0.46
Big	−0.13	−0.22	−0.65	0.40	0.40	−3.76	−5.25	−8.72	5.91	5.06	0.47

Table 5 : The Bartram-Grinblatt (2018) Agnostic Fundamental Analysis Portfolios, January 1977–December 2020

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 $t + 1$. 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}, $\beta_{\text{I/A}}$, 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 agnostic sorts

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.70	0.64	0.70	0.58	0.84	0.84	0.90	0.93	1.03	1.09	0.39	
$t_{\overline{R}}$	2.48	2.63	3.56	3.30	4.20	4.18	3.95	3.79	3.79	3.58	2.22	
α_q	0.10	0.02	0.04	0.05	0.18	0.14	0.15	0.12	0.19	0.33	0.22	0.20
t_q	0.86	0.16	0.48	0.49	2.26	1.33	1.09	0.81	1.16	1.78	1.03	
α_{q^5}	0.12	−0.02	−0.01	−0.03	0.11	0.16	0.25	0.26	0.36	0.47	0.35	0.11
t_{q^5}	0.93	−0.17	−0.20	−0.28	1.32	1.46	1.89	1.74	2.54	3.02	1.65	
	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	−0.05	0.32	0.57	−0.03	−0.20		−0.83	3.09	3.76	−0.20	−1.66	0.16

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
			$\overline{R}$							$t_{\overline{R}}$			
All	0.69	0.65	0.85	0.91	1.05	0.36		2.82	3.58	4.38	3.93	3.76	1.70
Micro	0.37	0.57	0.93	0.89	1.18	0.81		0.92	1.57	2.85	3.00	3.68	3.71
Small	0.70	0.93	0.88	1.02	1.12	0.42		2.11	3.29	3.30	3.83	3.73	2.09
Big	0.70	0.65	0.85	0.91	1.06	0.36		2.91	3.63	4.49	4.00	3.82	1.59
			α_q ($p_{\text{GRS}} = 0.00$)							t_q			
All	0.09	0.05	0.17	0.14	0.23	0.15		0.80	0.90	2.49	1.04	1.42	0.57
Micro	−0.05	−0.12	0.11	0.00	0.40	0.46		−0.21	−0.53	0.66	0.02	2.13	1.78
Small	0.06	0.13	−0.01	0.11	0.20	0.15		0.52	1.48	−0.14	0.92	1.25	0.61
Big	0.10	0.06	0.19	0.18	0.30	0.20		0.91	1.06	2.73	1.24	1.63	0.73
			α_{q^5} ($p_{\text{GRS}} = 0.00$)							t_{q^5}			
All	0.05	−0.03	0.14	0.25	0.39	0.34		0.52	−0.43	1.85	1.91	2.84	1.60
Micro	0.06	−0.04	0.05	0.01	0.47	0.42		0.19	−0.14	0.28	0.08	2.85	1.62
Small	0.09	0.12	0.00	0.21	0.36	0.27		0.85	1.23	0.05	1.88	2.62	1.33
Big	0.08	−0.02	0.16	0.30	0.44	0.36		0.76	−0.31	2.01	2.03	2.71	1.56
	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	0.07	0.34	0.80	−0.18	−0.30		0.96	1.61	4.08	−1.00	−1.85		0.24
Micro	0.01	−0.19	0.59	0.43	0.06		0.09	−1.94	3.23	1.97	0.33		0.19
Small	0.03	−0.33	1.00	0.16	−0.19		0.47	−1.87	5.75	0.80	−1.15		0.23
Big	0.11	0.12	0.73	−0.22	−0.25		1.52	0.61	3.91	−1.20	−1.36		0.14

Table 6 : The Operating Cash Flow-to-market Portfolios, January 1967–December 2020

Operating cash flow, denoted Cop, at the June-end of year t is total revenue (Compustat annual item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC), all from the fiscal year ending in calendar year $t-1$. Missing annual changes are set to zero. In Panel A, at the end of June of year t, we sort stocks into deciles based on the NYSE breakpoints of Cop for the fiscal year ending in calendar year $t-1$ over the December-end market equity (from CRSP). Monthly value-weighted decile returns are 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 Cop for the fiscal year ending in calendar year $t-1$ over the December-end market equity 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}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively. 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 operating cash flow-to-market

	L	2	3	4	5	6	7	8	9	H	H−L	p_{GRS}
$\overline{R}$	0.15	0.58	0.64	0.64	0.71	0.73	0.68	0.85	0.86	0.94	0.79	
$t_{\overline{R}}$	0.56	2.71	3.39	3.53	3.96	4.02	3.61	4.40	3.98	3.68	3.73	
α_q	−0.28	0.06	0.03	−0.04	−0.01	0.07	0.02	0.11	0.13	0.22	0.50	0.09
t_q	−2.56	0.64	0.42	−0.49	−0.14	0.83	0.22	1.16	1.14	1.70	2.89	
α_{q^5}	0.01	0.07	0.03	−0.07	−0.09	−0.04	−0.12	0.01	0.13	0.16	0.15	0.59
t_{q^5}	0.10	0.63	0.48	−0.83	−1.15	−0.48	−1.30	0.12	1.01	1.25	0.92	
	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	0.03	0.15	1.32	−0.54	0.53		0.60	2.04	8.86	−4.66	3.46	0.37

Panel B: Quintiles from two-way independent sorts on size and operating cash flow-to-market

	L	2	3	4	H	H−L		L	2	3	4	H	H−L
			$\overline{R}$							$t_{\overline{R}}$			
All	0.41	0.64	0.73	0.75	0.90	0.49		1.78	3.58	4.15	4.06	4.09	2.71
Micro	0.38	0.80	1.04	1.08	1.26	0.88		1.18	2.82	3.80	3.96	4.08	6.22
Small	0.40	0.90	0.96	1.04	1.01	0.61		1.38	3.68	3.95	4.18	3.65	3.75
Big	0.45	0.63	0.70	0.71	0.83	0.37		1.99	3.56	4.08	3.93	3.83	1.99
			α_q ($p_{\text{GRS}} = 0.00$)							t_q			
All	−0.03	0.02	0.04	0.07	0.17	0.21		−0.44	0.32	0.76	0.86	1.70	1.44
Micro	−0.20	0.05	0.28	0.26	0.34	0.55		−1.84	0.63	3.38	3.48	3.26	4.09
Small	−0.22	0.05	0.08	0.10	−0.02	0.20		−2.83	0.84	1.09	1.40	−0.15	1.38
Big	0.04	0.03	0.04	0.05	0.14	0.10		0.51	0.46	0.59	0.59	1.22	0.63
			α_{q^5} ($p_{\text{GRS}} = 0.00$)							t_{q^5}			
All	0.08	−0.01	−0.06	−0.06	0.15	0.06		1.07	−0.22	−0.97	−0.83	1.35	0.46
Micro	−0.14	0.08	0.25	0.27	0.37	0.51		−1.25	0.92	2.91	3.22	3.40	3.72
Small	−0.06	0.01	0.08	0.06	0.06	0.12		−0.78	0.14	1.08	0.75	0.51	0.85
Big	0.16	0.00	−0.07	−0.08	0.12	−0.03		1.92	0.01	−1.10	−1.03	0.99	−0.22
	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	0.01	0.28	1.11	−0.40	0.21		0.25	4.25	11.63	−4.19	1.68		0.38
Micro	0.03	−0.01	0.79	0.09	0.06		0.76	−0.17	7.85	0.80	0.50		0.23
Small	0.06	−0.01	1.10	−0.03	0.13		1.20	−0.12	9.44	−0.22	1.03		0.32
Big	0.01	0.25	1.14	−0.41	0.20		0.22	3.44	10.17	−3.76	1.49		0.34

Table 7 : The Penman-Zhu (2020) Expected-return Portfolios, Annually Formed, July 1982–December 2020

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}
$\overline{R}$	0.31	0.77	0.83	0.73	0.96	0.82	0.92	0.91	1.06	1.05	0.74	
$t_{\overline{R}}$	1.10	2.99	3.87	3.49	4.31	4.42	4.61	4.72	5.09	4.29	4.21	
α_q	−0.51	0.12	0.02	−0.03	0.16	−0.01	0.11	0.08	0.31	0.17	0.68	0.00
t_q	−5.27	1.40	0.22	−0.29	1.36	−0.18	1.46	0.90	3.01	1.34	4.08	
α_{q^5}	−0.33	0.20	0.05	−0.07	0.10	0.01	0.02	−0.04	0.24	0.03	0.36	0.01
t_{q^5}	−3.28	2.39	0.55	−0.68	0.73	0.14	0.23	−0.45	2.46	0.26	2.17	
	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	−0.25	0.56	−0.15	0.51		−0.70	−3.16	5.55	−1.96	4.59	0.29

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	0.54	0.77	0.89	0.89	1.08	0.54		2.06	3.75	4.51	4.74	5.04	3.93
Micro	0.46	1.01	1.05	1.04	1.18	0.72		1.24	3.09	3.40	3.43	3.98	4.42
Small	0.61	1.05	1.03	1.05	0.90	0.28		1.90	3.73	3.98	4.22	3.32	1.96
Big	0.57	0.76	0.89	0.88	1.07	0.50		2.26	3.76	4.54	4.73	5.06	3.50
			α_q ($p_{\mathrm{GRS}} = 0.00$)							t_q			
All	−0.18	−0.01	0.07	0.08	0.30	0.48		−2.79	−0.09	1.01	1.25	3.42	4.06
Micro	−0.12	0.31	0.32	0.26	0.44	0.57		−1.12	3.11	3.24	2.01	3.45	3.77
Small	−0.16	0.14	0.08	0.13	−0.04	0.11		−2.05	1.78	0.94	1.70	−0.43	0.92
Big	−0.16	−0.01	0.08	0.07	0.31	0.47		−2.21	−0.11	1.01	1.14	3.08	3.47
			α_{q^5} ($p_{\mathrm{GRS}} = 0.00$)							t_{q^5}			
All	−0.05	−0.02	0.05	−0.02	0.19	0.23		−0.74	−0.30	0.59	−0.36	2.24	2.16
Micro	−0.15	0.30	0.26	0.26	0.44	0.59		−1.36	2.93	2.62	1.98	3.18	3.74
Small	−0.07	0.11	0.14	0.16	−0.04	0.03		−0.89	1.15	1.84	2.15	−0.47	0.25
Big	−0.01	−0.02	0.05	−0.03	0.19	0.21		−0.21	−0.31	0.57	−0.46	2.03	1.69
	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	−0.05	−0.21	0.61	−0.14	0.39		−1.45	−4.60	6.97	−2.29	5.36		0.43
Micro	−0.11	−0.25	0.46	0.33	−0.04		−2.66	−3.53	3.89	3.69	−0.37		0.37
Small	−0.08	−0.21	0.70	0.15	0.13		−1.83	−3.21	8.32	1.56	1.52		0.42
Big	−0.05	−0.16	0.60	−0.20	0.41		−1.35	−3.04	5.81	−2.84	5.07		0.36

Table 8 : Top-20 Active Equity Funds in the CRSP Mutual Fund Database, January 1967–December 2020

We select top-20 active funds based on the full-life information ratio (IR). A fund's IR is its alpha divided by its residual volatility, both of which are estimated from the CAPM regression of monthly gross returns in its full-life sample. We include months with TNA below $15 million. We exclude funds that do not have the complete histories between their first and last months. We require a minimum track record of 10 years. We include both currently live and dead funds. The table shows the ranking in the descending order, fund name, the start and end month of a fund, the number of months in the database (#ms), monthly geometric average gross returns ($rret^g$, in %), monthly geometric average net returns ($mret^g$, in %), average monthly total net assets (TNA, in $ millions), gross CAPM alphas (α), their t-values (t_α), and IRs.

Rank	Fund Name	Start	End	#ms	$rret^g$	$mret^g$	TNA	α	t_α	IR
1	Pacific Capital Funds: Small Cap Fund	12/1999	6/2010	127	0.87	0.75	195.0	0.92	3.16	0.30
2	Monetta Trust: Monetta Core Growth Fund	7/2007	12/2020	162	1.07	0.97	69.1	0.33	3.13	0.29
3	Fidelity Select Portfolios: Medical Technology and Devices Portfolio	6/1998	12/2020	271	1.29	1.21	1,801.6	0.83	4.45	0.27
4	BlackRock Funds: BlackRock Health Sciences Opportunities Portfolio	1/2001	12/2020	240	1.18	1.05	2,769.7	0.69	3.88	0.26
5	Pioneer Series Trust X: Pioneer Fundamental Growth Fund	1/2007	12/2020	168	0.99	0.90	2,566.0	0.30	3.16	0.26
6	Advisors' Inner Circle Fund: CIBC Atlas Disciplined Equity Fund	1/2007	10/2020	166	0.84	0.77	559.1	0.17	3.09	0.25
7	Fidelity Select Portfolios: IT Services Portfolio	5/2008	12/2020	152	1.45	1.38	1,415.2	0.55	2.70	0.25
8	Templeton Growth Fund	1/1967	11/1990	287	1.39	1.32	579.8	0.66	3.87	0.25
9	Parnassus Income Funds: Parnassus Core Equity Fund	12/1997	12/2020	277	0.93	0.85	5,556.5	0.35	3.68	0.25
10	Vanguard Specialized Funds: Vanguard Health Care Fund	12/1985	4/2008	269	1.35	1.32	8,866.2	0.62	3.47	0.24
11	Columbia Funds Series Trust I: Columbia Strategic Investor Fund	7/2001	7/2012	133	0.61	0.51	662.7	0.31	2.34	0.24
12	Delaware Group Equity Funds IV: Delaware Healthcare Fund	12/2007	12/2020	157	1.36	1.25	374.2	0.67	2.88	0.24
13	Sit Mutual Funds, Inc: Sit Dividend Growth Fund	6/2004	12/2020	199	0.91	0.83	481.6	0.17	2.99	0.23
14	American Century Mutual Funds, Inc: Sustainable Equity Fund	6/2005	12/2020	187	0.94	0.84	369.2	0.15	2.79	0.23
15	Westport Funds: Westport Fund	12/1998	8/2016	213	0.94	0.82	222.9	0.49	3.49	0.23
16	Hartford Mutual Funds, Inc: Hartford MidCap Fund	12/1998	10/2020	263	1.04	0.93	4,423.1	0.44	3.23	0.23
17	Advisors' Inner Circle Fund: Edgewood Growth Fund	1/2007	10/2020	166	1.13	1.04	5,519.7	0.46	2.30	0.23
18	Ivy Funds: Ivy Global Natural Resources Fund	1/1998	4/2008	124	1.57	1.41	1,498.1	1.29	2.41	0.23
19	CRM Mutual Fund Trust: CRM Mid Cap Value Fund	12/1999	12/2020	253	1.03	0.95	1,719.2	0.50	2.70	0.23
20	Principal Funds, Inc: MidCap Fund	12/2001	12/2020	229	1.04	0.95	5,810.3	0.34	3.22	0.22

Table 9 : Explaining Active Equity Funds, January 1967–December 2020

"All, ew" and "All, vw" are the equal- and TNA-weighted aggregate fund portfolios, and "Top-20, ew" and "Top-20, vw" are the equal- and TNA-weighted portfolios of the top-20 funds, respectively. For each month, we use available top-20 funds to form the top-20 portfolios. Fund 1, ..., 20 are the top-20 funds (Table 8). For each fund, we report the average excess return, CAPM alpha, q-alpha, q^5 alpha, q^5 factor loadings, and R^2. The t-values beneath the estimates are adjusted for heteroscedasticity and autocorrelations.

Panel A: Explaining gross fund returns										
	$\overline{R}$	α	α_q	α_{q^5}	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
All, ew	0.62	0.03	−0.01	0.04	0.97	0.22	−0.06	0.09	−0.09	0.97
	3.17	0.66	−0.38	1.29	114.20	12.97	−2.91	3.55	−4.12	
All, vw	0.56	−0.03	−0.04	0.00	0.98	0.10	−0.09	0.08	−0.06	0.98
	2.91	−0.79	−1.16	0.11	110.89	6.11	−4.75	3.38	−3.24	
Top-20, ew	1.08	0.62	0.54	0.44	0.80	0.15	0.09	−0.05	0.16	0.76
	6.25	6.53	5.54	4.46	21.40	3.63	1.41	−0.90	3.07	
Top-20, vw	1.01	0.58	0.43	0.30	0.78	0.12	0.15	0.01	0.21	0.70
	5.89	5.63	3.73	2.45	20.17	3.03	1.82	0.22	3.28	
Fund 1	0.81	0.92	0.30	0.33	1.09	0.38	0.67	0.29	−0.07	0.83
	1.47	3.16	1.31	1.47	13.68	2.50	5.26	3.16	−0.51	
Fund 2	1.12	0.33	0.34	0.24	0.97	−0.04	0.05	−0.13	0.19	0.95
	3.06	3.13	2.64	2.48	28.39	−0.84	0.74	−1.17	1.95	
Fund 3	1.24	0.83	0.72	0.55	0.72	0.23	0.00	0.06	0.29	0.54
	4.60	4.45	3.79	2.53	10.48	3.78	0.02	0.63	2.27	
Fund 4	1.16	0.69	0.70	0.63	0.71	0.11	−0.11	−0.09	0.15	0.62
	3.94	3.88	3.74	3.43	13.41	1.74	−0.86	−0.65	1.18	
Fund 5	1.00	0.30	0.20	0.16	0.93	−0.14	−0.13	0.10	0.08	0.94
	3.10	3.16	2.32	1.96	32.81	−4.01	−2.76	2.53	1.36	
Fund 6	0.86	0.17	0.15	0.11	0.96	−0.08	0.02	−0.01	0.07	0.98
	2.53	3.09	2.55	1.86	58.55	−3.32	0.69	−0.40	1.96	
Fund 7	1.56	0.55	0.54	0.53	1.04	0.06	−0.50	0.00	0.01	0.86
	3.51	2.70	2.89	2.64	14.93	0.76	−4.14	−0.05	0.13	
Fund 8	0.89	0.66	0.52	0.38	0.71	0.20	0.07	−0.13	0.26	0.64
	3.17	3.87	2.36	1.72	11.63	2.83	0.56	−1.11	1.96	
Fund 9	0.85	0.35	0.29	0.19	0.85	−0.03	0.17	0.00	0.17	0.88
	3.70	3.68	3.00	2.13	34.43	−0.66	3.01	0.08	3.29	
Fund 10	1.07	0.62	0.25	0.09	0.85	0.07	0.17	0.23	0.27	0.67
	4.14	3.47	1.31	0.47	15.18	1.26	1.37	3.04	2.57	
Fund 11	0.59	0.31	0.23	0.23	1.03	0.11	0.09	0.03	0.01	0.94
	1.22	2.34	1.86	1.84	21.79	1.87	0.96	0.47	0.10	
Fund 12	1.44	0.67	0.74	0.65	0.79	0.28	−0.21	−0.23	0.18	0.72
	3.59	2.88	3.28	2.83	12.62	2.16	−1.19	−1.59	1.06	
Fund 13	0.88	0.17	0.12	0.13	0.92	−0.05	0.02	0.14	−0.04	0.97
	3.21	2.99	2.14	2.49	55.68	−1.97	0.68	4.55	−1.02	
Fund 14	0.93	0.15	0.10	0.10	0.99	−0.08	0.02	0.07	0.02	0.98
	2.93	2.79	2.23	1.96	87.86	−4.23	0.91	3.54	0.76	
Fund 15	0.89	0.49	0.38	0.40	0.89	0.22	0.03	0.05	−0.05	0.82
	2.74	3.49	2.94	3.25	18.22	2.93	0.25	0.63	−0.55	
Fund 16	1.03	0.44	0.36	0.38	1.01	0.33	−0.09	0.05	−0.02	0.91
	3.17	3.23	3.01	3.28	28.39	6.98	−1.12	0.67	−0.36	
Fund 17	1.18	0.46	0.43	0.31	0.98	−0.01	−0.57	−0.17	0.25	0.88
	2.91	2.30	2.59	2.04	18.86	−0.11	−5.44	−1.97	2.11	
Fund 18	1.52	1.29	1.00	1.05	0.95	0.30	0.26	0.16	−0.09	0.35
	2.46	2.41	1.92	2.05	4.76	1.62	0.95	0.67	−0.30	
Fund 19	1.01	0.50	0.29	0.32	0.94	0.23	0.32	0.21	−0.05	0.83
	3.28	2.70	2.01	2.26	15.84	2.51	2.86	2.49	−0.61	
Fund 20	1.03	0.34	0.32	0.43	0.88	0.11	−0.24	0.12	−0.24	0.90
	3.49	3.22	3.21	5.05	27.29	1.95	−2.58	1.71	−2.29	

Panel B: Explaining net fund returns										
Funds	$\overline{R}$	α	α_q	α_{q^5}	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
All, ew	0.54	−0.06	−0.10	−0.04	0.97	0.22	−0.06	0.09	−0.08	0.97
	2.73	−1.29	−2.81	−1.30	114.98	12.98	−2.95	3.53	−4.09	
All, vw	0.49	−0.10	−0.11	−0.07	0.98	0.10	−0.09	0.08	−0.06	0.98
	2.55	−2.91	−3.34	−2.11	111.14	6.13	−4.80	3.37	−3.23	
Top-20, ew	1.00	0.54	0.46	0.36	0.80	0.14	0.09	−0.05	0.16	0.76
	5.80	5.73	4.74	3.65	21.42	3.64	1.42	−0.88	3.08	
Top-20, vw	0.95	0.52	0.37	0.23	0.78	0.12	0.15	0.02	0.21	0.70
	5.51	5.01	3.19	1.92	20.17	3.03	1.83	0.23	3.28	
Fund 1	0.68	0.80	0.17	0.21	1.09	0.38	0.67	0.29	−0.07	0.83
	1.24	2.73	0.76	0.92	13.66	2.51	5.26	3.16	−0.51	
Fund 2	1.02	0.23	0.24	0.15	0.97	−0.04	0.05	−0.13	0.19	0.95
	2.79	2.19	1.87	1.48	28.43	−0.85	0.75	−1.17	1.95	
Fund 3	1.16	0.75	0.64	0.47	0.72	0.23	0.00	0.06	0.29	0.54
	4.29	4.01	3.36	2.16	10.48	3.79	0.01	0.64	2.25	
Fund 4	1.02	0.55	0.56	0.49	0.72	0.10	−0.11	−0.08	0.15	0.62
	3.44	3.08	2.91	2.58	12.77	1.60	−0.90	−0.55	1.16	
Fund 5	0.92	0.21	0.11	0.08	0.93	−0.14	−0.13	0.10	0.08	0.94
	2.82	2.23	1.31	0.91	33.01	−4.06	−2.77	2.54	1.36	
Fund 6	0.79	0.10	0.08	0.04	0.96	−0.08	0.02	−0.01	0.07	0.98
	2.32	1.81	1.33	0.72	58.66	−3.34	0.70	−0.39	1.97	
Fund 7	1.49	0.48	0.47	0.46	1.04	0.06	−0.51	0.00	0.01	0.86
	3.35	2.36	2.52	2.29	14.95	0.75	−4.15	−0.05	0.13	
Fund 8	0.81	0.58	0.44	0.30	0.71	0.20	0.07	−0.13	0.26	0.64
	2.90	3.44	2.02	1.38	11.64	2.83	0.57	−1.10	1.96	
Fund 9	0.77	0.28	0.21	0.11	0.85	−0.03	0.17	0.00	0.17	0.88
	3.36	2.88	2.21	1.26	34.45	−0.66	3.01	0.08	3.29	
Fund 10	1.04	0.59	0.22	0.06	0.85	0.07	0.17	0.23	0.27	0.67
	4.01	3.30	1.14	0.31	15.15	1.26	1.37	3.04	2.56	
Fund 11	0.50	0.22	0.14	0.13	1.03	0.11	0.09	0.03	0.01	0.94
	1.02	1.63	1.11	1.08	21.77	1.87	0.97	0.46	0.10	
Fund 12	1.33	0.55	0.63	0.53	0.79	0.28	−0.21	−0.23	0.18	0.72
	3.30	2.38	2.77	2.33	12.63	2.16	−1.20	−1.59	1.06	
Fund 13	0.80	0.09	0.03	0.05	0.92	−0.05	0.02	0.14	−0.04	0.97
	2.92	1.57	0.63	0.97	55.97	−1.99	0.66	4.53	−1.01	
Fund 14	0.83	0.05	0.01	0.00	0.99	−0.08	0.02	0.06	0.02	0.98
	2.63	0.97	0.21	0.03	89.86	−4.32	0.83	3.52	0.80	
Fund 15	0.78	0.37	0.26	0.29	0.89	0.22	0.03	0.05	−0.05	0.82
	2.39	2.68	2.06	2.34	18.23	2.93	0.25	0.64	−0.56	
Fund 16	0.92	0.33	0.25	0.27	1.01	0.33	−0.10	0.05	−0.02	0.91
	2.83	2.43	2.10	2.33	28.45	6.96	−1.15	0.69	−0.39	
Fund 17	1.09	0.37	0.34	0.22	0.98	−0.01	−0.57	−0.17	0.25	0.88
	2.70	1.88	2.08	1.48	18.86	−0.11	−5.44	−1.97	2.11	
Fund 18	1.36	1.13	0.84	0.90	0.95	0.30	0.26	0.16	−0.10	0.35
	2.20	2.10	1.60	1.74	4.77	1.63	0.93	0.70	−0.32	
Fund 19	0.93	0.41	0.21	0.24	0.94	0.23	0.32	0.21	−0.06	0.83
	3.01	2.26	1.44	1.68	15.86	2.50	2.86	2.49	−0.62	
Fund 20	0.95	0.26	0.24	0.34	0.89	0.11	−0.24	0.12	−0.24	0.90
	3.20	2.42	2.36	4.02	27.39	1.93	−2.60	1.71	−2.26	

Table 10 : Buffett's Alpha, February 1968–December 2020

For Berkshire excess returns, Panel A shows the average, $\overline{R}$, q-factor alpha, q^5 alpha, loadings on the market, size, investment, Roe, and expected growth factors, β_{Mkt}, β_{Me}, $\beta_{\text{I/A}}$, β_{Roe}, and β_{Eg}, respectively, and R-squares from the q-factor and q^5 regressions. Panel B reports the AQR 6-factor regressions, in which we use the QMJ factor from the AQR Web site. All the t-values reported in the rows beneath the corresponding estimates are adjusted for heteroscedasticity and autocorrelations.

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

Sample	$\overline{R}$	α	β_{Mkt}	β_{Me}	$\beta_{\text{I/A}}$	β_{Roe}	β_{Eg}	R^2
2/68–12/20	1.41	0.59	0.77	−0.04	0.59	0.38		0.19
	4.98	2.34	8.89	−0.24	3.82	3.31		
		0.74	0.74	−0.06	0.64	0.46	−0.23	0.19
		2.66	8.58	−0.35	4.06	3.40	−1.30	
11/76–3/17	1.51	0.47	0.87	−0.14	0.73	0.48		0.27
	4.81	1.72	10.29	−1.00	4.37	4.41		
		0.65	0.85	−0.16	0.78	0.58	−0.29	0.28
		2.07	9.72	−1.16	4.55	4.47	−1.44	

Panel B: 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
2/68–12/20	0.58	0.79	−0.12	0.33	−0.01	0.24	0.30	0.20
	2.07	8.99	−0.79	2.50	−0.12	2.51	2.13	
11/76–3/17	0.45	0.93	−0.18	0.40	−0.05	0.27	0.39	0.29
	1.67	10.67	−1.45	3.20	−0.91	2.98	2.79	